Sensor networks and data management in healthcare: Emerging technologies and new challenges

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***Abstract*— Smart pervasive sensor networks are becoming an important part of our daily lives. Low-power, high-availability and high-throughput 5G mobile networks provide the necessary communication means for highly pervasive sensor networks, introducing a technological disruption to health monitoring. The meaningful use of large concurrent sensor networks in healthcare requires multi-level health knowledge integration with sensor data streams. In this paper, we highlight some software engineering and data-processing issues that can be addressed by metamorphic testing. The proposed solution combines data streaming with filtering and cross-calibration, use of medical knowledge for system operation and data interpretation, and IoT-based calibration using certified linked diagnostic devices.**

Keywords - data streaming, digital wellbeing health monitoring, Internet of Things, oracle problem, sensor networks

I. Introduction

Wireless sensor networks (WSNs) are collections of spatially distributed specialized sensors that concurrently monitor, record and communicate data representing measurements of environmental variables or a given system's descriptors. WSNs can be distributed, such as those that monitor air quality in a defined geographic area; or localized, such as personal health monitoring sensor networks [1]. In the past, the main challenges facing WSNs were hardware constraints and limited energy resources. Now, the main problems relate to the ability to capture, process, store, synchronize, and manage multiple data streams from large and dynamic WSNs, and be able to respond in real time when needed [2]. Data accumulation rate is accelerating. According to popular estimates, the total amount of data doubles every two years, or even faster. The 5G mobile infrastructure, expected to roll out by 2020 will see rapid expansion of data capacity and usage (Table I) [3].

The increase of volume, speed, and coverage of data communication raises various technological, software, and societal challenges. Technological challenges include a need to improve energy efficiencies, miniaturization, robustness of sensors, and Internet of Things (IoT) device performance. Software challenges include the need to develop and implement software engineering solutions and robust algorithms for filtering, compression, and real-time decision making. Societal challenges relate to safety, security, and a range of ethical issues including ownership, privacy, and right to access and use data.

TABLE I. 5G MOBILE NETWORK CAPABILITIES [3]

5G capabilities	*Range*	*Improvement*
Latency of data travel between points	1 ms	10 times
Number of simultaneous connections	$5/m^2$	100 times
Peak data rates	50Gbit/s	50 times
Normal user data rates	1 Gbit/s	100 times
Traffic volume	50 Tbytes/s	100-1000 times

The physical scope of 5G networks is expanding, with WSNs introducing an additional layer of complexity. A 5G mobile phone will support at least 40 wide area network (WAN) bands and multiple radio frequencies for wireless local area networks (WLAN) [4]. Different types of LANs have been defined by size, such as personal area (PAN), home area (HAN), and storage (SAN) networks, as well as larger networks such as campus area (CAN) or metropolitan area (MAN). Table II shows some sample network types, according to physical scope.

The networking infrastructure has enabled connectivity and communication between devices, objects, systems, and living beings. Embedded sensors, electronics, communication devices and software provide for collection, processing and exchange of data and action or response to certain situations. These actions or responses may involve sensing of the environment and alerting and prompting people to respond to various situations and conditions. Alternatively, the responses can be automated. For example, a car sensor system may detect an approaching car and alert the driver if two cars are on a collision course. Self-driving cars will automatically adjust to the situation on the road. The systems, devices and objects that involve sensors, data communication, and real time responses are usually referred to as smart technologies. They include devices, such as smart phones, clocks, cameras, or appliances; systems such as smart cars, homes, buildings, or hospitals (or broader geographic areas, such as smart cities [13-15]). The convergence of sensor systems, embedded electronics, information and communications technology (ICT), real-time data analytics, machine learning, and artificial intelligence methods for decision making have enabled the emergence of the Internet of Things (IoT). IoT is the network of devices and systems, such as vehicles and home appliances, that interact, exchange data, and make decisions about their collective operations in response to changes or following pre-defined protocols [16].

TABLE II. NETWORK TYPES, BY PHYSICAL SCOPE

Type of network (area)	***Acronym***	***Range****	***Reference***
Nanoscale	–	MCF	[5]
Near field	NFC	D2D	[6]
Body	BAN	D2D	[7]
Personal	PAN	D2D	[7]
Near-me	NAN	D2D	[8]
Home	HAN	LAN	[9]
Airport	–	LAN	[9]
Storage	SAN	LAN	[10]
Campus	CAN	WAN	[11]
Metropolitan	MAN	WAN	[11]
Cloud	–	IAN	[12]

*MCF – molecular communication framework, D2D – device to device communication, LAN – local area network, WAN – wide area network, IAN – Internet area network.

Sensor systems and IoT generate huge amounts of data that are growing exponentially [17]. These data are termed Big Data – they have such a large size and high complexity that traditional methods for capture, processing, transferring, analysis and storage are inadequate. Some of the main characteristics of Big Data are that they have high volume, are not suitable for storage into relational databases, and are generated and processed at high speed [18]. Big Data are commonly characterized by Vs: volume, velocity, variety, variability, veracity, visualization, and value [18,19].

Data have been generated at a faster pace than we are able to process and analyze. Whereas traditional data analytics mainly employs statistics, Big Data analytics often involves machine learning (ML), mathematical modeling, and artificial intelligence (AI) [20-22]. Data accumulation, fueled by sensor networks and IoT devices, is faster than our ability to manage and use, creating several bottlenecks that need to be addressed: a) real-time pre-processing of data to reduce them to a workable size; b) synchronization of different data streams that enable extraction of critical information and provide context awareness; c) new algorithms for real time responses; and d) management of knowledge and its real-time deployment.

Although extensive literature is available in this field, some fundamental questions need clarification, and guidelines are weak. In this paper, we address some of these questions and provide guidelines for practical applications using sensor networks. First, we provide an analysis of data types generated by sensor networks and IoT devices and offer an insight into data management: filtering, synchronization, and their use in the context of knowledge management. Second, we examine practical examples and analyze key issues using health monitoring and wellbeing enhancement. Third, we provide an insight into the use of software engineering, including new requirements for software testing for the management and use of sensor systems.

II. SENSOR NETWORKS DATA AND DATA ANALYTICS

Data generated by sensor networks are different from those generated by data loggers because individual sensors generate data cooperatively and data are often processed and filtered at the source. Examples of sensor networks include those embedded in smart phones and watches, health bands, vehicles (cars, buses, drones), smart homes, security systems, and IoT devices, amongst others. In the past, data were typically collected and analyzed offline for future business decisions. Very few applications were real-time, such as critical applications in power grid management, intensive care monitoring, or autopilot systems. These applications were not adaptive – they were designed to respond to a set of pre-defined conditions. Contemporary sensor networks are multi-agent systems that can measure variables, and perceive the state and behavior of their environment, responding accordingly [23].

Technical design of sensor networks is well developed: the capture, storage and processing of data by small sensor networks is done routinely and reliably. On the other hand, learning from sensor network data has created new challenges – the large scale of data, understanding the data, energy requirements, and appropriate and timely responses [24]. The number of sensors may be very large, and they are distributed and often of different types. The data streams need to be combined and synchronized to adequately interpret continuously flowing data. Data represent continuous measurements of changing environments. Understanding, interpreting and learning from these data (and providing adequate responses or actions) requires the application of AI and ML. A common goal of sensor network systems research is to enable their intelligent behavior [23]. It is important to understand the new types of data generated by sensor networks and their analytics requirements. Among various data domains, biomedical data may be amongst the most complex to manage and use: such data are comprehensive, diverse, heterogeneous, and isolated to protect individuals' privacy.

Data processing distinguishes several layers of knowledge embedded in the original raw data. This is captured, for example, in the DIKW knowledge pyramid [29], which defines hierarchical relationships between data, information, knowledge, and wisdom. Our modification of the DIKW model is shown in Figure 1, where the raw data are analyzed using statistical methods or machine learning to obtain high value data such as summaries, reports, or critical information that can be used to support decision making and provide appropriate actions and responses [25].

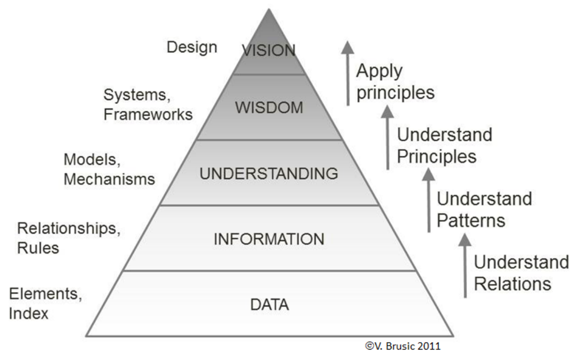

Fig. 1. Modified DIKW hierarchy (DIUWV). The data are basic elements without meaning, information level introduces the relationships or rules, understanding enables the description of patterns, wisdom is about the ability to understand and describe principles, while vision enables the application of these principles to new and useful designs

Defining biomedical data types is complex because of the multiple dimensions to be considered for understanding and classification. Biomedical data can be classified according to structure, data processing level, application domain, and intended purpose [25]. Data may be structured or unstructured. For example, a diagnosis can be recorded in a structured form such as ICD diagnostic codes [26], or unstructured, such as textual descriptions. Structured forms facilitate comparative analysis and easy generation of statistics. Disadvantages include the high rate of false coding (false positives or false negatives) [27], and the loss of information captured in a textual description, but not in the international classification of disease (ICD10) code. It may be difficult to record a correct diagnosis that combines multiple concurrent health conditions, typically stated as a primary diagnosis along with comorbidities [28].

Biomedical data are used in various types of information systems. Examples are administrative, financial, clinical, research, operations, pharmaceutical, laboratory, and radiology systems; electronic health records; clinical trials data; and clinical and disease registries [30]. The key issue with these systems is the interoperability of these independent information systems [31]. The rapid development of sensor networks and IoT have created new challenges for merging traditional biomedical information systems with massive data streams – creating challenges for real-time decisions making [32, 33].

The most granular level of biomedical data are specialized data types, including: demographics and socioeconomic data, patient encounters, medication, symptoms, diagnoses, diagnostics (laboratory, imaging, and other tests), genetics, social history, family history, lifestyle (fitness, purchases), environmental data/exposure (climate, weather, pollution, health maps, and others), and social networks. The growth of Big Data generated by sensor networks from data streams has created challenges for both integrating these massive amounts of data into information systems, and for the development of data-processing algorithms.

III. Monitoring Health and Wellbeing

Existing applications of WSN have mostly focused on monitoring [34] and management of identified health issues in individuals [35,36]. Wellbeing is defined as the psychological, social and physical resources needed to meet the specific psychological, social and/or physical needs of an individual [37]. It has three components: life satisfaction, pleasant affect, and unpleasant affect [37]. In this section we discuss how ubiquitous WSNs can help address these three considerations. These considerations affect our lives at varying degrees of scale, from the micro (individual/ personal) to the macro (societal/large populations). Wellbeing data largely overlap health data, and the same infrastructure can be used for data collection and processing. A major difference is that medical diagnosis devices typically require governmental agency, such as FDA, certification, but wellbeing sensor devices typically do not. This situation is changing, and the number of FDA certified wearables is increasing, blurring the distinction among medical, health, and wellbeing applications.

At the micro level, we consider body area networks (BANs) to be the primary source of data. BAN level sensors are wearable, non-invasive devices that provide a quantified measure of some physiological state or activity of the wearer [38]. Examples include electroencephalogram (EEG) headsets, heart rate (HR) and heart rate variation (HRV) bands and straps, and pedometers. Concerns have been highlighted over the validity and accuracy of consumer grade devices [39,40]. At the macro level, the inferences we can draw from combinations of multiple redundant sensors at the BAN level enable cross-calibration, and improvement in the accuracy and reliability of the measurements. Raw measurements by multiple sensors are commonly imprecise but their combinations, after calibration and data processing, offer resilience against inaccurate measurements in the network. Sensor systems provide for continuous monitoring of the environment and detect changes in environmental variables. Real-time algorithms enable responses including the adjustments of the environment or alerts to the individual about the need for response to the noted changes. These adaptations and responses to the streaming data can positively impact an individual's physical and psychological states. Furthermore, such adaptations can inform a broader, societal benefit: groups become healthier, with improved wellbeing. As the global population ages, pressure on healthcare systems is increasing. This is especially so for age-related diseases, such as cancer and heart disease, and for declines in mental health. The issue of continuous monitoring using sensors and wearables becomes ever more necessary [41].

The application of ubiquitous WSNs to health monitoring and societal wellbeing is a major disruptive trend for a traditional care-giving system. The availability of highly individualized data enables smart systems to direct a healthy lifestyle in individuals. This movement of highly personal and physically 'close' sensors will lead to every individual being responsible for creating their own Big Data and will drive further developments towards more ubiquitous BANs and PANs.

Existing BAN applications are primarily contextualized as fitness devices, with activity monitoring as the primary data. This provides a popular and relatively safe framing of the measurements, and the insights can lead to improved well-being e.g. habit-forming, gamified exercising and the introduction of social accountability [42]. When WSNs are used for health and medical monitoring, greater caution needs to be exercised and health care providers should be informed or involved in decision making in response to the analysis of data streams.

Key issues at the micro level are integration of multi-sensor data, their interpretation of sensor data, and ensuring the accuracy of measurements of individual sensors and the overall network. Dealing with these issues becomes increasingly complex as the number of sensors grow, particularly when we deal with the swarms of sensors. The application of BAN level sensors in a health context will require contextualization with the existing medical health records. For example, chronic lung disease patients may be particularly sensitive to variations in air pollution levels, relative to the normal population. When contextualized with this information, the smart system can tailor its suggestions, actions and reporting accordingly. For example, suggestions of physical activity might be more conservative in a polluted context. Additionally, control of the smart environment may use more air filtration but can be costly and energy consuming. Integration of existing medical record data into a smart system, while respecting the privacy rights of the individuals, and the local legal system, represents another challenge. This represents knowledge management for forming "smart algorithms," and refers to the understanding and wisdom levels of the DIUWV hierarchy shown in Figure 1. Adequate responses to changes detected in sensor data streams require management and use of appropriate knowledge. For example, the system must be aware of thresholds that define safe levels of air pollutants for both immediate exposure chronic exposure so that appropriate action can be made. Furthermore, the system should be aware of lover values of these thresholds if high-risk or vulnerable groups including children, pregnant women, and chronic patients, are present in the environment. Decision making requires integration of wisdom level (Fig. 1) knowledge to ensure adequate decision making.

Smart environments are promising areas for WSN applications in the context of both health and wellbeing. Modelling of health characteristics of an individual's environment both in real-time and over historical periods enables understanding of individual's exposure to potentially harmful substances. The critical data include environmental health metrics, including air pollutant (such as particulate matter, formaldehyde, or volatile organic compounds) concentrations, temperature, and humidity allows. Reactive systems look promising for the prevention of environment-based health risks. The detection of increased levels of pollution may trigger air-purification systems in the home or workplace. Conversely, low levels of pollution may lead to outside air being introduced into the living environment, providing a supply of fresh air in an energy efficient manner.

IV. Software Engineering Challenges

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar. Given the number and diversity of network sensors, and the data coming from overlapping coverage (e.g. continuous concurrent measurement of ECG, HR, and HRV) a key challenge of the system is to identify data that is trustworthy – accurate, precise, and reliable. If, for example, several sensors simultaneously covering the same data source supply differing or even conflicting data, this raises several key questions:

- What is the system actually intended to do?
- Which source (if any) should be considered canonical?
- What degrees of 'trust' or 'authority' should be given to one measure or another?
- How should this be established?
- How do we evaluate the correctness of our approach in an environment that is uncertain by design?

The problems of this nature are well-studied in software testing [43], and are known as the oracle problem [44]: Given a system whose output or behaviour can be observed, how can an observer know if this output or behaviour is correct? If there is a mechanism, automated or not, that the observer can use to decide, then this mechanism is called an oracle. If no oracle is available, or if one is available, but it is not practical to use it (perhaps owing to excessive overheads), then the system faces the oracle problem. In a large, distributed and free-form sensor network, the oracle problem is an inevitability. In sensor systems, the oracle problem can occur at both ends: the data acquisition level (sensors) and the data processing or interpretation (software) level.

A naive approach to dealing with multiple sensors providing different values for what should be the same data source might be analogous to software engineering's n-version programming (NVP) [45]. NVP essentially works by building several (n) implementations from the same specifications, and then executing all n for any given input. A form of voting or polling can then be used to decide on situations where the outputs or behaviours for the different implementations differ. However, in the context of large, complex sensor networks, the choice of the decision algorithm employed when implementing NVP is critical, and possibly undecidable, given the nature of the measures being observed [46]. Fundamentally, we are uncertain as to what a correct answer is at any given moment.

Metamorphic Testing (MT) is an alternative approach to alleviating the Oracle problem that has been growing in popularity in recent years [47,48,49]. Instead of attempting to identify the correctness of individual outputs (or executions), MT instead examines relationships amongst multiple executions that should hold for the system, called metamorphic relations (MRs): Without needing to identify any individual output as correct or incorrect, identification of a violation of the MR is sufficient to find an fault in the system in question. MT has been applied to a large amount of so-called untestable systems [50], overcoming the oracle problem obstacle, and uncovering previously unknown, real, bugs [51,52,53,54]. Critically, MT has been successfully applied to a number of areas and themes that we describe in this paper. MT has also been suggested as a suitable technique for analysing and verifying Big Data systems [48,55]. Similarly, MT has been successfully applied to large bioinformatics and health data, highlighting the suitability of the technique to this type of data [54,56].

V. Discussion and Conclusion

Health-related data, such as vital signs and various screening data, should produce similar values when detected by different sensors located at different parts of the body, or within the personal environment. The value of each data point for a given variable depends on the previous value, change of the status of the organism, and responses to various stimuli. Interpretation of the data depends on so-called medically established "normal values" that define healthy state. Furthermore, different states of the organism (such as resting, sleeping, exercising, walking or running) show characteristic trends of variable behavior. Pathological values are defined by specific thresholds and show specific trend deviations. Multiple sensors are expected to show the same trends for a given variable. They should agree with medical knowledge and conform to the value ranges characteristic for identified state.

Integration with IoT measurements, such as atmospheric variables or air pollution, provide additional information that can help both the interpretation of measured changes as well as the calibration of the sensor networks. For example, changes in wearable blood pressure (BP) measurement from a smart wrist band can be verified by a FDA certified IoT BP monitor, that can be requested automatically by the system. These data need to be cross-compared with HRV and weight data to identify possible causes of variability. Calibration of multiple sensors and sensor types from the network can, therefore, be done at the same time when measurement with certified instrument is performed. The recorded data then updates the individual's health history, and the past data can be corrected for systematic errors and explainable deviations. We propose the following starting points for the oracle problem questions:

What is the system actually intended to do? *The system is intended to collect vital data from individuals, the environment, assure accuracy, validity, and relevance of the data, provide interpretations, and act upon the patterns recognized in the data.*

Which source (if any) should be considered canonical? *The primary canonical data are those collected from certified medical devices, which can be used to calibrate other sensor data.*

What degrees of 'trust' or 'authority' should be given to one measure or another? *Higher trust is given to data of higher granularity, certified sensors, and certified medical instruments.*

How should this be established? *Unusual behavior or discrepancies can be explained, responded to, or corrected, through use of primary canonical data and the data from highly reliable IoT linked devices.*

How do we evaluate the correctness of our approach in an environment that is uncertain by design? *Compare data with the expected behavior (medical knowledge) and validate through regular medical diagnostic tests that are done on a regular schedule or on demand.*

Given the continuous reduction of sensor costs, and the emergence of 5G technologies, we foresee the growth of systems that combine large sensor networks with embedded redundancy, where multiple sensors measure the same variable and stream data to a control unit. The control unit will compare data between different streams, compare them with expected behavior based both on medical knowledge and the subject's individual characteristics. The system must apply filtering and corrections based on evidence, and provide reports followed by appropriate advice. When needed, standard medical diagnostic testing should be initiated and requested to validate changes indicated by WSN streams. The filtered, corrected, and summarized streamed data will be stored to form personal health histories. These personal health records will drive and complement both health and wellbeing personal care. Ownership of the data, plus ensuring safety and security of these data will require new implementation models.

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