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Mobile Health with Head-Worn Devices: Challenges and Opportunities

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ABSTRACT

Monitoring human behavior and health status using mobile devices, a.k.a. *Mobile Health*, has gained increasing attention from both academia and industry in recent years. It allows imperceptible health tracking from the users and remote health management from the healthcare service providers. Head-worn devices, such as earbuds, glasses, and BCIs (Brain Computer Interfaces), exhibit great potential for mobile health due to their advantageous wearing position, the human head, which is motion-resilient and full of human bio-signals. Although initial attempts have been conducted for different healthcare applications with head-worn devices, this fast-growing area is still under-explored and retains great promises. With this work, we investigate the most pressing challenges to fully exploit the potential of head-worn devices for mobile health, from the perspective of sensing, computing, and system design. Our exploration reveals key guidelines and lessons to inform future efforts in this space.

1 INTRODUCTION

Since the first smartphone hit the market, we have witnessed the rise of mobile computing, mobile sensing and wearable technologies. This has led to the development of what is known as *mobile health*, i.e., monitoring health metrics and aiding practitioners with information and data collection. Particularly, with the steady diffusion of wireless head-worn devices, such as helmets, earbuds, glasses, and BCIs, the past couple of years have attested a new trend for mobile health, i.e., head-worn based health monitoring.

Head-worn devices offer fascinating sensing opportunities as they are positioned at an extremely promising advantage point on the body: the user's head. Equipped with a multitude of sensors, they are thus able to measure various neurological, cardiovascular, and dietary signs, leading to the birth of a new core component of the mobile health wearable ecosystem. Compared to existing health and behaviour monitoring devices, head-worn platforms possess certain advantages: (i) unlike smartphones that can be located at different parts of the body, they have a stable position on the head, (ii) contrary smartwatches that suffer from wrist movements, head-worn wearables are less susceptible to motion noise —dampened by the musculoskeletal system.

We are still at very early stages of *sensing and computing via head-worn devices* and far from truly understanding their potential on mobile health. The limitations of existing research lie in the following four aspects. First, what types of health monitoring sensors can be integrated on head-worn devices and how they can aid practitioners in decision-making and continuous monitoring of patients remains unclear. Second, understanding how to exploit advancements in machine learning to facilitate and improve health detection and monitoring performance requires more exploration and implementation. Third, on the system side, how to reduce energy and computation overhead so that the device can support long-term and uninterrupted health monitoring is still challenging. Finally, in the continuous sensing scenario, how to upgrade the design to provide better usability requires innovative user interface and form factors.

This work aims at drawing up an agenda for head-worn device based health and behaviour monitoring. Specifically, we discuss the challenges and corresponding opportunities from five different aspects: multiple biosignals acquisition, health data analysis, system optimizations, usability and adherence, and data privacy. The rest of paper is organized as follows: Section 2 introduces the mobile health wearable ecosystem, reviews the literature, and lists the requirements of a mobile health platform; Section 3 presents the challenges and possible research avenues of head-worn devices; finally, Section 4 concludes the paper.

2 MOBILE HEALTH WITH HEAD-WORN DEVICES

2.1 The Ecosystem

Mobile health aims at providing cost-effective healthcare support, delivery, and intervention to a large populations

*Equal contribution, alphabetical order.

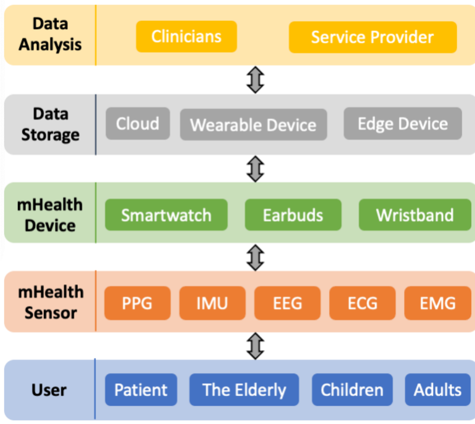

Fig. 1: The mobile health ecosystem. Sensing is provided by the multiplicity of sensors available in the mobile/wearable devices. The collected data is stored and processed in the cloud, edge devices or the wearable itself. Finally, a summary or clue is sent to the practitioner with a human-in-the-loop model, which provides the required human expertise for intervention.

via mobile technologies. Specifically, it relies on modern mobile devices to monitor human-related bio-metrics, and remotely communicate with healthcare providers, thus obviating physical presence at hospitals and direct contact with doctors. Mobile health enables a variety of services and applications such as: collecting community and clinical health data; sharing of healthcare information with practitioners, researchers, and patients; real-time monitoring of patient vital signs; direct provisioning of care (via mobile telemedicine); and training and collaboration of health workers.

Figure 1 presents the typical architecture of the mobile health ecosystem. Mobile health targets various user groups including patients with chronic disease, elderly people with health risks, children requiring special care, and general adults who want a better understanding of their physical fitness. The aforementioned users wear wearable devices (e.g., smartwatch, smart earbuds, glasses etc.) equipped with multiple sensors (e.g., photoplethysmography, inertial measurement units, electroencephalography, etc.) to measure their vital signs and keep a record of their daily activities. The collected data is then offloaded and stored in healthcare platforms either in the cloud or in edge devices. Finally, health experts, such as physicians or service providers, can interpret and analyze the data for better understanding of patients' health risks. In the case of intervention, the information would flow the reverse way, with doctors sending treatments or rehabilitation instructions (such as therapy and drug delivery) to the patients via the mobile health platform.

2.2 Existing Efforts

This section aims at providing an overview of the current bio-metrics and vital signs sensed around the head using head-worn devices.

2.2.1 Earbuds and Headphones. Ear-worn devices are a newcomer in the mobile health wearable ecosystem, nevertheless they have great capability and potential to become staple platforms for health monitoring. Kinetic earables [7] (i.e., earables equipped with inertial sensors) can be used to track human activities related to both fitness (e.g., step counting, exercise monitoring [12]) and dietary habits (e.g., food and beverage intake and classification). Additionally, medical conditions like teeth grinding (bruxism) or jaw clenching [17] could be easily detected by looking at the accelerometer and gyroscope data. Interestingly, similar sensing opportunities can be explored with alternative, more common, sensors such as in-the-canal microphones [12]. Further, if equipped with photoplethysmography sensors (PPG), earables can be used to screen two out of the four human primary vital signs(i.e., resting heart rate and respiratory rate), as well as other common fitness bio metrics (e.g., heart rate variability, blood oxygen saturation, energy expenditure). The ear canal is also a suitable place to monitor body-core temperature and blood pressure [1] (the two remainder primary vital signs). Moreover, the close proximity to the brain and eyes allows these platforms to expand more towards complex modalities such as electrooculography (EOG) and electroencephalography (EEG) which are often possible only via clinical devices.

2.2.2 Glasses. Smart glasses are another promising head-worn wearable for mobile health, due to their special shape and wearing position. Specifically, glasses can integrate various sensors for both contact (electrode on the nose pads or temple tips) and contactless (e.g., camera sensor on the frame or lens) measurements. As the most well-known smart glasses, Google Glass has demonstrated to be feasible and useful under different circumstances, such as complex and intensive care environments. Using the on-device camera, microphone, and motion sensors, Google Glass was employed for daily practice measurement and vital signs monitoring of the patients and users[16]. On the other hand, it can also be utilized by the clinicians and caregivers for medical image viewing, patient assessment and documentation. Recently, researchers have integrated additional sensors, like electrodes, to measure the electroencephalography (EEG) and electrooculography(EOG) signals for attention analysis and eye-related healthcare [8].

2.2.3 Brain Computer Interfaces. A rapidly expanding set of mobile brain-computer interfaces (BCI) delivers solutions for monitoring health, mental/emotional state (e.g., focus, anxiety, or motivation), or sleep quality [9]. Lately, relatively low-cost wearable BCIs are customized to support people with physical impairments or to improve smart living through BCI-assisted drones, robotic arms, wheelchairs, or mixed reality environments [4]. In addition, several proposals for utilizing BCI for multi-factor authentication and crypto-biometrics [5] are emerging. These devices (many available in the market Muse [1], NeuroSky [2], OpenBCI [3], Dreem [4], etc) are connected to a supporting device (such as smartphones) which collects the data stemming from EEG or electromyography (EMG) sensors for several applications ranging from mindfulness to gaming and entertainment. Their design is often optimized for comfort especially in applications for continuous sleep monitoring. At the current state, these head-worn BCIs and their accompanying applications mainly collect the data from the user's head, however recent efforts are going towards sending feedback signals to the devices too.

2.3 Unconventional Forms of Head Worn Devices

In addition to earables, smart glasses, and BCIs, the head-worn wearable ecosystem also features more unconventional devices. For instance, necklaces and neck-worn wearables have been proven to be effective in tracking eating episodes as well as dietary habits [2, 6]. For similar purposes, Chun et al. [18] have also explored jawbone-mounted wearables. The presence of similar existing efforts in the literature, suggests that the head is an advantageous position which would facilitate an increasing number of health monitoring applications.

2.4 Requirements

When dealing with health applications, there is a need for robust predictions which often requires validation from a clinician. Head-worn devices, being a crucial part of the mobile health ecosystem, need to conform to specific requirements that guarantee their reliable and safe adoption:

Reliability. Health is a critical aspect of our life, therefore, every technology related to it needs to be reliable for regulatory reasons too. This involves a careful study on the reliability of the incorporated sensors, their measurements and machine learning algorithms using their data. And it includes considering ways of detecting and removing noise in the measurements, understanding the uncertainty introduced by them and the models used for automatic predictions, and proposing solutions to mitigate the impact of these artifacts in the outcome.

Computation and latency. As battery-operated devices, head-worn wearables should aim for energy-savvy sensing techniques. This involves considering efficient scheduling methods which are always aware of the energy envelope and adapt the sensing algorithms accordingly. While the accuracy of the prediction is of absolute importance, the latency of operation is crucial too especially in real-time scenarios. Mobile health platforms need to carefully consider (online or offline) the trade-offs of accuracy versus latency especially in continuous sensing applications.

Safety and comfort. Starting with the form-factor, head-worn devices should be materialized in a wearable that can easily be worn several hours per day without causing discomfort or hazard to the user. To this purpose, longitudinal studies on materials and user experience, to best come with an optimal shape and functional design, are needed. Moreover, this requires considerations on different aspects of acceptability of these devices which can sometimes be stigmatised as in the case of hearing aids.

Privacy and security. The collected data around the head (including brain signals) is very private, therefore, it needs to be considered accordingly. Given the miniature nature of most head-worn form factos, it is understandable that the data might need to be transferred to the cloud or accompanying device. However, this transfer communication should preserve the privacy of the user by operating part of the computation or de-anonimization on-device. Another important aspect to safely use these devices is operating in a secure manner, which involves guaranteeing an acceptable level of security of the various layers of the earable platform pipeline: machine learning model and framework as well as considerations of safe primitives from the designated OS. Similar to other platforms, head-worn devices should run part of the encrypted deep learning models in secure enclaves.

The aforementioned requirements inspire our vision on the challenges that accompany the future of head-worn platforms in the mobile health domain.

3 CHALLENGES AND OPPORTUNITIES

In this section, we discuss seven identified challenges and corresponding potential research directions from the perspectives of biosignal acquisition, health data analysis, system optimization, usability and adherence, and data privacy.

3.1 Multiple Biosignal Acquisition

Challenge-A: *Existing works have individually demonstrated the capability of measuring various biosignals using*

[1]https://choosemuse.com/
[2]http://neurosky.com/
[3]https://openbci.com/
[4]https://dreem.com/

head-worn devices. To fully realize the promise of automatic and accurate mobile health, however, these biosignals should be measured simultaneously. Therefore, how to accurately and reliably acquire multiple biosignals concurrently using a single head-worn device is a big challenge. This originates from two facts - (1) head-worn devices might be in a small form factor, where the accommodation of multiple sensors is difficult and (2) human activities or other biosignals might interfere with one another, leading to a low signal-to-noise-ratio.

Opportunity 1: Sensing Modality Selection. To enable accurate measurement of multiple biosignals, we should consider the following three aspects. First, given that a biosignal might be detected with multiple modalities, identifying the best sensing modality is critical. For instance, heart rate can be measured with ECG, PPG, microphone, accelerometer, and camera. To select the best sensing modality, one should consider whether it is possible to sense multiple biosignals with a single modality, i.e., multiplexing, so that less overhead is incurred. Accelerometer, for example, can be used to sense jaw movement, human speech, as well as heart rate. Second, as a sensor has various specifications, we need to identify the best model for each modality. In this process, the size, power consumption, and data processing overhead of the associated model are the main considerations. Third, when multiple sensors are identified, we should consider the optimal position and arrangement such that (1) the signal can be accurately measured (e.g., to measure heart rate or blood pressure, the sensor has to be firmly attached to the vessels) and (2) the interference among sensor measurement is minimized (e.g., the speaker in the earbuds can interfere with the magnetometer readings).

Opportunity 2: Dual Sensing Channels. Even with proper placement and arrangement of the sensors, sensor data readings might still be polluted by environmental factors or human activities. Unlike non-head-worn wearables (e.g., smartwatch, wristband) that usually contain one sensing device only, some head-worn devices, such as earbuds and glasses, can have two symmetric measuring units as there are two associated organs (ears/eyes). These facts present an opportunity for sensor duality for accurate and reliable sensing. For example, earbuds are usually worn in pairs (one per ear). As a result, the two earbuds can work cooperatively to measure the same signal at different spots (i.e., two channels) thereby improving the sensing performance, or measure different signals at both ears thereby expanding the sensing scope. Particularly, if the dual sensors show significant disagreement in the measurements, it is very likely that one measurement might be corrupted and judicious strategies should be devised to identify the correct one. For instance, when measuring heart rate with a PPG sensor on the earbuds (which requires a stable position of the sensor on the vessel), we can assess whether other sensors (e.g., accelerometer) on the sensing unit also show unexpected values/errors (there will be a spike on the accelerometer signal if the earbud is dropped). In addition, as the two sensing elements can be worn and powered separately, when accommodating the sensors, we should consider the balance of sensor weight, size, and power consumption between the two earbuds.

3.2 Health Data Analysis

Challenge-B: *Head-worn devices are a continuous source of sensor data in health and safety-critical applications. These scenarios require crafting solutions which can guarantee efficient processing of the sensed data, algorithmic/system robustness and allow for human-in-the-loop approaches.*

Opportunity 1: Multi-channel Machine Learning. Head-worn devices benefit machine learning systems being a great source of data and offering a platform to run machine learning models online. The redundancy of the signals (i.e. predicting same aspects of user behaviour from multiple data sources) acts as an optimal data augmentation technique which allows to have more data samples for the same prediction class. This enables capturing different permutations of the signal to produce robust and reliable models which can handle samples coming from several head locations, independently. Another avenue which exploits the presence of multiple sensors are noise detection models. In many real-life scenarios, the sensor data is continuously missing or noisy leading to different techniques for handling them which often rely on sophisticated techniques to subtract the noise. In the head-worn device ecosystem, there is a natural way of doing this by exploiting the multiplicity, identity and vicinity of the devices and sensors within the same device. However, despite these advantages, further efforts are needed to explore the aforementioned opportunities. Important questions to explore include how to deal with disagreeing predictions stemming from data coming from different channels or sensors, how to understand which one to choose as right one, and how can it be done with or without the need of other devices like smartphones or watches acting as ground truth.

Opportunity 2: On-Device Machine Learning. When looking at machine learning algorithms for predictions, we can find tiny implementations that can run locally on the device itself. A very interesting line of work goes towards combining interoperability and independence by studying the trade-offs between communicating with the companion device or the cloud and running locally. If we consider the continuous sensing scenario (heart rate or voice monitoring), a series of main functionalities like noise cancellation and easy predictions can be done on the local device instead of communicating every time with the central device. These considerations could be exploited to provide several levels of accurate and robust predictions, i.e., the extremely resource constrained ear-worn device can provide a quick prediction which might be prone to uncertainty given the limitations and send for a more refined prediction to the smartphone.

Opportunity 3: Uncertainty-Aware Machine Learning and Clinician-in-the-Loop. When dealing with health applications, there is a need for robust predictions which might need to be often validated by a clinician. Traditional machine learning models have shown to achieve great predictive accuracy in many health-related tasks however they are unable to capture the predictive uncertainty stemming from noise in the data, the model parameters or other software and hardware diversity factors. This leads to over-confident wrong decisions when deploying in new environments, undermining the trust in these models. However, sending all sample predictions to practitioners is unfeasible in terms of both costs and practicality. Head-worn platforms have the capacity to run quick predictions on-device while also using the companion device for more accurate and uncertainty-aware predictions. This setting can aid clinician-in-the-loop frameworks, where the majority of tasks are automatically performed with high confidence and the uncertain ones sent to the human expert for further investigation.

Opportunity 4: Smart Personal Data Labelling. As we mentioned, these devices produce a huge amount of data which are not used in a supervised deep learning scenario. To this purpose, there is a need for approaches which do not rely on ground truth labels such as semi-supervised approaches or even self supervised ones. Nevertheless, even in such settings there is a need for careful orchestration on the amount of data and the most informative data to be used. This challenge opens the doors to techniques such as *active learning* where the user participates in labeling the data. However, this needs to be done in a non-overwhelming manner by choosing the data samples to ask user's opinion on. Uncertainty-aware approaches to deep learning, can not only provide robust predictions and indicate when human intervention is needed but also inform on which samples the current trained model is uncertain on and ask for user's input on only a portion of the total sensed data. Additionally, since each user is unique, there are certain characteristics which need to be used for further personalization and calibration. Personalizing the machine learning model to the specific user comes with the computation challenges of running training on tiny devices which is still a hard task. Therefore, head-worn platforms require the following system optimizations in order to provide a personalized user experience while preserving the privacy of the collected data.

3.3 System Optimizations

Challenge-C: *Generally, mobile health applications require continuous and long-term monitoring of various biomarkers or human behavior, which inevitably consumes power and drains the device battery quickly. For example, existing commercial earbuds can only operate continuously for several hours with a full charge. With the inclusion of more sensors, the power consumption will increase, further shortening the operation time. How to reduce the power consumption and extend battery lifetime is another pressing challenge.*

Opportunity 1: Health Detection Aware Duty Cycling. A common approach to reduce system power consumption is by judicious duty-cycling, i.e., keep the sensor in sleep mode the majority of time and wake it only when it is necessary. However, in multi-sensor based mobile health settings, special attention should be paid. We observed that there exist correlations between different biosignals, which could be utilized for power consumption optimization. For example, stress might lead to an increase of body temperature, heart rate, breathing rate, and disturbance of the EEG signal. Thus, only a part of the available sensors are needed to detect a stressful situation, while the rest can be in sleep mode. In addition, such correlation could also be used to prioritize different biosignals. As a result, only the sensors associated with high priority biosignals need to be sampled to reduce the power consumption. Furthermore, one biosignal can be used as the trigger to invoke the measurement of another biomarker that is supposed to be sampled periodically.

Opportunity 2: Energy Harvesting. In addition to minimize power consumption at the system level, actively harvesting energy from the context is another promising solution. Researchers have proposed various power sources for head-worn devices, including thermal energy (human body heat and sunlight), kinetic energy (ear canal deformation [3], jaw movement during chewing, and head motions), and electrical energy (endocochlear potential in the inner ear [14]). Nevertheless, realization of practical energy harvesting head-worn devices require significant efforts. First, the amount of harvested energy is positively correlated with the size (or weight) of the energy harvester, which is in conflict with the compact form factor of head-worn devices. Thus, miniaturization of energy harvesters or replacement of device components (e.g., shell) with energy harvesting materials (e.g., flexible solar panels) could be viable directions. Second, the availability of different energy sources varies with time (body heat is perpetual, while ear canal deformation only happens when the jaw moves). With such information, designers could schedule more frequent sensing when energy budget is abundant, and vice versa. Third, energy harvesting signal itself can reflect certain context[13]. Thus, reusing the energy harvester as a sensor to measure health-related information (e.g., the amount of thermal energy reflects the change of human body temperature) or trigger other sensors could also extend the battery lifetime.

Challenge-D: *The majority of existing head-worn devices (e.g., earbuds) need a companion device(e.g., a smartphone or a laptop) for data analysis and offloading. Although such devices are generally more powerful in terms of computation, storage, and battery, it also bounds or constrains the operation of the head-worn device. For instance, if the smartphone connected to the earbuds runs out of battery or requires the computation for other prioritized tasks, the earbud is overshadowed. How to decouple such dependency is a critical challenge.*

Opportunity: Stand-Alone Devices. The main reason for this dependency is the small and constrained form factor of head-worn devices, together with their limited computation resources and communication capabilities (i.e., the lack of another RF module other than Bluetooth). A possible research direction is to devise stand-alone head-worn devices that can operated independently. In this vision, the system requirement for stand-alone head-worn devices is even more stringent. Power consumption, latency, on-device processing versus offloading trade-offs, privacy, as well as dedicated operating systems (OS), and OS-level sensor scheduling should all be thoroughly investigated. We also expect the industry to extend their research efforts towards this direction and make concrete engineering contributions, further accelerating the development.

3.4 Usability and Adherence

Challenge-E: *Despite the great promise of mobile health with head-worn devices, the platforms are still at early stages without widespread adoption in human daily life. How to improve the usability (interaction) of head-worn device is a grand challenge and requires additional efforts.*

Opportunity: Unconventional UIs. One of the factors that affects user experience is the way people interact with the head-worn devices. While these platforms are continuously and passively monitoring human signals, users may need to interact with them for on-demand data uploading (to the smartphone or the cloud), audio information reporting, enabling/disabling certain sensors or changing the sensing duty-cycling, to name a few. However, more attention should be paid to the human-machine interaction (HCI) aspect. Depending on the type of the head-worn device, specific HCI techniques should be designed to enable a friendly user experience, especially for future stand-alone devices. For glasses, due to the large lens and their special location (in front of eyes), existing touch mechanism can be directly adopted [11, 20]. Moreover, since glasses are equipped with camera sensors, gaze-based interaction would be an appealing for specific applications, e.g., PDF reader. Contrary, for earables, because of the lack of screen for inputs and feedback, we envision gesture and voice based approaches as the be potential candidates for input. In-air gestures (like moving towards/away from the ear) could be detected with proximity, acoustic, or light sensors, whereas touch gestures (finger taps on the head) could be captured with vibration, acoustic, and pressure sensors [19]. However, as reported by Serrano et al., some gestures may not be socially acceptable, therefore, these social aspects should be taken into consideration when choosing the desired set of gestures [19]. Voice-based inputs are intuitively captured with microphones, however this might not always be a feasible solution depending on the scenarios, i.e. situations where the user cannot speak loudly or the noise in the environment interferes with the captured signal.

Challenge-F: *As head-worn devices for continuous health monitoring need to be worn for a long time, form is a crucial factor that will affect the adherence level. How to discover a brand new form or adapt existing forms for healthcare is a big challenge.*

Opportunity: New Forms for Healthcare. In exploring new forms for head-worn devices, there is a big pool of existing head accessories to use as a starting point. These existing forms have already been accepted by the users and have been proved to withstand the test of time, therefore the transition to a smart device is easier. Here we can mention practical accessories such as helmets and hats, but also more fashion accessories such as hair clips and bands, earrings, or even hair extensions. For example, (1) helmets, which are traditionally used for road safety, can be equipped with various sensors to monitor human health status, emotions, or drunk behavior during riding. Many athletes wear (2) head bands during training or official matches. By embedding lightweight sensors in the head band, it is possible to monitor their physiological and emotional status for performance improvement —as the head is an optimal position to capture these signals. (3) Clip-in hair extensions are a very popular fashion (and not only) instrument which are placed in various parts of the head. These accessories could be a potential novel form factor for placing invisible EEG electrodes close to the scalp while monitoring different brain areas. Another example for continuous monitoring of oral health is by embedding sensors in (4) the tooth filling or prosthetic device. The benefits of monitoring oral health are multi-fold with the latest studies associating poor oral hygiene with dementia[10]. Finally, the opportunities in using existing forms or introducing new ones is still an open research area worth exploring given the aforementioned benefits of head-worn devices.

3.5 Data Privacy

Challenge-G *Head-worn platforms open the door to sense new biological signals and bio-metrics, which uncovers unprecedented wealth of sensitive information about human. As stated by the European legislation regarding sensitive and private data (GDPR), it is of paramount importance to preserve the privacy of the users. This becomes even more pressing when it comes to sharing datasets collected for research purposes. While on-device computation aids preserving the privacy of user information and data, it might not be always feasible due to computation constraints. To address the privacy concerns stemming from sending the data to the cloud, privacy-preserving approaches are needed.*

Opportunity 1: Information Preserving User Obfuscation. While there has been great effort in trying to sanitize and anonymize network-traffic datasets and alike, dealing with user health data is a completely different challenge. Preserving the quality of the collected bio-signals, whilst preventing others from discovering the identity of the users (thus linking it to all sort of private and sensitive information) represents a top priority in the agenda of all researchers. This concern presents a great opportunity for studying to what extent the intercepted signal can lead to a specific individual as well as the amount of data needed to achieve this malicious goal.

Opportunity 2: Secure Networking. The head-worn device ecosystem needs a platform for secure communication between its member devices. Different to other broad IoT scenarios, this platform is characterized by cooperation of a limited number of devices and specific functionalities. Therefore, it can be designed to support only a few channels of communication and connected devices in order to avoid malicious connections. This allows for creating an ad-hoc secure system which can exploit hardware built-in security features[5] in an efficient manner by isolating most critical code or even the whole functionality (depending on the scale) into individual compartmentalised areas. This means that using the secure hardware capabilities in place of some or all memory addresses will improve the spatial memory safety, protecting the data and models in the aforementioned head-worn devices.

Opportunity 3: Human Anonymization. Some head-worn devices are equipped with sensors that can measure sensitive human information during the operation, which might invade the privacy of the surrounding users. For example, Google Glass is equipped with a camera sensor to monitor the environmental view of the user for applications, like outdoor navigation, during which the face of other people in the view can be also captured. As the face is a very powerful biometric widely used in different authentication systems, the exposure of other people's face might incur critical privacy and security issues. Therefore, there is an urgent need for techniques to anonymize the identity or even conceal facial characteristics of these people.

[5]https://www.arm.com/architecture/cpu/morello

4 FINAL REMARKS

This paper reviews current progress, identifies challenges, and points out the future research directions for head-worn sensing and computing. Our review revealed that current research trends on head-worn devices are closely related to health monitoring with both BCI, smart-glasses, and earables. Head-worn devices show great potential, for instance, to track infections. For example, in the sadly timely case of COVID-19, wearables such as earbuds or glasses could be used both as a health monitoring system (e.g. cough detection, temperature check, etc.), as well as for prevention (e.g. social distancing, face mask wearing detection, frequent touches of the face, etc.). Our findings, on one hand, suggest that head-worn wearables could play a critical major role for mobile health, and on the other hand indicate that there is large room for improving the compliance, robustness and usability of current systems. To provide the guidance and agenda for researchers interested in head-worn devices, we highlighted both challenges and opportunities stemming from their future development and usage. Further, as with all commercially available sensing platforms, ethics and privacy considerations arise with head-worn devices, too [15]. We have to acknowledge and embrace that *with great sensing capability comes great responsibility.* Therefore, sensory enhancements will inevitably come with new, stringent, privacy and ethical concerns and challenges the researchers will have to face and address.

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