Chapter 9
Affective Conversational Agents:
The Role of Personality and Emotion in Spoken Interactions

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ABSTRACT

In this chapter, we revisit the main theories of human emotion and personality and their implications for the development of affective conversational agents. We focus on the role that emotion plays for adapting the agents' behaviour and how this emotional responsivity can be conveniently modified by rendering a consistent artificial personality. The multiple applications of affective CAs are addressed by describing recent experiences in domains such as pedagogy, computer games, and computer-mediated therapy.

1 INTRODUCTION

Conversational agents (CAs) represent a higher level of intelligence with respect to traditional spoken interfaces as, especially in the case of embodied conversational agents (ECAs), they foster the so-called "persona effect", which refers to the credibility and motivation of agent based interfaces and its positive effect on the users' attitude towards the system (Lester et al., 1997). However, as Picard (2003) highlights, the more complex the system, the more complex the user's demands and when CAs are highly realistic but fail to sufficiently simulate humans, they may have a negative effect on the users, a phenomenon called

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"uncanny valley" (Beale & Creed, 2009). Thus, it is important to endow CAs with emotional and socially rich behaviours to make more natural and compelling interactions possible and meet the users' expectations.

Emotions provide an additional channel of communication alongside the spoken and graphical exchanges from which very valuable information can be obtained in order to adapt the CAs' behaviour (Ball, 2003). In contrast with the Descartian concept of *rational* intelligence, psychologists have introduced the term *emotional* intelligence to describe the necessary emotional processing to tailor our conducts and cognitions to our environment. To endow CAs with emotional awareness makes it possible to recognize the user's emotions and adapt the agent functionalities to better accomplish his/her requirements. Stern (2003) also provides empirical evidence that if a user encounters a virtual character that seems to be truly emotional, there is also a potential to form emotional relationships with each other.

Additionally, the similarity-attraction principle states that users have a better attitude toward agents which exhibit a personality similar to their own. Thus, personality plays a very important role on how users assess CAs and their willingness to interact with them. In the same way as humans understand other humans' behaviour and react accordingly to it in terms of the observation of everyday behaviour (Lepri et al., 2009), the personality of a CA can be considered as a relatively stable pattern that affects its emotion expression and behaviour and differentiates it from other CAs (Xiao et al., 2005).

2 BACKGROUND: HUMAN EMOTION AND PERSONALITY

Many authors in research fields such as psychology, biology and neurology have proposed different definitions of the term *emotion* from a diversity of perspectives, each of which has contributed significant insight into the emotion science. A relevant example is Darwin's evolutional explanation for emotional behaviour (Darwin, 1872), with which he gave evidence of the continuity of emotional expressions from lower animals to humans, and described emotions as being functional to increase the chances of survival. According to Plutchik (2003, chapter 2), one of the implications of these findings is that research in emotion was expanded from the study of subjective feelings to the study of behaviour within a biological and evolutionary context.

Based on the evolutionary perspective, Rolls (2007, chapter 2) states that genes can specify the behaviour of animals by establishing goals instead of responses. According to Rolls, these goals elicit emotions through reward and punisher evaluation or appraisal of stimuli. Due to a process of natural selection, animals have built receptors for certain stimuli in the environment and linked them to responses. Rolls suggests several levels of complexity of such mechanism, in the most complicated, the behaviour of humans is guided by syntactic operations on semantically grounded symbols.

Other authors have adopted a physiological perspective by studying how subjective feelings are temporally related to bodily changes such as heart rate, muscle tension or breathing rate. Some authors, leaded by the seminal work by James (1884), argue that humans feel emotions because they experience bodily changes. According to his theory, it is impossible to feel an emotion without experiencing any physiological change. James' work was fundamental for the development of studies on autonomic physiological changes in relation to emotion. In Section 4 we will describe several methods for emotion recognition based on such physiological autonomous changes.

However, James' theory was refuted by Cannon (1929), who probed that this cause-effect relationship was not possible and pointed out a more plausible sequence of events: the perception of a situation gives rise to an emotion, which is then followed by bodily changes. Cannon was interested not only in the behavioural and physiological correlates of emotion, but also on the neural correlates which indicate how emotions are represented within the brain.

Heath, Cox and Lustick (1974) pointed out that all major parts of the brain participate in emotional states. As described in (Fox 2008, chapter 1) recent research indicates that different brain circuits control different aspects of emotion and many brain areas involved in emotion also participate in a range of other functions. Emotion is highly related to cognition; in Section 3 we will study the implications of such relationships for modelling affect in CAs.

For a long time, introspection has been the main way of emotional research so that psychologists have based their work on self reports of emotions. However, as discussed in (Fox 2008, chapter 2), such subjective reports are generally not reliable. As Freud claimed, emotions are complex inner states subject to repression and modification for conscious as well as unconscious reasons. Thus, it is necessary to have information about the causes of emotion, as they can be elicited by the presence of non conscious stimuli which cannot be described with self reports. As will be addressed in Section 3, the representation of emotion in CAs is usually based on models of the emotions' causes and appraisals.

Several attempts have been made to identify the nature of eliciting situations. For example, Roseman, Spindle and Jose (1990) proposed five types of appraisals of events which determine which particular emotional responses are appropriate. Kentridge and Appleton (1990) suggested that the suitability of emotional responses and expression is assessed by humans to reduce the possibility of an undesirable event or increasing the chances of a desirable event, which demands sufficient cognitive capacities to predict future events.

Additionally, emotional expression is influenced by individual characteristics such as age. For example, Scheibe and Carstensen (2010) corroborate that older individuals regulate their emotions more frequently, especially in the case of negative affect. Personality also affects emotion perception and expression. Although there is no universal definition of personality, it can be described as a complex organization of mental and biological systems that uniquely characterize an individual's behaviour, temperament and emotion attributes.

Fox et al. (2008) argue that personality predicts emotional expression both in general and in particular scenarios, concretely they studied public and private interaction. Larsen and Ketelaar (1991) have detected that extraversion is associated with an increased responsivity to controlled inductions of positive (but not negative affect), whereas neuroticism would be associated with an increased responsivity to controlled inductions of negative (but not positive) affect. In Section 5, several applications of CAs using personality models to modify their emotional behaviour are described.

Additionally, personality does not only influence emotion perception and reaction, but also modulates neural mechanisms of learning (Hooker et al., 2008), which for example has a deep impact on intelligence and academic performance (Rindermann & Neubauer, 2001).

3 REPRESENTATION OF EMOTION AND PERSONALITY IN CAS

3.1 Basic Emotions and Personality Traits

As explained in (Plutchik 2003, chapter 4), one of the difficulties of reporting and understanding emotion is that we assume that the listener understands the terms we use when describing affect because of similar experiences and through empathy. However, it might not be so, precisely because of the inaccuracy of self reports, for example due to stimuli out of conscious awareness. Additionally, there are words that describe similar states, which are to some extent related by an implicit intensity dimension (e.g. sad and desolated), whereas there are other words which are considered to represent opposites (e.g. sad and happy).

This ambiguity in the language of emotion raised the question of whether there exists a reduced number of primary or basic emotions from which secondary emotions can be obtained by blending them in a similar way as colours can be obtained as a mixture of the basic ones. The underlying idea is that once an emotion is triggered, a set of easily and universally recognizable behavioural and physiological responses is produced. This can be empirically demonstrated by the fact that some emotions seem to appear in all cultures as well as across many animal species (Fox 2008, chapter 4).

Several authors have proposed lists of basic emotions – see (Plutchik 2003, chapter 4) for a comprehensive review – however, there has been no agreement about which emotions are primary or secondary and which features make an emotion fall into any of the two categories.

During the last decades, there have been numerous initiatives in which the main words related to emotion have been acquired and grouped using statistical factor analysis. At the same time, several authors such as Osgood, Suci & Tannenbaum (1957) computed correlations between each pair of emotions so that not only grouping could be made, but also it was possible to measure similarity between the categories. When converted into angular distances, these measures could be employed to arrange emotions in a circle as the one proposed by Conte & Plutchik (1981). This same experiment was carried out by Russell (1994) in other languages different from English, and most of the emotion words felt in similar locations on the circle. Also emotions which are intuitively considered as opposite were found in opposite locations in the circular representation.

Regarding personality, it describes what it is most typical and characteristic of an individual, distinguishing him/her from the rest. According to (Fox 2008, chapter 3), self-report instruments have been used to identify the key personality factors or traits that contribute the uniqueness of a person and explain how people differ from each other. Thus, according to Fox, when using the notion of traits it is assumed that people have a reduced number of core aspects of their personality than can influence how a particular situation might be perceived or appraised.

As explained in (Xiao et al., 2005) most trait theorists assume that all people have a fixed number of basic dimensions of personality. However although a consensus about the number of dimensions would be desirable (Eysenck, 1991), several authors have proposed different criteria. Some authors use a reduced number of traits, for example two in (Eysenck & Eysenck, 1963), whereas others take into account more than a dozen, such as Cattell (1943), who suggests 16 dimensions.

Although thousands of different trait words are used in natural language, only a relatively small number is employed in practice. With the aim of reasoning about personality, personality psychologists have tried to identify the most essential and universal terms. To do so, a similar procedure as in the case of emotions was used in which the typically adjectives for describing personality were collected and grouped using factor analysis (Allport & Odbert, 1936).

However, the most widespread grouping is the Five Factor Model (or Big Five), which has become a standard in psychology. Although slightly different words have been used for the five factors, generally the following terms are employed (McCrae & Costa, 1989):

1. Extraversion vs. Introversion (sociable, assertive, playful vs. aloof, reserved, shy);
2. Emotional stability vs. Neuroticism (calm, unemotional vs. insecure, anxious);

3. Agreeableness vs. Disagreeable (friendly, cooperative vs. antagonistic, faultfinding);
4. Conscientiousness vs. Un-conscientiousness (self-disciplined, organized vs. inefficient, careless);
5. Openness to experience (intellectual, insightful vs. shallow, unimaginative).

The five clusters of personality factors are also referred to as the OCEAN model (Openness, Conscientiousness, Extraversion, Agreeableness and Negative emotionality). Cross-cultural stability of the Five Factor Model has been demonstrated by various authors. For example, McCrae et al. (2005) found scalar equivalence of NEO-PI-R factors (a 240-item measure of the model) for 51 cultures.

3.2 Models of Emotion and Personality

The notion of primary emotions allows CAs developers to consider them as discrete categories. An alternative solution is placing them in a continuous case, representing them by coordinates in a space with a small number of dimensions. The typical approach is to use the bidimensional activation-evaluation space (Cowie et al., 2001), which emerged from the circumflex arrangement of emotions proposed by psychologists that was discussed in the previous section.

The first dimension of this space corresponds to the valence of the emotional state. Valence represents whether the emotion is perceived to be positive or negative. As discussed by Plutchik (2003), emotions cannot be considered positive or negative by themselves as, from the adaptive role that emotions play (from the evolutive perspective), no emotion can be considered negative (e.g. fear motivates withdrawal behaviour when a danger is perceived). Thus, valence does not deal with the positive/negative nature of emotion, but rather with the perception of the subject, that is, whether the person perceives the emotion to be positive or negative depending on the stimulus. The second dimension, activation (or arousal), measures the user disposition to take some action rather than none. This is linked with Darwin's theories which relate emotion with action.

According to Fragopanagos & Taylor (2005), the strength of the drive to act as a result of an emotion is an appropriate complement to the valence rating. However, sometimes it is necessary to contemplate additional dimensions to distinguish between similar emotions; for example, by taking into account the perceived control over the emotion or the inclination to engage.

Emotions can also be represented from a cognitive perspective that describes how users deal with the situation that caused the emotion. Ortony, Collins & Clore (1988) proposed a computationally tractable model of the cognitive basis of emotion elicitation which is known as the OCC model. This model argues that emotions derive from self appraisal of the current situation (consisting of events, agents, and objects) with respect to our goals and preferences. Usually this theory is employed for constructing rules for appraising the situations which generate the different emotion considered, which can be used by CAs to infer the user's emotion or to synthesize its own emotional state.

With respect to personality, most of the computational models that have been used in literature are based on trait theories, that is, on easily distinguishable categories or trait dimensions. Some CAs have implemented sophisticated models of personality which take into account a high number of dimensions, for instance the Cybercafé and Bui's ParleE (Bui et al., 2002) successfully applied the 16 dimensions of personality proposed by Rousseau (1996). However, the most employed is the Five Factor Model.

For example, Read et al. (2007) propose the Personality-Enabled Architecture for Cognition (PAC), which is based on the main five traits and designed to represent individual behavioural variability from personality. Their goal was to create agents who make different choices as a function of differences in their underlying motivational systems. Reithinger et al. (2006) also employ a five factor model of personality, in this case to bias the emotions intensities of the ECAs of the Virtual-Human system. The Virtual-Human system provides a knowledge-based framework to create interactive applications in a multi-user multi-agent setting.

4 RECOGNITION OF THE USER AFFECTIVE STATE

Emotion recognition for CAs is usually treated as a classification problem in which the input is the user last response (voice, facial expressions, body gestures…) and the output is the most probable emotional state. Many different machine learning classifiers have been employed for emotion recognition and frequently the final emotion is decided considering the results of several of these classification algorithms (López-Cózar et al., 2008). Some of the classifiers most widely used are K-nearest neighbours (Lee & Narayanan, 2005), Hidden Markov Models (Pitterman & Pitterman, 2006; Ververidis & Kotropoulos, 2006), Support Vector Machines (Morrison, Wang & Silva, 2007), Neural Networks (Morrison, Wang & Silva, 2007; Callejas & López-Cózar, 2008) and Boosting Algorithms (Sebe et al., 2004; Zhu & He, 2008). A detailed review can be found in (Ververidis & Kotropoulos, 2006).

In this chapter we will address the features employed for emotion classification, from which we will focus on physiological, neurological, acoustic, linguistic and visual features as summarized in Figure 1. This is not an exhaustive taxonomy, and there are other authors who also incorporate other sources of information such as dialogue-related (Callejas & López-Cózar, 2008) and cultural and social settings. In fact, according to Boehner et al. (2007) emotions are interactionally constructed and subjectively experienced, so that physiological, neurological and other approaches to emotion which measure emotion "objectively" fail to address how emotions are actually experienced.

4.1 Physiological Features

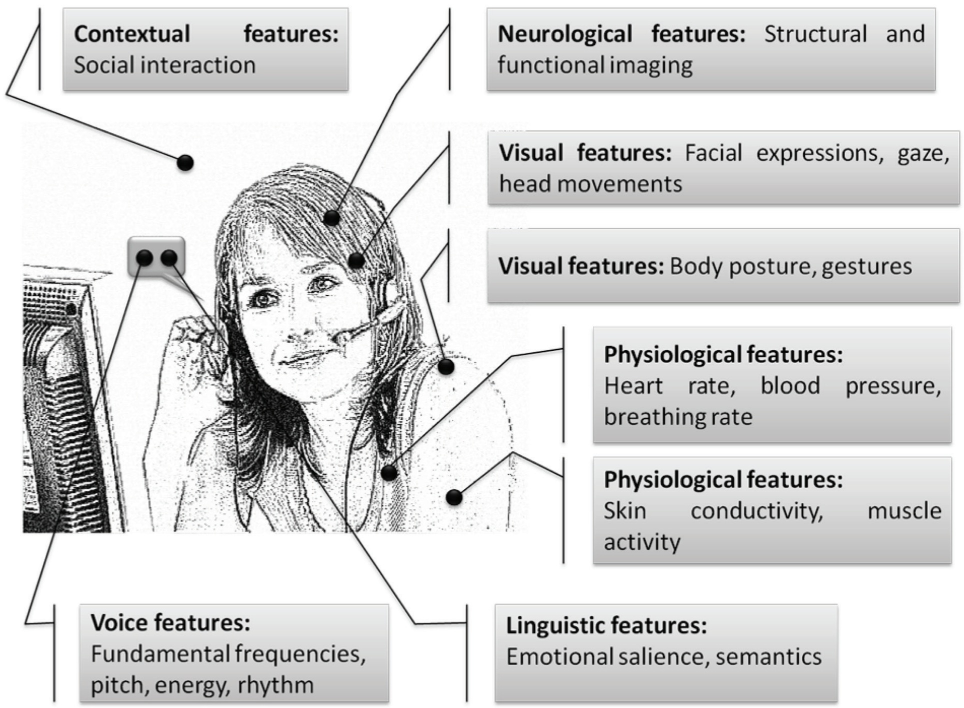
The autonomic nervous system controls the physiological changes associated to emotion sending signals to various body organs, muscles and glands (Fox 2008, chapter 2). These changes can be accounted using different measures such as:

- Galvanic skin response (GSR). There is a relationship between the arousal of emotions and changes in GSR.
- Heart rate and blood pressure. The number of heart bits per minute and the systolic and diastolic blood pressure can be good indicatives of changes in arousal.
- Breathing rate. The number of breaths per minute provides a good measure of physiological arousal.
- Electromyography (EMG). EMG can measure different muscle tension, activity and contractions related to emotion expression.

For example, the Emotion Mirror web-based application used physiological measures in a job interview scenario (Prendinger et al., 2003); finding that the users who interacted with a empathetic agent had lower skin conductance, and thus were less stressed than those that interacted with the non-empathetic agent. The empathetic ECA just mirrored the user emotion. In order to recognize it, they obtained a baseline for the bio-signals during an initial relaxation period and subsequently measured the GSR and EMG values during a job interview.

Lim & Reeves (2010) used physiological measures to compliment subjective reports about likeability of computer games and obtained that different patterns of physiological responses may be observed depending on the perceived agency of a co-player. For example, there was greater skin

Figure 1. Summary of the main features employed for emotion recognition



conductance activity, and thus more emotional engagement, with CAs controlled by humans (avatars) than with agents, which highlights the importance of providing more humanlike behaviours to CAs, such as for example endowing them with affective awareness and responsivity.

4.2 Neurological Features

Neurological features are related to the limbic system. Traditionally, the relationships between emotions and the brain have been discovered to a high extent thanks to the research with animals, usually employing surgery. However, during the last decades there has been a big technological advance which allows to reliably obtaining images of the brain and its activity. A detailed explanation of these methods and its relationship with emotions can be found in (Peper, 2006; Aleman, Swart & Rijn, 2008). We distinguish two main groups:

- Structural imaging methods, such as computerized tomography (CT) or magnetic resonance imaging (MRI).
- Functional imaging methods, such as positron emission tomography (PET), electroencephalography (EEG), functional magnetic resonance imaging (fMRI) or magnetoencephalography (MEG).

Despite their usefulness for measuring brain states, Cowie et al. (2001) claim that research cannot realistically expect brain imaging to identify emotion terms as they are used in natural language, as most of the previous techniques require restricting activity making it impossible to study whether normal activity would interfere with the detection of emotion. The authors argue that recognizing the emotional state of a person implicates subtle features of the ways in which neural systems operate rather than simply detecting whether they are active or not.

4.3 Voice Features

Speech is deeply affected by emotions: acoustic, contour, tone, voice quality and articulation change with different emotions. A comprehensive study of those changes is presented in (Cowie et al., 2001). We will distinguish four main groups of features: pitch, formant frequencies, energy and rhythm, a more detailed taxonomy can be found in (Batliner et al., in press).

Pitch depends on the tension of the vocal folds and the sub glottal air pressure (Ververidis & Kotropoulos, 2006), and can be used to obtain information about emotions in speech. As noted by Hansen (1996), mean pitch values may be employed as significant indicators for emotional speech when compared with neutral conditions.

Additionally, the first two formant frequencies (F1 and F2) and their bandwidths (B1 and B2) are a representation of the vocal tract resonances. Speakers change the configuration of the vocal tract to distinguish the phonemes that they wish to utter, thus resulting in shifts of formant frequencies. Different speaking styles produce variations of the typical positions of formants. In the particular case of emotional speech, the vocal tract is modified by the emotional state. As pointed out by Hansen (1996), in stressed or depressed states speakers do not articulate voiced sounds with the same effort as in neutral emotional states.

Energy is also considered a relevant indicative of emotion as it is related to its arousal level (Ververidis & Kotropoulos, 2006). The variation of energy of words or utterances can be used as a significant indicator for various speech styles, as the vocal effort and ratio (duration) of voiced/unvoiced parts of speech change. For example, Hansen (1996) demonstrated that loud and angry emotions significantly increase energy.

With regard to rhythm features, they are based on the duration of voiced and unvoiced segments and previous studies noted that the duration variance decreases for most domains under fast stress conditions (Boersma, 1993).

4.4 Linguistic Features

Emotion recognition from linguistic features deals with linguistic changes depending on the emotional state of the user. For this purpose the technique of word emotional salience has gained remarkable attention. This measure represents the frequency of apparition of a word in a given emotional state or category, and is calculated from the analysis of a sentence corpus (Lee & Narayanan, 2005).

Although it is a straightforward method to assign affinity of emotions to words, the probabilities calculated using this approach are highly dependent on the corpus used and have some disadvantages such as not accounting for polysemous words. In order to solve this problem, statistical natural language processing approaches have been used. From the lexical and syntactic perspective, Mairesse & Walker (2007, 2008) have proposed a comprehensive list of features which are indicative of different personality traits, whereas from the semantics perspective, approaches such as Latent Semantic Analysis are usually employed to detect the underlying affective meaning of texts. Semantic analysis of affective expressions is very complicated. This analysis is very complex in the case of unconstrained interactions, for which different strategies must be defined to tackle with ambiguity. For example, Smith et al. (2007) propose an approach to endow CAs with the capability of extracting affect cues from metaphors such as *"you are an angel"* or *"you are a pig"*.

In the ERMIS project (Fragopanagos & Taylor, 2005) a method was introduced which unified the previously described approaches and mapped words in the activation-evaluation space. In this space, the words formed a trajectory which represented the movement of emotion in the speech stream.

When linguistic features are employed, it is important to take into account contextual information such as age and cultural background, as it influences the lexical indicators of emotion and personality. This situation was addressed by Yildirim, Narayanan & Potamianos (in press) who analyzed the effect of age in polite and frustrated behaviour of children during spontaneous spoken dialog interaction with CAs in a computer game.

In other cases, the emotional salience of the linguistic contents can only be disambiguated using acoustic information. De Rosis et al. (2007) claim that rule-based recognition criteria including consideration of the context is necessary to study how the changes in prosody vary the interpretation of affect derived from the linguistic content.

4.5 Visual Features

In a conversation, the users convey non-linguistic visual messages which are useful to detect their affective state. Facial expressions, gaze, body posture, and head or hands movements are usually employed for emotion recognition.

The face plays a significant role in human emotion perception and expression. The association between face and affective arousal has been widely studied; a comprehensive review of the main psychological and biological studies on facial expression since Darwin theories is addressed in (Plutchik 2003, chapter 7).

Most studies of automatic emotion recognition focus on six basic facial expressions proposed by Ekman (1994) as universally perceived across cultures. These emotions are: happiness, sadness, anger, fear, surprise and disgust. Usually, in conversational systems facial expression is recognized along with vocal cues in order to differentiate emotional facial expressions and expressions which are caused by articulatory lip movements (Zeng et al., 2007). In (Chibelushi & Bourel, 2003) there is a survey of the main facial expression recognition approaches.

Some authors have focused on specific parts of the face such as gaze or smiles. For example, (Kumano et al., 2009) studied smile as a good indicator of interpersonal emotion in meetings and a cue for attention assessment. Morency, Christoudias & Darrell (2006) built an ECA which, based on the user gaze, could discriminate if he was thinking a response or waiting for the agent to intervene. Bee, André & Tober (2009) used eye-contact between the user and an ECA named Alfred to "break the ice" and determine the user's willingness to engage in an interaction with the agent.

Regarding body gestures, Shan, Gong & McOwan (2007) suggest that using information about body gesture and facial expression allows more accurate emotion recognition. For example, Kapoor & Picard (2005) classified children's affective state of interest when solving puzzles by combining information extracted form face videos, a chair which sensed body posture and the state of the puzzle.

4.6 Corpora

In order to train emotion recognizers it is necessary to have a corpus in which all the features used for classification are proportionally present. There are three main approaches for collecting emotional corpora: recording spontaneous conversations, recording induced emotions, and asking actors to simulate emotions. There is a compromise between naturalness of the emotions and control over the collected data: the more control over the generated data, the less spontaneity and naturalness of the expressed emotion, and vice versa.

Spontaneous conversations in the application domain of the emotion recognizer constitute the most realistic approach. However, a lot of effort is necessary for the annotation of the corpus, as it requires an interpretation of which emotion is being expressed in each recording (Callejas & López-Cózar, 2009). Sometimes, the corpus is recorded from human-to-human interaction in the application domain (Forbes-Riley & Litman, 2004). In these cases, the result is also natural but it is not directly applicable to the case in which humans interact with a CA.

Opposite to the previous approach, acted emotions are easier to manipulate and avoids the need for annotation, as emotions conveyed in each recording are known beforehand. The results obtained are highly dependent on the skills of the actors, which implies that the best results are obtained with actors with good drama preparation. When non-expert actors are used, another phase is necessary to discard the recordings that fail to reproduce the required emotion appropriately.

Induced emotions represent a trade-off between the two approaches discussed above. Emotions can be more natural, like the ones elicited when playing computer games (Johnstone, 1996), or easier to manipulate, like the ones induced by making people read texts that relate to specific emotions (Stibbard, 2000).

Due to its complexity, emotion recognition is a study field on its own. There are many researchers trying to find the most representative features for classification, and the most appropriate methods for emotion recognition. Many of them work considering acted emotions, and thus, their results cannot be directly applied to more realistic scenarios where the users behave spontaneously.

Batliner et al. (2004) consider this problem and state that a possible solution, in addition to colleting more data, is taking into account other information sources, such as for example monitoring the user's behaviour. Following this approach, we have obtained good emotion recognition results when considering contextual information about the interaction in an emotionally aware spoken dialogue system (Callejas & López-Cózar, 2008). Concretely, we considered adding information about the user's neutral voice and the dialogue history, which improved both automatic classification and human annotation of a corpus of spontaneous emotions. For illustration purposes, a benchmark with the success rates of different acoustic emotion recognition approaches for nine standard corpora can be found in (Schuller et al., 2009).

5 AFFECTIVE RESPONSIVITY AND ADAPTIVITY IN CAS

Picard (2003) poses the question of whether machines have emotions in the same way that humans do, and comes to the conclusion that we can never be sure that we have understood and thus imitated every mechanism involved in human emotion. Hence, we will never be completely confident that machines have emotions. However, she points out the possibility to agree in some value of N known human emotion mechanisms that suffices for a reasonable emotional behaviour.

We are still far from reaching an agreement in which mechanisms are part of this set of N, and every author considers a different mechanism that is relevant for his/her purposes and application domain. Usually, affective applications using CAs follow the so-called "affective loop", which represents the cycle of recognizing the user's emotion, selecting the most suitable action depending on the user state, and synthesizing the appropriate affective response (Höök, 2008, 2009).

Very representative examples of such interactions are interactive storytelling systems, in which expressive ECAs (virtual actors) interact with users involving them in the story. Cavazza, Pizzi and Charles (2009) highlight the importance of affective behaviour of such actors and present the EmoEmma demonstrator, in which an ECA represents Emma Bovary, the main character of Flaubert's novel Madame Bovary. In EmoEmma, the user can address the ECA or respond to her, impersonating her lover. The system recognizes the users' emotions from his utterances, which are analyzed in terms of the current narrative context including the characters' beliefs, feelings and expectations. The recognized emotion influences the ECA behaviour, achieving a high level of realism for the interaction.

Role-playing has also demonstrated being a powerful instrument for exploring social relationships, and to promote intra-psychic self reflection. Imholz (2008) claims that virtual worlds are a very powerful tool for using psychodrama as a therapeutic practice. From her study it seems that role-playing using avatars capable of affective interactions can be very useful for the treatment of affect disorders. However, Nomura (2005) argues that therapeutic agents may be employed just as tools that satisfy the users' desire to talk about themselves while hiding the things concealed in their narratives that would be unmasked by a human therapist. According to this perspective, if the agents are sophisticated enough to explicitly draw things concealed in the users' narratives, they would act contrary to the users' expectations, which may cause abusive behaviours toward the agents.

Many interaction logs show that some users are annoyed by these displays and feel compelled to challenge the agent's assumption of human traits, often expressing their dissatisfaction by verbally abusing the agents (Brahnam, 2005; Brahnam, 2009). Nijholt (2007) offers an interesting solution for the situation in which a CA is attacked because of imperfect behaviour, which is to anticipate it and use humour by endowing the agent with the capability for humorous act generation. The agent can then make fun of its own defects by generating humorous remarks, which is another type of affective behaviour. This way, humour appeals to positive emotion making the interaction between the user and the CA more enjoyable.

In the storytelling application domain, the user influences the agents' emotional state in order to develop the drama. In other applications, the objective is quite the contrary, that is, to endow the agents with persuasion capabilities. This is the case of virtual counsellors such as the one presented in (Schulman & Bickmore, 2009), an ECA which persuades the users to change their attitudes towards exercise. The authors claim that it is important to endow CAs with social dialogue and other relationship-building tactics for successful persuasion. Affective awareness in CAs has a great potential to reach this objective, as shown in (De Rosis et al., 2007), in which an ECA named Valentina adapts its behaviour to the attitude of its users, which makes its dietetic suggestions more effective.

Similarly, in pedagogic application domains, the CAs must be able to recognize the students' emotions. For example, the PrimeClimb agent (Conati & Maclaren, 2009) was able to assess the possible eliciting situations employing the OCC theory to recognize whether the reason for the emotion is something the user has done (e.g. pride or shame depending on his success), or it is because of the agent behaviour (e.g. admiration or reproach). Processing the eliciting situations allows the CA to tailor its responses and reinforce learning in the appropriate way by either making the student feel better towards him/herself and thus more motivated, or by tuning the behaviours which cause a negative effect on the user.

In order to follow the human mechanisms of affective behaviour, the affective response selected by a CA should be tailored to certain personality traits in such a way that personality modifies motivational intensity for decision making. De Sevin (2009) proposed an approach to action selection based on traits with a customizable virtual human and empirically demonstrated that it could be an easy way to test personality traits by tweaking the motivational intensities in order to obtain more distinct and believable virtual humans. For example, Maria & Zitar (2007) compared a regular intelligent agent with a personality-rich one in the domain of an "orphanage care problem", and obtained that the affective agent succeeded in adapting its priorities better based on a model of likes and dislikes.

Additionally, as argued by Ortony (2003), personality is important to build believable emotional agents, as it is needed to ensure situational and individual appropriate internal responses (emotions), external response (behaviours and behavioural inclination), and arrange for sensible coordination between internal and external responses.

Regarding individual responses, the Idolum framework demonstrated an idle-time behaviour of moods and emotions controlled by a consistent personality. In order to be more believable, Idolum took into account aspects of personality, mood and stimuli elements from psychological models such as a time cycle (winter/summer), the weather, or a manic/depressive cycle that can affect its emotional behaviour (Marriot, 2003).

Regarding situational responses, it is necessary to integrate contextual background in affective interactions. For example, Endrass, Rehm & André (2009) were interested in studying differences in communication management between Asian and Western cultures and their implications in developing ECAs. They recorded dialogues with German and Japanese human participants which revealed a different usage of pauses in speech and overlapping speech (Asian conversations contained more pauses and also more overlapping speech). They developed the Virtual Beergarden, a virtual meeting place in which culture-specific ECAs interact rendering the nonverbal behaviour observed with the human subjects. Their study reveals that German subjects seem to prefer communication management in dialogues between virtual agents which rehearse their culture-specific behaviour.

Another important application of affective systems is emotion mirroring (D'Mello et al., 2008). Affective CAs which imitate the user affective state are very useful to treat emotional and personality disorders. For example, in the FantasyA demonstrator of the SAFIRA project (Paiva et al., 2001), the users must interact with 3D conversational agents so that only when the user is able to make the CA portray the appropriate affective expressions, s/he can move to the next level of the game. Other authors (Bickmore & Picard, 2005; McQuiggan & Lester, 2007) have studied the role of empathy in ECAs. However, as stated by Beale & Creed (2009), more research is required still to understand the potential of such agents to help people change their habitual behaviour.

Also affective CAs can be used to simulate human emotion in order to obtain a better understanding of the mechanisms that underlay it. For example, Scheutz (2001) developed a multi-agent environment aimed at studying the role of emotions as motivations for action, and how affective states develop according to the results of the interactions between different types of agents.

An interesting peculiarity of this research domain is that negative emotions and extreme personalities can play a very interesting role. While in other applications it might not be desirable to build negative emotions, in this case, as stated by Becker, Kopp & Wachsmuth (2007), an adequate implementation of a model based on emotion psychology will automatically give rise to negative emotional states which can lead to true understating of human affect.

For example, in the NECA Project (Krenn, 2003), the "socialite" demonstrator was implemented for multi-user web-mediated interaction through CAs that play the role of avatars. These avatars are enhanced with affective reasoning and personality traits and carry out unsupervised interaction with each other in the virtual environment. Similarly the SAFIRA Toolkit for affective computing (Paiva et al., 2001) addressed affective knowledge acquisition, representation, planning, communication and expression with a fuzzy approach. Their goal was to explore the nature of affective interaction which is intentionally made fuzzy, complex and rich to simulate real emotions, which are usually open to interpretation.

Creed & Beale (2008) investigated the psychological impact of simulated emotional expressions in ECAs, accounting for the effect of mismatching the synthesized facial and audio emotional expressions of the agents, for example, by using emotional facial expressions with a synthetic monotone voice. They obtained that mismatched emotions confused the users and altered their perception of the simulated expression which can cause frustration, annoyance and irritation. Their results corroborated the psychological cognitive dissonance theory, which claims that inconsistency between cognitions leads to a negative affective state that can motivate changes in elements of knowledge (Harmon-Jones, 2001).

These results highlight the significance of rendering perfectly tuned multimodal emotional responses. Other authors have also indicated the importance of controlling the visual presence of CAs so that they render the ethnicity and gender which the user perceives as expert in application domains such as education and consumer marketing. For example, Pratt et al. (2007) used ECAs to confirm the theories of neurological activation associated with implicit and explicit prejudicial responses based on stereotyping.

As has been described before, there are many ways in which CAs can show affect, and usually they are tailored to their application domain. Thus, it is very difficult to find a measure to evaluate the "degree of affectiveness" or emotional intelligence of a CA. Some authors take into account the number of modes in which the agent can show an emotional behaviour and the coordination among them. For example, Burleson & Picard (2007) changed the behaviour of a learning companion according to three aspects: the type of intervention (affect support or task support), the level of congruence of the intervention with respect to a learner's frustration, and the presence or absence of social non-verbal mirroring. They considered the agents to show a higher level of emotional intelligence when all these behaviours were coordinated, which also had a positive impact on the students' learning experience.

Other authors evaluate the affective response of their agents focusing on the users' response. On the one hand, this can be done by asking the users to evaluate the agent and provide judgments about their experience interacting with it. For example, Bickmore et al. (2005, 2010) evaluate the behaviour of social agents in the health and adult-care domain by means of self-reported therapeutic alliance and empathy of the patients with the agent. On the other hand, it is possible to measure the affective response of the users by employing any of the different measures described in Section 4, or a combination of several of them to obtain a more reliable assessment (Cavicchio & Poesio, 2008).

6 CONCLUSION

Emotions have evolved as a result of biological evolution in the form of complex responses to significant events which involve different physiological, neural, behavioural and cognitive components. This chapter has presented a review of the main emotion theories coming from different study areas, which have tried to progressively understand the nature of emotions and the related concept of personality, which represents the unique characteristics of an individual which have a deep influence on his/her affective experiences.

Many authors have tried to identify the most essential emotional dimensions and personality traits, models which, due to its synthetic nature, are applicable to the computational recognition, treatment and synthesis of emotion and personality. We have discussed the main characteristics of such models for the development of affective conversational agents. As conversation is one of the main components of social behaviours, endowing these agents with the ability to elicitate, imitate and process emotions and personality is essential to obtain more believable and lifelike agents. In the chapter we have described the main methods available to achieve this goal, focusing on the recognition of the user emotional state and the affective adaptability and responsivity of the agents, and presenting some of their most compelling applications.

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KEY TERMS AND DEFINITIONS

Affective Computing: An interdisciplinary field of study concerned with developing computational systems which are able to understand, recognize, interpret, synthesize, predict and/or respond to human emotions.

Affective Loop: A cycle that relates emotional expressions with affective responses in human-computer communication. The affective loop consists mainly on four phases: eliciting the emotion, recognizing the user state, selecting the appropriate affective user response and rendering such response.

Five Factor (or Big Five or ocean) Personality Traits: A physiological model which considers five basic dimensions or factors (five) of personality which remain stable across the life span: openness, conscientiousness, extraversion, agreeableness and neuroticism (ocean).

Persona Effect: A phenomenon which describes the implications of the presence of lifelike agents in interactive systems in the user experience, especially in creating a positive illusion of human-to-human interaction.

Primary Emotions: The emotions considered to be the basic ones, being the rest derived as combinations of these basic ones. Different authors consider different sets of basic emotions compiled following disparate criteria such as bodily involvement, biological basis or universal expressions of emotion.

Similarity-Attraction Principle: A general psychological statement about interpersonal attraction which says that individuals are more attracted to those who have a personality similar to their own.

Uncanny Valley Effect: A metaphor employed to address the region of negative emotional response to lifelikeness in agents/robots which is between a scarcely human behaviour or appearance and the completely human appearance.