A Computational model of Social Attitudes for a Virtual Recruiter

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ABSTRACT

This paper presents a computational model of social attitude for virtual agents. In our work, the agent acts as a virtual recruiter and interacts with a user during job interview training. Training sessions have a predefined level of difficulty, which is used along with the perceived user's anxiety at each speaking turn to compute the objectives of the recruiter, namely to challenge or comfort the user. Given an objective, the recruiter chooses how to conduct the interview (i.e. the complexity of its questions), and which social attitudes to express toward the user. Social attitudes are defined along 2 dimensions, dominance and liking. Our model computes both the verbal and nonverbal behaviors of the virtual agent to express a given social attitude. A study on the perception of the attitude of the virtual recruiter endowed with our model has been conducted. We show how the different verbal and non-verbal behaviors defined to either challenge or comfort human interviewees enable the virtual recruiter to successfully convey social attitudes.

Categories and Subject Descriptors

H.5 [**Information Interfaces and Presentation**]: Multimedia Information Systems

General Terms

Design, Human Factors

Keywords

Virtual agents, Social attitude, Conversational agents, Multimodal behavior

1. INTRODUCTION

Employment interviews continue to be one of the most frequently used methods for candidate selection [19], and the preparation for such interviews plays an important role on the interviewee performance. Different studies show the wide variety of benefits achieved when training for these interviews. For example, [14] demonstrated that interview training and previous interviewing experience have a positive effect on the interviewee self-efficacy (the belief that they can do well in the interview) at the same time as it reduces anxiety; and [25] found that coaching allowed interviewees to provide better structured responses, develop fundamental interviewing skills such as eye contact, and respond to common questions.

The research presented in this paper is part of the EU project TARDIS[1], in which the objective is to develop a serious game to train youngsters for job interviews. Previous work has demonstrated that coaching young adolescents with their job-seeking skills is very beneficial for them to be more concerned and successful [9]. Playing the game, the youngsters should be able to practice with interviews of varying complexity with a conversational virtual agent that acts as the recruiter.

The recruiter personality has a significant impact on the interview performance, [14] describe that interviewees may have a more difficult time with introverted and/or less agreeable recruiters, while warm and caring recruiters reduce their anxiety. Thus, a fundamental aspect in the development of an recruiter agent is that it is able to render different interpersonal attitudes that will make the interviewee more or less comfortable or anxious. In our case, such attitudes are selected depending of a predefined difficulty level of the job interview and the perceived user's anxiety.

In this article, we propose a computational model that takes into account the user anxiety and the difficulty level selected for the interview to compute the objective at each speaking turn, namely to challenge or comfort the user. The objective selected is used to decide the best dialog strategy and the social attitude, which is expressed both through verbal and non-verbal behavior [6]. Our model follows the SAIBA architecture [16], and is composed of different modules that are interconnected to select the best system dialog act and social attitude at each turn, and render the multimodal output. We have developed a virtual recruiter endowed with the proposed computational model using our embodied conversational agent platform. As a first step for the evaluation of the model proposed, a perceptive study has been conducted to assess the perception of the social attitude rendered through the verbal and non-verbal behavior of the recruiter. The results show that it is possible to succesfully convey friendly and hostile social attitudes when using both modalities.

Appears in: *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*

[1] `http://researcher.tardis-project.eu/the-project/presentation`

The rest of the paper is organized as follows. Section 2 presents the related work contextualizing our proposal. Section 3 describes the proposed model. Section 4 presents the evaluation set up. Finally, in Section 5, we discuss the conclusions and present out future work.

2. RELATED WORK

Virtual agents that use social abilities like developing different relations or displaying different attitudes are usually referred to as *relational agents*. One of the first of these agents is Laura [4], a fitness coach that changes her relation with the user as they interact in the long-term. Her behavior becomes more friendly, she stands closer, engages in more mutual gaze and does more arm and head movements. In the project Demeanour [10], the gaze, gestures and postures of the agents change according to the affiliation between them. In [7], a study is conducted to assess how users perceive attitude (hostile, friendly) and extroversion during the first seconds of an encounter. In [18], they build a model of non-verbal behavior (gaze, posture and proximity) depending on the conversation role (speaker, addressee, side participant or bystander), the communicative act and the relations between the characters. This model was built by observing actors playing a scenario (the Gunslinger) involving the different roles and knowing the interpersonal relations between the characters. While several models of social attitudes for virtual agents have been proposed, they are generally limited to particular non-verbal behavior parameters. In our work, we go beyond by considering a larger set of behaviors and by using a particular methodology based on the user perception of the virtual agent behavior (Section 3.3).

With respect to the job interview domain, [5] presents a virtual reality setting considering two types of interview: challenging and supportive. The differences in the agent's behavior were mainly the interruptions and frequency of eye contact. The authors paid special attention to the context in which the interview takes place: in the challenging scenario the office was decorated with leather chairs, wooden furniture, and diplomas on the walls, whereas in the supportive scenario, the office had no windows or wall decoration to convey a lesser position in the company.

Similarly, [17] present a virtual job interview simulation at a university career service to help student populations with their first job interview. They investigated human anxiety state during the course of a job interview simulation. Their results showed that the participants who were exposed to the virtual job interview through immersive environments showed a higher level of involvement. However, the verbal behavior of the virtual agent remains limited. A list of 12 general-purpose questions are used, from which 9 are selected for each interaction.

In [13] they present the MACH agent to provide social skill training. The agent poses common interview questions from a list of 15 frequently used by human interview coaches, and after the interaction, it provides immediate feedback about the user performance in terms of appropriate nonverbal behaviors such as smiles, head movements, speech variation, filled pauses, loudness, emphasis and pauses. In this work, the focus with respect to the agent behavior is mainly on simulating head nods and arm movements when the agent listens to the user.

In all the works presented so far, the interview is conducted all the time in the same manner. There is a restricted set of phrases that are chosen either randomly or always in the same order without taking into account the user's state. In our work, we are interested in adapting the agent's dialog according to the user's anxiety. Our aim is to compute the best dialog strategy. We have defined 76 different system dialog acts (or questions types), with at least 3 different wordings associated to different attitudes (dominant, hostile, friendly). The dialog acts can be combined in different orders to generate a high number of interviews. We can modulate the behaviors of the virtual recruiter through several factors: the question type (dialog act), the wording (actual phrase used for the question type) and the non-verbal behavior, thus enhancing the variability of the agent's behaviors.

3. A MODEL OF VIRTUAL RECRUITER'S BEHAVIOR

We present a computational model of virtual recruiters that are responsive to the anxiety experienced by interviewees modulated by choosing a level of difficulty for the job interview. Responsiveness is carried out by selecting an adaptive interaction strategy and a social attitude. Social attitudes are displayed through verbal and non-verbal cues.

3.1 Architecture of the virtual recruiter

The architecture of the virtual recruiter is illustrated in Figure 1. The model follows the SAIBA architecture [16], an international common multimodal behavior generation framework.

As shown in Figure 1, in place of the Intent planner, there is our *Dialog Manager* that selects the appropriate system response (defined in terms of dialog acts) and the virtual recruiter's social attitude to express given the user's anxiety level (which may be computed through the analysis of user's audio-visual or physiological signals [2]). The virtual recruiter's social attitude is stored in the *Agent Mind*, which is queried by the *Natural Language Generator* (NLG) and the *Behavior Planner*. The NLG selects a phrase that reflects the attitude selected. The phrase corresponds to one of the possible wordings for the dialog act selected, and is included in a FML file [12] containing the associated dialog act. This file is used by the *Behavior Planner* to instantiate the appropriate non-verbal behaviors depending on the attitude and dialog act (communicative intention) of the agent. Finally, the *Behavior Realizer* and the Text-To-Speech (TTS) engine display the animation of the agent.

The objective of the dialog manager changes according to the different combinations of two inputs: the anxiety level of the user and the difficulty level of the game (Figure 1).

There are several ways in which anxiety or other related emotions such as nervousness, uneasiness, alertness or distress can be detected in real time from audiovisual cues or physiological sensors [1]. In our architecture, we do not focus on a particular system to detect user's anxiety. We suppose that the anxiety recognizer provides an anxiety level ranging in [0, 1]. Currently, we consider three intervals: low (below 0.25), medium (between 0.25 and 0.75) and high (higher than 0.75). Additionally, we consider six possible difficulty levels from 1 to 6, where 1 is the lowest difficulty and 6 the highest. The difficulty level is selected at the beginning of the game and does not vary during the interview.

At each turn, the dialog manager computes the objec-

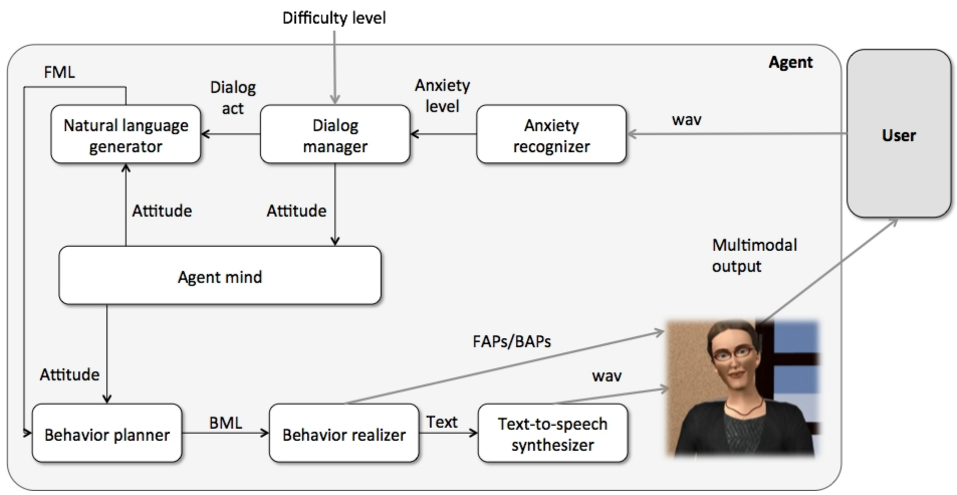

Figure 1: The architecture of the virtual recruiter.

tive of the system, which may be either to *comfort* or *challenge* the user. The calculation is carried out following the strategy in Figure 2. As can be observed, with higher difficulty levels the system is more prone to challenge the user, whereas for lower levels of difficulty it tries to calm the user down. However, in order to explore a wider space of dialog strategies, it is possible to consider different objectives according to a certain probability distribution. Additionally, the dialog strategy depends on the tendency of the anxiety level of the user, i.e. whether during the whole interaction the user tends to be relaxed or to increase his anxiety level. This tendency can be computed as the slope of the linear regression of all the anxiety values up to the current moment.

The system objective is implemented by selecting the complexity of the next dialog act (the type of question it will pose) and the social attitude with which it will modulate it. The complexity of the dialog act depends on the focus on negative facts as well as the openness of the question posed. This way, a question is considered more complex to respond if it is focused on negative facts (e.g. asking about a weakness of the interviewee) and if the response requires a long elaboration instead of a short and concise one. We have based this decision on the two phases of human anxiety processing: the perception of a threat, and how individuals evaluate the availability and effectiveness of their coping resources [3], which in our proposal relate to the presence of negative contents and the increased probability that open questions make applicants uncertain about their ability to elaborate a satisfactory response. For example, the DA *askCareerDowns* (e.g. "Why have you been out of work so long?") is a complex question, because it is open and focused on negative facts, while *askPreviousJobEndDate* (e.g. "When did you finish your previous job?") is easier to respond because even if it is focused on a negative fact, it requires a concise response.

The whole procedure is summarized in Figure 3. The system keeps asking questions until the user stays in a medium or low anxiety level for a certain number of turns. This number increases for the interactions with high difficulty.

Once the dialog manager has selected the DA and the system attitude in that turn, the natural language generator chooses a phrase the matches both, and the non-verbal generator renders a non-verbal behavior that corresponds with the system attitude and with the selected DA.

3.2 Verbal behavior

To reflect the virtual recruiter's social attitude computed by the dialog manager, we have used the guidelines of the PERSONAGE project [20]. Although the model in PERSONAGE is based on the OCEAN personality traits [21, 22], we have found that some of the cues for extroversion and introversion may also be relevant to generate friendly and hostile behaviors respectively, as suggested by [15].

Concretely, we have taken into account the number of self-references, the use of pronouns, the variety of vocabulary, the preference for nouns vs. verbs, the formality of the expressions, the length of the phrases and the preference for negative vs. positive contents. With respect to the self-references, we consider the expressions in which the agent talks about itself either explicitly (e.g. "I will interview you today") or including itself as part of the company (e.g. "What do you know about us?"). This way, when the agent is rendering a hostile attitude, it seldom talks about itself and always refers to the company by its name. For the friendly attitude we consider more pronouns, less synonyms and a more informal language, so that the phrases are more casual and give the impression to be less meditated. For the hostile attitude, the agent uses more formal language with a more varied vocabulary and avoids the use of pronouns, which provokes that the hostile phrases are longer. In the friendly phrases there are more verbs rather than nouns, thus conveying a preference for action. Additionally, in the hostile behavior, there are more negations and a preference for negative contents, which the agent highlights in the phrase and places before the positive ones. The opposite situation happens with the friendly attitude, in which positive contents are predominant.

For example, for the dialog act *provideNextSteps* in which the agent informs about the next steps after the interview, these are two of the phrases available for the friendly and hostile attitudes: "We will answer you in about a week" (friendly), and "You will receive an answer not earlier than a week from now" (hostile).

Anxiety level in the previous turn	Difficulty level	System objective for the current turn
Low	1 or 2	COMFORT
Low	3 or 4	If *tendency* = decreasing then COMFORT 90% - CHALLENGE 10% else then COMFORT 10% - CHALLENGE 90%
Low	5 or 6	If *tendency* = neutral then COMFORT else then CHALLENGE
Medium	1 or 2	COMFORT
Medium	3 or 4	If *tendency* = increasing then COMFORT 10% - CHALLENGE 90% Else then COMFORT 90% - CHALLENGE 10%
Medium	5 or 6	CHALLENGE
High	1 or 2	COMFORT
High	3 or 4	COMFORT 50% - CHALLENGE 50%
High	5 or 6	CHALLENGE

Figure 2: Strategy for dialog management.

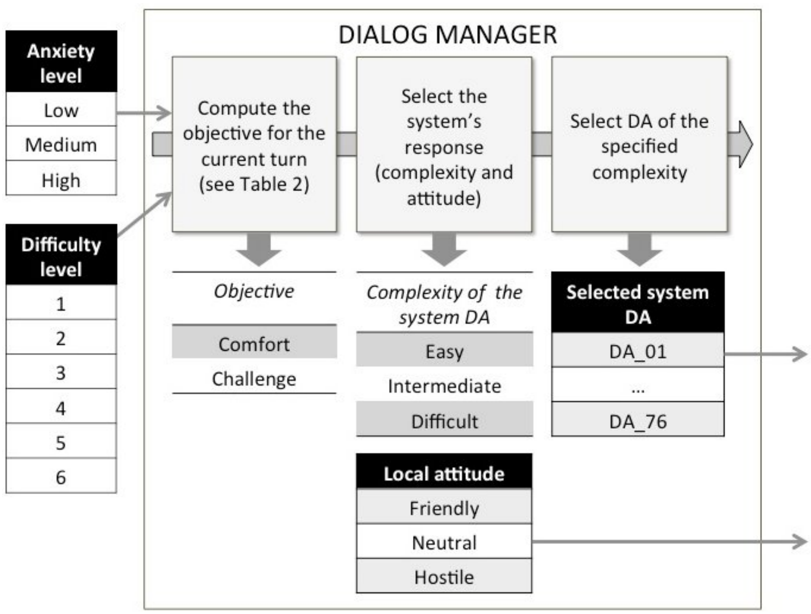

Figure 3: Behavior of the dialog manager.

As can be observed the friendly phrase is shorter, uses a more informal vocabulary (e.g. 'about'), it shows a preference for action (answer vs. receive), and uses self-reference ('we'), whereas the hostile phrase is longer, provides more details (e.g. a week 'from now'), and emphasizes negative content ('not earlier than').

We have created a database that contains at least a friendly, hostile and neutral phrase per dialogue act (a minimum of 228 phrases). When the dialog manager has selected the dialog act and attitude for the current turn, the natural language generator module queries the database to find a phrase. If several phrases are available for the selected dialog act and attitude, it chooses one randomly.

3.3 Non-verbal behavior

A social attitude is not only expressed through verbal behavior but also through non-verbal ones, such as gestures and facial expressions [6]. In order to give the capability to the virtual recruiter to adapt its non-verbal behavior according to the social attitude to express, we have integrated in the *Behavior Planner* (Figure 1) a model to compute the appropriate virtual agent's non-verbal behavior including shape and expressivity factors. This model is based on the data of a previous study consisting in asking directly the user to configure the non-verbal behavior of an agent with different social attitudes (dominant, submissive, friendly and hostile) [23]. In such a task, the users changed the values of the different non-verbal parameters: the facial expression (positive, negative or neutral), the activation of head and arm movements, the amplitude of arm movements (small, medium and large), the strength of arm movement (weak, normal, strong), the head orientation (downward, upward, tilted aside or straight) and the presence of gaze avoidance. These parameters have been selected based on the research in Human and Social Sciences showing their impact on the perception of attitude [6][8]. With this method, we collected 925 user descriptions of non-verbal behavior describing different attitudes [24].

From the data of this previous study, a Bayesian network was designed to retrieve the probabilities of different behaviors depending on an attitude and a dialog act [24]. The structure of the network was defined as follows. The network is composed of two input nodes, the attitude and the dialog act, and six output nodes corresponding to the non-verbal parameters considered. The edges between the nodes have been designed according to the statistical correlations between the variables. More precisely, if a significant correlation is computed between an input and an output variable, an oriented arc is defined between these variables. The statistical correlations are detailed in [24]. Learning the parameters of a Bayesian network consists in learning the conditional probability distribution for each node. The parameters of the model were learned from the collected data using Weka [11]. This network is then used to obtain the probability of each behavior parameter value depending on the attitude and the speech act the agent wants to express.

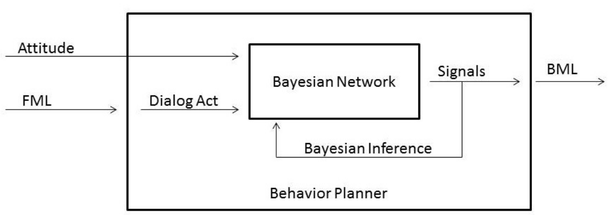

Figure 4: The Behavior Planner built with the Bayesian network.

An algorithm based on the Bayesian network has been integrated in the Behavior Planner to select the non-verbal behavior of the agent (Figure 4). The algorithm takes as input the attitude to express and the agent's dialog act (described in an FML file, Section 3.1). The Bayesian network is used to select the values for the non-verbal parameters following the probabilities of the model. So the behavior selected is not necessarily the one with the highest probability but it is more likely to be. Then, in order to ensure that the generated behavior corresponds to the desired attitude, the algorithm uses the Bayesian inference. From the generated behavior and with the Bayesian network, we compute the inferred probability of each attitude. The algorithm verifies that the inferred probability for the wanted attitude is greater than the inferred probabilities of the other possible attitudes. This method allows us to keep the variability of the probabilistic model, and also to prevent the system to generate a behavior which would not communicate the desired attitude. Finally, the resulting selection of behaviors and expressivity parameters is sent through BML (Behavior Markup Langage) to the *Behavior Realizer*. An example of the same dialog act expressed with either an hostile or a friendly attitude is shown Figure 5.

4. EVALUATION OF THE MODEL

In order to evaluate the proposed model, we have conducted a perceptive study. The objective of the study is to measure the capacity of a virtual recruiter endowed with the proposed model to convey different social attitudes through its verbal and non-verbal behavior. Note that this evaluation represents a first step in the validation of the model, focusing on the perception of attitude. The capacity of the model to change the objective and the virtual recruiter's behavior dynamically is not evaluated in this first study.

Hypotheses. The hypotheses we want to validate through the evaluation are the following:

1. The friendly (versus hostile) virtual agent's *non-verbal behavior* computed by our model gives the impression to the users that the virtual agent is expressing a friendly (versus hostile) attitude;

2. The friendly (versus hostile) virtual agent's *verbal behavior* computed by our model gives the impression to the users that the virtual agent is expressing a friendly (versus hostile) attitude;

3. The friendly (versus hostile) *multimodal behavior* of the virtual agent (verbal and non-verbal) significantly enhances the perception of the associated friendly (versus hostile) attitude.

More precisely, the evaluation aims to show that the behaviors computed by the proposed model convey the expected friendly or hostile attitude both if only one modality conveys the attitude (hyp. 1 and 2) and if the verbal and non-verbal modalities convey the attitude (hyp. 3).

Procedure. In order to verify these hypotheses, we have performed a perceptive study on the web. We have simulated a job interview between a virtual recruiter and an interviewee[2]. We have created video clips alternating a view of the animated virtual agent saying a sentence and a screen indicating what the interviewee has responded (Figure 6). The sentences and the non-verbal behavior of the virtual agent are computed by the proposed model. For each video clip, we asked the participants to indicate their perception of the virtual recruiter by indicating their agreement with the following sentences: (1) "The virtual recruiter behavior is believable", (2) "The virtual recruiter gives the impression to want to hire the interviewee", (3) "The virtual recruiter gives the impression to want to fail the interviewee", (4) "The virtual recruiter tries to make the interviewee at ease", (5) "The virtual recruiter wants to destabilize the interviewee", (6) "The virtual recruiter expresses an hostile attitude", (7) "The virtual recruiter expresses a friendly attitude" and (8)

[2]Note that we have chosen to present a simulated interview to the participants to control the dialog and to avoid an effect of the performance of the participants in their perception of the virtual agent's social attitude.

Figure 5: Friendly (left) and hostile (right) non-verbal attitude for the same dialog act.

"The virtual recruiter expresses a dominant attitude?". We suppose that the sentences (2), (4) and (7) convey the perceived friendly attitude of the agent and the sentences (3), (5) and (6) reflect the perceived hostile attitude. A 5 points Likert scale (from "Totally disagree" to "Totally agree") was set for each question.

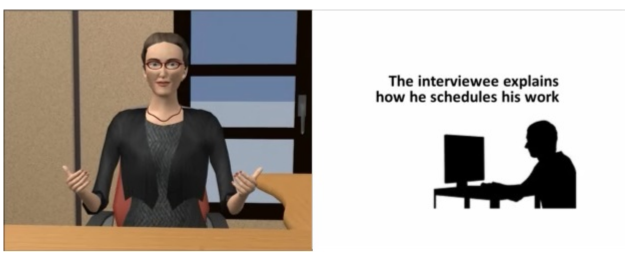

Figure 6: Screenshots of the simulated job interview: one the left, the virtual recruiter, and on the right, the response of the interviewee. In the video clip, these two screenshots do not appear at the same time but one the other.

Video Clips. To evaluate the perception of the virtual agent with and without the verbal and non-verbal behavior conveying an attitude, we have simulated the job interview in 4 conditions:

- *verbal only condition*: the virtual agent is expressing friendly or hostile attitude only through its verbal behavior. The non-verbal behavior of the virtual agent remains neutral;
- *non-verbal only condition*: the virtual agent is expressing friendly or hostile attitude only through its non-verbal behavior. The verbal behavior of the virtual agent remains neutral;
- *multimodal condition*: the virtual agent is expressing friendly or hostile attitude through its verbal and non-verbal behavior;
- *control condition*: the virtual agent displays a neutral attitude through its verbal and non-verbal behavior.

We have created in total 7 video clips: one with a friendly attitude and one with an hostile attitude for the verbal, non-verbal and multimodal condition and one with a neutral attitude for the control condition. In each video clip, the dialog scenario is the same: each video clip is composed of 9 dialog turns (10 sentences said by the animated virtual recruiter and 9 different screens showing the interviewee's response), the dialog acts and the screens showing the interviewee's response are the same in all the video clips and were presented in the same order. Only the non-verbal behavior[3] (i.e. head and gaze movements, facial expressions and gestures) and the verbal behavior (wording) of the virtual agent vary. Note that in each video clip the attitude of the virtual recruiter remains the same throughout the clip.

Participants. 110 individuals have participated to this evaluation on the web (48 females) with a mean age of 34 (SD=12). The participants were predominantly from France (N=60). Each participant has seen and rated 4 video clips (one video clip for each of the 4 conditions). The order of the presented video clips was counterbalanced to avoid any effect on the results.

Results. We have collected 440 video clips' ratings. An ANOVA and a post-hoc test HSD-Tukey were conducted to compare the participants' ratings of the video clips in each condition. The statistical results reveal significant differences. The virtual recruiter is perceived significantly more friendly in the friendly non-verbal behavior only condition than in the control condition ($p < .05$) or than in the hostile non-verbal only condition ($p < 0.05$). However, only one significant difference appears between the hostile non-verbal only condition and the control condition: the virtual recruiter is perceived significantly less friendly (sentence 7 in the perceptive test) when its displays an hostile non-verbal behavior than a neutral one ($p < 0.05$). Concerning the perception of the verbal behavior, no significant difference appears between the textual only condition and the control condition. If the virtual recruiter expresses a

[3]Given the role of the virtual agent, the non-verbal behavior of the virtual recruiter has been generated with a dominant attitude (Section 3.3).

friendly attitude through a verbal and non-verbal behavior (multimodal condition), it is perceived significantly more friendly than when it expresses neutral behavior (control condition) ($p < .05$) or hostile one (hostile multimodal condition) ($p < .05$). The virtual recruiter displaying an hostile multimodal behavior is perceived as significantly more hostile and giving the impression to want to destabilize the interviewee than in the control condition. Note that in this case, only the responses to sentences (5) and (6) show significant differences. Concerning the perception of believability, no significant difference appears. The virtual recruiter is perceived in average believable (M=3,1 on a Likert scale of 5 points). As expected, the virtual recruiter is perceived as dominant (M=2.99 on a Likert Scale of 5 points). However, the non-verbal and multimodal expression of friendliness significantly decreases the perceived dominant attitude ($p < .05$). To evaluate the effects of the participant's gender, we have measured the differences of ratings between male and female. The results show significant differences: the virtual recruiter is perceived significantly more believable and less hostile by women than by men. This result may be explained by the female gender of the virtual recruiter. Figure 7 shows the results for the friendly attitude.

Discussion The results show that the non-verbal behavior generated by our model enables the virtual recruiter to convey a friendly attitude. However, the participants' perception of the hostile non-verbal behavior reveals that the non-verbal parameters seem to not be sufficient to render an hostile attitude. In other words, our first hypothesis has been partially validated, only for the friendly attitude. Concerning the verbal behavior of the virtual recruiter, the statistical analysis shows that the friendly or hostile phrasing computed by our model is not sufficient to convey an attitude. Our second hypothesis has not been validated. The results on the perception of the multimodal behavior validate our third hypothesis: they show that the friendly and the hostile attitude of the virtual agent are perceived through both the verbal and non-verbal behavior. However, the results also reveal that the perception of the hostile attitude may depend on the similarity between the gender of the participant and of the virtual recruiter. More experiments should be conducted to validate such an hypothesis.

5. CONCLUSIONS

We have presented a computational model of social attitude for virtual recruiters. While most works in the literature focus on certain aspects of a predefined verbal and/or non-verbal behaviors, a key aspect of our model is to treat the agent's multimodal response as a means to achieve an adaptive dialog strategy that modulates its behaviors according to the desired difficulty for the interview and the anxiety experienced by the interviewee after each question. This way, it is possible to achieve a higher variability of agent's behaviors while making it adaptive to different dialog situations. In our model, responsivenes is carried out by selecting an adaptive interaction strategy (selecting different dialog acts according to the dynamic objective of challenging or comforting the user) and a social attitude (friendly, neutral or hostile), which are displayed through verbal and non-verbal cues. To evaluate our proposal, we have conducted a perceptive study with 110 individuals that rated 4 videoclips of an interview with a virtual recruiter endowed with the model. This evaluation is a first step in the validation of the model, in which we have focused on the perception of the attitude rendered by the verbal and non-verbal cues. The results show that when using both modalities, the agent is perceived as significantly more friendly or hostile, while the non-verbal behavior only enabled the perception of friendly attitudes but not hostile, and the verbal only was not sufficient to convey an attitude. This shows the importance of rendering a consistent multimodal social attitude. For future work, we plan to carry out a second study to evaluate whether the objectives computed dynamically by the agent during the interaction (whether to comfort or challenge the interviewee) are accomplished by means of the dialog acts and attitudes selected.

6. ACKNOWLEDGMENTS

This research has received partial funding from the European Union Information Society and Media Seventh Framework Programme FP7-ICT-2011-7 under grant agreement 288578 (TARDIS) and 287723 (REVERIE). We are very grateful to Cereproc (`www.cereproc.com`) for letting us use their voice synthesizer.

Zoraida Callejas was supported by the Spanish Ministry of Education, Culture and Sport under the programme "Programa Nacional de Movilidad de Recursos Humanos del Plan Nacional I-D+i 2008-201", José Castillejo mobility grant no. CAS12/00227.

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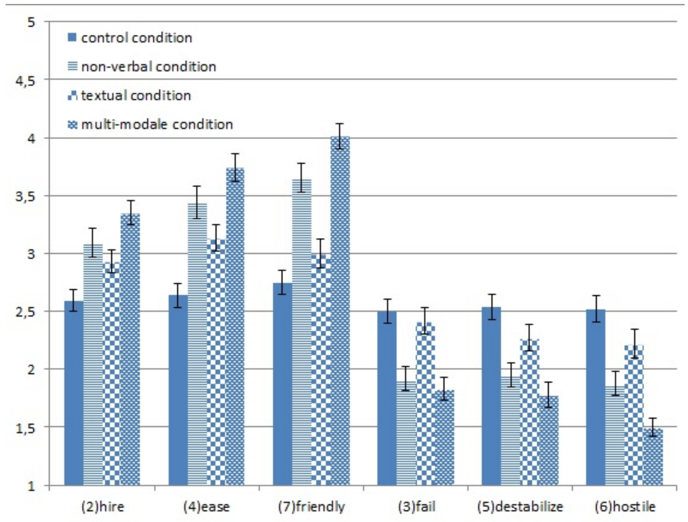

Figure 7: Means and standard errors of the participants' agreement to the sentences for the friendly attitude. In abscisa, the number between parenthesis corresponds to the id of the sentence.

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