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Wearable Biosensors

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ABSTRACT

One of the new technologies in the field of health is wearable biosensor, which provides vital signs monitoring of patients, athletes, premature infants, children, psychiatric patients, people who need long-term care, elderly, and people in impassable regions far from health and medical services. The aim of this study was to explain features and applications of wearable biosensors in medical services. Smart wearable in the technology industry for 2021 is one that is looking to be a big and profitable market. Wearable biosensors capable of continuous vital signs monitoring and feedback to the user will l be significantly effective in timely prevention, diagnosis, treatment, and control of diseases.

KEYWORDS: Wearable biosensors, Ring sensor, Smart devices, Healthcare Diagnosis

I. INTRODUCTION

Miniaturization of laboratory apparatus into microscale devices is a promising technology called lab-on-a-chip (LOC) [1]. About 30 years ago the concept of micro total analysis systems (μTAS) emerged from the field of semiconductor fabrication and was enhanced by microelectromechanical systems (MEMS) technologies [2–4]. The μTAS concept is to shrink an entire analytical procedure, such as cell sorting, single-cell capture, captured-cell transport, cell lysis, and intracellular analysis, into a miniaturized multifunctional chip [5–7], and nowadays its well-known synonym is called lab-on-a-chip (LOC) [3,4]. This growing field has garnered considerable attention since scaled-down biochemical analysis has several key advantages over both conventional and current laboratory benchtop methods [3,5]. These advantages are consistently demonstrated in clinical medicine, engineering, biology, and life science, etc., for example, to expedite the experimental process by embracing automation and parallelization [1,8,9]; to lower the cost by reducing the volume of expensive reagents [1,5,10,11]; to yield better interpretation of experimental results by gleaning vital information at cellular even molecular levels [12–14].

Interest in device miniaturization [15–17], combined with advances in bio microfabrication and enabling materials [18], is motivating various microfluidic methods in which microchips can be mass-manufactured at extremely low cost via polymers (e.g., polydimethylsiloxane, PDMS) and soft lithography for microfabrication [5,19]. Microfluidics is the science of microscale devices that process and manipulate extremely low (109 to 1018 L) amounts of fluids in microchannels with dimensions of tens of micrometers [10]. Conventional macroscale experimental technologies meet difficulties to deal with such low amounts of fluids, impeding their development in various fields. Conversely, microfluidic technologies begin to address numerous tough challenges, because fluid phenomena at the microscale are dramatically different from those at the macroscale [3].

Despite all the attractive capacities of LOC/microfluidics devices that have enabled the widespread implementation of microchip-based systems in biology and life science [3–5,22], microfluidic technologies often only improve the performance of existing macroscale assays or provide equivalent alternatives [13]. Conversely, they have not reached their full potential due to the lack of essentially new capacities [3]. In recent years, however, LOC/microfluidics technologies begin to address some problems that have not yet been solved by current laboratory benchtop methods. An excellent example can be found in wearable/ambulatory healthcare monitoring and sports analytics harnessing skininterfaced wearable biosensors [15,23]. Although this field is still in its infancy, the fundamentals of it are exceptionally strong: in the past decade, the wearable LOC devices gradually integrated with well-established techniques, including biocompatible materials [24,25], flexible electronics [26–30], optical/electrochemical sensors [14,26,31,32], microfluidics [21,33–35], near-field communications (NFC) [36], pain-free microneedles [37–40], as well as big data and cloud computing [14,41,42]. These above-mentioned enabling techniques establish the foundations for a new generation of wearable biosensors that directly interfaced with the human epidermis instead of rigid packages embedded in wrist straps or bands [23,43–45]. The distinguishing characteristics of the emerging wearable biosensors, lightweight, flexibility, and portability [31,36,46], have made them especially suitable for point-of-care testing (POCT). Therefore, brand-new wearable biosensors capable of real-time physiological monitoring quickly emerge, as shown in Figure 1. However, these wearable biosensors are mainly designed for health monitoring [15,34,41,45,47,48], especially, some of them are only developed to measure the physical strain/stress bending change [25,49,50]. Although many wearable devices have been deployed in sports, they are used to monitoring biophysical markers [23], such as movement [51] and cardiovascular information (e.g., blood oxygenation) [26,52,53].

On the business side, CDO needs to constantly review the governance policy and conflict management is important to follow the continual data change based on business changes. Also, the CDO needs to develop the governance policy to prevent the various risks for publishing only the minimum necessary information due to risks. Finally, short-term development and design based on implicit domain knowledge and assumptions can make data reuse more difficult. For such problems, IBM and Microsoft have proposed data management systems with a data catalog to establish the data governance method to eliminate the tradeoffs between analytics cost and operation cost.[16]

The term “visual analytics” was introduced as “the science of analytical reasoning facilitated by interactive visual interfaces” [7]. However, it was pointed out that, based on current practice, a more specific definition would be that visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision making based on large and complex datasets [8]. In systems like, for example, the Visual Cluster Rendering System (VISTA) [9], the objective is to display the dataset in such a way that it would be easy for a human to manually cluster data and verify existing clustering results visually.

In systems like the Visual Cluster Rendering System (VISTA) [9] the objective is to display the dataset in such a way that it would be easy for a human to manually cluster data and verify existing clustering results visually. While VISTA is often intended to import an existing clustering to validate or modify the clustering, it is also able to produce clustering by itself though its interactive visualizations.[17]

II. LITERATURE SURVEY

In this section, we discuss the literature supporting the use of wearable devices in cardiovascular patient care, reviewing the critical clinical studies on the most common cardiovascular applications published in the past 15 years

2.0.1 Risk assessment and lifestyle interventions.

Global cardiovascular disease risk assessment is traditionally based on clinical risk scores that estimate the 10-year risk. However, most of these scores do not capture the dynamic changes in personalized risk that closely follow lifestyle habits. The incorporation of subjective lifestyle behaviours in risk assessment has been challenging; therefore, objective data derived from wearables provide a renewed opportunity to make the assessment of the risk of cardiovascular disease more accurate, comprehensive and dynamic over a lifetime. Several studies have shown wearable-measured physical activity to have an inverse dose-dependent relationship with all-cause mortality5,34–38. Moderate-to-vigorous physical activity (MVPA), measured with the use of triaxial accelerometers, was associated with a lower mortality than light physical activity or sedentary behaviour in several US cohorts and in a Swedish population-based cohort34–38. Another study of women with a mean (s.d.) age of 72 (5.7) years showed that as few as 4,400 steps per day were significantly associated with a 41the benefits levelled at 7,500 steps per day39. Of note, stepping intensity was not associated with mortality after adjusting for steps per day. Wearable data also facilitate the application of realtime behavioural change techniques (BCTs) such as just-in-time adaptive interventions, designed to dynamically assess user needs and provide the appropriate amount and type of intervention at the relevant time. Several trials were designed to assess the benefits of wearable-guided BCTs. The mActive trial enrolled 48 outpatients from an academic.

2.1 Screening and diagnosis

2.1.1 Hypertension.

Initiating hypertension screening in young adulthood is widely recommended to prevent cardiovascular disease24. Oscillometric or cuff-less wearables that accurately measure BP and are continuously worn on the wrist might be more convenient in the ambulatory setting than traditional upper arm BP devices for the screening of hypertension, the selfmonitoring of BP and the titration of antihypertensive drugs48.

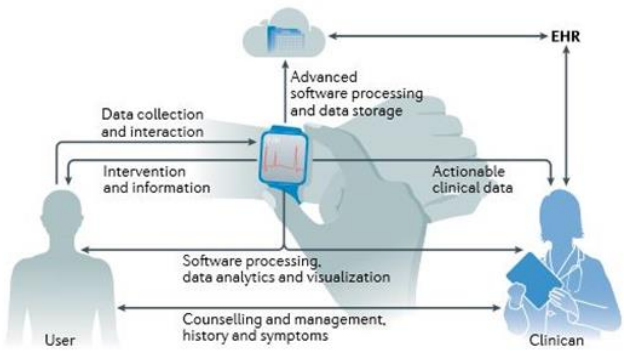

Fig. Smart wearable data workflow and integration in clinical practice

2.1.2 Atrial fibrillation and other arrhythmias

The global burden of AF and its association with stroke, HF and mortality have been well established49. Wearables might be a convenient tool to diagnose asymptomatic or symptomatic AF20. The mSToPS study50, which included both a randomized trial and a prospective cohort, evaluated the effect of immediate versus delayed continuous ECG monitoring with the use of a Zio patch (iRhythm Technologies, USA) on new AF diagnosis at 4 months and 1 year.

2.1.3 Other diagnostic applications

For risk factor screening, a semi-supervised learning algorithm, developed from ¿57,000 personweeks of data from Fitbit, Apple Watch and Wear OS (Google, USA), classified high cholesterol levels and hypertension with high accuracy (area under the curve (AUC) 0.7441 and 0.8086, respectively) using HR and step count data available from these commercial wearables59. In another study, a convolutional neural network developed with a training dataset of 35,970, 12-lead ECGs and validated in an independent dataset of 52,870 ECGs classified ventricular dysfunction with good accuracy60.

III. CONCLUSION

It is clearly evident that accelerometers and motion sensors, biochemical sensors, and photoplethysmography sensors are the most prominent wearable biosensor technologies. We know that each of these technologies has specific challenges that need to be addressed during the sensor design process. Accelerometers and motion sensors require the integration of another wearable physiological monitoring device as well as some type of computer software interface equipped with specific algorithms for signal manipulation and analysis. Biochemical sensors have more complex requirements concerned with the biocompatibility and other chemical properties of the human body. There must not only be consistent sample delivery to the active surface of the sensor, but also the long term stability of the sensing interface. In addition, low sample detection limits that require cumbersome and repetitive sensor calibration are other common issues. There are multiple environmental factors that must be considered including the sample having active interferences to overcome and biofouling in the joint of the sensor. Photoplethysmography sensors have the motion artifact challenge that needs to be addressed in order to ensure optimum signal quality. These types of sensors must deal with the fluctuation in light absorption from the exposure to various ambient lighting conditions as well. We know that all of these sensors must be comfortable and compact enough so that they can be worn everyday just like regular clothing. It is from this perspective that we must always take the overall safety of the patient into account during the sensor design process. The overall accuracy of accelerometers and their integration with physiological monitoring definitely could be addressed in the future to improve precision and effectiveness. The extreme versatility and flexibility of biochemical sensor applications make them always a candidate for further investigation and analysis. There may be more efficient methods to attenuate the effects of diverse ambient lighting conditions on photoplethysmography sensors. It is quite obvious there is a need for additional research into developing more technologies involving wearable biosensors because of their significant appeal for mobile monitoring in the medical device industry. This will provide us with even more methods to effectively monitor patients and provide healthcare practitioners with additional tools at their disposal.

IV. REFERENCES

[1]. Patel, S., et al., A review of wearable sensors and systems with application in rehabilitation. Journal of neuroengineering and rehabilitation, 2012. 9(1): p. 21.

[2]. Asada, H.H., et al., Mobile monitoring with wearable photoplethysmographic biosensors. Engineering in Medicine and Biology Magazine, IEEE, 2003. 22(3): p. 28-40.

[3]. Ming-Zher, P., N.C. Swenson, and R.W. Picard, Motion-tolerant magnetic earring sensor and wireless earpiece for wearable photoplethysmography. Information Technology in Biomedicine, IEEE Transactions on, 2010. 14(3): p. 786-794.

[4]. Fernandes, M.S., et al., Hydrogel-based photonic sensor for a biopotential wearable recording

system. Biosensors and Bioelectronics, 2010. 26(1): p. 80-86.

[5]. Altini, M., J. Penders, and O. Amft. Personalizing energy expenditure estimation using a cardiorespiratory fitness predicate. in Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2013 7th International Conference on. 2013.

[6]. Yaofeng, W., Y. Rong, and C. Yuquan. Heart rate monitoring in dynamic movements from a wearable system. in Medical Devices and Biosensors, 2008. ISSS-MDBS 2008. 5th International Summer School and Symposium on. 2008.

[7]. Yurtman, A. and B. Barshan, Automated evaluation of physical therapy exercises using multi-template dynamic time warping on wearable sensor signals. Computer Methods and Programs in Biomedicine, 2014. 117(2): p. 189-207.

[8]. Bandodkar, A.J., et al., Epidermal tattoo potentiometric sodium sensors with wireless signal transduction for continuous non-invasive sweat monitoring. Biosensors and Bioelectronics, 2014. 54(0): p. 603-609.

[9]. Chen, C.-Y., et al., Flexible PDMS electrode for one-point wearable wireless bio-potential acquisition. Sensors and Actuators A: Physical, 2013. 203(0): p. 20-28.

[10]. Lam, S.C.K., et al., A smartphone-centric platform for personal health monitoring using wireless wearable biosensors, in Proceedings of the 7th international conference on Information, communications and signal processing. 2009, IEEE Press: Macau, China. p. 192-198.

[11]. Chuang, M.-C., et al., Flexible thick-film glucose biosensor: Influence of mechanical bending on the performance. Talanta, 2010. 81(1–2): p. 15-19. 0

[12]. Morris, D., et al., Bio-sensing textile based patch with integrated optical detection system for sweat monitoring. Sensors and Actuators B: Chemical, 2009. 139(1): p. 231-236.

[13]. Paradiso, R., et al. Knitted bioclothes for cardiopulmonary monitoring. in Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE. 2003.

[14]. Zuliani, C. and D. Diamond, Opportunities and challenges of using ion-selective electrodes in environmental monitoring and wearable sensors. Electrochimica Acta, 2012. 84(0): p. 29-34.

[15]. Singh, R.R., S. Conjeti, and R. Banerjee, A comparative evaluation of neural network classifiers for stress level analysis of automotive drivers using physiological signals. Biomedical Signal Processing and Control, 2013. 8(6): p. 740-754.