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Commentary

ENHANCING HEALTHCARE VIA AFFECTIVE COMPUTING

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Abstract. Affective computing is a multidisciplinary field that studies the various ways by which computational processes are able to elicit, sense, and detect manifestations of human emotion. While the methods and technology delivered by affective computing have demonstrated very promising results across several domains, their adoption by healthcare is still at its initial stages. With that aim in mind, this commentary paper introduces affective computing to the readership of the journal and praises for the benefits of affect-enabled systems for prognostic, diagnostic and therapeutic purposes.

Keywords: affective computing, healthcare, emotion elicitation, emotion modelling, emotion detection

1 Introduction

Emotion can be defined as a conscious experience which is characterized by intense mental activity and varying degrees of pleasure or displeasure. The study of emotions and their links to mental and physical health is foundational to science (Hett, 1936). Given its importance to our very existence, emotion has been studied from a multitude of disciplines including social psychology, marketing, philosophy, neuroscience, and artificial intelligence. A relatively recent field at the crossroads of computer science, psychology and physiology, named affective computing (AC) (Picard, 1997), has shed some light on the relationship between the feeling of an emotion (i.e., affect) and its corresponding responses. In that regard, AC can be defined as the computational study of emotion and its manifestations through systems that enable a form of interaction between humans and computers.

Over the last two decades AC has experienced advancements that gradually grew the field to become an influential area for research and industrial development (Calvo et al., 2015). Nowadays software is able to detect human emotions with a supreme accuracy under particular conditions; hardware can sense manifestations of our physiology, our speech and

body motion and infer reliably in what emotional state we are currently in (Calvo et al., 2015).

While the benefits of AC are directly applicable to many health disciplines no study in the literature gives a comprehensive overview of what AC can offer to healthcare at large. Motivated by this lack of general overview, this paper takes a quick glance over the opportunities arising from the adoption of AC by healthcare. The paper introduces the various methods through which emotion can be recognized computationally and communicated to healthcare stakeholders including patients, doctors, healthcare educators, or medical administrators. As evidenced by the numerous studies referenced in this paper, this continuous dialog between health professionals and affect-based interactive systems can enhance directly the quality of both physical and mental healthcare services.

2 Affect Annotation

A fundamental challenge in AC is the labelling (or measurement) of emotions. The current dominant approach in AC is to represent emotions as interval values using the dimensions of arousal (or emotion intensity) and valence (or pleasantness) (Russell, 1980) and ask subjects to annotate arousal/valence values via continuous annotations (Cowie et al., 2000, Lopes et al., 2017). Alternative labelling methods include questionnaires that ask users to label particular categories of emotions (e.g., 'happiness'), or assign a value in a Likert scale. It is important to note, however, that a plethora of recent studies in affect annotation (Holmgard, et al., 2015, Martinez et al., 2014, Tognetti et al., 2010, Yannakakis & Hallam, 2011, Yannakakis et al., 2017, Yannakakis & Martinez, 2015a, Yannakakis & Martinez, 2015b) have shown the supremacy of ordinal (rank-based) emotion annotation schemes over interval and nominal types of annotation in yielding affect models of higher accuracy, reliability and generality.

3 Affective Computing: The Core Elements

Emotions can generally be elicited via stimuli offered during the interaction with the affective system. The elicitation of emotions naturally leads to bodily manifestations that can

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then be detected and modelled by assessing the responses of the user to the corresponding stimuli. Those models can in turn influence the way the affective systems respond. In the remainder of this section we cover the four basic sequential key phases that comprise a closed-loop fully realised affect enabled software named affective loop (Sundstrom, 2005).

3.1 Affect Elicitation

In the first phase the user expresses her emotions during the interaction. Broadly speaking emotion can be elicited via pictures, videos, sounds, or games. These elements (elicitors) in the domain of healthcare may include social interaction with other patients, particular visuals and sounds associated with traumatic experiences, bodily stance of avatars during a virtual therapy session, a virtual environment that simulates a rehabilitation exercise, etc.

3.2 Affect Sensing

In the second phase the system detects the emotional reactions of the user, since emotion is manifested via bodily or physiological re-actions. These reactions can be captured via a camera, a gaze tracker, a microphone, or a multitude of physiological sensors (Sharma & Gedeon, 2012) such as electrocardiography (Yannakakis et al., 2010), galvanic skin response (Holmgard et al., 2015, Holmgard et al., 2013, Mandryk et al., 2006), respiration (Tognetti et al., 2010), and EEG (Nijholt, 2009).

3.3 Affect Modelling

Once manifestations are captured via sensor technology and labels of affect are available the next step is to derive the mapping (i.e., the model) between user affect and her bodily or physiological manifestations. The core steps involved in this process (Calvo & D'Mello, 2010) include signal processing, feature extraction, and machine learning which are outlined here. In signal processing we are faced with time-series data (e.g., a skin conductance signal) that we need to remove noise from; noise in the data is usually caused by hardware limitations. Feature extraction refers to the process of designing appropriate data attributes from processing (e.g., average skin conductance). Note that important interaction events (e.g., the avatar smiled to the patient) should normally be used to determine the time window that features can be extracted from (Holmgard et al., 2015, Kivikangas et al., 2010, Ravaja et al., 2006). Modern machine learning approaches such as sequence mining (Martinez & Yannakakis, 2011)—i.e., statistical methods that identify frequently co-occurring events—and deep learning (Martinez et al., 2013)—i.e., multi-layered non-linear artificial neural networks—have given very promising results. In certain cases, the models are able to predict affective states with more than 90% accuracy.

If labelled data comes as an interval (e.g., today is 85% painful) or nominal (e.g., today is painful) value any regression or classification algorithm can be used to build affective

models. If instead labelled data is given in a rank format (e.g., today is more painful than yesterday) the problem becomes one of preference learning which involves statistical methods that rank lists or pairs of options (Furnkranz & Hullermeier, 2005, Yannakakis, 2009).

3.4 Affect-driven Adaptation

For the affective loop to be closed the affect-enabled software needs to be able to adapt to the current state of the user. Within the healthcare domain, one can envisage optimizing the behaviour of a virtual character or altering the environment (digital content) for minimizing pain, physical fatigue while at the same time maximizing engagement or even empathy towards a virtual character (Leite et al., 2010). The digital content may include every aspect of the environment the patient is interacting with such as lighting, visuals, stories, sound effects and music. An alternative way to adapt to a user's emotion is via virtual characters; these characters may act believably as their actions may be determined by emotional reactions to events. Popular examples of believable virtual character models include the EMA (Gratch & Marsella, 2004), the FATiMA (Lim et al., 2012) and the ALMA (Gebhard, 2005) models.

4 Healthcare Applications of Affective Computing

From a computational perspective, healthcare is not any different than any other domain in which AC has delivered successful and robust solutions. In that regard, all methods introduced by AC can aid the development of better affect-aware health technologies. Some of the most popular uses of affect-enabled systems are summarized below.

Autism: A popular application of affective systems to health is related to syndromes or developmental disorders such as Autism characterized by limitations on social interactions and on processing or expressing emotions. In particular, the primary focus has been on the assistance of parents, teachers and carers of children with autism (Kaliouby et al., 2006, Liu et al., 2008, Picard, 2009). These tools detect the affective state of children and communicate it to themselves or others, thereby enhancing communication and assisting social interaction.

Stress and anxiety: A significant part of the world's population is affected by depression, stress and anxiety-related disorders, which are interdependent and directly connected to emotion (World Health Organization, 2018). Affective systems have successfully been used as mental health interventions or as diagnostic and treatment tools for depression and numerous anxiety-related disorders. One popular such use is for the diagnosis and treatment of post-traumatic stress disorder (PTSD), which is developed after a person is exposed to a traumatic event, such as warfare. Among the possible ways of treating PTSD, computer games and virtual environments have a particular potential for eliciting stress in a controlled, graded fashion and can provide an immersive medium for stress management (Holmes et al.,

2009, Rizzo et al., 2009, Wiederhold & Wiederhold, 1998). Virtual reality (VR) therapy can be viewed as an extension of exposure therapy (an anxiety disorder technique that exposes the target patient to the anxiety source) as it can expose the patient to the original stressful, traumatizing situation; notable examples of that approach are the Virtual Iraq and Virtual Afghanistan applications (Reger et al., 2011, Rizzo et al., 2009). Other implementations have focused on appropriating principles from stress inoculation training—a type of therapy that blends cognitive and behavioural training techniques to target the stressors of a patient (Wiederhold & Wiederhold, 2008)—or even hybrids of exposure therapy and stress inoculation training (Holmgard et al., 2015, Holmgard et al., 2015a).

Physical health and rehabilitation: Beyond mental health applications, AC is directly applicable to physical healthcare tasks. A number of studies have focused on the use of tangible interactive systems that enhance the engagement of patients during a rehabilitation session (Yannakakis & Hallam, 2009). Emotion can be recognized through the body stance of the patient with the aim to relieve pain during an exercise (Newbold et al., 2016, Singh et al., 2014) or to increase engagement during interactive sessions with games (Dimovska et al., 2010, Hocine et al., 2015).

Call centres and tele-medicine: Applications of AC also expand to telemedicine (Kranzffelder et al., 2011, Pollak et al., 2007) as the very communication between the patient and the health practitioner is largely built on emotional traits and trust. Thus, detecting the affective state of the patient can assist the health practitioner to better understand the current emotional needs of the patient from a distance. In turn, this enhanced communication can improve the patient's satisfaction and lead to a more effective treatment (Lisetti et al., 2003). One common approach is to use virtual characters that are able to express emotion (Pasquariello & Pelachaud, 2002) and thus are capable of simulating patient-doctor dialogs or therapy sessions. Such characters have been shown to build the trust and therapeutic alliance which are necessary for a reliable healthcare practice (Lisetti et al., 2003).

5 Discussion and Conclusions

AC merges experimental approaches from psychology with methods derived from machine learning for the purpose of modelling emotion. This process comes with certain limitations: 1) given the subjective nature of emotions the very labels of affect are often of questionable validity, 2) methods used for eliciting emotion are often not natural (i.e., laboratory conditions), 3) hardware for capturing affect is often faulty due to the environment (e.g., light) or the subject (e.g., movement). Despite the limitations modern AC methods can capture approximates of human affect accurately and adapt to these predictions. Future promising avenues of research for AC include the reliable capture of social signals in groups of people and in natural setups away from the laboratory.

Healthcare is a natural application area for AC as the role of emotion is central to our health, both physical and mental.

This paper outlined the core elements of AC in the context of health, proposed a number of key application areas of AC in healthcare, and served as a quick guide to the benefits of affect-adaptive systems for the diagnosis and treatment of medical conditions, and for the improvement of health services such as call centres.

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