IEEE TRANSACTIONS ON MULTI-SCALE COMPUTING SYSTEMS

Wearable Medical Sensor-based System Design: A Survey

Arsalan Mosenia, *Student Member, IEEE,* Susmita Sur-Kolay, *Senior Member, IEEE,* Anand Raghunathan, *Fellow, IEEE,* and Niraj K. Jha, *Fellow, IEEE*

Abstract—Wearable medical sensors (WMSs) are garnering ever-increasing attention from both the scientific community and the industry. Driven by technological advances in sensing, wireless communication, and machine learning, WMS-based systems have begun transforming our daily lives. Although WMSs were initially developed to enable low-cost solutions for continuous health monitoring, the applications of WMS-based systems now range far beyond health care. Several research efforts have proposed the use of such systems in diverse application domains, e.g., education, human-computer interaction, and security. Even though the number of such research studies has grown drastically in the last few years, the potential challenges associated with their design, development, and implementation are neither well-studied nor well-recognized.
This article discusses various services, applications, and systems that have been developed based on WMSs and sheds light on their design goals and challenges. We first provide a brief history of WMSs and discuss how their market is growing. We then discuss the scope of applications of WMS-based systems. Next, we describe the architecture of a typical WMS-based system and the components that constitute such a system, and their limitations. Thereafter, we suggest a list of desirable design goals that WMS-based systems should satisfy. Finally, we discuss various research directions related to WMSs and how previous research studies have attempted to address the limitations of the components used in WMS-based systems and satisfy the desirable design goals.

Index Terms—Education, health care, human-computer interaction, machine learning, security, wearable medical sensor, wireless communication.

1 Introduction

Aging population and rapidly-rising costs of health care have triggered a lot of interest in wearable medical sensors (WMSs). Traditionally, in-hospital monitoring devices, such as electrocardiogram (ECG) and electroencephalogram (EEG) monitors, have been used to sense and store raw medical data, with processing being performed later on another machine, e.g., an external computer [1]. Several trends in communication, signal processing, machine learning, and biomedical sensing have converged to advance continuous health monitoring from a distant vision to the verge of reality. Foremost among these trends is the development of Internet-connected WMSs, which can non-invasively sense, collect, and even process different types of body-related data, e.g., electrical, thermal, and optical signals generated by the human body.

WMSs enable proactive prevention and remote detection of health issues, thus with the potential to significantly reduce health care costs [2], [3]. Since the introduction of the first wearable heart monitor in 1981 [4], numerous types of WMS-based systems have been proposed, ranging from simple accelerometer-based activity monitors [3], [5] to complex sweat sensors [6]. WMS-based systems have also been developed for continuous long-term health monitoring [1], [7].

In the last decade, with the pervasive use of Internet-connected WMSs, the scope of applications of WMS-based systems has extended far beyond health care. For example, such systems have targeted application domains as diverse as education, information security, and human-computer interaction (HCI). Park et al. [8] introduced a WMS-based teaching assistant system, called SmartKG. It collects, manages, and fuses data gathered by several wearable badges to prepare valuable feedback to the teacher. Mosenia et al. [9] proposed a continuous authentication system based on WMSs, called CABA. They demonstrated how an ensemble of medical data streams, i.e., a sequence of biomedical signal samples, enables accurate continuous user authentication. Barreto et al. [10] designed and implemented an EEG/Electromyogram (EMG) human-computer interface, which uses biomedical signals gathered from the subject's head to control computer cursor movements.

Despite the emergence of numerous WMS-based systems in recent years, potential challenges associated with their design, development, and implementation have not been well addressed. The main objective of this article is to give researchers new to the field an opportunity to explore the applications offered by such systems, their constituent components, challenges associated with their design and development, and how previous research studies have attempted to address these challenges. In particular, the article:

Acknowledgments: This work was supported by NSF under Grant no. CNS-1219570 and CNS-1617628.
Arsalan Mosenia is with the Department of Electrical Engineering, Princeton University, Princeton, NJ 08544, USA (e-mail: arsalan@princeton.edu).
Susmita Sur-Kolay is with the Advanced Computing and Microelectronics Unit, Indian Statistical Institute, Kolkata 700108, India (e-mail: ssk@isical.ac.in).
Anand Raghunathan is with the School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN 47907, USA (e-mail: raghunathan@purdue.edu).
Niraj K. Jha is with the Department of Electrical Engineering, Princeton University, Princeton, NJ 08544, USA (e-mail: jha@princeton.edu).

Digital Object Identifier no. 10.1109/TMSCS.2017.2675888

- explains in depth the scope of applications of WMS-based systems,
- describes the architecture of a typical WMS-based system and discusses constituent components, and the limitations of these components,
- suggests an inclusive list of desirable design goals and requirements that WMS-based systems should satisfy,
- lists various closely related research directions and discusses how previous research efforts have tried to satisfy the desirable design goals while taking into account the limitations of the system components, and
- provides a blueprint for the future of WMS-based systems and discusses how Fog computing can provide a promising alternative to Cloud computing for such systems.

The remainder of this article is organized as follows. We discuss the scope of applications of WMS-based systems in Section 2. In Section 3, we describe the architecture of a typical WMS-based system. Furthermore, we describe the components that constitute such a system, and their limitations. In Section 4, we provide a list of desirable design goals that WMS-based systems should satisfy and how the goals can be prioritized. In Section 5, we discuss several emerging research topics and directions. In Section 6, we discuss how the Cloud-based architecture is reaching its limitation and how Fog computing can offer a promising alternative. Finally, we conclude in Section 7.

2 Scope of Applications

In this section, we describe various applications of WMS-based systems (a summary is shown in Fig. 1).

2.1 Health care

Rapid advances in WMS-based systems are transforming and revolutionizing health care. Medical WMS-based systems are of two main types: (i) health monitoring systems that monitor the patient to prevent the occurrence of a medical condition or detect a disease at an early stage, and (ii) medical automation systems, which offer continuous treatment or rehabilitation services. Next, we describe each type.

2.1.1 Health monitoring systems

Prevention and early detection of medical conditions are essential for promoting wellness. Unfortunately, conventional clinical diagnostic practices commonly fail to detect health conditions in the early stages since diagnosis is typically performed after the emergence of major health symptoms, and previous medical data on the patient are often very sketchy. Furthermore, clinical practices are difficult to carry out in out-of-hospital environments.

In order to address the above-mentioned drawbacks of traditional clinical practices, several research studies have targeted WMS-based health monitoring systems. Such systems can be divided into two categories based on their main task: (i) preventive systems that aim to provide an approach to prevent diseases before the emergence of their symptoms, and (ii) responsive systems that attempt to detect health conditions at an early stage and provide health reports to the patient or the physician.

Preventive systems: Preventive health monitoring systems provide real-time feedback to the user in an attempt to correct behaviors that might lead to adverse health conditions in the future. They promote healthy behaviors and lower the probability of serious illness by automatically detecting/predicting unhealthy activities and warning the user about them [11]. Posture correctors and fitness trackers are two of the most widely-known types of preventive health monitoring systems.

1. Posture corrector: A poor posture results in muscle tightening, shortening, or weakening, causing several health conditions, e.g., back pain and spinal deformity [12]. Posture correctors [13]–[15] monitor the user's movements and habits and offer real-time feedback upon the detection of any posture abnormality, e.g., slouching when sitting in front of a computer display. In fact, they help the user maintain a healthy posture while performing daily activities.

2. Fitness tracker: Such trackers are in widespread use and their market is rapidly growing. Although they may use different sensing technologies, they all have a common characteristic: they non-invasively measure some types of fitness-related parameters, e.g., calories burned, heart rate, number of steps taken [16], and even sleep patterns [17].

State-of-the-art fitness trackers play a significant role in the Internet of Things (IoT) paradigm by enabling object-to-object communication, transmission of user's data to the Cloud, and remote monitoring of user's activities [18]. For example, a fitness tracker, which can communicate with other objects, may be able to gather data from gymnasium equipment to support aspects of fitness progress awareness, such as shopping suggestions to support the user's fitness regime [19].

Responsive systems: Responsive health monitoring systems aim to detect medical conditions at an early stage by monitoring and analyzing various biomedical signals, e.g., heart rate, blood glucose, blood sugar, EEG, and ECG, over a long time period. For example, the CodeBlue project [20] examined the feasibility of using interconnected sensors for transmitting vital health signs to health care providers. Nia et al. [1] proposed an extremely energy-efficient personal health monitoring system based on eight biomedical sensors: (1) heart rate, (2) blood pressure, (3) oxygen saturation, (4) body temperature, (5) blood glucose, (6) accelerometer, (7) ECG, and (8) EEG. MobiHealth [21] offered an end-to-end mobile health platform for continuous health care monitoring.

2.1.2 Medical automation systems

Unlike health monitoring systems, medical automation systems enhance the user's quality of life after/during the emergence of health issues. They mitigate health issues or minimize disease symptoms by actively providing essential therapy. Based on their functionality, medical automation systems can be divided into two main categories: drug infusion and rehabilitating systems.

Drug infusion systems: Drug infusion systems enable safe injection of pharmaceutical compounds, e.g., nutrients and medications, into the body to achieve desired therapeutic

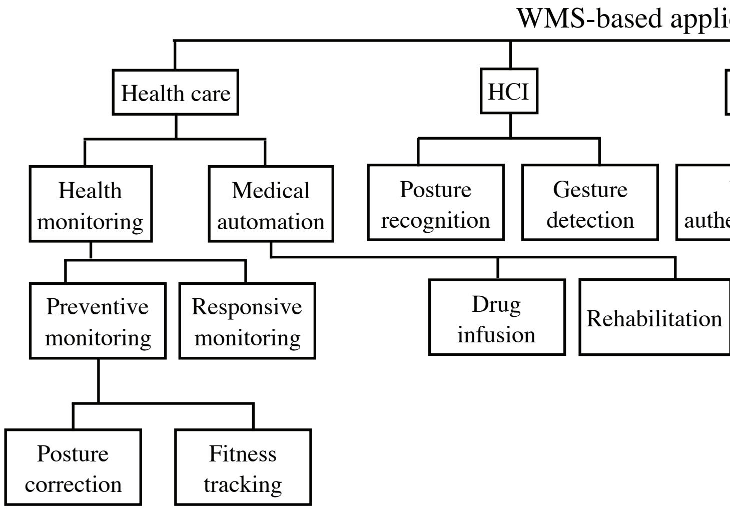

Fig. 1. The scope of applications of WMS-based systems

effects. Automatic drug infusion systems control the drug release profile, absorption, and distribution to enhance the treatment efficacy and safety as well as patient convenience and compliance [22]. Insulin delivery systems are one of the most commonly-used drug infusion systems. They continuously monitor the patient's blood glucose level using wearable glucose sensing patches and inject a prescribed amount of insulin into the blood stream when necessary.

Rehabilitation systems: Such systems have attracted a lot of attention in the past two decades. They are currently used by patients after a major operation, sensory loss, stroke, severe accident, or brain injury [23]. They are also used to help patients who suffer from serious neurological conditions, e.g., Parkinson's disease or post-stroke condition [24]. Gait and/or motor abilities analysis is often used in rehabilitation in hospitals and health care centers [25].

An example of WMS-based rehabilitation system is Valedo [26], which is a medical back-training device developed by Hocoma AG to enhance patient compliance. It gathers trunk movements using two WMSs, transfers them to a game environment, and guides the patient through exercises targeted at low back pain therapy. Another example is Stroke Rehabilitation Exerciser [27] developed by Philips Research, which coaches the patient through a sequence of exercises for motor retraining. Salarian et al. [28] proposed a method for enhancing the gait of a patient with Parkinson's disease. Hester et al. [29] proposed a WMS-based system to facilitate post-stroke rehabilitation.

2.2 HCI

In our daily conversations, the existence of common contexts, i.e., implicit information that characterizes the situation of a person or place that is relevant to the conversation, helps us convey ideas to each other and react appropriately. Unfortunately, the ability to share context-dependent ideas does not transfer well to humans interacting with machines. The design of WMS-based human-computer interfaces has notably improved the richness of communications in HCI [30]. In particular, various WMS-based gesture detection and emotion recognition systems have been proposed in the literature to enhance HCI.

2.2.1 *Gesture detection systems*

Several applications, such as sign-language recognition and remote control of electronic devices, need to respond to simple gestures made by humans. In the last decade, many WMS-based gesture recognition mechanisms have been developed to process sensory data collected by WMSs, e.g., magnetometer [31], [32], accelerometer [3], [5], and gyroscopes [33], to recognize user gesture and enable gesture-aware HCI.

Although gestures from any part of the body can be used for interacting with a computing device, previous experimental research efforts [34] have demonstrated that finger-based gesture detection mechanisms are more successful in practice since their information entropy is much larger than that of interactions based on other human body parts. As a result, several research studies [33], [35]–[37] have focused on developing algorithms to detect hand gestures in real-time. A promising example of WMS-based gesture detection systems is Pingu [33], a smart wearable ring that is capable of recognizing simple and tiny gestures from user's ring finger.

2.2.2 *Emotion recognition systems*

Wearable technology was first used to detect emotions/feelings by Picard et al. [38]. Since then, several researchers have used different sets of WMSs to detect different emotions/feelings, e.g., stress [39], [40], depression [41], and happiness [42]). However, we humans still cannot agree on how we define certain emotions, even though we are extremely good at expressing them. This fact has made emotion recognition a technically challenging field. However, emotion recognition is becoming increasingly important in HCI studies as its advantages become more apparent.

2.3 Information security and forensics

Next, we discuss two well-known types of WMS-based systems developed in the domain of information security and forensics for deception detection and authentication.

2.3.1 Deception detection systems

The examination of the truthfulness of statements made by victims, suspects, and witnesses is of paramount importance in legal settings. Real-time WMS-based deception detection systems attempt to facilitate security screening and criminal investigation, and also augment human judgment [43]. They process sensory data collected by various types of WMSs, commonly heart rate, blood pressure, and accelerometers, to detect suspicious changes in the individual's mental state (for example, a rapid increase in stress level), behavior (for example, involuntary facial movements), and physiological signals (for example, an increase in the heart rate). PokerMetrics [44] is a lie detection system that processes heart rate, skin conductance, temperature, and body movements to find out when the user is bluffing during a poker tournament. FNIRS-based polygraph [45] is another fairly accurate lie detection system that processes data collected by a wearable near-infrared spectroscope.

2.3.2 Authentication systems

Authentication refers to the process of verifying a user's identity based on certain credentials [46]. A rapidly-growing body of literature on the usage of behaviometrics (measurable behavior such as frequency of keystrokes) and biometrics (strongly-reliable biological traits such as EEG signals) for authentication has emerged in the last two decades [47]–[49].

Design of WMS-based authentication is an emerging research domain that is attracting increasing attention. Several research efforts have investigated the feasibility of using the data collected by WMSs as behaviometrics or biometrics. In particular, various research studies [50], [51] have demonstrated that the data collected by smart watches, e.g., acceleration, orientation, and magnetic field, can be used to distinguish users from each other. Furthermore, the use of EEG [52] and ECG [53] signals, as biomedical traits with high discriminatory power for authentication, has received widespread attention. Although EEG/ECG-based authentication systems have shown promising results, they have been unable to offer a convenient method for *continuous user authentication* for two reasons. First, the size/position requirements of the sensors that capture EEG/ECG signals significantly limit their applicability [53], [54]. Second, processing of EEG/ECG signals for authentication is resource-hungry [55]. A recently-proposed WMS-based authentication system, called CABA [9], has attempted to effectively address these drawbacks by using an ensemble of biomedical signals that can be continuously and non-invasively collected by WMSs.

2.4 Education

Next, we describe how technological advances in WMSs are transforming education by opening up new opportunities for employing smart tutoring and teaching assistant systems.

2.4.1 Smart tutoring

With the rapid development of online tutoring and exponential increase in the number of massive open online course websites, many research projects have been conducted on computer-based tutoring systems, which aim to select suitable instructional strategies based on the learner's reactions, mental conditions, emotional states, and feedback (see [56] for a survey). Moreover, there is a strong motivation in the military community for designing adaptive computer-based tutoring systems to provide effective training in environments where human tutors are unavailable [57], [58]. WMS-based tutoring systems can recognize the user's emotional condition, level of understanding, physical state, and stress level by collecting and processing sensory data, e.g., user's heart rate and blood pressure. They can also predict learning outcomes, e.g., performance and skill acquisition, and continuously adapt their teaching/training approaches to optimize learning efficiency [56].

2.4.2 Teaching assistant

WMS-based teaching assistant systems can continuously collect and process various forms of biomedical signals from students, and analyze their voices, movements, and behaviors in order to reach a conclusion about the lecturer's quality of presentation and listeners' level of satisfaction. They can facilitate the teaching process by continuously assisting the lecturer in delivering and subsequently making the learning process shorter, more efficient, more pleasant, and even entertaining. For example, Grosshauser et al. [59] have designed a WMS-based teaching assistant system that monitors movements of dancers and provides feedback to their teacher. Park et al. [8] have designed SmartKG that relies on several wearable badges to provide valuable information about kindergarten students to their teacher.

3 Architecture of Typical WMS-based Systems

In this section, we describe the architecture of typical WMS-based systems. As shown in Fig. 2, the architecture includes three main layers: (i) WMSs, (ii) base stations, and (iii) Cloud servers. In this architecture, the data typically flows from left to right. Although modern WMS-based systems commonly have all three layers, the last two layers may not be necessary for some applications. For example, for posture correction, the data can be processed in the first two layers [60]. Based on the applications enabled by the system and their requirements, each layer offers a variety of services. Next, we describe the role of each layer along with its limitations.

3.1 WMSs

The first layer of the architecture consists of different types of WMSs that can sense electrical, thermal, chemical, and other signals from the user's body. The majority of these sensors, e.g., EEG and ECG, directly sense and collect biomedical signals. However, a few sensors, e.g., accelerometers, gather raw data that can be used to extract health-related information. With continuing performance and efficiency improvements in computing and real-time signal processing, the number and variety of WMSs have increased significantly, ranging from simple pedometers to sophisticated heart-rate monitors. Table 1 lists various commonly-used WMSs in an alphabetical order, along with a short

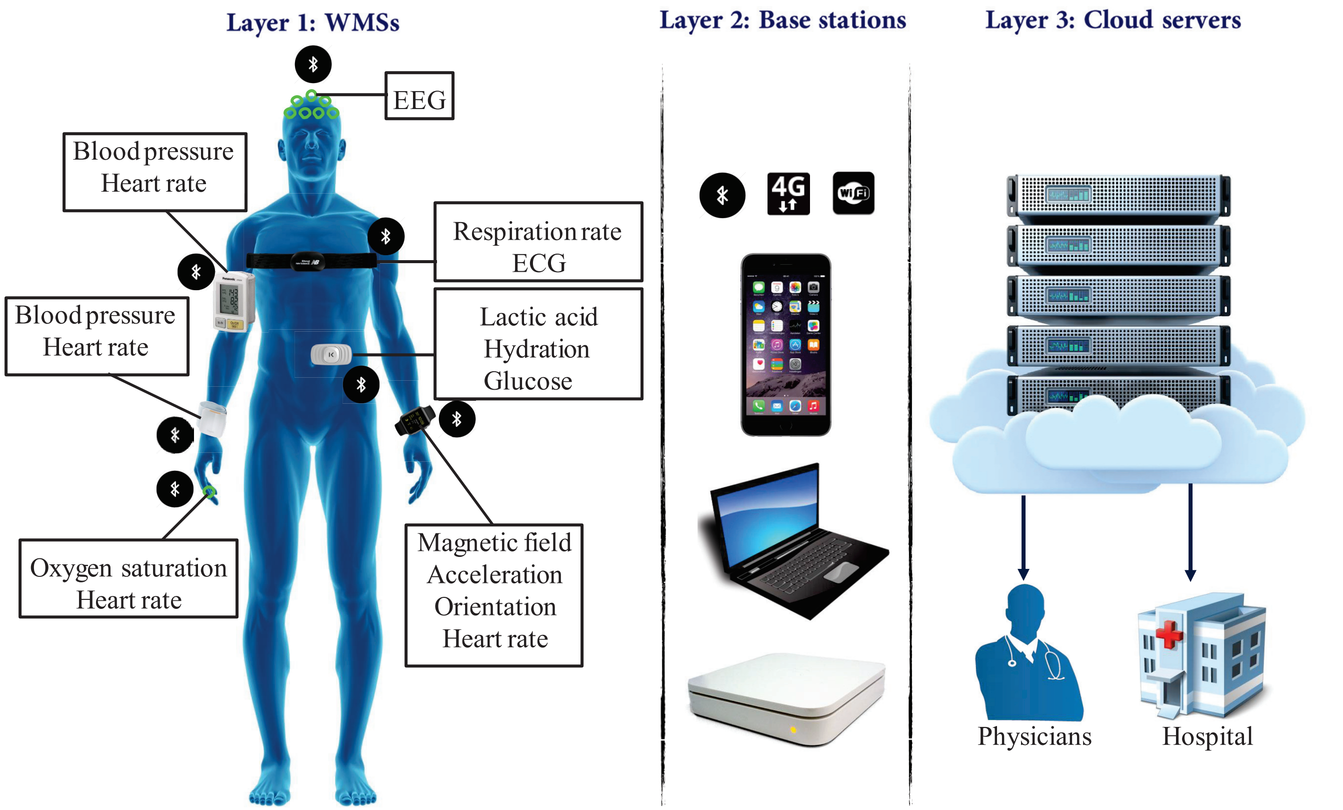

Fig. 2. Architecture of state-of-the-art WMS-based systems

description for each sensor. Despite the variety of WMSs available, they share two common limitations that must be considered while designing a WMS-based system: small storage capacity and limited energy.

Small storage: Storing a large amount of data in a WMS is not feasible for two reasons. First, adding a large storage to a WMS dramatically increases its energy consumption, and as a result, significantly decreases its battery lifetime [1]. Second, the size constraints of WMSs impose specific storage constraints. The WMS size needs to be kept small to ensure user convenience.

Limited energy: The small on-sensor battery with limited energy capacity is one of the most significant factors that limits the volume of data sampled and transmitted by WMSs. It is still feasible to wirelessly transmit all raw data without performing any on-sensor processing if devices are charged regularly, e.g., on an hourly basis. However, forcing the user to frequently recharge the WMSs would impose severe inconvenience. As described later in Section 5.1.3, on-sensor processing may significantly preserve battery lifetime by extracting salient information from the data and transmitting it. The above-mentioned limitations of WMS-based systems have three direct consequences. First, the data generated by WMSs cannot be stored on them for a long period of time and should be transmitted to other devices/servers. Second, only extremely resource-efficient algorithms can be implemented on WMSs. Third, WMSs cannot usually support traditional cryptographic mechanisms and are vulnerable to several security attacks, e.g., eavesdropping.

3.2 Base stations

Due to limited on-sensor resources (small storage and limited energy), the sensory data are frequently sent to external devices with more computation power (the second layer of the architecture). These devices are referred to as *base stations*. They may range from smartphones to specialized computing devices, known as central hubs [1]. They commonly have large data storage, and powerful network connectivity through cellular, IEEE 802.11 wireless, and Bluetooth interfaces, and powerful processors [61]. Smartphones have become the dominant form of base stations since they are ubiquitous and powerful and provide all the technologies needed for numerous applications [62]. Moreover, smartphones support highly-secure encrypted transmission, which deters several potential attacks against the system [9]. The base station has its own resource constraints, though much less severe, in terms of storage and battery lifetime. Continuous processing along with wireless transmission to the Cloud may drain the base station's battery within a few hours, and as a result, cause user inconvenience. Base stations typically perform lightweight signal processing on the raw data and re-transmit a fraction or a compressed form of data to the next layer (Cloud servers) for further analysis and long-term storage.

3.3 Cloud servers

Since both WMSs and base stations are resource-constrained, sensory data are commonly sent to Cloud servers for resource-hungry processing and long-term storage. Depending on the wireless technology used, the data can be sent either directly or indirectly (through a base station, such as a smartphone) to the Cloud. In addition to the huge storage capacity and high computational power that Cloud servers can provide for WMS-based applications, they facilitate access to shared resources in a pervasive manner, offering an ever-increasing number of online on-demand services. Furthermore, Cloud-based systems support remote update of software, without requiring that the patient install any software on the personal devices, thus making system maintenance quick and cost-effective. This makes Cloud-based systems a promising vehicle for bringing health care services to rural areas [63]. Despite the promise of Cloud servers in this context, utilizing them in WMS-based systems has two drawbacks. First, Cloud-based systems are dependent on the reliability of the Internet connection. Outage of Internet service may have serious consequences. For example, unavailability of a seizure prediction system (that tries to detect the occurrence of a seizure a few seconds before the patient's body starts shaking) may lead to a life-threatening situation. Second, the use of Cloud servers increases the response time (the time required to collect sensory data, process them, and provide a response or decision). As a result, there may be a significant deterioration in the quality of service in real-time applications.

4 Design goals and priorities

In this section, we first provide a wish list of design goals for WMS-based systems. Second, we discuss potential conflicts between two or multiple design goals and how designers may prioritize these goals.

4.1 Design goals

Although the scope of applications of WMS-based systems is quite wide, they share several common design goals. Unfortunately, no standard inclusive list of desirable goals has been presented in the literature. We have reviewed and examined many recent research studies on the design and development of different types of WMS-based systems to develop a wish list of design goals for WMS-based systems. Fig. 3 summarizes seven general design goals that should be considered in designing WMS-based systems. Next, we present the rationale behind each goal.

1. Accurate decisions: WMS-based systems process the input data, e.g., an EEG signal, and return decisions as output (for example, whether a seizure is occurring or not). The quality of service provided by a WMS-based system depends on the accuracy of decisions made by it. For instance, a WMS-based authentication system must confidently determine if the user is authorized to use restricted resources, or a posture corrector must accurately decide whether the user's posture is healthy.

2. Fast response: A short response time is a desirable design goal for the majority of systems. In order to ensure user convenience, it is obviously desirable for the system to quickly respond to user requests. Moreover, a short response time is essential for an authentication system, in which the system must quickly authenticate a legitimate user and reject an impostor [9]. Furthermore, a long response time may endanger user safety in some scenarios. For example, if an insulin pump fails to immediately detect an emergency, e.g., hyperglycemia or hypoglycemia, and provide a response when it is necessary, the patient might suffer from life-threatening conditions [64].

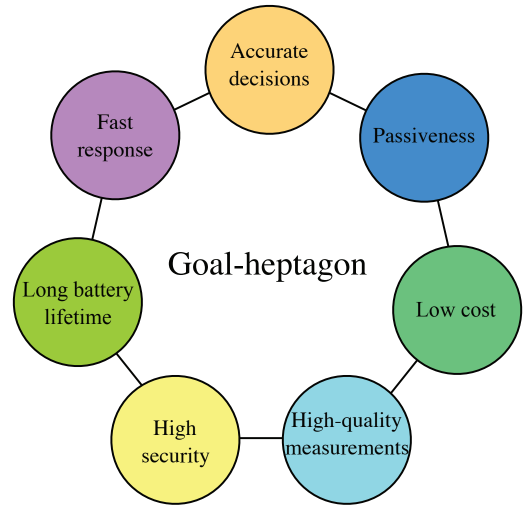

Fig. 3. Goal-heptagon: Desiderata for WMS-based systems.

3. Long battery lifetime: To ensure a long battery lifetime, all components embedded in a WMS and the signal processing algorithms implemented on the device must be energy-efficient. The battery used in a WMS is typically the greatest contributor to both size and weight. As a result, WMSs typically have very limited on-sensor energy [65]. Rapid depletion of battery charge, necessitating frequent, e.g., on an hourly basis, battery replacement/recharge would deter wide adoption of the device [66]. Hence, long battery lifetime is a fundamental design goal for a variety of WMSs.

4. High security: The emergence of the IoT paradigm has magnified the negative impact of security attacks on sensor-based systems. Furthermore, the demonstration of several attacks in recent research efforts (see [67] for a survey) has led to serious security concerns and highlighted the importance of considering security requirements. To ensure system security, different security requirements must be proactively addressed. Traditionally, security requirements are broken down into three main categories: (i) confidentiality, (ii) integrity, and (iii) availability, referred to as the CIA-triad [68]. Confidentiality entails using a set of policies to limit unauthorized access to restricted resources. Integrity ensures that the received commands and collected information are legitimate. Availability guarantees the system is fully functioning.

5. High-quality measurements: Undoubtedly, the quality of the decisions offered by a WMS-based system depends on the quality of sensory measurements provided by WMSs. It has been shown that user's activities may negatively impact the quality of data obtained by the WMSs, e.g., running significantly deteriorates the quality of the signal collected by EEG sensors [69]. Hence, WMSs should be designed to provide accurate and noise-robust measurements during different daily activities, especially intensely physical ones.

6. Low cost: Low cost is one of the most important success

TABLE 1
Common WMSs

Sensor	Description
Accelerometer	measures changes in the acceleration of the device caused by user's movements
Blood pressure sensor	measures systolic and diastolic blood pressures
Electrocardiogram sensor	measures the electrical activity of the heart
Electroencephalogram sensor	measures the electrical activity of the brain
Electromyogram sensor	records electrical activity produced by skeletal muscles
Glucometer	measures approximate blood glucose concentration
Galvanic skin response sensor	measures continuous variation in the electrical characteristics of the skin
Gyroscope	measures changes in device orientation caused by user's movements
Heart rate sensor	counts the number of heart contractions per minute
Magnetometer	specifies user's direction by examining the changes in the earth's magnetic field around the user
Microphone	records acoustic sounds generated by the human body (can be used for respiration analysis or emotion detection)
Near-infrared spectroscope	provides neuroimaging technology to examine an aspect of brain function
Oximeter	measures the fraction of oxygen-saturated hemoglobin relative to the total hemoglobin count in the blood
Pedometer	counts each step a person takes by detecting the motion of the person's hands or hips
Respiration rate sensor	counts how many times the chest rises in a minute
Strain sensor	measures strain on different body parts (can be used to detect when the user is slouching)
Thermometer	measures an individual's body temperature

factors for acceptance of WMSs in the market [70]. The failure of Microsoft's Smart Personal Object Technology [71] due to inadequate cost analyses shows the importance of considering cost of design and development.

7. Passiveness: Passiveness, i.e., minimal user involvement, is a key consideration in designing a WMS-based system. It is very desirable that WMSs be calibrated transparently to the user and sensory data be measured independent of user activities [72]. Obviously, if a wearable device (for example, a smart watch) asks the user to calibrate internal sensors (for example, accelerometers and magnetometers) manually, it may be quite annoying to the user [73]. Furthermore, to ensure user convenience, WMSs must be kept lightweight and as small as possible.

4.2 Design priorities

Although the Goal-heptagon (Fig. 3) provides an inclusive wish list, a conflict may arise between two or more of these design goals in various application domains. Such a conflict may be the result of application-specific requirements. For example, in health care applications, the designers may willingly sacrifice some security requirements to ensure a fast response time in a life-threatening condition [74], whereas high security may be preferred over a fast response time in user authentication systems [9]. Furthermore, there may be a natural trade-off between the design goals. For instance, enhancing the security of a WMS (e.g., implementing strong encryption mechanisms) may significantly increase the energy consumption of the WMS and decrease the device's battery lifetime. Hence, designers commonly prioritize these design goals based on application-specific requirements and limitations. Based on our examination of several survey and technical research papers in different application domains, we have constructed Table 2 that includes the two most commonly-prioritized design goals in each application domain. As a general guideline, long battery lifetime, high-quality measurements, and passiveness are usually given the highest priority for systems that monitor the user or his surroundings, whereas accurate decisions and fast response time are very important considerations for systems that actively interact with the user. The existing literature on design goals of health care- and HCI-related WMS-based systems is fairly mature, however, goals and requirements of other application domains (security and education) are not well-studied.

5 Emerging Research Directions

In this section, we describe several research directions that are closely related to the domain of WMSs and discuss how previous research studies have attempted to facilitate the design and development of WMS-based systems.

5.1 Design of low-power sensors

The on-sensor energy has three major consumers: (i) sampling, (ii) transmission, and (iii) on-sensor computation [1]. Thus, for each WMS, the energy consumption of one or a combination of these consumers should be reduced to enhance its battery lifetime. Next, we summarize what solutions previous studies have proposed to reduce the energy consumption of each of these energy consumers.

5.1.1 Sampling

The sampling energy is mainly the energy consumed by the analog front-end (AFE) and analog-to-digital converter (ADC). The analog front-end typically performs noise suppression, signal conditioning, and amplification [75]. In recent years, numerous AFE architectures have been proposed for acquisition of various biomedical signals (see [76], [77] for EEG and [75], [78] for ECG), which can be utilized in WMSs to significantly reduce sampling energy.

In addition to AFE, the ADC consumes a significant amount of energy. The total energy consumption of an ADC can be divided into: (i) I/O energy, (ii) reference energy, (iii) sample-and-hold energy, (iv) ADC core energy, and (v) input energy [79]. However, separate calculations of these values is difficult. Hence, the total on-chip ADC energy consumption per sample is commonly reported in the literature. In order to enhance ADC energy efficiency, several architectures have been proposed in the last two decades, including but not limited to, asynchronous [80], cyclic [81], and delta-sigma [82] (see [79] for a survey). However, as discussed in

TABLE 2
Commonly-prioritized design goals in different application domains

Application domain	Prioritized design goals
Health care	Accurate decisions and fast response (medical automation) Long battery lifetime and high-quality measurements (health monitoring)
HCI	Fast response time and passiveness
Security and forensics	High security and accurate decisions
Education	Long battery lifetime and passiveness

[1], with recent advances in the design and development of ADCs, their energy consumption has become negligible in comparison to the total energy consumption of WMSs.

In addition to reducing the energy consumption of AFEs and ADCs, a novel efficient sampling technique, called compressive sensing [83], has been proposed for acquiring and reconstructing a continuous signal. Compressive sensing exploits the sparsity of the signal to recover it from far fewer samples than required by the Shannon-Nyquist sampling theorem. Compressive sensing is recommended as a promising sampling technique in several recent research studies on WMSs [84], [85]. It significantly reduces the number of samples required to represent a signal and, at the same time, enables energy-efficient feature extraction and classification in the compressed domain [84].

5.1.2 Transmission protocols

A key consideration in the design of a WMS is the communication technology (radio and protocol) used to connect the WMSs with the base station. Several transmission protocols have been implemented on low-power wireless chipsets to enable energy-efficient data transmission. These protocols include, but are not limited to, ANT/ANT+ [86], ZigBee [87], Bluetooth Low Energy (BLE) [88], and Nike+ [89]. Among them, three protocols have become dominant in the market: ANT, ZigBee, and BLE. Dementyev et al. [90] analyzed the power consumption of these protocols. They found that BLE typically achieves the lowest power consumption, followed by ZigBee and ANT. BLE has become a promising solution for short-range transmissions between WMSs and the base station since it benefits from the widespread use of Bluetooth circuitry integrated in smartphones. In addition to energy-efficient transmission, new protocols commonly offer lightweight strong encryption, e.g., a modified form of Advanced Encryption Standard [91], to provide confidentiality as well as per-packet authentication and integrity. This prevents several security attacks, e.g., eavesdropping and integrity attacks, against WMS-based systems.

5.1.3 On-sensor computation

The required signal processing varies significantly from one application to another. In most applications, sensors perform lightweight signal processing (for example, compression) on the data using on-sensor resources and then transmit the processed data to the base station for further processing, e.g., indexing and machine learning. Due to limited on-sensor resources, on-sensor computation, with the attendant energy overhead, can be avoided for applications in which the sampling rate of biomedical signals is low, e.g., monitoring the patient's body temperature [1]. However, in some applications, on-sensor computation may be beneficial and preferred over off-sensor computation due to one of the following reasons. First, on-sensor computation may significantly reduce the transmission energy (and as a result the total energy consumption of the device) even though it imposes extra energy consumption for computation. For example, if an EEG sensor can detect abnormal changes in the data, it only needs to transmit a small fraction of the data that includes those changes. Second, for some applications, in particular mission-critical applications, the communication delay or the possibility of unavailability of the Cloud or Internet may not be tolerable.

Next, we briefly discuss three types of commonly-used on-sensor algorithms.

1. Aggregation: In practice, a WMS does not usually need to transmit data as fast as it collects them. Hence, it can first aggregate multiple sensory measurements in one packet and only then transmit the packet. In this scenario, the total number of bits transmitted remains the same. However, the average number of transmitted packets over a fixed time period is reduced due to the aggregation. This can significantly reduce the transmission energy of WMSs [92]. The number of samples that can be aggregated in a single packet varies from one device to another based on its resolution, and is specified based on what is a tolerable response time [1].

2. Compression: Compression algorithms reduce the number of bits needed to represent data. On-sensor compression is commonly used to decrease the transmission energy by reducing the total number of transmitted bits [93]. It can also reduce on-sensor storage by dropping non-essential information from the raw data [94]. Several techniques have been discussed in the literature to compress sensory data collected by WMSs. Depending on the recoverability of data, these techniques are divided into three categories: (i) lossless, (ii) lossy, and (iii) unrecoverable. Lossless compression ensures that the original signal can be completely reconstructed from its compressed form without any error, e.g., Huffman coding [95]. Lossy compression permanently removes certain information from the signal, especially redundant information and minor features, e.g., JPEG2000 used for EEG Compression [96]. Finally, in unrecoverable compression, the compression operation is irreversible. For example, one can compress a set of data values by taking their average. However, none of the original values can be extracted from this average [97]. Interested readers can refer to [97] or [98] for a survey on compression techniques.

3. Lightweight classification: Classification is defined as the problem of identifying to which category from a given set a new observation belongs. In a typical classification problem, a feature extraction procedure first extracts a set of features from the raw data. Then, a learning algorithm (also called classifier) trains a model based on a training set of data containing observations whose category membership is known. After training, the classifier infers the category of new observations using the trained model and the features extracted from the new data samples. As a resource-limited device, a WMS may consume a considerable percentage of its energy to extract features and classify data samples. In order to reduce the energy required for inference, both feature extraction and classification must be energy-efficient. Compressive sensing-based feature extraction and classification [84] can significantly reduce the number of features that need to be processed, while maintaining high accuracy. Simple classifiers (for example, decision trees [99] and perceptrons [100]) enable lightweight classification when the use of traditional classification methods (for example, Support Vector Machine [101]), which need more computational power and storage, is not tolerable. A few recent research studies have proposed application-specific classification algorithms, e.g., seizure detection based on EEG signals [102], arrhythmia detection based on ECG signals [103], and physical activity classification based on acceleration data [5], [104].

5.2 Minimally-invasive capture methods

As mentioned in Section 4.1, passiveness is one of the key design goals of a WMS-based system. In order to ensure passiveness, WMSs should exploit minimally-invasive capture methods. Prior to the emergence of WMSs, such methods were developed to enhance user convenience for in-hospital settings. For example, EEG capture was invented by Berger in 1924 [105]. The emergence of WMSs has magnified the need for such methods. As a result, several novel sensing approaches, e.g., for glucose sensing [106], [107] and sweat analysis [6], [108], have been developed for wearable watches and patches. They can non-invasively analyze on-skin chemical substances and minimize/eliminate the need for incisions or surgery. For example, Gao et al. [6] have proposed a wearable sweat-analyzing patch that selectively measures sweat metabolites (for example, glucose and lactate) and electrolytes (for example, sodium and potassium ions) from on-skin liquids. Designing novel minimally-invasive methods for gathering biomedical data using wearable technology is an ongoing research direction that has attracted significant attention in recent years.

5.3 Security and privacy

The pervasive use of WMSs, along with the emergence of the IoT paradigm during the last decade, has led to several threats and attacks against the security of WMS-based systems and the privacy of individuals [67]. Security and privacy of WMS-based systems have garnered rapidly increasing attention in recent years. We expect they will continue to attract attention due to the existence of domain-specific challenges, ubiquitous use of WMSs, and immaturity of existing solutions. The domain-specific design challenges are two-fold. First, as mentioned in Section 3, the WMS-based systems typically cannot utilize strong cryptographic mechanisms, which were mainly designed for computer systems, due to limited on-sensor resources, in particular, small storage and energy capacity. Second, they must ensure that their security measures do not endanger user safety. For example, in health care applications, physicians must be able to access the data collected by WMSs and control the devices without a notable delay in an emergency situation in which the patient needs immediate medical assistance.

Unfortunately, the security/privacy threats against WMS-based systems are not well-addressed. This has made WMSs targets of a multitude of adversaries, such as cybercriminals, occasional hackers, hacktivists, government, and anyone interested in accessing the sensitive information gathered, stored, or handled by WMS-based systems, e.g., health conditions or details of a prescribed therapy. Next, we briefly discuss the most well-known threats/attacks against WMS-based systems along with their known, but not yet widely accepted, countermeasures.

5.3.1 *Security threats and attacks*

Potential vulnerabilities of WMS-based systems and attackers' abilities may differ significantly from one application domain to another. However, only a few research studies have taken the application domain into account while considering security issues (see [9] for attacks against a WMS-based authentication system and [109] or [110] for concerns in health-related applications), and the majority of research efforts only focus on one of the three components of WMS-based systems, as discussed earlier in Section 3: WMSs, base station, and Cloud servers. Mosenia et al. [67] discuss 19 types of security attacks against the objects commonly used in IoT-enabled systems and their countermeasures. Since the majority of WMSs are connected to the Internet (either directly or through a smartphone), almost all such attacks are also applicable to WMS-based systems. Many survey articles [111]–[113] summarize security attacks against wireless sensor networks (WSNs) that are also applicable to WMS-based systems. Subashini et al. [114] describe various security attacks against the Cloud. These attacks/challenges include, but are not limited to, web application vulnerabilities such as Structured Query Language (SQL) injection, authorization/access control, integrity attacks, and eavesdropping. Among previously-proposed attacks against WMS-based systems, the most well-known ones are: (i) eavesdropping on the communication channel to record unencrypted packets (an attack against confidentiality), and (ii) injection of illegitimate packets into the communication channel by reverse engineering the communication protocol (an attack against integrity). Encryption is the most effective approach for preventing these attacks. However, traditional encryption mechanisms are not suitable for WMSs due to on-sensor resource constraints. In order to reduce the resource overheads of encryption, several lightweight encryption mechanisms [115], [116] have been proposed in recent studies. Unfortunately, finding a practical low-power key exchange mechanism to securely share the encryption key is still a challenge, but with some solutions on the horizon [117].

5.3.2 *Privacy concerns*

With the exponential increase in the number of WMS-based systems, ensuring user privacy is becoming a significant challenge. Smart wearable devices, e.g., smart watches, are equipped with many compact built-in WMSs (for example, accelerometers and heart rate sensors) and powerful communication capabilities in order to offer a large number of services. They collect, process, and store several types of private user-related data. Several recent research efforts have demonstrated how WMS-based systems may intentionally/unintentionally reveal the personal or corporate secrets of the user [118]–[120]. For example, Wang et al. [118] demonstrate the feasibility of extracting the user's password by processing data gathered by the smart watch. The use of encryption may reduce leakage of private information by protecting the communication channel. However, various side channels leak information even when the system uses encryption. For example, Nia et al. [121] propose a new class of information security attacks that exploit physiological information leakage, i.e., various forms of information that naturally leak from the human body and WMSs, to compromise privacy. Despite the existence of signal strength reduction, information reduction, and noise addition techniques [122], [123] that may partially address physiological information leakage, providing a comprehensive solution to address side channel information leakage in WMS-based systems is currently a challenging research topic.

5.4 Calibration and noise cancellation

The negative impact of various disturbances on the data collected by WMSs has been extensively discussed in recent research. In particular, it has been shown that environmental noise [124], [125], user movement [126], [127], and changes in sensor locations [128]–[130] can impact sensory measurements significantly. For example, Salehizadeh et al. [126] discuss how sudden user movements can negatively impact pulse oximetry measurements, thus leading to inaccurate readings and even loss of signal. Alinia et al. [128] demonstrate that a change in the location of an accelerometer can impact the quality of sensory readings.

The above examples demonstrate that the various sources of noise should be taken into account while designing WMSs, and each sensor should be calibrated to ensure reliability and validity of measurements [128]. Several noise cancellation and filtering techniques, e.g., for ECG [131] and EEG [132], have been proposed to mitigate the impact of noise. Furthermore, various user-independent and user-oriented calibration algorithms have been developed to calibrate different sensors, e.g., accelerometer [73], [133], magnetometer [134], and gyroscope [135]. Prior to a measurement, a user-independent (user-oriented) calibration algorithm calibrates the sensor without (with) the user's involvement based on the data gathered by the sensor itself and other sensors embedded in the system. However, there is still a significant gap between the quality of measurements provided by wearable sensors and that of in-hospital monitoring devices. Unlike the in-hospital environment in which the user remains almost stationary, the user's position frequently changes during various daily activities. This makes the design of high-precision WMSs, which can provide high-quality measurements comparable to in-hospital equipment, a very complex task.

5.5 Big data

WMSs have the potential to generate big datasets over a short period of time. For example, a typical wearable EEG sensor generates over 120 MB of data per day [1]. With improvements in battery, sensor, and storage technologies, even more data might be generated by WMSs. Processing such large datasets is a complex task due to the following reasons.

1) Data heterogeneity: Different WMSs collect different types of signals [136]. Moreover, due to on-sensor resource constraints, the data may not necessarily be acquired continuously or even at a fixed sampling rate, adding to the heterogeneity of data [137].
2) Noisy measurements: As mentioned earlier, there are numerous sources of noise and disturbances that can corrupt the raw data or deteriorate their quality. In addition, the dataset might have several hours of data missing, when the user is not wearing one or multiple WMSs [138].
3) Inconsistency in data representation: Two devices containing the same sensors may offer very different types of raw data, e.g., older activity monitors generate a proprietary measure called an activity count, i.e., how often the acceleration magnitude exceeded some preset threshold, whereas newer ones commonly provide raw acceleration data [137]. Often, researchers and the industry use their own (often proprietary) data types and standards to report raw data.

Previous WMS-related research on big data has mainly focused on either designing efficient software platforms for processing big datasets or proposing new energy-efficient high-performance architectures to perform computation on big data. Next, we discuss each of these directions.

5.5.1 Efficient software platforms

In order to address the previously-mentioned challenges associated with processing large datasets, two categories of algorithms/platforms have garnered increasing attention in recent years: data cleaning and data analytics platforms.

Data cleaning: One of the first steps in data processing is data cleaning. This is the process of identifying and fixing data errors [139]. Errors can be discovered in datasets by: (i) detecting violations of predefined integrity rules, (ii) finding inconsistent patterns in data, (iii) locating data duplicates, and (iv) searching for outlier values (see [140] for a survey). A few innovative systems, e.g., NADEEF [141] and Bigdansing [142], provide end-to-end solutions to data cleaning. However, there is still a lack of end-to-end off-the-shelf efficient systems for data cleaning [139].

Data analytics: Sensory data encode aspects of human movement, but simultaneously, and at a higher level of abstraction, sleep patterns, physical strength, and mobility, and even complex aspects of physical/mental health [143]. Data analytics entail developing new methods and technologies to analyze big datasets, enabling a variety of services. The aim is to provide efficient easy-to-use software platforms to extract valuable information and trends embedded in the large datasets generated by WMSs. During the last decade, several platforms have been proposed for large datasets. Among them, Google MapReduce [144], Microsoft Dryad [145], Apache Hadoop [146], and Apache Spark [147] have been widely used for large-scale data analysis and mining in health-related applications. They offer scalable, reliable, and distributed computing, especially developed to scale up from a single server to thousands of computing devices. For more technical details, interested readers can refer to above-cited references or see [148] for a survey.

5.5.2 New hardware architectures

In addition to efficient algorithms and software platforms, several novel architectures and hardware implementations have been proposed to address the computing requirements of big data. In addition to traditional central processing units (CPUs), they process data by using the inherent parallelizing capability of graphics processing units (GPUs) and field-programmable gate arrays (FPGAs) (see [149] for a survey). Such architectures enable effective distribution of the workload among the processors.

For example, Chen et al. [150] have utilized multiple GPUs, along with the MapReduce platform [144], to handle large-scale data processing. Wang et al. [151] presented SODA, a software defined FPGA-based accelerator for big data that can reorganize the acceleration engines and manage the multicore system architecture based on the requirement of the various data-intensive applications. Karam et al. [152] designed a reconfigurable hardware accelerator to improve performance and reduce power consumption of data analytics. By employing massively parallel kernel execution in close proximity to the data, they could effectively minimize required data transfers, thus reduce transfer latency and energy requirements. Neshatpour et al. [153] analyzed data mining and machine learning algorithms, which are extensively utilized in big data applications, using a heterogeneous CPU+FPGA platform. They proposed a technique to offload the compute-intensive kernels to the hardware accelerator to achieve the highest speed-up and best energy efficiency.

5.6 Cloud computing

As discussed in Section 3, a large number of WMS-based systems rely on Cloud servers. Despite the promise of the Cloud in this context (access to shared resources in a pervasive manner, large storage capacity, and high computational power), there are several challenges that need to be addressed for on-Cloud WMS-based services (see [154]–[157] for survey articles). We briefly summarize them next.

5.6.1 Availability/reliability

Many researchers have investigated the negative consequences of Cloud failure [158], [159]. Frequent failures of Cloud servers have serious consequences, e.g., increased energy consumption [160], propagated service disruptions [161], and, more importantly, adverse impact on the reputation of the provider [162]. In order to offer a smooth and continuous service, Cloud providers use redundancy techniques [163] (that back up data and store them in multiple data centers geographically spread across the world). As a result, the average system demand is several times smaller than server capacity, imposing significant costs on the provider. To alleviate this burden, an availability-tuning mechanism [164] has been suggested. It allows the customers to express their true availability needs and be charged accordingly.

5.6.2 Access control

The Cloud environment introduces new challenges to access control due to large scale, multi-tenancy (a software architecture in which a single instance of an application runs on a server and serves multiple groups of users), and host variability within the Cloud [165]. In particular, multi-tenancy imposes new requirements on access control as intra-Cloud communication (provider-user and user-user) becomes popular [166]. Recent research efforts have been targeted at new access control techniques [166]–[168], specifically designed for the Cloud. Masood et al. summarize and compare the majority of newly-proposed Cloud-specific access control methods [169].

5.6.3 Standardization and portability

Standardization of an efficient user interface is essential for ensuring user convenience. Web interfaces enable the user to access and analyze data on personal devices, e.g., a smartphone. Unfortunately, such web interfaces commonly impose a significant overhead because they are not specifically designed for smartphones or mobile devices [170]. In addition to standardizing the user interface, standardization of data formats is also essential to enable user-friendly services. If a Cloud provider stores data in its own proprietary format, users cannot easily move their data to other vendors [171].

5.6.4 Bandwidth limitation

This is one of the fundamental challenges that needs to be handled in on-Cloud WMS-based systems when the number of users increases drastically, in particular for applications that need frequent data upload/download. Managing bandwidth allocation in a gigantic infrastructure, such as the Cloud that consists of several heterogeneous entities and millions of users, is very difficult. Some recent research efforts [172], [173] propose efficient bandwidth allocation methods for Cloud infrastructures. For example, Wei et al. propose an allocation based on game theory [173].

6 A Notable Shift from Cloud to Fog

Rapid advances in communication protocols and the miniaturization of transceivers in 1990s, along with the emergence of different WMSs in the early 2000s, transformed the market of wearable technologies. Furthermore, in the last decade, the emergence of Cloud computing and IoT-enabled services has significantly extended the application landscape of WMS-based systems.

Cloud computing offers on-demand and scalable storage and processing services that can be used anytime from anywhere. Since the introduction of Cloud computing, numerous organizations worldwide and researchers have been involved in the design and development of Cloud-enabled WMS-based technologies and services (see [174] for a short survey). Despite the benefits that Cloud computing provides, it cannot be used in latency-sensitive WMS-based systems, such as real-time seizure detectors, due to the following reasons: the delay caused by transferring data to the cloud and back to the application may be intolerable or even a short time of unavailability caused by Cloud failure or lost Internet connection may be life-threatening.

In order to enable reliable service delivery with low response time and address several challenges associated with the use of Cloud computing, such as network delay, ensuring a reliable network connection, and extra costs, Fog computing [175] has been recently suggested. Fog computing is a distributed paradigm, which offers Cloud-like services by exploiting both edge-side and on-Cloud resources. Indeed, it enables real-time data processing by utilizing clients' devices to carry out a substantial amount of storage, communication, control, configuration, and management [176]. Driven by the rising market of personal smart devices, e.g., smartphones and tablets, that are powerful, ubiquitous, and can offer a variety of resources for Fog computing, Fog has emerged as an alternative to Cloud for WMS-based systems.

A few recent studies have discussed the advantages that Fog can offer for WMS-based systems. For example, Cao et al. [177] have proposed a Fog-based system to detect, predict, and prevent falls by stroke patients and demonstrated that their system has various advantages (significantly lower response time and energy consumption) over Cloud-based systems. Stantchev et al. [178] have discussed how Fog computing can offer low latency, mobility support, and privacy awareness for health care applications. To further boost the research on Fog computing, the OpenFog Consortium [179], founded in November 2015, has brought together several researchers and designers from the industry, academia, and non-profit organizations. However, it is still only taking its first research steps and several design challenges and trade-offs associated with the use of Fog computing in different WMS-based systems remain unaddressed. However, the current trend shows that Fog computing will become a very promising research direction in the near future and will continue to grow in importance and applications as IoT conquers new grounds [180].

7 Conclusion

With the pervasive use of Internet-connected WMSs, the scope of applications of WMS-based systems has extended far beyond what has been traditionally imagined. Unfortunately, potential challenges associated with the design, development, and implementation of such systems are not yet well-investigated. This article has attempted to introduce readers to applications offered by WMS-based systems, components that constitute such systems, challenges associated with their design and development, how/whether previous research studies address such challenges, and how Fog computing may transform the future of WMS-based systems.

References

[1] A. M. Nia, M. Mozaffari-Kermani, S. Sur-Kolay, A. Raghunathan, and N. K. Jha, "Energy-efficient long-term continuous personal health monitoring," *IEEE Trans. Multi-Scale Computing Systems*, vol. 1, no. 2, pp. 85–98, 2015.

[2] H. Ghayvat, J. Liu, S. C. Mukhopadhyay, and X. Gui, "Wellness sensor networks: A proposal and implementation for smart home for assisted living," *IEEE Sensors Journal*, vol. 15, no. 12, pp. 7341–7348, 2015.

[3] S. C. Mukhopadhyay, "Wearable sensors for human activity monitoring: A review," *IEEE Sensors Journal*, vol. 15, no. 3, pp. 1321–1330, 2015.

[4] "Olympic medical institute validates Polar RS800 running computer and training system," https://www.polar.com/us-en/about_polar/news/polar_R800, accessed: 10-9-2016.

[5] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Communications Surveys & Tutorials*, vol. 15, no. 3, pp. 1192–1209, 2013.

[6] W. Gao, S. Emaminejad, H. Y. Y. Nyein, S. Challa, K. Chen, A. Peck, H. M. Fahad, H. Ota, H. Shiraki, and D. Kiriya, "Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis," *Nature*, vol. 529, no. 7587, pp. 509–514, 2016.

[7] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Trans. Systems, Man, and Cybernetics*, vol. 40, no. 1, pp. 1–12, 2010.

[8] S. Park, I. Locher, A. Savvides, M. B. Srivastava, A. Chen, R. Muntz, and S. Yuen, "Design of a wearable sensor badge for smart kindergarten," in *Proc. IEEE Int. Symp. Wearable Computers*, 2002, pp. 231–238.

[9] A. Mosenia, S. Sur-Kolay, A. Raghunathan, and N. K. Jha, "CABA: Continuous authentication based on BioAura," *IEEE Trans. Computers*, DOI: 10.1109/TC.2016.2622262, 27 Oct., 2016.

[10] A. B. Barreto, S. D. Scargle, and M. Adjouadi, "A practical EMG-based human-computer interface for users with motor disabilities," *J. Rehabilitation Research and Development*, vol. 37, no. 1, p. 53, 2000.

[11] V. Pejovic, A. Mehrotra, and M. Musolesi, "Anticipatory mobile digital health: Towards personalised proactive therapies and prevention strategies," *arXiv preprint arXiv:1508.03722*, 2015.

[12] W. Y. Wong and M. S. Wong, "Smart garment for trunk posture monitoring: A preliminary study," *Scoliosis and Spinal Disorders*, vol. 3, no. 1, p. 1, 2008.

[13] A. Crane, S. Doppalapudi, J. O'Leary, P. Ozarek, and C. Wagner, "Wearable posture detection system," in *Proc. Annual Northeast Bioengineering Conference*, 2014, pp. 1–2.

[14] E. Sardini, M. Serpelloni, and M. Ometto, "Smart vest for posture monitoring in rehabilitation exercises," in *Proc. IEEE Sensors Applications Symposium*, 2012, pp. 1–5.

[15] H. Harms, O. Amft, G. Tröster, M. Appert, R. Müller, and A. Meyer-Heim, "Wearable therapist: Sensing garments for supporting children improve posture," in *Proc. ACM Int. Conf. Ubiquitous Computing*, 2009, pp. 85–88.

[16] B. Ainsworth, L. Cahalin, M. Buman, and R. Ross, "The current state of physical activity assessment tools," *Progress in Cardiovascular Diseases*, vol. 57, no. 4, pp. 387–395, 2015.

[17] M. de Zambotti, S. Claudatos, S. Inkelis, I. M. Colrain, and F. C. Baker, "Evaluation of a consumer fitness-tracking device to assess sleep in adults," *Chronobiology International*, vol. 32, no. 7, pp. 1024–1028, 2015.

[18] J. Wei, "How wearables intersect with the Cloud and the Internet of Things: Considerations for the developers of wearables," *IEEE Consumer Electronics Magazine*, vol. 3, no. 3, pp. 53–56, 2014.

[19] T. L. Koreshoff, T. Robertson, and T. W. Leong, "Internet of Things: A review of literature and products," in *Proc. AMC Australian Computer-Human Interaction Conference: Augmentation, Application, Innovation, Collaboration*, 2013, pp. 335–344.

[20] D. Malan, T. Fulford-Jones, M. Welsh, and S. Moulton, "CodeBlue: An ad hoc sensor network infrastructure for emergency medical care," in *Proc. Int. Wkshp. Wearable and Implantable Body Sensor Networks*, vol. 5, 2004.

[21] V. Jones, A. van Halteren, N. Dokovsky, G. Koprinkov, R. Bults, D. Konstantas, and R. Herzog, "Mobihealth: Mobile health services based on body area networks," Centre for Telematics and Information Technology, Tech. Rep., 2006.

[22] S. Ozcelik, "Drug infusion systems," *Encyclopedia of Medical Devices and Instrumentation*, pp. 495–508, 2006.

[23] A. Hadjidj, M. Souil, A. Bouabdallah, Y. Challal, and H. Owen, "Wireless sensor networks for rehabilitation applications: Challenges and opportunities," *J. Network and Computer Applications*, vol. 36, no. 1, pp. 1–15, 2013.

[24] A. Muro-de-la Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications," *Sensors*, vol. 14, no. 2, pp. 3362–3394, 2014.

[25] W. Tao, T. Liu, R. Zheng, and H. Feng, "Gait analysis using wearable sensors," *Sensors*, vol. 12, no. 2, pp. 2255–2283, 2012.

[26] "Valedo," https://www.valedotherapy.com/us_en/, accessed: 10-9-2016.

[27] G. Lanfermann, J. Te Vrugt, A. Timmermans, E. Bongers, N. Lambert, and V. Van Acht, “Philips stroke rehabilitation exerciser,” *Technical Aids for Rehabilitation*, 2007.

[28] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, “A review of wearable sensors and systems with application in rehabilitation,” *J. Neuroengineering and Rehabilitation*, vol. 9, no. 1, p. 1, 2012.

[29] T. Hester, R. Hughes, D. M. Sherrill, B. Knorr, M. Akay, J. Stein, and P. Bonato, “Using wearable sensors to measure motor abilities following stroke,” in *Proc. IEEE Int. Wkshp. Wearable and Implantable Body Sensor Networks*, 2006, pp. 4–8.

[30] A. K. Dey, D. Salber, G. D. Abowd, and M. Futakawa, “The conference assistant: Combining context-awareness with wearable computing,” in *Proc. IEEE Int. Symp. Wearable Computers*, 1999, pp. 21–28.

[31] E. Keyes, M. P. Johnson, and T. Starner, “Magnetometer-based gesture sensing with a wearable device,” 2015, US Patent 9,141,194.

[32] D. Kim, O. D. Hilliges, S. Izadi, P. L. Olivier, J. D. J. Shotton, P. Kohli, D. G. Molyneaux, S. E. Hodges, and A. W. Fitzgibbon, “Gesture recognition techniques,” 2014, US Patent 14,280,140.

[33] M. Roshandel, A. Munjal, P. Moghadam, S. Tajik, and H. Ketabdar, “Multi-sensor based gestures recognition with a smart finger ring,” in *Proc. Int. Conf. Human-Computer Interaction*. Springer, 2014, pp. 316–324.

[34] S. K. Card, J. D. Mackinlay, and G. G. Robertson, “A morphological analysis of the design space of input devices,” *ACM Trans. Information Systems*, vol. 9, no. 2, pp. 99–122, 1991.

[35] A. Ferrone, F. Maita, L. Maiolo, M. Arquilla, A. Castiello, A. Pecora, X. Jiang, C. Menon, and L. Colace, “Wearable band for hand gesture recognition based on strain sensors,” in *Proc. IEEE Int. Conf. Biomedical Robotics and Biomechatronics*, 2016, pp. 1319–1322.

[36] Y. Zhang and C. Harrison, “Tomo: Wearable, low-cost electrical impedance tomography for hand gesture recognition,” in *Proc. ACM Symp. User Interface Software & Technology*, 2015, pp. 167–173.

[37] Z. Lu, X. Chen, Q. Li, X. Zhang, and P. Zhou, “A hand gesture recognition framework and wearable gesture-based interaction prototype for mobile devices,” *IEEE Trans. Human-Machine Systems*, vol. 44, no. 2, pp. 293–299, 2014.

[38] R. W. Picard and R. Picard, *Affective Computing*. MIT press Cambridge, 1997, vol. 252.

[39] A. Sano and R. W. Picard, “Stress recognition using wearable sensors and mobile phones,” in *Proc. IEEE Conf. Affective Computing and Intelligent Interaction*, 2013, pp. 671–676.

[40] J. Wijsman, B. Grundlehner, H. Liu, J. Penders, and H. Hermens, “Wearable physiological sensors reflect mental stress state in office-like situations,” in *Proc. IEEE Conf. Affective Computing and Intelligent Interaction*, 2013, pp. 600–605.

[41] X. Li, B. Hu, J. Shen, T. Xu, and M. Retcliffe, “Mild depression detection of college students: An EEG-based solution with free viewing tasks,” *J. Medical Systems*, vol. 39, no. 12, pp. 1–6, 2015.

[42] H. W. Guo, Y. S. Huang, J. C. Chien, and J. S. Shieh, “Short-term analysis of heart rate variability for emotion recognition via a wearable ECG device,” in *Proc. IEEE Int. Conf. Intelligent Informatics and Biomedical Sciences*, 2015, pp. 262–265.

[43] T. O. Meservy, M. L. Jensen, J. Kruse, J. K. Burgoon, J. F. Nunamaker, D. P. Twitchell, G. Tsechpenakis, and D. N. Metaxas, “Deception detection through automatic, unobtrusive analysis of nonverbal behavior,” *IEEE Intelligent Systems*, vol. 20, no. 5, pp. 36–43, 2005.

[44] M. Sung and A. Pentland, “PokerMetrics: Stress and lie detection through non-invasive physiological sensing,” *Ph.D. thesis, MIT Media Laboratory*, 2005.

[45] M. R. Bhutta, M. J. Hong, Y.-H. Kim, and K.-S. Hong, “Single-trial lie detection using a combined fNIRS-polygraph system,” *Frontiers in Psychology*, vol. 6, p. 709, 2015.

[46] P. S. Teh, A. B. J. Teoh, and S. Yue, “A survey of keystroke dynamics biometrics,” *The Scientific World Journal*, vol. 2013, 2013.

[47] K. Delac and M. Grgic, “A survey of biometric recognition methods,” in *Proc. IEEE Int. Symp. Electronics in Marine*, 2004, pp. 184–193.

[48] W. Khalifa, A. Salem, M. Roushdy, and K. Revett, “A survey of EEG based user authentication schemes,” in *Proc. IEEE Int. Conf. Informatics and Systems*, 2012, pp. 55–60.

[49] S. P. Banerjee and D. L. Woodard, “Biometric authentication and identification using keystroke dynamics: A survey,” *J. Pattern Recognition Research*, vol. 7, no. 1, pp. 116–139, 2012.

[50] D. Gafurov, E. Snekkenes, and P. Bours, “Gait authentication and identification using wearable accelerometer sensor,” in *Proc. IEEE Wkshp. Automatic Identification Advanced Technologies*, 2007, pp. 220–225.

[51] A. Ferrari, D. Puccinelli, and S. Giordano, “Gesture-based soft authentication,” in *Proc. IEEE Int. Conf. Wireless and Mobile Computing, Networking and Communications*, 2015, pp. 771–777.

[52] M. Phothisonothai, “An investigation of using SSVEP for EEG-based user authentication system,” in *Proc. IEEE Asia-Pacific Signal and Information Processing Association Annual Summit and Conference*, 2015, pp. 923–926.

[53] Z. Zhao, L. Yang, D. Chen, and Y. Luo, “A human ECG identification system based on ensemble empirical mode decomposition,” *Sensors*, vol. 13, no. 5, pp. 6832–6864, 2013.

[54] M. Teplan, “Fundamentals of EEG measurement,” *Measurement Science Review*, vol. 2, no. 2, pp. 1–11, 2002.

[55] I. Nakanishi, S. Baba, and C. Miyamoto, “EEG based biometric authentication using new spectral features,” in *Proc. IEEE Int. Symp. Intelligent Signal Processing and Communication Systems*, 2009, pp. 651–654.

[56] J. Schneider, D. Börner, P. Van Rosmalen, and M. Specht, “Augmenting the senses: A review on sensor-based learning support,” *Sensors*, vol. 15, no. 2, pp. 4097–4133, 2015.

[57] J. A. Kulik and J. Fletcher, “Effectiveness of intelligent tutoring systems: A meta-analytic review.” *Review of Educational Research*, vol. 86, no. 1, pp. 42–78, 2016.

[58] B. Goldberg, “Intelligent tutoring gets physical: Coaching the physical learner by modeling the physical world,” in *Proc. Int. Conf. Augmented Cognition*. Springer, 2016, pp. 13–22.

[59] T. Großhauser, B. Bläsing, C. Spieth, and T. Hermann, “Wearable sensor-based real-time sonification of motion and foot pressure in dance teaching and training,” *J. Audio Engineering Society*, vol. 60, no. 7/8, pp. 580–589, 2012.

[60] Q. Wang, W. Chen, A. A. Timmermans, C. Karachristos, J.-B. Martens, and P. Markopoulos, “Smart rehabilitation garment for posture monitoring,” in *Proc. IEEE Int. Conf. Engineering in Medicine and Biology Society*, 2015, pp. 5736–5739.

[61] H. Alemdar and C. Ersoy, “Wireless sensor networks for healthcare: A survey,” *Computer Networks*, vol. 54, no. 15, pp. 2688–2710, 2010.

[62] K. Patrick, W. G. Griswold, F. Raab, and S. S. Intille, “Health and the mobile phone,” *American J. Preventive Medicine*, vol. 35, no. 2, p. 177, 2008.

[63] R. P. Padhy, M. R. Patra, and S. C. Satapathy, “Design and implementation of a Cloud based rural healthcare information system model,” *Universal J. Applied Computer Science and Information Technology*, vol. 2, no. 1, pp. 149–157, 2012.

[64] H. Thabit and R. Hovorka, “Closed-loop insulin delivery in Type-1 diabetes,” *Endocrinology and Metabolism Clinics of North America*, vol. 41, no. 1, pp. 105–117, 2012.

[65] D. Culler, J. Hill, M. Horton, K. Pister, R. Szewczyk, and A. Wood, “Mica: The commercialization of microsensor motes,” *Sensor Technology and Design*, vol. 19, pp. 40–48, 2002.

[66] T. Rault, A. Bouabdallah, and Y. Challal, “Energy efficiency in wireless sensor networks: A top-down survey,” *Computer Networks*, vol. 67, pp. 104–122, 2014.

[67] A. Mosenia and N. K. Jha, “A comprehensive study of security of Internet of Things,” *IEEE Trans. Emerging Topics in Computing*, DOI: 10.1109/TETC.2016.2606384, 7 Sept., 2016.

[68] Y. Cherdantseva and J. Hilton, “A reference model of information assurance & security,” in *Proc. IEEE Int. Conf. Availability, Reliability and Security*, 2013, pp. 546–555.

[69] S. E. Kerick, K. S. Oie, and K. McDowell, “Assessment of EEG signal quality in motion environments,” Defense Technical Information Center Document, Tech. Rep., 2009.

[70] “Simplicity and cost will be key to cracking open the wearable device market,” https://gigaom.com/2013/10/16/simplicity-and-cost-will-be-key-to-cracking-open-the-wearable-device-market/, accessed: 10-9-2016.

[71] B. Chris, “How microsoft lost the wrist-top,” *Wired*, vol. 18, no. 7, p. 27, 2010.

[72] T. Pylvänäinen, “Automatic and adaptive calibration of 3D field sensors,” *Applied Mathematical Modelling*, vol. 32, no. 4, pp. 575–587, 2008.

[73] A. Krohn, M. Beigl, C. Decker, U. Kochendörfer, P. Robinson, and T. Zimmer, “Inexpensive and automatic calibration for accelera-

tion sensors," in *Proc. Int. Symp. Ubiquitious Computing Systems*, 2004, pp. 245–258.

[74] T. Denning, K. Fu, and T. Kohno, "Absence makes the heart grow fonder: New directions for implantable medical device security," in *Proc. Wkshp. Hot Topics in Security*, 2008.

[75] C. J. Deepu, X. Xu, X. Zou, L. Yao, and Y. Lian, "An ECG-on-chip for wearable cardiac monitoring devices," in *Proc. IEEE Int. Symp. Electronic Design, Test and Application*, 2010, pp. 225–228.

[76] S. Lim, C. Seok, H. Kim, H. Song, and H. Ko, "A fully integrated electroencephalogram EEG analog front-end IC with capacitive input impedance boosting loop," in *Proc. IEEE Custom Integrated Circuits Conference*, 2014, pp. 1–4.

[77] K. A. Ng and P. K. Chan, "A CMOS analog front-end IC for portable EEG/ECG monitoring applications," *IEEE Trans. Circuits and Systems I: Regular Papers*, vol. 52, no. 11, pp. 2335–2347, 2005.

[78] T.-H. Tsai, J.-H. Hong, L.-H. Wang, and S.-Y. Lee, "Low-power analog integrated circuits for wireless ECG acquisition systems," *IEEE Trans. Information Technology in Biomedicine*, vol. 16, no. 5, pp. 907–917, 2012.

[79] B. E. Jonsson, "An empirical approach to finding energy efficient ADC architectures," in *Proc. IEEE Analog-to-Digital Forum*, 2011, pp. 1–6.

[80] S.-W. M. Chen and R. W. Brodersen, "A 6-bit 600-ms/s 5.3-mW asynchronous ADC in 0.13μm-CMOS," *IEEE J. Solid-State Circuits*, vol. 41, no. 12, pp. 2669–2680, 2006.

[81] C.-C. Lu, "A 1.2 V 10-bit 5 MS/s CMOS cyclic ADC," in *Proc. IEEE Int. Symp. Circuits and Systems*, 2013, pp. 1986–1989.

[82] T. Morita, "Delta-sigma ADC," 2013, US Patent 8,466,821.

[83] R. G. Baraniuk, "Compressive sensing," *IEEE Signal Processing Magazine*, vol. 24, no. 4, pp. 118–120, 2007.

[84] M. Shoaib, K. H. Lee, N. K. Jha, and N. Verma, "A 0.6-107uW energy-scalable processor for seizure detection with compressively-sensed EEG," *IEEE Trans. Circuits and Systems I*, vol. 61-I, no. 4, pp. 1105–1118, Apr. 2014.

[85] M. Zhang, M. M. Kermani, A. Raghunathan, and N. K. Jha, "Energy-efficient and secure sensor data transmission using encompression," in *Proc. IEEE Int. Conf. VLSI Design*, 2013, pp. 31–36.

[86] "ANT basics," https://www.thisisant.com/developer/ant/ant-basics, accessed: 10-9-2016.

[87] P. Kinney, "ZigBee technology: Wireless control that simply works," in *Proc. Communications Design Conference*, vol. 2, 2003, pp. 1–7.

[88] C. Gomez, J. Oller, and J. Paradells, "Overview and evaluation of Bluetooth Low Energy: An emerging low-power wireless technology," *Sensors*, vol. 12, no. 9, pp. 11 734–11 753, 2012.

[89] N. Kane, M. Simmons, D. John, D. Thompson, and D. Basset, "Validity of the Nike+ device during walking and running," *Int. J. Sports Medicine*, vol. 31, no. 02, pp. 101–105, 2010.

[90] A. Dementyev, S. Hodges, S. Taylor, and J. Smith, "Power consumption analysis of Bluetooth Low Energy, ZigBee and ANT sensor nodes in a cyclic sleep scenario," in *Proc. IEEE Wireless Symposium*, 2013, pp. 1–4.

[91] J. Daemen and V. Rijmen, *The Design of Rijndael: AES-The Advanced Encryption Standard*. Springer Science and Business Media, 2013.

[92] H. Ghasemzadeh and R. Jafari, "Data aggregation in body sensor networks: A power optimization technique for collaborative signal processing," in *Proc. IEEE Communications Society Conf. Sensor, Mesh and Ad Hoc Communications and Networks*, 2010, pp. 1–9.

[93] N. Kimura and S. Latifi, "A survey on data compression in wireless sensor networks," in *Proc. IEEE Int. Conf. Information Technology: Coding and Computing*, vol. 2, 2005, pp. 8–13.

[94] M. A. Razzaque, C. Bleakley, and S. Dobson, "Compression in wireless sensor networks: A survey and comparative evaluation," *ACM Trans. Sensor Networks*, vol. 10, no. 1, p. 5, 2013.

[95] M. Nelson and J.-L. Gailly, *The Data Compression Book*. M&T Books New York, 1996, vol. 2.

[96] G. Higgins, S. Faul, R. P. McEvoy, B. McGinley, M. Glavin, W. P. Marnane, and E. Jones, "EEG compression using JPEG2000: How much loss is too much?" in *Proc. IEEE Int. Conf. Engineering in Medicine and Biology Society*, 2010, pp. 614–617.

[97] Y.-C. Wang, "Data compression techniques in wireless sensor networks," *Pervasive Computing*, vol. 61, no. 1, pp. 75–77, 2012.

[98] B. Singh, A. Kaur, and J. Singh, "A review of ECG data compression techniques," *Int. J. Computer Applications*, vol. 116, no. 11, pp. 1–6, 2015.

[99] S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Trans. Systems, Man, and Cybernetics*, vol. 21, no. 3, pp. 660–674, 1991.

[100] Y. Freund and R. E. Schapire, "Large margin classification using the perceptron algorithm," *Machine Learning*, vol. 37, no. 3, pp. 277–296, 1999.

[101] J. A. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," *Neural Processing Letters*, vol. 9, no. 3, pp. 293–300, 1999.

[102] B. Liu, Z. Zhang, G. Xu, H. Fan, and Q. Fu, "Energy efficient telemonitoring of physiological signals via compressed sensing: A fast algorithm and power consumption evaluation," *Biomedical Signal Processing and Control*, vol. 11, pp. 80–88, 2014.

[103] M. Shoaib, N. K. Jha, and N. Verma, "Algorithm-driven architectural design space exploration of domain-specific medical-sensor processors," *IEEE Trans. Very Large Scale Integration Systems*, vol. 21, no. 10, pp. 1849–1862, Oct. 2013.

[104] Y. Liang, X. Zhou, Z. Yu, and B. Guo, "Energy-efficient motion related activity recognition on mobile devices for pervasive healthcare," *Mobile Networks and Applications*, vol. 19, no. 3, pp. 303–317, 2014.

[105] D. Millett, "Hans Berger: From psychic energy to the EEG," *Perspectives in Biology and Medicine*, vol. 44, no. 4, pp. 522–542, 2001.

[106] S. K. Vashist, "Non-invasive glucose monitoring technology in diabetes management: A review," *Analytica Chimica Acta*, vol. 750, pp. 16–27, 2012.

[107] A. J. Bandodkar, W. Jia, C. Yardımcı, X. Wang, J. Ramirez, and J. Wang, "Tattoo-based noninvasive glucose monitoring: A proof-of-concept study," *Analytical Chemistry*, vol. 87, no. 1, pp. 394–398, 2014.

[108] V. F. Curto, S. Coyle, R. Byrne, N. Angelov, D. Diamond, and F. Benito-Lopez, "Concept and development of an autonomous wearable micro-fluidic platform for real time pH sweat analysis," *Sensors and Actuators B: Chemical*, vol. 175, no. 4, pp. 263–270, 2012.

[109] M. McCarthy, "Experts warn on data security in health and fitness apps," *British Medical Journal*, vol. 347, p. 1, 2013.

[110] M. Al Ameen, J. Liu, and K. Kwak, "Security and privacy issues in wireless sensor networks for healthcare applications," *J. Medical Systems*, vol. 36, no. 1, pp. 93–101, 2012.

[111] A.-S. K. Pathan, H.-W. Lee, and C. S. Hong, "Security in wireless sensor networks: Issues and challenges," in *Proc. IEEE Int. Conf. Advanced Communication Technology*, vol. 2, 2006, p. 6.

[112] M. Al Ameen, J. Liu, and K. Kwak, "Security and privacy issues in wireless sensor networks for healthcare applications," *J. Medical Systems*, vol. 36, no. 1, pp. 93–101, 2012.

[113] M. M. Patel and A. Aggarwal, "Security attacks in wireless sensor networks: A survey," in *Proc. IEEE Int. Conf. Intelligent Systems and Signal Processing*, 2013, pp. 329–333.

[114] S. Subashini and V. Kavitha, "A survey on security issues in service delivery models of Cloud computing," *J. Network and Computer Applications*, vol. 34, no. 1, pp. 1–11, 2011.

[115] J. Zhen, J. Li, M. J. Lee, and M. Anshel, "A lightweight encryption and authentication scheme for wireless sensor networks," *Int. J. Security and Networks*, vol. 1, no. 3-4, pp. 138–146, 2006.

[116] C. H. Lim and T. Korkishko, "mCrypton–a lightweight block cipher for security of low-cost RFID tags and sensors," in *Proc. Int. Wkshp. Information Security Applications*, 2005, pp. 243–258.

[117] Y. Kim, W. S. Lee, V. Raghunathan, N. K. Jha, and A. Raghunathan, "Vibration-based secure side channel for medical devices," in *Proc. IEEE Design Automation Conference*, 2015, pp. 1–6.

[118] C. Wang, X. Guo, Y. Wang, Y. Chen, and B. Liu, "Friend or foe?: Your wearable devices reveal your personal PIN," in *Proc. ACM Asia Conf. Computer and Communications Security*, 2016, pp. 189–200.

[119] H. Wang, T. T.-T. Lai, and R. Roy Choudhury, "Mole: Motion leaks through smartwatch sensors," in *Proc. ACM Annual Int. Conf. Mobile Computing and Networking*, 2015, pp. 155–166.

[120] X. Liu, Z. Zhou, W. Diao, Z. Li, and K. Zhang, "When good becomes evil: Keystroke inference with smartwatch," in *Proc. ACM SIGSAC Conf. Computer and Communications Security*, 2015, pp. 1273–1285.

[121] A. M. Nia, S. Sur-Kolay, A. Raghunathan, and N. K. Jha, "Physiological information leakage: A new frontier in health information security," *IEEE Trans. Emerging Topics in Computing*, vol. 4, no. 3, pp. 321–334, 2016.

[122] S. Chen, R. Wang, X. Wang, and K. Zhang, "Side-channel leaks in web applications: A reality today, a challenge tomorrow," in *Proc. IEEE Symp. Security and Privacy*, 2010, pp. 191–206.

[123] D. Agrawal, B. Archambeault, J. R. Rao, and P. Rohatgi, "The EM side channel(s)," in *Cryptographic Hardware and Embedded Systems*. Springer, 2003, pp. 29–45.

[124] J. Kim, T. Lee, J. Kim, and H. Ko, "Ambient light cancellation in photoplethysmogram application using alternating sampling and charge redistribution technique," in *Proc. Annual Int. Conf. IEEE Engineering in Medicine and Biology Society*, 2015, pp. 6441–6444.

[125] P. E. Clayson, S. A. Baldwin, and M. J. Larson, "How does noise affect amplitude and latency measurement of event-related potentials (ERPs)? a methodological critique and simulation study," *Psychophysiology*, vol. 50, no. 2, pp. 174–186, 2013.

[126] S. Salehizadeh, D. K. Dao, J. W. Chong, D. McManus, C. Darling, Y. Mendelson, and K. H. Chon, "Photoplethysmograph signal reconstruction based on a novel motion artifact detection-reduction approach," *Annals of Biomedical Engineering*, vol. 42, no. 11, pp. 2251–2263, 2014.

[127] H. Han and J. Kim, "Artifacts in wearable photoplethysmographs during daily life motions and their reduction with least mean square based active noise cancellation method," *Computers in Biology and Medicine*, vol. 42, no. 4, pp. 387–393, 2012.

[128] P. Alinia, R. Saeedi, R. Fallahzadeh, A. Rokni, and H. Ghasemzadeh, "A reliable and reconfigurable signal processing framework for estimation of metabolic equivalent of task in wearable sensors," *IEEE J. Selected Topics in Signal Processing*, vol. 10, no. 5, pp. 842–853, 2016.

[129] O. Banos, M. A. Toth, M. Damas, H. Pomares, and I. Rojas, "Dealing with the effects of sensor displacement in wearable activity recognition," *Sensors*, vol. 14, no. 6, pp. 9995–10 023, 2014.

[130] P. Alinia, R. Saeedi, B. Mortazavi, A. Rokni, and H. Ghasemzadeh, "Impact of sensor misplacement on estimating metabolic equivalent of task with wearables," in *Proc. Int. Conf. Wearable and Implantable Body Sensor Networks*, 2015, pp. 1–6.

[131] B. Chandrakar, O. Yadav, and V. Chandra, "A survey of noise removal techniques for ECG signals," *Int. J. Advanced Research in Computer and Communication Engineering*, vol. 2, no. 3, pp. 1354–1357, 2013.

[132] J. A. Urigüen and B. Garcia-Zapirain, "EEG artifact removal–state-of-the-art and guidelines," *J. Neural Engineering*, vol. 12, no. 3, p. 31001, 2015.

[133] J. Almazán, L. M. Bergasa, J. J. Yebes, R. Barea, and R. Arroyo, "Full auto-calibration of a smartphone on board a vehicle using IMU and GPS embedded sensors," in *Proc. IEEE Intelligent Vehicles Symposium*, 2013, pp. 1374–1380.

[134] M. Kok, J. D. Hol, T. B. Schön, F. Gustafsson, and H. Luinge, "Calibration of a magnetometer in combination with inertial sensors," in *Proc. IEEE Int. Conf. Information Fusion*, 2012, pp. 787–793.

[135] Y. Li, J. Georgy, X. Niu, Q. Li, and N. El-Sheimy, "Autonomous calibration of MEMS gyros in consumer portable devices," *IEEE Sensors Journal*, vol. 15, no. 7, pp. 4062–4072, 2015.

[136] J. Andreu-Perez, C. C. Poon, R. D. Merrifield, S. T. Wong, and G.-Z. Yang, "Big data for health," *IEEE J. Biomedical and Health Informatics*, vol. 19, no. 4, pp. 1193–1208, 2015.

[137] S. Redmond, N. Lovell, G. Yang, A. Horsch, P. Lukowicz, L. Murrugarra, and M. Marschollek, "What does big data mean for wearable sensor systems?" *Yearbook of Medical Informatics*, vol. 9, no. 1, pp. 135–142, 2014.

[138] N. Eagle and A. S. Pentland, "Reality mining: Sensing complex social systems," *Personal and Ubiquitous Computing*, vol. 10, no. 4, pp. 255–268, 2006.

[139] N. Tang, "Big data cleaning," in *Proc. Asia-Pacific Web Conference*, 2014, pp. 13–24.

[140] E. Rahm and H. H. Do, "Data cleaning: Problems and current approaches," *IEEE Data Eng. Bull.*, vol. 23, no. 4, pp. 3–13, 2000.

[141] M. Dallachiesa, A. Ebaid, A. Eldawy, A. Elmagarmid, I. F. Ilyas, M. Ouzzani, and N. Tang, "NADEEF: A commodity data cleaning system," in *Proc. ACM SIGMOD Int. Conf. Management of Data*, 2013, pp. 541–552.

[142] Z. Khayyat, I. F. Ilyas, A. Jindal, S. Madden, M. Ouzzani, P. Papotti, J.-A. Quiané-Ruiz, N. Tang, and S. Yin, "Bigdansing: A system for big data cleansing," in *Proc. ACM SIGMOD Int. Conf. Management of Data*, 2015, pp. 1215–1230.

[143] C. Gurrin, A. F. Smeaton, and A. R. Doherty, "Lifelogging: Personal big data," *Foundations and Trends in Information Retrieval*, vol. 8, no. 1, pp. 1–125, 2014.

[144] J. Dean and S. Ghemawat, "MapReduce: Simplified data processing on large clusters," *Communications of the ACM*, vol. 51, no. 1, pp. 107–113, 2008.

[145] M. Isard, M. Budiu, Y. Yu, A. Birrell, and D. Fetterly, "Dryad: Distributed data-parallel programs from sequential building blocks," in *Proc. ACM Operating Systems Review*, vol. 41, no. 3, 2007, pp. 59–72.

[146] V. K. Vavilapalli, A. C. Murthy, C. Douglas, S. Agarwal, M. Konar, R. Evans, T. Graves, J. Lowe, H. Shah, S. Seth *et al.*, "Apache Hadoop yarn: Yet another resource negotiator," in *Proc. ACM Symp. Cloud Computing*, 2013, p. 5.

[147] H. Karau, A. Konwinski, P. Wendell, and M. Zaharia, *Learning Spark: Lightning-fast big data analysis*. O'Reilly Media, Inc., 2015.

[148] D. Singh and C. K. Reddy, "A survey on platforms for big data analytics," *J. Big Data*, vol. 2, no. 1, p. 8, 2015.

[149] M. Saecker and V. Markl, "Big data analytics on modern hardware architectures: A technology survey," in *Business Intelligence*. Springer, 2013, pp. 125–149.

[150] Y. Chen, Z. Qiao, H. Jiang, K.-C. Li, and W. W. Ro, "Mgmr: Multi-GPU based MapReduce," in *Proc. Int. Conf. Grid and Pervasive Computing*, 2013, pp. 433–442.

[151] C. Wang, X. Li, and X. Zhou, "SODA: software defined FPGA based accelerators for big data," in *Proc. IEEE Conf. Design, Automation & Test*, 2015, pp. 884–887.

[152] R. Karam, R. Puri, and S. Bhunia, "Energy-efficient adaptive hardware accelerator for text mining application kernels," *IEEE Trans. Very Large Scale Integration Systems*, vol. 24, no. 12, pp. 3526–3537, 2016.

[153] K. Neshatpour, M. Malik, M. A. Ghodrat, A. Sasan, and H. Homayoun, "Energy-efficient acceleration of big data analytics applications using FPGAs," in *Proc. IEEE Int. Conf. Big Data*, 2015, pp. 115–123.

[154] Q. Zhang, L. Cheng, and R. Boutaba, "Cloud computing: State-of-the-art and research challenges," *J. Internet Services and Applications*, vol. 1, no. 1, pp. 7–18, 2010.

[155] R. Moreno-Vozmediano, R. S. Montero, and I. M. Llorente, "Key challenges in Cloud computing: Enabling the future Internet of services," *IEEE Internet Computing*, vol. 17, no. 4, pp. 18–25, 2013.

[156] A. N. Toosi, R. N. Calheiros, and R. Buyya, "Interconnected Cloud computing environments: Challenges, taxonomy, and survey," *ACM Computing Surveys*, vol. 47, no. 1, pp. 7–47, 2014.

[157] C. Rong, S. T. Nguyen, and M. G. Jaatun, "Beyond lightning: A survey on security challenges in Cloud computing," *Computers & Electrical Engineering*, vol. 39, no. 1, pp. 47–54, 2013.

[158] C. Cérin, C. Coti, P. Delort, F. Diaz, and M. Gagnaire, "Downtime statistics of current Cloud solutions," International Working Group on Cloud Computing Resiliency, Tech. Rep., 2013.

[159] K. V. Vishwanath and N. Nagappan, "Characterizing Cloud computing hardware reliability," in *Proc. ACM Symp. Cloud Computing*, 2010, pp. 193–204.

[160] P. Garraghan, I. S. Moreno, P. Townend, and J. Xu, "An analysis of failure-related energy waste in a large-scale Cloud environment," *IEEE Trans. Emerging Topics in Computing*, vol. 2, no. 2, pp. 166–180, 2014.

[161] Y. Wei and M. B. Blake, "Service-oriented computing and Cloud computing: Challenges and opportunities," *IEEE Internet Computing*, vol. 14, no. 6, p. 72, 2010.

[162] S. M. Habib, S. Ries, and M. Muhlhauser, "Cloud computing landscape and research challenges regarding trust and reputation," in *Proc. Int. Conf. Ubiquitous Intelligence & Computing*, 2010, pp. 410–415.

[163] H. Abu-Libdeh, L. Princehouse, and H. Weatherspoon, "RACS: A case for Cloud storage diversity," in *Proc. ACM Symp. Cloud Computing*, 2010, pp. 229–240.

[164] M. Shahrad and D. Wentzlaff, "Availability knob: Flexible user-defined availability in the Cloud," in *Proc. ACM Symp. Cloud Computing*, 2016, pp. 410–415.

[165] K. Ren, C. Wang, and Q. Wang, "Security challenges for the public Cloud," *IEEE Internet Computing*, vol. 16, no. 1, pp. 69–73, 2012.

[166] L. Popa, M. Yu, S. Y. Ko, S. Ratnasamy, and I. Stoica, "Cloudpolice: Taking access control out of the network," in *Proc. 9th ACM SIGCOMM Wkshp. Hot Topics in Networks*, 2010, p. 7.

[167] X.-Y. Li, Y. Shi, Y. Guo, and W. Ma, "Multi-tenancy based access control in Cloud," in *Proc. IEEE Int. Conf. Computational Intelligence and Software Engineering*, 2010, pp. 1–4.

[168] J. M. A. Calero, N. Edwards, J. Kirschnick, L. Wilcock, and M. Wray, "Toward a multi-tenancy authorization system for Cloud services," *IEEE Security & Privacy*, vol. 8, no. 6, pp. 48–55, 2010.

[169] R. Masood, M. A. Shibli, Y. Ghazi, A. Kanwal, and A. Ali, "Cloud authorization: Exploring techniques and approach towards effective access control framework," *Frontiers of Computer Science*, vol. 9, no. 2, pp. 297–321, 2015.

[170] A. Alamri, W. S. Ansari, M. M. Hassan, M. S. Hossain, A. Alelaiwi, and M. A. Hossain, "A survey on sensor-Cloud: Architecture, applications, and approaches," *Int. J. Distributed Sensor Networks*, vol. 2013, 2013.

[171] D. Petcu, G. Macariu, S. Panica, and C. Crăciun, "Portable Cloud applications–from theory to practice," *Future Generation Computer Systems*, vol. 29, no. 6, pp. 1417–1430, 2013.

[172] G. Nan, Z. Mao, M. Yu, M. Li, H. Wang, and Y. Zhang, "Stackelberg game for bandwidth allocation in Cloud-based wireless live-streaming social networks," *IEEE Systems Journal*, vol. 8, no. 1, pp. 256–267, 2014.

[173] G. Wei, A. V. Vasilakos, Y. Zheng, and N. Xiong, "A game-theoretic method of fair resource allocation for Cloud computing services," *J. Supercomputing*, vol. 54, no. 2, pp. 252–269, 2010.

[174] J. Wei, "How wearables intersect with the Cloud and the Internet of Things: Considerations for the developers of wearables," *IEEE Consumer Electronics Magazine*, vol. 3, no. 3, pp. 53–56, 2014.

[175] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, "Fog computing and its role in the Internet of Things," in *Proc. First ACM Wkshp. Mobile Cloud Computing*, 2012, pp. 13–16.

[176] A. V. Dastjerdi and R. Buyya, "Fog computing: Helping the Internet of Things realize its potential," *IEEE Computer*, vol. 49, no. 8, pp. 112–116, 2016.

[177] Y. Cao, S. Chen, P. Hou, and D. Brown, "FAST: A Fog computing assisted distributed analytics system to monitor fall for stroke mitigation," in *Proc. IEEE Int. Conf. Networking, Architecture and Storage*, 2015, pp. 2–11.

[178] V. Stantchev, A. Barnawi, S. Ghulam, J. Schubert, and G. Tamm, "Smart items, Fog and Cloud computing as enablers of servitization in healthcare," *Sensors & Transducers*, vol. 185, no. 2, p. 121, 2015.

[179] "OpenFog Consortium," https://www.openfogconsortium.org/, accessed: 10-9-2016.

[180] "How Fog computing pushes IoT intelligence to the edge," https://techcrunch.com/2016/08/02/how-fog-computing-pushes-iot-intelligence-to-the-edge/, accessed: 10-9-2016.

Arsalan Mosenia received his B.S. degree in Computer Engineering from Sharif University of Technology, Tehran, Iran, in 2012, and M.A. degree in Electrical Engineering from Princeton, NJ, in 2014. He is currently pursuing a Ph.D. degree in Electrical Engineering at Princeton University, NJ. His research interests include wireless sensor networks, Internet of things, computer security, distributed computing, mobile computing, and machine learning.

Anand Raghunathan is a Professor and Chair of VLSI in the School of Electrical and Computer Engineering at Purdue University, where he leads the Integrated Systems Laboratory. His research explores domain-specific architecture, system-on-chip design, embedded systems, and heterogeneous parallel computing. Previously, he was a Senior Research Staff Member at NEC Laboratories America and held the Gopalakrishnan Visiting Chair in the Department of Computer Science and Engineering at the Indian Institute of Technology, Madras. Prof. Raghunathan has co-authored a book ("High-level Power Analysis and Optimization"), eight book chapters, 21 U.S patents, and over 200 refereed journal and conference papers. His publications have been recognized with eight best paper awards and four best paper nominations. He received the Patent of the Year Award (recognizing the invention with the highest impact), and two Technology Commercialization Awards from NEC. He was chosen by MIT's Technology Review among the TR35 (top 35 innovators under 35 years, across various disciplines of science and technology) in 2006, for his work on "making mobile secure". Prof. Raghunathan has served on the technical program and organizing committees of several leading conferences and workshops. He has chaired the ACM/IEEE International Symposium on Low Power Electronics and Design, the ACM/IEEE International Conference on Compilers, Architecture, and Synthesis for Embedded Systems, the IEEE VLSI Test Symposium, and the IEEE International Conference on VLSI Design. He has served as Associate Editor of the IEEE Transactions on CAD, IEEE Transactions on VLSI Systems, ACM Transactions on Design Automation of Electronic Systems, IEEE Transactions on Mobile Computing, ACM Transactions on Embedded Computing Systems, IEEE Design & Test of Computers, and the Journal of Low Power Electronics. He was a recipient of the IEEE Meritorious Service Award (2001) and Outstanding Service Award (2004). He is a Fellow of the IEEE, and Golden Core Member of the IEEE Computer Society. Prof. Raghunathan received the B. Tech. degree in Electrical and Electronics Engineering from the Indian Institute of Technology, Madras, and the M.A. and Ph.D. degrees in Electrical Engineering from Princeton University.

Susmita Sur-Kolay (SM05) received the B.Tech. degree in electronics and electrical communication engineering from Indian Institute of Technology, Kharagpur, India, and the Ph.D. degree in Computer Science and Engineering from Jadavpur University, Kolkata, India. She was in the Laboratory for Computer Science, Massachusetts Institute of Technology, Cambridge, MA, USA, from 1980 to 1984. She was a Post-Doctoral Fellow in the University of Nebraska-Lincoln, Nebraska-Lincoln, NE, USA, in 1992, a Reader in Jadavpur University from 1993 to 1999, a Visiting Faculty Member with Intel Corporation, Santa Clara, CA, USA, in 2002, and a Visiting Researcher at Princeton University in 2012. She is a Professor in the Advanced Computing and Microelectronics Unit, Indian Statistical Institute, Kolkata. She has co-edited two books, authored a book chapter in the Handbook of Algorithms for VLSI Physical Design Automation, and co-authored about 100 technical articles. Her current research interests include electronic design automation, hardware security, quantum computing, and graph algorithms. Prof. Sur-Kolay was a Distinguished Visitor of the IEEE Computer Society, India. She has been an Associate Editor of the IEEE Transactions on Very Large Scale Integration Systems, and is currently an Associate Editor of ACM Transactions on Embedded Computing Systems. She has served on the technical program committees of several leading conferences, and as the Program Chair of the 2005 International Conference on VLSI Design, the 2007 International Symposium on VLSI Design and Test, and the 2011 IEEE Computer Society Annual Symposium on VLSI. Among other awards, she was a recipient of the President of India Gold Medal from IIT Kharagpur.

Niraj K. Jha (S'85-M'85-SM'93-F'98) received his B.Tech. degree in Electronics and Electrical Communication Engineering from Indian Institute of Technology, Kharagpur, India in 1981, M.S. degree in Electrical Engineering from S.U.N.Y. at Stony Brook, NY in 1982, and Ph.D. degree in Electrical Engineering from University of Illinois at Urbana-Champaign, IL in 1985. He is a Professor of Electrical Engineering at Princeton University.

He has served as the Editor-in-Chief of IEEE Transactions on VLSI Systems and an Associate Editor of IEEE Transactions on Circuits and Systems I and II, IEEE Transactions on VLSI Systems, IEEE Transactions on Computer-Aided Design, Journal of Electronic Testing: Theory and Applications, and Journal of Nanotechnology. He is currently serving as an Associate Editor of IEEE Transactions on Computers, IEEE Transactions on Multi-Scale Computing Systems, and Journal of Low Power Electronics. He has served as the Program Chairman of the 1992 Workshop on Fault-Tolerant Parallel and Distributed Systems, the 2004 International Conference on Embedded and Ubiquitous Computing, and the 2010 International Conference on VLSI Design. He has served as the Director of the Center for Embedded System-on-a-chip Design funded by New Jersey Commission on Science and Technology. He is the recipient of the AT&T Foundation Award and NEC Preceptorship Award for research excellence, NCR Award for teaching excellence, and Princeton University Graduate Mentoring Award. He is a Fellow of IEEE and ACM. He received the Distinguished Alumnus Award from I.I.T., Kharagpur in 2014.

He has co-authored or co-edited five books titled Testing and Reliable Design of CMOS Circuits (Kluwer, 1990), High-Level Power Analysis and Optimization (Kluwer, 1998), Testing of Digital Systems (Cambridge University Press, 2003), Switching and Finite Automata Theory, 3rd edition (Cambridge University Press, 2009), and Nanoelectronic Circuit Design (Springer, 2010). He has also authored 15 book chapters. He has authored or co-authored more than 430 technical papers. He has coauthored 14 papers, which have won various awards. These include the Best Paper Award at ICCD'93, FTCS'97, ICVLSID'98, DAC'99, PDCS'02, ICVLSID'03, CODES'06, ICCD'09, and CLOUD'10. A paper of his was selected for "The Best of ICCAD: A collection of the best IEEE International Conference on Computer-Aided Design papers of the past 20 years," two papers by IEEE Micro Magazine as one of the top picks from the 2005 and 2007 Computer Architecture conferences, and two others as being among the most influential papers of the last 10 years at IEEE Design Automation and Test in Europe Conference. He has co-authored another six papers that have been nominated for best paper awards. He has received 16 U.S. patents. He has served on the program committees of more than 150 conferences and workshops.

His research interests include embedded computing, FinFETs, low power hardware/software design, computer-aided design of integrated circuits and systems, quantum computing, and secure computing. He has given several keynote speeches in the area of nanoelectronic design and test.