Editorial
Special Issue on Unobtrusive Physiological Measurement Methods for Affective Applications

IN THE formative years of Affective Computing [1], from the late 1990s and into the early 2000s, a significant fraction of research attention was focused on the development of methods for *unobtrusive physiological measurement*. It quickly became obvious that wiring people with electrodes and strapping cumbersome hardware to their bodies was not only restricting the types of experiments that could be performed but also was not conducive to unbiased observations. For instance, subjects with fingers wrapped with electrodermal activity (EDA) and photoplethysmography (PPG) sensors could hardly type, drive or sleep comfortably. Hence, there was a need for more elegant and scalable physiological measurement methods [2].

A combination of wearable and contact-free technologies began to accelerate the possibilities for affective computing. First came heart rate [3], breathing rate [4], and EDA measurements [5] via thermal imaging of the face. Shortly thereafter heart rate [6], heart rate variability, and breathing rate measurements [7] via visual imaging of the face. Thermal imaging methods had research importance because they demonstrated that contact-free physiological measurements were not science fiction [8]. Visual imaging methods had practical importance because they demonstrated that contact-free physiological measurements could be performed even with ubiquitous sensors [9], [10]. In the mid 2010 s, with the advent of wearable technology, affective computing measurements blended into electronics that can be seamlessly worn on our body and clothes, [11], thus becoming part of our daily lives.

As we stand at the beginning of a new decade, it is an opportune time to review the landscape of unobtrusive measurement methods, how they are being applied and look to what the future might hold. This special issue features four papers that span the spectrum, from ubiquitous, non-contact sensing to emotion and depression classification to multi-party, multi-modal analyses of synchrony in social interactions.

Gu et al. [12] introduce the first bimodal fusion of WiFi and cameras for contact-free gesture and facial emotion recognition. Specifically, by leveraging the Channel State Information (CSI) of WiFi, the authors managed to extract detailed gesture features from 10 participants who were acting emotionally. Combining these gesture features with visually extracted facial expression features, the investigators report solid emotion recognition results. Feature fusion is operationalized through a deep learning framework called Multi-Source Learning (MSL), which fits the bimodal nature of the data. Using multiple encoders, MSL acquires spatio-temporal features from the WiFi and visual modalities, treating them as two information channels that describe the same emotion but from different perspectives. This paper is accompanied by the first WiFi and camera dataset, a resource that will help advance this innovative field of passive and potentially highly scalable measurement.

The second paper provides an example of affective classification improvements realized not through a new physiological modality, but through a novel measure in a well-established modality. Using wearable BIOPAC MP160 sensors, Li et al. [13] collected EDA, electrocardiographic, and respiratory signals from 60 participants engaging in game play. They labeled the data as low, medium, and high arousal based on participants' self-assessments. The investigators demonstrated that if the commonly used measures of Skin Conductance (SC) and Heart Rate Variability (HRV) were accompanied by the less commonly used Breath Rate Variability (BRV) measure, then classification of emotional arousal significantly improved across several machine learning (ML) methods. This work illustrates that there remain many opportunities for feature and representation learning that can improve affect classification.

Zheng et al. [14] introduce an intriguing deep learning method for the recognition of emotions and the detection of depression. Their method includes three blocks: a) a temporal convolutional transformer block that learns multimodal embeddings; b) a knowledge-embedded transformer block that exploits medical knowledge from graphs; and, c) a task-oriented attention block that focuses on the joint learning of emotion recognition and depression detection. The said method is tested on several well-known datasets, including the MODMA [15] and DAIC-WOZ [16]. The performance of their models compares favorably to the performance of other knowledge embedding methods, such as k-ELECTRA [17] and KEA-ELECTRAv [18].

The final paper introduces physiological synchrony among members of an interacting group as an additional measure for improving arousal and valence classification. Bota et al. [19] have an unusual take on human physiology and its affective meaning. In their paper, physiological indicators are not viewed

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in strict individualistic terms but partly as results of social cross-influences. Physiological synchrony between a target participant and the remaining participants was measured via the relative distance between their physiological signals, namely EDA and HRV. The emotion label of the target participant was predicted by taking a weighted average of the emotion labels of the remaining participants, where the emotion label of each of the remaining participants was weighted proportionately to their physiological synchrony with the target participant. This interpersonal physiological model is tested on the AMIGOS [20] and K-EmonCon [21], exhibiting significant performance improvements with respect to classic models based on intra-personal physiological considerations.

We believe the sample of articles in this special issue is representative of the broader physiological measurement trends in Affective Computing. Accordingly, we note the following observations:

Multimodal: It is notable that all the special issue papers present multimodal measurement solutions. The importance of multimodality has long been known; however, it is now arguably the status quo for affective computing. We expect this trajectory to continue with unimodal research becoming an increasingly small minority.

Benchmark datasets: A significant part of physiological research in Affective Computing is centered on the analysis of existing datasets rather than the construction of new ones. To some degree, this is pragmatic, but it is also a sign of maturation in the field. Rather than new physiological modalities, new metrics and classification methods on existing physiological modalities appear to dominate the current research landscape.

Not so unobtrusive? Most of the data in these benchmark datasets were not collected with the contact-free methods that looked so promising in the early days of Affective Computing. Instead, the said data were collected with wearable sensors and, in several instances, even with tethered sensors. For the latter, the characterization ‘unobtrusive measurement’ is generous, and it is the very thing Affective Computing pioneers were trying to avoid. Perhaps truly unobtrusive physiological measurement methods are not as important to Affective Computing as originally thought and are not yet perceived as suitably accurate and sensitive; or, perhaps the current benchmark datasets are associated with highly stylized scenarios and things may change in the future, as more naturalistic datasets from free-ranging human behaviors enter the arena.

Indirectly physiological: The few current efforts that focus on the development of new measurement modalities are as innovative as the original efforts back in the 2000s. They appear, however, to ‘stretch’ the concept of physiological measurements. For instance, using WiFi for sensing gestures [12], only indirectly relates to physiology, if one accounts that observable limb movements are the results of muscle-skeletal functions. We view this expansion from direct to indirect physiological measures as a natural evolution, while researchers in this area continue to seek to break new ground.

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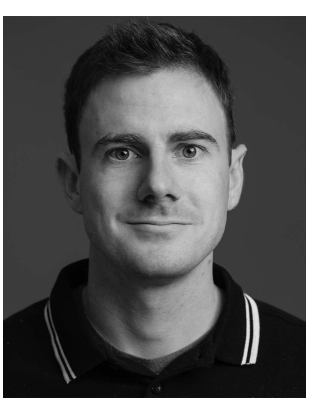

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