At-Home Healthcare Through Smart-Environmental Sensing, Including Biometrics for Multi-Factor Authentication

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Wes Anderson
Department of Biomedical Engineering
Colorado State University
Fort Collins, CO, 80523, USA
wes.anderson@colostate.edu

Steven J. Simske
Department of Systems Engineering
Colorado State University
Fort Collins, CO, 80523, USA
steve.simske@colostate.edu

***Abstract*—There is a growing need for at-home, personalized, accessible, and accurate healthcare. The potential of Internet of Things (IoT) enabled sensors for non-invasive medical diagnostics and therapeutic monitoring as well as for environmental monitoring through a "smart-home" system and multi-factor authentication using various biometrics, create a vast number of possibilities for further implementation of these sensing opportunities into society.**

Keywords—biometrics, artificial intelligence, mobile healthcare, privacy, personalized healthcare

I. Introduction

Over the past few decades, Internet of Things (IoT) enabled sensors have been increasingly adopted for a wide variety of purposes. Sensors for air quality monitoring, movement and gait analysis, and location services have been increasingly adopted in today's society. In fact, the International Data Corporation (IDC) estimated that there will be 41.6 billion connected IoT devices by the year 2025 [1]. These sensors include, but are not limited to, gas sensors, pressure sensors, temperature and humidity sensors, miniaturized microphones, GPS units, and inertial measurements units (IMU), such as accelerometers and gyroscopes. The need for more comprehensive environmental monitoring due to a quickly changing climate is becoming more apparent, and the technological advancements in the field of IoT's have made this more feasible.

The capabilities of these IoT enabled sensors have expanded due to research into the field of non-invasive medical diagnostics and therapeutic monitoring techniques. This leads to the potential for at-home healthcare opportunities, both for those in assisted care situations – in which frequent diagnostics may be necessary – and for those who have limited availability to proper healthcare services and are thus in need of frequent diagnostics, such as patients with diabetes. This is addressed through a combination of data collection, connectivity of multiple types and units of sensors, and artificial intelligence (AI) and machine learning (ML) algorithms, as well as "smart home" environments. In the midst of the COVID-19 pandemic, the need to stay home when possible has become a familiar part of life. In developing countries, where healthcare infrastructure is often limited, and the burden of disease is high, technology for monitoring of specific biosignals will also be immensely beneficial. This is also true of remote locations in any locale. The most recent PMC report of the year stated that one of the most important goals of healthcare moving forward is to implement better personalized healthcare in order to optimize medical decisions, improve medical treatments, and reduce waiting lists and financial costs [2]. Mobile diagnostics give the opportunity for both of these goals, and many others, to be met. The two main methods of mobile medical diagnostics are through sensing and imaging. This paper will focus on the potential for IoT sensing capabilities in the field of mobile health diagnostics.

The vast amount of data collection available with this technology will require security measures such as multi-factor authentication to protect the individual's privacy rights, and thus ensure data security for the system. Three important considerations for privacy include the frequency of data upload, the user focus (e.g., the anonymization of lack thereof of the user), and the proactivity of the user with the device (e.g., the control of collection frequency by the user) [3]. If the dataset is de-identified, the number of threats to the data producer (e.g., the user) decreases [4]. Patients in assisted care living, who are frequently less technologically grounded, benefit from a form of system activation that concurrently provides security and privacy for the acquired data. Recently, physical and continuous biometrics have surged in usage for multi-factor authentication through human-computer interface (HCI) in cellular devices, personal computers, and elsewhere. The methods of at-home diagnostics, which include measurements of exhaled breath (EB), voice, wearable monitors (heart rate and blood pressure), and measurements of movement and gait through inertial measurement units (IMUs). These methods can be simultaneously employed as biometrics; either individually as continuous biometrics, or in combination as hybrid biometrics [5]. This form of authentication is able to eliminate a level of identification (or at least reduce the exposure to a single type of biometric) while simultaneously adding user focus to the situation. The purpose of this article is to provide a practical insight into the use of multiple IoT sensors for a combined decision regarding 1) the user's health status, 2) the status of the surrounding environment, 3) the security of the data collected by the system through dynamic biometrics, and 4) the hybridization (or merging) of these systems through synergistic implementation as a single, portable system. Potential components of the system will be analyzed for their practicality, cost, size, power consumption, and accuracy when combined with ML/AI methods. Ultimately, a more general system optimization, based on evolutionary or agent-based modeling principles, can be formulated for different applications of interest.

II. IoT Sensors for At-Home Healthcare

A. *Environmental Gas Sensor Arrays for Non-Invasive Diagnostics and Exposure Analysis*

The knowledge that breath odors can be used for diagnostic purposes goes back as far as 400 B.C, where it is mentioned by Hippocrates as a diagnostic tool [6]. In recent years, 1765 different gases/VOC's (volatile organic compounds) have been recognized in EB [7]. The methods of measuring these components include gas chromatography (GC), mass spectrometry, laser-absorption spectroscopic techniques, and chemical sensors and sensor arrays [7]. For sensing or detection methods to be viable, they must have sufficient sensitivity, high selectivity, and system stability [8].The cheaper and simpler alternative to GC, which has been the most common method to this point, are chemical sensor arrays, which have shown promising results in medical diagnostics for kidney disease, diabetes, Alzheimer's, Parkinson's, and lung cancer. Multiple reviews have summarized the potential uses of sensitive materials in the form of semiconductor-based chemiresistors or sensor arrays, which include metal oxides, graphene, and carbon nanotubes, among others [7,8,9]. Chemiresistive gas sensors are reasonably applicable to the field of early disease screening through EB measurements due to their recent advancements in compact size, low power consumption, inexpensive price, and easy integration into sensor arrays [10].

TABLE I: Examples of verified biomarkers present in EB, and their respective diseases.

Gas/VOC	Corresponding Disease(s) for which the gas/VOC has relevant diagnostic value
Acetone	Diabetes[7]
Ammonia	Kidney disease[6] and renal function[7]
Carbon Monoxide	Lung inflammation[7]
Dimethyl Sulfide	Liver Disease[7]
Ethane	Schizophrenia[7]
Hydrogen Cyanide	Bacterial Infection[7]
Nitric Oxide	Asthma[7]
Methane	Irritated bowl syndrome, oxidative stress, etc.[8]
Carbon dioxide	Helicobacter pylori infection[9]

Examples of VOC's and their corresponding diseases are shown in Table 1. These diseases range from minor bacterial infections to major diagnoses, such as liver or kidney disease. Major diseases, such as lung cancer, colorectal cancer, breast cancer, and tuberculosis have biomarkers identified, but more studies are needed to verify and simplify these [11]. Saidi et al. recently discovered four new biomarkers for lung cancer through exhaled breath analysis and showed that electronic nose (e-nose) type sensor arrays are viable for not only determining the presence of lung cancer, but also the histological type of lung cancer [12]. Further studies of this sort must continue to help narrow down the most descriptive biomarkers, as many of these major diseases need early detection and diagnosis for improved treatment options and results. Sensor arrays are generally useful for distinguishing the presence of a single disease from a healthy person; however, the ability to distinguish the presence of different diseases from each other is not yet possible due to the vast overlap of biomarkers between diseases [11]. The ability to distinguish patterns for distinct diseases is available; this method is analogous to a "fingerprint" measurement of a person. "Fingerprints" of biomarkers can be determined through further studies to give a more in-depth distinction between sets of biomarkers present in the state of a disease.

Lung function analysis, or finding the spot where expiration ends and the consecutive inspiration starts, is a crucial step in pulmonary function testing [13]. Changes in the respiratory cycle, including frequency and continuity of breathing, are other informative measurement made possible through sensor arrays. Individual psychological stress caused by cardiac and arterial vascular dysfunction can be monitored [10], and the presence of lung diseases and infections can be detected and diagnosed at early stages through the tracking of this cycle. The final use of EB measurements is the tracking of environmental exposure through VOC detection. Most of the VOC's found in EB are in fact due to this environmental exposure, which has practical uses in the broader area of personalized medicine, wherein measurement, diagnosis, prognosis, and therapy are customized to the individual.

B. *Diagnostics Through Voice Recordings*

Microphones have been integrated into much of the current technology used in today's world, including cellular devices, laptops, the interiors of cars, and many others. The low cost, low powered devices give high-quality signals that allow for speech recognition, and the expanding research on noise cancellation creates superb results. Multiple studies have recently recognized that, because of the direct correlation between voice impairments and Parkinson's disease in 90% of patients, a voice recognition method is very useful for early detection of the disease [14,15,16,17,18], which affects seven to ten million people worldwide [17]. Similarly, speech analysis has been used by groups like Koing et al to diagnosis mild cognitive impairment (MCI) and early stage Alzheimer's disease with as high as 87% accuracy [19]. Kaminska et al. showed that, through speech analysis and acoustic features, the four states of bipolar disorder (mania, euthymia, depression, and normal) were able to be monitored with varied success through clustering methods (up to 80% correlation of clustering) [`0]. Early diagnosis and frequent monitoring of these diseases improves treatment options for those who suffer the effects, and speech analysis through data acquisition using microphones are making this more and more possible.

Speech analysis has also been utilized for pathology detection in patients by multiple research groups [21,22,23]; in these studies, those participants who are healthy and who are sick are recognized correctly with as high of accuracy as high as 98.23% was achieved [22]. Though this type of analysis is not specific to any certain disease, some groups are attempting to use speech analysis to diagnose specific illnesses. Brown et al. have begun studies into using recordings of both speech and coughing, along with an input of symptoms by the user, to diagnose COVID-19 with mild success to date [24]. Similarly, Lei et al. used recordings of breathing sounds for both classification between healthy and pathological patients and as reliable diagnostic suggestions the flu, pneumonia, and bronchitis [25]. Detecting voice disorders, which can occur after a lasting cold or flu, a continuing virus or bacteria, or from vocal abuse, are important as well. Akbari et al. was able to distinguish between subsets of different voice disorders with varying success, including paralysis, hyperfunction, unilateral vocal fold paralysis, vocal fold polyp, vocal fold nodules, A–P squeezing, and gastric reflux, with classification of one subset reaching as high as 97% [26]. From these results, it is clear that the clinical relevance of diagnostics based on voice data and speech analysis is practical for implementation in a mobile healthcare system.

C. *Wearable Monitors for Vital Recordings, Motion, Gait, and Related Therapeutics*

The ability to portably monitor heart rate and blood pressure has gained relevance in the past few decades [27] .This has been made possible through wearable monitors, such as pulse oximeters, through photoplethysmography, and wearable cuffs, which are now commonly found in many smartwatch products, such as the AppleWatch. Data from these sensors are of great importance, as hypertension, or high blood pressure, is an often-undetected health disorder that can lead to more severe diseases, such as heart disease (including congestive heart failure) or renal dysfunction [28]. This issue can be resolved through wearable monitoring systems that communicate alert messages to the patient and healthcare provider when these sensors detect alarming measurements [29]. These wearable monitors can also be utilized to measure stress levels, as studied by Can et al., who were able to achieve 97.92% accuracy for three-level stress detection with their person-specific models [30]. When integrated into a system of other IoT's, the impact of these wearable monitors will only increase.

IMUs have been integrated into many of the same technologies that microphones have, including cellular devices, newer drive-assist vehicles, and various others. These IoT sensors have also been heavily studied as wearable sensors for their ability to monitor the various stages of rehabilitation for patients with cerebral palsy [31,32,33]. This is important, as the high incidence of and cost associated with cerebral palsy means improved rehabilitation strategies are necessary [33]. Rehabilitation post-stroke is a similar situation that can require high incidence and improved rehabilitation strategies [34,35]. Laudanski et al. able to recognize overground walking, stair ascent, and stair descent with 100% accuracy and overground walking, stair ascent, and descent with a distinction between stepping pattern used while negotiating stairs (step-over-step (SOS) and step-by-step (SBS)) with 94% accuracy for post-stroke patients [34].

The same sensors have been utilized to monitor everyday function for signs of something out of the ordinary for elderly patients, or those at high risk for injury [36]. Similarly, these sensor systems can monitor rehabilitation motions of patients suffering from frozen shoulder, knee surgery, and hip surgery with recognition rate above 85% [37]. While results of wearable IMU devices for different rehabilitation tracking and monitoring techniques is proven to be sufficient, the number of IMUs needed for these applications is difficult to determine, as a review by Reich et al. noted, because comparison between descriptions of positions of these sensors throughout the different studies is not precise enough, and thus the comparison lacks uniformity [38]. This does not deter from the fact that these sensors have shown their utility within their own systems and would be beneficial when included in an at-home healthcare system with other IoT sensor systems.

D. *Effects of Environmental Pollution on Human Health Conditions*

Air pollution exists in many different forms and has a major impact on the lives of those that live in its midst. Many studies agree on the major impacts that air pollution has on respiratory diseases, functions, and inflammations, as well as cardiovascular diseases and functions. [39,40,41,42]. The World Health Organization estimates that particulate matter (PM) air pollution contributes to approximately 800,000 premature deaths each year through these impacts [41], and the six major air pollutants include particle pollution, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides, and lead [42]. PM pollution, which comprises particulates in the air between the sizes of 2.5 and 10 microns, can be readily detected through sensor arrays. This is of the utmost importance, as susceptible populations, such as the elderly, asthmatics, or those infected with COVID-19, may benefit from limiting their outdoor activity during times where pollution is at a peak, and when poor air quality days are occurring.

Changes in this manner may benefit individual patients in both short-term, symptomatic control and in long-term cardiovascular and respiratory complications [41]. The use of these sensor arrays, in combination with breath analysis, will be beneficial in informing public officials of the presence of such pollution spikes in hopes of mitigation, as well as for the spread of public knowledge of the timings and locations of such occurrences. It is also estimated that 4.3 million people die from household air pollution every year globally [42]; localized mitigation, therefore, is also of the utmost importance. Integration of the same sensor arrays used for breath analysis into a monitoring system would be advantageous for these purposes[3].

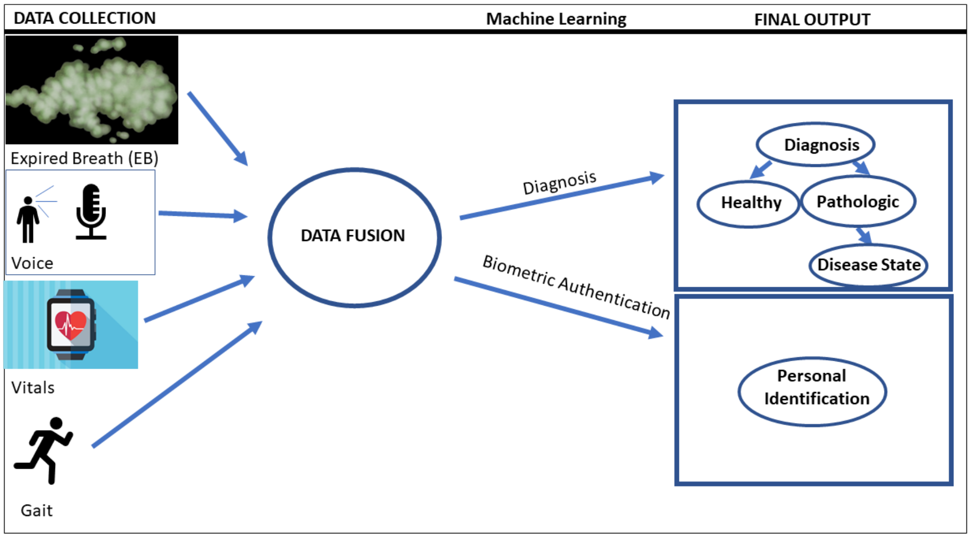

Figure 1: Integration of IoT sensors into one comprehensive system in which data fusion allows for biometrics and diagnostics cohesively.

III. Biometrics, and Multi-Factor Authentication

Biometrics, or the assignment of identity through the measurement of physical attributes or behavior [5], has recently been at an extensive rate for security purposes. This is due to the fact that, when used individually, many former security measures, such as passcodes and pins, are easily stolen or lost, which eliminates that attempt at protection of information in whatever form. Thus, a recent push to use physical biometrics has taken place.

Physical biometrics include facial recognition, fingerprint or iris/retina scans [5], which are still the most popular forms [43]. When combined with other security measures, such as pin codes and passwords, multiple levels of authentication are created. This is a form of identification scheme that pairs a “who-you-are” with a “what-you-know” technique [44]. Another form of identification, “what-you-have”, can also be utilized as a level of authentication; an example of this would be an RFID card, or an e-token [44]. The location of the user is an often forgotten biometric, but it can be utilized in any setting where the location data is readily available.

Similarly, biometrics can be extended to continuous forms, which include arm sweeps, finger writing, gestures, handwriting, keystroke, heartbeat, voice recordings, and gait analyses [5]. With the availability of IoT technology through mobile devices, these biometrics are all readily available for use. Recently, a study by Zhao et al. showed that recordings of intervocalic breath sounds, or sounds made through inhalation of air during speech, was successfully used as a biometric; the group was able to recognize individuals using this biometric with a CNN-LSTM method at 91.3% accuracy [45].

Biometrics are part of the continuum between inspection (or validation) and the forensic identification of a single individual, item, or process. Because of this, IoT sensors of different types also contribute a biometric of their own to the system. Therefore, in order to achieve multi-factor authentication, one must only select the best performing biometrics, whether that be individually or as a combination of two or more through hybrid biometrics. This decision, along with a set of sensor biometrics and a location determination using a GPS unit, provide a path to three-factor authentication, ensuring with even higher confidence the security of the system.

IV. Integration of IoT Sensors into “Magic Wand” Appliance

A system that integrates multiple of IoT sensors for personalized medicine through expired breath analysis, voice recordings, vital monitors, and gait analysis (Figure 1) is able to output both 1) the status of the user, both with respect to the user’s body and their surroundings, and 2) the security of the data from the system. This mobile healthcare and environmental monitoring are given through the magic wand appliance (Figure 2) [47].

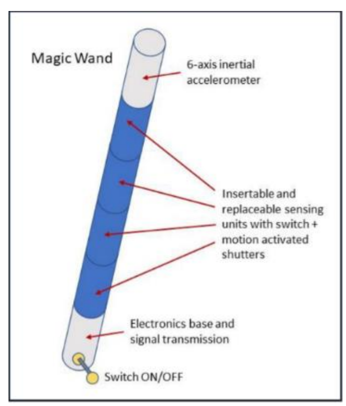

Figure 2: Integration of IoT sensors into one comprehensive system in which data fusion allows for biometrics and diagnostics cohesively [47].

When combined with a ML/AI algorithm for classification, the system will be able to combine outputs from the sensing options mentioned and make a combined decision on the user’s health status while simultaneously validating the identification of the user through multiple biometrics. When applied to specific application areas, evolutionary and agent-based models will also be employed for overall system design, deployment, test, and measurement optimization. For successful output of the system, it is likely that a Bayesian algorithm will be effective for classification of both health status and biometric validation. Communication of the system can be easily implemented through cellular devices, as over 94% of the world population-- that is, 6.8 billion people-- are the subscribers of cell phone and an estimated 2.7 billion subscribers are using Internet [46]. This platform can be employed to assess all necessary health conditions of the user and help educate and empower individuals and communities to understand their local environment and associated health effects. This, in turn, allows them to actively participate in avoidance and/or remediation strategies; that is, personalized healthcare.

V. Conclusions, and Future Works

The many applications and capabilities of IoT sensors and monitors were discussed in depth, and the strengths and potential of each sensing option in the field of personalized healthcare were considered. More systems-level research will be required to determine the most applicable algorithms and biometrics to use for the wide variety of applications and services that are current, or envisioned, elements in personalized medicine.

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