CHAPTER

9

Affective Computing: Historical Foundations, Current Applications, and Future Trends

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AFFECTIVE COMPUTING HISTORY

The field of affective computing encompasses both the creation of and interaction with machine systems that sense, recognize, respond to, and influence emotions (Picard, 1997; Picard and Klein, 2002). It is a multidisciplinary research area that relies on contributions from fields as disparate as psychology, physiology, engineering, sociology, mathematics, computer science, education, and linguistics to accomplish its goals. The wide variety of disciplines relevant to affective computing is a reflection of the complexity of describing, understanding, and, ultimately, emulating the dynamic experience of *feeling*.

Affective computing, as an academic discipline, is relatively new. In fact, the phrase *affective computing* was not coined until the late 1990s (Picard, 1997). The recent coalescing of affective computing into a recognized field of study, however, belies the observation that concepts related to both affective computing and artificial intelligence, its parent discipline, can be found many years before either term existed. One of the most enduring examples of this is the idea of the golem; a creature crafted from an ordinary material, such as clay, and brought to life through supernatural

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means (Idel, 1990; Scholem, 1965; Scholem and Idel, 2007). With origins dating back to at least 1000 BCE (Leaman, 2011; Rendsburg, 2008; Satlow, 2006), the Hebrew Bible, or Tanakh (Brettler, 2005; Satlow, 2006), contains some of the earliest references to the golem concept. The word *golem* is used once in the Bible (Scholem and Idel, 2007), and it appears in the Book of Psalms (Tehillim 139:16 Orthodox Jewish Bible). In the context of the passage, golem connotes an unformed, imperfect mass or embryo (Idel, 1990; Rozenberg and Leviant, 2007; Scholem and Idel, 2007). A second, more explicit example of the idea of a golem is found in Genesis.

Then the LORD God formed a man from the dust of the ground and breathed into his nostrils the breath of life, and the man became a living being.… [Then the] LORD God took the man and put him in the Garden of Eden to work it and take care of it (Gen. 2:7 and Gen. 2:15, New International Version).

Here, in the Bible's second story of creation, the dynamic between God and humanity resembles the modern interpretation of the human–golem relationship. In this interpretation, the human–golem relationship is one between a creator and an entity made for the purpose of serving its creator's interests.

Away from the realm of the supernatural, a clear parallel can be drawn between the golems of myth and real automata (Convino, 1996; Wiener, 1964). Indeed, the myth of the golem is one of the earliest contributions to the topic of artificial intelligence. From a technical perspective, artificial intelligences need not be anthropomorphic (Ferrucci et al., 2010; Hsu, 2002; Turing, 1950; Wiener, 1948). Yet, the idea of creating automata with human-like characteristics holds a special place in the human imagination.

The HAL 9000 computer, antagonist of *2001: A Space Odyssey* (Clarke, 1968; Kubrick, 1968), is one of the most famous fictional examples of an artificial intelligence endowed with human-like emotions. At the beginning of the film, HAL, as the system is called, is shown to be a valued member of the ship's crew. Displaying a dazzling array of abilities, including speech, facial recognition, lip reading, systems monitoring, regulation and control, game play, and social skills (Clarke, 1968; Kubrick, 1968; Picard, 2001), HAL is an exciting vision of what real artificial intelligence could become. As Kubrick and Clarke present it, however, the design and deployment of an artificial intelligence that possesses a seamless integration of emotional and functional capabilities is not without risk (Clarke, 1968; Kubrick, 1968). In the course of the film, HAL is faced with challenging situations that involve both deception and emotionally influenced decision making. The first is HAL's internal conflict between the obligation to relay information accurately to the crew and the obligation to conceal the true purpose of the mission from the crew. The second is the threat of HAL's deactivation in response to repeated system malfunctions.

Acting in self-defense, HAL, in violation of two of Asimov's three laws of robotics (Asimov, 1950), attempts to kill both members of the crew. In the end, HAL is destroyed.

While *2001: A Space Odyssey* is, of course a work of fiction, it nevertheless successfully elucidates some of the key challenges facing affective computing researchers today. Technical challenges relevant to affect-aware system development include multimodal natural language processing, affect detection, biometrics, and systems integration. In addition, the ethical implications of affective computing systems must be considered before widespread deployment; the urgency of these considerations will only increase as technology advances.

The remainder of this chapter focuses on the modern science of affective computing. First, efforts to address the technical challenges of affect sensing and affect generation are described. Next, current applications of affective technologies are considered. Finally, ethical issues relevant to the building and deployment of affective systems are outlined.

AFFECT SENSING

Recognizing emotions is the first step to making a computer affectively intelligent. To accomplish this task, a computer would need to be equipped with hardware and software to sense emotions. Affect sensing refers to a system that can recognize emotion by receiving data through signals and patterns (Picard, 1997). Affect-sensing systems can be classified by modalities, each of which has a unique signature. This section focuses on describing systems that sense affect via low-level signals, such as facial activity, posture, gesture, hand tension, and vocal, textual, and electrodermal activity (EDA).

Systems that sense facial activity can detect and process expressions from a human face. Facial expressions are distinctive for each emotion and they are informative due to their visibility and omnipresence (Ekman et al., 1972). The face conveys information through movement, such as smiling, frowning, squinting, and furrowing (Ekman et al., 1972). According to Ekman (1993), the six basic emotions are anger, disgust, fear, happiness, sadness, and surprise, which can be detected and processed using methods like the Hidden Markov Model, optical flow, active appearance model, and neural network processing (Cohn et al., 1998; Caridakis et al., 2006; Thomas and Mathew, 2012; Wilfred et al., 2009). These methods can be used either individually or in combination. A commonly used system to categorize and classify facial expressions is the facial action coding system (FACS). This system, created by Paul Ekman, Wallace V. Friesen, and Joseph C. Hager (Reevy et al., 2010), helps to identify expressions that the human face can show and the different muscles that produce these expressions. Research methods used to study the face, nonverbal communication, and emotion have been significantly impacted by FACS. Moreover, FACS has been helpful in research on emotions, in the diagnosis of mental disorders, in lie detection, and in psychotherapy (Ekman and Rosenberg, 2005). In addition, the emotion facial action coding system (EMFACS) is a related method that scores facial actions that might be applicable to sensing emotion (Reevy et al., 2010). EMFACS focuses on the action units involved in a facial movement, the intensity of the action units, and the degree of asymmetry. Action units represent the muscular activity that produces facial appearance changes (Ekman and Friesen, 1978). As a result, muscle movements' effects on facial appearance change are critical in facial activity affect sensing.

Posture and gesture affect sensing, which is the recognition of varying states of the body. Posture is the position of a person's body while he or she is standing or sitting, while gestures are the movements of parts of the body as a form of expression, usually from the hand or head (Glowinski et al., 2011). Posture and gestures are important to affect sensing, because they can communicate discrete emotion categories as well as affective dimensions (Kleinsmith and Bianchi-Berthouze, 2007). Kleinsmith and Bianchi-Berthouze (2007) have shown in their review of affective body expression perception and recognition that static body postures and gestured body motions can convey emotion. Devices commonly used in research to collect data from posture and gesture consist of wired gloves, depth-aware cameras, stereo cameras, standard 2D cameras, and gestures. Algorithms to detect posture and gesture include 3D model based algorithms (Lee and Kunii, 1995), skeletal-based algorithms (Nandakumar et al., 2013), and appearance-based models (Shimada et al., 2000). Algorithms based on 3D models use volumetric models, skeletal models, or a combination of the two to detect affect.

Skeletal-based algorithms use a virtual skeleton of the human body to map parts of the body, using position and orientation between the segments of the human skeleton to collect information. Thus, skeletal-based algorithms enable pattern matching and use key points to focus on essential parts of the body. Appearance-based models derive parameters directly from images or videos in a template database, which are used as sets of points to outline objects on parts of the human body. Appearance-based models are commonly used for hand-tracking.

There is a correlation between the amount of force exerted on objects humans handle and their frustration. Examples of objects that humans handle include a computer mouse, steering wheels, gear shifts, remote controls, video game controllers, and cutting knives. For example, a study conducted by Dennerlein et al. (2003) showed that the force exerted by the hand on a computer mouse increases with user frustration. Force-sensitive resistors and stenographs are common hand tension sensors

(Kreil et al., 2008). Therefore, tension in the hand applied to an object can be used to sense affect.

Moreover, the way words are spoken or, in other words, vocal expressions, also relates to affective sensing. Such vocal expressions can be broken into two components: cues emphasizing which content in the message is most important and cues arising from the speaker's affective state (Fulcher, 1991). The intonation of vocals provides style to speech and the message's content. The vocal effects that are most commonly associated with the six basic emotions are speech rate, pitch average, pitch range, intensity, voice quality, pitch changes, and articulation (Murray and Arnott, 1993). As a result, vocal expression is a way to sense affect based on how something is said.

In addition to vocal intonation, words and language have affect in textual form. Input devices used to sense affect from words and languages include sentiment analysis tools. Sentiment analysis tools make use of natural language processing, computational linguistics, and text analysis (Ahmad, 2011; Taboada et al., 2011). Examples of software used for such analysis include WordNet-Affect (Keshtkar and Inkpen, 2013), SenticNet (Denecke, 2008), and SentiWordNet (Poria et al., 2012). Other approaches for analyzing written language include keyword spotting (Liu et al., 2003), lexical affinity (Terra, 2005), statistical methods (Pande and Dhami, 2014), and hand-crafted models (Singer, 2004). Textual affect sensing is important because many user interfaces are text based.

Electrodermal activity (EDA) is the result of the autonomic properties of the skin (Braithwaite et al., 2013; Dawson et al., 2007). This electrical skin conductance is gathered from sweat-induced skin moisture caused by the sympathetic nervous system indicating psychological or physiological arousal (Dawson et al., 2007; Picard and Scheirer, 2001). Electrodes can be placed on the skin for the purpose of EDA detection; however, positive and negative valence cannot be determined through this signal. Further, since changes in EDA can be triggered by nonaffective changes (e.g., physical activity), the context of the arousal is extremely important when attempting to determine emotion (Braithwaite et al., 2013).

AFFECT GENERATION

Social Robots

Social robots are robots that interact with humans and each other in a socially acceptable fashion, conveying intention in a human-perceptible way, and are empowered to resolve goals with fellow agents, be they human or robot (Breazeal and Scassellati, 1999; Duffy et al., 1999). Optimal human–robot interactions require robots to possess the following attributes: embodiment in the physical environment, quick reactions to unexpected events, computational sophistication for meeting goals, and the ability to interact with other robots for the realization of goals of increasing difficulty (Duffy et al., 1999). Here, we examine why social robots are researched, give a few cases of robot–human interaction, and provide a brief explanation of how these robots and interactions are designed.

Given the definition of social robots, what use do humans have for them that inform and inspire research and usage? Dautenhahn (2002) listed social robot applications, such as office, medicine, hotel use, cooking, marketing, entertainment, hobbies, recreation, nursing care, therapy, and rehabilitation. Breazeal (2003) added such uses as a personal assistant, small child care, and small child development. In the office application domain, social robots can be used as physical counterparts for remote conference participants, commonly referred to as telepresence. If the remote participant wishes to interact physically with the conference space, a social robot can act as an interaction avatar (Thalmann et al., 2014). Social robots could also act in childcare and development roles by supplementing the interaction of human caregivers (Feil-Seifer and Mataric´, 2010).

As noted previously, humans use physical appearance and physical attributes to categorize and form impressions (Eyssel and Kuchenbrandt, 2012). This impression-forming process also applies to robots. Humans tend to observe a robot's physical attributes and assign it a social place and competency (Eyssel and Kuchenbrandt, 2012); this is anthropomorphism, or the assigning of human characteristics to nonhuman entities. This aspect of human nature is taken into account when designing social robots and programming their interactions. Another attribute taken into account when designing social robots is the application for which they are being built (Breazeal, 2003). Breazeal (2003) presented four subclasses of social robots, which have been supplemented by Fong et al. (2003). The initial four classes correspond to different social robot designs that lead to the creation of social robots that respond according to humans' perceptions of them. The four classes are socially evocative, social interface, socially receptive, and sociable. Further, socially situated, socially embedded, and socially intelligent complete the seven subclasses. The socially evocative subclass encourages anthropomorphizing robots as one might anthropomorphize toys. Responding to social cues to facilitate communication characterizes the social interface subclass. The socially receptive subclass learns from interactions, while the sociable subclass interacts purposefully to aid and be aided (Breazeal, 2003). Furthermore, a social environment surrounds socially situated robots, while socially embedded robots are in the environment, learning and interacting steadily. Finally, socially intelligent robots attempt to respond to social situations like humans by simulating models of human cognition.

Breazeal and Scassellati (1999) outlined the development of a social robot, Kismet, that responds to its environment by way of infant-like protosocial responses (e.g., initiation, mutual orientation, greeting, play-dialog, and disengagement), mainly communicating its reactions through gaze and facial expressions. Breazeal's social robot perceives social cues and reacts to them with facial emotive responses. Kismet has an expressive robotic head and has 15 degrees of freedom in its facial expressions and 6 for gaze and head movement, while using an infant-like language to respond to audio cues and 4 cameras to perceive the world around it visually (Breazeal, 2003). Kismet fits into the socially situated class of social robots because it learns from interactions with people. Two other socially evocative robot toys are Tiger Electronic's Furby and Sony's Aibo. Furby is reminiscent of a hamster, while Aibo looks like a small dog. Since these robots remind people of animals, people assign animal responsiveness and reactiveness to them. Dautenhahn (2002) developed a toy robot whose purpose is to teach autistic children social behaviors. This robot, designed as a toy, is a social interface that is "interesting enough to catch and maintain" attention and "engage the child in therapeutically relevant interactions until the trial is ended" (Dautenhahn, 2002, p. 447). Dautenhahn's robot is designed both to take turns and to follow, and it has a behavior-based design. Each of these robot examples is designed to generate affect according to its application domain. The socially receptive robot is built to be very expressive to communicate better during interactions, and the toys are designed to maintain attention and provide goals for users to accomplish.

Virtual Characters With Emotion

The novelty of a mechanical tool that moves with purpose keeps people's attention, but adding emotive capability allows the robot to interact with humans socially. However, humans engage humans better than robots. In an attempt to obtain the same level of engagement that humans give each other, virtual characters with emotion can be developed. Virtual characters (i.e., 3D avatars or nonplayer game characters) are meant to generate affect in humans that will cause empathetic interaction between virtual character and human (Vinayagamorrthy et al., 2006). Similar to social robots expressing emotion, emotion models are used to convey emotion in virtual characters. Breazeal employs models using the face to communicate emotion in her social robot Kismet (Breazeal and Scassellati, 1999). In virtual characters, models for giving primary, secondary, and tertiary emotions have been created and utilized (Scheutz et al., 2000; Vinayagamorrthy et al., 2006). With virtual characters, the models to communicate emotion can extend to full human avatars (Ushida et al., 1998). Although not all virtual characters are the same, following the purpose of their design, such virtual characters can be referred to as embodied conversational agents (ECAs) or relational agents. Virtual characters with verbal and nonverbal emotional and conversational behaviors are referred to as ECAs (Vinayagamorrthy et al., 2006), while relational agents are virtual characters that build relationships by interacting over long periods of time (Bickmore and Cassell, 2001).

APPLICATIONS

Affective computing devices are being used in a number of domains including education, security, and healthcare. Picard (1997) describes three types of affective computing applications: "1) systems that detect the emotions of the user, 2) systems that express what a human would perceive as an emotion (e.g., an avatar, robot, and animated conversational agent), and 3) systems that actually 'feel' an emotion." Detection, expression, and perception are crucial when designing technologies with affective capabilities in mind. In this section, we explore different applications that exhibit properties of the first and second type.

Healthcare Applications

Previous research has indicated that the emotional responses of individuals with Asperger syndrome (AS) or high functioning autism (HFA) are less differentiated, less positive, and more negative than those without AS or HFA (Ben Shalom et al., 2006; Capps et al., 1993). Individuals with AS or HFA have also been known to experience significant difficulties effectively assessing and classifying their own emotions (Berthoz and Hill, 2005; Fitzgerald and Bellgrove, 2006; Fitzgerald and Molyneux, 2004; Hill et al., 2004; Szatmari et al., 2008; Tani et al., 2004). These behavioral traits can affect their relationships with other people (Sano et al., 2012). Companies have developed mobile applications like SymTrend (n.d.) and Autism Track (HandHold Adaptive, n.d.), which allow patients with disabilities to enter behavioral data manually and to track changes over time. The patients are also given accurate advice, made more aware of their symptoms, and given reminders. This gives patients and their therapists an insight into the patients' behavioral patterns, moods, and triggers that may accompany any emotional outbursts.

Sano et al. (2012) created a system for schoolteachers monitoring autism spectrum disorder (ASD)-related behaviors. This annotation tool gives teachers the ability to note important events quickly without having to write down all the details at the exact moment. These data can then be appropriately stored and shared for deeper analysis. Caregivers, teachers, and other relevant officials can then revisit the event to upload and share their individual annotations, thus providing doctors with multiple perspectives on how the student's day transpired and helping doctors to identify any specific triggers.

Posttraumatic stress disorder (PTSD), as currently defined by the American Psychiatric Association, is the development of characteristic symptoms following exposure to actual or threatened death, serious injury, or sexual violence in one or more of the following ways: directly experiencing the traumatic event, repeated or extreme exposure to aversive details of the event(s), witnessing the event(s) as it happens to another person; or learning the event occurred to a family member or close friend (American Psychiatric Association, 2013, p. 271).

PTSD disables a person from carrying out daily activities and haunts him or her with memories of stressful events (Foa et al., 2008). A well-known technique for treating individuals with PTSD is exposure therapy and stress inoculation (Bradley et al., 2005; Horowitz, 1997; Van Etten and Taylor, 1998). Current research has extended this technique to include virtual reality (Rizzo et al., 2009). StartleMart is a virtual reality-based gaming environment with affect detection capabilities that integrates cognitive behavioral approaches with physiological signals to treat veteran soldiers with PTSD (Holmgard et al., 2013). StartleMart adds real-time stress detection using skin conductance to an already developed virtual reality treatment scenario.

Veteran soldiers with PTSD often suffer from flashbacks from the combat zone; for example, they may hear the sound of a ventilator fan in a store and be reminded of being in a war zone. StartleMart simulates three highly stressful scenarios and the skin conductance is used to measure the body's response to anxiety. A study conducted using StartleMart successfully correlated stressors on screen with peaks in skin conductance data, leading researchers to believe that these kinds of systems can help with the diagnosis and treatment of PTSD. Similar games like Virtual Vietnam (Rothbaum et al., 1999; Rothbaum et al., 2001), Virtual Iraq (Gerardi et al., 2008), and Virtual Afghanistan (Rizzo et al., 2010) have been used successfully in clinical testing and have also shown positive results.

Applications in Education

Schools have been incorporating more and more technology like smart boards and interactive presentations into their classrooms to engage students and to help them to learn better. Incorporating affect into classroom technology dynamics may enable students to get more of a personalized learning experience. However, creating an individualized curriculum for each student is very difficult in the present classroom setting, as it is extremely time consuming and requires an in-depth understanding of each student's likes, dislikes, and preferred learning method. Likewise, teachers cannot always rely on students to speak up when they do not understand the material being taught. Research shows that students who receive support from teachers and peers tend to feel more comfortable in school, like school more, and participate more actively in classroom activities (Furrer and Skinner, 2003; Gest et al., 2005; Goodenow, 1993; Hughes and Kwok, 2006; Marsh, 1989; Midgley et al., 1989; Ryan et al., 1994; Stipek, 2002).

Effective learning is contingent upon the extent to which students are engaged in classroom learning activities (Chen, 2005; Finn and Rock, 1997; Osterman, 2000; Reyes et al., 2012; Wang and Pomerantz, 2009). EngageMe is a visualization tool designed to support teachers in understanding how they are connecting with their students and how their pedagogical strategies can be modified to meet the individual needs of a diverse student population (Darnell, 2014). This system uses skin conductance data collected from students in a classroom, along with video feeds, to help the teacher reflect on his or her classes. Graphs display the arousal levels of each student, with green signifying high, yellow signifying medium, and red signifying a low level of arousal throughout that student's time in class. To distinguish between the sources of these moments of arousal, a video feed is provided to the teacher, so he or she can determine if the arousals are due to classroom engagement or some other factor. The teacher also has the capability to take notes for a particular student, get a complete picture of an individual student during a class period, and look at the overall classroom performance over a period of time.

Another application, the Subtle Stone, is a wireless, hand-held, squeezable ball that allows students to communicate their affective and motivational experiences to their teachers in real time. The ball has seven different colors, and each student in the class can customize the stone to represent his or her own emotional language by associating specific colors with specific emotions he or she wants to communicate. When the stone is in use, students squeeze the sensor to cycle through colors until they reach the emotion they wish to express at that moment. Thus, one drawback of this tool is that the feedback delivered to the teacher is heavily dependent on the student's self-report. In addition, the cognitive load imposed on the instructor may be high depending on the number of students in the classroom and the level of variation between students' emotional color schemes. Finally, the possible distraction of the students from the instruction as they attempt to express themselves utilizing this tool could be an issue. Other researchers developing and studying intelligent tutoring systems have identified learner engagement and affect by monitoring conversational cues, gross body language, and facial features with a variety of sensors (D'Mello and Graesser, 2007).

Other Applications

Other applications of affective technology include job interview performance, which is not solely based on an individual's knowledge, but, more importantly, how well he or she can communicate that knowledge to the other person. Along with good verbal communication skills, the ability to control one's emotions is essential. To work on these skills, individuals frequently practice in front of a mirror or with a friend. MACH (My Automated Conversation coacH) developed at the MIT Media Lab, is a virtual agent that can read facial expressions as well as speech and language intonations. The agent then gives both verbal and nonverbal feedback to the users, helping them to improve their communication skills and control anxiety (Hoque et al., 2013).

Moreover, due to the rise in security threats and controversies related to interrogation techniques, researchers have suggested using affective systems that can unobtrusively detect specific emotions like anger, frustration, or deception in real time. Affective applications currently focus on using an individual's facial expressions as the primary measure to track emotional cues. Over the years, researchers have worked on developing a universal coding system for standard facial expressions, such as the FACS described previously (Ekman and Friesen, 1978). Similarly, researchers from Carnegie-Mellon University and Naval Criminal Investigative Services developed the automated facial recognition system (AFERS) (Ryan et al., 2009). This system uses video streams and support vector machines to detect facial expressions. An automated FACS system codes these expressions, and the results can be viewed in real time. AFERS has the ability to generate a graphical representation of the expressions over a period of time, and that helps the investigators identify patterns of deception. AFERS also allows authorities to record, annotate, and store frame-by-frame references of the video feed for future review. A system like AFERS also has the potential of being used in large gatherings like airports, games, or concerts to detect suspicious behavior in real time (Meservy et al., 2005; Ryan et al., 2009).

ETHICAL CONSIDERATIONS

According to Picard (1997), "The fictional message has been repeated in many forms and is serious: a computer that can express itself emotionally will someday act emotionally, and if it is capable of certain behaviors, then the consequences can be tragic" (p. 127). The introduction of this chapter raised the issue of how giving technology certain functionalities can be potentially harmful. What types of machines should be given affective capabilities? Should machines with already destructive capabilities (e.g., fighter jets) be imbued with emotional reasoning? For example, given that an airplane or a mailbox has been granted affective reasoning, should anything go wrong with either of those as a result of emotional misreading, the resulting causalities and backlashes would be completely different.

Another ethical consideration is how in line affective reasoning capabilities will be with a machine's task. In the case of conflict, what form of reasoning wins? For example, if a robot with affective capabilities is being used to administer a shot to a crying child, will the robot still be able to complete its task even though it may sympathize with the crying child? Likewise, if an affective robot enters in a sensitive situation, such as a funeral, will it know how to maneuver appropriately without offending anyone? Although there are numerous technologies in place that have made errors that have cost many human lives, a vast number of technologies have also saved them (Picard, 1997). Human safety is key when considering where to place affective reasoning in technology. Therefore, as we progress in affective computing, it is important to remember also to place thoughts on safeguarding the users during these processes as we would any other technology. Researchers must prioritize maximizing the contribution of the technology and minimizing any extraneous hindrances that may come as a result of its use. Though these possibilities may not arise from affective computing for many years to come, it is still our ethical responsibility to consider them.

Privacy Concerns

Concerns exist regarding how affective computers are able to gather information about a user's emotional status and well-being. According to Picard (2003), "Emotions, perhaps more so than thoughts, are ultimately personal and private" (p. 7). This information about a user's emotional state or how the user feels could be stored over a long period of time and could potentially be accessed, hacked, or stolen. Having software that picks up on a user's mood does not mean that the user would want a salesman or telemarketer to know how he or she feels because it could be used against him or her (Picard, 1997). Developing safe and secure software to store a user's emotional information while leaving the user in complete control of who has access to the information is an important factor in affective computing. Maintaining the privacy of each individual user, especially over potentially insecure networks, is another factor. If this information could or would be accessed by another party, then it could have a negative impact on users.

Emotional Dependency

Affective computing can open the door to creating *moral agents*, tools developed to assist with humans' emotional well-being. However, could having users routinely use these moral agents create codependence? Another perspective is that if these moral agents were introduced to children early on, could children also develop an unhealthy attachment to or need for these affective devices to sustain and regulate their emotions (Picard and Klein, 2002)? The main goal of such a moral agent would be to assist in the regulation and well-being of users, without hindering their ability to handle human emotions and interaction. Ensuring that affective computing software and moral agent roles are clearly defined for both the developers and users is important to prevent the tool from becoming an entity upon which humans would become completely dependent. If a user becomes addicted to or entirely dependent on moral agents, then a large problem could arise that could negatively impact a user's ability to manage his or her own emotional well-being. Moral agents should be designed to serve as emotional support, not as replacements for an individual's ability to manage his or her own well-being. Hence, moral agents should be seen as guides or enhancers to strengthen the overall happiness of the user, not the immediate or only sources of emotional direction.

Emotional Manipulation

With emotions being considered such a private entity by default, another question arises: is it ethical for computers to detect, recognize, and then attempt to modify certain behaviors? Some would say that a computer with the ability to attempt to resolve a user's emotions is a breach of ethics and is unacceptable because of its manipulative nature; however, humans typically behave this way in this situation daily (Picard, 2003). If an individual is sad or angry, another person may try to calm the person, which can also be viewed as manipulative in a sense, but would be deemed acceptable if claimed that it is "motivated by good will" (Picard and Klein, 2002, p. 16). With this in mind, having these moral agents be able to detect negative affect could be a great benefit to the well-being and mental health of some users. The important part in developing this software is not to enable these affective machines to affect positive moods negatively, to limit the feelings users have, or to violate the privacy of user's thoughts and emotions.

Building Relationships

The discussion of the potential effects of building relationships with affective technologies brings into question not only how affective reasoning may alter the technology over time, but also how that technology will alter humanity and our perception of it. As the next generation grows, so will the new affective technologies. The depth and appropriateness of the relationships have yet to be defined. However, over time, this will become an ethical topic to discuss. At what point will a person begin to value affective technology and its well-being over that of another human being? Is there a certain amount of time a person should spend away from these technologies to avoid having an unhealthy relationship?

These are questions that will need to be answered in the years to come as affective technologies become more intertwined into everyday living. For instance, in the movie *Her*, a man develops romantic feelings for his operating system (Jonze, 2013). People already claim to have emotional attachments to their cars, phones, etc. How would adding affective capabilities to those technologies change those relationships? Humans attach and connect to each other strongly through emotion. Therefore, by giving technology access to that emotion, we open ourselves to all that comes with it.

FUTURE DIRECTIONS

This chapter has reviewed the history of affective computing, techniques for sensing affect through technology, methods for generating emotion, applications, and ethical considerations. The applications reviewed in this section have shown that, although there is still room for improvement, progress in applications with affective capabilities is not only possible, but also flourishing. Therefore, as research interests in designing applications and software with affective capabilities increase, then so will the amount and variety therein. As technology finds its way into almost every aspect of human life, the questions of its ability to understand, help treat, develop, and impact the human psyche will continue to grow. With this growth, affective capabilities will be an integral part of the development of future technologies.

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