Wireless Sensor Networks for Healthcare

JeongGil Ko[1] Chenyang Lu[2] Mani B. Srivastava[3] John A. Stankovic[4] Andreas Terzis[1] Matt Welsh[5]
Department of Computer Science, Johns Hopkins University[1]
Department of Computer Science and Engineering, Washington University in St. Louis[2]
Electrical Engineering Department, University of California, Los Angeles[3]
Department of Computer Science, University of Virginia[4]
School of Engineering and Applied Sciences, Harvard University[5]

Abstract— **Driven by the confluence between the need to collect data about people's physical, physiological, psychological, cognitive, and behavioral processes in spaces ranging from personal to urban and the recent availability of the technologies that enable this data collection, wireless sensor networks for healthcare have emerged in the recent years. In this review we present some representative applications in the healthcare domain and describe the challenges they introduce to wireless sensor networks due to the required level of trustworthiness and the need to ensure the privacy and security of medical data. These challenges are exacerbated by the resource scarcity that is inherent with wireless sensor network platforms. We outline prototype systems spanning application domains from physiological and activity monitoring to large-scale physiological and behavioral studies and emphasize ongoing research challenges.**

I. Introduction

Driven by technology advances in low-power networked systems and medical sensors, we have witnessed in recent years the emergence of wireless sensor networks (WSNs) in healthcare. These WSNs carry the promise of drastically improving and expanding the quality of care across a wide variety of settings and for different segments of the population. For example, early system prototypes have demonstrated the potential of WSNs to enable early detection of clinical deterioration through real-time patient monitoring in hospitals [13], [42], enhance first responders' capability to provide emergency care in large disasters through automatic electronic triage [23], [49], improve the life quality of the elderly through smart environments [71], and enable large scale field studies of human behavior and chronic diseases [44], [57].

At the same time, meeting the potential of WSNs in healthcare requires addressing a multitude of technical challenges. These challenges reach above and beyond the resource limitations that all WSNs face in terms of limited network capacity, processing and memory constraints, as well as scarce energy reserves. Specifically, unlike applications in other domains, healthcare applications impose stringent requirements on system reliability, quality of service, and particularly privacy and security. In this review paper we expand on these challenges and provide examples of initial attempts to confront them.

These examples include: **(1)** network systems for vital sign monitoring that show that it is possible to achieve highly reliable data delivery over multi-hop wireless networks deployed in clinical environments [13], [42]. **(2)** Systems that overcome energy and bandwidth limitations by intelligent pre-processing of measurements collected by high data rate medical applications such as motion analysis for Parkinson's disease [48]. **(3)** An analysis of privacy and security challenges and potential solutions in assisted living environments [71], and **(4)** technologies for dealing with the large scale and inherent data quality challenges associated with in-field studies [44], [57].

The remainder of the paper is structured as follows. The next section reviews background material in medical sensing and wireless sensor networks, while Section III describes several promising healthcare applications for wireless sensor networks. We highlight the key technical challenges that wireless sensor networks face in the healthcare domains in Section IV and describe representative research projects that address different aspects of these challenges in Section V. We conclude with an outline of the remaining challenges and future directions for wireless sensor networks in healthcare.

II. Background

A. Medical Sensing

There is a long history of using sensors in medicine and public health [2], [73]. Embedded in a variety of medical instruments for use at hospitals, clinics, and homes, sensors provide patients and their healthcare providers insight into physiological and physical health states that are critical to the detection, diagnosis, treatment, and management of ailments. Much of modern medicine would simply not be possible nor be cost effective without sensors such as thermometers, blood pressure monitors, glucose monitors, EKG, PPG, EEG, and various forms of imaging sensors. The ability to measure physiological state is also essential for interventional devices such as pacemakers and insulin pumps.

Medical sensors combine transducers for detecting electrical, thermal, optical, chemical, genetic, and other signals with physiological origin with signal processing algorithms to estimate features indicative of a person's health status. Sensors beyond those that directly measure health state have also found use in the practice of medicine. For example, location and proximity sensing technologies [38] are being used for improving the delivery of patient care and workflow efficiency in hospitals [21], tracking the spread of diseases by public health agencies [27], and monitoring people's health-related behaviors (e.g., activity levels) and exposure to negative environmental factors, such as pollution [57].

There are three distinct dimensions along which advances in medical sensing technologies are taking place. We elaborate on each of the three in the paragraphs that follow.

Sensing Modality: Advances in technologies such as MEMS, imaging, and microfluidic and nanofluidic lab-on-chip are leading to new forms of chemical, biological, and genomic sensing and analyses available outside the confines of a laboratory at the point-of-care. By enabling new inexpensive diagnostic capabilities, these sensing technologies promise to revolutionize healthcare both in terms of resolving public health crisis due to infectious diseases [78] and also enabling early detection and personalized treatments.

Size and Cost: Most medical sensors have traditionally been too costly and complex to be used outside of clinical environments. However, recent advances in microelectronics and computing have made many forms of medical sensing more widely accessible to individuals at their homes, work places, and other living spaces.

- The first to emerge [2] were *portable medical sensors* for home use (e.g., blood pressure and blood glucose monitors). By enabling frequent measurements of critical physiological data without requiring visits to the doctor, these instruments revolutionized the management of diseases such as hypertension and diabetes.
- Next, *ambulatory medical sensors*, whose small form factor allowed them to be worn or carried by a person, emerged [2]. Such sensors enable individuals to continuously measure physiological parameters while engaged routine life activities. Examples include wearable heart rate and physical activity monitors and Holter monitors. These devices target fitness enthusiasts, health conscious individuals and observe cardiac or neural events that may not manifest during a short visit to the doctor.
- More recently *embedded medical sensors* built into assistive and prosthetic devices for geriatrics [77] and orthotics [17] have emerged.
- Finally, we are seeing the emergence of *implantable medical sensors* for continuously measuring internal health status and physiological signals. In some cases the purpose is to continuously monitor health parameters that are not externally available, such as intraoccular pressure in glaucoma patients [19]. The goal in other cases is to use the measurements as triggers for physiological interventions that prevent impending adverse events (e.g., epileptic seizures [61]) and for physical assistance (e.g., brain-controlled motor prosthetics [46]). Given their implantable nature, these devices face severe size constraints and need to communicate and receive power wirelessly.

Connectivity: Driven by advances in information technology, medical sensors have become increasingly interconnected with other devices. Early medical sensors were largely isolated with integrated user interfaces for displaying their measurements. Subsequently, sensors became capable of interfacing to external devices via wired interfaces such as RS 232, USB, and Ethernet. More recently, medical sensors have incorporated wireless connections, both short-range, such as Bluetooth, Zigbee, and near-field radios to communicate wirelessly to nearby computers, PDAs, or smartphones, and long-range, such as WiFi or cellular communications, to communicate directly with cloud computing services. Besides the convenience of tetherless operation, such wireless connections permit sensor measurements to be sent to caregivers while patients go through their daily work life away from home, thus heralding an age of ubiquitous real-time medical sensing. We note that with portable and ambulatory sensors, the wired or wireless connectivity to cloud computing resources is intermittent (e.g., connectivity may be available only when the sensor is in cellular coverage area or docked to the user's home computer). Therefore such sensors can also record measurements in non-volatile memory for uploading at a later time when they can be shared with healthcare personnel and further analyzed.

B. Wireless Sensor Platforms

Recent years have witnessed the emergence of various embedded computing platforms that integrate processing, storage, wireless networking, and sensors. These embedded computing platforms offer the ability to sense physical phenomena at temporal and spatial fidelities that were previously impractical. Embedded computing platforms used for healthcare applications range from smartphones to specialized wireless sensing platforms, known as *m*otes, that have much more stringent resource constraints in terms of available computing power, memory, network bandwidth, and available energy.

Existing motes typically use 8 or 16-bit microcontrollers with tens of KBs of RAM, hundreds of KBs of ROM for program storage and external storage in the form of Flash memory. These devices operate at a few milliwatts while running at about 10 MHz [60]. Most of the circuits can be powered off, so the standby power can be about one microwatt. If such a device is active for 1% of the time, its average power consumption is just a few microwatts enabling long term operation with two AA batteries. Motes are usually equipped with low-power radios such as those compliant with the IEEE 802.15.4 standard for wireless sensor networks [32]. Such radios usually transmit at rates between 10-250 Kbps, consume about 20-60 milliwatts, and their communication range is typically measured in tens of meters [6], [70]. Finally, motes include multiple analog and digital interfaces that enable them to connect to a wide variety of commodity sensors.

These hardware innovations are paralleled by advances in embedded operating systems [20], [29], component-based programming languages [24], and networking protocols [9], [25].

In contrast to resource-constrained motes, smartphones provide more powerful microprocessors, larger data storage, and higher network bandwidth through cellular and IEEE 802.11 wireless interfaces at the expense of higher energy consumption. Their complementary characteristics make smartphones and motes complementary platforms suitable for different categories of healthcare applications, which we discuss in the section that follows.

III. Healthcare Applications

Wirelessly networked sensors enable dense spatio-temporal sampling of physical, physiological, psychological, cognitive, and behavioral processes in spaces ranging from personal to buildings to even larger scale ones. Such dense sampling across spaces of different scales is resulting in sensory information based healthcare applications which, unlike those described in Section II-A, fuse and aggregate information collected from multiple distributed sensors. Moreover, the sophistication of sensing has increased tremendously with the advances in cheap and miniature, but high quality sensors for home and personal use, the development of sophisticated machine learning algorithms that enable complex conditions such as stress, depression, and addiction to be inferred from sensory information, and finally the emergence of pervasive Internet connectivity facilitating timely dissemination of sensor information to caregivers.

In what follows, we introduce a list of healthcare applications enabled by these technologies.

Monitoring in Mass-Casualty Disasters: While triage protocols for emergency medical services already exist [30], [69], their effectiveness can quickly degrade with increasing number of victims. Moreover, there is a need to improve the assessment of the first responders' health status during such mass-casualty disasters. The increased portability, scalability, and rapidly deployable nature of wireless sensing systems can be used to automatically report the triage levels of numerous victims and continuously track the health status of first responders at the disaster scene more effectively.

Vital Sign Monitoring in Hospitals: Wireless sensing technology helps address various drawbacks associated with wired sensors that are commonly used in hospitals and emergency rooms to monitor patients [42]. The all too familiar jumble of wires attached to a patient is not only uncomfortable for patients leading to restricted mobility and more anxiety, but is also hard to manage for the staff. Quite common are deliberate disconnections of sensors by tired patients and failures to reattach sensors properly as patients are moved around in a hospital and handed-off across different units. Wireless sensing hardware that are less noticeable and have persistent network connectivity to back-end medical record systems help reduce the tangles of wires and patient anxiety, while also reducing the occurrence of errors.

At-home and Mobile Aging: As people age, they experience a variety of cognitive, physical, and social changes that challenge their health, independence and quality of life [75]. Diseases such as diabetes, asthma, chronic obstructive pulmonary disease, congestive heart failure, and memory decline are challenging to monitor and treat. These diseases can benefit from patients taking an active role in the monitoring process. Wirelessly networked sensors embedded in people's living spaces or carried on the person can collect information about personal physical, physiological, and behavioral states and patterns in real-time and everywhere. Such data can also be correlated with social and environmental context. From such "living records", useful inferences about health and well-being can be drawn. This can be used for self-awareness and individual analysis to assist in making behavior changes, and to share with caregivers for early detection and intervention. At the same time such procedures are effective and economic ways of monitoring age-related illnesses.

Assistance with Motor and Sensory Decline: Another application of wireless networked sensing is to provide active assistance and guidance to patients coping with declining sensory and motor capabilities. We are seeing the emergence of new types of intelligent assistive devices that make use of information about the patient's physiological and physical state from sensors built in the device, worn or even implanted on the user's person, and embedded in the surroundings. These intelligent assistive devices can not only tailor their response to individual users and their current context, but also provide the user and their caregivers crucial feedback for longer-term training. Traditional assistive devices such as canes, crutches, walkers, and wheel chairs can fuse information from built-in and external sensors to provide the users with continual personalized feedback and guidance towards the correct usage of the devices. Such devices can also adapt the physical characteristics of the device with respect to the context and a prescribed training or rehabilitation regimen [77]. Furthermore, wireless networked sensing enables new types of assistive devices such as way-finding [16] and walking navigation [8] for the visually impaired.

Large-scale In-field Medical and Behavioral Studies: Body-worn sensors together with sensor-equipped Internet-connected smartphones have begun to revolutionize medical and public health research studies by enabling behavioral and physiological data to be continually collected from a large number of distributed subjects as they lead their day to day lives. With their ability to provide insight into subject states that cannot be replicated in controlled clinical and laboratory settings and that cannot be measured from computer-assisted retrospective self-report methods, such sensing systems are becoming critical to medical, psychological, and behavioral research. Indeed, a major goal of the Exposure Biology program under NIH's Genes and Environment Initiative (GEI) is to develop such field deployable sensing tools to quantify exposures to environment (e.g., psychosocial stress, addiction, toxicants, diet, physical activity) objectively, automatically, and for days at a time in the participants' natural environments. Researchers, both within the GEI program (e.g. [34], [44], [57]) and elsewhere (e.g. [26], [54], [62]), have also recognized the utility of such sensing in making measurements for longitudinal studies ranging from the scale of individuals to large populations.

As the four examples above show, the applications enabled by wireless networked sensing technologies are distributed across multiple dimensions. One dimension is the spatial and temporal scope of distributed sensing. The spatial scope can range from sensory observations of health status made when an individual is confined to a building (e.g., home, hospital) or a well-defined region (e.g., disaster site) to observations made as an individual moves around during the course of daily life. The temporal scope can range from observations made for the duration of an illness or an event to long term observations made for managing a long term disease or for public health purposes. Different spatial and temporal scopes place different constraints on the availability of energy and communications infrastructure, and different requirements on ergonomics.

A second dimension is that of the group size, which can range from an individual patient at home, to groups of patients at a hospital and victims at disaster sites, and all the way to large dispersed population of subjects in a medical study or an epidemic.

The last critical dimension is the type of wireless networking and sensing technologies that are used: on-body sensors with long range radios, body-area networks of short-range on-body sensors with a long-range gateway, sensors implanted in-body with wireless communication and power delivery, wireless sensors embedded in assistive devices carried by individuals, wireless sensors embedded in the environment, and sensors embedded in the ubiquitous mobile smartphones. Clearly, there is a rich diversity of wireless sensing technology with complementary characteristics and catering to different applications. Typically, more than one type of sensing technology gets used for a single application.

IV. Technical Challenges

In the paragraphs that follow we describe some of the core challenges in designing wireless sensor networks for healthcare applications. While not exhaustive, the challenges in this list span a wide range of topics, from core computer systems themes such as scalability, reliability, and efficiency, to large scale data mining and data association problems, and even legal issues.

A. Trustworthiness

Healthcare applications impose strict requirements on end-to-end system reliability and data delivery. For example, pulse oximetry applications, which measure the levels of oxygen in a person's blood, must deliver at least one measurement every 30 seconds [36]. Furthermore, end-users require measurements that are accurate enough to be used in medical research. Using the same pulse oximetry example, measurements must deviate at most 4% from the actual oxygen concentrations in the blood [36]. Finally, applications that combine measurements with actuation, such as control of infusion pumps and patient controlled analgesia (PCA) devices, impose constraints on the end-to-end delivery latency. We term the combination of data delivery and quality properties the *trustworthiness* of the system and claim that medical sensing applications require high levels of trustworthiness.

A number of factors complicate the systems' ability to provide the trustworthiness that applications require. First, medical facilities, where some of these systems will be deployed, can be very harsh environments for radio frequency (RF) communications. This harshness is the result of structural factors such as the presence of metal doors and dividers as well as deliberate effort to provide radiation shielding, for example in operating rooms that use fluoroscopy for orthopedic procedures. In fact, Ko et al. recently found that packet losses for radios following the IEEE 802.15.4 standard is higher in hospitals than other indoor environments [41]. Moreover, devices that use 802.15.4 radios are susceptible to interference from WiFi networks, Bluetooth devices, and cordless phones all of which are heavily used in many hospitals.

The impact of obstacles and interference is exacerbated by the fact that most wireless sensor network systems use low-power radios to achieve long system lifetimes (i.e., maximizing the battery re-charging cycle). The other implication of using low-power radios is that the network throughput of these devices is limited. For example, the theoretical maximum throughput of IEEE 802.15.4 radios is 250 Kbps and much lower in practice due to constraints posed by MAC protocols and multi-hop communications. Considering that applications such as motion and activity monitoring capture hundreds of samples per second, these throughput limits mean that a network can support a small number of devices or that only a subset of the measurements can be delivered in real-time.

In some cases the quality of the data collected from wireless sensing systems can be compromised not by sensor faults and malfunctions, but by user actions. This is true even for smartphone based sensing systems for which many of the above mentioned RF challenges are less severe. Considering that wireless sensing systems for healthcare will be used by the elderly and medical staff with little training, loss in quality due to operator misuse is a big concern. Moreover, because wireless sensing enables continuous collection of physiological data under conditions not originally envisioned by the sensors' developers, the collected measurements may be polluted by a variety of artifacts. For example, motion artifacts can impact the quality of heart rate and respiration measurements. Therefore, estimating the quality of measurements collected under uncertain conditions is a major challenge that WSNs for healthcare must address. In turn, this challenge means that WSNs need to employ techniques for automated data validation and cleansing and interfaces to facilitate and verify their correct installation. Last but not least, WSNs in healthcare should provide metadata that inform data consumers of the quality of the data delivered.

B. Privacy and Security

Wireless sensor networks in healthcare are used to determine the activities of daily living (ADL) and provide data for longitudinal studies. It is then easy to see that such WSNs also pose opportunities to violate privacy. Furthermore, the importance of securing such systems will continue to rise as their adoption rate increases.

The first privacy challenge encountered is the vague specification of *privacy*. The Heath Insurance Portability and Accountability Act (HIPPA) by the U.S. government is one attempt to define this term [1]. One issue is that HIPPA as well as other laws define privacy using human language (e.g., English), thus, creating a semantic nightmare. Nevertheless, privacy specification languages have been developed to specify privacy policies for a system in a formal way. Once the privacy specifications are specified, healthcare systems must enforce this privacy and also be able to express users' requests for data access and the system's policies. These requests should be evaluated against the predefined policies in order to decide if they should be granted or denied. This framework gives rise to many new research challenges, some unique to WSNs, as we describe in the paragraphs that follow.

- Since context can affect privacy, policy languages must be able to express different types of context from the environment such as time, space, physiological parameter sensing, environmental sensing, and stream based noisy data. Moreover, most of the context must be collected and evaluated in real-time. Since context is so central it must also be obtained in a secure and accurate manner.
- There is a need to represent different types of data owners and request subjects in the system as well as external users and their rights when different domains such as assisted living facilities, hospitals, and pharmacies interact. One of the more difficult privacy problems occurs when interacting systems have their own privacy policies. Consequently, inconsistencies in such policies may arise across different systems. For this reason, on-line consistency checking and notification along with resolution schemes are required.
- There is a need to represent high-level aggregating requests such as querying the average, maximum, or minimum reading of specified sensing data. This privacy capability must be supported by anonymizing aggregation functions. This need arises for applications related to longitudinal studies and social networking.
- There is a need to support not only adherence to privacy for data queries (e.g., data pull requests), but also the security for push configuration requests to set system parameters (e.g., for private use or configuring specific medical actuators).
- Because WSNs monitor and control a large variety of physical parameters in different contexts, it is necessary to tolerate a high degree of dynamics and possibly even allow temporary privacy violations in order to meet functional, safety or performance requirements. For example, an individual wearing an EKG might experience heart arrhythmia and the real-time reporting of this problem takes precedence over some existing privacy requirements. In other words to send an emergency alert quickly it may be necessary to skip multiple privacy protections. Whenever such violations occur, core healthcare staff members must be notified of such incidents.

In addition to policy and database query privacy violations, WSNs are susceptible to new side channel privacy attacks that gain information by observing the radio transmissions of sensors to deduce private activities, even when the transmissions are encrypted. This physical layer attack needs only the time of transmission and the fingerprint of each message, where a fingerprint is a set of features of a RF waveform that are unique to a particular transmitter. Thus, this is called the Fingerprint and Timing-based Snooping (FATS) attack [66].

To execute a FATS attack, an adversary eavesdrops on the sensors' radio to collect the timestamps and fingerprints of all radio transmissions. The adversary then uses the fingerprints to associate each message with a unique transmitter, and uses multiple phases of inference to deduce the location and type of each sensor. Once this is known, various private user activities and health conditions can be inferred.

For example, Srinivasan et al. introduce this unique physical layer privacy attack and propose solutions with respect to a smart home scenario [66]. Three layers of inference are used in their work. First, sensors in the same room are clustered based on the similarity of their transmission patterns. Then the overall transmission pattern of each room is passed to a classifier, which automatically identifies the type of room (e.g., bathroom or kitchen). Once the type of room is identified, the transmission pattern of each sensor is passed to another classifier, which automatically identifies the type of sensor (e.g., a motion sensor or a refrigerator door). From this information, the adversary easily identifies several activities of the home's residents such as cooking, showering, and toileting, all with consistently high accuracy. From such information it is then possible to infer the residents' health conditions.

Fortunately, many solutions with different tradeoffs are possible for this type of physical layer attack. Such solutions include (i) attenuating the signal outside of the home to increase the packet loss ratio of the eavesdropper, (ii) periodically transmitting radio messages whether or not the device has data to be sent, (iii) randomly delaying radio messages to hide the time that the corresponding events occurred, (iv) hiding the fingerprint of the transmitter, and (v) transmitting fake data to emulate a real event.

Unfortunately, an adversary can combine information available from many (external) sources with physical layer information to make inferences even more accurate and invasive. New solutions that are cost-effective, address physical layer data, protect against inferences based on collections of related data, and still permit the original functionality of the system to operate effectively are needed.

A related fundamental problem, yet unsolved in WSNs is dealing with security attacks. Security attacks are especially problematic to low-power WSN platforms because of several reasons including the strict resource constraints of the devices, minimal accessibility to the sensors and actuators, and the unreliable nature of low-power wireless communications. The security problem is further exacerbated by the observation that transient and permanent random failures are common in WSNs and such failures are vulnerabilities that can be exploited by attackers. For example, with these vulnerabilities it is possible for an attacker to falsify context, modify access rights, create denial of service, and, in general disrupt the operation of the system. This could result in a patient being denied treatment, or worse, receiving the wrong treatment.

Having in mind such unique challenges, new lightweight security solutions that can operate in these open and resource-limited systems are required. Solutions that exploit the considerable amount of redundancy found in many WSN systems are being pursued. This redundancy creates great potential for designing WSN systems that continuously provide their target services despite the existence of failures or attacks. In other words, to meet realistic system requirements that derive from long lived and unattended operation, WSNs must be able to continue to operate satisfactorily and effectively recover from security attacks. WSNs must also be flexible enough to adapt to attacks not anticipated during design or deployment time. Work such as the one proposed by Wood et al. provides an example of how such problems are addressed, by proposing to design a self-healing system with the presence and detection of

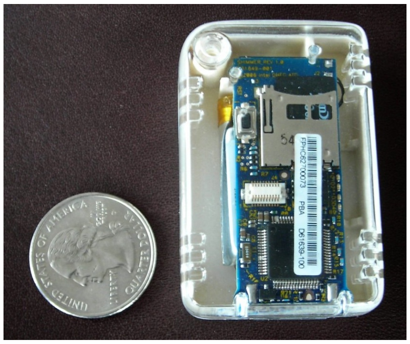

Fig. 1. The SHIMMER wearable sensor platform. SHIMMER incorporates a TI MSP430 processor, a CC2420 IEEE 802.15.4 radio, a triaxial accelerometer, and a re-chargeable Li-polymer battery. The platform also includes a MicroSD slot supporting up to 2 GBytes of Flash memory.

attacks, rather than trying to build a completely secure system [76].

C. Resource Scarcity

In order to enable small device sizes with reasonable battery lifetimes, typical wireless sensor nodes make use of low-power components with modest resources. Figure 1 shows a typical wearable sensor node for medical applications, the SHIMMER platform [33]. The SHIMMER comprises an embedded microcontroller (TI MSP430; 8 MHz clock speed; 10 KB RAM; 48 KB ROM) and a low-power radio (Chipcon CC2420; IEEE 802.15.4; 2.4 GHz; 250 Kbps PHY data rate). The total device power budget is approximately 60 milliwatts when active, with a sleep power drain of a few microwatts. This design permits small, re-chargeable batteries to maintain device lifetimes of hours or days, depending on the application's duty cycles.

The extremely limited computation, communication, and energy resources of wireless sensor nodes lead to a number of challenges for system design. Software must be designed carefully with these resource constraints in mind. The scant memory necessitates the use of lean, event-driven concurrency models, and precludes conventional OS designs. Computational horsepower and radio bandwidth are both limited, requiring that sensor nodes trade off computation and communication overheads, for example, by performing a modest amount of on-board processing to reduce data transmission requirements. Finally, application code must be extremely careful with the node's limited energy budget, limiting radio communication and data processing to extend the battery lifetime. While smartphone-based systems typically enjoy more processing power and wireless bandwidth, the fact that they are less flexible compared to customizable mote platforms, limits their capability to aggressively conserve energy. This leads to shorter re-charge cycles and can limit the types of applications that smartphones can support.

Another consideration for low-power sensing platforms is the fluctuation in the resource load experienced by sensor nodes. Depending on the patient's condition, the sensor data being collected, and the quality of the radio link, sensor nodes may experience a wide variation in communication and processing load over time. As an example, if sensor nodes perform multihop routing, a given node may be required to forward packets for one or more other nodes along with transmitting its own data. The network topology can change over time, due to node mobility and environmental fluctuations in the RF medium, inducing unpredictable patterns of energy consumption for which the application must be prepared.

V. Systems

Next, we present several wireless sensing system prototypes developed and deployed to evaluate the efficacy of WSNs in some of the healthcare applications described in Section III. While wireless healthcare systems using various wireless technologies exist, this work focuses on systems based on low-power wireless platforms for physiological and motion monitoring studies, and smartphone based large-scale studies.

A. Physiological Monitoring

In physiological monitoring applications, low-power sensors measure and report a person's vital signs (e.g., pulse oximetry, respiration rate, temperature). These applications can be developed and deployed in different contexts ranging from disaster response, to in-hospital patient monitoring, and long-term remote monitoring for the elderly.

While triage protocols for disaster response already exist (e.g., [30], [69]), multiple studies have found that they can be ineffectual in terms of accuracy and the time to transport as the number of victims increases in multi casualty incidents [5], [64]. Furthermore, studies in hospitals report that patients are left under-monitored [15] and emergency departments today operate at or over capacity [4]. Finally, anecdotal evidence suggest that this lack of patient monitoring can lead to fatalities [14], [53], [67].

Therefore, systems that automate patient monitoring have the potential to increase the quality of care both in disaster scenes and clinical environments. Systems such as CodeBlue [49], MEDiSN [42], and the Washington University's vital sign monitoring system [13] target these application scenarios. Specifically, CodeBlue [49] aims to improve the triage process during disaster events with the help of WSNs comprising motes with IEEE 802.15.4 radios. The CodeBlue project integrated various medical sensors (e.g., EKG, SpO_2, pulse rate, EMG) with mote-class devices and proposed a publish/subscribe-based network architecture that also supports priorities and remote sensor control [11]. Finally, victims with CodeBlue monitors can be tracked and localized using RF-based localization techniques [47].

Ko et al. proposed MEDiSN to address similar goals as CodeBlue (e.g., improve the monitoring process of hospital patients and disaster victims as well as first responders), but using a different network architecture [42]. Specifically, unlike the ad-hoc network used in CodeBlue, MEDiSN employs a wireless backbone network of easily deployable relay points (RPs). RPs are positioned at fixed locations and they self-organize into a forest rooted at one or more gateways (i.e., PC-class devices that connect to the Internet) using a variant

Fig. 2. Medical information tag, or miTag for short, used in MEDiSN [42]. The miTag is a Tmote mini [52] based patient monitor that includes a pulse oximetry sensor with LEDs, buttons and a LCD screen. The miTag is powered using a re-chargeable 1,200 mAh 3.7 V Li-Ion battery and external finger tip sensors are used to make the pulse oximetry measurements.

of the Collection Tree Protocol (CTP) [25] tailored to high data rates. Motes that collect vital signs, known as *miTags* (see Fig. 2), associate with RPs to send their measurements to the gateway. The dedicated backbone architecture that MEDiSN incorporates significantly reduces the routing overhead compared to a mobile ad-hoc network architecture and results in two major benefits. First, it allows the network's operator to expand its coverage and engineer its performance by altering the number and position of RPs in the backbone. Second, since miTags do not have to route other nodes' data, they aggressively duty cycle their radio to conserve energy. The Washington University's patient monitoring has adopted a similar wireless backbone network to take advantage of similar benefits [12], [13].

The systems described above were deployed in disaster simulations [23] and hospital pilot studies [13], [40], [41]. These studies showed that wireless sensing systems can in fact overcome the challenging RF conditions that exist in these environments to meet the applications' stringent trustworthiness requirements [41].

Chipara et al. found that another source of unreliability in clinical environments is the outage of the sensing capability itself [13]. The authors show that the distribution of sensing outages is heavy-tailed containing prolonged outages caused by sensor disconnections. Their experience reveals that the use of automatic sensor disconnection alarms and over-sampling can enhance system reliability. Finally, the pilot studies above also report that the satisfaction levels of healthcare personnel and users such as patients or disaster victims is high and conclude that the systems are practically feasible.

While the systems introduced above deal with improving the quality of patient care in hospitals or disaster scenarios, researchers and practitioners noticed that the coming worldwide silver tsunami [68], where a large number of retiring elders overload the capacity of current hospitals, is stressing the traditional concept of healthcare which is focused on clinical and emergency medical service (EMS) settings. Specifically, it is economically and socially advantageous to reduce the burden of disease treatment by enhancing prevention and early detection while allowing people to stay at home for as long as possible. This requires a long-term shift from a centralized, expert-driven, crisis-care model to one that permeates personal living spaces and involves informal caregivers, such as family, friends, and members of the community.

A typical home healthcare system based on WSN is AlarmNet [74], [75], an assisted-living and residential monitoring network for pervasive, adaptive healthcare. AlarmNet is a system based on an extensible, heterogeneous network architecture targeting ad-hoc, wide-scale deployments. It includes custom and commodity sensors, an embedded gateway, and a back-end database with various analysis programs. The system includes protocols such as context-aware protocols informed by circadian activity rhythm analysis for smart power management. It supports real-time on-line sensor data streaming and an inference system to recognize anomalous behaviors as potential indicators of medical problems. Privacy control is based on access control lists and all queries are logged. Future work is planned to use data mining on the query logs to detect privacy attacks. All messages are encrypted to ensure data confidentiality.

Intel Research Seattle and the University of Washington have built a prototype system that can infer a person's activities of daily living (ADLs) [58]. In their system, sensor tags (both passive and active) are placed on everyday objects such as a toothbrush or a coffee cup. The system tracks the movement of tagged objects with tag readers. Their long-term goal is to develop a computerized and unobtrusive system that helps manage ADLs for the senior population [37].

University of Rochester is building the Smart Medical Home [45], which is a five-room "house" outfitted with infrared sensors, computers, bio-sensors, and video cameras for use by research teams to work on research subjects as they test concepts and prototype products. Researchers observe and interact with subjects from two discreet observation rooms integrated into the home. Their goal is to develop an integrated personal health system that collects data for 24 hours a day and presents it to the healthcare professionals.

Georgia Tech built an Aware Home [39] as a prototype for an intelligent space. This space provides a living laboratory that is capable of gathering information about itself and the different types of activities of its inhabitants. The Aware Home combines context-aware and ubiquitous sensing, computer vision-based monitoring, and acoustic tracking all together for ubiquitous computing of everyday activities while remaining transparent to its users.

The Massachusetts Institute of Technology is working on the PlaceLab initiative [35], which is a part of the House_n project. The mission of House_n is to conduct research by designing and building real living environments—"living labs"—that are used to study technology and design strategies in context. The PlaceLab is a one-bedroom condominium with hundreds of sensors installed in nearly every part of the home.

The systems introduced above provide useful physiological information to medical personnel using resource constrained devices. Nevertheless, these systems deal with only the simplest aspects of medical data security. For example, MEDiSN performs 128-bit AES-based encryption and authentication to secure all physiological data [31] but does not provide any of the policy controls described above. Another limitation of existing systems is the small number of sensors that each mobile device can support due to hardware constraints. Developing new platforms that integrate stronger security and privacy mechanisms with more diverse sensing and processing capabilities is likely to increase the range of physiological monitoring applications that WSNs can support.

B. Motion and Activity Monitoring

Another application domain for WSNs in healthcare is high-resolution monitoring of movement and activity levels. Wearable sensors can measure limb movements, posture, and muscular activity, and can be applied to a range of clinical settings including gait analysis [59], [63], [72], activity classification [28], [51], athletic performance [3], [50], and neuromotor disease rehabilitation [48], [56]. In a typical scenario, a patient wears up to eight sensors (one on each limb segment) equipped with MEMS accelerometers and gyroscopes. A base station, such as a PC-class device in the patient's home, collects data from the network. Data analysis can be performed to recover the patient's motor coordination and activity level, which is in turn used to measure the effect of treatments.

In such studies, the size and weight of the wearable sensors must be minimized to avoid encumbering the patient's movement. The SHIMMER sensor platform shown in Figure 1 measures $44.5 \times 20 \times 13$ mm and weighs just 10 g, making it well-suited for long-term wearable use.

In contrast to physiological monitoring, motion analysis involves multiple sensors on a single patient each measuring high-resolution signals, typically six channels per sensor, sampled at 100 Hz each. This volume of sensor data precludes real-time transmission, especially over multihop paths, due to both bandwidth and energy constraints. The SHIMMER platform incorporates a MicroSD interface, permitting up to 2 GBytes of storage — enough to store up to a month of continuously-sampled sensor data. While the energy consumption of flash I/O is non-negligible, it is about $\frac{1}{10}$th the energy cost to transmit the same amount of data over the radio. As a result, it is necessary to carefully balance data sampling, storage, processing, and communication to achieve acceptable battery lifetimes and data fidelity.

Two systems, SATIRE [22] and Mercury [48], typify the approach to addressing these challenges. SATIRE is designed to identify a user's activity based on accelerometers and GPS sensors integrated into "smart attire" such as a winter jacket. SATIRE nodes measure accelerometer data and log it to local flash. This data is opportunistically transmitted using the low-power radio when the SHIMMER node is within communication range with the base station. Once the data is collected at the base station, the collected data is processed offline to characterize the user's activity patterns, such as *walking*, *sitting*, or *typing*. Sensor nodes perform aggressive duty cycling to reduce power consumption, extending lifetimes from several days to several weeks.

The goal of the Mercury system is to permit long-term studies of a patient's motor activity for neuromotor disease studies, including Parkinson's disease, stroke, and epilepsy. Energy is far more constrained in Mercury than in SATIRE, due to the use of lightweight sensor nodes with small batteries. Mercury builds upon SATIRE's approach to energy management and integrates several energy-aware adaptations, including dynamic sensor duty cycling, priority-driven data transmissions, and on-board feature extraction. Mercury is being used in several studies of Parkinson's and epilepsy patients [48].

While SATIRE and Mercury show the feasibility of using low-power wireless platforms to perform longitudinal studies of human activity, issues related to improving node lifetime and providing stronger security and privacy guarantees remain areas of active research.

C. Large-Scale Physiological and Behavioral Studies

The final application of WSNs in healthcare that we discuss is their use in conducting large-scale physiological and behavioral studies. The confluence of body-area networks of miniature wireless sensors (such as the previously mentioned miTag and SHIMMER platforms), always-connected sensor-equipped *smartphones*, and cloud-based data storage and processing services is leading to a new paradigm in population-scale medical research studies, particularly on ailments whose causes and manifestations relate to human behavior and living environments.

Traditionally such studies are either conducted in controlled clinical laboratory settings with artificial stimuli, or rely on computer-assisted retrospective self-report methods. Both of these approaches have drawbacks: the complex subtleties of real-life affecting human behavior can rarely be recreated accurately in a laboratory, and self-report methods suffer from bias, errors, and lack of compliance. However, the combination of body-area wireless sensor networks, smartphones, and cloud services permits physical, physiological, behavioral, social, and environmental data to be collected from human subjects in their natural environments continually, in real-time, unattended, and in an unobtrusive fashion over long periods. Typically, data is collected from wireless sensors worn by subjects, wireless medical instruments, and sensors embedded in devices such as smartphones. After local validation, artifact removal, and local processing, sensor data is wirelessly transmitted using cellular or WiFi networks to cloud-based services for subsequent analysis, visualization, and sharing by researchers. Such systems provide insight into subject states that traditional study methods simply cannot achieve. Consequently, research efforts such as the Exposure Biology program under NIH's Genes and Environment Initiative (GEI) are developing field deployable wireless sensing tools to quantify exposures to environments (e.g., psychosocial stress, addiction, toxicants, diet, physical activity) objectively, automatically, and for multiple days in participants' natural environments.

One example of such systems is AutoSense [44], in which objective measurements of personal exposure to psychosocial stress and alcohol are collected in the study participants natural environments. A field-deployable suite of wireless sensors form a body-area wireless network and measure heart rate, heart rate variability, respiration rate, skin conductance, skin temperature, arterial blood pressure, and blood alcohol concentration. From these sensor readings, which after initial validation and cleansing at the sensor are sent to a smartphone, features of interest indicating onset of psychosocial stress and occurrence of alcoholism are computed in real-time. The collected information is then disseminated to researchers answering behavioral research questions about stress, addiction, and the relationship between the two. Moreover, by also capturing time synchronized information about a subject's physical activity, social context, and location, factors that lead to stress can also be inferred, and this information can potentially be used to provide personalized guidance about stress reduction.

A second example is a portable system called the Physical Activity and Location Measurement System (PALMS) developed at UCSD [57]. PALMS aims at monitoring study subjects in everyday life for long enough periods of time to detect patterns in physical activity and energy expenditure. These information (collected from combined heart rate and motion sensors) and location (from GPS units) are collected in the natural environment of the study participants. The system helps answer questions about the energy used by a person during different activities in the course of the day and the variance across a population of subjects. The synchronized geolocation information permits understanding how physical activity and energy expenditure varies by location and is influenced by environmental factors such as the built environment, crime, the availability of parks, and recreation facilities, or terrain.

These systems for population-scale medical studies are still in their early stages, and several technical and algorithmic challenges remain to be addressed. Energy is certainly one challenge. While some on-body sensors have high sampling rates leading to significant energy consumption (i.e., low battery life), the desire to facilitate easy compliance with the study protocols preclude a frequent charging schedule.

However, a bigger challenge with this technology is the issue of information privacy, and its tension with the quality and value of information [18]. Contemporary privacy practices center on the notion of "personally identifiable information" and "informed consent". However, with these systems, the traditional intuitive notion of privacy is not enough. Privacy is not just about removing explicit identifiers, encrypting data, using trusted software, and securing servers. These are easily done, though imperfectly. Sensory information traces captured by these systems are highly personal. Embedded in them is information that correlates with our identity and our behaviors. When combined with publicly available innocuous facts - the so called "digital footprints" and "information breadcrumbs" that we all leave behind as we lead our lives - these sensor information traces can be de-anonymized, and subjects' identities and life patterns can be inferred statistically.

For example, Chaudhuri and Mishra showed that personal information may be identified even from anonymized and sanitized population level data sets [10]. Similarly, Krumm has shown that location traces can be de-anonymized via statistical analysis to infer subjects' home location with high probability [43], which then can be used to reveal their identity using information that is freely available on the web such as reverse white-page lookup.

Likewise, traditional prior informed consent is not adequate when sensors may capture data in unanticipated situations and the sheer amount and nature of sensor data makes information leakage risks hard to comprehend. Collecting data continuously as subjects go through their daily lives at their homes, offices, and other places means that it is impossible to anticipate upfront, and accordingly inform subjects about, the complete nature of information that the sensor data may reveal. Some of the seemingly innocuous sensor data thus collected in relatively uncontrolled settings may capture information about confidential aspects of subjects' life patterns, personal habits, and medical condition.

One answer to these problem can be to allow the study subjects and patients to retain control over their raw sensor data throughout its life cycle: its capture, sharing, retention, and reuse [7], [65]. However, giving study subjects control over data raises concern about quality of data for researchers. As it is, ensuring high quality trustworthy information from sensors out in the real world is hard due to malfunctions, misbehaviors, and lack of compliance. Letting subjects selectively hide or perturb data raises the issue of bias and availability, and thus utility. Quoting Ohm from a recent article: "Data can either be useful or perfectly anonymous, but never both" [55]. Technology assists such as automated validation procedures, audit traces, and incentive mechanisms to ensure compliance and encourage sharing may provide further help.

VI. Future Directions

Driven by user demand and fueled by recent advances in hardware and software, the first generation of wireless sensor networks for healthcare has shown their potential to alter the practice of medicine. Looking into the future, the tussle between trustworthiness and privacy and the ability to deploy large-scale systems that meet the applications' requirements even when deployed and operated in unsupervised environments is going to determine the extent that wireless sensor networks will be successfully integrated in healthcare practice and research.

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