Expressing Social Attitudes in Virtual Agents for Social Coaching

(Extended Abstract)

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ABSTRACT

This paper presents a model of social attitudes for reasoning about the appropriate attitude to express during an interaction. It combines a theoretical approach with a study of a corpus of human-to-human interactions.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Intelligent Agents

Keywords

Social Attitudes, Affective computing, Non-verbal behaviour

1. INTRODUCTION

In the context of social inclusion, the TARDIS project[1] proposes to use virtual agents to support job interview simulation and social coaching. The use of virtual agents in social coaching has increased rapidly in the last decade [9] provide evidence that virtual agents can help humans improve their social skills and, more generally, their emotional intelligence [3]. Most of the models of virtual agent in social coaching domain have focused on the simulation of emotions [9], however a virtual agent should be able to express different social attitudes. In this paper, we propose a model of social attitudes that enables a virtual agent to adapt its social attitude during the interaction with a user in a job interview simulation context. The methodology used to develop such a model combines a theoretical and an empirical approach.

2. CORPUS

To build our social attitude model, we combined a theoretical approach, *i.e.* obtaining knowledge about the relationship between attitudes, emotions, moods, with an empirical approach, *i.e.* collecting a corpus of real interactions where social attitudes are expressed, which we used for knowledge elicitation, to build our model and to evaluate it.

The corpus we collected consists of 9 videos of real interpersonal interactions between 5 professional recruiters and 9 job seekers interviewees. We have annotated 3 of the videos (approximately 50 minutes of video) with the non-verbal behaviours of the recruiter, the turn-taking, and the attitude of the recruiter. The coding scheme, the resulting annotations, and the inter-annotators agreements are described in more details in [2]. These annotations have been used to construct the animation module for the virtual agent's expression of social attitudes and for the evaluation of the affective model to check that it produces outputs that correspond to the human behaviour.

In addition to these annotations, post-hoc interviews with the recruiters were used to elicit knowledge about the expectations and mental states during the interview. This knowledge was used in the affective module to select the relevant social attitudes and to set up the rules to give the capability to the virtual agent to select the appropriate social attitude to express.

3. AFFECTIVE MODULE

We used the post-hoc interviews with the recruiters to define the relevant emotions, moods and attitudes. The attitudes used in the model are the following : *Friendly*, *Aggressive*, *Supportive*, *Dominant*, *Attentive*, *Inattentive*, *Gossip*.

Relations between attitudes and personality, and moods and attitudes [10] have been found. Based on this knowledge, we define a set of rules that compute categories of emotions, moods and attitudes for the virtual recruiter, based on the contextual information given by the scenario and the detected affects of the participant. The details of the computation of emotions and moods can be found in [6]. The computation of attitudes follows this principle: an agent can adopt an attitude according to its personality or according to its mood. For example, an agent with a non-aggressive personality will nevertheless show an aggressive attitude if its mood becomes very hostile. According to [10], aggressive attitudes are more present in non-agreeable and neurotistic personalities and is correlated to the *hostile* mood [4]. Thus, we define the following rule:

$$\text{If } \Big((val(A) < \theta) \wedge val(N) > \theta\Big) \vee (val(hostile_f) > \theta),$$

$$then : val(aggr) = max(val(hostile_f), val(N), 1 - val(A))$$

[1] `http://www.tardis-project.eu/`

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In clearer terms: if the agreeableness ($val(A)$) of the recruiter is inferior to a threshold (θ) and the neuroticism ($val(N)$) of the recruiter is superior to a threshold (θ), then the recruiter will feel an aggressive attitude ($val(aggr)$) equal to the maximum between the amount of hostile mood he feels ($val(hostile_f)$), its neuroticism ($val(N)$), and the inverse of its agreeableness ($1 - val(A)$). We have defined similar rules for every attitudes identified in the post-hoc interviews.

The non-verbal behaviour model of our agent, presented in the next section, does not work directly with the categories that were identified in the post-hoc interviews. To allow more variability, it makes use of continuous values, relying on the annotation of corpus which uses the Friendly and Dominant dimensions of Argyle's model of attitudes [1]. We converted the attitudes represented by categories into continuous values of dimensions using the work of Isbister [5]. As a result, the affective model gives a level of dominance and friendliness that represents the current attitudes of the agent.

4. EXPRESSION OF ATTITUDES

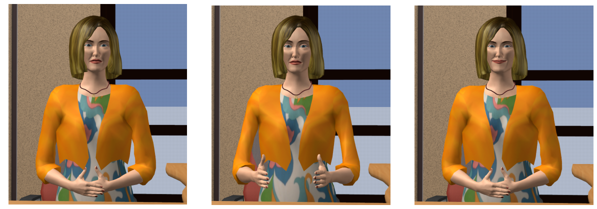
Most existing approaches to social attitude expression only consider the meaning of one signal independently of the other surrounding signals, however it is insufficient: for instance, a smile is a sign of friendliness, but a smile preceded by a head and gaze aversion conveys submissiveness [7]. Our work is the first attempt at using sequence mining technique to find the relationship between sequences of non-verbal signals and interpersonal attitudes.

Our methodology consists of the following steps : 1) We identify segments where the annotated attitude begins to vary (*attitude variation events*). 2) We separate attitude variation events into classes (*e.g.* small increase in dominance). 3) We segment the non-verbal behaviour streams using attitude variation events, obtaining a set of non-verbal behaviour sequences for each attitude variation class. 4) We extract frequent sequences using the Generalised Sequential Patterns algorithm [8] on the non-verbal behaviour sequences set of each attitude variation class. Extracted sequences are characterised with *confidence* (*i.e.* how frequently a sequence is found before an attitude variation) and *Lift* (*i.e.* how the sequence occurs before an attitude variation more than if they were independent) quality measures. An example of a non-verbal sequence is shown by Figure 1.

When the social attitude model sends a new value for *Dominance* and *Friendliness*, the sequence with the highest *Lift* and *Confidence* values for both dimensions is chosen. For example, the sequence of signals $HeadStraight \rightarrow Gesture \rightarrow RaiseEyebrows \rightarrow Smile$ is the best scoring sequence for large increases in dominance, with a *Confidence* of 0.6 and *Lift* of 5.38.

5. CONCLUSION

This paper proposes a new model for expressive agents to reason about and display social behaviours. It relies on an affective model that computes agent affects according to expected and perceived affects of the user. Contrary to most existing models of communicative behaviours for ECAs, we generate a sequence of non-verbal signals taking into account the signals the agent has shown previously. We used a data mining approach to identify sequences of non-verbal behaviours that display variations in attitudes.



(a) HeadAway (b) Communicative gesture (c) Smile

Figure 1: Example of non-verbal sequence

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