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Affective Computing: Challenges and Prospect

Nitigya Sambyal
Department of Computer Science & IT, University of Jammu, J&K, India
Email address: nitigyasambyal@rediffmail.com

***Abstract*—**Affective computing simulates empathy through machine that could recognize, interpret, process and respond to human affects. With the use of sensors and computational devices, it proposes to exhibit either innate emotional capabilities or that is capable of convincingly simulating emotions. The paper focuses on varied challenges and future scope of affective computing. The technologies for affective computing are varied but expression if not natural may not yield 100% accurate results. The systems may lack rotational movement freedom and also ignores situational factors in emotional understanding.

***Keywords*—**Human computer interaction; emotions.

I. Introduction

Face-to-face communication involves continuous coordination and processing of information obtained from speech, lips, facial expressions, eye gaze, hand gestures etc. Human- Computer Interaction (HCI) is taken to a new level by designing a machine that could interpret the emotional state of humans and give an appropriate response e.g. if a user's is becoming frustrated or annoyed with using a software, he would "send out signals" to the computer, at which point the application might respond in a variety of ways: like it may close or provide other alternatives to do a job or list out some suggestions to fasten the processing. While the origins of the field may be traced as far back as to early philosophical enquiries into emotion,[1] the more modern branch of computer science originated with Rosalind Picard's 1995 paper[2] on affective computing [3], [4].

II. Areas and Technologies

Affective computing involves detecting and recognizing emotional information by using sensors e.g. a video camera might capture facial expressions, body posture and gestures, while a microphone might capture speech and physiological data can be taken by measuring skin temperature, heart rate etc. Sensors capture data about the user's physical state or behavior.The captured information then requires the extraction of meaningful patterns from the gathered data. This is done using machine learning techniques such as speech recognition, natural language processing, or facial expression detection etc. The information, thus obtained is used to produce appropriate response. Another aspect of affective computing is the design of computational devices proposed to exhibit either innate emotional capabilities or that are capable of convincingly simulating emotions.
The technologies of affective computing are:

A. Emotional Speech

Emotional speech processing recognizes the user's emotional state by analyzing speech patterns. For example, speech produced in a state of fear, anger or joy becomes faster, louder, precisely enunciated with a higher and wider pitch range. Vocal parameters and pitch variables and speech rate are analyzed through pattern recognition [5], [6].

B. Algorithm

The process of speech/text affect detection requires the creation of a reliable database, knowledge base, or vector space model, [7-9] broad enough to fit every need for its application, as well as the selection of a successful classifier which will allow for quick and accurate emotion identification.

Most frequently used classifiers are linear discriminant classifiers (LDC), k-nearest neighbour (k-NN), Gaussian mixture model (GMM), support vector machines (SVM), artificial neural networks (ANN), decision tree algorithms and hidden Markov models (HMMs) [10]. An appropriate classifier can significantly enhance the overall performance of the system. A brief description of each algorithm is given below:

- *LDC* **–** Classification happens based on the value obtained from the linear combination of the feature values, which are usually provided in the form of vector features.
- *K-NN* **–** Classification is done by locating the object and comparing it with the k nearest neighbours (training examples).
- *GMM* **–** It is a probabilistic model used for representing the existence of sub-populations within the overall population. Each sub-population is described using the mixture distribution, which allows for classification of observations into the sub-populations.
- *SVM* **–** It is a type of (usually binary) linear classifier which decides in which of the two (or more) possible classes, each input may fall into.
- *ANN* **–** It is a mathematical model, inspired by biological neural networks that can better grasp possible non-linearities of the feature space.
- *Decision tree algorithms* – The work based on following a decision tree in which leaves represent the classification outcome, and branches represent the conjunction of subsequent features that lead to the classification.
- *HMMs* **–** In a statistical Markov model, the series of outputs dependents on the states are visible. In the case of affect recognition, the outputs represent the sequence

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of speech feature vectors, which allow the deduction of states' sequences through which the model progressed. The states can consist of various intermediate steps in the expression of an emotion, and each of them has a probability distribution over the possible output vectors. The states' sequences allow us to predict the affective state which we are trying to classify and predict.

C. *Databases*

The vast majority of present systems are data-dependent. This creates one of the biggest challenges in detecting emotions based on speech, as it implicates choosing an appropriate database used to train the classifier. However, for real life application, naturalistic data is preferred. A naturalistic database can be produced by observation and analysis of subjects in their natural context. Ultimately, such database should allow the system to recognize emotions based on their context as well as work out the goals and outcomes of the interaction. The nature of this type of data allows for authentic real life implementation, due to the fact it describes states naturally occurring during the human-computer interaction (HCI).

D. *Speech Descriptors*

The complexity of the affect recognition process increases with the amount of classes (affects) and speech descriptors used within the classifier. It is crucial to identify those speech characteristics that are redundant and undesirable in order to optimize the system, and increase the success rate of correct emotion detection. The most commonly speech characteristics are categorized in the following groups [11], [12].

- Frequency characteristics ,
- Time-related features and
- Voice quality parameters and energy descriptors.

E. *Facial Affect Detection*

The detection and processing of facial expression is achieved through various methods such as optical flow, hidden Markov model, neural network processing etc. More than one modalities can be combined or fused (multimodal recognition, e.g. facial expressions and speech prosody [13] or facial expressions and hand gestures) [14] to provide a more robust estimation of the subject's emotional state.

F. *Emotion Classification*

The emotions are categorised as: Anger, disgust, fear, happiness, sadness, surprise. However in the 1990s basic emotions were extended to include amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, shame etc.

G. *Facial Action Coding System*

It includes defining expressions in terms of muscle actions. The central concept of the Facial Action Coding System, or FACS, as created by Paul Ekman and Wallace V. Friesen in 1978 [15] are action units (AU) which area contraction or a relaxation of one or more muscles and assigning facial cues to their corresponding action unit code.

H. *Body Gesture*

Gestures could be efficiently used as a means of detecting a particular emotional state of the user, especially when used in conjunction with speech and face recognition. There are many proposed methods [16] to detect the body gesture; the most common is through the use of cameras.

I. *Physiological Monitoring*

This could be used to detect a user's emotional state by monitoring and analysing their physiological signs. These signs range from their pulse and heart rate, to the minute contractions of the facial muscles. For example blood volume pulse can be measured by a process called photoplethysmography, which produces a graph indicating blood flow through the extremities.

III. Areas and Technologies Mechanism of Affective Computing

The modelling of affective states can be adapted to reflect a particular user's affective map. Therefore, the notion of systems that learn from user interaction can be imported into the affective pattern recognition problem to develop robust systems. The extraction stage takes affective signals (facial expression, body posture, heart rate etc) as input which is then checked against predefined pattern stored in databases. The pattern, thus obtained is then evaluated to produce appropriate response. The figure 1 shows the affective computing mechanism:

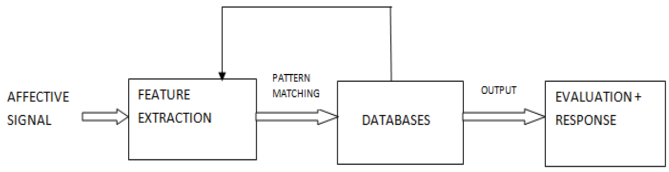

Fig. 1. Mechanism of affective computing.

IV. Application Areas

The most fundamental application of affective computing will be to inform next-generation human interfaces that are able to recognize and respond to, the emotional states of their users. The various application areas of affective computing are:

A. *Affective Learning Companion*

It enables a computational agent to sense and respond, in real time, to a user's non-verbal emotional cues, using video, postural movements, mouse pressure, physiology, and other behaviours communicated by the user e.g. If user is in state of curiosity, the tutor adds information.

B. *RoCo: A Robotic Computer*

A robotic computer that moves its monitor "head" and "neck," but that has no explicit face is being designed to interact with users in a natural way for applications such as learning, rapport-building, interactive teaching, and posture improvement. Toward this goal, the system is given the ability

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to recognize states of the user and also to have subtle expressions.

C. E-Therapy

It provides psychological health services revealing the emotional state of the user. Through affective computing the patient's posture, face expression and gesture in real world leads to accurate evaluation of psychological state.

D. Affective Tangibles

The purpose of the affective tangibles project is to develop physical objects that can be grasped, squeezed, thrown, or otherwise manipulated via a natural display of affect. Constructed tangibles include a pressure mouse, affective pinwheels that are mapped to skin conductance, and a voodoo doll that can be shaken to express frustration.

V. CHALLENGES BEFORE AFFECTIVE COMPUTING

The challenges before affective computing as follows:

A. At times the posed expressions by subjects may not be natural, and therefore affective computing may not be 100% accurate.
B. The systems may lack rotational movement freedom. Affect detection works very well with frontal use, but upon rotating the head more than 20 degrees, "there will be problems.
C. People's expression of emotion is so idiosyncratic and variable, that there is little hope of accurately recognizing an individual's emotional state from the available data.
D. The role of situational factors in emotion expression is poorly understood.
E. Existing models of emotion use highly stylized stereotypes of personality types and emotional responsiveness, which do not correspond to real behaviour in real people.
F. Any errors in physiological monitoring would result in incorrect response.
G. A slight error in the implementation of classifiers would result in incorrect output.
H. Use of instruments to record affective signals is expensive, thereby increasing the overall cost of the system.

VI. PROSPECTS OF AFFECTIVE COMPUTING

Affective computing is still an area of research. Imparting emotional intelligence to computers so that they respond just like humans is challenging task. However once done it can prove to be very beneficial, it can improve e-learning process by providing more explanations and examples if the user is found to be in state of confusion. By identifying the user's posture, machine can automatically shut down if user is tired or asleep. If user is frustrated due to low internet speed, machine can automatically check for errors and fix them. If a user deletes an important file and then panics, the system can identify the last few actions done and can undo those tasks etc.

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