

ARIA-VALUSPA Full-term Report – Public version –

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1 EXECUTIVE SUMMARY

This final report describes the activities conducted during the 36-month ARIA-VALUSPA Horizon 2020 project. We will restate the main goals, describe our noteworthy outputs technical and scientific, detail our public engagement and impact activities, dwell on the challenges and unresolved issues faced during the project, and provide a task-by-task report of work-package activities.

Please let us start by restating our main goals. Task-specific AI is attaining superhuman performance in an increasing number of domains. In the near future, virtual humans (VHs) will be the human-like interface for increasingly capable AI systems, in particular information retrieval systems.

However, there remains a large gap in the smoothness of the interaction between interacting with either a current VH or another human being. In ARIA-VALUSPA we aim to drastically reduce this gap.

This means first and foremost that interacting with the ARIA-agents should be engaging and entertaining. They should display interactive believable behaviour that feels real. They should be adaptive to the user at various levels, from adapting to a user's appearance, age, gender, and voice, to sudden changes in the dialogue initiated by the user.

Some particular challenges that we set ourselves in the project were to deliver a reusable framework that can be used to create Virtual Humans with different personalities, behaviours, and underpinning knowledge bases. We have done so through the ARIA-VALUSPA Platform (AVP), of which the latest version is 3.0. It is described as a noteworthy output of the project in section 2. AVP is in principle independent of the language spoken by the user. We show this by delivering the assets of the system in three languages - English, French, and German.

Another important challenge that we set ourselves is to be able to deal with unexpected situations, in particular interruptions initiated by the user. This is a hard problem that has not been addressed previously. Interruption handling is integrated throughout the framework, enabling the detection of interruptions, planning new utterances when an interruption by the user has been detected, and abruptly stopping and replacing behaviour generation when necessary. The scientific breakthroughs to this are described in section 3.9, but aspects of interruptions feature in most work-package reporting.

A challenge in Text to Speech (TTS) systems is creating smooth, natural sounding voices with affect. One of our biggest achievements is the development of an affective TTS that can turn neutral speech into emotional speech using a markup language to markup the original (neutral) text. Through working closely with the visual behaviour generation team, seamless lip synchronisation has been achieved.

The behaviour analysis systems, from audio, video, or using combined audio-visual features, is truly state of the art and has progressed markedly over the period of the project. Integrated in the Social Signal Interpretation (SSI) framework, it includes the fastest and most accurate face tracker, state of the art re-trainable ASR, emotion, gender, and age estimation, and a number of other features.

In terms of impact, we have consistently engaged with the general population through a series of blog-posts on our webpage (https://aria-agent.eu), and through open-science

Affective Retrieval of Information Assistants - Virtual Agents with Linguistic Understanding, Social skills, and Personalised Aspects (ARIA-VALUSPA)

events such as the London Science Museum's Lates, and the University of Nottingham's Wonder festival. In terms of academic impact, the project has led to 100 peer-reviewed academic papers, which have already attracted more than 1,000 citations between them¹. More than 20.5 M EURO has been awarded in follow-up funding.

 $^{^{-1}}$ As measured by Google Scholar on 23 February 2018

Affective Retrieval of Information Assistants - Virtual Agents with Linguistic Understanding, Social skills, and Personalised Aspects (ARIA-VALUSPA)

2 NOTEWORTHY OUTPUTS

A number of outputs of the project are particularly worthwhile, and are highlighted below in some detail. Note that these outputs often bring together contributions from more than one work-package and more than one task, and as such their full value would not come to justice if read from the individual work-package report sections.

2.1 AVP: ARIA-VALUSPA PLATFORM FOR VIRTUAL HUMANS

The ARIA-VALUSPA Platform from Virtual Humans (AVP) is a general-purpose, modular software platform for the creation of virtual humans. It is developed in this project based on the lessons learned from the SEMAINE project and the Virtual Human Toolkit. It is free of use for non-commercial purposes, with large parts available as open source and the remainder as publicly available compiled library interfaces.

AVP is currently at version 3.0 and is available from GitHub: https://github.com/ ARIA-VALUSPA/AVP, where you can also find all installation instructions and detailed documentation for the various modules and their configurable settings.

2.1.1 AVP ARCHITECTURE

AVP is essentially an architecture for interconnected modules each with a specific functionality, which run independently but communicate through an ActiveMQ layer to update the agent's state and ultimately generate the most relevant behaviour when interacting with a user. Fig. 2.1 shows the high-level architecture of AVP. It consists of three mayor blocks: an input or *Behaviour Sensing* block, an *Agent Core* block, and a *Behaviour Generation* block. Blocks can and do consist of multiple modules. For example, the Behaviour Sensing block consists of the Automatic Speech Recognition module (ASR), the visual analysis module (eMax), and the audio-based paralinguistic analysis module (OpenSmile).

The three blocks can be briefly described as:

- The Behaviour Sensing block: responsible for collecting and processing audio-visual data about the user in terms of spoken words, recognised emotion, and estimated identity and demographics. This data would then be fed to the Agent Core.
- The Agent Core block: responsible for receiving the Input module's data, analysing it and deciding on the agent's response and behaviour. This module is also in charge of maintaining an information state that captures the agent's knowledge about the world. Finally, it is responsible for feeding back information to the Input module when incorrect information is detected.
- The Behaviour Generation block: responsible for determining fine-grained expressive behaviour, rendering the Character and playing the speech through a text to speech (TTS) component, and ensuring that the speech and character animations are synchronous and believable.



Figure 2.1: The ARIA-VALUSPA Platform (AVP) architecture.

The three blocks use ActiveMQ as a message broker for communication. This architecture allows us the flexibility of using different implementation languages and even deploy multiple machines to run the different modules, with the added overhead that all modules should interface with the ActiveMQ broker. One significant example of this modular approach is that we are actively developing three Graphics Behaviour Generation modules, that we can use to easily switch between a more polished-looking but animation-driven agent (Living Actor) with more limited behaviour or one that is more suitable for researching the minutiae of expressive behaviour (Greta). The third graphics realiser is the popular Unity3D graphics engine, which allows seamless integration of ARIA agents in games, augmented reality and virtual reality projects. Note that all three visual behaviour generation options require Greta to run to interpret FML from the Agent Core block.

In order to demonstrate how the ARIA Framework can be used to address the reality of the user's needs the project has delivered a number of instances of two use cases. One use-case is a smart and interactive book reader, and the other is an end user support system for advice on stain removal. If the first use-case - called the Book-ARIA - is an academic implementation of the ARIA Framework, the second use-case - called the Industry-ARIA - is backed by a large corporate entity. For sake of confidentiality their identity, and most details of the Industry-ARA, is removed from this public version of the final report.

2.1.2 AVP IMPLEMENTATION

Each of the three blocks (Behaviour Sensing, Agent Core, and Behaviour Generation) are run as separate binaries, and communicate using ActiveMQ. Below we describe the three blocks in some detail:

Behaviour Sensing: We use the Social Signal Interpretation (SSI) framework, developed at the University of Augsburg, to grab the audio-visual input of the user. This allows us to have a layer of abstraction from the raw input, but also ensures that different sub-modules will be synchronised even if they need different amounts of time to process a frame/period. SSI also collects the output of different components into a single XML file, which can be sent over ActiveMQ to the Agent Core module.

The behaviour sensing block was built by integrating three different processing components, as shown in Fig. 2.2: eMax, Kaldi (ASR), and OpenSmile. Each component is in charge of three different aspects of the interactions between humans and agents:

- 1. Visual Behaviour: eMax is used for visual analysis of a user's facial appearance and expressive behaviour. Processing consists of face detection, face recognition, facial point detection and alignment, estimation of head-pose, and finally recognition of the displays of six basic expressions and a number of facial muscle actions (FACS Action Units [18]). In addition, age and gender are estimated from the face shape and appearance. Due to processing power constraints, a fixed framerate of 5 video frames per second was used. After processing a frame, the basic expression output consists of the 6 basic emotions (anger, disgust, fear, happiness, sadness, surprise), which are further processed to provide a prediction for valence and arousal. Deep-learning based face frontalization will soon be added.
- 2. Audible Behaviour: Opensmile is used to recognise interest, gender, age, and emotions from audio. Arousal and valence are reported as values between 0 and 1, with 0.5 being neutral. Interest is reported as values between 0 and 1, 0 indicating low interest and 1 high interest. Age is reported as a probability of the user belonging to one of four categories (child, youth, adult, senior), while gender is reported as the probability of the user being either male or female.
- 3. Speech Recognition: Kaldi is used for automated speech recognition (ASR) into SSI. Unlike the rest of the framework, the ASR must run on a separate Linux server, as there is no Windows OS version available. To maintain consistency, audio is still recorded through SSI, and as a result we are opening a direct port between the machine running SSI and the machine running Kaldi, through which audio is sent and a transcript is received. The ASR outputs predictions in two versions: at word-level and sentence-level. Word-level prediction returns predictions faster but with a higher error, as it lacks the opportunity to use between-word correlation. Speech is recognised in three languages: English, French, and German.

Each 500 milliseconds a summary of the latest output of each component is added to an XML file and it this is sent through ActiveMQ for use by the Agent Core and Output modules.



Figure 2.2: Input Module Visualisation

Agent Core: This module is implemented in Java. It contains the dialogue manager, the knowledge base, the information state, and an ActiveMQ receiver that can parse the XML files sent by the Input block. This ActiveMQ receiver converts the information contained in an XML file into objects that can be used by the dialogue manager component.

The dialogue manager was implemented using Flipper 2.0, itself based on Flipper [43], a template-based library for specifying dialogue rules for dialogue systems. Based on the user's reported emotions, gender, age, and speech transcript a response would be composed in form of a BML file, which contains the agent's behaviour and response. This is passed using ActiveMQ to the Output block where either Greta or Living Actor are responsible for interpreting and displaying the agent's response. The templates have tags that allow the agents to generate behaviours that communicate different emotions for the same utterance.

For testing purposes, a separate window was added, in which the user's speech can be written as text, was added. This text is set as the transcript to the XML file received from the Input module, as such there is no perceivable difference to a real transcript. This can also be used to monitor the conversation between the two parties. An example of this window is shown in Fig. 2.3.

Behaviour Generation: The visual behaviour is prepared by Greta, and realised (turned into graphics) by either Greta, developed by CNRS, Living Actor, developed by Cantoche, or Unity, the 3D environment development kit of choice for researchers and professionals alike. Both Greta and Living Actor instantiate a character capable of interpreting Behaviour Markup Language (BML) files. Unity uses a combination of Mpeg-4 FAP and BML, both produced by Greta. The speech synthesis is realised by CereProc. Responsibility for activating the speech synthesis and maintaining synchronisation of the visual and auditive behaviour generation (in particular lip movements) rests with both Greta and Living Actor, separately and individually.

hello Hi, you sound sad, are you alright? yes I am how are you I am ok, but you sound sad. Shall we talk about Alice in Wonderland to cheer you up? who is alice Alice is a sensible prepubescent girl who ends up in the wonderland.



2.1.3 System Launcher

As the system is composed of three different windows binaries (Behaviour Analysis, Dialogue Management and Behaviour Generation) and a Linux binary (ASR) that communicate using ActiveMQ, a launcher program is required to start and stop the whole system. The launcher first ensures that ActiveMQ is started and ready to use, then starts the Input block, followed by the Agent Core, followed by the Output block. It also ensures an easy way to stop the whole system.

The launcher has a small number of XML configuration files, which include the location of the binaries, which Behaviour Generation version to use (Greta or Living Actor). A separate configuration file is maintained for each block, with two variants currently available for the Output block. Having separate configuration files for each block allows us to dynamically start and stop whole blocks while the rest of the Framework continues running. Figure 2.4 shows a screenshot of the graphical launcher interface.

2.2 ARIA INSTANTIATIONS

One of the project's main aims is to be able to create different Virtual Humans, with different personalities, behaviours, and knowledge-bases, all based on the same framework. To proof this, we have developed the Book-ARIA and the Industry ARIA, described in the sections below. In addition, we have developed a version for the Unity 3D programmable gaming environment.

2.2.1Воок-ARIA

From the onset of the project a virtual human representing the characterization of a novel has been developed. The large number of public domain novels that can be adapted means there is an immense potential for the creation of very rich and diverse agent personalities. Moreover, the Book-ARIA is believed to have commercial value in its own right. More



Figure 2.4: Graphical user interface for the AVP system launcher

generally, the Book-ARIA functions as a showcase of what rich personalities can be generated with ARIA-VALUSPA and how they function as interfaces for information retrieval for more complex tasks, that is, questions about the novel's content, characters, author, etc. For the purpose of this project, the novel *Alice in Wonderland* by Lewis Caroll has been selected as an illustrative example.

Alice has been created by Cantoche for WP5 to be the face of the Book-ARIA, and she quickly became the effigy of the ARIA-VALUSPA project, featuring in the project's logo and generally becoming the poster girl for all outward facing activities. Some examples of the Living-Actor version of Alice are shown in Fig. 2.5

To give life to Alice, we use the Living Actor technology which allow to convert a 3D mesh to an animated object that could be used in videos, html pages as well as 3D applications.

PROOF OF CONCEPT The Book-ARIA subject has been split in two steps. First a Proof of Concept (PoC) was made using existing technologies and solutions, and this has then been followed by an implementation in the ARIA Framework. The PoC consists of an HTML page containing an animated character and an extract of the "Alice in Wonderland" novel (see Figure 2.6). The PoC is available online from http: //www.livingactor.com/clients/ARIABook/. On the request of the user, the avatar starts reading the novel, her voice is dynamically generated by Cereproc using their text to speech (TTS) API. The user can interrupt the speech when he wants in order to ask a



Figure 2.5: Samples of Alice expressive posing.

question to the avatar about the author, a character, or a chapter, and then resume the reading where he stopped. The question answering technology used to interact with the user is set up by Cantoche.

POC LIMITATIONS In the PoC, we use an HTML5 compliant avatar. Even though the Living Actor Avatars are built in 3D, we use pre-generated 2d animations due to device technical limitations. The HTML5 Living Actor Avatar is not a video, but an animated object which can be controlled by JavaScript in order to trigger a selected animation at a specific time and for a specific duration. Even though it's sufficient for the PoC, the project has more ambitious goals that can not be reached with this kind of solution. For example, the avatar has pre-generated animations that limit its possible behaviours. Lip synchronisation with the speech, and interruptions mid-animation are also issues that are inherently difficult to fix with the HTML5 avatar.

MAIN IMPLEMENTATION The final implementation of the Book-ARIA is the Alice in Wonderland scenario, which allows users to chat with Alice about the book written be Lewis Carol. Two scenarios are available: a standard chat, without any particular goal for the user, and a 'quest' scenario, where the user is expected to retrieve personal information from Alice, which she will only divulge after her personal relation with the user is strong enough. See the deliverable on the system assessment (D6.4) for full details on how Alice and the user build a personal relation over time.

2.2.2 Industry-ARIA

At the end of year 1, several companies presented an application to be involved in the project. The management board has selected xxx as a partner, who presented the most



Figure 2.6: Screenshot of the Book-ARIA POC web page.

promising business case (See Deliverable D7.2 for a description of the selection process). The Industry-ARIA is confidential and it, nor information about it, will not be made

publicly available, but will be demonstrated at the final review meeting.

2.3 NoXI: Multilingual, Multimodal Database of Novice-Expert Interactions with Interruptions

An important contribution of the ARIA-VALUSPA project is the NoXi database, now consisting of two main parts: one a set of Human-Human mediated Novice-Expert interactions, and the other a set of Human-Agent interactions with the AVP system. NoXi was designed to provide spontaneous interactions with emphasis on adaptive behaviours and unexpected situations (e.g. conversational interruptions) and was recorded with the aim to be of wide use, beyond the direct goals and aims of the ARIA-VALUSPA project.

The resulting NoXi database was published and presented with a poster at the International Conference on Multimodal Interaction in November 2017, in Glasgow, UK [13]. This presentation described only the Human-Human partition. A presentation on the full database including Human-Agent interactions should follow. The poster presentation drew a lot of interest, both in the database and in the NoVa annotation tool that we used to create annotations for it (see section 2.4). At the time of writing, the NoXi database has 22 users, 12 of which are from outside the ARIA-VALUSPA consortium.

The Human-Human part of the database consists of 84 dyads recorded in 3 locations



Figure 2.7: NOXI Recording setup: Novice (left) and expert (right) having a screenmediated conversation. The interaction is monitored (middle) and recorded in sync.

(Paris, Nottingham, and Augsburg) spoken in 7 languages (English, French, German, Spanish, Indonesian, Arabic and Italian). Expert/Novice pairs discussed 58 wildly different topics and more than 25 hours of synchronized audio, video, and depth data was collected. Efforts have been made and are currently ongoing to add semi-automatic annotations to this data. See D6.2 for a full description of the Human-Human part of the NoXi database.

The Human-Agent part of the database consists of ... recorded in Nottingham, spoken in English. The same room and sensor setup was used as for the Human-Human interactions. See D6.4 for a full description of the Human-Human part of the NoXi database.

We have also added a collection of early Wizard of Oz interactions between a human and a agent controlled by a wizard, which was used to explore interactions with agents in the Book-ARIA domain (described in detail in D6.1 and below in section 6.3.5). This data, called the HAI data, is not structured in the same way as the NoXi Human-Human and Human-Agent partitions. Instead, a link to a single archive file is provided on the NoXi database website.

NoXi is made freely available to the research community and for non-commercial uses. It is available through a web interface at: https://noxi.aria-agent.eu/ after users create an account and sign the EULA.

Figure 2.7 shows a sketch of the NoXi recording setup for the Human-Human and Human-Agent interactions. We see that participants are located in separate rooms having a screen-mediated conversation. To this end, audiovisual data is streamed from one room to the other and replayed on a screen (a third end-point was added to silently monitor the recorded streams). We used Microsoft Kinect 2 to capture various signals from each participant including HD video, depth data, skeleton and face tracking. In addition we used high-quality head mounted microphones to obtain clean speech recordings. This summed up to a bandwidth of 9.3 GB per minute and user (1.4 GB after compression).



Figure 2.8: Snapshots of a novice-expert dyad in a recording session.

To keep recorded signals in sync we implemented the system with the Social Signal Interpretations (SSI) framework developed at the Augsburg University [50]. Figure 2.8 shows a snapshot of the recording.

However, NoXi not only contains a massive amount of raw interaction, but also comes with a large number of annotations. Some of the annotations have been created completely manually, while other were derived in fully or at least semi-automated way. Annotations accomplished so far range from speech and filler transcriptions, over body movements and facial features, to affective dimensions and interest scores. In the following section we will introduce a tool that we have developed to accomplish this task.

2.4 NOVA: Multimedia Annotation Tool with Integrated Machine Learning

To handle the vast amount of data in the NoXi database within the limited time span of the project, we opted for a collaborative and semi-automated workflow. Since no tools were available that would suit our needs, we decided to implement a novel annotation tool: NOVA ((Non)Verbal Annotation) for the Windows OS under the GPL 3.0 license. This tool has now been made public to the general research community, and is available on GitHub here: https://github.com/hcmlab/nova. A paper describing it is currently under peer review, but while presenting NoXi at ICMI 2017 in Glasgow, there was already a lot of interest in NoVa.

The main features of NOVA are:

- 1. Support for multiple annotation schemes (e.g. discrete labels vs. continuous scores).
- 2. Support for viewing content beyond audiovisual media (e.g. visualisation of tracking information).
- 3. Database back-end to centrally store annotations and access data from multiple sites.



- Figure 2.9: NOVA allows it to visualise various media and signal types and supports different annotation schemes. From top down: full-body videos along with skeleton and face tracking, and audio streams of two persons during an interaction. In the lower part several discrete and continuous annotation tiers are displayed. Annotations can be edited on a static fraction of the recording or interactively during playback.
 - 4. Advanced user management to share annotation tasks among multiple raters (including strategies to combine annotations of several users).
 - 5. Access to machine learning tools to create semi- and fully-automated annotations on the fly.

Figure 2.9 shows the main interface of NOVA. We can see that apart from audiovisual content, also facial and body tracking data can be displayed. NOVA is also not limited to a specific annotation scheme, but supports time-discrete and time-continuous annotations either based on a set of pre-defined labels or within a value range. There is no limitation on the number of data and annotation tracks that can be loaded and edited.

The real power of NOVA, however, is the full support of a cooperative machine-learning work-flow as shown in Figure 2.10. In fact, the meaning of *cooperative* is two-fold. On the one hand, NOVA allows multiple annotators to work on the same database. User rights are centrally managed and allow users to display (and sometimes even edit) annotations of other users. If multiple annotations are available for the same content they can be



Figure 2.10: CML integration in NOVA: (A) A database is populated with recordings of human interaction. (B) NOVA functions as interface to the data and provides a database to distribute and accomplish annotation tasks among human annotators. (C) At times, CML is applied to automatically complete unfinished fractions of the database: (C-I) A session-dependent model is trained on a partly annotated session and applied to complete it. (C-II) A pool of annotated sessions is used to train a session-independent model and predict labels for the remaining sessions. In both cases, confidence values guide the revision of predicted segments (here marked with a pattern).

merged to establish a gold standard. On the other hand, users can draw on machine-aided predictions, too. For instance, a rater can ask NOVA to automatically complete a partially finished annotations. The tasks of first extracting features from the raw media files and afterwards learning a classification model are automatically handled by NOVA. A user only needs to choose from a set of available feature extraction and learning algorithms. Hence, using these tools in NOVA does not require a signal processing or machine learning background. Yet, skilled users can add their own feature extraction methods and extend NOVA with new learning algorithms.

NOVA has seen tremendous progress during ARIA-VALUSPA, with no less than 810 commits and 82 releases made since December 2017. It is now at version 1.0.1.8.

2.5 Idlak Tangle: a free DNN-based Text-To-Speech Toolkit

Statistical parametric speech synthesis based on Hidden Markov Models (HMMs) has become a common method for generating highly intelligible, flexible speech output. The dominant system, HTS [56], has been developed for over a decade, and led the way in developing parametric synthesis approaches and algorithms.

More recently, spurred on by the success of Deep Neural Networks (DNNs) in speech recognition [24], significant research has been carried out investigating the use of DNNs in parametric speech synthesis [31].

Idlak is a project to build an end-to-end parametric synthesis system within Kaldi [37], a liberally licensed Automatic Speech Recognition (ASR) toolkit. As part of Idlak, a front-end that generates full-context models compatible with HTS has been developed [4]. This front-end performed well in an evaluation against Festival, a standard front-end used by HTS. We have now released a system based on one of Kaldi's DNN frameworks as an alternative to the standard HTS/HTK modelling framework. We have called this end-to-end TTS-DNN system *Tangle*. Although other open source systems are available none offer a single framework with text normalisation and back-end processing in the same environment.

Idlak Tangle first uses Kaldi to carry out a phoneme alignment on a single-speaker corpus. This alignment is then used to train two cascading DNNs: one to predict unit durations, and a second for predicting acoustic output. Also incorporated are analysis and synthesis tools to perform MLSA vocoding with mixed excitation [54] and a simple recipe to encourage other research groups to reproduce our results. All the necessary code can be downloaded from the Kaldi-Idlak repository https://github.com/bpotard/idlak² allowing our results to be reproduced. Tangle only depends on tools that use either BSD (SPTK, expat, PCRE), Apache (Kaldi, openfst), or MIT (pugixml) licenses, allowing the use of Tangle for both commercial or academic applications. Tangle and Idlak are both released under the Apache license.



Figure 2.11: Tangle DNN training architecture

The primary motivation for our work can be summarised as follows:

²Currently the Idlak branch of Kaldi can be installed with git clone https://github.com/bpotard/idlak.git

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- 1. It is part of a long-term goal to produce a Kaldi-based end-to-end parametric speech synthesis system. HTS suffers from licensing restrictions that prevent a standard open-source model. In addition, many new approaches in ASR are already implemented within Kaldi, such as sophisticated DNNs [49] and sub-space modelling [36]. This would allow current and future ASR developments to be directly incorporated into speech synthesis as they become available and vice versa.
- 2. High quality vocoders are a requirement for a good sounding parametric TTS system; however most of the available ones are either low quality or suffer from licensing restrictions that make them unsuitable to be included directly into an open source project with a liberal license. By re-implementing state-of-the-art vocoding techniques into Kaldi, we hope to bridge that gap and offer the first free high quality parametric Text-to-Speech system.
- 3. By making our system openly available, together with the tests we describe, we offer a useful test harness and a better sounding baseline than HTS-demo to the community.

3 Noteworthy Scientific and Technical Breakthroughs

Like the noteworthy outputs described in section 2, a number of scientific and technical breakthroughs are worth highlighting here separately.

3.1 Incremental Cascaded Continuous Regression for Real-time Face Tracking

The core of the visual part of eMax is the Face Tracking system, in which an indexed set of 66 points, representing the location of key parts, such as the nose, the eyes, the mouth, or the contour, are tracked along the video sequence. All the other visual blocks build on accurately localising these points. The field of Face Tracking has long been an active research topic, aiming to develop fast and accurate methods. The state of the art method for Face Tracking, capable of working in real-time, is the Cascaded Regression of Xiong and De la Torre [52], known as Supervised Descent Method (SDM), in which an initial guess or estimate of the shape (the facial points), is passed through a cascade of linear regressors, each taking as input some local information extracted from the image around the given points (the features), and outputting a displacement towards the target locations. These regressors are fixed, and are learnt from a set of images for which the points have been manually annotated (the training set). To train the first regressor, for each of the images the initial shape guess is computed, given as random variations on the ground-truth data according to some statistics modelling how shapes vary within consecutive frames. Then, the features are collected for the training images in the given initial shapes, and a regressor is learnt through minimising the least-squares error. This regressor is then used to update the initial shapes, and the process is repeated, until the incremental improvement is too small (typically after 4 or 5 iterations).

The main problem of this approach is that the training needs to be done sequentially, and the models cannot adapt to the user once they have been trained, as this would require re-training the models again, which can take up to several hours. It has been shown that models trained to track specific and known faces are more robust than generic models, trained on a fairly big training set of images. Given that it is infeasible to train person-specific models, it is a desired target to incorporate the current information from the user to the models as the tracking is ongoing. This is known as incremental learning. The sequential learning procedure of SDM impedes its application. However, it has been shown that an SDM can be trained in parallel [3], bringing the possibility of incremental learning for the first time, at a cost of 4 seconds per frame, still far from real-time performance.

Thus, as part of the research conducted in ARIA, we have developed a novel approach to learn each of the regressors, resulting in a very fast learning method that also enables the use of incremental learning in real time. Our new method, coined incremental Cascaded Continuous Regression (iCCR), applies a Functional Regression approach to the least squares problem, assuming the target variables (the points) to be part of a continuous space, and considering an infinite set of perturbations when training the model.

More specifically, instead of generating samples at the perturbed locations, Continuous Regression approximates all of them by a first-order Taylor expansion, effectively marginalising the perturbations from the feature extraction process. This expansion linearises the features with respect to the perturbations, and enables the possibility of integrating over an infinite set of perturbations, yielding a closed-form solution. Moreover, contrary to previous works on Functional Regression, the proposed formulation integrates the space of perturbations over a non-Euclidean manifold, in which the correlation between variables are considered, thus avoiding non plausible perturbations.

They key aspect of the solution resides in the fact that it only needs the features to be extracted at the ground-truth positions, as well as that it depends on the statistics of the displacements that would be applied in the sampling-based approach. This implies that all regressors in the cascade can be trained just by replacing the statistics, thus making the effective training time to be reduced to seconds. Once the features are extracted at the annotated positions, the training process is carried out very fast.

The fact that features need to be extracted only once, at the ground-truth solution, also enables the use of incremental learning in real-time. During tracking, once a frame has been correctly fitted, we need to extract the features at the estimated points; we don't need to collect samples as in [3]. This, along with a re-arrange in the recursive least-squares update, reduces the complexity of incremental learning in one order of magnitude with respect to the most expensive operation. This improvement brings the time complexity for incremental learning down from the 4 seconds per frame in [3] to 0.15 seconds in a Matlab prototype, allowing for the first time the use of incremental learning in real time. Its implementation in the eMax C++ library incorporates the incremental learning in parallel threading, keeping a faster than real time speed.

The new proposed iCCR generated a scientific impact with top-tier publications: one at the 14th European Conference on Computer Vision (ECCV, [40]), and one in the IEEE

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Transactions on Pattern Analysis and Machine Intelligence journal (TPAMI, [39], IF 8.23). To validate the proposed approach, the iCCR implementation was tested in the most extensive benchmark that exists to date for Face Tracking, the 300VW dataset ([42]). The results attained by our tracker surpassed state of the art methods, thanks to the incremental learning approach. These results are summarised in Table 3.1, in which the Area Under the Curve (AUC) for the error is reported (the higher the AUC, the better the performance), and compared against the top performance methods on the benchmark.

Method	Category 1	Category 2	Category 3
Yang et al. [53]	0.5981	0.6025	0.4996
Xiao et al. [51]	0.5814	0.6093	0.4865
iCCR	0.5978	0.5918	0.5141
CCR	0.5657	0.5539	0.4410

Table 3.1: AUC for 49 points configuration for the different categories.

This fast tracker is deployed as part of eMax, and has been implemented to run on an iPhone 6 at less than 20ms per frame, as part of a royalty bearing license agreement with MeoGraph, who are releasing their Augmented Reality messaging system based on our tracker mid-February 2018.

Code for iCCR is available from http://www.cs.nott.ac.uk/~psxes1/.

3.2 Dynamic Convolutional Neural Networks for Facial Expression Recognition

Facial expression recognition is a core part of human-human interaction. Replicating this ability is essential for building a fully functional human-machine interface. The Facial Action Coding System (FACS) developed by Ekman and Friesen [18], provides a systematic and objective way to study any kind of facial expression, by representing them as a combination of individual facial muscle actions known as Action Units (AU). However, automatic recognition of facial AUs resulting from spontaneous facial expressions is a hard task. It depends on multiple factors including shape, appearance and dynamics of the facial features, all of which are adversely affected by environmental noise and low intensity signals typical of such conditions.

As a part of the ARIA project, we developed a dynamic deep learning framework for facial AU recognition, to the best of our knowledge the first Deep method for AU detection. The framework uses deep Convolutional Neural Networks (CNN) to learn models of facial Action Units (AU). It is aimed at incorporating the three important characteristics which distinguishes one AU from another: shape, appearance and dynamics. The appearance is modelled through local image regions relevant to each AU. Shape is encoded using binary masks computed from automatically detected facial landmarks. This enables us to learn the relevant shape features instead of using hand-crafted geometric features. Dynamics is



Figure 3.1: A graphical overview of our training pipeline: The colored rectangles in the input image sequence shows the different image regions selected for different AUs. Here we show the extraction of image regions (A) and binary masks (S) for AU 12. These are used as input to the train the CNN. Features extracted from the trained CNN (at the fully connected layer) denoted here as F are used to train a BLSTM network to get final output prediction values O.

modelled in two ways. Short term dynamics is encoded using a short sequence of images as input to CNN. For modelling long term dynamics, the system employs Bi-directional Long Short-Term Memory (BLSTM) recurrent neural networks.

Fig. 3.1 shows a graphical overview of our system. The system uses a CNN consisting of two input streams. The first input streams takes a transformed sequence of image regions as input (for modelling appearance). The second stream takes a transformed sequence of binary masks as input (for modelling shape). The output of the CNN after the fully connected layer (FC) is used for learning a BLSTM (for modelling long term dynamics). In contrast to previous approaches, our system learns all the key features (appearance, shape and dynamics) jointly using a deep learning framework.

The method was evaluated on a number of databases (SEMAINE, BP4D and DISFA) showing state-of-the-art performance on AU detection task. Fig. 3.2 shows the average performance (F1 measures) for AU occurrence detection on the FERA2015 Challenge dataset which is a combination of SEMAINE and BP4D datasets. The performance (2AFC scores) for occurrence detection on the DISFA dataset are shown in Fig. 3.3. Performance per AU is shown in Fig. 3.4. The proposed methodology was presented at the IEEE Winter Conference on Applications of Computer Vision (WACV) 2016 [26].

Code for the Dynamic CNN for Facial Expression Recognition method can be found from http://www.cs.nott.ac.uk/~psxsj3/.

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Figure 3.2: Weighted average performance on FERA-2015 test set (BP4D and SEMAINE) for AU occurrence. Our method is compared against DLE [55], PSN [6], DCNN [22] and Geometric and LGBP feats [48].



Figure 3.3: Average performance (2AFC scores) comparison on SEMAINE, BP4D, and DISFA databases for AU occurrence detection task (using 5 fold cross validation). The proposed approach is compared against CNN based approach [20], DFR [27] and IB-CNN [23]

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Figure 3.4: Per-AU performance (2AFC scores) comparison on SEMAINE, BP4D, and DISFA databases for AU occurrence detection task (using 5 fold cross validation).

3.3 Expressive and Reactive Text To Speech

Recently, the quality of speech synthesis has greatly improved. In many cases this speech is impossible to tell apart from real human speech. Two approaches dominate the field in terms of creating such synthetic speech, and both are based on large corpora of pre-recorded natural speech:

- 1. Unit Selection: New speech is generated by taking segments (or units) of these recordings, cutting them up and sticking them back together in a different order [25, 15, 28].
- 2. Parametric Synthesis: A statistical model, typically using hidden Markov models or deep neural nets, is created from the recorded speech. At synthesis, the model generates parameters for creating speech using vocoder techniques [56, 57].

Current systems are acceptable for reading neutral material such as bank balances, but sound unacceptable if used to read longer texts or more personal information, and in contexts that require responsive communication such as human-computer dialogue. This is a critical problem for applications where maintaining engagement with the user is a key requirement, for example in affective information retrieval applications where maintaining user motivation is crucial. In such use cases we require speech synthesis that can mimic the emotional, reactive and expressive dimension of human speech. Within this challenge ARIA has resulted in two breakthrough technologies: 1) The development of a reactive speech synthesis API which has been integrated into the ARIA-VALUSPA framework (See also section 3.9), and 2) an algorithmic approach to altering voice quality which allows emotion to be added to a previously neutral speech synthesis voice without recording additional data.

3.3.1 Reactive Speech Synthesis

The ability to be interrupted and react in a realistic manner is a key requirement for interactive speech interfaces. While previous speech synthesis systems have long implemented techniques such as 'barge in' where speech output can be halted at word or phrase boundaries, less work has explored how to mimic human speech output responses to real-time events like interruptions which require a reaction from the system. Unlike previous work which has focused on incremental production, we developed a novel replanning approach. The system is versatile and offers a large range of possible ways to react.

Previous work has made the implicit assumption that reactive synthesis has to be incremental e.g [7, 10]. This is not the case, it just needs to be stoppable. To be reactive, the synthesis has to be fast enough to re-plan content (re-planning) and insert it (splicing). It is true that incremental systems offer locations for insertion but, given that any system has full timings described, such insertion points can be chosen without the need for incremental generation.

The re-planning and splicing approach is as follows: given a required latency, e.g. 200 ms, the system must operate fast enough to resynthesise the current chunk of speech with an alternative ending within that time. The initial part of the synthesis must match exactly the initial part of the original chunk. The new audio can then be seamlessly re-spliced into the audio stream replacing the original planned output. This requires tight control of audio playback, but has the advantage of being agnostic to the type of synthesis system you are using.

CereProc's SDK [5] synthesises on a phrase-by-phrase basis, firing a callback between phrases. During the callback a special audio buffer is available which contains the audio of the phrase as well as some metadata. This buffer is queued for playback. We created new functionality in the SDK that takes as input one of these buffers, a minimum interruption time, t_r , and an interruption type, and returns a new buffer. In this buffer the audio up to t_r is guaranteed to be identical to the original buffer. After that it will be interrupted at $t_i \geq t_r$. t_i will be a natural point for interruption, i.e. a syllable nucleus or boundary. Once this buffer is available the agent can seamlessly swap the audio buffer that is being played at some point $t_s < t_r$. By setting this time slightly in the future of when the interruption is needed some latency for processing can be added. This is illustrated diagrammatically in Figure 3.5.

Depending on the call the system has multiple strategies for finishing the phrase:

- stopping immediately,
- tailing off over a few words (a polite turn pass),
- adding Lombard effects for a few words (an angry turn pass),
- completing the original phrase with Lombard effects added.

The system can then add additional speech before returning to the original queue if appropriate. Otherwise it may need to drop some phrases that have been resynthesised

Audio Buffer Play Queue



Figure 3.5: Example of the use of the interruption API, showing the changes in audio buffers. Final played audio is in blue and orange boxes, red and grey boxes are dropped. Note that $t_r - t_0$ must be larger than the maximum system latency.

differently, or empty the queue entirely, depending on the application. The approach we have developed forms the basis of a patent application (No. GB1713273.9).

3.3.2 Algorithmic Modification of Voice Quality

The CereVoice speech synthesis system uses a distinct set of sub-corpora containing different voice qualities to achieve a more subtle change in the perceived emotion in an utterance. Voice quality is an important factor in the perception of emotion in speech. However, unlike speech rate and pitch, which can be modified relatively easily using digital signal processing techniques such as PSOLA, modifying voice quality is more difficult, especially if it is important to retain naturalness. Being able to modify the voice quality, just as we modify pitch and duration, would dramatically improve the quality of emotional voices, reduce their memory footprint and allow us to alter neutral voices to make them sound more emotional.

Key to this approach is work carried out on closed phase LPC vocoding and reported in the ARIA-VALUSPA project's mid-term report. By decomposing the speech into a voicing component and a filter component we can attempt to modify the voicing and put the resulting elements back together. Although LPC vocoding is not a new technique, until recently it was used mostly to compress speech for efficient transmission and storage. The use of LPC analysis for decomposing and modelling elements of the approach are less explored and a subject of current international research.

We term our process Voice Modification via Glottal Signal Modelling (VMGSM). VMGSM is a novel voice transformation technique that relies on human speech source filter uncoupling to specifically model and modify the glottal signal, which contain most of the "voice quality", which is one of the main components of affective speech.

The possibility to explicitly model the glottal part of the speech signal has many advantages, as this can allow the generation of expressive and emotional speech from neutral speech, thus allowing us to add emotional characteristics to any voice. On the other hand, the decomposition of speech is a difficult problem, relying on simplifying assumptions on the form of the voice signal, which inevitably creates artefacts in the resulting modified speech.

While it introduces artefacts, it allows one to deal better with low coverage of unit selections databases, as it contribute to reduce some of the artefacts in unit selection joints, and at the same time can produce large artificial sub-genres for emotional synthesis.

The artefacts introduced by VMGSM make the resulting output currently unsuitable as a generic replacement for the synthesis of neutral speech, however it proves its usability as a possible replacement for specialised use, such as emotional speech synthesis.

Listening tests run internally (and illustrated below) show that while VMGSM is not as effective at generating expressive speech as specially recorded sub-genres, the gap in quality is not as wide as with neutral speech. In addition, the possibility to create fully artificial sub-genres allowed us to add emotional speech capabilities to the "Alice" voice distributed freely with the AVP toolkit. This voice is built from the freely available "SLT" database from CMU, which only contains neutral speech from a single female speaker.

Voice Modification via Glottal Signal Modelling (VMGSM) was inspired by [41]. We



Figure 3.6: Left: Neutral speech (VMGSM modified - red vs. conventional unit selection - blue) Right: Emotional speech (VMGSM modified -red vs. conventional unit selection - blue). Figures show results of an A-B comparison tests where subjects indicated their preference on a 5-point Likert scale.

start with Pitch-Synchronous Iterative Adaptive Inverse Filtering [1], an algorithm widely used and accepted as a method of extracting a glottal signal from recorded speech. Whilst we cannot fully verify the validity of the signal output by this algorithm (indeed there is no ground-truth benchmark), there are certain attributes of a glottal signal we can expect. Spectral flatness, or a familiar pulse-like appearance for example. A more quantitative method of assessing these is via cross-correlation coefficients. The need for this measure is actually two-fold; not only does it help verify the signal, but it also assists in the optimal parameterization of the PSIAIF process for a particular speaker.

Keeping in mind the overarching goal here is voicing modification, manipulating a raw glottal signal estimate that PSIAIF produces can be a somewhat meaningless procedure; to do anything meaningful we need reliable notions of glottal characteristics. Looking at a raw glottal signal, one could guess where these regions are and tweak these durations, but there is no guarantee the modified version will retain any perceptual characteristics we consider to be voice-specific. Instead we can start with a well-formed glottal pulse whose perturbations result in another well-formed glottal pulse. An LF pulse parameterized in the traditional way [30] is an ideal candidate to perform some sort of fitting routine - and a modified version of VOICEBOX's glotlf.m function [8] takes 4 parameters to fully describe an LF-pulse within a pitch-synchronously derived frame of speech. These parameters can be estimated from a raw glottal signal to produce an LF pulse that *fits* the speech frame being analysed.

Going through this procedure per frame yielded glitchy output speech however, as pulses can vary wildly across adjacent frames. Using simple static averaging of parameters within stable regions across an entire spurt of speech, we can obtain a *default* pulse. In order to get this as faithfully close to a speaker's glottal signal as possible, we optimize PSIAIF parametrization via brute-force search, picking values that yield the highest cross-correlation score. Using optimized PSIAIF to yield a reasonable glottal signal, we then fit a modelled LF signal, enabling us to manipulate glottal signal and achieve effects such as the stressed and relaxed outputs demonstrated here; instead of an averaged LF pulse being fed into the analysis, an LF pulse derived from *irritated* and *happy* genres respectively was used. Analysis was run across all spurts available in each genre within the voice's corpus for a particular set of phonemes, alongside some additional tweaking to LF parameters that follow accepted notions of heightening or lowering vocal effort. This approach assumes that genre data was present in the first instance; for a limited corpus in which genre data is not available, we rely only on theoretical knowledge of vocal effort and glottal stress to modify the speaker-specific LF pulse. For a 7-level VMGSM voice, 6 candidate pulses of varying stress were derived from the default neutral pulse. fed into the synthesis stage of an LPC-based vocoder whose output was then added to the original corpus, expanding its emotional coverage. Other auxiliary effects were then used to augment the desired emotion (such as post-synthesis warmth and clarity filtering as well as global pitch modification).

The 7-level emotional voice using VMGSM is freely available and distributed with the ARIA VALUSPA Platform (AVP) via Github. See D7.6 for full details on how to download, install, and customise the AVP.

3.4 END-TO-END AUDIO-VISUAL EMOTION RECOGNITION USING DEEP NEURAL NETWORKS

Following a recent trend in machine learning that aims at building intermediate representations of raw input signals in order to extract task-specific information (which usually leads to a better performance on the recognition task), we used Convolutional Neural Networks (CNNs) to extract features from the speech, and a deep residual network (ResNet) of 50 layers for video. These models were then combined with a Long Short-Term Memory (LSTM) network, and trained in an end-to-end fashion where - by taking advantage of the correlations of each of the streams - we manage to significantly outperform the traditional approaches based on auditory and visual hand-crafted features for the prediction of spontaneous emotional displays.

For the visual domain, we used a deep residual network (ResNet) of 50 using the pixel intensities from the cropped faces of the subject \hat{A} / \hat{Z} s video. The first layer of ResNet-50 is a 7x7 convolutional layer with 64 feature maps, followed by a max pooling layer of size 3x3. The rest of the network comprises of 4 bottleneck architectures, where after these architectures a shortcut connection was added. These architectures contain 3 convolutional layers of sizes 1x1, 3x3, and 1x1, for each residual function. After the last bottleneck architecture an average pooling layer is inserted (see Figure 3.7).

In relation to speech, we learn the feature extraction and regression steps in one jointly trained model for predicting the emotion. The input to the model is a 6 s long segment of the raw waveform to sampled at 16 kHz (this corresponds to a 96000-dimensional input vector). Inputs were normalised to have zero mean and unit variance to account for variations in different levels of loudness between the speakers. Then, we include a temporal convolution layer with F = 20 space time finite impulse filters with a 5ms window in order to extract fine-grained spectral information from the input signal. The output of this layer is then pooled across time. The impulse response of each filter is passed through a half-wave rectifier (analogous to the cochlear transduction step in the human ear) and then downsampled to 8 kHz by pooling each impulse response with a pool size = 2. It follows a temporal convolution, for which we have used M = 40 space time finite impulse filters of 500ms window. These filters are used to extract more long-term characteristics of the speech and the roughness of the speech signal. Finally, we performed max-pooling across the channel domain with a pool size of 10 to reduce the dimensionality of the signal while preserving the necessary statistics of the convolved signal.

The final time-continuous models for the prediction of spontaneous and natural emotions (arousal and valence) were developed on the audio-visual database RECOLA. The dataset was split in three partitions - train (16 subjects), validation (15 subjects) and test (15 subjects) by stratifying (i.e., balancing) the gender and the age of the speakers. For training the models we utilised the Adam optimisation method, and a fixed learning rate of 10-4 throughout all experiments. For the audio model we used a mini-batch of 25 samples. Also, for regularisation of the network, we used dropout with p = 0.5 for all layers except the recurrent ones. This step is important as our models have a large amount of parameters (≈ 1.5 M) and not regularising the network makes it prone on over-fitting on the training data. For the video model, the image size used was 96 × 96 with mini-batch

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Figure 3.7: The network comprises of two parts: the multimodal feature extraction part and the RNN part. The multimodal part extracts features from raw speech and visual signals. The extracted features are concatenated and used to feed 2 LSTM layers. These are used to capture the contextual information in the data.

of size 2. Small mini-batch is selected because of hardware limitations. The data were augmented by resizing the image to size 110×110 and randomly cropping it to equal its original size. This produces a scale invariant model. In addition, colour augmentation is used by introducing random brightness and saturation to the image. Finally, we conducted a series of experiments using a chain of post-processing methods applied to the predictions obtained on the development set: (i) median filtering (with size of window ranging from 0.4 s to 20 s), (ii) centring (by computing the bias between gold-standard and prediction), (iii) scaling (using the ratio of standard-deviation of gold-standard and prediction as scaling factor), and (iv) time-shifting (by shifting the prediction forward in time with values ranging from 0.04 s to 10 s), to compensate for delays in the ratings. Post-processing steps were kept when an improvement was observed on the model performance on the validation set, and applied then with the same configuration on the test partition.

Our experiments included comparisons between single- and multi-modal models. Results show that our the present multimodal approach models achieves significantly better performance in the test set in comparison to state-of-the-art models using the RECOLA database (including those submitted to the AVEC2016 challenge). This is particularly evident for the Valence dimension. A full description of the results and approach can be found in [47].

3.5 COOPERATIVE LEARNING

Like many other data-driven fields, paralinguistic speaker analysis substantially depends on the availability of labelled data, which are difficult and expensive to obtain. Within our project, a novel generic annotation framework has been developed, with the aim to achieve the optimal trade-off between label reliability and cost reduction by efficiently distributing the labelling work amongst human and machine. For the purpose of arbitration, a deep-learning based uncertainty measure is used to pass the most informative instances (with high prediction uncertainty) to human assessment, whereas those instances in a database predicted with high model confidence are labelled by machines. Further, an inter-rater agreement threshold serves as an early stopping criterion to terminate the annotation process when enough ratings have been obtained to determine each instance's gold-standard label. The efficacy of this approach is demonstrated on the "Degree of Nativeness" task of the INTERSPEECH Computational Paralinguistics Challenge. In the result, the novel dynamic cooperative learning algorithm yields .424 Spearman's correlation coefficient compared to .413 with passive learning, while reducing the number of human annotations by 74%. For the annotation of NoXi, the proposed framework has been integrated into the social signal interpreter (SSI) and the nonverbal behaviour analyser (NOVA).

3.6 ALIGNMENT

In order to characterize verbal alignment processes for improving virtual agent communicative capabilities, we propose a framework to quantify the verbal alignment interactive process and the self-repetition behaviour of dialogue partners in dvadic textual dialogues [17]. This framework focuses on lexical patterns appearing in dialogue utterances. The code of the framework is available at https://github.com/ARIA-VALUSPA/ ARIA-DialogueManagement/tree/NLG/ARIA-NLG. It distinguishes two main types of such patterns. The first type is *shared* lexical patterns between dialogue partners (DP) i.e. patterns that are initiated (or primed) by a speaker, subsequently adopted by the other speaker and possibly reused during dialogue by any speaker. These patterns are directly related to the verbal alignment interactive process, a particular type of on-the-fly linguistic adaptation. They can be seen as shared dialogue routines at the lexical level. They are a way to verbally align and ultimately share a common language to improve understanding, collaboration and the social connection to a conversational partner. The second type is lexical *self*-repetition. Contrary to the previous type which considers patterns that are shared between DPs, self-repetition considers each DP in isolation. Self-repetitions are lexical patterns appearing at least two times in the dialogue utterances of a given DP, independently of the other DP's utterances. Self-repetitions are directly related to the self-consistency of the linguistic production of a given DP.

The general idea of the framework is depicted in Figure 3.8. The main concept behind our model is the automatically built *lexicon*. Lexicons keep track of lexical patterns (shared ones and self-repetitions) as well as valuable features of these patterns (e.g., frequency, turns in which they appear). Lexicons can be built automatically for an entire

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Figure 3.8: Proposed framework: automatic building of the shared expression lexicon and the self-repetition lexicons to derive offline and online measures of verbal alignment and self-repetition behaviour. Shared lexical patterns are shown on the dialogue transcript.

dialogue (i.e. offline) or incrementally for a given dialogue history (i.e. online). Our model considers three lexicons: a shared expression lexicon for shared lexical patterns, and two self-repetition lexicons (one for each DP). Lexicons and the dialogue transcript are leveraged by deriving offline and online measures to quantify aspects of the verbal alignment process and the self-repetition behaviour of DPs. Offline measures are intended to be used for past dialogue interactions (e.g., corpus studies) while online measures are intended for use in a dialogue system.

3.7 Context-sensitive analysis of complex multi-modal social signals

For the recognition of social attitudes, such as the engagement/interest of a person towards the agent, we consider Dynamic Bayesian Networks (DBNs) [34] as modelling approach. DBNs are probabilistic models that allow to design correlation between nodes in a network, but also between a node and it's state earlier in time. Even-tough the probabilities for such nodes, and even the overall network structure can be learned with machine learning techniques, it allows to retrace the decisions the DBN makes for each node or layer of nodes. One could think about using alternative models, such as deep end-to-end learning with artificial neural networks [47]. While such approaches deliver promising results on audio-visual data they only give little insights on *how* and *why* they predict behaviours the way they do. Especially in scenarios where it is essential to know why a person is interpreted as e.g. "strongly disengaged", often the idea is to identify cues that led to this interpretation, providing an additional abstraction layer. While a DBN's structure may be modelled based on a theory, our framework offers the possibility to prepare data in a way, so that the DBN learn correlations between the parallel appearance of behaviours, context and complex phenomena.

To this End, the previously introduced NOVA tool exports parallel annotations form the Annotation Database, so that a DBN may learn temporal correlations between multiple

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cues. In the ARIA-Valuspa Project we focused on the detection of the complex behaviour 'Engagement' (respectively the sub-concept Interest).

Figure 3.9: The structure of the engagement network used in the AVP

The NOVA tool, introduced in section 2.4 allows learning of parameters of a (Dynamic) Bayesian Network to fuse multiple observations for a prediction model. As training data, annotations from various annotators are combined. In Figure 3.10 we see the engagement annotation the Gold Standard user on the upper tier. The Gold Standard annotations are created by combining annotations from multiple raters to gain the ground truth. As this will be the node of interest, no evidence will be delivered later during runtime, but rather the degree of engagement will be inferred from other observations. Other annotations, such as the arms-openness, facial expressions or the amount of hand movement have been automatically created using existing models or other recognizers. Finally, manual or semi-automated annotations have been added from a human annotator, that have been created using the Cooperative Machine Learning techniques (see D6.4).

Once the data sheet is created, it is combined with a Bayesian network to automatically map the nodes of the network with annotator/scheme combinations from NOVA. The network used to infer engagement in the AVP is shown in Figure 3.9

To learn parameters in the model the expectation-maximization (EM) algorithm [32] is applied.



Figure 3.10: The gold standard annotation for engagement (top tier) and the prediction of the DBN (lower tier) shown in the NOVA tool

For training models with the NOVA tool, annotations are used to generate data sheets to learn the probabilities in the network. There has to be a trade-off between using sheer manual annotations, which represent the "ground truth" and deliver a perfect foundation for creating the models, and on the other hand automatically created annotations that represent outputs that our classifiers are actually able to predict. By using the cooperative machine learning we are able to adapt the outcomes of the machine already during the annotation process, so that the models reach a state where we can "trust" them to output annotations just like a human annotator would do. That means in conclusion, for our model to work as expected, we need to find social cues that are recognized reliably well, and that represent the problem at hand. Of course, the complex behaviour needs manual annotations to represent the ground truth. As complex behaviours, such as our use-case "engagement" are not straight-forward in terms of interpretation, it's preferable (one could say necessary) to have multiple raters for the given problem. In the Aria-Valuspa Platform we constantly infer the user's engagement/interest based on observations of social cues in multiple modalities, while at the same time considering background context such as the role, gender and turn-taking.

Once we learned the parameters of our DBN, we may use it either for statistical prediction purposes, or in a real-time scenario by updating the nodes with evidences received from our Social Signal Interpretation component, as well as external sources such ARIA's dialogue management system. We receive these evidences by using the network in a SSI [50] pipeline, updating evidences with observations from multiple social signal recognizers, but optionally also external information. Figure 3.10 shows and example instance of the NOVA tool, showing the gold standard annotation for engagement on the upper tier (green), as well as the prediction on the lower tier (blue).
3.8 SITUATION-DRIVEN DIALOGUE MANAGEMENT

Dialogue management requires knowledge about the domain that the agent should be knowledgeable about. This means that domain experts are often called upon when the behaviours of an agent are crafted. However, domain experts often have limited knowledge about dialogue systems making it difficult for them to provide the necessary information. That is why we designed our dialogue management system in a situation-driven manner. This means that domain experts with limited programming knowledge can specify the dialogues an agent should be able to have, by describing situations they expect the agent to be in and describing what the agent should do in those situations. Within dialogue management we distinguish three concepts:

- **Dialogue Manager**. This deals with how the agent behaves in an interaction. This is specified in Management templates: the rules that govern the considerations that the agent can have and all the behaviours that the agent can decide to do. These templates are the abstract framework of the dialogue manager. For example, these templates govern what the situation is when the agent speaks and the user also starts speaking (that would be an interruption).
- **Dialogues**. These describe the scenario that the agent knows about and can converse about. They are defined in a Dialogue Structure consisting of Move templates (see below). Scenarios consisting of Move templates are what a domain expert has to write to create their agent. These templates contain the behaviour that an agent can do and the rules that define when this behaviour is appropriate. For example, when the agent is talking about rabbits and the user interrupts with a question about other animals, an appropriate response can be talking about other animals that the character Alice encountered.
- **Dialogue Engine**. This is the component that performs the underlying tasks that are necessary to create a dialogue manager. The dialogue engine we developed is called Flipper 2.0³: an extended and improved version of the original Flipper engine described in [44].

The Dialogue Manager takes a scenario and situation- driven approach to creating dialogue structures based on conversational acts, and is therefore called Situation-driven Dialogue Manager (SDDM). It shares some properties with current tools for the development of dialogues, such as the use of dialogue trees from DISCO [38] and the use of question-answer matching for information retrieval from the NPC Editor of the Virtual Human Toolkit [29]. Similar to the FLoReS dialogue manager of Morbini et al. [33], the SDDM has been set up to facilitate the creation of structured dialogues with the use of domain experts.

Dialogues for the ARIA system are defined in terms of hierarchical dialogue acts in a Dialogue Structure, see Figure 3.11:

• **Dialogue structure**: this is the root. The name should refer to the name of the character for which the dialogues are defined.

 $^{^{3}}$ https://github.com/hmi-utwente/Flipper-2.0

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Figure 3.11: The hierarchical dialogue structure.

- **Episode**: an episode covers a phase of a conversation (e.g. social, Q&A, reading along with the agent, unexpected situations).
- **Episode.Exchanges**: episodes are made up of exchanges that are related to a topic in the episode (e.g. greeting, farewell, return_greeting).
- Episode.Exchanges.Moves: an exchange is made up of several moves (conversational acts, based on DIT++ [9]). A move can be realized with an utterance, nonverbal behaviour, or a combination of the two. A move has a goal that can be achieved by the behaviour and a status for that goal. Moves are selected for execution based on how relevant they are to the situation in the conversation. Rules define when a move becomes relevant.

Moves are the atomic units (dialogue items) in the Dialogue Manager. A move can refer to a dialogue act of the user or the agent. A move can be listening or speaking, depending on its DIT++ category. We distinguish three types of moves, depending on the information they carry:

- Content/Dialogue Act (C): C-Moves contain the content of the agent or user's utterances, for example if the user asked the question "What can you tell me about Alice in Wonderland?". This is the main move type, see also the next paragraph.
- Interaction Management (I): I-Moves contain information about the interaction. These moves are descriptors for the state of the floor and the agent uses these to decide when to speak. For example, the information that the agent and user are both speaking. This information is obtained from SSI (for the user) and from feedback from the embodiment (for the agent).
- Socio Emotional (S): S-Moves contain information that has to do with the social and emotional state of the agent or user. For example the valence of the user's emotional state as obtained from SSI. A computational emotional model can generate these moves for the agent (currently this task is done by the DM).

The content moves (C-Moves) for the agent are further subdivided depending on the type of content that is contained within the move. This division helps with planning the agent moves (for example combining content with an opinion) and helps a dialogue scenario author to keep track of what purpose a move has:

- Content (C-tag): For the Alice character, this is the type of C-Move that contains factual information from the book, for example which events happened and whom Alice met. An example is: "When I saw the White Rabbit, I chased him into a rabbit hole."
- Opinion (O-tag): A C-Move with an opinion tag contains an opinion, for example Alice's opinion about events or characters from the book, such as: "I thought it was rather strange to see a white rabbit with a watch."
- Meta information (M-tag): A C-Move with a meta information tag contains information on a meta level about the interaction. Using such moves, the agent can talk about the interaction, for example during a lull in the conversation the agent might say "Do you want to continue talking about this?".

The Dialogue Engine (Flipper 2.0) stores all information the agent knows in the Information State. Information comes from various sources and is represented in the form of Moves. During an interaction, the moves of the user are created by the system via the Input Understanding component. Some examples of user moves are:

- The user has made an utterance, and the automatic speech recognition (ASR) outputs a string of words: a C-type user move is generated holding the ASR output.
- The user has started speaking, and this is detected by the Voice Activity Detection: an I-type user move is generated stating that the user has started speaking (and when the agent was also speaking that this is an interruption).
- The user has started smiling, and the SSI updates the valence of the user: an S-type user move is generated holding the user valence.

Additionally, information about the agent's actions is received as input (i.e. feedback) from the behaviour realiser. The behaviour realiser (e.g. Greta) sends continuous feedback about what behaviour has been carried out. Feedback can be:

- BML Callbacks: the BML realiser sends information about which behaviour (BML block) has started, ended, or has been stopped.
- Time Markers Callbacks: during the agent behaviour, the realiser sends feedback on the exact timing of each behaviour that is executed. This is done using time-markers (see section 3.9). For agent utterances this is done on word level.

The feedback allows the Input Understanding to keep track of the floor (i.e. turn-taking) and the completion of the goals of the agent. For example, knowing from the feedback when the agent has stopped speaking and knowing from the ASR when the user has started speaking allows us to determine whether there is overlapping speech and thus whether the user has interrupted the agent. Additionally, the time markers allow us to know what part of the agent utterance has been said uninterrupted (and thus was heard by the user) and what part was not heard because it was interrupted. The agent can concatenate moves, for example a C-tagged C-move ("The White Rabbit had a watch") with an O-tagged C-move ("I liked that watch"). Time marker feedback is used to determine whether the goal of the agent's move was accomplished: if the agent was interrupted before it could complete the utterance, the goal of the move (e.g. of conveying this information) is not accomplished. This may lead the agent to repeat the move.

Moves have rules that determine when the move becomes relevant. The move an agent carries out is selected based on its relevance. We view relevance as the utility value of a move, where the agent is trying to maximize the utilities of moves and plans the moves with the highest relevance above a certain threshold. This threshold is dynamic and decreases when for a certain amount of time no move has been performed and increases when the agent is speaking.

The relevance of a move gets updated by the Agent Move Updater. Relevance is based on the rules in the move. When a rule (akin to a precondition) is met, the relevance of the move increases. Additionally, when the user has said something, this utterance can be compared to utterances predefined in the move to which this move would be an appropriate response. This is an extension of the QA Matching approach. Furthermore, relevance of a move increases if closely related moves (e.g. moves in the same exchange) become more relevant. We use Management templates in Flipper to update the relevance of the dialogue structure.

The Agent Move Selector keeps track of the relevance of all the moves in the Dialogue Structure. Once it has found a move with relevance above the threshold, it selects this move and sends this move to the Move Planner. Additionally, it sends the selected move to the Move Generator for execution by the agent embodiment. The Move Planner keeps track of the current agent move and the planned agent move. It gets information from the move selector and the Input Understanding modules for observed and predicted user moves.

Once an agent move has been selected and put in the move planner, this move is translated to FML-APML. First, the agent's verbal utterance (if present) is extracted from the selected move, and time markers are added to it. Secondly, the emotion of the agent is set, based on the current emotional state of the agent stored in the information state. Furthermore, additional parameters (e.g. backchannel, stance) in the move can be used to fill the placeholders in the FML-templates. Finally, the agent can align the verbal content of its move to the user's word choice by taking the dialogue history into account.

3.9 INTERRUPTIONS

Interruptions are phenomena that frequently occur in human interaction. To study and model interruptions, we first defined a taxonomy of interruptions and measured how different types of interruptions may affect the perception of the social attitude of the interrupter and her level of engagement in the interaction (see D6.1). Interruption may

be characterized in two broad types: disruptive or cooperative [12]. They correspond to different strategies which are expressed by the interrupter through different dialogue acts (i.e. communicative functions). Interruptions may also be distinguished by their temporal relation with the interlocutor's speech. We consider overlaps, silence and replanning.

We dealt with three aspects:

- 1. Studying interruptions and their meaning and effects during the interaction;
- 2. Detecting when a user's interruption occurs;
- 3. Reacting appropriately (i.e. agent) when such interruptions occur.

In regards to the first aspect, we conducted a web study aimed at investigating the effects of interruption strategies and types, in agent-agent interactions, on human perception of both agents' interpersonal attitudes (dominance and friendliness) towards each other, of their level of engagement, and involvement in the interaction (See D6.1). We considered a dyadic agent interaction as it allowed us a complete systematic control of both the interrupter and the interruptee's behaviour. Our next step was to study human-human interruptions. With SSI developed within WP2, we annotated the NoXi corpus [13] to extract information when interruption occurs (see D6.2). This annotation was done, in most part, automatically. We looked at the reactions deployed in response to an interruption at the behaviours level and at the strategy level (see D4.2). Regarding the last aspect, we model different interruption types for the agent. That is we model an agent stopping and holding its gesture; continuing speaking, thus overlapping with user's speech, while marking an increase of emphasis; and replanning what to say and what to gesture. Regarding the third aspect, to characterize precisely the behaviour of the virtual character, we conducted an experimental study where users chose interactively the video of the virtual agents (see D4.3). Videos were ordered following a genetic algorithm. We have identified a large number of parameters that described the virtual agent's behaviours. Manipulating these parameters one per one is very cumbersome. So we proposed to use a web study where participants could visualize four videos of an agent reacting to an interruption. The animations of the virtual characters within the four videos are computed on the fly using genetic algorithm (See D6.4).

3.10 Modelling social attitudes

Interpersonal attitudes and emotions can be characterized by "multimodal non-verbal sequences". We have proposed a model of social attitude as sequences of behaviour. To develop this model, we rely on a sequence-mining method to extract, for each attitude type, (1) the most relevant quantitative timing, and (2) the sequential non-verbal behaviour representing this attitude.

In a first step, we relied on the annotation of an existing database [14]. The annotation is done at two levels: non-verbal behaviour and expressed attitudes (see D6.1). For the non-verbal behaviour annotation we consider the following modalities: gesture (e.g., communicative gestures), hand position (e.g., hands together), posture (e.g., leaning

backwards), head movement and direction (e.g., nods), gaze (e.g., looking at the interlocutor), facial expression (e.g., eyebrow). For social-attitude representation, we use Argyle's bi-dimensional model of attitudes [2], with an affiliation dimension ranging from hostile to friendly, and a status dimension ranging from submissive to dominant. We applied temporal sequence mining so as to find temporally frequent sequences called patterns from a sequence database [16]. We built four datasets of non-verbal signal sequences representing the four attitude variations: dominance increase, dominance decrease, friendliness increase, and friendliness decrease (see D4.2).

Our next step was to evaluate the extracted sequences and measure if they convey a given attitude variation. To this aim we conducted an evaluation study where the behaviour of a virtual character reproduced the annotated sequences (see D6.4). We have used the Greta/VIB platform to generate videos of a virtual agent displaying non-verbal patterns. As our model only considers nonverbal behaviour, we left aside the content of the speech. For this, each non-verbal pattern was shown while the agent spoke the same nonsense speech. For each video, participants rated their perceived attitudes of the agents along 16 adjectives following Leary's model [45].

To model a virtual agent communicating with different social attitudes, we have developed a behaviour planner, called Sequential Attitude Planner (see D4.3). It takes as input an FML file (utterance to be said by the agent) and the attitude variation that the agent will express toward the user. Four steps defined the Sequential Attitude Planner: 1) FML-sequence generation: generation of a sequence of non-verbal signals that expresses the communicative intentions. 2) Attitude-sequence selection: from the sequence dataset that represents the attitude variation that the agent will express, the algorithm selects the most similar sequence to the FML-sequence. 3) FML-sequence enrichment: all signals in the attitude-sequence that do not appear in the FML-sequence are considered to be added to the FML-sequence. 4) Priority signals selection: we designed a Bayesian Network (BN) to model the occurrence probability of non-verbal signals for each attitude.

We have integrated the Sequential Attitude Planner into the Greta/VIB agent platform. Finally we have evaluated this last model. As for the first evaluation study, participants had to evaluate the perceived attitude changes in videos of agents (see D6.4). We found significant differences for two variations, dominance increase and friendliness decrease. We also highlighted correlations between both attitude dimensions, friendliness and dominance, as well as asymmetric correlations between the two extremities of the friendliness axis, friendly vs hostile.

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4 Public engagement

Below we list the various ways in which the ARIA-VALUSPA project engaged with the public.

4.1 Blogs

We established the website http://aria-agent.eu that contains blog entries and news from all partners of the project (see Fig. 4.1.) It further features a list of publications and demo videos, as well as direct download links of the AVP system, the NOVA tool and the NoXi corpus.



Figure 4.1: The Aria Valuspa Blog.

Further we disseminated blog entries on the Social Media Platforms Facebook 4 and twitter $^5.$

4.2 Science Museum Lates

A team from CereProc supported by Dr Eduardo Manuel De Brito Lima Ferreira Coutinho from Imperial College demonstrated various aspects of speech synthesis at the Science Museum in London, as part of the Royal Society's 'The Next Big Thing' project.

⁴https://www.facebook.com/ariavaluspa/

⁵https://twitter.com/ariavaluspa

Lates is a prestigious free public event held once a month where adults take over the Science Museum. Every event has a different theme, covering a wide range of topics, from climate change to alcohol, from childhood to robots. These showcases have turned out to be extremely popular and attract around 5000 visitors per night.

Not surprisingly then, CereProc / ARIA team was kept busy all night. Our main activity was 'Bot or Not' – a quiz that lets you test your ability to recognise a synthetic voice and learn about speech synthesis in the process. Everyone who took part was added to the leader board and received a personalised message from Donald Trump (totally fake of course, generated using CereProc's prototype Trump voice).

Feedback showed that most players found it a lot more difficult than they thought it would be, and no one has yet reached the perfect score of 20/20.

We also introduced visitors to (the voice of) Roger who gets very cross if you try to interrupt him while he's speaking. The interruption demo was created as a test harness for the reactive speech synthesis framework, and used a set of different strategies to respond to user's and demonstrator's interruptions. These varied from gracefully ceding the floor and restarting, to holding the floor with tense voice quality (see section 3.3 for more details).

In addition, Dr Coutinho presented his work on sentiment analysis by demonstrating how to tell if a politician is being sincere when giving a speech. Once again, Mr Trump took a centre stage! Visitors also got a chance to record and analyse their own speech for signs of dis-ingenuousness.

4.3 BOOK DEAL

This section has been redacted from the public version of this report.

4.4 Public panels, talks, and keynotes

A large number of public panels, academic talks and invited keynotes were delivered that featured (research conducted in) ARIA-VALUSPA. Below is a full list of such talks:

- Matthew P. Aylett: Bot or Not? Exploring the perception of acted, modified and synthetic speech. Keynote, workshop "Investigating Social Interactions with Artificial Agents", ICMI November 2017
- Matthew P. Aylett: Delighting the User with Speech Synthesis. Invited talk. Symposium on speech synthesis with special emphasis on non-verbal control KTH, January 2017
- Matthew P. Aylett: Delighting the User With Speech Synthesis. Glasgow Social Robotics, invited talk. November 2015
- Dirk Heylen: Keynote. On Labels, Theory, Methodology, Practice. Boston. Society for Affective Science, April 2017

- Dirk Heylen: Keynote. Reflections on Data Collection and Annotation. IEEE SMCS Technical Committee on Computational Psychphysiology. Beijing. May 2017.
- Dirk Heylen: Keynote. Engagement in Conversation Revisited. ACII Workshop on User Engagement and Interaction. San Antonio. October 2017.
- Catherine Pelachaud: Keynote, workshop "Investigating Social Interactions with Artificial Agents", ICMI November 2017
- Catherine Pelachaud: Keynote, 3rd Global Conference on Artificial Intelligence, Miami, USA, October 2017.
- Catherine Pelachaud: Keynote, ACM Symposium on Applied Perception, SAP'17, Cottbus, Germany, Sept 17
- Catherine Pelachaud: Keynote, Robotics and Emotions, International Robotics Festival, Pisa, September 2017
- Catherine Pelachaud: Keynote, Interaction with Agents and Robots: Different Embodiments, Common Challenges, satellite workshop of IVA'17, Stockholm, August 2017
- Catherine Pelachaud: Keynote, 3rd Workshop on virtual social interaction, Bielefled, Allemagne, July 2017
- Catherine Pelachaud: Keynote, Interspeech, Stockholm, August 2017
- Björn Schuller: Keynote "LP in Tomorrow's Profiling Words May Fail You", 14th International Conference on Natural Language Processing (ICON 2017), Kolkata, India, 18.-21.12.2017.
- Björn Schuller: Keynote "Mental Health Monitoring in the Pocket as a Life Changer? The AI View.", ISRII 9th Scientific Meeting, International Society for Research on Internet Interventions (ISRII), Elsevier, Berlin, Germany, 12.-14.10.2017.
- Björn Schuller: Keynote "Big Data, Deep Learning At the Edge of X-Ray Speaker Analysis", 19th Conference on Speech and Computer (SPECOM 2017) jointly with 2nd International Conference on Interactive Collaborative Robotics (ICR 2017), Hatfield, UK, 12.-16.09.2017.
- Björn Schuller: Keynote "Automatic Speaker Analysis 2.0: Hearing the Bigger Picture", The 9th Conference on Speech Technology and Human-Computer Dialogue (SpeD 2017), IEEE/EURASIP, Bucharest, Romania, 06.-09.07.2017.
- Björn Schuller: Keynote "24/7 Computational Psychophysiology", IEEE SMCS Technical Committee Workshop on Computational Psychophysiology, IEEE, Beijing, P.R. China, 22.-23.05.2017.

- Björn Schuller: Opening Plenary "Artificial Emotional Intelligence A Game Changer for AI and Society?", Annual Conference of the Society for the Study of Artificial Intelligence and Simulation of Behaviour (AISB), AISB, Bath, UK, 19.-21.04.2017.
- Björn Schuller: Keynote "Reading the Author: A Holistic Approach on Assessing What is in one's Words", 18th International Conference on Intelligent Text Processing and Computational Linguistics (CICLing), Springer, Budapest, Hungary, 17.-23.04.2017.
- Björn Schuller: Plenary Keynote "Tiefes Lernen und die breiten M[']oglichkeiten Anwendungen invited talk, MobileTechCon, Munich, Germany, 13.-16.03.2017.
- Björn Schuller: Keynote "Engage to Empower: Emotionally Intelligent Computer Games & Robots for Autistic Children", Conference on âĂIJThe world innovations combining medicine, and technology in autism diagnosis and therapy", SOLIS RADIUS, Rzeszow, Poland, 29.09.2016.
- Björn Schuller: Keynote "Intelligent Diagnosis and Monitoring of Autism", Conference on âĂIJThe world innovations combining medicine, and technology in autism diagnosis and therapy", SOLIS RADIUS, Rzeszow, Poland, 29.09.2016.
- Björn Schuller: Keynote "Computational Paralinguistics in Everyday Environments", The 4th International Workshop on Speech Processing in Everyday Environments (CHiME 2016 Workshop), San Francisco, CA, 13.09.2016.
- Björn Schuller: Keynote "7 Essential Principles to Make Multimodal Sentiment Analysis Work in the Wild", 4th Workshop on Sentiment Analysis where AI meets Psychology (SAAIP 2016), IJCAI 2016 Workshop, IJCAI/AAAI, New York, NY, 10.07.2016.
- Björn Schuller: Keynote "Say no more the computer already deeply knows you?", SWS 2016 Speech Signal Processing Workshop, ACL/ACLCLP, National Taiwan University, Taipei, Taiwan, 18.03.2016.
- Björn Schuller: Keynote "'Less Input': Cooperative Learning for Emotionally Intelligent Systems", 4th Machine Learning for Interactive Systems Workshop (MLIS 2015) held at the International Conference on Machine Learning (ICML'15), Lille, France, 11.07. 2015.
- Björn Schuller: Keynote "Computational Paralinguistics: Breaking the Voice", UK SPEECH 2015 4th Meeting of the UK and Irish Speech Science and Technology Research Community, Norwich, UK, 01.-02.07.2015.
- Björn Schuller: Keynote "Speech Analysis in the Big Data Era", 18th International Conference on Text, and Dialogue (TSD 2015), Springer LNCS/LNAI, Plzen, Czech Republic, 14.-17.09.2015.

5 Economic Impact

Below we give an estimate of the economic impact, for as far as we are able to judge this.

5.1 INDUSTRIAL IMPACT

Economic impact on our industrial partners was assessed but has been redacted from this public version of the report.

5.2 New funded activities directly following ARIA work

A number of projects and activities are the direct result of research, technology, and know-how developed in ARIA-VALUSPA. The total worth of these new projects is more than 14.5 Million Euros.

5.2.1 Affective Language

The University of Twente has received a 236,663 EURO award (total funding: 733,800 EURO) from the Dutch NWO funder, for the project 'Affective Language'. This project aims to investigate (1) how the emotional states of speakers influence the language they produce and (2) how the influence of emotion on language production can be modeled in computational tools for affective natural language generation.

5.2.2 ALTCAI

The 338,000 Euro ALTCAI project funded by the UK's DIFFID department has been awarded to Dr Valstar of the University of Nottingham to research using ARIA agents to deliver health-care advice to people in sub-Saharan Africa.

The University of Nottingham's 5-year, 26,600,000.- EURO Biomedical Research Centre has adopted the ARIA-VALUSPA code-base, ensuring access and improvements to AVP until at least April 2022. Valstar is the deputy director of the Mental Health theme making up 20% of the total centre's activities, and will use ARIA agents to create diagnostic, monitoring, and treatment tools for people with major depression disorder.

5.2.3 COUCH

The University of Twente and UPMC-CNRS have received 3,704,000 EURO, (UPMC-CNRS 657,500 EURO, U Twente 777,357 EURO) for a Horizon 2020 project called COUCH: Council of Coaches. In COUCH, multiple virtual coaches form a personal council that supports the user in their health and well-being. Individual coaches have their own area of expertise, personality, and style of coaching. Join a council meeting! Give the council your thoughts, or listen and observe how the individual coaches exchange their views on your health behavior. Take what you've learned into your daily life, and if the need arises, contact any of the coaches anytime, anywhere.

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5.2.4 EVA

The University of Augsburg has won funding from the German Science Foundation (DFG) to support two research associates, student researchers, travel for EVA: How to Win Arguments - Empowering Virtual Agents to Improve their Persuasiveness . The EVA project, we will simulate argumentation dialogues between humans through embodied conversational agents. We will rely on Reinforcement Learning (RL) to optimize the agents' argumentation strategies in an interaction with a simulated opponent.

5.2.5 EMMA

The University of Augsburg has won funding from the German Federal Ministry of Education and Research (BMBF) worth ca. 1 M Euro for EMMA: EmmA âĂŞ Emotionaler mobiler Assistent. In the EMMA project, Augsburg will investigate the use of a socioemotional assistance system for improving the psychological health of people at work.

5.2.6 FIODSpraak

The University of Twente received a 207,349 EURO award from the FIOD - the Dutch Fiscal Information and Investigation Service, to realise an infrastructure (based on a set of software tools, available data and protocols) to speed up and improve the analysis of recorded conversations.

5.2.7 GrassrootWavelengths

CereProc's involvement in the GrassrootWavelengths project is a direct result of our success in working with academics and publishing innovative work on expressive speech synthesis - a key area of innovation in the ARIA project.

The Grassroot Wavelengths is a 2.17M EURO project that will create a game-changing network of inclusive digital platforms for citizen engagement, community deliberation, and the free flow of information within, into, and out of discrete geographic communities by piloting solutions for connected, inexpensive, community owned and operated radio across Europe. See https://cordis.europa.eu/project/rcn/213180_en.html for more details.

5.2.8 R3D3

The University of Twente has received 110,250 EURO (total funding: 247,500 EURO) for R3D3: Rolling Receptionist Robot with Double Dutch Dialogue from COMMIT - Zwaluw Project. The R3D3 project investigated situated natural language dialogue systems that combine limited natural language understanding with the understanding of non-verbal behaviour of the users in a real-life context.

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5.2.9 VIVA

The University of Augsburg has won funding from the German Federal Ministry of Education and Research (BMBF) worth ca. 2 M for VIVA - Vertrauen und Sympathie schaffender lebendiger sozialer Roboter. The objective of the VIVA project is the development of a hardware and software platform as a basis for the creation of lively social robots that establish trust and empathy.

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6 SUMMARY OF TECHNICAL EFFORT PER WORK-PACKAGE

This section provides a brief summary of all work done, structured by work-package and task. Rather than repeat reports, we reference heavily to relevant previous deliverables or sections of this final report. For the technical work-packages, we also report on the progress made after July 2017, which is not captured by any dedicated work-packages.

6.1 WP1: System design and realisation for web and mobile device Environments

6.1.1 1.1 System integration

Task 1.1 is all about continuously integrating the various processing components. By having a dedicated scientific programmer at Nottingham, this was ensured. Only when this post changed from the original member of staff to a new member of staff was there a period of about 3 months where continuous integration was paused. We employed an early integration approach, and had a fully functioning minimal viable product at the end of year 1 (Milestone 1, or AVP 1.0). The aim was to continuously keep the components created by all partners in synchrony to have a working system all the time even while new functionality is added. This was mostly successful, although there were invariably times where progress in one module broke functionality of another, requiring us to temporarily use an older version of the offending module while the problem was resolved.

The task was kick-started using the SEMAINE system, insofar that we used the same messaging protocol (ActiveMQ) and messaging formats, as well as the general system divide of behaviour analysis, dialogue management, and behaviour generation. But in AVP, the three blocks are themselves larger integrated entities and most ActiveMQ communication is between these three blocks, rather than a very large number of small modules all communicating through ActiveMQ.

Where possible, we adhered to software engineering best practices, such as continuous integration, and relatively short release cycles. AVP was released as versions 1.0 (12 months), 2.0 (24 months), 2.1 (26 months), 2.2 (28 months), 2.3 (30 months), 2.4 (32 months), and 3.0 (36 months). Clearly, as all partners were closer to integrating their research into software, there was a greater need and opportunity for new releases. This was particularly the case for the Dialogue Management, on which work did not seriously start until month 15 of the project.

All partners received training on software during two courses, one in Augsburg (month 12) and the other in Twente (month 19), as part of face to face consortium meetings.

6.1.2 Task 1.2 End-to-end system realisation on web and smartphone technology

The original proposal envisaged the realisation of ARIAs on mobile devices using web browser technology. However, after the mid-term review the official advice was not to pursue this goal. Nevertheless, some progress has been made. The iCCR face-tracker was deployed to the iOS platform, running on a native platform in less than 20 ms/frame, i.e. at 50 frames per second, allowing some additional processing on top of the face tracker while maintaining a 30 frames per second throughput. The AVP allows sending of audio and video data using webRTP from a chrome browser to a server running AVP. Cantoche have made a streaming server to send video of the generated Living Actor from this AVP server back to the browser. So, in theory a fully reactive web-enabled system has been delivered, however it isn't seamlessly integrated with the main AVP codebase, and has not been extensively tested.

6.1.3 TASK 1.3 REALISATION OF A REAL-TIME DISTRIBUTED SYSTEM

This task focuses on delivering a real-time distributed system. Thankfully, by employing the SEMAINE Active-MQ system and existing components such as eMax, SSI, and Greta, such a system came virtually for free from Milestone 1 (AVP 1.0) onwards. AVP runs seamlessly on multiple machines. Because the ASR is the only module that requires Linux as the operating system, this either runs in a virtual machine, but in most of our experiments on a separate physical machine. eMax works best on machines with a decent Graphics card, so it can utilise the GPU. In practice, we often use two or three machines to run ARIA interactions.

6.1.4 TASK 1.4 SUPPORT FOR USER-PROFILES

The user adaptation capabilities in WP 2-4 crucially depend on the system's ability to represent and remember a user's profile. To do so, we use a simple but effective face recognition system based on the facial point tracking and appearance of the face, and integrate this in eMax as part of the visual behaviour analysis. The face recognition performs well for well-lit, frontal-view faces. The user ID utilised in the eMax face recognition module is sent by SSI over ActiveMQ to the Dialogue manager, which links it to its in-built user profile system. This system stores the agent's belief of a user's age, gender, and preferred language. Unfortunately, recognising and pronouncing people's names is a very hard problem, so we don't store or use people's names. Instead, the DM can say "Hi again!" when we recognise someone as being in the database, and "Hi, we haven't met before, have we? It's nice to meet you." when the user-id is new. It also allows us to count the number of interactions with a person, which can be used to build e.g. longer term personal relations. Combined with storing the interaction history, that is the dialogue history together with the interest level at different times, allows the agent to learn longer term what a user finds interesting and what not. This long-term adaptation remains future work.

6.1.5 TASK 1.5 IMPLEMENTATION OF STANDARDS

Several web standards that will be used by us are in the process of formal specification. Many of these are highly relevant for the future commercial success of ARIA-VALUSPA technology. Among them are the W3C HTML Speech Incubator Group and the W3C Emotion Markup Language. We have adhered to these standards wherever possible.

6.2 WP2: Multi-Lingual audio-Visual-Modal speech and affect Recognition

6.2.1 TASK 2.1 CROSS-DOMAIN, AUDIO-VISUAL MULTI-LINGUAL DETECTION OF VERBAL AND NON-VERBAL CUES

This task is focused on recognition of naturalistic speech in three languages, as well as affect and interest recognition from nonverbal cues from prosodic and facial dynamics.

SPEECH RECOGNITION We have developed a fully Automatic Speech Recognition system for English, French and German languages that is real-time capable with very low latency. The objective of this module is to recognise the verbal content of user's voice and send that information to the dialogue system for further processing and the generation of the verbal interaction. The basic architecture of our ASR system was created using the Kaldi toolkit, a very well-known open-source ASR toolkit that is well tested, optimised and actively maintained by many researchers to support the state-of-the techniques (and therefore can easily be extended and further developed). Deliverable 2.1 includes a complete technical description of the ASR system. The final versions of our ASR models have the following Word Error Rates: 39.0% (English), 28.8% (German) and 40.2% (French). These values were estimated on a subset of the NoXi database. See Deliverable 2.2 for further details on the ASR implementation and performance.

RECOGNITION OF THE USER AFFECTIVE STATE AND INTEREST LEVEL In the context of this task, we started our work by developing single modality classifiers for affect – Arousal (high, low) and Valence (positive, negative) – and interest – uninterested, neutral, interested – recognition systems. For arousal, we obtained an Unweighted Average Recall (UAR) of 68.9%, for valence, 61.6%. We developed well-established models (Support Vector Machines) and engineered features sets (using the openSMILE audio feature extractor). Arousal and Valence from video was established based on the 6-basic emotion prediction. Full details of this initial is presented in Deliverable 2.1.

6.2.2 TASK 2.2 AUTOMATIC AUDIO-VISUAL USER PROFILING

USER TRAITS ESTIMATED FROM VOCAL PATTERNS We implemented models for the recognition (classification tasks) of the following traits for creating the user profiles; class labels and the classifier performances (UAR) are also given:

- Age: children, youth, adults and seniors; (UAR = 48.91%)
- Gender: children, female, and male; (UAR = 81.21%)

These long-term traits are used to profile the users. Furthermore, according to the WP, we have conducted research on the recognition of the big five personality traits (mean

UAR = 71.4 %), native language (L1) (UAR = 47.5 % for eleven classes), and health condition (UAR = 70.2 % for cold vs non-cold), as well as drowsy state induced by alcohol intoxication or sleep deprivation (UAR = 69.0 % for drowsy vs non-drowsy). The obtained results are consistently significant above chance. In addition, we proposed a multi-task learning method based on deep neural network with shared hidden layers for universal speech emotion recognition. Thus, our system is able to predict various emotion representations based on categorical, dimensional, and appraisal modelling conceptions. Full details about these models are described in Deliverable 2.1 and in our recent publications as listed in Section 7.3.

6.2.3 TASK 2.3 ADAPTATION TO USER, CONTEXT, AND ENVIRONMENT

The goal of Task 2.3 is to endow the ARIA-VALUSPA Platform (AVP) with capabilities of learning and adapting to user characteristics with enhanced context awareness.

In relation to demographic information, user traits extracted from utterances in Task 2.2 (automatic user analysis) were used for

- preselecting interest and emotion models that best fit the user profile (e.g. age group, gender, Speaker ID);
- as high-level features for adapting the dialogue management system;
- automatically adapting emotion and interest recognition models to the speaker's voice in the course of the dialogue.

We achieved these outcomes through the creation of a novel learning framework for acoustic model adaptation that allowed us to train customised models for a single user and user groups during long-term interaction with ARIA. In order to identify the user at each moment and initiate user adaptation strategies, we implemented reliable face identification algorithms (see Fig. 6.1). When a specific, known user is identified, the respective user profile is retrieved and previously adapted models are initiated. Otherwise, other models that are as close as possible to the new user profile are used (see Fig. 6.2 for a visualisation of the adaptation process). Full details on these features are provided on Delivery 2.3.

We also endowed our ASR systems with the capacity to adapt to a specific user voice in real-time. This is achieved through the generation of speaker dependent acoustic features that provide the acoustic models with a vector of speaker-dependent features (iVector) in addition to the standard un-adapted and non-normalised MFCC features. The iVector in our system include 100 features that provide the acoustic models with sufficient knowledge about the speaker characteristics. This vector is estimated in a left-to-right way, i.e., at a certain time t, it sees input from time zero (beginning of the segment) to t (present moment). It also receives information from previous utterances of the current speaker, i.e., from the beginning of the session and will therefore improve over time.



Figure 6.1: User re-identification procedure: While the tracking is ongoing with no failure, the user-specific features are stored in a sliding window of 50 frames. When the tracker needs to be reinitialised, the new features are first compared to the statistics stored for the previous user (mean and covariance of the features). When the distance is higher than a threshold, the system detects a new user, and the data collection re-starts.

6.2.4 TASK 2.4 AUDIO-VISUAL FUSION FOR SOCIAL AND EMOTIONAL SKILL ENHANCEMENT

Human emotions are expressed non-verbally in multiple ways, being the face and the voice two of the most important modalities. Not only information from both these modalities is important, but the interplay between the expression of emotion in both face and voice are relevant for the communication of particular emotions. In order to create a more robust emotion recognition system, we developed a novel framework for time-continuous audio-visual emotion recognition – Dynamic Difficulty Awareness Training (DDAT). The DDAT framework consists of a multi-task learning scenario to train a Deep Neural Network whereby, in addition to predicting Arousal and Valence affective dimensions, the uncertainty level of these predictions based on the agreement level between annotators is also predicted. The emotion prediction uncertainty is used in this context as a proxy for the "difficulty level" of the task, and together with audio-visual features, is fed to the input layer of the DNN at the following time step (see Fig. 6.3a, i.e., the estimated "difficulty" of the task is regarded as a complementary descriptor of the audio-visual



Figure 6.2: Real-time workflow for user adaptation in ARIA.

features and combined with them to form an extended feature set for emotion recognition (both during training and testing phases). The goal of this approach is to allow the model to create an expectation of the difficulty level for emotion prediction at any given moment, and eventually use this knowledge to improve the learning process. This assumption is inspired by human learning processes in which levels of attention are normally higher when learning difficult or ambiguous tasks.

6.2.5 Advances made after July 2017

Intermediate audio-visual behaviour representation Following a recent trend in machine learning that aims at building intermediate representations of raw input signals in order to extract task-specific information (which usually leads to a better performance on the recognition task), we used Convolutional Neural Networks (CNNs) to extract features from the speech, and a deep residual network (ResNet) of 50 layers for video (see Fig. 6.4. These models were then combined with a Long Short-Term Memory (LSTM) networks, and trained in an end-to-end fashion where - by taking advantage of the correlations of the each of the streams - we manage to significantly outperform the traditional approaches based on auditory and visual hand-crafted features for the prediction of spontaneous emotional displays.

Face frontalization Another problem we worked on is the automatic frontalization of face images, i.e. creating a canonical frontal view representation of a face of arbitrary head-pose. Recent advances in deep learning have led to high performing facial expression recognition algorithms. However, their performance can still severely degrade with large variation in head pose. Rotating the face to a reference position (as a pre-processing step)



(a) Dynamic Difficulty Awareness Training (DDAT) framework. Aug-(b) mented inputs are updated using emotion perception uncertainties.



before being used as input to a classifier/regressor is an effective solution to overcome this problem. However, this frontalization step becomes especially challenging when out of plane rotations are involved as that results in non-linear transformations of the face shape and appearance, and often parts of the face are self-occluded. With this goal in mind we developed a data driven approach for generating frontalized face images using deep Convolutional Neural Networks.

We trained a hourglass network [35] to generate frontalized version of the input faces. The network consists of 4 residual modules designed to capture information at multiple scales. Following these modules, there are 4 additional layers to do the up-sampling and combining features across adjacent resolutions. The input to the network is a cropped face image which can be in any pose. The network is trained to output frontalized face image using Mean Squared error loss. The method was trained and evaluated on the BP4D dataset [58] and it achieved a RMSE of 0.11 on a validation set. Some results from our proposed method are shown in Fig. 6.5. If it is found that the frontalisation is indeed helpful for further face analysis, this method will be introduced into eMax, and thus the Behaviour Analysis pipeline in due course.

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Figure 6.4: The network comprises of two parts: the multimodal feature extraction part and the RNN part. The multimodal part extracts features from raw speech and visual signals. The extracted features are concatenated and used to feed 2 LSTM layers. These are used to capture the contextual information in the data.

6.3 WP3: Multi-modal dialogue management for Information Retrieval

6.3.1 TASK 3.1 MULTI-LINGUAL NATURAL LANGUAGE UNDERSTANDING

This task concerns the way the ARIA-VALUSPA dialogue management system handles the understanding of the user's utterances in the three natural languages targeted by the project: English, French and German.

In the dialogue management system, user intents are defined independent of language, according to the DIT++ (Dynamic Interpretation Theory) taxonomy of communicative functions [9]. Intents include greeting, approach, topic introduction, inform, question, valediction, thanking and apologizing. These intents are generally applicable for all languages and only require a translation of the verbal parts.

As described in Section 6.2.1, an automatic speech recognition (ASR) system has been developed for English, French and German. For the subsequent step of handling multi-lingual user input, we have opted for a shallow understanding approach that is not dependent on the availability of language-specific resources. After the utterance recognized by the ASR has been put in the information state, and a user move has been created (see section 3.8), the Input Processing component checks if the user's utterance matches any of the predefined user utterances in the agent's moves (where a match



Figure 6.5: Some generalisation results from our face frontalization algorithm on a left-out test set. The top row shows the input (non-frontal pose) face images. The bottom row shows the frontalized face images generated from the network.

would make the agent move relevant). This matching of user utterances is done in a language-independent fashion by measuring unigram overlap between sentence strings; it does not involve any syntactic or semantic parsing.

The user utterances specified in the agent moves have been written in English, but simply translating them is sufficient to have dialogues in French or German as well.⁶ Future users of the system can author the dialogue templates in their preferred language, provided that an ASR component and a text-to-speech component are available for that language. For non-verbal behaviour specified in the moves, we make the simplified assumption that there is no difference amongst the different languages.

6.3.2 TASK 3.2 TASK-ORIENTED DIALOGUE MANAGEMENT

This task involves the implementation of an information state-based architecture for dialogue management that can run different dialogue management dimensions in parallel, focusing on interaction management aspects such as turn taking, repair mechanisms, and floor management.

The dialogue management system uses an information-state based approach. The information state according to Traum and Larsson represents "the information necessary to distinguish it [= the current dialogue] from other dialogues, representing the cumulative additions from previous actions in the dialogue and motivating future action" [46]. An advantage of the information-state based approach is the ability to formalize linguistic models which in turn enables easier integration in a computer system.

The dialogue engine underlying the dialogue management system is called Flipper 2.0: an extended and improved version of the Flipper engine described in [44]. Development of Flipper 2.0 involved multiple steps. We first built an extension of the original Flipper to enable a multi-agent approach and facilitate integration with other dialogue system components. We also made some other improvements to Flipper, such as making it possible to load dynamic classes which can be called. We then updated Flipper to Flipper 2.0 by using more standardizations such as JavaScript and JSON. This makes

⁶The dialogue templates used in the book personification demonstrator have already been translated to French; translation to German is work in progress.

the dialogue engine less computationally expensive and also creates more flexibility in defining dialogues, useful for creating more dynamic conversations.

Based on Flipper 2.0. we designed a dialogue manager that provides a dialogue structure based on the DIT++ standard. We have extended DIT++ with some domain-dependent functions (see next section), making it possible to specify domain-specific as well as domain-independent dialogue moves that cover multiple conversational dimensions. The dialogue manager takes a scenario and situation-driven approach to creating dialogue structures based on conversational acts; see Section 3.8 for more details.

6.3.3 TASK 3.3 USER-ADAPTIVE DIALOGUE STRATEGIES

A special new feature of the ARIA-VALUSPA dialogue management is adaptation to the user. Adaptation, or alignment, in natural dialogues appears in many aspects of dialogue. This task involves the implementation of different adaptive strategies that are relevant to the application.

One simple form of user adaptation is by making use of the input provided by the SSI framework. The SSI can detect demographics of a user (e.g. the gender) and this can be used by the agent to create an appropriate of responses, for example, 'Hello Sir' versus 'Hello Madam'. Other, more advanced forms of adaptation we have focused on are adaptation in terms of turn-taking and alignment of the agent's word choice to that of the user. Here focus on the alignment.

We measured the verbal alignment between the user and the agent in a small corpus of Wizard of Oz dialogues (the HAI corpus; see D6.1 and section 6.3.5) and used this as a basis to create an algorithm that performs verbal alignment, as shown in Figure 1.

```
Data: Dialogue history, planned agent utterance

Result: List of all possible (un)aligned agent utterances

initialization;

while NPs with modifiers remaining in agent utterance do

select NP;

if aligning then

remove modifiers not used by user;

add modifiers used by user;

else

remove modifiers used by user;

replace modifiers with synonyms;

end

end
```

Algorithm 1: Verbal alignment generation

Using this algorithm makes it possible for the agent to use referring expressions that are preferred by the user (as shown by the dialogue history). An example is talking about the 'tiny golden key' found by Alice in the book Alice in Wonderland. Depending on the expression used by user, the agent can refer to it in the agent utterance as 'key', 'golden key', 'tiny key' or 'tiny golden key'. If the user uses a particular description, the agent is able to mirror this.

6.3.4 TASK 3.4 REINFORCEMENT LEARNING BASED ON USER FEEDBACK

This task refers to training the system's adaptive dialogue strategies using reinforcement learning. Our approach to dialogue management lends itself to online learning. Our dialogue policy is based on a single value of relevance (described in section 2), used to select behaviours of the agent. The multi-modal information from the agent's mental model (the information state) could be encoded to use the relevance value as a reward. The dialogue history could be used as an input for learning as well, in addition to all possible dialogue moves the agent can make. We have collected data (WOZ) and implemented relevance values that could be learnt from. Actually performing reinforcement learning experiments on these data remains as future work.

6.3.5 TASK 3.5 DEALING WITH UNEXPECTED SITUATIONS

This task concerns enabling the ARIA agents to deal with unexpected situations that occur during an interaction. For this task, we started out by collecting Wizard-of-OZ dialogues in the Alice in Wonderland domain. The goal of the data collection was to create a corpus with unexpected situations that can occur during a conversation between a virtual agent and a user, such as misunderstandings, (accidental) false information, and interruptions by another person. In a classic WOz approach where the wizard uses a button interface, it is nearly impossible to improvise in unexpected situations. This is why we gave our wizard the freedom to choose his own words and facial expressions to respond to and initialize unexpected situations. The corpus, called HAI (Human-Agent Interaction) Alice, consists of 15 conversations and more than 900 utterances.

One type of unexpected situation occurs when the agent gives an unexpected answer due to speech recognition errors or knowledge base limitations. We carried out a few additional WOz studies to investigate the use of dialogue repair strategies in this type of situation. In the first study, we investigated which repair strategies the users employed in reaction to off-topic answers by the agent. In most cases, they reacted with a clarification question or a follow-up question about the unexpected answer. The next most frequent reaction was to simply ignore the answer and ask a different, unrelated question. This is a strategy we do not expect to see much outside the experimental context, where the participants have no real information need. Therefore, in the next experiment we investigated the effects of adding some simple repair strategies to the agent's repertoire: instead of giving an irrelevant answer, the agent asked the user to rephrase their question, or said that it could not answer the question. These repair strategies slightly improved the performance of the virtual agent (i.e. more questions were answered correctly). Ironically, they also caused the participants to perceive the agent as less intelligent, presumably because the repairs drew attention to the agent's limitations. For this reason we have not implemented such strategies in the dialogue manager.

Instead, we have implemented a strategy where the agent only initiates a repair strategy

if the user explicitly signals that the agent has made an inappropriate response. If the user has a negative reaction to the agent's response, the agent will politely apologize and repeat what she thought the user said. This way the agent does not repeat itself and gives the user some feedback on what it has recognized. This gives the user an opportunity to voluntarily rephrase their earlier utterance, while maintaining the current topic of the conversation.

Finally, we have implemented a method in the dialogue manager to deal with interruptions based on the personality traits of the agent. For example, you can set the agent to be dominant and she will talk louder and finish her behaviour, even if the user tries to interrupt her. You can also make a more submissive agent that stops talking as soon as she hears the user speak, or minimizes the overlap with the user's speech. It is also possible to dynamically alter the approach to user-interruptions, making the agent less or more receptive to user interruptions.

6.3.6 Task 3.6 Generation of Dialogues for Book Personification Demonstrator

For the generation of dialogues for the book personification application, we aimed to create a set of dialogue structures that covers the themes in the book and avoids open domain conversation. In preparation for this, we performed an analysis of a subset of the NoXi corpus of novice - expert conversations (see Section 2.3). Our focus was on determining the general discourse structure of these conversations, following the intentions of the interlocutors. More details can be found in Deliverable 3.2, Section 2.3.

A first version of the book personification demonstrator was described in Deliverable 3.2. For this first version, We extended DIT++ with domain-dependent functions, such as talking about a character in the book or storytelling about an event in the book. We use a simple semantic representation of utterance content, making it possible to specify the topic and type of open questions, thus refining the general category of 'setQuestion' (open question) in DIT++.

Since then, the demonstrator has been extended with question-answer (QA) matching functionality comparable to that of the VH Toolkit [21]. A question by the user is mapped to the most similar question found in a database with question-answer pairs, and the corresponding answer is returned.

In addition to the HAI Alice corpus (see above) through which question-answer pairs were collected, we carried out several other small WOz studies to obtain more questionanswer pairs and to populate the initial knowledge base of our agent.

To easily expand the range of user questions that the Book Personification agent can answer through QA matching, we have developed a question generation system that takes text as input and generates a large number of QA pairs from it [19]. This form of question generation can be used to complement or replace data collection with human users. For example, based on the input sentence (from a summary of Alice's Adventures in Wonderland) 'Her giant tears form a pool at her feet' the following questions can be generated: 'What happens at her feet?' Or: 'What happens to her giant tears at her feet?' The answer to both questions is 'Her giant tears form a pool'. The software for

Table 6.1: An example dialogue with the Book ARIA. (Sp=Speaker, U=User, A=Agent)

#	Sp.	Utterance
1	U	Hello
2	А	Hello to you too, human!
3	U	What is your name?
4	А	I'm Alice, from the book Alice in Wonderland.
5	U	What can you do?
6	А	I can tell you about the book Alice in Wonderland.
7	U	Tell me about the book.
9	А	I followed the rabbit into a hole and then fell down a very deep well! I came upon a heap of sticks and dry leaves and found myself in a long, low hall. There, on a stool, was a tiny golden key!
10	U	What did you do with the key?
11	А	I looked around and I found a little door. The key fitted in the lock, but the door was too small for me to pass! I looked around again and found a bottle with 'drink me' on it.
12	U	Did you drink the bottle?
13	А	The 'drink me' bottle did not have poison written on it, so I drank it! Then I felt myself shrinking, until I was only 10 inches high.
14	U	What is your name?
15	А	My real name is Alice Liddell.
16	U	Do you have any siblings?
17	А	My parents had nine children. When I was born, I had an older
		brother and sister, and a younger sister.
18	А	Right, look at the time! I am afraid I must go at once, tea time with my cat!
19	U	Alright, goodbye.
20	А	Goodbye!

this question generation can be found on GitHub⁷.

6.3.7 Task 3.7 Generation of Dialogues for Industry Associate Demonstrator

This task is devoted to the Industry Associate application. It encompasses defining the exact mission of the Virtual Assistant, creating a dialogue scenario to achieve this goal, and building adaptive and task-oriented dialogues in multiple languages.

The remainder of this section has been redacted for the public version of this report.

6.3.8 Advances made after July 2017

After the last deliverable in July, the team in Twente worked to improve the system and prepare it for the final evaluation in October and November.

In September we integrated the new dialogue engine, Flipper 2.0, into the dialogue manager. We implemented most of what was described in Deliverable 3.3, Section 2.1. We defined episodes, exchanges and content, interaction and social moves in the format that the Dialogue Engine can more easily work with. We created new templates and added relevance values to each template to match up to our dialogue structure.

We implemented the GOAL markers that have been introduced in GRETA in the DM templates as well. These markers indicate whether a sentence said by the agent is completed and or accomplished. We do this by using the tags DMBegin and DMEnd for indication if the agent has completed her sentence and the tags DMImpBegin and DMImpEnd for indication of accomplishing the intent of the agent. The latter tags were used to mark the most important aspects of the utterance of the agent. With these markers we have more expressive behaviour in the agent and we can adapt our interruption strategy. For example, the agent will not repeat the sentence if the most important aspect has already been said.

We modified the knowledge base to match to the concept of dialogue moves better, so that the system can make better use of the dialogue structure we defined. Each move has a goal formatted as episode_exchange_move, making it easy to determine the current episode the conversation is in, and also to measure distance between different types of moves, based on if they are in the same exchange and/or episode.

After July we integrated the verbal alignment tool (see Section 6.3.3 in the agent. We set up a server on which the algorithm runs and included an API to perform verbal modifications. We can save the dialogue history and adapt the agent utterances in the long term (across interactions with the same user). The verbal alignment tool only works for English.

For the final evaluation of the system we have worked together with the partners at UoN to set up a game with the book demonstrator. We developed a scenario where the user is engaged in a conversation with Alice. Alice believes that her adventures in Wonderland are real and wants to talk about this. She does not like to talk about her 'real life', especially not to strangers. The user is instructed to discover the truth about

⁷https://github.com/evania/alice-qg

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Alice and is instructed to learn more about her and eventually develop a trust bond with her. Once Alice trusts the user, Alice will tell something about her real life, such as her real name. We have augmented the dialogue moves of the agent with more FML capabilities described in [11].

The method to measure trust is based on an interest level that has been developed by our partners at the University of Augsburg. We kept track of the long-term interest level of the user and used this as the measure of trustworthiness. The interest level was based on multi-modal input from the user, namely the arousal and valence level of the user, together with the amount of head movement and gaze.

Finally, regarding Task 3.7, the prototype task-oriented demonstrator for the Industry-ARIA was implemented after July.

6.4 WP4: Context-sensitive generation of acoustic and visual Agent behaviour

6.4.1 TASK 4.1 OVERALL DYNAMIC NON-VERBAL COMMUNICATIVE BEHAVIOUR MODEL

For the generation of dynamic non-verbal communicative behaviour we implemented a solution that remains SAIBA compliant and spans over different components of the ARIA system. Figure 6.6 depicts the proposed architecture of the ARIA system. We made an important change compared to common SAIBA platform. The Intent Planner is placed inside the Dialogue Manager (DM) component. The role of the DM is to produce the communicative intents and dialogue acts for the agent by choosing among several FML templates corresponding to the desired intents to communicate. FML templates are a specialized version of FML-APML containing more advanced constructs. They also offer several input parameters that support online dynamic changes in order to produce different FML that can be processed by Greta. A translator component (FML Translator in Figure 6.6) transforms a given FML template and its input parameters into a valid FML-APML script.

6.4.2 Task 4.2 Adaptive nonverbal communicative behaviour generation model

FML TEMPLATES The DM has an FML manager component in the DM is responsible of the communicative behaviour generation. This FML manager (1) selects one of the available FML-templates according to the communicative intents to accomplish, (2) fills the available placeholders (each template supports a set of parameters) with information extracted from the Information State in the Dialogue System (e.g. a subject in an utterance or an emotion) and (3) sends the template filled in with information to an FML Translator component that in turn produces a regular FML-APML script for Greta.

The FML Templates are based and categorized according to the Dynamic Interpretation Theory (DIT++) taxonomy of communicative functions ⁸. The DM can pass in input

⁸Bunt, Harry. "The DIT++ taxonomy for functional dialogue markup." AAMAS 2009 Workshop, Towards a Standard Markup Language for Embodied Dialogue Acts. 2009.



Figure 6.6: Overall architecture following SAIBA

different types of parameters such as: emotion label and its intensity, pitch accent, certainty level, different words alternative. Once the DM has selected an FML template and instantiated its parameters, it sends the template to the FML Translator. His task is to transform each FML Template and its parameters into FML-APML for Greta.

EXPRESSING INTERPERSONAL ATTITUDES CNRS developed a model for making the ARIA agent capable of expressing different interpersonal attitudes, for example dominant or hostile, toward the user. Attitudes are displayed through sequences of multimodal behaviours. A corpus was annotated along 2 dimensions: multimodal behaviors and social attitudes. Attitudes are represented as the 2D space (Friendly, Dominance). We were interested in looking at the behaviours that trigger a change of attitude perception. The data was segmented to identify the non-verbal behaviors that characterize a variation (increase or decrease) in attitude. We have applied HCApriori, a temporal sequence mining algorithm, to extract temporal patterns of nonverbal signals expressing the four attitude variations and two 'neutral' attitudes (neutral dominance, and neutral friendliness).

First study: Extraction of multimodal behaviors patterns

We have evaluated our algorithm that extracts patterns of multimodal behaviors in link with attitude variation. We have performed two types of evaluation: objective and subjective. For the former, we compared our algorithm against four state-of-theart algorithms: QTIPrefixSpan-Kmeans, QTIPrefixSpan-AP, QTIApriori-Kmeans, and PESMiner. For this, we rely on two criteria: the pattern extraction accuracy and the empirical efficiency (running time). We found that our algorithm HCApriori outperforms the other algorithms and is able to achieve over 0.92 accuracy whereas the runner-up achieves 0.70.

We have also run an empirical study to investigate whether non-verbal patterns extracted

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with our model for a given attitude variation are perceived as conveying the same attitude variation. We evaluated eight non-verbal patterns for the perception of dominance variation (4 for dominance increase vs. 4 for dominance decrease) and eight nonverbal patterns for the perception of friendliness variation (4 for friendliness increase vs. 4 for friendliness decrease). We also evaluated 2 non-verbal patterns for the perception of neutral attitude (1 for neutral dominance and 1 for neutral friendliness). We used Greta to generate videos of ECA displaying non-verbal behaviour patterns. As our model only consider nonverbal behavior, we left aside the content of the speech. For this, each non-verbal pattern was shown while the agent spoke nonsense speech. For measuring each attitude's dimension we relied on Leary's model and used 16 variables (four for each attitude): helpful, cheerful, cooperative, warm, leaderlike, assertive, domineering, forceful, aggressive, arrogant, defiant, distant, withdrawn, timid, depend and unauthoritative. To asses if there is a significant difference between the reference video and the comparison videos, we conducted a Wilcoxon test. We found that: (1) patterns representing dominance increase are evaluated as more dominant, more hostile and less friendly compared to the reference video. (2) patterns representing dominance decrease are evaluated as more submissive compared to the reference video. (3) patterns expressing friendliness decrease are evaluated as more hostile and more dominant compared to the reference video. (4) patterns expressing friendliness increase were perceived as equivalent to the neutral expression.

Model of Sequential Attitude Planner Once our extraction model has been validated, we have implemented a new module in the ARIA system that we call Sequential Attitude Planner to generate the non-verbal behaviour of the ARIA agent expressing an attitude variation. The Sequential Attitude Planner takes as input an FML file (as produced by the Dialogue Manager through the FML Translator) and the attitude variation that the agent will express toward the user. These information are defined with the Functional Markup Language (FML) [3]. Our Sequential Attitude Planner is composed of four steps:

- 1. From FML to BML Sequence generation: The first step of our model is generating a sequence of non-verbal signals expressing the communicative intentions contained in the input FML file.
- 2. BML Attitude sequence selection: from a dataset of behaviours sequences expressing attitude variations, the algorithm selects the sequence that is closer to the behaviours (or sequence of behaviours) that the original behaviour planner in ARIA-Greta proposed when transforming the FML into a sequence of BML descriptors.
- 3. BML Sequence enrichment: all signals in the attitude-sequence previously selected that do not appear in the original sequence of behaviours generated by the ARIA-Greta behaviour planner are added to the produced sequence of behaviours that the agent will exhibit.
- 4. Priority signals selection: we designed a Bayesian Network to model the probability of occurrence for non-verbal signals for each attitude. Based on these probabilities,

the algorithm replaces a signal in the final behaviour sequence with a mapped signal expressing a specific interpersonal attitude, if the probability of this last signal is higher than the probability of the first one for expressing that attitude.

Second study: Sequential Attitude Planner

We report on the evaluation study we conducted on our Sequential Attitude Planner. We follow the same evaluation protocol as the first study with one difference: this time the agent did not say nonsense utterances but said meaningful utterances. So we have added four dependent variables: dominant, friendliness, submissive. The agent utters the same utterance in the reference video and in the comparison ones. The behavior of the agent in the reference video has been generation by the Greta/VIB behavior planner without using the sequential attitude model. In the reference video, the agent displays the behaviors generated by our sequential attitude planner. 64 participants took part of the study. We ran t-test to compare the results on the reference video with the comparison ones. We found two significant results: for dominance decrease and friendliness increase. The results are similar to the first study.

6.4.3 Task 4.3 Emergence of synchrony during engagement phases between ECA and User

The relationship between user and agent during the interaction can be characterized through the emergency of synchrony and, in particular, alignment. More specifically, the recognized user's emotion through facial expressions can elicit an agent's emotional response through the generation of appropriate facial expressions. The agent responds by aligning its nonverbal behaviour to the user's detected emotional state defined as empathy level (0-1). The agent's behaviour alignment with user's detected empathy level can be mapped with agent's disengagement (low user's empathy) and full engagement (high user's empathy). CNRS created a graphical tool in Greta that allows simulating the detected user's empathy and map it into animation parameters in real-time for the agent as depicted in Figure 6.7.

Regarding verbal alignment, CNRS has provided measures characterising verbal alignment processes based on repetitions between dialogue partners. To this end, CNRS has proposed a framework based on repetition at the lexical level which deals with textual dialogues (e.g., transcripts), along with automatic and generic measures indicating verbal alignment between interlocutors.

6.4.4 Task 4.4 Adaptive speech synthesis

The task comprised of two elements, reactivity and expressive and conversational speech.

1. A ground breaking reactive speech synthesis API was designed, built, tested and integrated with the ARIA-VALUSPA code base. This allows speech synthesis to be altered during production without requiring a pause, for example increasing vocal effort to hold the floor, or using conversational speech elements to gracefully cede the floor.



Figure 6.7: Graphical tool to define behaviours mapping

2. CereProc APIs for controlling phrasing, reduction and non-verbal cues were integrated into the ARIA-VALUSPA framework and made available to the dialog and graphic rendering modules. Conversational speech was recorded as part of Task 6.4 and integrated into a voice released to ARIA-VALUSPA as part of the Industry ARIA allowing blending of acted conversational speech with more formal read style speech. Significant work in exploring closed phase LPC vocoding techniques was carried out. This work was also extended to produce Idlak Tangle, an open source speech synthesis system based on deep neural nets (DNNs) (see section 2.5). DNN approaches were also applied to prosody modelling which resulted in higher quality synthesis, especially for more sparse genre synthesis. The vocoding approach was then used to model tense and lax voice qualities. This approach was then used to produce two voices for ARIA-VALUSPA, the first a version of the Alice voice used in the book ARIA. The second a voice created using freely available Arctic data which can be freely distributed with the project outputs. Although the quality of the resulting algorithmic modelling of voice quality was not sufficient for replacing the Alice voice, it allowed the release of the freely available emotional voice. Finally unit selection approaches to controlling emphasis were added and integrated into the ARIA-VALUSPA framework.

For more details and a focus on the breakthrough elements of this work see section 3.3.

6.4.5 TASK 4.5 SYNTHESIS-ANALYSIS FEEDBACK LOOPS

The ARIA agent can adapt to the user's socio-emotional state detected by the INPUT module of the ARIA system (e.g. user's presence, voice activity, speech, etc.). This adaptation can be used to create synthesis-analysis loops of adaptive audio-visual behaviours. CNRS added two adaptive features in the ARIA system that supports Task 4.5: the handling of Interaction States and the realtime Language (audio synthesis) switch.

The ARIA agent can be in 4 different states with respect to a dyadic interaction with a user:

- IDLE
- ENGAGING
- ENGAGED
- DISENGAGING

The INPUT module informs the ARIA system about the detection of multimodal signals. The Dialogue Manager keeps track of this information and informs all other components, including ARIA-Greta that synthesizes appropriate multimodal behavior according to the current interaction state of the ARIA agent.

ARIA agents are multilingual (English, French and German) and can adapt its language to their users. Therefore, in addition to the Interaction State, the Dialogue Manager holds information about the current language of the ARIA agent. CNRS implemented a dynamic language switch that can be done in real-time when the Dialogue Manager informs ARIA-Greta of a language change. This change affects Cereproc's synthesised speech because ARIA-Greta loads in the speech engine the new language modules in real-time. UAugsburg and ICL worked on the real-time detection of user's language changes (among the three system languages). This supports an adaptive analysis-synthesis loop in which a change in the language is automatically detected by the INPUT module of the ARIA system and the ARIA agent dynamically adapts to it.

6.4.6 Task 4.6 Multimodal behaviour response model to unexpected situations

At CNRS we focused on dealing with interruptions as unexpected situation that may occur during the user-agent interaction. We tackled three questions:

- 1. Study interruptions and their meaning and effects during the interaction;
- 2. Detect when a user's interruption occurs;
- 3. React appropriately (i.e. agent) when such interruptions occur.

For the first question, we proposed a taxonomy for modelling user's interruptions and we evaluated the impact of interrupting behaviour, based on this taxonomy, on interpersonal attitude and engagement judgements from a third person point of view⁹. The proposed taxonomy embeds two main categories: the interruption type, whether or not the speaker-switch is successful and the presence or not of simultaneous speech and the strategies underlying the interruption, namely **disruptive** or **cooperative**.

⁹A. Cafaro, N. Glas, and C. Pelachaud. 2016. The Effects of Interrupting Behavior on Interpersonal Attitude and Engagement in Dyadic Interactions. In Proceedings of the International Conference on Autonomous Agents & Multiagent Systems (AAMAS '16), 911-920.

When dealing with the second question, it was important to differentiate backchannelling behaviour (i.e. when the user gives vocal feedback while listening to the agent) and interrupting behaviour. We approached this problem by taking advantage of the data collected for the NoXi database and developed a corpus-based machine learning approach. We learned from annotated interactions whether the speaker's acoustic features (e.g. prosody) allow discerning if the user is interrupting (as opposed to back-channelling) and in this case which the employed strategy (disruptive or cooperative) is.

Regarding the third question, we first enhanced the animation capabilities of the Greta virtual agent. The current behaviour of the agent can be:

- Ended: the formerly specified behaviour(s) finished (i.e. has been displayed).
- **Stopped**: the formerly specified behaviour has been stopped (e.g. due to a newly created FML-APML set in replace mode).
- Aborted: the formerly specified behaviour failed to be displayed for some error(s).

And a new behaviour can be:

• **Started**: the formerly specified behaviour(s) started (i.e. is being displayed).

It is the dialogue manager that re-plans the communicative intentions as reaction to the interruption. It sends these new intentions to Greta using the FML template mechanism, but in **replace** mode. The dialogue manager makes use of two parameters, namely **reaction type** and **reaction duration**, to specify how the agent reacts to the interruption.

Finally, we conducted an experiment to determine the multimodal behaviour of the agent when reacting to different interruption types. From a careful analysis of human data using the NoXi database, we extracted multimodal behaviours that are commonly displayed during an interruption. To validate these behaviours on the virtual agent, we defined an interface with four videos of the agent. In these videos the agent's animation is obtained by manipulating the different multimodal behaviour using a genetic algorithm. We asked human participants to choose the videos that correspond best to the reactive behaviour to an interruption. New videos of the agent are computed on the fly. Participants continue selecting videos of the agent until they are satisfied with the results. As such we were able to characterize precisely which multimodal behaviour an agent should display as a reaction to an interruption.

6.4.7 Advances made after July 2017

Since the last deliverable, the CNRS team worked on integrating the sequential attitude planner into the Aria platform. The dialogue manager sends the attitude change the agent should display. The attitude planner computes how to display the communicative intention with this attitude change. This integration of the attitude planner and the communicative intention planner was evaluated through perceptive study. The results of this study validated the computational model. The CNRS team worked also on developing a perceptual study to characterize the reactive behaviour of the agent to an interruption. Through an interface, participants viewed four videos of the interruptee agent. Participants select which videos correspond best to a reactive behaviour. Participants can select videos as long as they wish. New videos are rendered on the fly where the behaviours of the agent are manipulated using a genetic algorithm. When they are satisfied with a video, they select it and precise their level of satisfaction.

6.5 WP5: REALISATION OF USE-CASES AND PORTABILITY

6.5.1 TASK 5.1: Specification of use-cases

Specifications of the Book-ARIA and the industry-Associate ARIA have been delivered on time. Similar specifications were applicable in each case. These specifications determine what implementation and RnD efforts are necessary for the realisation of the Embodied Conversational Agent using the capabilities developed in WPs 1-4 and to ensure the cross-domain portability of the ARIA-VALUSPA technologies.

Uses cases utilise Living Actor technology and the dialogue management system integrated with Living Actor avatars and CereProc voice synthesis.

The POC is in English, French, and German languages and used for the realisation of Book-ARIA, using a HTML5 rendering system. The POC demonstrated several limitations regarding the rendering and the portability so the specifications where modified.

The behaviour of the avatar was fluid and able to react almost immediately to user events. Existing options to display real-time 3D animations in a web-based application (Unity, WebGL) may not have functioned properly on all mobile devices, but this was a limitation that was accepted as creating native applications for all mobile platforms was beyond the scope of this project. We decided to work on a streaming system to generate 3D animation on a remote server and the streaming of live videos, similar to a teleconference call.

Examples of specifications for the application include

- Vocal dialogue. In the solution provided by WP3, the user is able to interact with the ARIA directly by voice. This system is able to dynamically adapt the speech according to the user's reactions, take initiative if the user is passive, and deal gracefully with interruptions.
- This vocal solution could handle 3 languages: English, German and French.
- 3D real time avatar as streaming
- Empathic avatar: The animation of the avatar and its behaviour incorporated the developments from the WP4 to be more efficient and accurate.
- The ARIA analysed a live video capture of the user thanks to the developments of the WP2, in order to detect engagement, mood and specific behaviours that could enhance the Industry-ARIA experience. For example, if the user attention was



Figure 6.8: Alice model

caught by something else, or if the environment sound changed suddenly, the ARIA would be able to adapt the dialogue and wait for the user.

A detailed account of specifications can be found in the specification documentation.

6.5.2 Task 5.2 Realisation of Industry Associate-ARIA using affective technology

This section has been redacted from the public version of the deliverable.

6.5.3 TASK 5.3 REALISATION OF BOOK-ARIA

The goal of the Book-ARIA was to provide an interactive book experience to users of all ages. The interaction was performed by an embodied agent simulating a character, the author, or another person related to the book. This demonstration application featured Alice from "Alice in Wonderland" (Lewis Carroll). In the demonstration application, the user stands in front of the computer and is able to interact with Alice in a natural way using voice to discuss the novel featuring her. Once the application detects the user's presence, the ARIA (Alice) initiates the dialogue. Alice introduces herself and asks about the user's knowledge of the Alice in Wonderland novel. If the user does not come up with a question to ask, the agent proposes some topics to discuss. The user is not required to have read the book.

This application was available in 3 languages: English, French and German. The agent adapts its behaviour to the user. From the onset of the project a virtual human
representing the characterisation of a novel agent (called a Book-ARIA) was developed. Book-ARIAs are believed to have commercial value in their own right. More generally, the Book-ARIAs could function as a showcase of what rich personalities could be generated with ARIA-VALUSPA and how they could function as interfaces for information retrieval for more complex tasks, including, questions about the novel's content, characters, author, etc.

In the Book Personification scenario, a user could interact with a character representing the book, asking it questions related to the book and the character. This scenario was chosen because while Virtual Assistants are often very goal oriented, for reasons of optimizing public relations of companies, they do not allow for a diverse range of personalities. On the other hand, the book personifications that we developed were not similarly constrained, and allowed us to explore the interaction between users and exaggerated personalities within the well-defined context of the book they were based on. The selected book was determined and was intended to be different for each language taking in account that it was a classic novel of each language literature. The virtual character had the mission to personify the book.

Realising the Book-ARIA application discussed above required technical effort. For example, a new rendering mode was added to Living ActorTM 3D to send audio and video streams directly to a web page instead of rendering the avatar on the user's screen. The animation of the avatar was no longer rendered in the software window but in a memory buffer called offscreen, which can be stored in a file directly on the computer or sent as stream data. The real-time generated audio and video are sent through an http stream pipe as soon as they were generated by the 3D animation module. The data were then received by a server based on NodeJS which converts it to a websocket. The websocket is then received in a web page that plays it automatically.

As of December 2017, the streaming capability sending the video and audio data through an http stream pipe is technically working. The data is well sent and received, but there are some issues regarding the quality of the video displayed on the web page. It seems that the origin of the issue is located in the NodeJS server when converting the http flux to a websocket. Currently, developers have not succeeded in displaying an output that is non-pixilated, with no latency video output.

Finally, there is another issue directly linked to the 3D engine used by Living ActorTM 3D to render 3D avatars. When rendering to a memory buffer, an 'out of memory' error occurs regularly and most of the time the 3D rendering engine has to reboot in order to correctly render subsequent frames. Cantoche does not have control over the main memory leak inside the rendering engine. However, this was managed and reduced as best as possible, but the error still occurs and prevents developers from having the continuous flow of data streaming needed.

6.6 WP 6: Hypothesis testing, data collection and global Evaluation

6.6.1 TASK 6.1 ETHICAL POLICIES

For each partner of the project we obtained their ethical policies and documented them in deliverable 6.5. This mostly concerns the protection of data as well as the protocol for ethical clearance. All personal data collected in the project is treated according to EU law. In particular, in ARIA-VALUSPA personal is anonymised as best as possible (i.e. face and voice data will be kept intact). Anonymised demographic data is stored on user-level access controlled file servers.

6.6.2 TASK 6.2 EXPERIMENTAL INDUCTION

As reported in deliverable 6.1 we initially set up two experiments. In this first stage of data collection, we aimed at collecting data that is necessary to develop the DM module with verbal inputs:

- Dataset 1. Set of recordings of a scripted dialogue between several users and the agent for testing the ASR module with contextualised vocabulary.
- Dataset 2. Set of recordings to obtain verbal inputs for the dialogue management system including unexpected situations, user engagement and general dialogue strategies in a Wizard of Oz (WoZ) scenario

For the first dataset, in order to collect realistic testing data for the ASR module a SSI pipeline of the user-agent interaction was set up. Interaction follows a static script in which the user and Alice talk in turns. The dialogue starts by presenting the user a sentence he or she should read out loud. After the end of a voice is detected, a picture of Alice is displayed and an appropriate answer is played back to the user (see Fig. 6.9. The results of the interpersonal stance ASR recording pipeline.). All speech input of the user is stored in separate audio files and will be used to refine the ASR models. Next, the scripted dialogue is replaced by the actual ASR output and the result is sent to the Dialogue manager.

We recorded 16 participants in Germany, France and the UK, all reading the English sentences. The training data was meant to improve the model by not only training on native speakers but also on persons with foreign dialects. The sentences were automatically separated into 16 chunks per participant and therefore automatically labelled.

As a second initial dataset University of Twente set up a wizard of of scenario with two goals in mind. Firstly, this data collection helped developing multi-modal interaction between users and agents. Secondly it supported the development and evaluation of a system that allows DM in the early development stages of virtual humans.

The participants for this study were split to run experiments under two conditions (8 per condition). In the first condition there were 7 male and 1 female participants (2 native English speakers) with an average age of 30.38 years. In the second condition were 4 male and 4 female participants (no native speakers) with an average age of 34.13 years. Most participants have seen an Alice in Wonderland movie, but none of them recently read the book. The data that was collected during the experiment allows to select the



Figure 6.9: Example for the initial dataset of collected speech examples.

knowledge that is required to give appropriate answers in dialogues in later stages of the project.

6.6.3 TASK 6.3 RECORDING OF INTERACTIONS WITH ARIA-VALUSPA PLATFORM

We opted to go for a mediated human-human interaction database already in early stages of the project that could be used for the development of the single components of ARIA-Valuspa. To this end we recorded the NoXi database, as described in 2.3. In NoXi an expert talks about a topic to a novice who is interested in the topic via a screen, which is close to the final interaction with an agent on the screen. We further added "unexpected" events to the recordings, such as phone calls and walk-ins. Overall we recorded 84 sessions with 2 participants per session, which results in an overall 25 hours of audio, video and depth information data.

6.6.4 Task 6.4 Annotation of emotion, social cues, etc., transcription of spoken content

In ARIA-Valuspa we went for a mixed approach for annotating the previously recorded NoXi database. Thereby we partly annotated the database in a manual effort, for other cues we used SSI's capabilities of automatically annotating specific social cues. Finally we used the NOVA tool for cooperatively annotating social cues, together with machine learning algorithms. The annotations are described in deliverable D6.2. In conclusion we manually labelled speech transcriptions for English and German sessions, Speech/Filler/Breath annotations that have been performed partly in a manual way, and partly with cooperative learning. We automatically performed annotations of interruptions by analysing the alignment of speech turns of both participants in the corpus, see Fig. 6.10.



Figure 6.10: Example for automatically extracted interruption annotations in the NOVA tool.

Further we employed a couple of recognisers for gestures and expressiveness features: Movement Energy/Power represents the dynamic properties of a movement (e.g. weak versus strong).

Overall Activation (represents the quantity of the movement (passive versus active). I Spatial Extent is modelled as the space that is used for gesturing in front of the recorded person.

Fluidity differentiates smooth movements from jerky ones. This feature aims to capture the continuity between movements.

Gestures and Postures are recognised using an event-based mechanism that triggers an event each time the beginning or the end of a social signal, such as a particular arm configuration, is detected. The detected events are saved in an XML-based structure including a synchronised time stamp and the event's duration. For event-based behaviour analysis, our system makes use of the Full Body Interaction Framework (FUBI).

Further we automatically collected continuous measurements along the two affective dimensions valence and arousal. Each dimension is represented by a single value in the range [0..1]. For details see Chapter 2 'Nonverbal Social Signal Processing' in D2.1.

We manually annotated the conversational "Engagement" for all French and German sessions (English session are currently annotated) on a continuous scheme ranging from 0..1. These annotations represent the interest of a person in the interaction. Figure 6.11 shows the gold standard annotations of engagement that have been merged from annotations from multiple raters. The expert's (on the left) engagement is shown on the upper tier, the novice's (on the right) engagement is shown on the lower tier

6.6.5 TASK 6.5 RECORDINGS OF VOICE TALENTS FOR SPEECH SYNTHESIS

A within domain 4,000 word script was created based on 100 example sentences and a list of 500 key within domain words resulting in 1.5 hours of within domain audio data. Acted conversational speech was recorded using two interviews with academics with the recording engineer acting as the dialog partner. The created a 14,000 word script



Figure 6.11: An example of the Gold Standard annotation of engagement in the NOVA tool.

resulting in 2.5 hours of acted conversational genre speech. Lombard speech was recorded by playing noise to the voice talent over headphones. A standard phonetically balanced script was used of 5,000 words resulting 2 hours of Lombard speech audio. Quality control was carried out on the recorded audio and a voice was released to the project.

Work on algorithmic extension of expressive speech was carried out on data already collected by CereProc which was used to build a freely available emotional voice (see section 3.3).

6.6.6 TASK 6.6 SYSTEMATIC EVALUATION OF INDUSTRY ASSOCIATE DEMONSTRATOR

In the following, we will describe the data recordings with the full interactive AVP system. Recordings took place at Nottingham University between 2017/10/26 and 2017/12/15. In total, we recorded 40 unique individuals during 226 sessions. 49.1% of people reported their gender as Female, and 6.64% as 'Other'. 49% claimed to be native English speakers, 44.24% to have high proficiency, and 6.63% intermediate proficiency in English. We started with the initial system, which we used in week 1 and 2 (wk12). Afterwards, we identified a couple of shortcomings. For instance, the agent sometimes repeated the same sentence within a session. Consequently, we enriched the knowledge base of the dialog manager with more alternatives. We prepared an improved system, which we used in week 3 and 4 (wk34). Afterwards we took a two weeks break to prepare the final system. Besides further improvements of the dialog manager we also added the possibility to



Figure 6.12: Some of the questions visualised as bar charts with respect to the three system stages (wk12=initial, wk34=intermediate, wk68=final). The height of the bar represents the average score (an error bar gives the standard deviation). The red line indicates the average over all sessions.

capture the agent screen along with the other signals. The total length of all recordings sums up to more than 20 h. Figure 6.13 shows a screenshot of the interaction visualised with the NOVA tool.

During the interaction the agent represented the little girl, who inspired Lewis Carroll to write his book, whose name is Alice Liddell. Users had to convince her to reveal some personal details of her life. In order, to receive the correct answer the user had to gain the trust of the agent first. The trust level took into account the verbal part of the conversation, as well as, the user's non-verbal expressions. After each quest, we asked participants to fill in a questionnaire. Each question had to be answered on a Likert scale from 1 (strongly disagree) to 5 (strongly agree). We were particularly interested to measure the relative improvement between the initial (wk12), intermediate (wk34), and final system (wk68).

Results showed that the system usability generally improved over time and was less complex to follow. The final system was perceived user friendly and users believed that new subjects are able to quickly learn to interact with the system. We also noted that the users found the plot of the interaction more engaging in the final system. However, there seemed to be no improvement regarding the perception of the conversations. People interacting with the final version were generally more satisfied and had more fun using the system. They also noted that they would recommend the system to other users. The awareness of the user inputs increased with the improved system, too. This is true for the verbal aspects, as well as, the non-verbal aspects. The non-verbal responds of the

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agent was also judged more positively. However, there was no improvement regarding the verbal response. Some of the results are visualised in Figure 6.12. More details can be found in D6.4.

6.7 WP7: Impact Delivery

6.7.1 TASK 7.1 PROJECT WEBSITE

We set up a project website immediately after starting the project describing the project's objective and motivation, as well as who is involved. The project can be found at **aria-agent.eu**. After the mid-term review, we have regularly added blob-posts to this, approximately one per month. The website also provides access to information about the current results of the project (reports, publications, software releases, and demo videos).

There are clear descriptions of and links to the three most successful outputs of ARIA-VALUSPA: the ARIA-VALUSPA Platform (AVP) on GitHub, our NoXi web database, and the NoVa annotation tool, again on GitHub.

6.7.2 TASK 7.2 DATA ACCESS

Access to almost all of the data collected in ARIA-VALUSPA is provided on-line through the NoXi database for both project internal and external use. See sections above as well as the dedicated deliverable D6.2. This include recordings of human-human and human-agent interactions, relevant annotations. As part of task 7.2, the NoXi web-database was set up, with an end-user license agreement for the corpus, which is in line with the project's and partner's IPR policy as well as providing and maintaining resources for hosting the data.

6.7.3 Task 7.3 Software releases

To release the AVP and NOVA software, we have used the popular service called GitHub. This service allows users to download data, suggest new edits to code, report issues and make suggestions for improvement. GitHub also provides a WiKi which serves as our detailed documentation of AVP and NOVA.

- The ARIA-VALUSPA Platform (AVP) can be found at https://github.com/ ARIA-VALUSPA/AVP.
- NOVA can be found at https://github.com/hcmlab/nova.

6.7.4 TASK 7.4 CONTRIBUTION TO STANDARDS

We have adhered to existing standards, but have not actively engaged in the creation of new or modification of existing standards.

6.7.5 TASK 7.5 WORKSHOPS AND TUTORIALS

Two workshops were given to stakeholders, both industrial and academic, to allow them to get accustomed with AVP and NOVA. The workshops were held in 2017, the first one in London, the second one in Paris.

The two meetings followed the same structure:

- 1. a presentation on the overall motivation behind the ARIA project was given by the coordinator of the project, and two of the three main outputs of the project were presented (AVP and NoVa).
- 2. NoXi was only presented in passing as due to ethics and privacy constraints the NoXi database cannot be shared with non-academic entities.
- 3. NoVa was presented by Tobias Baur, representing the university of Augsburg and the 'Framework' aspect of the project.
- 4. After this, the stakeholders were matched in turn with a representative from the Behaviour Analysis, Dialogue Management, Behaviour Generation, and Framework modules of AVP. They could speak to them for 15 minutes at a time, after which the stakeholders moved to the next representative.
- 5. At the end of the meeting, the companies reported on how they thought they could use the AVP and/or NoVa.

The proceedings of these meetings have been redacted from this public version of the document.

6.7.6 TASK 7.6 WRITING OF ARIA-VALUSPA BOOK

From our experience in the SEMAINE project, publishing a description of the entire final system in a traditional journal outlet is very difficult. Given the extent and tight integration of the project, it is very hard to fit the abundance of information describing it in a single paper. For ARIA-VALUSPA it will only be harder to write a similar paper, as the system is bound to be that much more complex. We will therefore write a book titled 'Building Virtual Humans', focused on teaching students and developers how to build their own Virtual Humans and/or interactive Artificial Intelligence agents. In addition it will cover some of the scientific and experimental elements, as well as describing the publicly available framework. The book will include hands-on examples complete with code snippets, as most of the source code will be publicly available. This way, the book will both be a description of the system, a guide to creating sensitive artificial listeners, and a manual to use the ARIA- VALUSPA framework.

6.7.7 TASK 7.7 DEVELOPMENT OF BUSINESS CASES

Business cases have been developed by the Industry Partners Cantoche and CereProc, and are described in section 5. The Industry Associates wrote business cases for creation of Industry-ARIAs, which are described in D7.2 and D5.2.

7 ACADEMIC OUTPUTS

In this section we enumerate our academic outputs.

7.1 Keynotes given

Keynotes and other talks given were previously listed in the Impact section 4.4.

7.2 Workshops and Tutorials organised

Workshop on Conversational Interruptions in Human-Agent Interactions. This workshop was held at IVA 2017 in Stockholm on August, 27th. The aim is to bring together researchers from a variety of fields interested in the study of conversational interruptions in multimodal human-human, human-agent (both virtual and robotic) or agent-agent interactions. Our aim is to address current challenges in this area (as well as identifying new ones) and to set a research agenda to make IVAs capable of believably react and adapt to unexpected situations such as conversational interruptions. Organisers: Angelo Cafaro, Eduardo Coutinho, Patrick Gebhard and Blaise Portard. Website: http://workshopcihai2017.doc.ic.ac.uk. Published proceedings: http://ceur-ws.org/Vol-1943/.

Audio/Visual Emotion Challenge and Workshop (AVEC 2017) @ACM Multimedia 2017 The Audio/Visual Emotion Challenge and Workshop (AVEC 2017) will be the seventh competition event aimed at comparison of multimedia processing and machine learning methods for automatic audio, visual, and audiovisual depression and emotion analysis, with all participants competing under strictly the same conditions. <u>Organisers</u>: Fabien Ringeval, Michel Valstar, Jonathan Gratch, Björn Schuller, Roddy <u>Cowie, Maja Pantic. Website</u>: http://sspnet.eu/avec2017/. <u>Published proceedings</u>: http://www.sigmm.org/opentoc/AVEC2017-T0C.

Audio/Visual Emotion Challenge and Workshop (AVEC 2016) @ACM Multimedia 2016 The Audio/Visual Emotion Challenge and Workshop (AVEC 2016) "Depression, Mood and Emotion" will be the sixth competition event aimed at comparison of multimedia processing and machine learning methods for automatic audio, visual and physiological depression and emotion analysis, with all participants competing under strictly the same conditions. <u>Organisers</u>: Michel Valstar, Jonathan Gratch, Björn Schuller, Fabien Ringeval, Roddy Cowie, Maja Pantic. <u>Website</u>: http://sspnet.eu/avec2016/. Published proceedings: http://www.sigmm.org/opentoc/AVEC2016-T0C.

Multimodal Emotion Recognition Challenge (MEC 2017) @ 2018 Asian Conference on Affective Computing and Intelligent Interaction (AACII) The Multimodal Emotion Recognition Challenge (MEC 2017) will be the second competition event aimed at the comparison of multimedia processing and machine learning methods for automatic audio and visual emotion analysis, with all participants competing under strictly the same conditions. The goal of the Challenge is to provide a common benchmark data set and to bring together the audio and video emotion recognition communities, and to promote the research in multimodal emotion recognition. Organiser: Jianhua Tao,

Affective Retrieval of Information Assistants - Virtual Agents with Linguistic Understanding, Social skills, and Personalised Aspects (ARIA-VALUSPA)

Björn Schuller Website: http://www.chineseldc.org/htdocsEn/emotion.html.

Workshop on Tools and Algorithms for Mental Health and Wellbeing, Pain, and Distress (MHWPD) @ACII 2017 This workshop is in the field of affective health computing, focusing on detection and intervention techniques for mental health and wellbeing, pain and distress. We invite contributions from researchers with multidisciplinary expertise (computer science, engineering, psychology and medicine), both in academia and industry, in the following domains: Distress - e.g. pain, panic, confusion, itching in patients with restricted communicative verbal abilities such as neonates and children, somnolent patients and patients with dementia is difficult to diagnose. <u>Organisers</u>: Akane Sano, Steffen Walter, Ognjen (Oggi) Rudovic, Nadia Bianchi-Berthouze, Björn Schuller, Rosalind W. Picard. <u>Website</u>: http://mhw.media.mit.edu/.

Computational Paralinguistics Challenge (ComParE), Interspeech 2017 The Interspeech 2017 Computational Paralinguistics ChallengE (ComParE) is an open Challenge dealing with states and traits of speakers as manifested in their speech signal's acoustic properties. There have so far been eight consecutive Challenges at INTER-SPEECH since 2009 (cf. the repository), but there still exists a multiplicity of not yet covered, but highly relevant paralinguistic phenomena. Thus, we introduce three new tasks by the Addressee Sub-Challenge, the Cold Sub-Challenge, and the Snoring Sub-Challenge. Organisers: Björn Schuller, Stefan Steidl, Anton Batliner, Elika Bergelson, Jarek Krajewski, Christoph Janott. Website: http://emotion-research.net/sigs/speech-sig/is17-compare.

Computational Paralinguistics Challenge (ComParE), Interspeech 2016 The Interspeech 2016 Computational Paralinguistics ChallengE (ComParE) is an open Challenge dealing with states and traits of speakers as manifested in their speech signal's acoustic properties. There have so far been seven consecutive Challenges at INTERSPEECH since 2009 (cf. the repository), but there still exists a multiplicity of not yet covered, but highly relevant paralinguistic phenomena. Thus, we introduce three new tasks by the Deception Sub-Challenge, the Sincerity Sub-Challenge, and the Native Language Sub-Challenge. Organisers: Björn Schuller, Stefan Steidl, Anton Batliner, Julia Hirschberg, Judee K. Burgoon, Eduardo Coutinho. Website: http://emotion-research.net/sigs/speech-sig/is16-compare.

Workshop on Affective Social Multimedia Computing ASMMC 2017 Affective analysis of social multimedia is attracting growing attention from industry and businesses that provide social networking sites, content-sharing services, distribute and host the media. This workshop focuses on the analysis of affective signals in interaction and social multimedia (e.g., twitter, wechat, weibo, youtube, facebook, etc). Organisers: Dong-Yan Huang, Björn Schuller, Jianhua Tao, Lei Xie, Jie Yang, Sven Bölte, Dongmei Jiang, Haizhou Li. Website: http://www.nwpu-aslp.org/asmmc2017/ content/committee.html.

Agents in Practice - Designing for Dialogues. SIKS workshop/tutorial. 2017, March The Netherlands Research School for Information and Knowledge Systems (SIKS) organised a course on 'Trends and Topics in Multi Agent Systems'. As part of this course, we gave a tutorial session on the design of dialogues for agents. We showed the ARIA-demo and how you can use the components of our system to design an intelligent agent. In particular we focused on turn management in dialogues. Organisers: Merijn Bruijnes and Jelte van Waterschoot Website: http://www.siks.nl/Agent-2017.php

7.3 Papers published

At the mid-term review there was some concern that it wasn't easily visible how the papers we reported were associated with the project. Therefore, we have now organised all papers in the appendix, and for every paper we clarify which of the authors were (partly) employed by ARIA-VALUSPA, and we provide up to 100 words justifying why the paper relates to the project.

We have also conducted a citation impact analysis. Despite the project having finished only recently, the academic papers listed here have already attained 1,008 citations, according to Google Scholar on 13 February 2017. The project has an h-index of 14. Table 7.1 shows a distribution of paper citations.

Citation range	The number of papers
0	24
1-5	34
6-10	16
11-50	14
> 51	5
total	93
h-index	14

Table 7.1: Citation statistics of ARIA paper outputs



Figure 6.13: A user interaction in NOVA. Top: Videos of user and agent. Middle: Audio waveform and facial features. Bottom: Affect annotations and transcriptions.

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8 APPENDIX A - ACADEMIC PAPERS PUBLISHED

					<i>a</i> .			
Title	All authors	Authors funded by ARIA	Journal / proceedings	Year	Category	Keywords	Related Task	1 100-word justification of relevance
Afunctional regression approach to facial landmark tracking	E. Sánchez- Lozano, G. Tzimiropou- los, B. Martinez, F. De la Torre, M. Valstar	Enrique Sánchez- Lozano and Brais Martinez and Michel Valstar	IEEE Transactions on Pattern Analysis and Machine Intelligence (in press)	2017	Behaviour Analysis	Computer Vision, Face Tracking, Face Analysis	WP2, T2.1	This paper presents the theoretical development of Continuous Regression, the key component of iCCR, the state of the art face tracking system, capable of performing incremental learning in real time. The paper presents a novel approach to solve the least squares problem, the main learning problem in Cascaded Regression, and derives a close-form solution that includes the infinite set of facial landmarks configuration. The new solution results in a much faster training algorithm, that also benefits from a real-time incremental learning the user's information into the model). The facial tracker system of eMax is currently the implementation of the prototype developed for the paper.
The NoXi Database: Multimodal Recordings of Mediated Novice-Expert Interactions.	Angelo Cafaro, Johannes Wagner, Tobias Baur, Soumia Dermouche, Mercedes Torres, Catherine Pelachaud, Elisabeth André, Michel Valstar.	Angelo Cafaro, Johannes Wagner, Tobias Baur, Soumia Der- mouche, Catherine Pelachaud, Elisabeth André, Michel Valstar.	In Proceedings of the 19th ACM International Conference on Multimodal Interaction	2017	Corpus	Multimodal Corpora, Database	WP6	This work describes a multi-lingual database of natural dyadic novice-expert interactions, named NoXi, featuring screen-mediated dyadic human interactions in the context of information exchange and retrieval. NoXi has been designed to provide spontaneous interactions with emphasis on adaptive behaviors and unexpected situations (e.g. conversational interruptions). A rich set of audio-visual data, as well as continuous and discrete annotations is publicly available through a web interface. Audio-visual data and available annotations are used transversally used within the ARIA-VALUSPA project for designing, building and testing modules of the ARIA-System.
Selecting and Expressing Communicative Functions in a SAIBA-Compliant Agent Framework.	Angelo Cafaro, Merijn Bruijnes, Jelte van Waterschoot, Catherine Pelachaud, Mariët Theune, Dirk Heylen.	Angelo Cafaro, Merijn Bruijnes, Jelte van Water- schoot, Catherine Pelachaud, Mariët Theune, Dirk Heylen.	In Proceedings of the 17th International Conference on Intelligent Virtual Agents (IVA'17).	2017	Behaviour Genera- tion	Dialogue manage- ment, commu- nicative function, FML, mul- timodal behaviour, SAIBA	WP3, WP4	In SAIBA-compliant agent systems, the Function Markup Language (FML) describes the agent's communicative functions that are transformed into utterances with appropriate non-verbal behaviours. This work defined an improvement of the FML standard in order to create FML Templates that the Dialogue Manager in the ARIA framework can dynamically select and fill with a variety of parameters (e.g. emotional expression) that are used by the behavior generation system (ARIA-Greta) to generate behaviors.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
The Effects of	Angelo	Angelo	In Proceedings of	2016	Behavior	Turn-	WP4	This user study investigated
Interrupting	Cafaro,	Cafaro,	the 16th		Genera-	taking,		the effects of interruption
Behavior on	Nadine Glas,	Catherine	International		tion	interrup-		strategies (disruptive vs.
Interpersonal	Catherine	Pelachaud.	Conference on			tions,		cooperative) and reactions
Attitude and	Pelachaud.		Autonomous			interper-		(long, medium, short overlap)
Engagement in			Agents and			sonal		between two agents on a
Dyadic Interactions.			Multiagent			attitude,		third person human observer.
			Systems			engage-		Results have been used to
			(AAMAS'16).			ment,		define a taxonomy of
						empirical		interruption strategies (for
						evaluation		the interrupter) and reactions
								(for the interruptee) in the
								context of unexpected
								situations in ARIA.
Speech Synthesis for	Aylett, M.P.,	Aylett,	IEEE	2017		Speech	WP4	Speech synthesis can be used
the Generation of	Vinciarelli,	M.P., &	Transactions on			synthesis,	T4.4	to personify the interface. In
Artificial Personality	A. & Wester,	Wester,	Affective			Unit	WP5	this paper we investigate the
-	М.	M.	Computing			selection,	T5.3	direct relationship between
						paramet-		expressive synthesis and the
						ric		perception of character in
						synthesis,		order to support the
						Emotion,		development of
						Personifi-		personification in the book
						cation.		ARIA.
Real-time reactive	Wester, M.,	Wester,	In Proceedings of	2017		Reactive	WP4	This work directly addresses
speech synthesis:	Braude,	M.,	the 18th Annual			speech	T4.4	the challenge of improving
incorporating	D.A.,	Braude,	Conference of the			synthesis.		the reactivity of and
interruptions.	Potard, B.,	D.A.,	International			Adaptive		embodied conversational
	Aylett, M.P.,	Potard,	Speech			speech		system. It relates closely
	& Shaw, F.	B., Aylett,	Communication			synthesis.		with work carried out by
		M.P., &	Association					CNRS on implementing
		Shaw, F.	(Interspeech 2017)					reactivity in Greta and is the
								subject of a current patent
								submission by CereProc.
Bot or Not?	Wester, M.,	Wester,	In Proceeding of	2017		Expressive	WP4	This paper describes the
Exploring the Fine	Aylett, M.P.	М.,	the 19th ACM			speech	T4.4	Science Lates demo Bot or
Line between Cyber	& Braude, D.	Aylett,	International			synthesis.		Not. This work explored the
and Human Identity.	А.	M.P. &	Conference on			Personifi-		extent expressive speech
		Braude,	Multimodal			cation.		synthesis and modified speech
		D. A.	interaction(ICMI			Emotion.		affected the perception of
			2017)					authenticity. The results
								form this work support the
								personification work carried
								out in WP5 T5.3
Don't Say Yes, Say	Aylett, M.P.,	Aylett,	In Proceedings of	2016		AAC, in-	WP4	Developing expressive speech
Yes: Interacting	Pullin, G.	M.P.,	the 2016 HI			teractive	14.4	synthesis is a key requirement
with Synthetic	Braude,	Braude,	Conference			media,		for WP4 14.4. This paper
Speech Using	D.A.,	D.A. &	Extended			speech		describes a technical probe
Tonetable	Potard, B.,	Potard,	Abstracts on			synthesis		created in collaboration with
	Henning, S.	в.	Human Factors in					Dundee college of art which
	& Antunes		Computing					explored subjects experience
	Ferreira, M.		Systems (CHI EA					and needs for expressivity in
			(16)					limited conversational
Cross Modal	Potard P	Potard	In Proceedings of	2016		Speech	WP4	Creating and assessing the
Evaluation of High	Avlott M D	B Avlatt	the 16th	2010		synthesis		effect of emotional apos-
Quality Emotional	ly Braudo	MP &	International			Unit	14.4	synthesis is control to
Speech Synthesis	D A	Broudo	Conformação			coloction		anosting expressive speech
with the Virtual	D.A.	D A	Intelligent Virtual			Expres		suppose How this interacts
Human Toolkit		D.A.	$\Delta gents$ (IVA'16)			sive		with a rendered graphical
			.15cmo (1 + A 10).			speech		head supports ABIA
						synthesis		integration with Greta
						Emotion		meesianon with Gieta.
						Prosody		
						Facial		
						animation		

					-			
Title	All authors	Authors funded by	Journal / proceedings	Year	Category	Keywords	Related Task	100-word justification of relevance
Idlak Tangle: An Open Source Kaldi Based Parametric Speech Synthesiser based on DNN	Potard, B., Aylett, M.P., Braude, D.A. & Motlicek, P.	Potard, B., Aylett, M.P., & Braude, D.A.	In Proceedings of the 17th Annual Conference of the International Speech Communication Association (Interspeech 2016)	2016		Speech synthesis, Kaldi, Idlak, HTS, DNN	WP4 T4.4	As stated in the proposal we remain agnostic on whether parametric or unit selection speech synthesis techniques for embodied conversational agents. DNN approaches to speech synthesis have demonstrated increased expressivity compared to other parametric techniques. This work describes a baseline freely available DNN system developed within a Kaldi framework and support expressive speech synthesis work in the parametric domain
Demo of Idlak Tangle, An Open Source DNN-Based Parametric Speech Synthesiser	Potard, B., Aylett, M.P. & Braude, D.A.	Potard, B., Aylett, M.P. & Braude, D.A.	In Proceesings of the 9th ISCA Speech Synthesis Workshop (SSW2016)	2016		Speech synthesis, Kaldi, Idlak, HTS, DNN	WP4 T4.4	domain. This paper describes the live demo of the Idlak DNN parametric system 'Tangle' which forms a baseline for expressive synthesis work using parametric approaches to speech synthesis (such as Wavenet etc).
Automatic Measures to Characterise Verbal Alignment in Human-Agent Interaction	Dubuisson Duplessis, G.; Clavel, C.; Landragin, F.	Dubuisson Duplessis, G.; Clavel, C.	18th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL)	2017	Emergence of synchrony between ECA and User	Adaptation, NLG, verbal alignment	WP3, WP4	This work provides verbal alignment measures based on repetition between dialogue participants at the lexical level. These measures can be leveraged in a NLG process to adapt system utterance to the user.
Shared acoustic codes underlie emotional communication in music and speech - evidence from deep transfer learning.	Eduardo Coutinho, Björn Schuller	Eduardo Coutinho, Björn Schuller	PLOS ONE, 12 (e0179289): 1-24, June 2017.	2017	Behaviour Analysis	speech, music, emotion, deep tranfer learning	2.1	Music and speech exhibit striking similarities in the communication of emotions in the acoustic domain. From a Machine learning perspective, the overlap between acoustic codes for emotional expression in music and speech opens new possibilities to enlarge the amount of data available to develop speech (and music) emotion recognition systems. In this research we investigated the Transfer Learning between these domains and demonstrated an excellent cross-domain generalisation performance in both directions. This directly feeds into the improvement of speech emotion recognition.
Automatically estimating emotion in music with deep longshort term memory recurrent neural networks.	Eduardo Coutinho, George Trigeorgis, Stefanos Zafeiriou, and Björn Schuller.	Eduardo Coutinho, Björn Schuller	Proceedings of MediaEval Multimedia Benchmark Workshop, satellite of INTERSPEECH, volume 1436, Wurzen, Germany, September 2015. CEUR.	2015	Behaviour Analysis	speech, music, emotion, deep tranfer learning	2.1	In this work we applied our speech emotion recongnition techniques to music emotion recognition. Given the striking similarities in the communication of emotions in music and speech, this work directly contributed to the improvement os speech emotion recognition models.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
Exploring the	Hesam	Eduardo	Proceedings of	2015	Behaviour	perceived	2.3,	The goal of this study was to
importance of	Sagha,	Coutinho,	International		Analysis	emotion,	4.1	evaluate the impact of the
individual	Eduardo	Björn	Workshop on			affect		inclusion of listener-related
differences to the	Coutinho,	Schuller	Audio/Visual			induction,		factors (individual
automatic	and Björn		Emotion			personal-		differences) on the prediction
estimation of	Schuller.		Challenge			ity,		of music induced affect (the
emotions induced by			(AVEC)			emotional		context in which the work
music.						intelli-		was developed). We identified
						gence,		individual trists that have a
						mood		significant explanatory power
						states,		over the affective states
						physiologi-		induced in the listeners. Our
						cal		results snow that
						signals		incorporating information
								differences permits to identify
								more accurately the affective
								states induced in the
								listeners which differ from
								those expressed by the music.
								This work has direct
								implications to
								user-adaptation in the
								context of emotional speech
								synthesis.
The icl-tum-passau	George	Eduardo	Proceedings of	2015	Behaviour	face,	2.1,	In this paper we describe our
approach for the	Trigeorgis,	Coutinho,	MediaEval		Analysis	speech,	2.4	participation in the
mediaeval 2015	Eduardo	Björn	Multimedia			emotion,		MediaEval's 'Affective Impact
'affective impact of	Coutinno,	Schuller	Washahas			deep		of Movies' challenge, which
movies task	Bingeval		(satellite of			learning		detection of affective (arousal
	Erik Marchi		INTERSPEECH)					and valence) and violent
	Stefanos		vol. 1436.					content in movie excerpts.
	Zafeiriou,		Wurzen, Germany,					This effort had a direct
	and Björn		September 2015.					impact on the audio-visual
	Schuller.		CEUR					emotion recognition work
								developed in this project.
Building	Marc	Björn	Proceedings of	2015	Behaviour	real-time	All	This paper describes a
autonomous	Schroeder,	Schuller,	Conference on		Analysis	interac-	WPs	substantial effort to build a
sensitive artificial	Elisabetta	Michel	Affective			tive		real-time interactive
listeners (extended	Bevacqua,	Valstar	Computing and			multi-		multimodal dialogue system
abstract).	Roddy		Intelligent			modal		with a focus on emotional
	Cowie,		Interaction			dialogue		and non-verbal interaction
	Florian		(ACII), pages			system,		capabilities a fully
	Hatico		450-402, Al all, F.			vorbal		real time system created in
	Gunes Dirk		September 2015			interac-		previous work The systems
	Hevlen		IEEE			tion		combines incremental
	Mark ter					sensitive		analysis of user behaviour.
	Maat, Garv					artificial		dialogue management, and
	McKeown,					listener		synthesis of speaker and
	Sathish							listener behaviour of an
	Pammi,							artificial character displayed
	Maja Pantic,							as a virtual agent. Principles
	Catherine							that should underlie the
	Pelachaud,							evaluation of these systems
	Björn							are also discussed. This
	Schuller,							paper described the
	Etienne de							groundwork that established
	Sevin, Mi-L-1							a departure point for ARIA.
	Valstar and							
	Martin							
	Woellmer.							

	Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
			funded by	proceedings		0 0		Task	relevance
			ARIA	1					
Senti	ment analysis	Biörn	Biörn	WIBEs Data	2015	Behaviour	Sentiment	21	Sentiment analysis is the task
and or	ninion mining	Schuller	Schuller	Mining and	2010	Analysis	analysis	2.1,	of identifying the polarity
	n optimal	Amr.	Schunch	Knowledge		7111019515	opinion	2.0	and subjectivity of
		El Dasalas		Discourse			opinion		de auto subjectivity of
para	ameters and	EI-Desoky		Discovery,			mining,		documents using a
per	formances.	Mousa,		5:255-263,			parame-		combination of machine
		Vryniotis		September 2015.			ters,		learning, information
		Vasileios.					perfor-		retrieval, and natural
							mance,		language processing
							machine		techniques. This paper
							learning		focuses on practical issues in
									statistical machine learning,
									and specifically to tedtermine
									the best feature selection
									methods, dimensionality
									reduction algorithms and
									classification techniques.
									This work has a direct impact
									to the recognition of affective
									information from linguistic
									context of the users' speech.
Face	reading from	Fabien	Björn	Proceedings of	2015	Behaviour	face.	2.1.	We present in this paper the
speed	h - predicting	Ringeval.	Schuller	INTERSPEECH.		Analysis	speech.	2.4	verv first attempt in using
facial	l action units	Erik Marchi.		pages 1977-1981.		0	facial		acoustic cues for the
from	audio cues.	Marc Méhu,		Dresden,			action		automatic detection of FACS
		Klaus		Germany,			units.		AU, as an alternative way to
		Scherer, and		September 2015.			audio		obtain information from the
		Biörn		ISCA.			cues.		face when such data are not
		Schuller					machine		available Besults show that
							learning		features extracted from the
									voice can be effectively used
									to predict different types of
									FACS AU This work
									provides a new solution to
									improve the robusteness of
									emotion recognition from
									facial cues, even when the
									image information is not
									available.
AVE	C 2015: The	Fabien	Biörn	Proceedings of	2015	Behaviour	audio.	2.4	The fifth Audio-Visual
5th i	international	Ringeval.	Schuller.	ACM		Analysis	video.		Emotion Challenge and
211	dio/visual	Biörn	Michel	International		1111019515	emotion		workshop AVEC 2015 was
emot	ion challenge	Schuller	Valstar	Conference on			challenge		held in conjunction ACM
and	workshop	Michel		Multimedia			8-		Multimedia'15 The
	· · · · · · · · · · · · · · · · · · ·	Valstar.		pages 1335-1336.					workshop/challenge_addresses
		Boddy		Brisbane.					the detection of affective
		Cowie and		Australia					signals represented in
		Maia Pantic		October 2015					audio-visual data in terms of
		maja i antic.		ACM					high level continuous
				nem.					dimensions. The goal of the
									Challenge is to provide a
									common bondbrook tost set
									for multimodal information
									for multimodal miormation
									together the audie wider and
									physiological anatica
									physiological emotion
									recognition communities, to
									compare the relative merits
									of the three approaches to
									emotion recognition under
									well-defined and strictly
									comparable conditions and
									establish to what extent
									nusion of the approaches is
									possible and beneficial.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
	D 1 ·	ARIA		0.015			0.1	
AV+EC 2015 - the	Fabien	Bjorn	Proceedings of	2015	Behaviour	audio,	2.4	This paper described the first
recognition	Biörn	Michel	Workshop on		Analysis	physiol		recognition Challenge and
challenge bridging	Schuller	Valstar	Audio/Visual			ogy		workshop ($AV \pm EC$ 2015)
across audio, video.	Michel	vaistai	Emotion			emotion.		aimed at comparison of
and physiological	Valstar.		Challenge, pages			challenge		multimedia processing and
data.	Shashank		3-8, Brisbane,					machine learning methods for
	Jaiswal, Erik		Australia,					automatic audio, visual and
	Marchi,		October 2015.					physiological emotion
	Denis		ACM.					analysis. The goal of the
	Lalanne,							Challenge is to provide a
	Roddy							common benchmark test set
	Cowie, and							for multimodal information
	Maja Pantic.							processing and to bring
								physiological emotion
								recognition communities to
								compare the relative merits
								of the three approaches to
								emotion recognition under
								well-defined and strictly
								comparable conditions and
								establish to what extent
								fusion of the approaches is
	D	D		0015	Dala ta	G	WDO	possible and beneficial.
the big data era	Schuller	Schuller	International	2015	Applysic	apalveis	WF2	issues related to data scarcity
the big data era.	Schuher	Schuner	Conference on		Analysis	paralin		in spoken language analysis
			Text. Speech and			guistics.		tasks. This contribution
			Dialogue, volume			big data.		shows the de-facto standard
			9302 of Lecture			self-		in terms of data-availability
			Notes in			learning		in a broad range of speaker
			Computer Science					analysis tasks that can be
			(LNCS), pages					explored to improve the
			3-11. Springer,					state-of-the-art in spoken
			September 2015.					language analysis, including
								the work developed in the
								achieving these goals (e.g.
								'cooperative' learning.
								dynamic aactive learning,
								multitask learning). New
								directions are also discussed.
Automatic	Eduardo	Eduardo	Science, Special	2015	Behaviour	computation	al 2.1,	This is an invited
estimation of	Coutinho	Coutinho,	Supplement on		Analysis	paralin-	2.3	contribution in which we
biosignals from the	and Björn	Björn	Advances in			guistics,		provide an overview of how
human voice.	Schuller	Schuller	Computational			applica-		Computational
			Psychophysiology,			tions,		Paralinguistics can offer new
			50 October			ostima		recognition of physiological
			2015			tion		parameters (biosignals) from
			2010.			0.011		the voice alone. This work
								has a direct impact to the
								recognition of user states
								(affective and cognitive).
Semi-supervised	Wenjing	Eduardo	PLoS ONE,	2016	Behaviour	active	2.3	This work described the
active learning for	Han,	Coutinho,	11(9):e0162075,		Analysis	learning,		application of the algorithms
sound classification	Eduardo	Björn	2016.			sound		developed in ARIA for the
in hybrid learning	Coutinho,	Schuller				events		reduction of annotated effort
environments.	Huabin					classifica-		and increasing the ammount
	Haifeng Li					annota		improvement of modelling
	and Biörn					tion effort		tasks to a new domain
	Schuller					reduction		environmental sounds
	Somunor							classification. This work has
								a direct impact to the
								recognition of contextual cues
								in the content
								human-machine
								communication.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
Description	Dest	ARIA	D l' Of	0017			NU	
Deep recurrent	Sabathe	Coutinho	International	2017		music	none	state-of-the-art in automatic
Memory-enhanced	Eduardo	Biörn	Joint Conference			composi-		music composition through
variational	Coutinho	Schuller	on Neural			tion		the use of truly generative
autoencoder-based	and Biörn	Domanor	Networks			evaluation		models based on Variational
musical score	Schuller		(IJCNN), pages			metric,		Autoencoders. We also
composition and an			3467-3474, May			varia-		introduce and evaluate a new
objective measure			2017.			tional		metric for an objective
						autoen-		assessment of the quality of
						coders,		the generated pieces. We
						generative		demonstrate that our model
						models		can generate music pieces
								characteristics of a given
								composer or musical genre
								and that the newly proposed
								measure permits investigating
								the impact of various
								parameters and model
								architectures on the
								compositional process and
	C.	D	D	0010	Dolor 1	1.		output.
Adieu features?	George	Bjorn	Proceedings of	2016	Applyaic	end-to-	2.1,	The automatic recognition of
emotion recognition	Fabien	Schuner	5200-5204		Analysis	learning	2.4	speech is a challenging task
using a deep	Ringeval.		Shanghai, P. R.			raw		On the one hand, acoustic
convolutional	Raymond		China, March			waveform,		features need to be robust
recurrent network.	Bruckner,		2016. IEEE.			emotion		enough to capture the
	Erik Marchi,					recogni-		emotional content for various
	Mihalis					tion, deep		styles of speaking, and while
	Nicolaou,					learning,		on the other, machine
	Bjorn Sabullan and					L CININ,		learning algorithms need to
	Stefanos					LOIM		while being able to model the
	Zafeiriou							context. In this paper, we
								propose a novel solution to
								the problem of
								'context-aware' emotional
								relevant feature extraction in
								order to automatically learn
								the best representation of the
								speech signal directly from
								(end-to-end speech emotion
								recognition) This research
								established the ground work
								for ARIA's audio-visual
								emotion recognition system.
Does my speech	Lucas Azais,	Eduardo	Proceedings of	2015	Behaviour	Automatic	2.2,	This paper describes an
rock? automatic	Adrien	Coutinho,	INTERSPEECH,		Analysis	Public	2.3	investigation of which
assessment of public	Payan, Tianijao	Bjorn Schuller	pages 2519-2523, Dresden			Assoss		suprasegmental speech
speaking skins.	Sun	Schuner	Germany			ment		evaluating oratory speaking
	Guillaume		September 2015			database		skills. It also provides a new
	Vidal. Tina		ISCA.			classifica-		annotated database for the
	Zhang,					tion,		development of Automatic
	Eduardo					regression,		Public Speech Assessment
	Coutinho,					prosody		(APSA) models. In the
	Florian							context of ARIA, this work is
	Eyben, and							particularly relevant for the
	Björn							development of realistic
	Schuller							speech synthesisers by
								evaluation of the oratory
								quality of the synthesized
								speech.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
Assessing the prosody of non-native speakers of english: Measures and feature sets.	Eduardo Coutinho, Florian Hoenig, Yue Zhang, Simone Hantke, Anton Batliner, Elmar Noeth, and Björn Schuller	Eduardo Coutinho, Yue Zhang, Björn Schuller	Proceedings of Language Resources and Evaluation Conference (LREC), pages 1328-1332, Portoroz, Slovenia, May 2016. ELRA.	2016	Behaviour Analysis	non- native speech, prosody, feature evaluation	2.2, 2.3	In this paper, we describe a new annotated database with audio recordings of non-native (L2) speakers of English, and the perceptual evaluation experiment conducted with native English speakers for assessing the prosody of each recording. We also compared the relevance of different feature groups modelling prosody in general (without speech tempo), speech rate and pauses modelling speech tempo (fluency), voice quality, and a variety of spectral features. We also discuss the impact of various fusion strategies on performance. This work is directly relevant user-adaptation in terms of individual differences in linguistic fluency that are relevant from Automatic Speech Recongnition.
Enhanced semi-supervised learning for multimodal emotion recognition	Zixing Zhang, Fabien Ringeval, Bin Dong, Eduardo Coutinho, Erik Marchi, Björn Schuller	Zixing Zhang, Eduardo Coutinho, Björn Schuller	Proceedings of ICASSP, pages 5200-52004, Shanghai, P. R. China, March 2016. IEEE.	2016	Behaviour Analysis	Multimodal emotion recogni- tion, enhanced semi- supervised learning	2.1, 2.4	In this paper, we propose an enhanced semi-supervised learning (SSL) approach to address two issues of SSL in the context of emotion recognition: I) performance degradation; 2) noise accumulation problem. Initially, we exploit the complementarity between audio-visual features to improve the performance of the classifier during the supervised phase. Then, we iteratively re-evaluate the automatically labeled instances to correct possibly mislabeled data and this enhances the overall confidence of the system's predictions. This work directly contributed to the improvement of multi-modal emotion recognition models by leveraging largely-available unlabelled data.
Facing realism in spontaneous emotion recognition from speech: Feature enhancement by autoencoder with LSTM neural networks	Zixing Zhang, Fabien Ringeval, Jing Han, Jun Deng, Erik Marchi, Björn Schuller	Zixing Zhang, Björn Schuller	Proceedings of INTERSPEECH, pages 3593-3597, San Francisco, CA, September 2016. ISCA	2016	Behaviour Analysis	emotion recogni- tion, sponta- neous speech, additive and con- volutional noises, feature enhance- ment, autoen- coder, LSTM Neural Networks	2.3	This work address the performance degradation problem when putting the speech emotion recognition systems in real-life conditions, where environmental additive and convolutional noises severely impact the system performance. We proposed to evaluates the impact of a front-end feature enhancement method based on an autoencoder with long short-term memory neural networks, for robust emotion recognition from speech. Support Vector Regression is then used as a back-end for time- and value-continuous emotion prediction from enhanced features.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
Towards intoxicated speech recognition	Zixing Zhang, Felix Weninger, Martin Woellmer, Jing Han, Björn Schuller	Zixing Zhang, Björn Schuller	Proceedings of International Joint Conference on Neural Networks (IJCNN), pages 1555-1559, 2017. IEEE.	2016	Behaviour Analysis	speech recogni- tion, speaker intoxica- tion	2.1, 3.5	In a real-life scenario, the acoustic characteristics of speech often suffer from the variations induced by diverse environmental noises and different speakers. Almost all previous studies only considered the speakers' long-term traits, such as age, gender, and dialect. Speakers'
								example, affect and intoxication, are largely ignored. This paper address one particular speaker state, alcohol intoxication, which has rarely been studied. This work has direct implications to user-adaptation in the context of speech recognition.
Towards cross-lingual automatic diagnosis of autism spectrum condition in children's voices	Maximilian Schmitt, Erik Marchi, Fabien Ringeval, Björn Schuller	Björn Schuller	Proceedings of ITG Symposium on Speech Communication (ITG SC), pages 264-268, Paderborn, Germany, 2016. VDE, IEEE	2016	Behaviour Analysis	autism detection, cross- linguistic	2.1, 2.2	The work focusses on automatic diagnosis of Autism Spectrum Conditions (ASC) from the voice in cross-lingual situation, which is rarely studies previously. We conducted extensive cross-lingual evaluations based on four databases collected in English, French, Hebrew, and Swedish. The datasets contain speech of children with ASC and typically developing (TD) children matched in both age and gender. We demonstrate automatic ASC vs TD classification to be feasible despite such variation with a remaining error. In the context of ARIA, this work is particularly relevant to the analysis of user profiling
Classification of the excitation location of snore sounds in the upper airway by acoustic multi-feature analysis	Kun Qian, Christoph Janott, Vedhas Pandit, Zixing Zhang, Clemens Heiser, Winfried Hohenhorst, Michael Herzog, Werner Hemmert, Björn Schuller	Zixing Zhang, Björn Schuller	IEEE Transactions on Biomedical Engineering, 64(8):1731-1741, 2017. IEEE	2017	Behaviour Analysis	Snore Sound Classifica- tion, Multi- Feature Analysis	2.1, 2.2	This work systematically compares different acoustic features, and classifiers for their performance in the classification of the excitation location of snore sounds. Snore sounds from 40 male patients have been recorded during Drug-Induced Sleep Endoscopy, and categorized by ENT experts. Crest Factor, Fundamental Frequency, and the others have been extracted and fed into several classifiers. Using the ReliefF algorithm, features have been ranked and the selected feature subsets have been tested with the same classifiers. In the context of ARIA, this work is particularly relevant to the analysis of user profiling.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
Bird sound	Kun Qian,	Zixing	Proceedings of	2015	Environmen	t Bird	2.3	In this paper, we present a
classification by	Zixing	Zhang,	IEEE Global		Anavlysis	Sounds,		novel framework for bird
large scale acoustic	Zhang,	Björn	Conference on		0 0	p-centre,		sounds classification from
features and	Fabien	Schuller	Signal and			openS-		audio recordings. Firstly, the
extreme learning	Bingeval	bonunor	Information			MILE		p-centre is used to detect the
machine	Biörn		Processing			ReliefF		'syllables' of bird songs
macinite	Schuller		(ClobalSIP)			Extreme		which are the units for the
	Schuner		(Giobaisii),			Loarning		recognition task: then we use
			Orlando EI			Machina		own openSMUE toollist to
			December 2015			wiachine		out openswith tookit to
			IFFF					acoustic features from
			TEEE.					abunked units of analysis (the
								'aullables') PoliofE holps to
								reduce the dimension of the
								footure appage I pathy ap
								Furthermo Learning Machine
								(FIM) common for designer
								(ELM) serves for decision
								diment imported to the
								direct impact to the
								recognition of
								environmental/contextual
								cues in the content
								human-machine
N								communication.
Non-linear	Erik Marchi,	Bjorn	Proc. of	2015	Behaviour	Acoustic	2.2,	Novelty detection is a
prediction with	Fabio	Schuller	International		Analysis	novelty	3.5,	challenging task, and it aims
LSTM recurrent	Vesperini,		Joint Conference			detection,	4.6	at recognising situations in
neural networks for	Felix		on Neural			realistic		which unusual events occur.
acoustic novelty	Weninger,		Networks			and unex-		In this paper, we present a
detection.	Florian		(IJCNN), pages			pected		novel approach based on
	Eyben,		1-7, Killarney,			situations		non-linear predictive
	Stefano		Ireland, July					denoising autoencoders. The
	Squartini,		2015. IEEE.					autoencoder is trained on a
	and Björn							public database which
	Schuller							contains recordings of typical
								in-home situations such as
								talking, watching television,
								playing and eating. The
								evaluation was performed on
								more than 260 different
								abnormal events. In the
								result, our novel approach
								significantly outperforms
								existing methods. This work
								directly contributes to the
								ARIAs' abilities for handling
								unexpected situations and
								environmental conditions.
Adeep matrix	George	Björn	arxiv.org	2015	Behaviour	face recog-	2.2	Non-negative matrix
factorization	Trigeorgis,	Schuller			Analysis	nition,		factorization (NMF) can be a
method for learning	Konstanti-					blind		successful dimensionality
attribute	nos					audio		reduction technique over a
representations.	Bousmalis,					source		variety of areas including, but
	Stefanos					separation		not limited to,
	Zafeiriou,							environmetrics, microarray
	and Björn							data analysis, document
	Schuller							clustering, face recognition,
								blind audio source separation
								and more. In this work, we
								propose a novel model, Deep
								Semi-NMF, that is able to
								learn such hidden
								representations that allow
								themselves to an
								interpretation of clustering
								according to different,
								unknown attributes of a
								given dataset. Within the
								context of ARIA, the novel
								deep framework for matrix
								factorization is suitable for
								clustering of multimodally
								distributed objects such as
								faces.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
	<i>a</i>	ARIA	D (1995	0.01.0				
Deep canonical time warping.	George Trigeorgis, Mihalis A.	Björn Schuller	Proc. of IEEE Conference on Computer Vision	2016	Behaviour Analysis	Temporal Alignment of	2.2	In this work, we present the Deep Canonical Time Warping (DCTW), a method
	Nicolaou, Stefanos		and Pattern Becognition			multiple		which automatically learns
	Zafeiriou,		(CVPR), pages			sequences		representations of multiple
	and Björn		5110–5118, Las			-		time-series. On four real
	Schuller		Vegas, NV, June					datasets, we show that the
			2016. IEEE.					representations learnt via the
								outperform state-of-the-art
								methods in temporal
								alignment, elegantly handling
								heterogeneous features, such
								as the temporal alignment of
								acoustic and visual features.
								applications range from the
								temporal alignment of facial
								expressions and motion
								alignment for human action
								recognition, and speech.
Dynamic active	Yue Zhang, Eduardo	Yue	Proc. of International	2015	Behaviour	Active	2.2,	Active Learning (AL) is a technique to reduce human
agreement and	Coutinho,	Eduardo	Conference on		Anarysis	annota-	0.5	effort and thus costs and
applied to emotion	Zixing	Coutinho,	Multimodal			tion,		time for the annotation of
recognition in	Zhang, Cajijao	Björn Schuller	Interaction (ICMI) pages			NOXI		emotion, social cues, etc. In
spoken interactions.	Quan, and	Schuller	275-278, Seattle,					AL algorithm, termed
	Björn		WA, November					Dynamic Active Learning
	Schuller.		2015. ACM.					(DAL), which?makes the decision on a per instance
								level how many human
								annotators are required to
								label.?To this end, an early
								stopping criterion based on
								inter-rater agreement is
								efficiency, this novel approach
								has a direct positive?impact
								on the project by considerably accelerating the
								annotation process of NOXI.
Agreement-based	Yue Zhang,	Yue	Proc. of Advances	2015	Behaviour	Confidence	2.2,	Cooperative Learning (CL) is
learning with least	Eduardo Coutinho.	Zhang, Eduardo	In Active Learning:		Analysis	annota-	6.3	a recently introduced methode to efficiently share
and medium	Zixing	Coutinho,	Bridging Theory			tion,		the labelling work between
certainty query	Zhang,	Björn	and Practice			NOXI,		human and machine, when
strategy.	Quan,?and	Schuller	conjunction with			551		ever-present issue in
	Björn		the International					data-driven fields. The idea
	Schuller.		Conference on Machina Learning					is to adopt the machine
			(ICML), Lille,					predicted with high
			France, July 2015.					confidence, and only query
			IMLS.					human oracles in case of medium / low confidence
								Based on our previous works
								on CL and DAL, we
								scrutinise the confidence levels for maximum efficiency.
								For speech emotion
								recognition, our results show
								the same accuracy, but
								requires up to 67% less
								human annotations for the medium certainty and 70%
								for the least certainty query
								strategy. This approach has
								Deen intergrated into the

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
		ADIA	1					
	37 70	AIGA		0015	D 1 1			T .1. 1
On rater reliability	Yue Zhang,	Yue	Proc. of Affective	2015	Behaviour	Rater	2.2,	In this work, we propose
and agreement	Eduardo	Zhang,	Computing and		Analysis	reliability,	6.3	several variations of the DAL
based dynamic	Coutinho.	Eduardo	Intelligent			inter-rater		method, taking into account
active learning	Ziving	Coutinho	Interaction			agree-		inter-rater reliability and
active learning.	Zhana	D:::	(ACII) =====			agree-		inter-rater remaining and
	Znang,	Бјоги	(ACII), pages			ment,		inter-rater agreement. By
	Michael	Schuller	70?76, X1?an, P.			NOVA		query the most reliable rater
	Adam, and		R. China,					first, we could achieve further
	Björn		September 2015.					cost reduction for large-scale
	Schuller.		IEEE.					data annotation.?This
								approach opens up new
								realisation possibilities for
								the NO No half A state
								the NOn-verbal Annotator
								(NOVA) tool developed
								within the ARIA project.
Multitask deep	Yue Zhang,	Yue	Proc. of ICASSP,	2017	Behaviour	Affect	2.1,	For speech emotion
neural network with	Yifan Liu.	Zhang.	New Orleans, LA.		Analysis	recogni-	2.4	recognition, label scarcity
shared hidden lavors:	Folix	Biörn	March 2017		1111013010	tion ?emotion	2.1	presents a particular
D l' l'under layers.	TTT ·	DJOIN	IDDD			tion, emotion		presents a particular
Breaking down the	weninger,	Schuller	IEEE.			represen-		challenge as the limited
wall between	and Bjorn					tations		available databases are
emotion	Schuller							usually associated to
representations.								diversified emotion
								conceptions, derived from
								categorical dimensional and
								appraisal-based approaches
								In this much me advesses the
								In this work, we advocate the
								usage of multi-task deep
								neural networks with shared
								hidden layers.?In this
								way,?an utterance can be
								interpreted in manifold ways
								according to various emotion
								representations, which is of
								representations, which is of
								particular importance for the
								affect recognition system
								(WP 2).
Language	Yue Zhang,	Yue	Proc. of ACM	2016	Behaviour	Native	2.4	The first Language (L1)
proficiency	Felix	Zhang,	International		Analysis	language		influences the non-native
assessment of	Weninger	Biörn	Conference on			identifica-		prosody of users speaking
English L2 speakers	Anton	Schuller	Multimodal			tion		English as a second language
based on isint	Datiman	Schuner	Internetion			1		(I 2) 21 an arrange and fair and
based on joint	Batimer,		Interaction			language		(L2). Language pronciency
analysis of prosody	Florian		(ICMI), Tokyo,			profi-		assessment is highly
and native language.	H?nig, and		Japan, November			ciency		important for the user
	Björn		2016. ACM.			assess-		adaptivity of the ARIA
	Schuller		274?278.			ment,		system. ?For example,
						user adap-		context-aware spoken
						tation		dialogue systems can exploit
						tation		analogue systems can explore
								accent-specific acoustic
								models, adapt the tempo of
								speech synthesis to the
								language proficiency of
								individual speakers, or even
								switch to a user's native
								language in case of difficulties
								with the interaction in the
								default language Deal'
								default language. Realising
								these capabilities in
								automatic systems
								conceivably leads to more
								natural and human-like
								interaction.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
Semiautonomous	Yue Zhang,	Yue	Proc. of ICASSP,	2016	Behaviour	Label en-	2.2	In this work, we propose a
data enrichment	Yuxiang	Zhang,	pages 6090?6094,		Analysis	richment,		novel approach for large-scale
based on cross-task	Zhou, Jie	Björn	Shanghai, P. R.			data ag-		data enrichment, addressing
labelling of missing	Shen, and	Schuller	China, March			gregation		the scarcity of multi-label
targets for holistic	Björn		2016. IEEE.					databases. The idea of our
speech analysis.	Schuller							work is to join existing data
								resources into one universal
								database with a
								multi-dimensional label space
								by using semi-supervised
								learning techniques to predict
								missing labels. We evaluated
								the proposed method for
								likability, personality, and
								emotion recognition as
								exemplary tasks from the
								Challenge (ComParE) This
								work apples the model
								training on aggregated data
								for the holistic speaker
								analysis, which is a key
								component for the ARIA
								system.
Sincerity and	Yue Zhang,	Yue	Proc. of	2016	Behaviour	Non-	2.2,	Identifying contexts and
deception in speech:	Felix	Zhang,	INTERSPEECH,		Analysis	verbal	2.3	capturing non-verbal
Two sides of the	Weninger,	Björn	pages 2041?2045,			social		behavioural cues present a
same coin? a	Zhao Ren,	Schuller	San Francisco,			cues,		central aspect of social
transfer- and	and Björn		CA, September			context		intelligence, and thus is
multi-task learning	Schuller		2016. ISCA.			under-		highly important for the
perspective.						standing		ARIAs to be able to naturally
								interact with human users. In
								this work, we propose a novel
								multi-task learning method
								for recognising speech
								deception and sincerity. 10
								this end, we employ our
								for data aggregation by
								somi supervised cross tool
								label completion In the
								result our approach achieves
								significant error rate
								reductions compared to
								state of the art systems

Title	All authors	Authors	Journal /	Year	Category	Keywords	Belated	100-word justification of
		funded by	proceedings				Task	relevance
		ARIA	1					
The	Björn	Yue	Proc. of	2017	Behaviour	Speaker	2.1.	The INTERSPEECH 2017
INTERSPEECH	Schuller,	Zhang,	INTERSPEECH,		Analysis	analysis	2.2,	Computational
2017 Computational	Stefan	Björn	pages 3442?3446,		0	, i i i i i i i i i i i i i i i i i i i	2.3	Paralinguistics Challenge
Paralinguistics	Steidl.	Schuller	Stockholm.					addresses three different
Challenge:	Anton		Sweden, August					problems for the first time in
Addressee, Cold &	Batliner.		2017. ISCA.					research competition under
Snoring.	Elika							well-defined conditions: In
	Bergelson,							the Addressee sub-challenge,
	Jarek							it has to be determined
	Krajewski,							whether speech produced by
	Christoph							an adult is directed towards
	Janott,							another adult or towards a
	Andrei							child; in the Cold
	Amatuni,							sub-challenge, speech under
	Marisa							cold has to be told apart
	Casillas,							from ?healthy? speech; and
	Amanda							in the Snoring sub-challenge,
	Seidl,							four different types of snoring
	Melanie							have to be classified. Thus,
	Soderstrom,							this work addes new aspects
	Anne							for the speaker analysis of
	Warlaumont,							the ARIA system.
	Guillermo							
	Hidalgo,							
	Sebastian							
	Schnieder,							
	Clemens							
	Heiser,							
	winfried							
	Honennorst,							
	Inchael							
	Meningilian							
	Schmitt							
	Kun Ojan							
	Yue Zhang							
	George							
	Trigeorgis							
	Panagiotis							
	Tzirakis, and							
	Stefanos							
	Zafeiriou							
The	Björn	Yue	Proc. of	2016	Behaviour	Speaker	2.1,	The INTERSPEECH 2016
INTERSPEECH	Schuller,	Zhang,	INTERSPEECH,		Analysis	analysis	2.2,	Computational
2016 Computational	Stefan	Eduardo	pages 2001?2005,				2.3	Paralinguistics Challenge
Paralinguistics	Steidl,	Coutinho,	San Francisco,					addresses three different
Challenge:	Anton	Björn	CA, September					problems for the first time in
Deception &	Batliner,	Schuller	2016. ISCA.					research competition under
Sincerity.	Julia							well-defined conditions:
	Hirschberg,							classification of deceptive vs.
	Judee K.							non-deceptive speech, the
	Burgoon,							estimation of the degree of
	Alice Baird,							sincerity, and the
	Aaron							identification of the native
	Elkins, Yue							language out of eleven L1
	Zhang,							classes of English L2 speakers.
	Eduardo							Given the three different
	Coutinho,							languages used in the ARIA
	and Keelan							system, native language
	Evanini							particularly important
								for user adaptation

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
Towards human-l holisitc machim perception of speaker states ar traits.	ike Yue Zhang, Yifan Liu, and Björn ad Schuller	Yue Zhang, Björn Schuller	Proc. of the Human-Like Computing Machine Intelligence Workshop (MI20-HLC), pages 1?3, Windsor, U.K., October 2016. Springer.	2016	Behaviour Analysis	Speaker analysis	2.1, 2.2, 2.3	In this work, we advocate the usage of multi-task deep neural networks with shared hidden layers for various paralinguistic tasks. To this end, the feature transformations are shared across dierent tasks, while the softmax layers are separately associated with each target label. As a new milestone in holistic speech processing, we constructed a multilabel database, thus enabling large-scale data aggregation for better recognition performance. In ARIA, this work allows SSI to emcompass all paralinguistic
								speech phenomena featured
A paralinguisti approach to speal diarisation.	Yue Zhang, Felix Weninger, Boqing Liu, Maximilian Schmitt, Florian Eyben, and Björn Schuller	Yue Zhang, Björn Schuller	Proc. of ACM International Conference on Multimedia, pages 387?392, Mountain View, CA, October 2017. ACM.	2017	Behaviour Analysis	Speaker diarisa- tion	2.2, 3.5, 4.6	in the ComParE challenges. Speaker diarisation is the task of determining ?who speaks when? in an audio stream.?In this work, we present a new view on automatic speaker diarisation, based on the recognition of speaker traits such as age, gender, voice likability, and personality. Since in real-life, ARIAs would encounter situations when they deal with multiple users at once, speaker diarisation is highly relevant for ARIAs to handle challenging and unexpected situations.
Cross-domain classification of drowsiness in spec The case of alcob intoxication and sleep deprivatio	Yue Zhang, Felix Ech: Weninger, ol and Björn I Schuller n	Yue Zhang, Björn Schuller	Proc. of INTERSPEECH, Stockholm, Sweden, August 2017. ISCA.	2017	Behaviour Analysis	Speaker analysis	2.1, 2.2, 2.3	In this work, we study the drowsy state of a speaker, induced by alcohol intoxication or sleep deprivation. In particular, we show that an effective, general drowsiness classifier can be obtained by aggregating the training data from both domains.?Since ARIAs can be integrated in self-driving cars and other safty and security sensitive environments, these recognition models can be highly useful in practical use.
Infected Phonem How a Cold Impa Speech on a Phonetic Level	es: Johannes irs Wagner, Thiago Fraga-Silva, Yvan Josse, Dominik Schiller, Andreas Seiderer, and Elisabeth Andr'e	Johannes Wagner, Elisabeth Andr'e	Proc. of INTERSPEECH, Stockholm, Sweden, August 2017. ISCA.	2017	Behaviour Analysis	Speaker analysis	2.1, 2.2, 2.3	In this work we investigate the audible effects of a cold on a phonetic level. Results on a German corpus show that the articulation of consonants is more impaired than that of vowels. With such knoweldge we can improve the robustness of the paralinguistic analysis integrated in the ARIA system.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
MobileSSI: Asynchronous Fusion for Social Signal Interpretation in the Wild	Simon Flutura, Johannes Wagner, Florian Lingenfelser, Andreas Seiderer, and Elisabeth André	Johannes Wagner, Elisabeth André	Proceedings of the 18th ACM International Conference on Multimodal Interaction	2016	Behaviour Analysis	Speaker analysis	2.1, 2.2, 2.3	In this paper MobileSSI, a port of the Social Signal Interpretation (SSI) framework to Android and embedded Linux platforms is introduced. It is tested to what extent it is possible to run sophisticated synchronization and fusion mechanisms in an everyday mobile setting and compare the results with similar tasks in a laboratory environment. This can be helpful to run parts of the ARIA detection system natively on a mobile device.
Asynchronous and Event-based Fusion Systems for Affect Recognition on Naturalistic Data in Comparison to Conventional Approaches	F. Lingenfelser and J. Wagner and J. Deng and R. Bruckner and B. Schuller and E. André	Johannes Wagner, Elisabeth André	IEEE Transactions on Affective Computing	2017	Behaviour Analysis	Speaker analysis	2.1, 2.2, 2.3	Recognition results gained on a naturalistic conversational corpus show a drop in recognition accuracy when moving from unimodal classification to synchronous multimodal fusion. In this article, we taggle this problem and present a novel real-time system for affect recognition in a naturalistic setting. Since ARIA makes use of multiple modalities, the tested techniques may be applied in the future to improve the robustness of the uni-modal recognizers.
Combining Hierarchical Classification with Frequency Weighting for the Recognition of Eating Conditions	Wagner, Johannes and Seiderer, Andreas and Lingenfelser, Florian and Andre, Elisabeth	Johannes Wagner, Elisabeth André	INTERSPEECH 2015, 16th Annual Conference of the International Speech Communication Association, Dresden, Germany, September 6-10, 2015	2015	Behaviour Analysis	Speaker analysis	2.1, 2.2, 2.3	In this paper we classify whether a speaker is eating or not, and if so, which type of food the speaker is currently tasting. To allow for a fine-grained adaption to the characteristic spectrum of single food types we adopt a hierarchical tree structure and decompose the classification task into a sequence of binary decisions. This may help to improve the robustness of the paralinguistic analysis integrated in the ARIA system.
Cumulative attributes for pain intensity estimation	Edege, J. and Valstar, M.	Michel Valstar	Proceedings of the 19th ACM International Conference on Multimodal Interaction	2017	Behaviour Analysis	Pain esti- mation; Attribute learning; Multi- output regression; Relevance Vector Machines	WP2, T2.1	This paper presents a novel approach to automatic pain estimation, in which different set of features (appearance and shape) are used to predict an output vector lying in what is referred to as a Cumulative Attribute (CA) space. The CA encodes all the ordinal levels of pain up to the one that corresponds to the target frame. The CA outputs are finally regressed to give a final pain estimate. The paper is relevant to ARIA as it offers an efficient method for pain estimation, using a technique that can be extended to predicting the intensity of Action Units, which are used in the visual part.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
		ARIA						
Automatic Analysis	Brais	Brais	IEEE	2017	Behaviour	*facial	WP2,	This paper presents a
of Facial Actions: A	Martinez,	Martinez	Transactions on		Analysis	expression	T2.1	thorough review of the state
Survey	Michel F	and	Affective			recogni-		of the art techniques and
	Valstar,	Michel	Computing (in			tion,		databases in Facial Action
	Bihan Jiang,	Valstar	press)			action		Units detection and intensity
	Maja Pantic					units		estimation. The paper
								includes a detailed review of
								the main components that
								face analysis systems need. It
								also summarises the existing
								includes an evenuious of the
								challenges that remain to be
								solved. The paper is relevant
								to ABIA to illustrate what
								are the challenges and
								opportunities in the task of
								Action Unit detection and
								intensity estimation. These
								tasks are key in the visual
								part of eMax, as it is
								responsible for returning the
								values for the Action Units
						***		intensities.
Fusing deep learned	Joy Egede,	Michel	12th IEEE	2017	Behaviour	*feature	WP2,	The paper proposes an
and hand-craited	Valetar	valstar	International Conference on		Analysis	rusion,	12.1	fusion to automatically
appearance shape	Brais	Martinez	Automatic Face &			mation		estimate the level of pain
and dynamics for	Martinez	IVIAI UIIIEZ	Gesture			mation		from the face Considering
automatic pain			Recognition (FG					the lack of annotated data for
estimation			2017), pp.					the task of pain estimation, a
			689-696					deep neural network tasked
								with detecting Action Units,
								is used, given that these
								correlate with the level of
								pain. The deep learned
								features are thus those
								extracted in the last level of
								the network. These features
								are combined with
								those given by the
								appearance (HOG) and the
								facial landmarks (geometric)
								Each of the three set of
								features is the input of a
								corresponding Relevance
								Vector Regressor (RVR), and
								the output of each RVR feeds
								a second-level RVR, which
								returns the final score. The
								results of this paper are of
								interest for future issues of an
								ARIA framework, desired to
								understand whether a user is
								sumering pain, for instance in
			I					a task-assisted scenario.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
	<u>Cl. 1 1 1</u>	ARIA	10(1 1555	0017	Dala is	***	WDO	D
Automatic Detection of ADHD and ASD from Expressive Behaviour in RGBD Data	Jaiswal, Michel F Valstar, Alinda Gillott, David Daley	Valstar	International Conference on Automatic Face & Gesture Recognition (FG 2017), pp. 762-769	2017	Analysis	ADED, Action units	WP2, T2.1	nethod to aid the diagnostic of Attention Deficit Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD). The questionnaires that are generally employed by experts to evaluate the patient behaviour are shown and analysed automatically by the proposed system. This system employs RGBD data from a Kinect 2 camera, and extracts a set of high-level descriptors, including Action Units, Head Pose, Speed of Head movement, Cumulative distance, and response times. These features are then fed to a classifier that returns the expected ADHD/ASD score. The results of this paper are of interest for future issues of an ARIA framework capable of automatically report these specific disorders.
ACNN cascade for landmark guided semantic part segmentation	Aaron S Jackson, Michel Valstar, Georgios Tz- imiropoulos	Michel Valstar	Computer Vision – ECCV 2016 Workshops: Amsterdam, The Netherlands, October 8-10 and 15-16, 2016, Proceedings, Part III, pp. 143-155	2016	Behaviour Analysis	*CNN, face segmenta- tion, face analysis	WP2, T2.1	The paper presents a deep Convolutional Neural Network (CNN) cascade for facial parts segmentation. These segments correspond to meaningful parts of the face, such as the mouth or the eyes. The CNN performs first facial localisation, and it is followed by the part segmentation. The results of the proposed approach show that guiding the segmentation from the landmark localisations improves the performance drastically. The paper is of relevance to ARIA in the sense that it provides with an accurate understanding of facial parts, which can thereafter guide the detection of Action Units.
Cascaded Continuous Regression for Real-time Incremental Face Tracking	Enrique S?nchez- Lozano, Brais Martinez, Georgios Tz- imiropoulos, Michel Valstar	E. S?nchez- Lozano, M. Valstar, B. Martinez	Computer Vision – ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VIII, pp. 646-661	2016	Behaviour Analysis	*face tracking, incremen- tal learning, continu- ous regression, functional regression	WP2, T2.1	The paper presents a novel approach to facial landmark tracking using Cascaded Regression, by extending the linear regression problem to the continuous domain. Instead of generating samples, the paper proposes to use a first-order Taylor approximation of the feature space, yielding a close-form solution for the linear regressor. Its inclusion into the Cascaded Regression approach, and the development of the incremental learning rules allows the method to perform incremental learning in real-time, being the first (and so far the only) tracker that incorporates this capacity. The tracker resulting out of this paper was the preliminary one used in the visual part of ARIA.
Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
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		funded by	proceedings			-	Task	relevance
		ARIA						
Cascaded regression	Enrique	E	Pattern	2016	Behaviour	Supervised	WP2	The paper presents a
with sparsified	S?nchez-	S?nchez-	Becognition		Analysis	descent	T2 1	Cascaded Begression
feature covariance	Lozano and	Lozano	Letters 73 pp		711101y515	method	12.1	approach for facial landmark
matrix for facial	Dozano and Draio	M	10.26			Cocondod		localization in which the
landmanla dataatian	Mantinan	Valatan D	19-20			Cascaded		linean accession and law
landmark detection	and Michol	Martinor				Engine		according the correlation that
	Valatan	Martinez				racial		considers the correlation that
	vaistar					point io-		landmarks. The solution to
						Calisation		the least sevenes method
								the least-squares problem
								considers the covariance of
								the features extracted at the
								landmark localisations. This
								paper proposes a
								sparsification of the
								covariance matrix towards
								removing the influence of the
								features extracted at
								positions that might be
								highly uncorrelated with the
								target landmark. The paper
								is relevant to the visual part
								of ARIA, given that the
								tracker's initialisation uses
								this method to detect the
								facial landmarks for the first
								frame.
Deep Learning the	Shashank	M.	IEEE Winter	2016	Behaviour	*deep	WP2,	The paper presents a Deep
Dynamic	Jaiswal and	Valstar	Conference on		Analysis	learning,	12.1	Learning approach to Facial
Appearance and	Michel		Applications of			action		Action Unit detection. The
Shape of Facial	Valstar		Computer Vision			units,		proposed approach first slides
Action Units			(WACV)			lstm,		the image into regions of
						optical		interest, and then computes a
						flow		combination from the
								appearance of the first frame
								with the optical flow
								computed for the rest of the
								trames, as well as a set of
								binary masks for each of the
								frames, responsible of
								encoding the shape variations.
								Each of the regions for each
								of the images of a given
								sequence feeds a
								Convolutional Neural
								Network that computes a set
								of features that are
								subsequently used with a
								Bi-directional LSTM,
								responsible for encoding the
								temporal consistency. The
								proposed approach is key to
								the ARIA visual part, as it
								has proved to be the best
								iramework on the FERA 2015
								dataset. This system is being
								currently used to extract the
								Action Units, which are part
								of the features returned by
1	1	1		1				eMax.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
L2;1-based regression and prediction accumulation across views for robust facial landmark detection	Brais Martinez and Michel Valstar	B. Martinez and M. Valstar	Image and Vision Computing, vol. 47, pp. 36-44. 2016	2016	Behaviour Analysis	*facial landmark localisa- tion, multiview, face alignment, cascaded regression	WP2, T2.1	The paper presents a Cascaded Regression approach to facial landmark tracking, in which the regression problem, typically learnt through Least-Squares, is replaced by the L2,1 norm, making it more robust to poor initialisations or partial occlusions. The L2,1 norm provides a sparse representation of the per-landmark localisation error, thus enforcing the error of occluded landmarks not to contribute to the total cost in a dramatic way. Besides, the paper proposes to use multiple initialisations that are efficiently combined to improve the accuracy of the final landmark localisations. The paper is relevant to the ARIA visual system, and was used at first as an estimator, before the development of the accurate and fast face tracker
IProbe, Therefore I Am: Designing a Virtual Journalist with Human Emotions.	Bowden, K., Nilsson, T., Spencer, C., Cengiz, K., Ghitulescu, A. and van Waterschoot, J.	Alexandru Ghit- ulescu and Jelte van Wa- terschoot	Proceedings of the 12th Summer Workshop on Multimodal Interfaces (eNTERFACE (16), pp. 47-53, July 18 ? August 12, Enschede, The Netherlands	2017	Dialogue Manage- ment	user adap- tation, emotions	WP 3.2, 3.3	described in this report. In this paper we discuss a Virtual Human Journalist, a project employing a number of novel solutions from these disciplines with the goal to demonstrate their viability by producing a humanoid conversational agent capable of naturally eliciting and reacting to information from a human user. We argue that naturalness should not always be seen as a desirable goal and suggest that deliberately suppressing the naturalness of virtual human interactions, such as by altering its personality cues, might in some cases yield more desirable results.
HAI Alice - An Information- Providing Closed-Domain Dialog Corpus	Jelte van Waterschoot, Merijn Bruijnes, Guillaume Dubuisson Duplessis and Dirk Heylen	Jelte van Water- schoot, Merijn Bruijnes, Guillaume Dubuisson Duplessis and Dirk Heylen	In Press	2018	Behaviour Synthesis	user adap- tation, verbal alignment	WP 3.3	The contribution of this paper is twofold 1) we provide a public corpus for Human-Agent interaction (where the agent is controlled by a Wizard of O2) and 2) we show a study on verbal alignment in Human-Agent interaction to exemplify the corpus' use. The goal of the data collection was to create a corpus with unexpected situations that can occur during a conversation between a virtual agent and a user, such as misunderstandings, (accidental) false information, and interruptions by another person. The HAI Alice-corpus consists of 15 conversations and more than 900 utterances. We transcribed the corpus and as a use-case example we measured the verbal alignment between the user and the agent. The paper contains information about the set-up of the data collection, the unexpected situations and a description of our verbal alignment study.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		funded by	proceedings				Task	relevance
		ARIA		0.01	D 1 .	*** • •	IUDA	
Advances, Challenges, and Opportunities in Automatic Facial Expression Recognition.	Brais Martinez and Michel Valstar	funded by ARIA B. Martinez and M. Valstar	proceedings Book Chapter in ?Advances in Face Detection and Facial Image Analysis?, pp 63-100.	2016	Behaviour Analysis	*facial expression recogni- tion, face analysis, action units	Task WP2, T2.1	relevance This book chapter summarises the state of the art techniques in Facial Expression Recognition (FER), including a review of all the blocks of which these techniques build on. It first starts describing the possible use cases of a FER system, by means of the model target. These are the categorical emotions (anger, happiness?), the FACS code system (Action Units), or the dimensional emotions (valence and arousal). Then, it describes the standard pipeline: face and landmark localisation and tracking, feature extraction, and machine learning techniques. Finally, it reviews the remaining challenges. This work is relevant to ARIA to illustrate the drawbacks of existing FER systems, given that these are needed to
								analyse users? interaction
		D				*		with the agent.
Learning to transfer: transferring latent task structures and its application to person-specific facial action unit detection	Timur Almaev, Brais Martinez, Michel Valstar	B. Martinez and M. Valstar	Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 3774-3782	2015	Behaviour Analysis	*action units, multi-task learning	WP2, T2.1	The paper proposes a novel approach to Multi-Task learning, in which the latent structure between different Action Units is also considered. The method approaches targeting specific Action Units when these are only annotated for a subset of the training images. Thus, it is possible to train a classifier for all the target Action Units using different datasets even when these barely share the target annotations. The proposed approach is relevant to the ARIA visual part, as it was an efficient and relatively cheap method for Action Unit detection, needed to generate the visual features of the visual part.
TRIC-track: Tracking by Regression with Incrementally Learned Cascades	Xiaomeng Wang, Michel Valstar, Brais Martinez, Muhammad Haris Khan, Tony Pridmore	B. Martinez and M. Valstar	Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 4337-4345	2015	Environmen Anaylysis	t *object tracking, super- vised descent method, cascaded regression	WP2, T2.1	The paper presents a method for part-based object tracking, in which the only given information is the bounding box of the target object in the first frame of a video sequence. The proposed approach trains a set of cascaded regressors on the go, whilst encoding certain shape constraints. These regressors are subsequently updated as the tracking is ongoing, updating the appearance around the current location of the target object, making it more accurate. The proposed framework was used at an early stage of the ARIA visual part to perform the needed face tracking.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
AVEC 2017 ? Real-life Depression, and Affect Recognition Workshop and Challenge	Fabien Ringeval, Björn Schuller, Michel Valstar, Jonathan Gratch, Roddy Cowie, Stefan Scherer, Sharon Mozgai, Nicholas Cummins, Maximilian Schmi, Maja Pantic	B. Schuller and M. Valstar	Proceedings of the 7th International Workshop on Audio/Visual Emotion Challenge. New York : ACM, 2017, p. 3-9, held in conjunction with ACM Multimedia	2017	Behaviour Analysis and Corpus	Affective Comput- ing; Social Signal Process- ing; Auto- matic Emo- tion/De- pression Recogni- tion	WP2, T2.1, T2.4	The paper presents the seventh competition and workshop aimed at comparing methods for automatic audiovisual depression and emotion analysis. A new dataset, SEWA, is used in this edition for the Affect Sub-Challenge. The paper presents a baseline system and encourages participants to submit their methods for a strict comparison under the same benchmark. The paper is relevant to ARIA as it brings a gathering of state of the art methods in emotion and depression recognition, and helps understand the current limitations in the field. This is important for the visual input of ARIA, eMax, as it is responsible of outputting the affectional dimensions of users in unconstrained conditions
FERA 2017- Addressing Head Pose in the Third Facial Expression Recognition and Analysis Challenge	Michel F Valstar, Enrique S?nchez- Lozano, Jeffrey F Cohn, L?szl? A Jeni, Jeffrey M Girard, Zheng Zhang, Lijun Yin, Maja Pantic	E. S?nchez- Lozano, M. Valstar	12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)	2017	Behaviour Analysis and Corpus	*facial expression recogni- tion, face analysis, action units, multiview	WP2, T2.1	The paper presents the third FERA challenge. The novelty with respect to previous challenges resides in that the database is now prepared to cover a wide range of head poses, toward developing the state of the art in facial expression recognition to unconstrained scenarios, in which the camera view is not predefined. A new database, synthesised using 3D models of an extended version of the FERA 2015 data (BP4 dataset), is released, and results are given both overall and per-view, illustrating the challenges yet to be covered in the field. The paper points out the conditions on which facial expression recognition systems are prone to fail. These are of importance to ARIA as the framework is expected to work in unconstrained scenarios
AVEC 2016 ? Depression, Mood, and Emotion Recognition Workshop and Challenge	Michel Valstar, Jonathan Gratch, Björn Schuller, Fabien Ringeval, Dennis Lalanne, Mercedes Torres Torres, Stefan Scherer, Giota Stratou, Roddy Cowie, Maja Pantic	M. Valstar, Bjorn Schuller	Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge, pp. 3-10. Held in conjunction with ACM Multimedia	2016	Behaviour Analysis and Corpus	*Affective Comput- ing, Social Signal Process- ing, Auto- matic Emo- tion/De- pression Recogni- tion	WP2, T2.1, T2.4	The paper describes the challenge and baseline for the sixth series of competitions on multimedia processing and machine learning for automatic video, visual, and physiological depression and emotion analysis. AVEC 2016 basically re-runs AVEC 2015 in the emotion recognition sub-challenge, but introduces a novel dataset for the depression severity estimation sub-challenge. The paper aims at proposing a common benchmark to evaluate the state of the art on emotion recognition, which is of relevance for ARIA both in the audio and the visual systems, which are responsible of analysing the users? emotions.

Affective Retrieval of Information Assistants - Virtual Agents with Linguistic Understanding, Social skills, and Personalised Aspects (ARIA-VALUSPA)

Title	All authors	Authors funded by	Journal / proceedings	Year	Category	Keywords	Related Task	100-word justification of relevance
ChaLearn Looking at People and faces of the world: face analysis workshop and challenge 2016	Sergio Escalera, Mercedes Torres Torres, Brais Martinez, Xavier Bar?, Hugo Jair Escalante, Isabelle Guyon, Georgios Tz- imiropoulos, Ciprian Corneou, Marc Oliu, Mohammad Ali Bagheri, Michel Valstar	ARIA B. Martinez and M. Valstar	Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshop "Looking at People"	2016	Behaviour Analysis and Corpus	*complemen face analysis	ts,WP2, T2.1	This paper presents a three-competition challenge, addressing age estimation, accessory classification and smile and gender classification, respectively. The dataset has been collected and labelled following a crowd-sourcing approach, using a custom-built application. The paper includes the results attained by participants. The work aims at providing a unified framework for facial analysis in unconstrained conditions, and presents an analysis of state of the art methods, gathering under the proposed benchmark. The paper sheds light on the state of the art in three important challenges that are necessary in facial analysis, and thus are of relevance to the visual part of ARIA (eMax).
Ask Alice: an artificial retrieval of information agent	Michel Valstar, Tobias Baur, Angelo Cafaro, Alexandru Ghitulescu, Blaise Potard, Johannes Wagner, Elisabeth André, Laurent Durieu, Matthew Aylett, Soumia Dermouche, Catherine Pelachaud, Eduardo Coutinho, Björn Schuller, Yue Zhang, Dirk Heylen, Mari?t Theune, Jelte van Waterschoot	Michel Valstar, Tobias Baur, Angelo Cafaro, Alexandru Ghit- ulescu, Blaise Potard, Johannes Wagner, Elisabeth André, Laurent Durieu, Matthew Aylett, Soumia Der- mouche, Catherine Pelachaud, Eduardo Coutinho, Björn Schuller, Yue Zhang, Dirk Heylen, Mari?t Theune, Jelte van Water- schoot	Proceedings of the 18th ACM International Conference on Multimodal Interaction, pp. 419-420	2016	Dialogue Manage- ment	Virtual Humans, Technol- ogy Demon- strator, Affective Comput- ing,	*WP5	The paper presents a demonstration of the ARIA framework, in which Alice, the virtual human placed on top of the framework, acts as the expert on the book ?Alice in Wonderland?. The framework incorporates the recent advances in the project in facial and speech analysis, and can deal with interruptions in a gracefully way. This work incorporates all the building blocks of ARIA. The Core Agent block keeps the agent?s information state, and is responsible for making queries to its domain-knowledge database to answer questions. It is also responsible for deciding which information, and which intents, the agent will express. This work is key to ARIA as it was a proof of concept at an intermediate state of the project

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
Playing with Social	Andry	ARIA M.	International	2016	Dialogue	Social	*WP3	The paper presents a Game
Game Companions	Martin	vaistar	Intelligent Virtual		manage- ment and	Process-		Non-player Character (an
	Flintham,		Agents, pp. 85-95		Behaviour	ing		agent) the users interact with
	Peter				Analysis			when playing a game. The
	Blanchfield,							game companion analyses the
	Michel Valstar							introduces a dialogue
	vaistai							management system, that
								helps the user develop an
								affective and social relation
								also studies the effect of this
								agent in users? engagement,
								by studying the interaction of
								users with two agents with
								paper is relevant to ARIA in
								the sense that it introduces a
								social behaviour to the agent,
								which helps the user to
Topic Switch Models	Wenjue Zhu,	М.	International	2016	Dialogue	Social re-	*WP3	The paper presents a novel
for Dialogue	Andry	Valstar	Conference on		Manage-	lationship,		Topic Switch Model for a
Management in	Chowanda,		Intelligent Virtual		ment	Frame-		Dialogue Management, which
virtual Humans	Valstar		407-411			Game-		topics and between topics
						agents,		and utterances, enabling the
						Interac-		selection of sentences that
						tions		match the considered topic. The Dialogue Management
								works in a text-based manner.
								The agent responds to the
								user's topic whilst
								set of topics, and switching
								between them according to
								certain statistics. The paper
								is relevant to the ARIA project given that Alice needs
								to switch between subtopics
								in a natural way to the user,
Computational	Andre	м	Proceedings of	2016	Dialoguo	Came	*11/D2	should they want to do so
Models of Emotion,	Chowanda,	Valstar	the 2016	2010	Manage-	Environ-	W15	model for Non Player
Personality, and	Peter		International		ment	ment,		Character, endowed with
Social Relationships	Blanchfield,		Conference on			Computa-		emotions, personality, and
Games (Extended	Flintham.		Autonomous Agents &			Models.		NPC is introduced into a
Abstract).	Michel		Multiagent			Social		commercial game, to help
	Valstar		Systems, pp.			Relation-		users improve their
			1343-1344			ships,		experience. The study shows that players reported
								significant changes in their
								social relationship with the
								two different types of agents.
								appear to display an
								enhanced emotional
								attachment to the NPCs, and
								appear to forge relationships with them. The paper is
								relevant to ARIA because it
								demonstrates how users
								perceive a better experience
								in a social manner.

Title	All authors	Authors funded by	Journal / proceedings	Year	Category	Keywords	Related Task	100-word justification of relevance
Play SMILE Game with ERiSA: a user study on game companions	Andry Chowanda, Peter Blanchfield, Martin D Flintham, Michel F Valstar	M. Valstar	Workshop on Engagement in Social Intelligent Virtual Agents in Fifteenth International Conference on Intelligent Virtual Agents	2015	Dialogue Manage- ment	Social In- teractions	*WP3	The paper presents a study conducted to evaluate the interaction between two different virtual agents and a set of participants. The virtual agents were differing in their personality, by means of extraversion and neuroticism. Users were interacting with the agent whilst playing the smile game, meant to enforce different facial expressions. A different set of annotations were collected, including the topic of the conversation with the agent, the facial expressions, and the turns. The paper is relevant to ARIA in the sense it helps understanding how users interact with agents and how these are being parceived
Learning to combine local models for facial action unit detection	S. Jaiswal and B. Martinez and M. Valstar	B. Martinez and M. Valstar	IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015), FERA 2015 Challenge and Workshop	2015	Behaviour Analysis	*action untis, facial expression recogni- tion	WP2, T2.1	perceived. This paper presents a simple neural network approach to facial action unit detection. Each of the network's input neurons is assigned with the bin of the histogram of pixels computed at a specific predefined image region. Instead of using a fully connected network, that would need an exponential number of parameters, the network reduces the dimensionality locally and gets to local predictions, which are ultimately fused in a low-dimensional network. This makes the network sparse. The approach meant the first steps towards the ARIA's visual system, which computes the user's emotion in real time, thus requiring such a sparse representation
FERA 2015 ? Second Facial Expression Recognition and Analysis Challenge	M. F. Valstar and T. Almaev and J. M. Girard and G. McKeown and M. Mehu and L. Yin and M. Pantic and J. F. Cohn	M. Valstar	IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015), FERA 2015 Challenge and Workshop	2015	Behaviour Analysis	*action untis, facial expression recogni- tion, FACS system	WP2, T2.1, T2.4	This paper presents the second challenge on facial expression recognition and analysis, in which participants are encouraged to submit their systems to be evaluated following a pre-defined protocol, using the new dataset BP4D, collected at Binghamton University. The goal of the challenge is to provide the community with a unified framework and benchmark for the evaluation of facial expression analysis systems. Such a framework helps defining the challenges and opportunities in the field. The broad acknowledge of this challenge indicates its successfulness. The paper is relevant to ARIA's visual system, given that eMax is responsible of analysing users? emotions, and therefore it is important to have a deep understanding of the state of the art in facial expression recognition

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	1 100-word justification of
		ARIA	proceedings				Task	relevance
Topic-Based Personalization of Dialogues with a Virtual Coach	J. van Waterschoot and M. Theune	J. van Wa- terschoot and M. Theune	Proceedings of the workshop on Persuasive Embodied Agents for Behavior Change, at Intelligent Virtual Agents 2017	2017	Dialogue Manage- ment	dialogue manage- ment, personal- ization, topic man- agement	Task 3.3 User- adaptiv dia- logue strate- gies	We present an approach for establishing a personal relationship between a human re and a virtual agent by employing topic management in human-agent dialogues. We describe a data-driven method for determining topic recognition and topic transition strategies, and discuss how the personalized agent can be evaluated. Although originating from the ARIA VALUSPA project, in this paper these ideas are discussed in the context of a virtual coach application
Topic recognition and management in conversational agents	J. van Waterschoot	J. van Wa- terschoot	Young Researchers? Roundtable on Spoken Dialog Systems 2017 (poster abstract)	2017	Dialogue Manage- ment	dialogue manage- ment, personal- ization, topic man- agement	Task 3.3 User- adaptiv dia- logue strate- gies	This poster briefly discusses the turn-taking and interruption management e strategies employed in ARIA-VALUSPA, as well as the ideas about topic management in ARIA agents. It focuses on the plans for designing data-driven transition strategies, describing how a Wizard-of-Oz corpus study could be used to find out how the agent can gracefully introduce new topics or steer towards topics that it wants to discuss, and how it can recognize the user's topics of interest.
Interacting with Virtual Agents in Shared Space: Single and Joint Effects of Gaze and Proxemics	J. Kolkmeier, J. Vroon and D.K.J. Heylen	D.K.J. Heylen	International Conference on Intelligent Virtual Agents (IVA) 2016	2016	Behaviour Genera- tion	virtual humans, gaze, proxemics	Task 4.1 Over- all dy- namic con- verbal com- mu- nica- tive be- havioun model	In human-human interactions, gaze and proxemic behaviours work together in establishing and maintaining intimacy. In this study we examine how these behaviours affect the perceived personality of virtual agents in immersive Virtual Reality. Agents that exhibited more directed gaze and reduced interpersonal distance were attributed higher scores on intimacy related items than agents that exhibited averted gaze and increased interpersonal distance. These findings could inform the behaviour model of the ARIA agents.

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings			-	Task	relevance
		ARIA	. 0					
Sequence-based	Soumia	Soumia	ACM	2016	Behaviour	Virtual	Task	The goal of this work is to
Multimodal	Dermouche	Der-	International		Genera-	agent	4.2	model a virtual character
Pehavior Modeling	Cathorino	Del-	Conformação on		tion	interner	Adap	able to converse with
Benavior Modernig	Datalerine	mouche,	Conference on		61011	interper-	Adap-	able to converse with
for Social Agents	Pelachaud	Catherine	Multimodal			sonal	tive	different interpersonal
		Pelachaud	Interaction ICMI			attitudes;	non-	attitudes. To build our
			2016			non-	ver-	model, we rely on the
						verbal	bal	analysis of multimodal
						behavior,	com-	corpora of non-verbal
						Temporal	mu-	behaviors. The interpretation
						Sequence	nica-	of these behaviors depends on
						Mining	tive	how they are sequenced
						8	be-	(order) and distributed over
							haviou	time To encompass the
							gon	dynamics of non-yorbal
							gen-	dynamics of non-verbar
							era-	signals across both modalities
							tion	and time, we make use of
							model	temporal sequence mining.
								Specifically, we propose a
								new algorithm for temporal
								sequence extraction. We
								apply our algorithm to
								extract temporal patterns of
								non-verbal behaviors express-
								ing interpersonal attitudes
								from a corpus of job
								interviewa We demonstrate
								the effective of even
								the efficiency of our
								algorithm in terms of
								significant accuracy
								improvement over the
								etate of the art algorithms
								state-of-the-art algorithms.
Computational	Soumia	Soumia	ACM	2016	Behaviour	Virtual	Task	This paper presents a plan
Computational Model for	Soumia Dermouche	Soumia Der-	ACM International	2016	Behaviour Genera-	Virtual agent,	Task 4.2	This paper presents a plan towards a computational
Computational Model for Interpersonal	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on	2016	Behaviour Genera- tion	Virtual agent, interper-	Task 4.2 Adap-	This paper presents a plan towards a computational model of interpersonal
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal	2016	Behaviour Genera- tion	Virtual agent, interper- sonal	Task 4.2 Adap- tive	This paper presents a plan towards a computational model of interpersonal attitudes and its integration
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes;	Task 4.2 Adap- tive non-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016. Doctoral	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non-	Task 4.2 Adap- tive non- ver-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal	Task 4.2 Adap- tive non- ver- bal	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodied conversational agent (ECA). The goal is to endow an ECA with the
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior	Task 4.2 Adap- tive non- ver- bal com-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal	Task 4.2 Adap- tive non- ver- bal com- mu-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence	Task 4.2 Adap- tive non- ver- bal com- mu- nica-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodied conversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence Mising	Task 4.2 Adap- tive non- ver- bal com- mu- nica- tive	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence Mining	Task 4.2 Adap- tive non- ver- bal com- mu- nica- tive	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction context. Interpersonal
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence Mining	Task 4.2 Adap- tive non- ver- bal com- mu- nica- tive be-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction context. Interpersonal attitudes can be represented
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence Mining	Task 4.2 Adap- tive non- ver- bal com- mu- nica- tive be- haviou	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction context. Interpersonal attitudes can be represented by sequences of non-verbal
Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence Mining	Task 4.2 Adap- tive non- ver- bal com- mu- nica- tive be- havioun gen-	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction context. Interpersonal attitudes can be represented by sequences of non-verbal behaviors. In our work, we
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Computational Model for Interpersonal Attitude Expression	Soumia Dermouche	Soumia Der- mouche	ACM International Conference on Multimodal Interaction ICMI 2016, Doctoral Consortium	2016	Behaviour Genera- tion	Virtual agent, interper- sonal attitudes; non- verbal behavior, Temporal Sequence Mining	Task 4.2 Adap- tive non- ver- bal com- mu- tive be- havioum gen- era- tion model	This paper presents a plan towards a computational model of interpersonal attitudes and its integration in an embodiedconversational agent (ECA). The goal is to endow an ECA with the capacity to express different interpersonal attitudes depending on the interaction context. Interpersonal attitudes can be represented by sequences of non-verbal behaviors. In our work, we rely on temporal sequence mining algorithms to extract, from a multimodal corpus, a set of temporal patterns representing interpersonal attitudes. Specifically, we propose a new temporal sequence mining algorithm called HCApriori and we evaluate it against four state-of-the-art algorithms. Results show a significant improvement of HCApriori over the other algorithms in terms of both pattern extraction accuracy and running time. The next step is to implement the temporal patterns extracted with

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		funded by	proceedings				Task	relevance
D (C)		ARIA		0015	D 1 ·			T .1. 1
Beat Gesture	Varun Jain,	Varun	3rd Workshop on	2017	Behaviour	virtual	Task	In this work we present a
Prediction using	Chlo? Clavel	Jain,	Virtual Social		Genera-	agent,	4.1	machine learning approach to
Prosodic Features	and	Catherine	Interaction		tion	gesture,	Over-	gesture prediction using
	Catherine	Pelachaud	VSI/17			prosody	all	prosodic features. We use
	Pelachaud						dy-	conditional random fields to
							namic	predict the presence of beat
							non-	gestures using the following
							verbal	prosodic features: pitch,
							com-	pitch-derivatives, intensity
							mu-	and absence or presence of
							nica-	factures are related and
							he	overlapping aliding windows
							be-	big enough to average out the
							model	high frequency variations
							model	according with pitch and
								intensity at the cyllable level
								We found that the results
								improve remarkably when the
								classification is treated as a
								multi-class problem as
								opposed to a binary problem
								with the two classes: presence
								and absence of gesture.
Automatic Measures	Dubuisson	Dubuisson	18th Annual	2017	dialogue	verbal	Task	This work aims at
to Characterise	Duplessis,	Duplessis.	Meeting of the	-01'		aligne-	3.3	characterising verbal
Verbal Alignment in	G.; Clavel.	G.	Special Interest			ment	User-	alignment processes for
Human-Agent	C.:		Group on				adaptiv	e improving virtual agent
Interaction	Landragin,		Discourse and				dia-	communicative capabilities.
	F.,		Dialogue				logue	We propose computationally
	,		(SIGDIAL)				strate-	inexpensive measures of
							gies	verbal alignment based on
							_	expression repetition in
								dyadic textual dialogues.
								Using these measures, we
								present a contrastive study
								between Human-Human and
								Human-Agent dialogues on a
								negotiation task. We exhibit
								quantitative differences in the
								strength and orientation of
								verbal alignment showing the
								ability of our approach to
								characterise important
								aspects of verbal alignment.
AWeb-Based	Langlet, C.;	Dubuisson	17th International	2017	dialogue	verbal	Task	This paper introduces a
Platform for	Dubuisson	Duplessis,	Conterence on			content	3.3	web-based platform dedicated
Annotating	Duplessis,	G.	Intelligent Virtual			annota-	User-	to the annotation of
Bhonor-related	G.; Clavel,		Agents (IVA			tion,	adaptiv	in human agent
Phenomena in	C.		2017)			virtual	dia-	in numan-agent conversations.
Human-Agent						agent,	logue	I ne platform focuses on
Conversations,						sentiment	strate-	deliberately sets as
						anaiysis	gies	non verbal features. It is
								designed for managing two
								dialogue featureau adiagongu
								pair and conversation
								progression Two apposition
								tasks are considered: (i) the
								detection of sentiment
								expressions (ii) the ranking
								of user's preferences These
								two tasks focus on a set of
								specific targets. With this
								demonstration, we aim to
								introduce this platform to a
								large scientific audience and
								to get feedback for future
								improvements. Our long-term
								goal is to make the platform
								available as open-source tool.

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		funded by	proceedings				Task	relevance
		ARIA				_		
From analysis to	Soumia	Soumia	The 11th	2018		Engagement	, WP6	In this work, two types of
modeling of	Dermouche,	Der-	International			Non-		manual annotation of NoXi
engagement as	Catherine	mouche,	Conference on			verbal		corpus were conducted:
sequences of	Pelachaud	Catherine	Language			behavior;		non-verbal signals such as
multimodal		Pelachaud	Resources and			ECA,		gestures, head movements
behaviors			Evaluation:			Human-		and smiles; engagement level
			LREC			agent		of both expert and novice
						interac-		during the interaction. I nen,
						tion		we used a temporal sequence
								mining algorithm to extract
								variation of ongagement
								perception Our aim is to
								apply these findings in
								human-agent interaction to
								analyze user's engagement
								level and to control agent's
								behavior. The novelty of this
								study is to consider explicitly
								engagement as sequence of
								multimodal behaviors.
Expert-Novice	Soumia	Soumia	MULTIMODAL	2018			WP6	In this demonstration, we
Interaction:	Dermouche,	Der-	CORPORA 2018:					present the NoXi corpus of
Annotation and	Catherine	mouche,	Multimodal Data					expert-novice interactions,
Analysis	Pelachaud	Catherine	in the Online					our annotations and analysis.
		Pelachaud	World, MMC					To analyze the data we apply
								HCApriori, a Temporal
								Sequence Mining algorithm
								converges for both supert
								and novice. NoXi provides
								over 25 hours of dvadic
								interactions recorded in
								different languages, mainly
								English, French, and German.
								The annotation tool NOVA
								allows annotating data using
								discrete and continuous
								schema. We use NOVA to
								manually annotate behaviors
								(discrete annotation) and
								engagement levels
	~						TTE A	(continuous annotation).
Social Context	Curran,	Elisabeth	Frontiers in	2018	Behaviour	Laughter,	WP6	Despite being a pan-cultural
Disambiguates the	William;	Andre,	Psychology, Vol.		Analysis	Multi-		phenomenon, laughter is
Interpretation of	McKeown,	Johannes	8, 2342			modal		arguably the least understood
Laughter.	Gary; Buchlowsko	wagner				Corpus		internation As well as being
	Magdalena:							a response to humour it has
	André							other important functions
	Elisabeth:							including promoting social
	Wagner,							affiliation, developing
	Johannes;							cooperation and regulating
	Lingenfelser,							competitive behaviours.
	Florian.							Understanding these
								functions can lead to a better
								contextual interpretation of
								laughter during a
								conversation, e.g. during the
								interaction with agent (like in
	T.1.	T.1.		0010	Dala	a	WDo	ARIA).
Real-time Sensing of	Johannes	Johannes	The Handbook of	2018	Behaviour	Social	WP6	The most promising way to
Affect and Social	Wagner,	Wagner,	Multimodal-		Analysis	Signal		encourage developers to put
Multimodel	Andrá	Andrá	Interfaces			ing		online systems is by
Framework	Andre	Andre	Volume 2: Signal			Beal time		providing adequate tools that
Practical Approach			Processing			recogni-		take as much work off their
			Architectures.			tion.		hands as possible. In this
			and Detection of			Multi-		book chapter we present the
			Emotion and			modal		open-source framework SSI,
			Cognition			fusion		which has been called to life
								for this very purpose. The
								ARIA recognition system is
	1	1				1		implemented with SSI

Affective Retrieval of Information Assistants - Virtual Agents with Linguistic Understanding, Social skills, and Personalised Aspects (ARIA-VALUSPA)

Title	All authors	Authors	Journal /	Year	Category	Keywords	Related	100-word justification of
		ARIA	proceedings				Task	relevance
Modeling User?s	Tobias Baur,	Tobias	Emotions and	2017	Behaviour	User	2.3	In this article we describe an
Social Attitude in a	Dominik	Baur,	Personality in		Analysis	Modelling,		approach for modelling Social
Conversational	Schiller,	Elisabeth	Personalized			Engage-		Attitudes, such as the
System	Elisabeth	André	Services pp			ment		Engagement of a User in an
	André		181-199					Interaction with a
								Conversational System, such
								as the ARIA-Valuspa virtual
		T 1		0010	D 1 ·			humans
Applying	Jonannes	Jonannes	https://arxiv.org/al	s/2018	Benaviour	Annotation,	6.2,	In this paper we describe the
Machina Learning to	Tobing Pour	Tobing	1802.02505		Analysis	Coopera-	0.5	loorning approach developed
Speed Up the	Vuo Zhang	Baur Vuo				Learning		in the ARIA Valuena Project
Annotation of Social	Michel F	Zhang				Interac-		We shortly introduce the
Signals in Large	Valstar	Michel F				tive		NoXI Database and the
Multi-modal	Biörn	Valstar.				Learning.		NOVA tool, and describe an
Corpora	Schuller,	Björn				Data		evaluation of the approach on
-	Elisabeth	Schuller,				Collection		the NOXI corpus
	André	Elisabeth						
		André						
Context-Aware	Tobias Baur,	Tobias	ACM	2015	Behaviour	Annotation,	6.2,	In this journal article we
Automated Analysis	Gregor	Baur,	Transactions on		Analysis	User	2.3	introduce of the NOVA tool
and Annotation of	Mehlmann,	Johannes	Interactive			Modelling,		in earlier stages and of the
Social	Ionut	Wagner,	Intelligent			Engage-		user model to detect
Human-Agent	Damian,	Elisabeth	Systems (TiiS) -			ment		enaggement. We examplified
Interactions	Florian	André	Special Issue on					this with a virtual agent
	Lingenteiser,		Benavior					
	Jonannes		Understanding for					
	Birgit		Entertainment					
	Lugrin		(Part 1 of 2)					
	Elisabeth		Volume 5 Issue 2					
	André,							
	Patrick							
	Gebhard							

Affective Retrieval of Information Assistants - Virtual Agents with Linguistic Understanding, Social skills, and Personalised Aspects (ARIA-VALUSPA)