Wearable Sensing of Facial Expressions and Head Gestures

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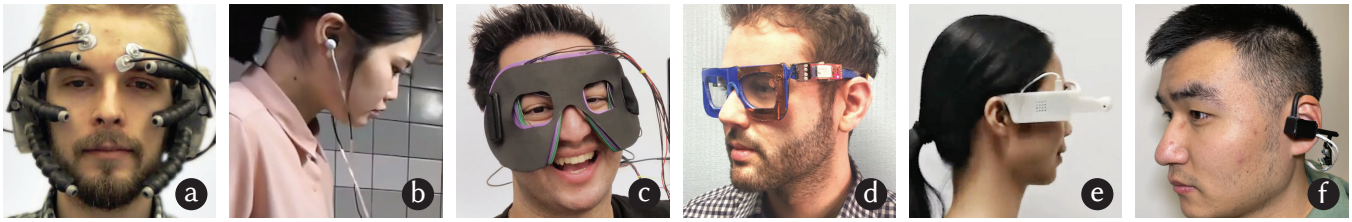

Figure 1: Example artifacts: a) face hugger using capacitive sensing by Rantanen et al. [40], b) in-ears using a barometer by Ando et al. [1], c) face mat using acoustic interferometry by Iravantchi et al. [17], d) glasses using capacitive sensing by Matthies et al. [32], e) glasses using camera sensing by Yan et al. [50], and f) earable using acoustic sensing by Li et al. [22].

ABSTRACT

This paper provides a survey of wearable sensing approaches for detecting facial expressions and head gestures, which provides a way to measure people's natural emotions. Reliable facial expression and head gesture detection can contribute to a better understanding of an individual's state of mind and to enrich human–computer interaction. In this paper, we survey artifacts and discuss opportunities and challenges in wearable sensing.

CCS CONCEPTS

• **Human-centered computing → Interaction devices**; **Ubiquitous and mobile computing systems and tools**; **Ubiquitous and mobile devices**.

KEYWORDS

Facial Expressions; Head Gestures; Wearable Sensing; Survey; Affective Computing; Empathic HCI

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1 INTRODUCTION

The human face provides an important visual cue for emotions [14], and an important basis of affective computing [36] and empathic HCI [37]. We can use facial expressions for emotion detection, to infer user context [10], and for implicit interaction [46], such as adjusting a system's behaviour based on the user's mental state in order to make it more effective. We can also employ facial expressions and head gestures for explicit control using quickly executable Microinteractions [3]. Short natural gestures do not overtax the user's attention, so they enable peripheral interaction[4]. Moreover, reflexive interaction [31] may be enabled by a hands-free and parallel execution, which does not interrupt the primary task.

Given the importance of face expression and head motion, a range of different technologies have been developed to sense facial expressions and head gestures. This paper presents a survey of wearable systems in this space, and discusses key opportunities and challenges for research in this area.

2 RELATED WORK

For a several decades there has been a number of wearable interfaces developed that can track facial expressions and head gestures. These artifacts are briefly elaborated in this section.

Facial gestures (used here as a term to summarize head gestures and facial expressions) can be detected through using visual approaches, such as camera tracking [5]. This has been extensively used in the area of affective computing [11]. For example, Wei et al. [49] recently presented a complex facial expression mapping to a virtual avatar using a GAN Deep-Learning approach with 9 Infrared (IR) cameras attached to a Virtual Reality (VR) head mounted display (HMD) . However, this approach was computationally expensive and immobile. In a mobile context, when the user is walking, it is unusual to have a camera positioned in front of the user's face. Even wearable micro-cameras have the drawback of being heavily impacted by light conditions. Therefore, other wearable sensing technologies must be used.

Some mobile facial gesture control prototypes based on muscle motion have been developed. For example, San Agustin et al. [44] used an Electromyography (EMG) headband to detect frowning or the tightening of the user's jaw. EMG senses electric activity generated between two opposing electrodes. A similar setup using multiple electrodes by Chen et al. [8] could discriminate between

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Table 1: A selection of the state-of-the-art artifacts for wearable sensing of facial expressions and head gestures. The number of gestures that can be recognized excludes the default (resting/neutral) gesture.

Name	Venue 'Year	Technology	Location	$n_{Gestures}$	Accuracy	Dependency	Classifier
Saponas et al. [45]	UIST '09	Infrared Sensing	in mouth	4	90%	cross-user	DT
Rantanen et al. [40]	IEEE Sensors '13	Capacitive Sensing	on face	4	88% – 93%	cross-user	LR
Ishimaru et al. [18]	AH '14	Infrared Sensing	face (glasses)	1	93%	per-user	DT
Zhang et al. [51]	CHI '14	Electromyography	on throat	5	94.17%	per-user	SVM
Gruebler & Suzuki [13]	IEEE TAC '14	Electromyography	on temple	2	95%	per-user	NN
Kanoh et al. [20]	EMBC '15	EOG	face (glasses)	1	94.3%	cross-user	n/a
Chen et al. [8]	Neurocomputing '15	Electromyography	face (headband)	4	97.12%	per-user	NN
AffectiveWear [26]	ISWC '15	Photo LEDs	face (glasses)	6	98.7%	per-user	SVM
Bitey [2]	MobileHCI '16	Bone-Conduction Mic.	back of head	5	78%	per-user	SVM
EarFieldSensing [30]	CHI '17	Electrical Field Sensing	in ear	5	90%	per-user	DT
CanalSense [1]	UIST '17	Barometer	in ear	10	87.6%	per-user	RF
W!NCE [41]	IMWUT '19	EOG + IMU	face (glasses)	4	88%	per-user	CNN
Interferi [17]	CHI '19	Acoustic Interferometry	on face	8	89%	per-user	RF
ChewIt [12]	CHI '19	Accelerometer + Button	in mouth	9	86.1%	per-user	DT
KissGlass [23]	AHs '20	EOG + IMU	face (glasses)	3 (10)	74.33%	cross-user	kNN
Masai et al. [25]	AHs '20	Photo-reflective Sensors	face (glasses)	7	89.1%	per-user	SVM
Expressure [52]	MDPI Sensors' 20	Force Sensitive Resistors	face (headband)	2	82.4%	cross-user	SVM
Matthies et al. [33]	Adjunct UbiComp '21	Capacitive Sensing	face (glasses)	11	63.3%	per-user	RF
CapGlasses [32]	AHs '21	Capacitive Sensing	face (glasses)	11	89.6%	per-user	RF
EarIO [22]	IMWUT '22	Acoustic Sensing	ear (ear)	9	87%	per-user	CNN
EmoGlass [50]	CHI '22	Camera Sensing	face (glasses)	6	73%	per-user	CNN

5 facial expressions by a neuronal network approach with a relatively high accuracy of 97%. A rather unobtrusive wearable device that attaches EMG electrodes to the temple region distinguishes between 'smiling', 'frowning', and a 'neutral expression' [13]. Another headband that can distinguish 'raising eyebrows' and 'lowering eyebrows' from the default state uses force sensitive resistors (FSR) [52]. In 2012, Matthies et al. [28] used an Electroencephalogram (EEG) headset to detect eye winks and head movements. The EEG working principle is similar to EMG, although it utilizes greater amplification. These systems can typically only reliably distinguish between a few facial expressions.

Other approaches are more obtrusive, such as gluing a magnet to one's tongue [43] or applying EMG electrodes directly onto the user's face [51], or the cheeks in the form of some kind of skin tattoo [16]. Nine facial gestures are detectable with bio-acoustic sensing [17], applying a rather obtrusive sensing layer onto the face. Sensors can also be attached to a Virtual Reality (VR) head-mounted display (HMD) and pressed against the face. Li and Reyes [24] have demonstrated attaching five infrared proximity sensors to VR HMDs to infer continuous lip and jaw motions by measuring deformations of the cheeks and temples. Another VR HMD by Bernal et al. [6] enables the classification of a variety of emotional states using EMG, Electrooculography (EOG) (for measuring eye movement), Electrodermal activity (EDA), and EEG sensors. Recently, OpenBCI introduced Galea, a VR headset that integrates EEG, EMG, EDA, PPG, and eye-tracking also to detect facial expressions [35].

Measurements from the ear can also be used. An in-ear prototype with EEG sensing detects ear wiggling and eye winks [27]. An ear plug [30] reliably distinguishes five facial expressions ('eye wink', 'head right', 'open mouth', 'say SH', 'smile'). Project EarIO [22] uses low-powered acoustic sensing in an earable, and detects nine gestures with 87% accuracy using a user-depended CNN-model.

Glasses provide a less obtrusive form factor. Ishimaru et al. [18] demonstrate blink detection based on the infrared proximity sensor of Google Glass. Bulling et al. [7] developed EOG Glasses with six electrodes that allow for the tracking of eye movements. Masai et al. [26] attached eight photo reflective sensors to a glasses frame, which detected 'smile', 'laugh', 'disgust', 'angry', 'sad' and a 'surprise' gesture. For photo reflective sensing, one usually uses an emitting LED plus optical sensing diods. Kanoh et al. [20] and Rostaminia et al. [41] use a commercial EOG glasses (J!NS MEME) to classify facial expressions. In 2010, Rantanen et al. [39] present a pair of glasses using CapSense, or capacitive sensing. Rantanen et al. [39] is capable of detecting 'frowning' and 'lifting of eyebrows' to execute click-events with an average accuracy of 83%, which leaves space for improvement in terms of the variety of detected gestures. In 2021, Matthies et al. introduces a series of CapSense prototypes [33] that can detect 12 (11 + default) gestures, at an accuracy of 89.6% by a per-user trained machine learning model [32]. EmoGlass [50] is a single-camera-mounted glasses that can detect 7 (6+1 default) facial expressions with an average accuracy of 73% using a user-dependent trained model.

Table 1 provides an overview of some wearable sensing prototypes. While similar gestures can be recognized with a variety of prototypes, one must acknowledge that each technology has its (dis-/)advantage and use cases. For example, cameras fail with bad light, Inertial Measurement Unit (IMU) sensors barely work when walking or in a car, mouth-placed sensors might not be acceptable, and so forth. Another aspect worth looking at is the model's dependency. Since the face has a very individual form and expression, in previous research, models for machine learning were trained in a personalized (per-user) and not generalizable (cross-user) manner. Cross-user models seem only to support a limited number of gestures, as indicated in Table 1.

3 DISCUSSION

3.1 Opportunities

3.1.1 The Power of Facial Expressions. Facial gestures are ubiquitous in everyday interactions, so sensing those can enable enriched explicit or implicit interactions while tapping into this huge reservoir of data humans produce naturally without mental effort every day. In mobile and everyday contexts,a wearable sensing artifact can provide safety benefits by allowing the user to reflect on their current state, such as the level of tiredness [47], but aid in several other ways. The detection of shock, stress, joy, and other parameters can provide additional benefits, such as to infer on task engagement.

3.1.2 Use Cases. Sensing the user's context is an essential aspect of future assistive technology [9]. Context information includes the mental and physical state, which can be inferred by facial expressions. For example, an assistive system could increasingly support the user when engaged in critical work tasks and activities, such as driving a car. Moreover, such a system can assess the user's unease or the difficulty experienced when performing a task. In a learning scenario, the task difficulty could be individually adjusted to the user's current performance level. In most clinical settings, tracking the mood and stress of a user is important. Currently, users are often required to manually track such parameters at certain intervals. Further, tracking facial expressions could be used to substantially enrich social interaction in virtual environments, creating a higher level of immersion and social presence. We can also use explicit gestures to input commands that are hands-free, thus safe to use when on the go and enabling more efficient multitasking.

3.1.3 Glasses Form Factor. Research has shown that using a pair of glasses to measure facial expressions and head gestures is an elegant solution. Glasses are not an additional sensing device and are already worn by many users, so it allows for the subtle implementation of sensing technology. Since the frame and the glass itself offers a large surface area, we can use these to implement area electrodes, which are sensitive enough to sense any facial and head movements using capacitive sensing.

3.1.4 Empathic Computing. Empathy is the ability to understand and share the emotions of others, as defined by the Perception Action Model [38]. Researchers showed that sharing emotional cues such as facial expressions and eye gaze improves remote collaboration [21, 37]. In the same way, interacting with a virtual agent who displays empathy and expressions produces similar feelings as interacting with a real person [34]. Generally, the main goal of Empathic Computing applications is to enhance remote communication by measuring the emotion of people teleconferencing together or with machines [37]. As a result, by improving emotion recognition systems and sharing emotional cues using robust wearable sensors, we can increase empathy and improve the quality of human-human and human-machine interactions [37, 48].

3.2 Challenges

3.2.1 Environmental Influences. Literature reveals that the most competing technology seems to be an optical sensing approach, such as demonstrated by Masai et al. [25]. However, environmental factors substantially influence the sensor data, so their prototype only works when the user does not angle their head in a different direction as illumination conditions change. The feasibility in an actual mobile scenario is thus compromised. Other prototypes also demonstrate the use of electric field / capacitive sensing, which is not impacted by these issues. However, this technology is also impacted by other environmental influences, namely in environments where many electric devices are emitting considerable EM-waves.

3.2.2 Intrinsic Influences. Humans experience constant changes to the body, so challenges arise in the set-up of wearable sensing. Researchers have also shown that electric field sensing signals may not be absolutely stable, as signals slightly fluctuate from day-to-day, depending on a variety of factors, such as the user's electrical charge and neighbouring devices being switched on/off. Further, varying humidity and dryness of the skin could influence the readings. In particular, EOG, EMG, Bioaccustic, and Capacitive sensing is affected by the constant change of our body. An ultimate long-term evaluation of this effect is still pending, although an attempt in an interaction setting has been studied [29].

3.2.3 Individual Factor. Many researchers identifying facial gestures using wearable sensors fall back on a user-dependent / per-user trained model instead of performing a leave-one-user-out cross-validation. This is because individual factors are strongly pronounced, which includes the physiological shape of the face. Also, the habits of how users perform certain gestures are different. Furthermore, cultural differences, gender, and age are some important factors that lead to different expressions in the same situation. Further research is required to make user-independent models that consider all individual factors.

3.2.4 Reported Accuracy. Researchers prefer reporting high accuracy in face expression detection. However, very often, we must consider these rates as a theoretical maximum accuracy level, captured under "laboratory conditions". It is good practice to record gestures from different sessions, but these reported accuracies can still only be seen as a performance indicator. In practice, performance is very likely to drop when noise from causative (extrinsic & intrinsic), intermediate, and deterministic factors occur.

3.2.5 Practicability & Mobility. Designing a practical device that is fully mobile has certain challenges. For instance, embedding a computational expensive classification into a small wearable is difficult, as expensive processing is often performed at a workstation. To provide a truly mobile solution that enables rich sensing without being tethered to mains ground/earth and to additional computational resources remains a challenge. In practice, we may also require instant feedback, and thus a real-time classifier becomes necessary. The development of such a live classifier with low recognition delay may require optimized data processing pipeline, a powerful edge-AI microcontroller, and some further research.

4 CONCLUSION

Recognizing emotions using a single input modality is a challenging task because of each sensor's limitations. Identifying emotions solely by facial expressions may not be reliable since they can be faked or controlled [15]. Similarly, physiological and neural signals are weak and subject to noise [19]. Fusing different input modalities may be a solution [42]. Still, the development of a multimodal emotion recognition system, requires designing multipurpose wearable sensors and models, which requires further research.

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