Affective computing

Affective Computing is also the title of a textbook on the subject by Rosalind Picard.

Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects. It is an interdisciplinary field spanning computer science, psychology, and cognitive science.[1] While the origins of the field may be traced as far back as to early philosophical enquiries into emotion,[2] the more modern branch of computer science originated with Rosalind Picard's 1995 paper[3] on affective computing.[4][5] A motivation for the research is the ability to simulate empathy. The machine should interpret the emotional state of humans and adapt its behaviour to them, giving an appropriate response for those emotions.

1 Areas of affective computing

1.1 Detecting and recognizing emotional information

Detecting emotional information begins with passive sensors which capture data about the user's physical state or behavior without interpreting the input. The data gathered is analogous to the cues humans use to perceive emotions in others. For example, a video camera might capture facial expressions, body posture and gestures, while a microphone might capture speech. Other sensors detect emotional cues by directly measuring physiological data, such as skin temperature and galvanic resistance.[6]

Recognizing emotional information requires the extraction of meaningful patterns from the gathered data. This is done using machine learning techniques that process different modalities, such as speech recognition, natural language processing, or facial expression detection, and produce either labels (i.e. 'confused') or coordinates in a valence-arousal space.

1.2 Emotion in machines

Another area within affective computing is the design of computational devices proposed to exhibit either innate emotional capabilities or that are capable of convincingly simulating emotions. A more practical approach, based on current technological capabilities, is the simulation of emotions in conversational agents in order to enrich and facilitate interactivity between human and machine.[7] While human emotions are often associated with surges in hormones and other neuropeptides, emotions in machines might be associated with abstract states associated with progress (or lack of progress) in autonomous learning systems. In this view, affective emotional states correspond to time-derivatives (perturbations) in the learning curve of an arbitrary learning system.

Marvin Minsky, one of the pioneering computer scientists in artificial intelligence, relates emotions to the broader issues of machine intelligence stating in *The Emotion Machine* that emotion is "not especially different from the processes that we call 'thinking.'"[8]

2 Technologies of affective computing

In cognitive science and neuroscience, there have been two leading models describing how humans perceive and classify emotion. the continuous and the categorical model. The continuous model defines each facial expression of emotion as a feature vector in a face space. This model explains, for example, how expressions of emotion can be seen at different intensities. In contrast, the categorical model consists of C classifiers, each tuned to a specific emotion category. This model explains, among other findings, why the images in a morphing sequence between a happy and a surprise face are perceived as either happy or surprise but not something in between.

These approaches have one major flaw in common- they can only detect one emotion from an image, this is generally done by a winner takes it all method. Yet, everyday we can perceive more than one emotional category from a single image. Both the categorical and continuous model are unable to identify multiple emotions, so a new way to model it is to consider new categories as overlap of a small set of categories. A detailed study related to this topic is given in "A model of the perception of facial expressions of emotion by humans: research overview and perspectives" [9]

The following sections consider the possible features which can be used for the task of emotion recognition.

2.1 Emotional speech

One can take advantage of the fact that changes in the autonomic nervous system indirectly alter speech, and use this information to produce systems capable of recognizing affect based on extracted features of speech. For example, speech produced in a state of fear, anger or joy becomes faster, louder, precisely enunciated with a higher and wider pitch range. Other emotions such as tiredness, boredom or sadness, lead to slower, lower-pitched and slurred speech.[10] Emotional speech processing recognizes the user's emotional state by analyzing speech patterns. Vocal parameters and prosody features such as pitch variables and speech rate are analyzed through pattern recognition.[11][12]

Speech recognition is a great method of identifying affective state, having an average success rate reported in research of 63%.[13] This result appears fairly satisfying when compared with humans' success rate at identifying emotions, but a little insufficient compared to other forms of emotion recognition (such as those which employ physiological states or facial processing).[13] Furthermore, many speech characteristics are independent of semantics or culture, which makes this technique a very promising one to use.[14]

2.1.1 Algorithms

The process of speech/text affect detection requires the creation of a reliable database, knowledge base, or vector space model,[15][16] 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.

Currently, the 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).[17] Various studies showed that choosing the appropriate classifier can significantly enhance the overall performance of the system.[13] The list below gives a brief description of each algorithm:

- 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 happens by locating the object in the feature space, and comparing it with the k nearest neighbours (training examples). The majority vote decides on the classification.
- GMM – 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.[18]
- SVM – 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 – is a mathematical model, inspired by biological neural networks, that can better grasp possible non-linearities of the feature space.[19]
- Decision tree algorithms – 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 – a statistical Markov model in which the states and state transitions are not directly available to observation. Instead, the series of outputs dependent on the states are visible. In the case of affect recognition, the outputs represent the sequence 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 this is one of the most commonly used techniques within the area of speech affect detection.

It is proved that having enough acoustic evidence available the emotional state of a person can be classified by a set of majority voting classifiers. The proposed set of classifiers is based on three main classifiers: kNN, C4.5 and SVM RBF Kernel. This set achieves better performance than each basic classifier taken separately. It is compared with two other sets of classifiers: one-against-all (OAA) multiclass SVM with Hybrid kernels and the set of classifiers which consists of the following two basic classifiers: C5.0 and Neural Network. The proposed variant achieves better performance than the other two sets of classifiers. [20]

2.1.2 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. Most of the currently possessed data was obtained from actors and is thus a representation of archetypal emotions. Those so-called acted databases are usually based on the Basic Emotions theory (by Paul Ekman), which assumes the existence of six basic emotions (anger, fear, disgust, surprise, joy, sadness), the others simply being a mix of the former ones.[21] Nevertheless, these still offer high audio quality and balanced classes (although often too few), which contribute to high success rates in recognizing emotions.

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).

Despite the numerous advantages which naturalistic data has over acted data, it is difficult to obtain, and usually has low emotional intensity. Moreover, data obtained in a natural context has lower signal quality, due to surroundings noise and distance of the subjects from the microphone. The first attempt to produce such database was the FAU Aibo Emotion Corpus for CEICES (Combining Efforts for Improving Automatic Classification of Emotional User States), which was developed based on a realistic context of children (age 10-13) playing with Sony's Aibo robot-pet.[22][23] Likewise, producing one standard database for all emotional research would provide a method of evaluating and comparing different affect recognition systems.

2.1.3 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 therefore crucial to select only the most relevant features in order to assure the ability of the model to successfully identify emotions, as well as increasing the performance, which is particularly significant to real-time detection. The range of possible choices is vast; with some studies mentioning the use of over 200 distinct features.[17] It is crucial to identify those 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[22][23]

1. Frequency characteristics
    - Accent shape – affected by the rate of change of the fundamental frequency.
    - Average pitch – description of how high/low the speaker speaks relative to the normal speech.
    - Contour slope – describes the tendency of the frequency change over time, it can be rising, falling or level.
    - Final lowering – the amount by which the frequency falls at the end of an utterance.
    - Pitch range – measures the spread between maximum and minimum frequency of an utterance.
2. Time-related features:
    - Speech rate – describes the rate of words or syllables uttered over a unit of time
    - Stress frequency – measures the rate of occurrences of pitch accented utterances
3. Voice quality parameters and energy descriptors:
    - Breathiness – measures the aspiration noise in speech
    - Brilliance – describes the dominance of high Or low frequencies In the speech
    - Loudness – measures the amplitude of the speech waveform, translates to the energy of an utterance
    - Pause Discontinuity – describes the transitions between sound and silence
    - Pitch Discontinuity – describes the transitions of fundamental frequency.

2.2 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 or active appearance model. More than one modalities can be combined or fused (multimodal recognition, e.g. facial expressions and speech prosody[24] or facial expressions and hand gestures[25]) to provide a more robust estimation of the subject's emotional state.

2.2.1 Emotion classification

Main article: Emotion classification

By doing cross-cultural research in Papua New Guinea, on the Fore Tribesmen, at the end of the 1960s Paul Ekman proposed the idea that facial expressions of emotion are not culturally determined, but universal. Thus, he suggested that they are biological in origin and can therefore be safely and correctly categorised.[21] He therefore officially put forth six basic emotions, in 1972:[26]

- Anger
- Disgust
- Fear
- Happiness
- Sadness

- Surprise

However in the 1990s Ekman expanded his list of basic emotions, including a range of positive and negative emotions not all of which are encoded in facial muscles.[27] The newly included emotions are:

1. Amusement
2. Contempt
3. Contentment
4. Embarrassment
5. Excitement
6. Guilt
7. Pride in achievement
8. Relief
9. Satisfaction
10. Sensory pleasure
11. Shame

2.2.2 Facial Action Coding System

Main article: Facial Action Coding System

Defining expressions in terms of muscle actions A system has been conceived in order to formally categorise the physical expression of emotions. The central concept of the Facial Action Coding System, or FACS, as created by Paul Ekman and Wallace V. Friesen in 1978[28] are action units (AU). They are, basically, a contraction or a relaxation of one or more muscles. However, as simple as this concept may seem, it is enough to form the base of a complex and devoid of interpretation emotional identification system.

By identifying different facial cues, scientists are able to map them to their corresponding action unit code. Consequently, they have proposed the following classification of the six basic emotions, according to their action units ("+" here mean "and"):

2.2.3 Challenges in facial detection

As with every computational practice, in affect detection by facial processing, some obstacles need to be surpassed, in order to fully unlock the hidden potential of the overall algorithm or method employed. The accuracy of modelling and tracking has been an issue, especially in the incipient stages of affective computing. As hardware evolves, as new discoveries are made and new practices introduced, this lack of accuracy fades, leaving behind noise issues. However, methods for noise removal exist including Neighbourhood Averaging, linear Gaussian smoothing, Median Filtering,[29] or newer methods such as the Bacterial Foraging Optimization Algorithm.[30][31][32]

It is generally known that the degree of accuracy in facial recognition (not affective state recognition) has not been brought to a level high enough to permit its widespread efficient use across the world (there have been many attempts, especially by law enforcement, which failed at successfully identifying criminals). Without improving the accuracy of hardware and software used to scan faces, progress is very much slowed down.

Other challenges include

- The fact that posed expressions, as used by most subjects of the various studies, are not natural, and therefore not 100% accurate.

- The lack of rotational movement freedom. Affect detection works very well with frontal use, but upon rotating the head more than 20 degrees, "there've been problems".[33]

2.3 Body gesture

Main article: Gesture recognition

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. Depending on the specific action, gestures could be simple reflexive responses, like lifting your shoulders when you don't know the answer to a question, or they could be complex and meaningful as when communicating with sign language. Without making use of any object or surrounding environment, we can wave our hands, clap or beckon. On the other hand, when using objects, we can point at them, move, touch or handle these. A computer should be able to recognize these, analyze the context and respond in a meaningful way, in order to be efficiently used for Human-Computer Interaction.

There are many proposed methods[34] to detect the body gesture. Some literature differentiates 2 different approaches in gesture recognition: a 3D model based and an appearance-based.[35] The foremost method makes use of 3D information of key elements of the body parts in order to obtain several important parameters, like palm position or joint angles. On the other hand, Appearance-based systems use images or videos to for direct interpretation. Hand gestures have been a common focus of body gesture detection, apparentness methods[35] and 3-D modeling methods are traditionally used.

2.4 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. This area of research is still in relative infancy as there seems to be more of a drive towards affect recognition through facial inputs. Nevertheless, this area is gaining momentum and we are now seeing real products which implement the techniques. The three main physiological signs that can be analysed are: blood volume pulse, galvanic skin response, facial electromyography.

2.4.1 Blood volume pulse

Overview A subject's blood volume pulse (BVP) can be measured by a process called photoplethysmography, which produces a graph indicating blood flow through the extremities.[36] The peaks of the waves indicate a cardiac cycle where the heart has pumped blood to the extremities. If the subject experiences fear or is startled, their heart usually 'jumps' and beats quickly for some time, causing the amplitude of the cardiac cycle to increase. This can clearly be seen on a photoplethysmograph when the distance between the trough and the peak of the wave has decreased. As the subject calms down, and as the body's inner core expands, allowing more blood to flow back to the extremities, the cycle will return to normal.

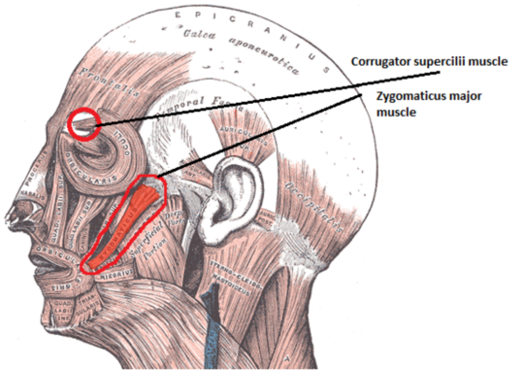
Methodology Infra-red light is shone on the skin by special sensor hardware, and the amount of light reflected is measured. The amount of reflected and transmitted light correlates to the BVP as light is absorbed by hemoglobin which is found richly in the blood stream.

Disadvantages It can be cumbersome to ensure that the sensor shining infra-red light and monitoring the reflected light is always pointing at the same extremity, especially seeing as subjects often stretch and readjust their position whilst using a computer. There are other factors which can affect one's blood volume pulse. As it is a measure of blood flow through the extremities, if the subject feels hot, or particularly cold, then their body may allow more, or less, blood to flow to the extremities, all of this regardless of the subject's emotional state.

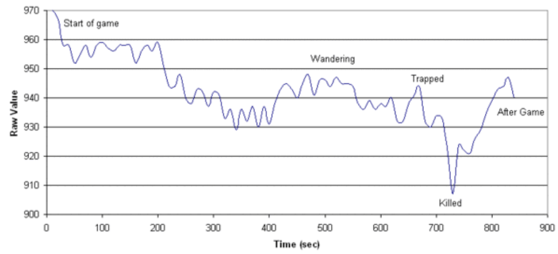
2.4.2 Facial electromyography

Main article: Facial electromyography

Facial electromyography is a technique used to measure the electrical activity of the facial muscles by amplifying the tiny electrical impulses that are generated by muscle fibers when they contract.[37] The face expresses a great deal of emotion, however there are two main facial muscle groups that are usually studied to detect emotion: The corrugator supercilii muscle, also known as the 'frowning' muscle, draws the brow down into a frown,[37] and therefore is the best test for negative, unpleasant emotional response. The zygomaticus major muscle is responsible for pulling the corners of the mouth back when you smile,[37] and therefore is the muscle used to test for positive emotional response.



The corrugator supercilii muscle and zygomaticus major muscle are the 2 main muscles used for measuring the electrical activity, in facial electromyography



Here we can see a plot of skin resistance measured using GSR and time whilst the subject played a video game. There are several peaks that are clear in the graph, which suggests that GSR is a good method of differentiating between an aroused and a non-aroused state. For example, at the start of the game where there is usually not much exciting game play, there is a high level of resistance recorded, which suggests a low level of conductivity and therefore less arousal. This is in clear contrast with the sudden trough where the player is killed as one is usually very stressed and tense as their character is killed in the game

2.4.3 Galvanic skin response

Main article: Galvanic skin response

Galvanic skin response (GSR) is a measure of skin conductivity, which is dependent on how moist the skin is. As the sweat glands produce this moisture and the glands are controlled by the body's nervous system, there is a correlation between GSR and the arousal state of the body. The more aroused a subject is, the greater the skin conductivity and GSR reading.[36]

It can be measured using two small silver chloride electrodes placed somewhere on the skin, and applying small voltage between them. The conductance is measured by a sensor. To maximize comfort and reduce irritation the electrodes can be placed on the feet, which leaves the hands fully free to interface with the keyboard and mouse.

2.5 Visual aesthetics

Aesthetics, in the world of art and photography, refers to the principles of the nature and appreciation of beauty. Judging beauty and other aesthetic qualities is a highly subjective task. Computer scientists at Penn State treat the challenge of automatically inferring aesthetic quality of pictures using their visual content as a machine learning problem, with a peer-rated on-line photo sharing website as data source.[38] They extract certain visual features based on the intuition that they can discriminate between aesthetically pleasing and displeasing images.

3 Potential applications

In e-learning applications, affective computing can be used to adjust the presentation style of a computerized tutor when a learner is bored, interested, frustrated, or pleased.[39][40] Psychological health services, i.e. counseling, benefit from affective computing applications when determining a client's emotional state.

Robotic systems capable of processing affective information exhibit higher flexibility while one works in uncertain or complex environments. Companion devices, such as digital pets, use affective computing abilities to enhance realism and provide a higher degree of autonomy.

Other potential applications are centered around social monitoring. For example, a car can monitor the emotion of all occupants and engage in additional safety measures, such as alerting other vehicles if it detects the driver to be angry. Affective computing has potential applications in human computer interaction, such as affective mirrors allowing the user to see how he or she performs; emotion monitoring agents sending a warning before one sends an angry email; or even music players selecting tracks based on mood.

One idea, put forth by the Romanian researcher Dr. Nicu Sebe in an interview, is the analysis of a person's face while they are using a certain product (he mentioned ice cream as an example).[41] Companies would then be able to use such analysis to infer whether their product will or will not be well received by the respective market.

One could also use affective state recognition in order to judge the impact of a tv advertisement through a real-time video recording of that person and through the subsequent study of his or her facial expression. Averaging the results obtained on a large group of subjects, one can tell whether that commercial (or movie) has the desired effect and what the elements which interest the watcher most are.

Affective computing is also being applied to the development of communicative technologies for use by people with autism.[42]

4 Critical perspectives

Mainstream Affective Computing, as it has been characterized above, is critically discussed, e.g., within the field of Human-Computer Interaction.

When Rosalind Picard coined the term 'affective computing', she outlined a cognitivist research program whose goal it is to "[...] give computers the ability to recognize, express, and in some cases, 'have' emotions".[43] A range of researchers have criticized this research program and outlined a post-cognitivist, "interactional" perspective which, as Kirsten Boehner and collaborators suggest, "[...] take[s] emotion as a social and cultural product experienced through our interactions". [44] [45] [46] They criticize the Picardian approach for its cognitivist notion of emotion that they also describe as an "information model" of emotion:

> Both cognition and emotion are construed here as inherently private and information-based: biopsychological events that occur entirely within the body. Like cognition, emotion can be modeled as a form of information processing, and another set of inputs to cognitive processing. This information account of emotion talks about it as a form of internal signaling, providing a context for cognitive action.[47]

The information model treats emotion as "objective, internal, private, and mechanistic". It reduces emotion to discrete psychological signal that are assumed to be formalizable and measurable in rather unproblematic ways. [48] Critics of the Picardian approach to affective computing hold that such an understanding of emotion undercuts the complexity of emotional experience.

The post-cognitive, interactional approach to affective computing departs from the Picardian research program in three ways: First, it adopts a notion of emotion as constituted in social interaction. This is not to deny that emotion has biophysical aspects, but it is to underline that emotion is "culturally grounded, dynamically experienced, and to some degree constructed in action and interaction". [49] Second, the interactional approach does not seek to enhance the affect-processing capacities of computer systems. Rather, it seeks to help "[...]

people to understand and experience their own emotions” [49] Third, the interactional approach accordingly adopts different design and evaluation strategies than those described by the Picardian research program. Interactional affective design supports open-ended, (inter-)individual processes of affect interpretation. It recognizes the context-sensitive, subjective, changing and possibly ambiguous character of affect interpretation. And it takes into account that these sense-making efforts and affect itself may resist a computational formalization. [50]

To summarize, Picard and her adherents pursue a cognitivist measuring approach to users' affect, while the interactional perspective endorses a pragmatist approach that views (emotional) experience as inherently referring to social interaction.[51] While the Picardian approach, thus, focuses on human-machine relations, interactional affective computing focuses primarily on computer-mediated inter-personal communication. And while the Picardian approach is concerned with the measurement and modeling of physiological variables, interactional affective computing is concerned with emotions as complex subjective interpretations of affect, arguing that emotions, not affect, are at stake from the point of view of technology users.

5 See also

- Affect control theory
- Affective design
- Affective haptics
- Chatterbot
- CyberEmotions
- Emotion Markup Language (EmotionML)
- Kismet (robot)
- Sentiment analysis
- Wearable computer

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8 External links

- Affective Computing Research Group at the MIT Media Laboratory
- Computational Emotion Group at USC
- Emotive Computing Group at the University of Memphis
- 2011 International Conference on Affective Computing and Intelligent Interaction
- Brain, Body and Bytes: Psychophysiological User Interaction *CHI 2010 Workshop* (10-15, April 2010)
- International Journal of Synthetic Emotions
- IEEE Transactions on Affective Computing *(TAC)*
- Renu Nagpal, Pooja Nagpal and Sumeet Kaur, "Hybrid Technique for Human Face Emotion Detection" International Journal of Advanced Computer Science and Applications(IJACSA), 1(6), 2010
- openSMILE: popular state-of-the-art open-source toolkit for large-scale feature extraction for affect recognition and computational paralinguistics

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