Affect Recognition for Interactive Companions

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ABSTRACT
Affect sensitivity is an important requirement for artificial companions to be capable of engaging in social interaction with human users. This paper provides a general overview of some of the issues arising from the design of an affect recognition framework for artificial companions. Limitations and challenges are discussed with respect to other capabilities of companions and real world scenarios for affect sensitive human-companion interaction.

Categories and Subject Descriptors
I.2.11 [**Distributed Artificial Intelligence**]: Intelligent agents.

General Terms
Algorithms, Human Factors, Theory.

Keywords
Interactive companions, affect recognition, affective cues, socially intelligent behavior.

1. INTRODUCTION
Building artificial companions capable of interacting with humans in the same way that humans communicate with each other has always been a major goal of the research in artificial intelligence. Current prototypes of artificial companions (e.g., robots, virtual agents, etc.) still lack of some important capabilities, which often impedes human users to establish bonds with them.

One of the main requirements for an artificial companion to be able to engage in a natural interaction with human users is the ability to display a social, affective behavior [1] [2]. Social capabilities are necessary for all those applications in which a robot or a virtual agent needs to interact with humans as a companion, a partner or a friend [3]. Companions can represent a valuable resource in many different contexts. For example, they can offer assistance in the care for elderly or in therapy applications, with the purpose not to replace human contact but to provide additional functionalities. Companions can be used as personal assistants for domestic applications or to help the user wherever she goes (e.g., at work, on a trip, etc.). They can also be employed to entertain and motivate users, for example for edutainment purposes or in entertainment industry (e.g., socially interactive games).

Interactive companions must be capable of sensing, processing and interpreting information about the user and the context in which the interaction takes place, in order to be able to plan and generate an appropriate response. Understanding the user's affective or mental states from her verbal and more subtle non-verbal behavior is of vital importance for a companion to be able to act socially [4]. A socially intelligent companion, for example, would try to ensure that the user is interested in maintaining the interaction or to act empathically towards her if she is sad or not willing to engage in an interaction, e.g., it would not disturb her trying to engage her in some activity if she does not approach it.

The ability to attribute affective or mental states to the user can be referred to as 'affect sensitivity' or also 'Theory of mind' [5]. It refers to the way social affective cues conveyed by people's behavior can be used to infer behavioral states, such as affective or mental states. These span from basic emotions (such as joy, anger, sadness, etc.) to more complex affective and mental states such as interest, boredom, frustration, etc.

This paper reviews some of the issues arising in the process of endowing interactive companions with affect sensitivity. Challenges in the design of an affective perceptual framework able to work over extended periods of time are discussed. Issues related to the need for systems to work in real-time and real environments are also examined and some examples of real world scenarios for affect sensitive companions are provided.

2. AFFECT RECOGNITION FOR INTERACTIVE COMPANIONS
Endowing a robot or a virtual agent with affect sensitivity is a complex task. Researchers have been increasingly addressing the design of systems endowed with this ability. Nevertheless, the attempts that have been made towards the development of virtual agents and robots capable of inferring the user's states in real-time are still not numerous. Further, not many system prototypes have been designed which can work in real environments in the long term. The need for artificial companions to work in the user's own social settings and to create long-term relationships with humans requires then research on affect recognition to be

taken beyond the state of the art. In the following we review some of the challenges and relevant issues for the design of interactive companions from the perspective of affect recognition.

2.1 Beyond Prototypical Emotions

Many of the affect recognition systems described in the literature mainly focused on the recognition of basic emotions (e.g., joy, sadness, disgust, surprise, fear, anger, etc.). While the automated recognition of more complex states has started to receive some attention only lately [6], research on artificial companions requires the design of an affective framework in which the companion's affect sensitivity goes beyond the ability to recognize prototypical emotions, and allows for more variegated affective signals conveying more subtle states such as, for example, boredom, interest, frustration, agreement, etc., to be captured. To date, some efforts have been made to detect such non basic affective states. Kapoor et al. [7], for example, presented an automated method to predict frustration using multimodal non-verbal cues including facial expressions, head movement, posture, skin conductance and mouse pressure data. El Kaliouby and Robinson [8] developed a computational model that detects in real-time complex mental states such as *agreeing, concentrating, disagreeing, interested, thinking and unsure* from head movement and facial expressions in video. Yeasin et al. [9] proposed an approach that recognizes six universal facial expressions and uses them to compute levels of interest.

Other attempts to infer other affective expression nuances have been reported in the literature. Caridakis et al. [10] presented a dynamic approach based on facial expressions and speech data to interpret coarse affective expressions in terms of a dimensional space representing activation and valence. Castellano et al. [11] proposed an approach to analyze emotional expression in music performance aiming to discriminate emotionally expressive intentions (i.e., *sad*, *allegro*, *serene*, *personal* and *overexpressive*) of a pianist using movement expressivity features. Some efforts have been made to detect other complex mental states such as shame, depression or pain. Littlewort et al. [12], for example, used an automated system for facial expression recognition to detect expressions of pain. See Zeng et al. [6] for an extensive overview.

It is important to stress that the inclusion of affect representation into a framework for affect recognition is of primary importance. Incorporating models and paradigms developed by psychologists for the classification of affective states [13] is a pressing need, but is still a challenging issue. Strengthening the connection with psychological models would allow for the first steps towards the detection of more complex affective states (e.g., appraisals, blends of emotions, preferences, mood, attitudes, etc.) to be undertaken.

2.2 Spontaneous versus Acted

The design of most existing affect recognition systems was largely based on databases of acted affective expressions [6]. While acted affective expressions, contrary to spontaneous expressions, can be defined precisely, allow for the recording of several affective expressions for the same individual, and can be characterized by very high quality, they often reflect stereotypes and exaggerated expressions, not genuine affective states, and they are often decontextualized [14].

To date, some efforts to develop systems for the automatic analysis and detection of spontaneous affective expressions have been reported. Examples include the neurofuzzy system for emotion recognition by Ioannou et al. [15], which allows for the learning and adaptation to specific users' naturalistic facial expression, the approach proposed by Caridakis et al. [10], that models affective expressions from naturalistic video sequences using facial expressions and speech prosody-related features, the system by Kapoor et al. [7], that uses multimodal non-verbal cues to detect frustration in students using a learning companion, the work by Devillers and Vasilescu [16], who reported results on detection of affective states in a corpus of real-life dialogs collected in call centers using linguistic and paralinguistic features. Noteworthy efforts are those of Valstar et al. [17] et al. and Littlewort et al. [12], who reported results on the automatic discrimination between posed and spontaneous facial expressions.

The design of an artificial companion would certainly benefit from the development of affect detectors which are trained and tested with spontaneous, real-life expressions. Collection of naturalistic data involves several issues, such as the difficulty of recording several emotional reactions for the same individual. Nevertheless, this is an issue that must be addressed in the design of an affect sensitive companion, in which personalization plays an important role.

2.3 Multimodal Affective Expressions

Another important issue for affect sensitive artificial companions is the need for a multimodal affect recognition system. It is expected that a companion is endowed with the ability to analyze different types of affective expressions, depending on the specific scenario of interaction with the user. On the other hand, fusing different affective cues can allow for a better understanding of the affective message communicated by the user to be achieved. While unimodal systems (mainly based on facial expression or speech analysis) have been deeply investigated, studies taking into account the multimodal nature of the affective communication process are still not numerous [6]. To date, some efforts to combine two modalities of expressions for the purpose of affect recognition have been reported in the literature, namely based on the fusion of facial expressions and body gesture data (e.g., [18]), facial expressions and head gesture (e.g., [8]), head and body gesture (e.g., [11]), facial expressions and speech (e.g., [10]), physiological signals and speech (e.g., [19]). Some attempts of using multiple modalities include the system developed by Kapoor et al. [7], which allows for the detection of frustration using multimodal non-verbal cues such as facial expressions, blink, head movement, posture, skin conductance and mouse pressure, the work by Castellano et al. [20], in which facial expressions, body gesture and speech data is fused at the feature and decision level to predict eight emotional states in a speech-based interaction, the study conducted by Valstar et al. [17], which combines multimodal information conveyed by facial expressions, head and shoulders movement to discriminate between posed and spontaneous smiles.

An issue of primary importance in multimodal affect recognition is represented by the fusion of different modalities. Features from different modalities of expressions can be fused at different levels (e.g., feature level or decision level fusion). Results from studies in psychology and neurology [21] [22] suggest that the integration of different perceptual signals occur at an early stage of human processing of stimuli. This suggests that different modalities of expression should be processed in a joint feature space rather than combined with a late fusion. Features from different modalities are often complementary and redundant and their relationship is unknown. For this reason it is important to highlight that combination schemes other than the direct feature fusion must be investigated. The development of novel methods for multimodal fusion should take into consideration what are the underlying relationships and correlation between the feature sets in different modalities [23] [24], how different affective expressions influence to each other and how much information each of them provides about the communicated affect.

2.4 Working in Real World Scenarios

Artificial companions have to be designed so as to be able to work in the users' own settings. This requires for a companion's affect recognition system to be robust in real world conditions: face detectors and body and facial features tracking systems which are robust to occlusions, noisy background (e.g., shadows, illumination changes) [25], rigid head motions [26], etc., are some of the most important requirements for a companion to successfully work in real environments.

Real world scenarios means that the companion must infer the user's state in real-time. This poses several issues, such as, for example, the segmentation and the analysis of the temporal dynamics of face or body gestures and expressions, since the possibility for a user's affective state to start at any time is a crucial factor in real-time affect recognition [6]. Further, detecting blends of affective states is still an open issue, as well as establishing their boundaries.

The dynamics of affective expressions is a primary factor in the understanding of human behavior. Affective expressions vary over time, together with their underlying affective content: analysis of static affect displays cannot account for the temporal changes in the response patterning characterizing an emotional reaction. It is therefore crucial for artificial companions to be capable of analyzing the temporal dynamics of affective expressions and their temporal correlation in order to be able to establish a long-term interaction with the user, which is dynamic by definition. Detection of temporal segments of affective expressions and analysis of their temporal evolution are then primary issues in the design of an affect recognition system for artificial companions. To date, some efforts towards a dynamic account for affective expressions have been reported in the literature. Examples include the work by Pantic and Patras [25], which deals with facial actions dynamics recognition, the study by Valstar et al [17], which showed the important role of the temporal dynamics of face, head and shoulder expressions in discriminating posed from spontaneous smiles, and the works by Castellano et al. [11] [27], which investigated the role of the dynamics of the expressivity of human movement (specifically upper-body and head gestures) and reported that features related to the timing of movement expressivity (e.g., expressive motion cues such as the quantity of motion and the velocity) are more effective for the discrimination of affective states than traditional statistical features.

2.5 Personalization

Individual differences cannot be neglected while designing an affect recognition system for artificial companions. People differ for culture, gender, personality, preferences, goals, etc. and do not express the same affective state in the same way. Affect sensitive artificial companions must then be endowed with a personalized affective framework: their recognition abilities must be designed so as to be person-dependent and to adapt to a specific user over time. Ioannou et al. [15], for example, developed a neurofuzzy rule-based system in which an initial set of rules can be modified via a learning procedure to adapt to a specific user's affective facial expressions.

An important issue to be considered in the design of an affect recognition system for artificial companions is represented by taking into consideration the context in which an affective expression is displayed (e.g., characteristics of the person expressing the emotion, environment in which the emotion is displayed, what the person is doing (i.e., her task), underlying mood, presence of other people, etc.). As suggested by Scherer [28], there can be as many emotions as the patterns of appraisal results. This highlights the importance of the evaluation of a stimulus event for the generation of the emotional response. In the same way, artificial companions must be able to evaluate how the recognized affective state relates with the conditions external to an individual that elicited the emotional response. See [7] for an example of system in which the role of context in affect recognition is addressed.

Finally, artificial companions must be designed so as to be capable of engaging in a long-term relationship with users (e.g., over periods of weeks or months). Previous studies showed that the novelty effect often quickly wears out [29] and people change their attitude towards the companion over time and their engagement decreases. For the purpose of the design of an affect recognition system for artificial companions this is an issue that must be addressed. An affect recognition framework which is adaptive over time (e.g., designed so as to work with rules that change according to how the level of engagement of the user towards the companion varies over different sessions of interaction) is required.

2.6 Closing the Affective Loop

Affect sensitivity is a prerequisite for a companion to act socially and generate responses appropriate to the user's behavior, and hence impacts other capabilities of companions.

An artificial companion must be endowed with mechanisms for expressing social, affective behavior. These should include non-verbal (e.g., facial and bodily expressions of the companion) and verbal communicative expressions. These mechanisms should be integrated with an architecture that includes memory, emotion, personality, adaptation and autonomous action-selection [see, for example, 30]. Adaptive models and mechanisms that support both collaborative and autonomous decision-making influenced by the companion's internal state and past experiences must be developed.

Information on the user's affective states can be used to modulate the companion's internal state, memory, expressive and cognitive behavior such as decision-making and planning. For example, a companion needs to know what to remember and what to forget.

Hence, memory of companions can be designed so that emotional episodes can be remembered more and information about the user's affective state during specific sessions of interaction can be used to retrieve relevant information when new interactions take place.

Moreover, analysis of the user's affective behavior can be used to influence the way a companion acts or communicates. For example, a companion can respond to low-level affective cues such as the way the user gestures (e.g., the expressivity of her movement) or to higher level data abstractions such as recognized facial expressions by exhibiting a low-level generated affective behavior (e.g., affective copying, mimicry) [31], or try to infer the user's affective state in order to plan a more complex response.

3. REAL WORLD SCENARIOS

This Section provides two examples of real world scenarios for affect sensitive artificial companions. These scenarios, developed in the framework of the EU project LIREC[1] (LIving with Robots and Interactive Companions), are discussed in terms of issues related to affect sensitivity.

3.1 MyFriend: Game Companion

This scenario deals with a game companion for young students that plays educational games such as chess. This companion interacts with students through a real robot, such as the Philips iCat (see Figure 1), or through embodied conversational agents on a screen. The companion acts like a game buddy, playing board games (e.g., chess) with the user whenever she wants. During the game the user may interpret social cues displayed by the companions (e.g., facial expressions or body gestures) to try to understand what happens in the game and eventually improve her chess skills and cognitive abilities. The companion may adapt its personality to the user's personality and memorize relevant episodes and other information such as who won the game or the emotions experienced by the companion itself or the user during a given session of interaction, in order to retrieve appropriate information in future interactions.

Such a scenario introduces several challenges from the perspective of affect recognition. First of all, the interaction may benefit from the companion's initial assessment of the user's attitude or mood (e.g., active/passive, positive/negative) towards the companion itself or the game. Second, the companion may use multimodal affective cues displayed by the user (e.g., cues typical of a face-to-face interaction, such as facial expressions, head movements, body pose, speech-related cues, etc.) to infer some information about the user's affective or mental state and plan and change its actions during the game in an appropriate way. The companion's sensitivity towards social, affective cues of this kind may contribute to underpin an empathic interaction. Analysis of the user's affective behavior may also be exploited for the purpose of monitoring the user's level of engagement over time, within each session and over different sessions of interaction. This is especially important to evaluate how the acceptance and user experience vary in the long term and requires the design of a dynamic, adaptive affective framework, which takes into account that the novelty effect of the companion may decrease in the user over time. Finally, a human-companion interaction needs to be personalized. This is possible not only by creating models of the user at the beginning of the first game session, but also through the automatic analysis of the user's behavior: detection of affective cues may be used to link emotional episodes to what the user likes or dislikes and be used in future interactions.

Figure 1: iCat engaged in a chess game (http://lirec.eu/).

3.2 Spirit of the Building: Team Buddy

The key idea for this scenario is a robot acting as friendly helper for a mall group of collaborative workers by maintaining a collective memory. Team Buddy interacts with members of the group through a real robot, a Pioneer with suitable sensors and camera. This robot companion acts as a workplace buddy within a given lab inhabited by a small group of people. It may keep track of who is there, remember for people who are not there when they have gone and why, remember important collective events in the lab like demos or equipment upgrades or important individual events like paper deadlines and project meetings and acquire and remember personal information for individuals, such as, for example, what they did at the weekend, etc. During the first interaction, the companion may be introduced to each member of the team and acquire some basic information about them.

In this kind of scenario analysis and interpretation of the user's affective behavior can play a major role in the initiation and evolution of the interaction with the companion. First of all, as for the MyFriend scenario, the companion must be aware of the user's attitude (e.g., active, passive) towards interacting with it. Such first assessment does not require the interpretation of complex states of the user, but can be limited to the analysis of low-level cues. An example of cues useful for assessing an "interaction initiation" condition may be the amount of the user's movement and face and motion direction. Affective cues of this kind, together with speech-related cues, can also help to evaluate whether the user is interested in maintaining the interaction. Coarse affect-related cues such as the amount of people present in the room and the frequency with which each person moves in proximity of the companion during an interaction session may be of help to the companion in determining whether it is still required or not and from which user. As in the MyFriend scenario, personalization is a key factor for Team Buddy and

[1] http://lirec.eu/

information about a specific user may be also acquired through the analysis of the verbal and non-verbal behavior at the level of one single user or multiple users acting in the scene. Further, the acquisition of this kind of information may also benefit from the development of a dynamic framework that can allow the companion to adapt its behavior over different sessions of interaction.

4. CONCLUSION

This paper provides an overview of some of the issues and challenges in the design of an affect recognition framework for interactive artificial companions. As a requirement to allow for artificial companions to engage in a social interaction with human users, affect sensitivity is discussed with respect to key issues such as the ability to perceive spontaneous and subtle affective cues for the detection of affective states different from basic emotions, the ability to analyze multiple modalities of expression, the robustness to real world scenarios, the personalization of the affect recognition abilities and the ability to adapt over time to changes of attitude of the user towards the companion.

Current findings in the domain of affect recognition represent a valuable resource for the design of affect sensitive companions. One of the drawbacks of this richness of studies in the field is that results and performances are often not comparable due to the different experimental conditions, the different databases of affective expressions used to train the affect detectors, the different data used, etc. Research on artificial companions should aim to establish common guidelines for the design of affect recognition frameworks suitable for real world applications.

An issue worth to be investigated in future work on artificial companions is how such frameworks should be designed depending on the type of companion the user is interacting with, for example depending on its embodiment. Different embodiment means different hardware and software resources and this may impact the recognition abilities of companions. An agent on a PDA, for example, will certainly not be able to analyze the user's facial expressions and hence will require an affective framework capable of perceiving lower level affective cues and providing more coarse interpretations of the user's behavior.

Finally, it is important to highlight that the development of companions endowed with the above mentioned affective capabilities raises some issues related to ethics and privacy. What does the companion have the right to know about the user's state? What type of cognitive and affective behavior can it express? For example, motivating a user perceived as not active to engage in an interaction can be interpreted or perceived by the user herself as an inappropriate and upsetting attempt of persuasion, which may impact the current user experience and acceptance over the long term. This and others of this kind remain open issues and need to be investigated further.

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