UNIVERSITÀ DEGLI STUDI DI PADOVA

DIPARTIMENTO DI INGEGNERIA DELL'INFORMAZIONE

UNIVERSITY OF PADUA
DEPARTMENT OF INFORMATION ENGINEERING

MASTER'S OF SCIENCE IN
ICT FOR INTERNET AND MULTIMEDIA

EFFICIENT INFORMATION DISTRIBUTION IN THE INTERNET OF MEDICAL THINGS

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ACADEMIC YEAR 2021-2022
Date of graduation 28/02/2022

Abstract

Towards the world of Internet of Things, people utilize knowledge from sensor streams in various kinds of smart applications including, but not limited to smart medical information systems. The number of sensed devices is rapidly increasing along with the amount of sensing data. Consequently, the bottleneck problem at the local gateway has become a huge concern given the critical loss and delay intolerant nature of medical data. Orthogonally to the existing solutions, we propose sensor data prioritization mechanism to enhance the information quality while utilizing resources using Value of Information (VoI) at the application level. Our approach adopts signal processing techniques and information theory related concepts to assess the VoI. We introduce basic yet convenient ways to enhance the efficiency of medical information systems, not only when considering the resource consumption, but also when performing updates, by selecting appropriate delay for wearable sensors to send data at optimal VoI. Our analysis shows some interesting results about the correlation and dependency of different sensor signals, that we use for the value assesment. This preliminary analysis could be an initiative for further investigation of VoI in medical data transmission using more advanced methods.

Acknowledgements

I would like to thank my supervisor Professor Giulia Cisotto. I am sincerely grateful for providing me with this opportunity and for the scientific guidance and generous support during my studies. I would also like to express my gratitude to my co-supervisor Professor Marco Giordani. His expert advice, teaching, and commitment to high quality research have helped me develop my research work. This thesis would not have been possible without their profound knowledge, experience, and thoughtful discussions. I would also like to thank Professor Leonardo Badia for shedding light on my research in a priceless way that has always fascinated and motivated me. Having the opportunity to work with him is a great honor. Words cannot express how lucky I am to have friends to share this journey in Unipd. Victor, Jin, Marco and Madhushika, thank you for all the support. Above all, I would like to thank my loving husband, parents and my brothers, for the unconditional love, motivation, and support they always provide me.

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Chapter 1

Introduction

Remote healthcare monitoring is based on non-invasive wearable sensors and actuators that are integrated with modern communication and information technologies, which allow people to stay in their comfortable home environment instead of forcing them to visit expensive healthcare facilities for clinical monitoring. It allows healthcare personnel or caregivers to monitor important physiological signs including heartbeat, blood pressure, respiratory rate, temperature, glucose level and movements of their patients in real time, to diagnose health conditions and provide feedback from distant facilities [4],[5]. While enabling an efficient and cost-effective facility, these systems need to satisfy certain medical and ergonomic requirements. For example, they should generate reliable and timely medical information ensuring measurement accuracy, efficient data processing, information security, and low power consumption as well as the Quality of Service (*QoS*) [6].

However, developing such an efficient system suitable for medical applications is quite challenging. The applications can be driven by not only a high volume of collected values and metadata, but also by the variety and velocity of the streams that are continuously being transmitted through the local area network as well as the Internet [7]. It is often likely that the capacity of a communication link between a gateway at monitoring field and a faraway server is limited. Due to limited available hardware resources, such a large amount of data coming from different sensor nodes may generate heavy time-varying traffic. This can cause significant impact on the system reliability and *QoS*. The delay in providing results and generating alerts due to data loss, buffering, network communication errors, monitoring or processing could be intolerable in sensitive healthcare applications. Thus, it is essential to prioritise and limit the data transmission using appropriate mechanisms in order to increase the efficiency.

As a result of dedication and contribution of many researchers over the last decade, several optimization models and techniques which can be used on service level and application level are already available. A resource optimization could be accomplished on service level by aggregation and compression techniques related to the Quality of Service (QoS) such as specifying and controlling throughput and delay. On the other hand, the optimization on application level focuses on data contents and contexts [7].

Considering the existence of various types of wireless channels as well as different control loops, many of which have their own advantages and disadvantages, it is possible to achieve better and more efficient results in terms of network efficiency using control metrics for network design[8]. In particular, we will focus on two performance metrics that have raised the interest in sensor data optimization recent years. Age-of-Information (AoI) is a metric for network operation with sensor applications, which measures the information freshness from the application layer perspective and is applicable for any kind of network control scenario[9]. In order to maximize the target application utility while using limited transmission resources, a discrimination based on the Value of information (VoI) [10] can also applied[11].

In this thesis work, we will give an overview to the VoI and AoI in the medical context and discuss efficient data distribution methods based on VoI and AoI, to prioritize data transmission and enhance the efficiency of the Internet of Medical Things ($IoMT$)[12]. Further, we exploit signal processing techniques to extract the characteristics and pair wise similarities of sensor data and visualize them for better comparison. Preliminary, the Pearson's correlation was applied in the perspective of homogeneous and heterogeneous data sources and those results were compared in order to prioritize the sensors according to the uniqueness of information they could provide to the receivers. Based on the autocorrelation results of the signals, an appropriate transmission delay was calculated for each sensor. Later the Information Theory was applied to calculate the mutual information of sensor data over time and then the value of information was derived based on mutual information.

The objective of all these analyses was to prioritize data transmission of the sensor signals according to the degree of value of information obtained through simple yet interesting techniques which can be easily applied before proceeding with further analysis using advanced methods proposed in the literature. A publicly available data set called OPPORTUNITY activity recognition, that was recorded in an indoor scenario where a number of sensors acquired human and environmental data was used for the simulation.

The rest of this thesis work is organized as follows:

Chapter 1 - Section §1.1 gives an overview to the $IoMT$ and in section §1.2 we describe the Wireless Sensor Networks(WSN) and communication standards. In section §1.3 Requirements for WSN in healthcare, we explain the problem domain which is the efficiency of data distribution in smart medical applications and possible approaches to address the issue and why we chose VoI.

Chapter 2 - Background: In section §2.1 we talk about the motivation for this study. In sections §2.2 we introduce the idea of VoI and AoI in the medical context and important attributes. In §2.3, Information Theory related concepts such as entropy and mutual information and in §2.4 the signal processing techniques which will be used in the analysis are explained. Final section §2.5 of this chapter contains a list of papers from the review of the State of Art.

Chapter 3 - Data analysis and results: An explanation to our contribution in this context can be found in section §3.1 , An introduction to the data set, data collection methods and sensor types are described in section §3.2. Sections §3.3 is dedicated to the data analysis, pre-processing techniques and graph interpretation of the results obtained.

Chapter 4 - Discussion and Conclusion: summarize the thesis and discuss the limitations and future perspectives.

1.1 Internet of Medical Things (IoMT)

In recent years, the internet of things (IoT) [13] has gained a huge popularity in various domains such as entertainment, health, smart cities, sustainability and many others due to its low cost autonomous sensor operations [14]. Since the health industry is always at the forefront of innovation adoption, it has become one of the most promising industries for IoT applications. There are numerous IoT applications in the medical field such as Ambient Assisted Living (AAL), remote monitoring, medication control, personal health devices, ubiquitous health monitoring system, support for elderly and disabled people, mobile health, Telemedicine, improvement of quality of care and patient safety etc [12]. Particularly in the healthcare domain, it is defined as the Internet of Medical Things (IoMT) [13] which is a platform consisting of sensors and electronic devices to acquire biomedical signals from patients, processing units to process the signals, network devices to transmit the data over a network, temporary or permanent storage units and artificial intelligence analytics to diagnose and take medical decisions according to the convenience of physicians [13][15]. Moreover, IoMT is not only an optimization tool for hospitals and healthcare centers that allow for a faster and better way of gathering valuable data and make a better use of physicians' time, but also it can assist medical professionals in clinical decision-making with Machine Learning and Deep Learning techniques [16]. The revolution of IoMT has improved the well being of people and quality of life by offering cost effective smart health care services in a huge range of applications that utilize the potential of existing technologies and ultimately increase the life expectancy.

1.1.1 Basic architecture of IoMT

A typical IoMT system has three main stages, the first one being the device layer (sensor network) which establishes an effective and accurate sensing technology to collect distinct types of health-based data such as electrocardiogram (ECG), electromyogram (EMG), heart rate (HR), body temperature, electrodermal activity (EDA), arterial oxygen saturation (SpO2), blood pressure (BP) and respiration rate (RR) [4]. These data is usually acquired using bio-sensors and exists in the form of analog signals, which often have a low amplitude and are contaminated by noise [16]. Therefore, these signals need to be preprocessed and digitized using amplification and filtration operations.

It is essential to ensure that the information is well persevered and not lost during the acquisition stage because it may lead to wrong decisions during diagnosis. For example, if it happens that the data acquired from a cardiac event device that records the electrical activity of your heart such as heart rate and rhythm, is lost or not well preserved in the acquisition stage, it can lead to disastrous scenarios. By reading this erroneous data, doctors might think that the patient is affected by heart diseases such as the cardiomyopathies.

The second layer is the communication gateway that connects the sensors, intelligent devices, cloud and data systems to one another[17]. Since the data transferred to the cloud/data system or vice versa goes through the gateway, it can be viewed as a communication bridge between the smart devices in the medical field. Generally, the gateway has a processing unit (CPU) and wireless field connectors (WFC)[16] such as Bluetooth, ZigBee, Radio Frequency Identification (RFID), WI-FI or some other connection types which acquire information from wireless sensors. The gateway is responsible for data collection, pre-processing and data management. After the data is pre-processed and filtered out, the IoMT gateway sends the data to the cloud/data center for further processing and analysis.

The third layer is the cloud service layer (data layer). In this layer, the cloud acquires patients' information to analyze, process and store the data. [18]. Data processing includes signal identification, enhancement, feature extraction, classification and analysis of results using Data Mining techniques such as Machine learning, Artificial intelligence, Statistics, Probability [16]. The data is then stored and made available to users for diagnosis and feedback.

As shown in Fig.1.1 wireless sensors are attached to the persons body and textile and these sensors will connect to the mobile device (the central node) and will form the Wireless Body Area Network (WBAN)[1]. Through WBAN it is possible to remotely monitor the status of patients' health while communication technologies are used to send the information to the interested third parties via local gateways and the Internet.

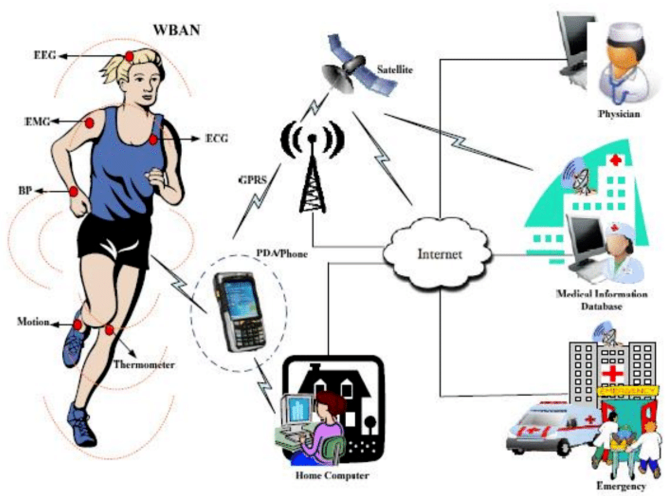


Figure 1.1: *Basic structure of an e-health system [1]*

1.2 Wireless sensor networks (WSN)

As we have stated before, the first layer is concerned with wireless sensors. Generally, in the IoT field, the wireless sensor networks (WSNs) are made of lightweight, usually small low power sensor nodes with sensing, computational, and wireless communication capability that are spatially deployed in the areas of interest for the purpose of monitoring environmental and physical conditions [19].

WSNs in modern IoT applications, often use the Micro-Electro-Mechanical Systems (MEMS) technology [20] which has smart sensor nodes where low power devices are equipped with one or more sensors, a processor, memory, power supply, radio and an actuator. Smart sensors are enhanced by the use of MEMS technology, as it allows many different types of micro sensors to be included in a device or a single chip. In WSNs, it is utterly important to have intelligent sensor components with the capability to sense multiple parameters, at a lower cost, even remotely. MEMS technology is considered as a very good solution to match all these requirements and it seems to offer an appropriate flexibility in remote health monitoring.

The WSNs used in health applications and generally in the IoMT field however, may include different types of smart medical sensors and devices called wearables [21] that are integrated into textile fiber, clothes, smart watches and elastic bands or directly attached to the human body, which can monitor and record real-time information about patient's physiological condition and motion activities. As the wearables are installed to continuously monitor the medical parameters in real-time, they offer better physical flexibility and mobility to the patient without any interruption to the daily living.

Physiological signals such as electrocardiogram(ECG), electromyogram (EMG), heart rate (HR), body temperature, electrodermal activity (EDA), arterial oxygen saturation (SpO2), blood pressure (BP) and respiration rate (RR) could help to detect and diagnose several cardiovascular, neurological and pulmonary diseases at their early stages [4]. MEMS based motion sensors such as accelerometers, gyroscopes, and magnetic field sensors measure activity related signals to be used in health applications like fall detection, quantifying sports exercise, management of chronic diseases, and monitoring the elderly to ensure that they maintain sufficient activity in the daily routine etc. Apart from these wearable sensors, environmental sensors such as barometric pressure sensors, ambient light sensors, humidity and temperature sensors that measure the surrounding information could also be highly useful in some IoMT systems like safety applications. Data from these sensors can be collected, analyzed and made available to the wearers, caregivers, healthcare professionals or any other responsible parities with the goal of improving the management and delivery of care, engaging patients and encouraging independent living.

Basically we can identify two types of WSN applications in $IoMT$, one which is designed for vital status monitoring and the other one which is used for remote healthcare surveillance. In vital status monitoring applications, patients wear sensors that measure their vital parameters in order to identify emergency situations such as cardiac arrest, sudden fall or epilepsy seizure detection. In such events, sensed data are sent to the responsible parties such as hospitals and emergency treatment centers where doctors need to respond effectively. In remote healthcare surveillance, wireless sensors can be used to gather clinically relevant information that are not vital, for applications such as rehabilitation supervision or elderly monitoring. Moreover, they can also be used to address the issues of managing chronic diseases or to monitor postoperative rehabilitation patients or persons with special disabilities who are forced to stay at home for long periods of time where falling or getting hurt cannot be disregarded.

The majority of wearable systems in remote health monitoring and activity recognition applications, use multiple sensor types to collect data from a single body location (multimodality single-location) [22]. The rationale behind this idea is to select sensors that are complementary and allows to recognize wide range of activities. For example, using an accelerometer and a gyroscope together can differentiate whether the person is walking forward or walking left/right while an accelerometer used alone can only determine that the person is walking [23]. This multi-modal sensor systems are convincing in terms of performance, since the information gained from multi-modal sensors can offset the information lost when activity data is collected from a single location [22]. According to the purpose of IoMT application, most relevant and convenient heterogeneous sensors can be chosen to create an intuitive virtual environment in order to accurately observe motion of the human body.

1.2.1 Communication standards of IoMT

Overall transmission of measured sensory data in a remote health monitoring system needs to be performed through two different phases. First, to transfer the collected physiological signals from the biosensors to the central node of WSN, and then to send the aggregated measurements from the WSN to a remote server or emergency services. Within the WSN, short-range transmission can be handled by multiple wireless links where sensor nodes can form a Body Area Network (BAN) in the basic configuration of a star topology. The central node of BAN can be a Personal Digital Assistant (PDA), a smart-phone, personal computer or a microcontroller device [24].

The most used wireless communication standards in BANs are IEEE 802.15.1 (Bluetooth Low Energy) and 802.15.4 (Zigbee) [24]. In regards to Zigbee, It is a standard that is more suitable for low cost, low complexity and low data-rate solutions. It operates in 16 channels in the 2.4 GHz band, in 10 channels in the 915

MHz band and in 1 channel in the 868 MHz band. The transmission range can go as far as 75 meters. It is also important to mention that Zigbee uses a complex encryption algorithm (AES) in order to protect the privacy and the integrity of the messages.

As for the BluetoothLE standard (IEE 802.15.1), it is an industry specification for short range connectivity between usually portable but also fixed devices. Similarly to Zigbee, it is also a low cost and low power standard, but it only operates in the 2.4 GHz band. The maximum transmission range in this case is bigger than that of Zigbee since it can arrive to 100 meters but it usually works best in the 10 meters range. Since encryption is optional, the Bluetooth framework is usually more vulnerable than Zigbee and more susceptible to possible attacks [24], [25].

Apart from Zigbee and BluetoothLE, other communication technologies can be used. One of these is the infrared (IrDA) [24], an extremely low cost communication protocol for exchange of information over infrared light. The main disadvantage in this case is that the range is even shorter than the ones of BluetoothLE and Zigbee. Moreover it requires line-of-sight communication. Although less popular, it's also worth mentioning other communication technologies in the medical field such as medical implant communication service (MICS), primarily used to transmit data for devices such as pacemakers, and UWB, which operates in the frequency range of 3.1-10.6 GHz .

For the long-range communication between the WSN and a remote station, there is a wide variety of available wireless technologies which can offer wide coverage and ubiquitous network access. Such technologies include Wireless Local Area Network (WLAN), Cellular Network Communication (GSM, GPRS, UMTS), and Worldwide interoperability for Microwave Access (WiMAX) [25]. Furthermore, future advances in 5G (fifth generation) mobile communication systems are expected to guarantee worldwide seamless access to the Internet at much higher data rates, and thus to facilitate more efficiently the need for gathering real-time measurements from a wearable health-monitoring system at a remote location.

1.3 Requirements for WSN in healthcare

However, like in every other WSN system, IoMT has various requirements that must be met in order to guaranty a reliable and effective service. Providing high bandwidth, low energy consumption, QoS, node mobility, congestion control, detection and mitigation, reliability, scalability, data aggregation, information security, availability and integrity are some of the general challenges in WSNs [19]. In particular, for healthcare applications, WSNs need to combine different sensing modalities and must handle several types of traffic with different characteristics such as continuous real-time health data, critical alerts and multimedia streams, etc. On the other hand resource limitation of the sensor nodes (battery, memory, available bandwidth and processing capabilities) and unreliability of low-power wireless links can be major concerns in designing an efficient communication mechanism. For example, when WSNs are integrated with the hospital information systems, the critical information such as alarm notifications share the bandwidth with less important data such as room temperature. In such cases, traffic prioritizing is essential to make sure that the critical information is delivered with the minimum loss and delay. Indeed, WSNs used in healthcare must guarantee to have minimum real time data delivery delays while supporting the *QoS* because, in an early detection of life-critical emergencies such as cardiac arrest and sudden fall, the real-time data transmission is crucial. In such events, situation identification and decision-making must be done as quickly as possible to save the person's life. In terms of data delivery, network reliability is also a critical aspect. Especially in vital signal monitoring, packet losses during the medical data transmission may have disastrous impacts on a patient's diagnosis.Traditionally, mechanisms such as multi path routing, local retransmission and reliable transport protocols are used in data transmission to overcome loss of packets [26]. Another important requirement for wireless healthcare applications is the node mobility support [27], which ensures the continuity of service when both patients and caregivers are on the move. Let us consider an ambulance or a vehicle, which is moving through different e-health domains and also supporting different e-health applications. The monitoring applications and the medical data source may be connected through different wireless technologies available, while the vehicle is moving. Thus, the decision of the proper channel assignment for the connection may be based on optimal network requirements and on the emergency nature of information according to the application requirements [26]. However, in an emergency condition or a time critical situation the prime condition that would be checked is the network availability together with the *QoS* constraints of the application.

In numerous cases, energy consumption is not a major concern for *QoS* in healthcare applications as the sensors are reachable and thus easy to replace the batteries. Nevertheless, it is still important to minimize the power consumption to reduce the burden of maintenance.

QoS in the context of WSN for healthcare may refer to the degree to which the system performs its intended functions along with the mechanisms implemented to provide them[26]. And supporting *QoS* is undoubtedly a challenging task as the different applications may have different requirements, thus no single *QoS* model can fit all the applications. Moreover, *QoS* provisioning is required in all layers of WSN architecture to guarantee the efficiency and reliability of health monitoring system.

Over the years, a number of researches have been carried out and came up with lot of reliable solutions. Various *QoS* provisioning frameworks [28] , energy efficient and *QoS* aware multi path routing protocols and congestion control methods [29] are just to name a few attempts to fulfill end-to-end delay and bandwidth requirements [30]. However these solutions have their own drawbacks which open other issues to be addressed such as data redundancy[31] and design complexity. On the other hand, with the rapid advancements in sensor devices and technologies, WSNs generate large volumes of data. Hence, these traditional mechanisms fail to satisfy the expected *QoS* in IoMT applications.

As a result, modern approaches such as cloud enabled health monitoring, Mobile Edge Computing(MEC)[32] and 5G enabled health monitoring have become promising solutions for the efficient information distribution in IoMT.

Recent advances in integrated cloud computing enables flexible and energy-efficient solutions for remote health monitoring. Some examples include personalized health monitoring frameworks which can distinguish emergencies from normal circumstances with the assistance of cloud computing and big data [33]. Moreover machine learning based classifiers for pattern recognition and activity recognition, and also cloud-based health monitoring infrastructures can be used to decrease the loads of data analysis at the central base station [34]. However, in cloud based health monitoring systems, data transmission to the distance cloud data centers will always be an impact to the latency.

MEC satisfies the delay constraint of the time sensitive tasks for medical information analysis by offloading the medical analysis task to the edge server in proximity [32]. It releases the burden of local devices and thus improves the capability of IoMT by providing sufficient computation resources. Nevertheless, this can results lack of information in the end server.

The prominent rise of 5G technology has enhanced the channel spectrum utilization efficiency, thanks to millimeter waves which enables the communication through 5G networks [35]. Uniformly, the signal frequency is high, usually 3.5GHz, as opposed to traditional cellular communication where the signal frequency is definitely lower. In the paper [36] the author explains the need for intelligence in the future IoT-based 5G networks and argues that there is a genuine need for AI in the future cellular networks. Further, the necessity of networks that are capable to self-organize, and to learn from the environment and make decisions using machine learning, game theory and optimization algorithms.

Even though these modern approaches have some significant influence towards the efficiency and resource utilization in $IoMT$, none of these can guarantee the maximum QoS. As a result of that, researchers focus on context aware solutions to deliver information to consumers by filtering, prioritizing and transmitting only the useful subsets. In fact, determining the Value of Information (VoI) [37] as an enabler for the effective decision making and thus enabling efficient information distribution in IoT applications has become a trending research area. Solutions that can analyze information and infer its value related to the application requirements, can ensure that important and high-priority medical information will reach the users in a timely manner. Also, it can reduce the bandwidth requirements, communication latency[30] and information overload.

Chapter 2

Background methods

In this chapter we discuss the idea of VoI and AoI in the context of IoT for health applications and some of the possible approaches that other researchers have used to asses the VoI in different applications. Further we explain the signal processing techniques and Information theory related concepts with formulas which will be used in later part of the thesis.

2.1 Motivation

Recent technological advances in sensors, low-power integrated circuits, and wireless communications have enabled the design of low-cost, lightweight, and intelligent physiological sensor nodes. These nodes are capable of sensing, processing, and communicating integrated with wireless personal or body networks for health monitoring. These networks allow inexpensive, non-invasive, continuous health monitoring with almost real-time updates of medical records via the Internet.

However, developing flexible, reliable, secure, and power-efficient systems suitable for medical applications is quite challenging. Because the applications can be driven by not only a high volume of collected values and metadata, but variety and velocity of the streams. Such streams are continuously transmitted to the cloud service to obtain some knowledge about patients behavior according to user requirements. Different data sources may generate heavy time-varying traffic which may lead to intolerant abeyance in wireless wearable sensors [38]. One of the most common issues with wearable systems is the delay in providing results and generating alerts due to data loss, buffering, network communication, monitoring or processing.

Throughout the last decade, many researchers have dedicated their contributions to handling this bottleneck issue. Thanks to their effort in many years of experiments, it has become evident that significant benefits can be obtained by limiting the amount of information which broadcasts over bandwidth constrained communication channels [11]. However there is no uniform superstructure which provides an information centric mechanism to serve this purpose. Existing application requirement based data dissemination methods, often consider a common usage context of the sensor data while ranking the transmission against different requirements of the application. For example, low latency is considered to be common for the QoS requirements of all the applications. But in reality, not every application query is executed in real-time and thus, low latency can not be a generic temporal requirement. It can be considered more as an application-specific usage context of the real time data streams [39].

In service level, a data reduction could be accomplished by aggregation and compression techniques, regardless of application information. Along with reducing amount, the QoS such as throughputs and delays could also be specified and controlled [7]. Not only in the service level but also the solutions on application level can be exploited according to user specified requirements to draw only requested data streams. For example, in a lighting control system of smart building, the data from movement and occupancy sensors are significant while data from temperature and heat detectors are disregardable. The key idea is that the importance of any specific sensing data for one application can be different for the other applications.

Giordani et al [11], introduces two reliable approches to use the limited transmission resources in a way that maximizes the utility for the target applications, particularly in vehicular networks. One approach is to set a bound on the age of information (AoI) to make sure the broadcast is never older than the intertransmission period. The other approach is to discriminate the value of information (VoI). Four effective methods that are ideal to efficiently disseminate the most valuable pieces of information over wireless networks have been summarized as Heuristic Approaches, Adaptive Approaches, Machine Learning (ML) Approaches and Analytic Approaches where each approach has its fors and againsts.

Motivated by this vehicular network investigation research, we focus on prioritizing sensor data based on the VoI and AoI, for the efficient information distribution of $IoMT$. In this context we use the analytical approach where VoI estimation is achieved through signal processing techniques and information theory mathematical models.

However, the prioritizing mechanisms we used in this context are, preliminary on-board processing of sensor observations, which allow the sender to validate the integrity of the acquired information and determine whether it embeds valuable characteristics for receiver(s), which will also prevents the transmission of redundant or duplicate data. This basic analytical approach could be used as an initiative to the further analysis using Machine Learning algorithms or Analytical Hierachy Process (AHP). Which can be employed to value information of wearable sensor data based on pairwise comparisons of specific criteria and to ultimately score the different data dissemination alternatives [11].

2.2 Value of Information

The concept VoI was originated in economic and decision making research communities, with the purpose of investigating the advantages that additional information provided to decision makers. Eventually, many domains such as vehicular networks [40][11], underwater sensory networks [41] [42], tactical edge networks [43], tracking systems or smart cities have been evaluated using different methods to assess VoI for the purpose of efficient data transmission. As a result of diversity of these domains, it is still difficult to give a precise definitions for VoI. However, VoI is formally defined as an assessment of the utility of an information product when used in a specific usage context [44]. Moreover, $Value$ of an information product associated with a sensor service can be defined as its importance in the particular application usage context [39]. In other words, a sensor service that is more valuable in one usage context can be mildly important in another. This importance or the $value$ can be determined by the attributes specific to each usage context or the application of the particular information.

In remote health monitoring domain, there are several types of applications such as safety, sleep monitoring, drive monitoring and fall detection which use wearable sensor data for decision making. According to the taxonomy of VoI (figure 2.1), there are several important attributes which influence the value assessment of these applications. The attributes can be listed as timeliness, quality of information, space dependency, dataset heterogeneity, signal variance, age of information, urgency and novelty. As mentioned earlier, significance of these attributes can differ from one medical application to another. In this research we contemplate three main attributes which can be considered more important for the VoI in fall detection application that are the dataset heteroginity, time dependency and AoI. These on the other hand are convenient to analyze using the

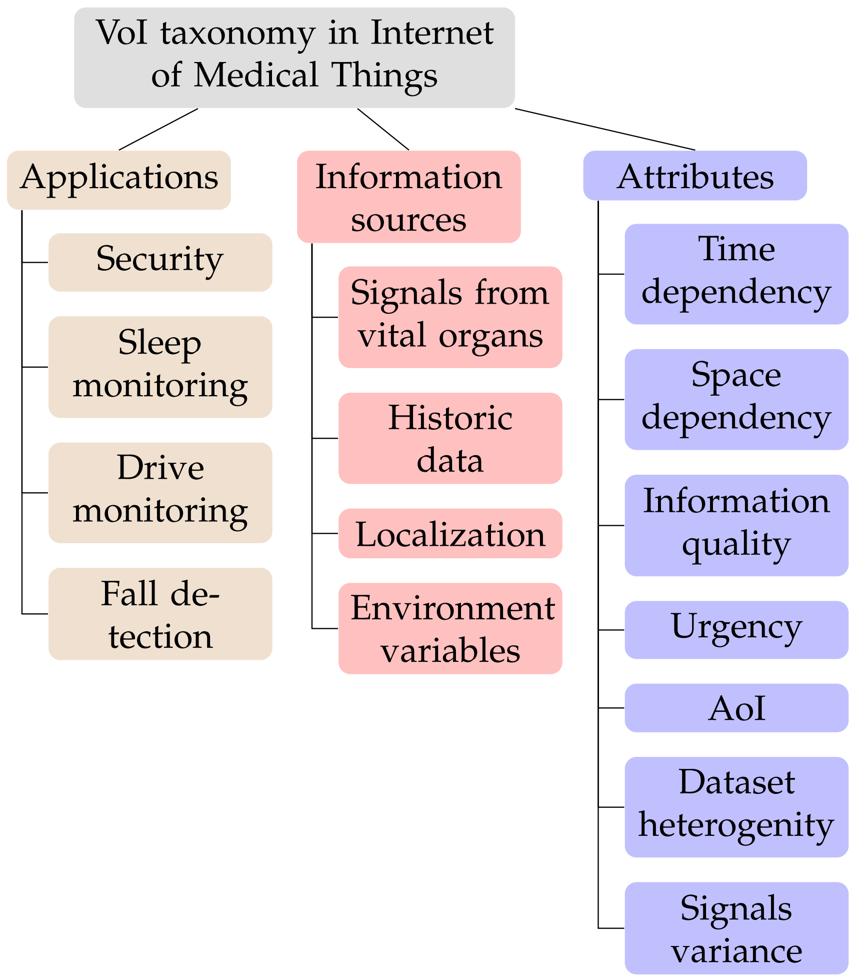


Figure 2.1: *Taxonomy of VoI in IoMT presented in thesis by Anselmi*

dataset chosen.

2.2.1 Age of Information

Generally, in the medical field it is very important to keep track of the novelty or the freshness of information. AoI is a novel concept that has been introduced around 2010 which can be used to estimate the obsolescence and freshness of information in communications, and information systems [45]. Until recent years, researchers have focused their studies mainly on delay or latency in information systems, when it comes to the data transmission efficiency and freshness of data that are receiving.

It is extremely valuable to have such kind of an approach, specially in the medical field where it is nearly impossible to update the information in real time, due to the constraints of wireless communication channels. Thanks to AoI's tools and metrics, researchers can keep the monitored health information updated and avoid information starvation.

However it is important to notice that AoI gives us information on how obsolete or fresh the data are, but it does not provide any information on the usefulness of the current data. Although the AoI grows over time with a unit rate, the performance degradation caused by information aging may not be a linear function of time. Thus we have to consider other metrics such as cost of updating delay and/or data staleness based on the specific applications. Even though it is a bad practice, most of the mechanisms focus on only one kind of requirement to be fulfilled when ranking the importance of data to be transmitted. As a better mechanism, VoI based information dissemination has been investigated recently in several application areas where wireless sensor networks are involved.

2.3 Information theory

The information theory is a branch of probability and statistics that has been developed since the 1920s and has found wide application in different fields such as telecommunication, physics, bio engineering and many others [46][47]. In the case of communication of information over a noisy channel, Information can be thought of as the resolution of uncertainty [48]. The fundamental quantities of information theory are entropy and mutual information which are defined as functional of probability distributions [49]. They characterize the behavior of long sequences of random variables and allow us to estimate the probabilities of rare events. Entropy is a measure of information in a single random variable, and mutual information is a measure of information in common between two random variables.

2.3.1 Entropy

Entropy is the avarage level of ”information surprise” or the ”uncertainity inherent to the possible outcome of a random variable[48]. [49]. Let X and Y be the discrete random variables with the respective probability mass function $p(x) = Pr\{X = x\}, x \in X$ and $p(y) = Pr\{Y = y\}, y \in Y$. Thus, $p(x)$ and $p(y)$ refer to two different random variables and are in fact different probability mass functions, $p_X(x)$ and $p_Y(y)$, respectively. The entropy $H(X)$ of a discrete random variable X is defined by;

$$H(X) = -\sum_{x\in X} p(x) \log p(x) \tag{2.1}$$

Entropy is measured in bits, and it is a functional of the distribution of X, which does not depend on the actual values taken by the random variable X, but only on the probabilities. We denote expectation by E. Thus, if $X \sim p(x)$, the expected value of the random variable $g(X)$ is written;

$$E_p g(X) = \sum_{x\in X} g(x)p(x) \tag{2.2}$$

2.3.2 Joint entropy and conditional entropy

The definition of entropy of a single random variable can be extended to a pair of random variables. The joint entropy $H(X,Y)$ of a pair of discrete random variables (X,Y) with a joint distribution $p(x,y)$ is defined as;

$$H(X,Y) = \mathbb{E}_{X,Y}[-\log p(x,y)] = -\sum_{x,y} p(x,y) \log p(x,y) \tag{2.3}$$

which can also be expressed as

$$H(X,Y) = -E \log p(X,Y) \tag{2.4}$$

The conditional entropy quantifies the amount of information needed to describe the outcome of a random variable Y given that the value of another random variable X is known.

$$H(X|Y) = \mathbb{E}_Y[H(X|y)] = -\sum_{y\in Y} p(y) \sum_{x\in X} p(x|y) \log p(x|y) = \sum_{x,y} p(x,y) \log(\frac{p(y)}{p(x,y)}) \tag{2.5}$$

$$H(X|Y) = H(X,Y) - H(Y) \tag{2.6}$$

The naturalness of the definition of joint entropy and conditional entropy is exhibited by the fact that the entropy of a pair of random variables is the entropy of one plus the conditional entropy of the other [49].

2.3.3 Relative entropy or Kullback-Leibler distance

The entropy of a random variable is a measure of the uncertainty of the random variable; it is a measure of the amount of information required on the average to describe the random variable. The relative entropy is a measure of the distance between two distributions. In statistics, it arises as an expected logarithm of the likelihood ratio. The relative entropy $D(p||q)$ is a measure of the inefficiency of assuming that the distribution is q when the true distribution is p. For example, if we knew the true distribution p of the random variable, we could construct a transmission code with average description length $H(p)$. If, instead, we used the code for a distribution q, we would need $H(p) + D(p||q)$ bits on the average to describe the random variable.

The relative entropy or Kullback–Leibler distance between two probability mass functions $p(x)$ and $q(x)$ is defined as

$$D(p||q) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)} = E_p \log \frac{p(X)}{q(X)}. \tag{2.7}$$

2.3.4 Mutual information

Mutual information is a measure of the amount of information that one random variable contains about another random variable. It is the reduction in the uncertainty of one random variable due to the knowledge of the other. If we consider two random variables X and Y with a joint probability mass function $p(x,y)$ and marginal probability mass functions $p(x)$ and $p(y)$, the mutual information $I(X;Y)$ is the relative entropy between the joint distribution and the product distribution $p(x)p(y)$. By combining equations 2.3, 2.3, 2.4 and 2.5:

$$
\begin{aligned}
I(X;Y) &= \sum_{y \in Y} p(y) \sum_{x \in X} p(x|y) \log \frac{p(x|y)}{p(x)} = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \\
&= H(X) - H(X|Y) \\
&= H(X) + H(Y) - H(X,Y) \\
&= \mathbb{E}_{p(y)}[D_{KL}(p(X|Y=y))]||p(X))] \\
&= D_{KL}(p(X,Y)||p(X)p(Y))
\end{aligned}
\tag{2.8}
$$

2.4 Correlation Coefficient

In statistical terms, correlation is a method of assessing a possible linear association between two continuous variables [50]. Correlation is measured by a statistic called the correlation coefficient, which represents the strength of the putative linear association between the variables in question. It is a dimensionless quantity that takes a value in the range -1 to $+1$ [51]. A correlation coefficient of zero indicates that no linear relationship exists between two continuous variables, and a correlation coefficient of -1 or $+1$ indicates a perfect linear relationship. The strength of relationship can be anywhere between -1 and $+1$. The stronger the correlation, the closer the correlation coefficient comes to ± 1. If the coefficient is a positive number, the variables are directly related (i.e., as the value of one variable goes up, the value of the other also tends to do so). If, on the other hand, the coefficient is a negative number, the variables are inversely related (i.e., as the value of one variable goes up, the value of the other tends to go down).

Size of Correlation	Interpretation
.90 to 1.00 (-.90 to -1.00)	Very high positive (negative) correlation
.70 to .90 (-.70 to -.90)	High positive (negative) correlation
.50 to .70 (-.50 to -.70)	Moderate positive (negative) correlation
.30 to .50 (-.30 to -.50)	Low positive (negative) correlation
.00 to .30 (.00 to -.30)	negligible correlation

Table 2.1: *Rule of Thumb for Interpreting the Size of a Correlation Coefficient [3]*

2.4.1 Pearson's correlation

Pearson's correlation can be considered as a measure of the linear relationship between the random variables. The Pearson Correlation Coefficient, which can be calculated using the expression given in the below equation 2.9, is used to evaluate the linear correlation between two variables X, Y. The function $cov(X, Y)$ is the covariance of X and Y. σ_X and σ_Y are the deviations of X and Y, respectively, while μ_X and μ_Y are the respective means. $\rho_{X,Y}$ ranges from $+1$ to -1. A value of $+1$ implies that X is completely positively linearly correlated to Y. On the other hand, a value of 0 indicates that X is not linearly correlated to Y at all. Finally, a value of -1 implies that X is completely negatively linearly correlated to Y. In most cases, X and Y show an extremely strong correlation to each other when $\rho(X, Y)$ is greater than 0.8. Further, X and Y can be said to be strongly correlation to each other when $\rho(X, Y)$ is greater than 0.6 [52].

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{\mathbb{E}[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}. \tag{2.9}$$

2.4.2 Auto correlation

Autocorrelation can also be referred to as lagged correlation or serial correlation, as it measures the relationship between a variable's current value and its past values. In other words it represents the degree of similarity between a given time series and a lagged version of itself over successive time intervals. When computing autocorrelation, the resulting output can range from -1 to 1. An autocorrelation of +1 represents a perfect positive correlation (an increase seen in one time series leads to a proportionate increase in the lagged time series). An autocorrelation of -1, on the other hand, represents perfect negative correlation (an increase seen in one time series results in a proportionate decrease in the lagged time series).

2.5 Review of the State of the Art

In this subsection, a review of some of the recent and important research papers that employed the sensor data prioritizing in $IoMT$ are presented. The table summarizes the studies and the techniques employed in the experimental and analysis setup.

REF	DESCRIPTION
Efficient Dynamic Sensing for Continuous Activity Monitoring, Lawrence K et al., 2011 [53]	**Dataset:** 2 subjects, sensors: triaxial accelerometers on right wrist, waist and right ankle **analysis method:** Partially Observable Markov Decision Process (POMDP) **Performance:** classification accuracy 95%, energy reduction 40%
Viterbi-based context aware mobile sensing to trade-off energy and delay, Amiri et al., 2020 [54]	**Dataset:** 1subj / 25 different activities, 12min each. sensors: PPG sensor (HR, Respiration rate, SPO2), IMU Acquired **analysis method:** MDP method compared to myopic strategy **Performance:** average of 12% reduction in energy consumption.
Scalable and energy-efficient context monitoring framework for sensor-rich mobile environments, Kang et al., 2008 [55]	**Dataset:** Acquired dataset, (1 / 12h). sensors: Light sensor, temperature/humidity sensor, 2-axial accelerometer, software sensors for time and indoor location, GPS (Blood Volume Pulse sensor, Galvanic Skin Response sensor) **analysis method:** Context dynamics are monitored through the analysis of selected sensors that can reveal a change in the current state. **Performance:** Reduction of more than 90% of data transmission. Find a trade-off between processing efficiency and energy efficiency
The Jigsaw continuous sensing engine for mobile phone applications, Lu et al., 2010 [56]	**Dataset:** acquired dataset (16 / -). sensors: Accelerometer, microphone, GPS Accelerometer **analysis method:** different processing pipelines for the three sensors , **Performance:** accuracy: 95.1% , Microphone recall:85.35%, Significant reduction of the power usage while keeping the average error low.
Power-aware computing in wearable sensor networks: An optimal feature selection, Ghasemzadeh et al., 2014 [57]	**Dataset:** acquired dataset (3 / 14 transitional movements for 10 times each) sensors: three-axis accelerometer and a two-axis gyroscope **analysis method:** Information theory measure (symmetric uncertainty) to quantify correlation between two features or between a feature and a class, **Performance:** 30.7% energy savings, 96,7% classification accuracy, can be applied to sensor selection (eliminating redundant sensor nodes).

A context-aware mhealth system for online physiological monitoring in remote healthcare, Zhang et al., 2016 [58]	**Dataset:** acquired dataset, (5 / 24h) sensors: Accelerometer, ECG **analysis method:** context-aware physiological analysis with regard to daily activities **Performance:** 95.56% classification accuracy for activity recognition..

Chapter 3

Data analysis and results

This chapter contains a description about the data set which includes data collection methods, environmental set up and locomotion sensor details. Moving forward with the data prepossessing and analysis part, it explains the correlation, mutual information and VoI analysis results with relevant numerical and graph interpretations. The analysis was conducted using signal processing methods to compare the sensor signal correlation and their characteristics.

3.1 OPPORTUNITY Activity Recognition Dataset

The OPPORTUNITY activity recognition dataset is a benchmark for human activity recognition algorithms which offers a rich playground to assess methods for sensor selection, feature extraction, classifier calibration and adaptation, multimodal data fusion, automatic segmentation, among others[2][59].

The dataset consists of complex naturalistic activities with a particularly large number of atomic activities collected in a sensor rich environment using networked sensor system integrated in the environment, in objects, and on the body. The activity recognition environment and scenario were designed to generate many activity primitives in a realistic manner[60]. In this research we use the same subset employed in the OPPORTUNITY Activity Recognition Challenge[61] which contains recordings of four subjects performing activities of daily living, ranging from simple motion primitives to complex gestures. We take into account only the locomotion data collected by body worn sensors. This includes 5 commercial RS485-networked XSense inertial measurement units (IMU) attached in a custom-made motion jacket (figure 3.1), 2 commercial InertiaCube, 3 inertial sensors located on each foot (figure3.2b) and 12 Bluetooth acceleration sensors on

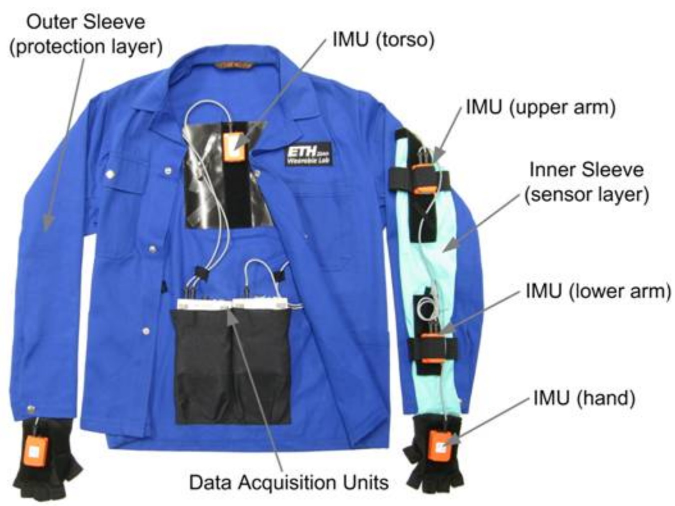
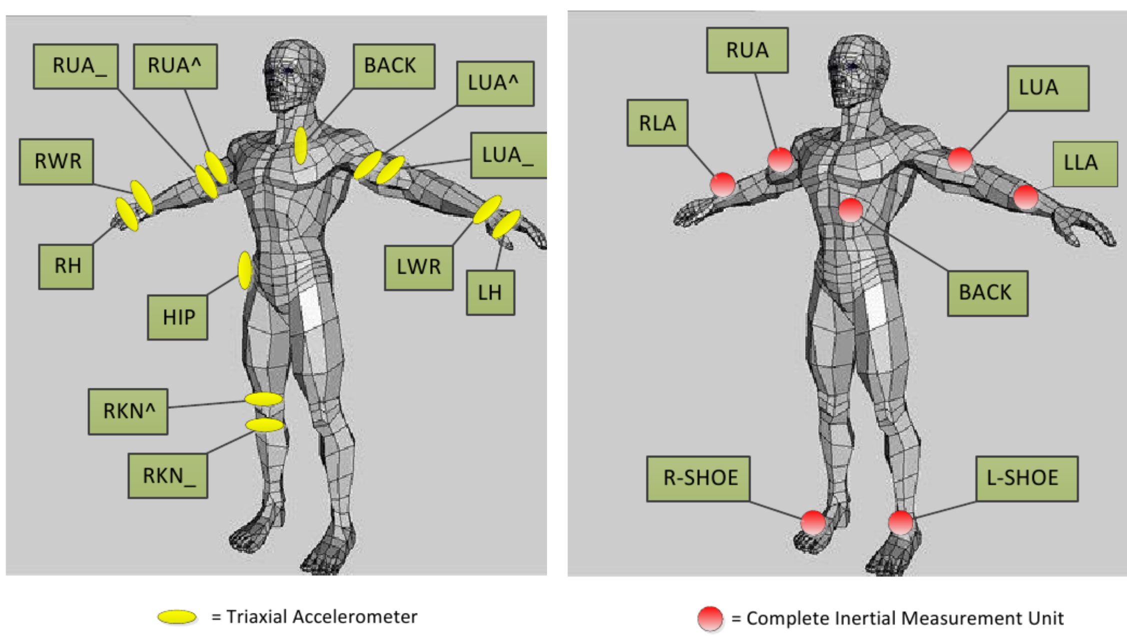


Figure 3.1: *wearable motion jacket [2]*



(a) *Tri-axial Accelerometer placement* **(b)** *Inertial Measurement Unit placement*

Figure 3.2: *Multi model on-body sensor placement over the subjects' body [2]*

the limbs (figure3.2a). Each IMU is composed of a 3D accelerometer, a 3D gyroscope and a 3D magnetic sensor, offering multimodal sensor information. Each sensor axis is treated as an individual channel yielding an input space with a dimension of 113 channels at the sample rate of these sensors is 30 Hz.

For each subject there have been recorded six different runs where five of them are activity of daily living (ADL) and subjects are free to perform the activities without any restriction, by following a loose description of the overall actions to perform. For example, prepare a coffee with milk and sugar using the coffee machine and take coffee sips, move around in the environment. The remaining run is a drill run where subjects were instructed to perform 20 repetitions of the given activity sequence which has been designed to collect many activity instances. For the simulations we have considered four different modalities that are sit, walk, stand and lie.

ADL run

The ADL run consists of the following sequence of activities:

1. Start: lying on the deckchair, get up.
2. Relax: go outside and have a walk around the building.
3. Prepare coffee: prepare a coffee with milk and sugar using the coffee machine.
4. Drink coffee: take coffee sips, move around in the environment.
5. Prepare sandwich: include bread, cheese and salami, using the bread cutter and various knifes and plates.
6. Eat sandwich.
7. Cleanup: put objects used to original place or dish washer, cleanup the table.
8. Break: lie on the deckchair.

Drill run

The drill run consists of the following sequence of activities:

1. Open then close the fridge.

2. Open then close the dishwasher.
3. Open then close 3 drawers (at different heights).
4. Open then close door.
5. Switch on and switch off the light.
6. Clean the table.
7. Drink while standing.
8. Drink while seated.

3.2 Sensor types

In this study we analyse locomotion sensor data collected by motion sensors which sense the movements, such as tilt, shake, rotation, or swing. Basically the accelerometers and gyroscopes. They have become the most used motion sensors in the study of human movement because they are small, light, wearable and non-invasive [62]. These sensors are commonly used with a micro controller that is able to process the measurements obtained, and peripherals such as Bluetooth modules to enable communication with other devices [63]. Systems made up from a combination of these characteristics are called Inertial Measurement Units (IMU) that can work autonomously for long periods [64], [63]. Apart from the main sensor components of wearable sensor systems, there are InertiaCubes and Quaternions which provide real-time orientation data and represents the device orientation.

3.2.1 Accelerometer

Accelerometers can be used for body position and posture sensing. In particular, using triaxial accelerometer, we can measure the linear acceleration of movement by reading the data it provides on the three Cartesian axes X, Y, Z, thanks to which velocity and displacement can also be calculated. An example for this, is the Apple's iLife Fall Detection sensor, that uses an accelerometer and a microcomputer in order to detect falls, shocks or other movements [65]. Another important use of accelerometer is the safety application of the elderly. When walking, frail or elderly patients may suddenly lose consciousness and fall, especially in hospitals. The fall may cause or lead to paralysis or even death. By using special types of fall detection accelerometers, it is possible to understand if and when the fall occurs and provide timely assistance thus saving their lives [66]. Because of these and other reasons, accelerometers are considered amongst the most interesting sensors in the IoMT field. The main problem with the data provided by them however, is that they do not provide information on the lateral orientation or tilt during the movement. Moreover, sometimes the data we receive from the accelerometer can be affected by noise. To solve this problem, the 3-axis accelerometer information is combined with the 3-axis gyroscope data, another important sensor of which we will talk below, in order to get an output that is both clean and responsive.

3.2.2 Gyroscope

Gyroscope sensor is a device that can measure the orientation and angular velocity of an object. These are more advanced than accelerometers, because gyroscope sensors can measure the tilt and lateral orientation of the object whereas accelerometer can only measure the linear motion. Usually these sensors are installed in the applications where the orientation of the object is difficult to sense by humans. Thanks to their ability to provide dynamic information through the angular speed, gyroscope sensor measurements have been useful in the analysis of human movements such as gait posture transitions or falls. In some activity recognition researches, where gyroscope is used to assist the mobile orientation detection, the rotation angle produced by gyroscope is identified to be the key performance booster for fall detection [65]. Gyroscope sensor outputs are analog, which results a considerable decrease of power consumption compared with the digitization of the signal[67]. While the accelerometers can only detect whether an object has moved or is moving in a particular direction, Gyroscopes can obtain accurate measurements of complex motion in multiple dimensions, tracking the position and rotation of a moving object. Another important characteristic compared to accelerometers and compasses, is the fact that gyroscopes are not affected by errors related to external environmental factors such as gravity and magnetic fields. Due to these reasons, gyroscopes can highly influence the motion sensing capabilities of advanced motion sensing applications in consumer devices such as full gesture and movement detection and simulation in video gaming.

3.2.3 Magnetometer

A magnetometer sensor is also known as a compass sensor that measures magnetic fields and the magnetization of materials. It can also be employed to measure direction, strength, or relative change of a magnetic field at a given location. This sensor is usually based on the electromagnetic property of the Earth. Just like a simple compass can detect the direction with respect to the North pole of the Earth by the use of magnetism, a magnetometer sensor for smart-phones works with a similar functionality. For example, compass sensors are used in consumer devices for reorienting a displayed map to match up with the direction where user is facing. In other words compass readings can be used to detect the direction change in the user's motion. [22]. Magnetic sensors can also be used to correct errors from other sensors such as accelerometers. An advantage of using a magnetometer over accelerometer for breathing rate measurement is that the magnetometer data does not require complex processing to obtain movements of the chest. In the case of the accelerometer, the movement of the chest must be obtained from integration of the acceleration using sophisticated algorithms [68]. Hence, the magnetometer and signal processing algorithm can be programmed in a low-power on-site microcontroller, without using an external computational unit. This enables transmitting real-time processed data to a gateway while saving the battery lifetime and bandwidth.

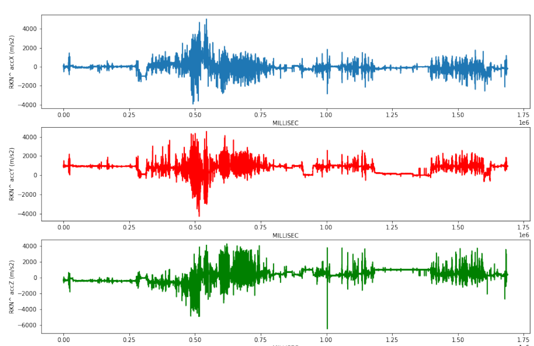
However, the magnetometer measurements are very sensitive to external interference and magnetic changes produced by nearby ferromagnetic objects. For this reason, magnetometers are often used as a complement to gyroscopes and accelerometers by means of fusion algorithms [67].

3.3 Data analysis

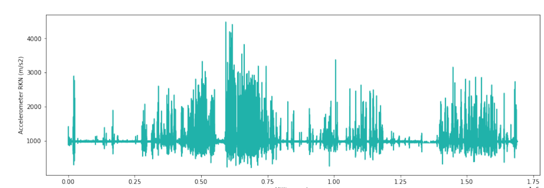
The analysis was carried out under the signal processing and Information theory related methods discussed in section 2.3 and 2.4 to favor the main objective of this research which is to identify reliable mechanisms to prioritize the sensor data transmission based on VoI. Each analysis was performed on both of the homogeneous and heterogeneous perspective of sensory data.

3.3.1 Data Pre-processing

To evaluate the correlation, mutual information, entropy and VoI we used the ADL run dataset relative to one representative subject, to which we will refer to as ”test subject”. We selected ADL run dataset, because its subjects execute daily activities without thorough instructions thus it is richer in activities than the drill run dataset. The ADL run dataset can be represented as a matrix, where every column is containing data coming from a sensor. In the dataset, there were no sensor names to identify the data in each column, instead there were labels, and the meaning of those labels were given in a separate text file. So first we extracted sensor names and assigned to the columns in order to ease the analysis using Python. There was a considerable amount of missing data in the dataset mainly due to disconnection of wireless sensors. The missing data are indicated by ”NaN” (not-a-number) in the dataset. First we identified the columns which have more than 50% of NaN values and discarded those columns. Although many complex methods have been proposed to tackle this issue, in this study we simply replaced the missing values with mean imputation. Mean imputation involves replacing any missing value with the mean of the present values, which has the benefit of preserving the mean of the observed data. So, if the data are missing completely at random, the estimate of the mean remains unbiased. Plus, by imputing the mean, we can keep our sample size up to the full sample size [69].



(a) *Acceleration of right knee in 3 dimensions*



(b) *Combined acceleration of right knee*

Figure 3.3: *Converting 3 axis sensor data into one axis*

Since each axis of three dimensional and two dimensional sensors are treated as one channel in the data set, first we combined them in to single channels. There is no such hard or fast rule but several approaches such as normalizing the data, in other words converting all data into values between 0 and 1. But the simplest and perhaps one of the best and commonly used approaches is squaring the data and combining as one dimension. For combining, the data was squared and summed up and finally the square root of the sum was taken as the reading:

$$Acc = \sqrt{acc_x^2 + acc_y^2 + acc_z^2} \tag{3.1}$$

In figure 3.3a we show the acceleration on the X, Y, and Z axes, respectively of the right knee. Figure 3.3b shows the combined acceleration calculated as the square root of the sum of the squares of the component accelerations. It is more convenient to use the combined acceleration data in the analysis as shown in figure 3.3b.

3.3.2 Correlation analysis

3.3.2.1 Homogeneous sensor signal analysis

The most common technique used in the analysis of signals or time series data is autocorrelation. In technical terms, autocorrelation means how much the data at time stamp T is correlated with T-1 of a signal. The higher the value, the higher the positive correlation and the data is redundant.

Figure 3.4 shows the autocorrelations of body worn sensors. The entire signal has been taken in to account and calculated the autocorrelation using default lag(33ms) or the original transmission delay. It is less efficient to transmit data using those particular sensors continuously, because more or less the same information is being transmitted. In order to increase the value of information or optimize the usage of bandwidth we can decide which sensors should be transmitting data continuously and which should not, based on autocorrelation of the signal.

According to table 2.1 the sensors with more than 0.7 of autocorrelation are considered as highly correlated and thus transmit redundant information. Continuous data transmission should be delayed for such sensors. For instance, LocationTags sensors have autocorrelation close to 1. We can assume the reason for such higher correlation for Location Tags is, because a person cannot change his position (move) that much in every 33 milliseconds. Therefore, the data transmitted by these sensors is highly redundant, their transmission should be delayed.

The strategy can be derived by calculating autocorrelation at different lags and find which one is the most suitable delay for each sensor. The correlation values in figure 3.4 has been calculated after every 33 milliseconds (lag=1). Here we test autocorrelation coefficient for different lags(from 1 to 1000) in ascending order. If the autocorrelation coefficient on a particular lag is less than 0.5 , we assume at that exact lag, the signal is not highly correlated and information sent

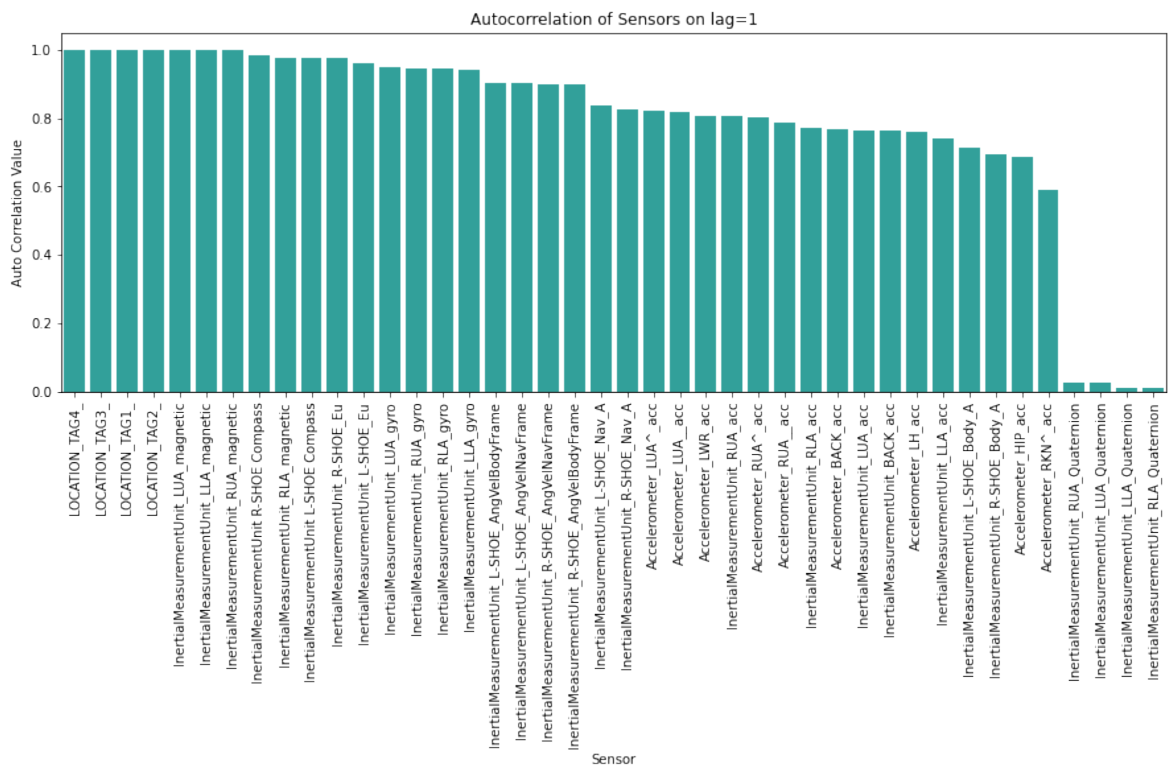


Figure 3.4: *Autocorrelation of each sensor*

is valuable. Then that lag value has been converted into milliseconds to decide the delay. If the sensor is not highly correlated at lag $= 1$ then we could say that its transmission should not be delayed anymore. Likewise we can come to a conclusion that is, when the autocorrelation of a signal is more than 0.5, we should delay the transmission by $(lag - 1) * 33$ milliseconds. Ideal transmission delay according to the autocorrelation of each signal is given in table 3.1 For instance, Quaternion sensors data is highly uncorrelated and the transmission should not be delayed for the sensors, while Locomotion tags are highly correlated and their transmission can be delayed from 10 to 32 seconds.

Sensor	**Delay(ms)**
InertialMeasurementUnit L-SHOE Compass	5445
InertialMeasurementUnit R-SHOE Compass	7557
Accelerometer-RKN-acc	33
Accelerometer-HIP-acc	33

Accelerometer-LUA-acc	66
Accelerometer-RUA-acc	66
Accelerometer-LH-acc	66
Accelerometer-BACK-acc	33
Accelerometer-RUA-acc	66
Accelerometer-LUA-acc	66
Accelerometer-LWR-acc	66
InertialMeasurementUnit-BACK-acc	33
InertialMeasurementUnitLUAacc	33
InertialMeasurementUnitRUAacc	66
InertialMeasurementUnitLUAgyro	297
InertialMeasurementUnitRUAgyro	264
InertialMeasurementUnitLUAmagnetic	5181
InertialMeasurementUnitRUAmagnetic	3993
InertialMeasurementUnitLLAacc	33
InertialMeasurementUnitRLAacc	66
InertialMeasurementUnitLLAgyro	264
InertialMeasurementUnitRLAgyro	231
InertialMeasurementUnitLLAmagnetic	4422
InertialMeasurementUnitRLAmagnetic	3663
InertialMeasurementUnitL-SHOEEu	6336
InertialMeasurementUnitR-SHOEEu	16962
InertialMeasurementUnitL-SHOENavA	99
InertialMeasurementUnitR-SHOENavA	99
InertialMeasurementUnitL-SHOEBodyA	66
InertialMeasurementUnitR-SHOEBodyA	33
InertialMeasurementUnitL-SHOEAngVelBodyFrame	231
InertialMeasurementUnitR-SHOEAngVelBodyFrame	231
InertialMeasurementUnitL-SHOEAngVelNavFrame	231
InertialMeasurementUnitR-SHOEAngVelNavFrame	231
LOCATIONTAG1	9999
LOCATIONTAG2	6930
LOCATIONTAG3	32934
LOCATIONTAG4	32934
InertialMeasurementUnitLUAQuaternion	0
InertialMeasurementUnitRUAQuaternion	0

InertialMeasurementUnitLLAQuaternion	0
InertialMeasurementUnitRLAQuaternion	0

Table 3.1: *Appropriate delay of transmission based on autocorrelation*

3.3.2.2 Heterogeneous sensor signal analysis

Pearson correlation method is commonly used for finding cross-correlations between two independent variables, in this case two different sensors. We have presented the cross correlations values between each different pair of sensors belong to the same category in heat maps (figure 3.8). Given color bar indicates the corresponding Pearson correlation value with color shades (-0.4 to 1) where the darkness increases with the value. The assumption here is same as before, the higher the correlation (negative and positive), the more redundant the data.

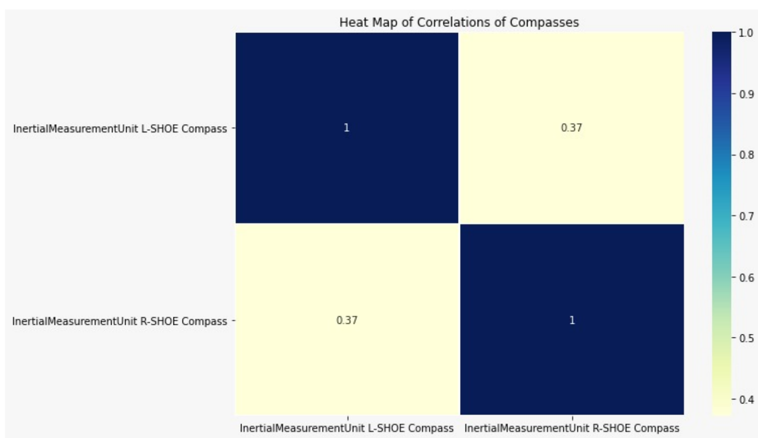


Figure 3.5: *Cross correlation of InertialMeasurementUnit Shoe Compass sensors*

For example, the Right Shoe Compass (InertialMeasurementUnit R-SHOE Compass) and the Left Shoe Compass (InertialMeasurementUnit L-SHOE Compass) has lower correlation with each other with Pearson correlation value of 0.37933 (figure 3.5). Based on that we can assume both of these sensors are sending different yet valuable information about the particular activity instance and both of them should be transmitting data in order to make accurate decisions.

As shown in figure 3.6 the Hip Accelerometer is highly correlated (more than 0.7) with Accelerometr BACK, Accelerometer Left Upper Arm and Accelerometr Right Upper Arm sensors while moderately correlated (more than 0.5) with Ac-

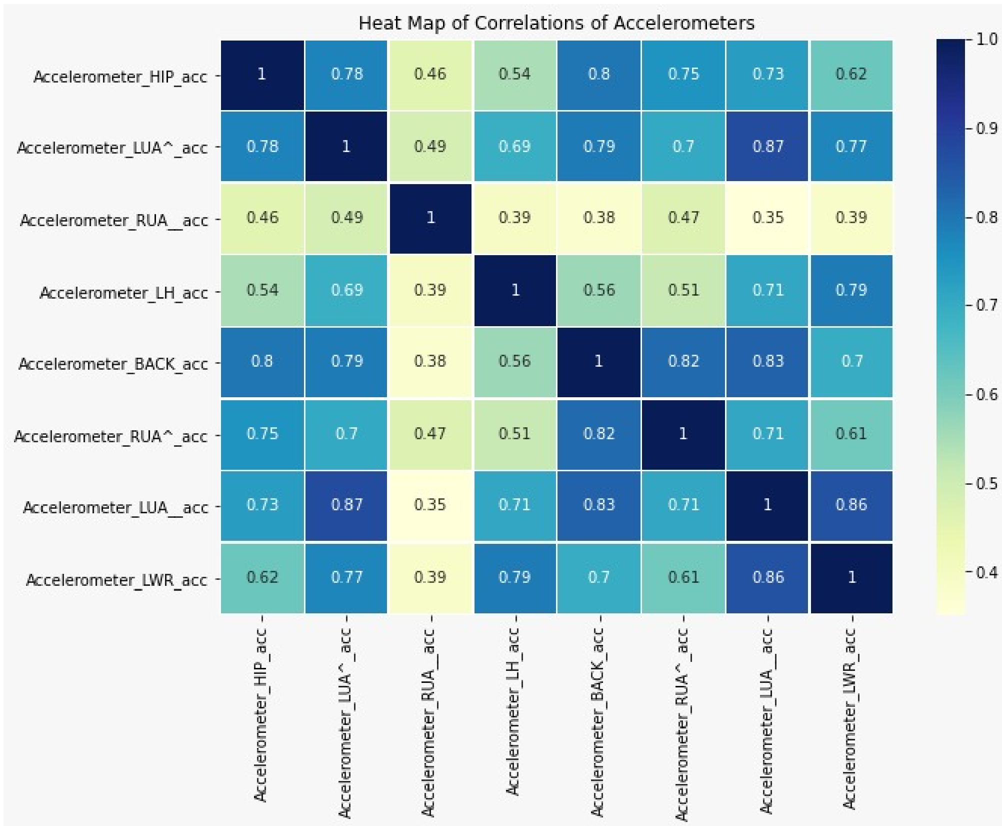


Figure 3.6: *Cross correlation of Accelerometer sensors*

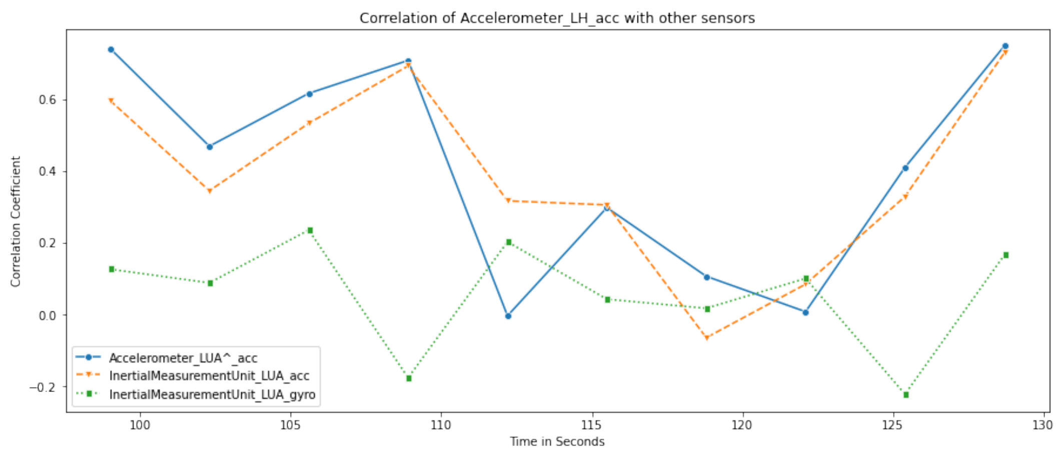
celerometr Left Wrist, Accelerometer Left Hand sensors. According to that observation we could say the Hip Accelerometer is not a critical sensor in decision making and its data would not severely affect the final decision, since the other highly correlated sensors can be used in such incidence. Another possibility of optimizing the resources would be selecting one or two sensors of theses accelerometers rather than use all of them for transmitting data at once. In that case the other aspects can be considered such as cost, complexity, durability, etc. As discussed in the examples, using this comparison of correlation values, we can decide many efficient ways to broadcast information through sensors. When an attribute (signal) is highly uncorrelated with other signals, it is important to prioritize the transmission of that signal. Let's assume a sensor is highly correlated with two other sensors; then only one of those 3 sensors should transmitted given that the signal characteristics are quite similar. In that case selecting the most useful and convenient sensor is challenging. We can check the missing values for each sensors and the one that with the lowest number of missing values should be chosen. Again, if two or more sensors have identical number of missing values then we can choose based on sensor quality, sensor manufacturer, sensor implantation location (where the sensor is on body or object) etc. If such choice is difficult to be made, then the sensor can also be chosen randomly or cost effectively.

Moving forward, we calculated the cross correlation of randomly selected baseline sensors with other heterogeneous sensors placed in the same area of the test subjects body. In 3.7 we can see the cross correlation of each different sensor placed on the left upper 3.7a and lower 3.7b arms with the base line sensor called Left hand accelerometer. As we can see in the graph, the left hand accelerometer sensor has higher positive correlation with the left lower arm accelerometer sensor. In fact, the position of hand and lower arm are very close and they move together and both of the sensors are accelerometers. It explains why there is such a high correlation. However, graph shows there are some points where the data has no correlation, which means in some intervals both sensors are transmitting different data.

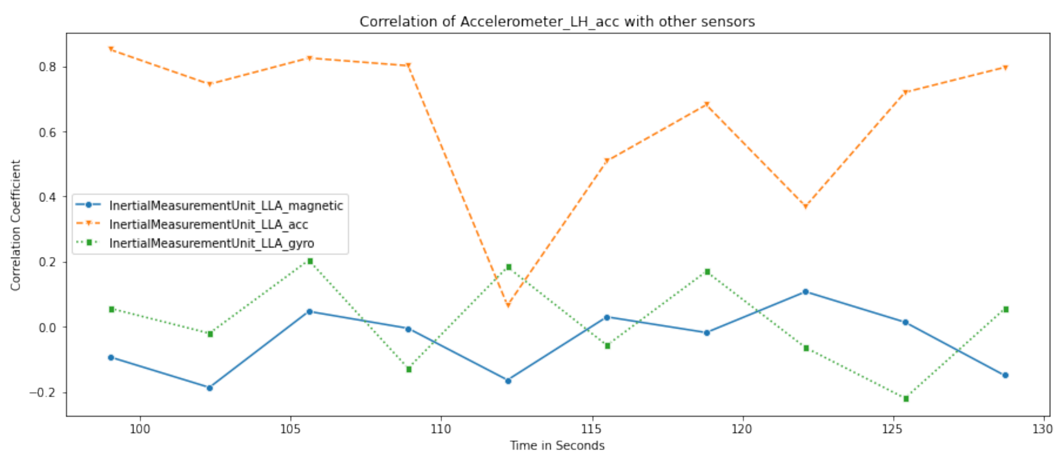
Figure 3.8 shows the cross correlation of Left shoe compass sensor with the other sensors placed in the same shoe. It is safe to say there is a moderate correlation between the sensors.

Figure 3.9a presents the cross correlation of Location tag 1 with the other location tag sensors. It seems to be is highly correlated with location tag 2 (both positively and negatively). For tag 3, there is an inconclusive pattern, half of the time it is highly correlated and then it has moderate or low correlation with tag 1. Location tag 4 does not have much correlation with tag 1 for most of the time. However it is difficult to say whether they are highly correlated witch each other or not, as they drastically vary over time. In figure 3.9 we can see the cross correlation of Location tag 2 with the other locomotion sensors and the observation is quite similar to the figure3.9a.

Cross-correlation only tells us how similar two different signals are from one another. It doesn't tell us however anything about the information carried by these signals. If we want to understand the amount of information carried by these signals and how important the information of a certain signal is with respect to the information of another signal, we have to use the concepts of Information theory. Mutual Information (*MI*) can be thought of as a non-linear function of correlation. As introduced in section 2.3.4 , *MI* between two random variables is the amount of information that one gains about a random variable by observing the value of the other. It is linked to another key concept in Information Theory,



(a)



(b)

Figure 3.7: *Correlation of Left hand accelerometer with other sensors*

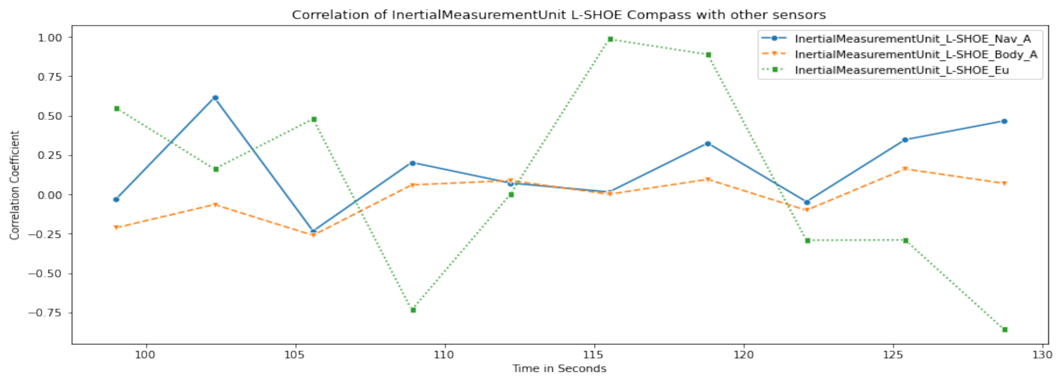
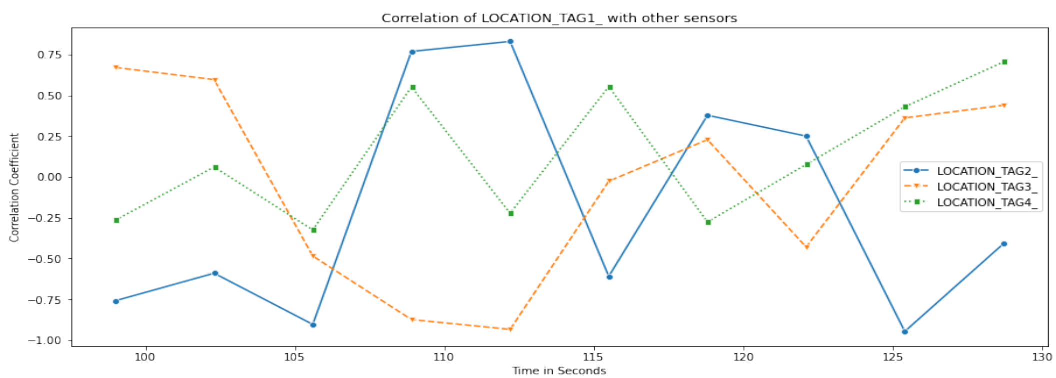
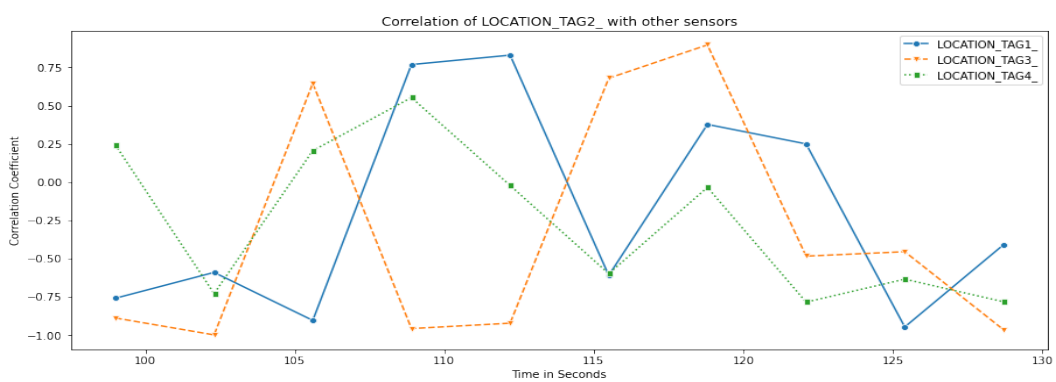


Figure 3.8: *Correlation of L_Shoe_Compass with other sensors*



(a)



(b)

Figure 3.9: *Correlation of Location_Tag with other sensors*

that is the entropy, which can be thought of as how surprised one can be on average when observing a random variable. MI and entropy are measured in bits. It is considered more general than correlation and handles nonlinear dependencies and discrete random variables. Thus, we move on to the next part of our analysis towards the VoI, using MI.

3.3.3 Mutual information based VoI analysis

Initially we computed the MI between different pairs of sensors in the dataset. Then evaluated those values under three categories. First approach was to compute MI between two homogeneous sensors placed on two parts of the body, over time. Secondly, we determine the MI of one sensor shifted in time. Finally we calculate the MI between two heterogeneous sensors.

MI depends on the time window of interest: ideally, we have computed the mutual information between one sample t of the first signal and the same sample $t + T$ of second signal. In practise, we should consider a time window T, and evaluate the mutual information within that window. Different values of T could be considered in simulations. We used a window of 1000 samples and then segmented or made sliding windows of 100 samples from that window.

At first, we set the VoI as VoI = 1 - MI. This preliminary evaluation will indeed help us identify the most valuable signals. For example, if the MI between two heterogeneous signals is higher, it means that they are quite correlated and that we can reconstruct the former with the latter with quite high accuracy. This could be the initial step for more advanced analyses in which we can define more sophisticated methods to evaluate the VoI from the mutual information. MI and VoI are inversely proportional, in other words if VoI is increasing then MI would be decreasing and vice versa. For a better visualization, the calculated MI and VoI were plotted in line graphs where x-axis is corresponding time-stamp and y-axis is the values of MI and VoI.

Figure 3.10 represents the VoI and MI between two gyropass sensors: IMU Left Lower Arm gyropass and the IMU Right Lower Arm gyropass which are homogeneous sensors placed on left and right arms. As we can see in the graph, within 30 seconds the VoI is drastically vary, which means the two sensors are not much dependent on each other and both of them should be transmitting data despite the fact that they are homogeneous sensors.

Figure 3.11 represents the VoI and MI between two heterogeneous sensors that are IMU Left Lower Arm accelerometer and Right Shoe Navigator sensors. Within the time window considered, the overall VoI seems to be very high be-

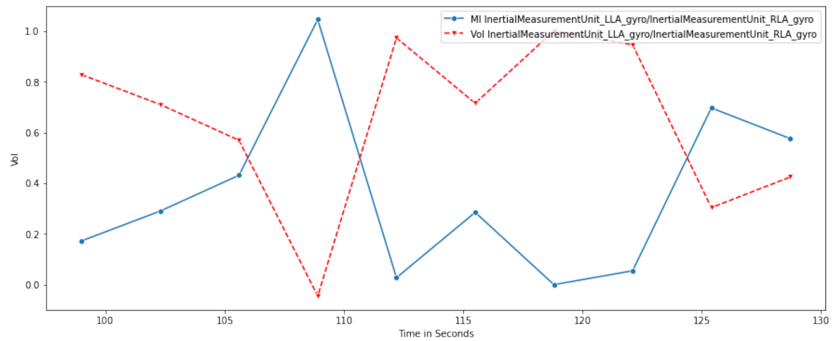


Figure 3.10: *VoI and MI between two gyropass sensors: IMU Left Lower Arm gyropass and the IMU Right Lower Arm gyropass*

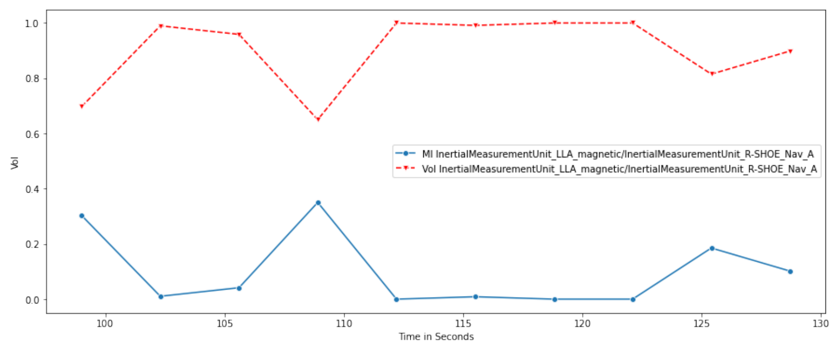


Figure 3.11: *VoI and MI between two heterogeneous sensors that are IMU Left Lower Arm accelerometer and Right Shoe Navigator*

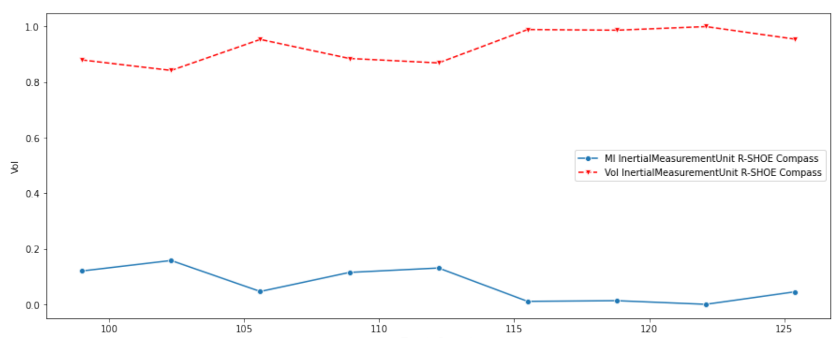


Figure 3.12: *VoI and MI of Right Shoe Compass while subject is walking*

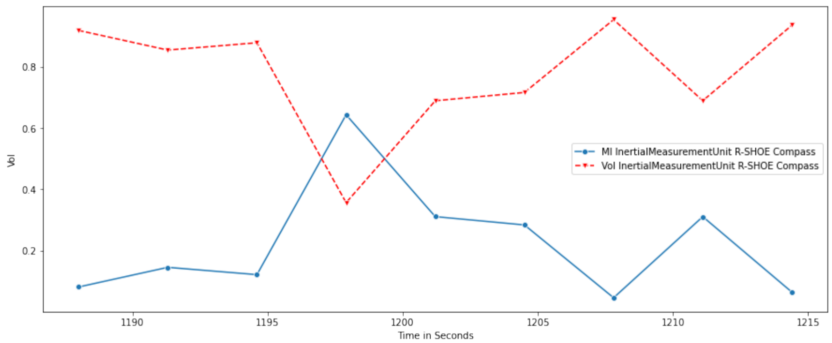
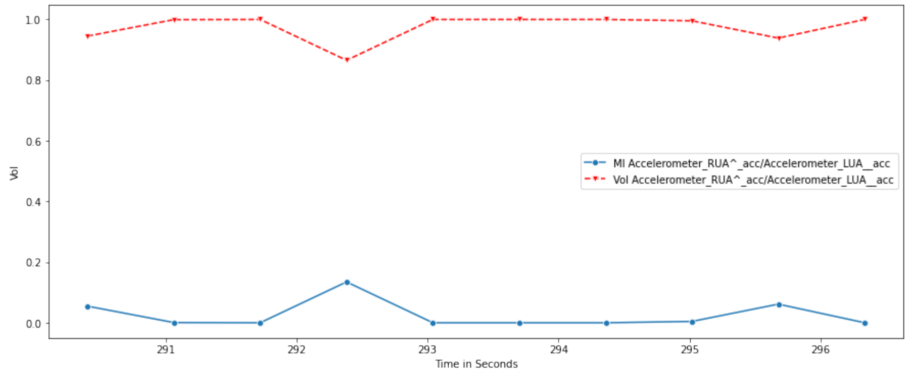


Figure 3.13: *VoI and MI of Right Shoe Compass while subject is sitting*

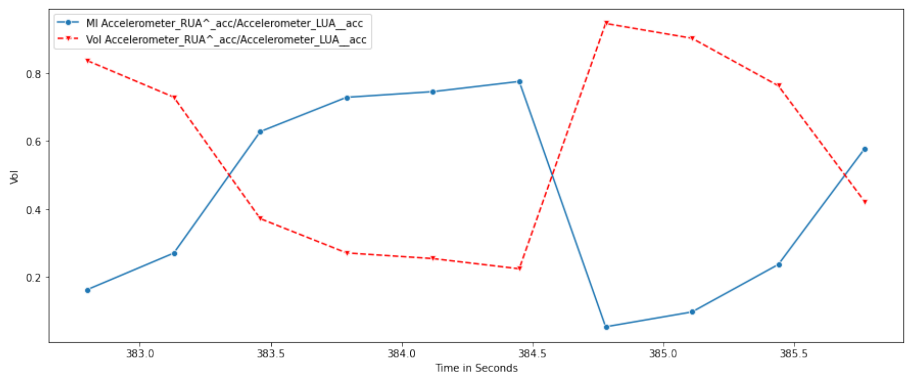
tween two signals while *MI* is significantly low. Which indicates the two signals are not much correlated, which proves the fact that heterogeneous sensors placed on different body parts are important to increase the value of information of the system.

We considered walking and sitting activities performed by subject in order to analyse the *MI* and *VoI* comparatively using the same sensor. Figure 3.12 and figure 3.14 represent the *VoI* and *MI* of Right Shoe Compass while subject is walking and sitting respectively. According to the graph, value of information is very high (more than 0.8) during the considered sample window where subject is walking. On the other hand value of information suddenly decreases lower than 0.4 and then gradually increases while the subject is sitting. Given to the two different observations we can decide that this sensor should be transmitting data over the entire time.

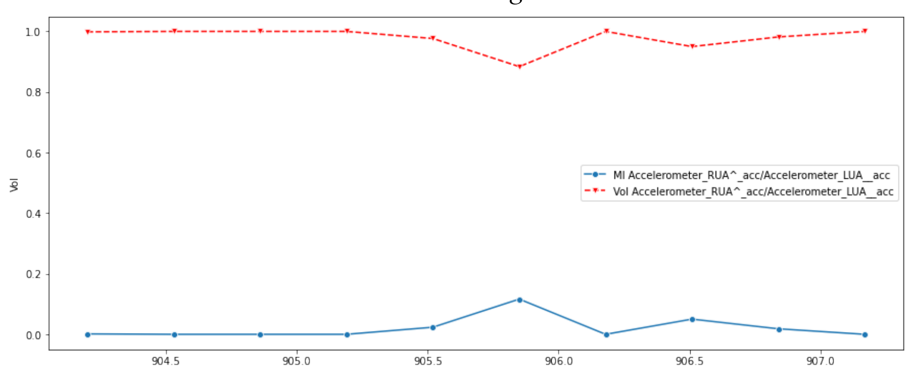
It is possible to analyze the correlation between the signals in the various combinations we have considered and more. Consequently, we can determine the VoI of each signal, on the impact of other signals as well as the variation of the signal itself according to subjects physical activity. In figures 3.14, 3.15 and 3.16 contains the graph representations of *MI* and *VoI* of selected Accelerometer, Gyroscope and Compass sensors compared to their exact opposite sensors placed on the other side of the body. In particular, left and right upper arms accelerometer sensors, left and right lower arms gyroscope IMU sensors and left and right shoes compass IMU sensors. Here we observe how the *MI* and *VoI* vary over time with respect to the activity performed. According to the results observed, it is easy to comprehend that, high MI implies a low VoI and, on the contrary, low MI implies a high VoI and requires the transmission of both signals at equal priority.



(a) *Lying.*

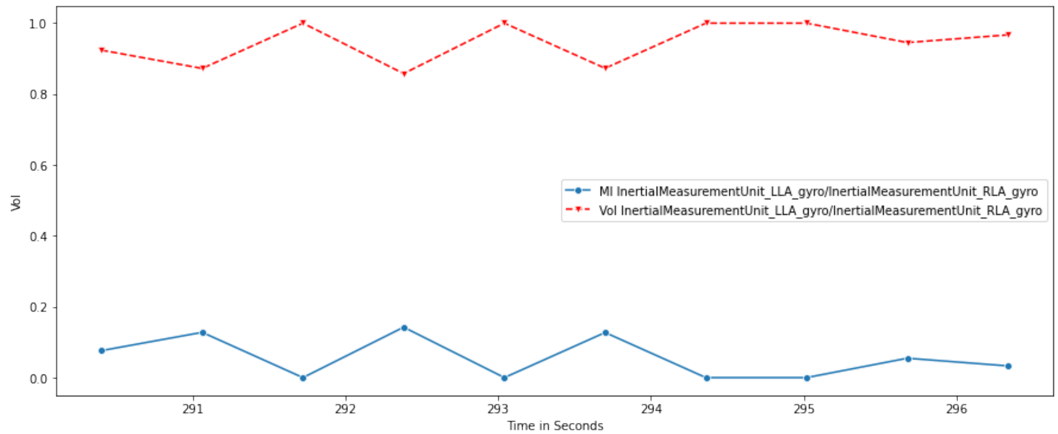


(b) *Walking.*

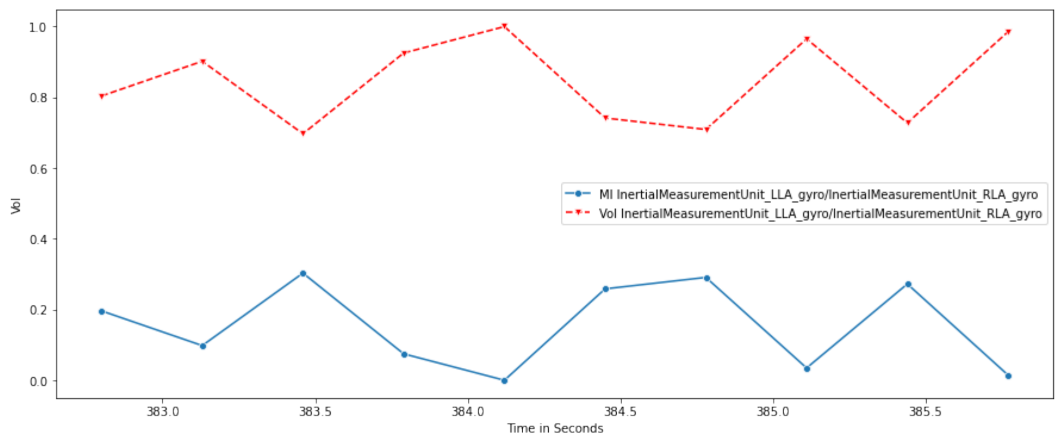


(c) *Sitting.*

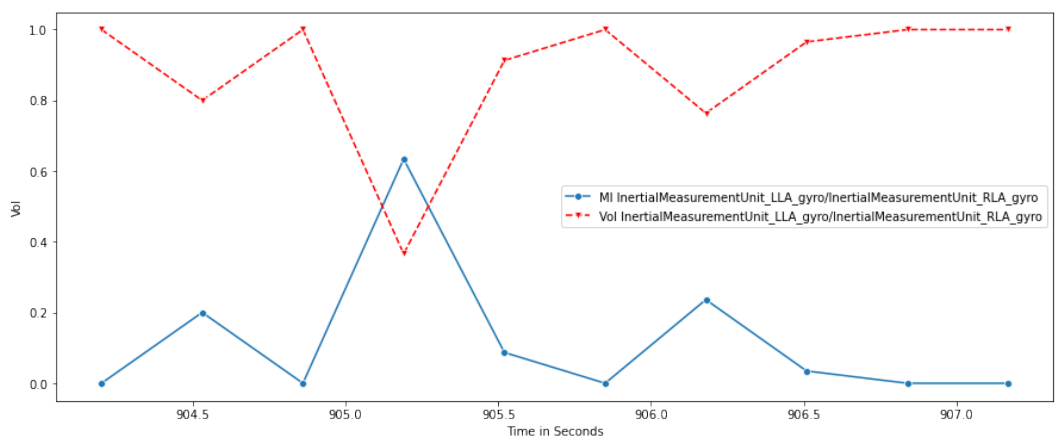
Figure 3.14: *VoI and MI of Right upper arm and Left upper arm accelerometers, when different activities were performed in different time windows*



(a) *Lying.*

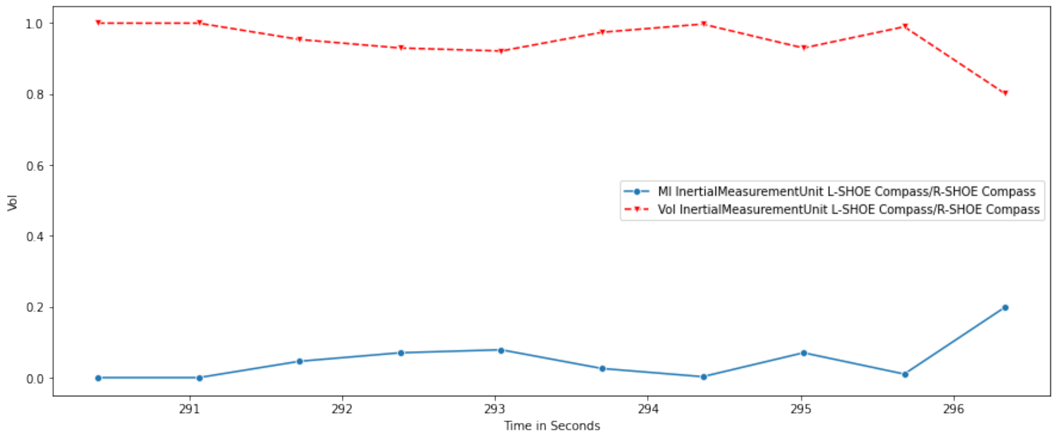


(b) *Walking.*

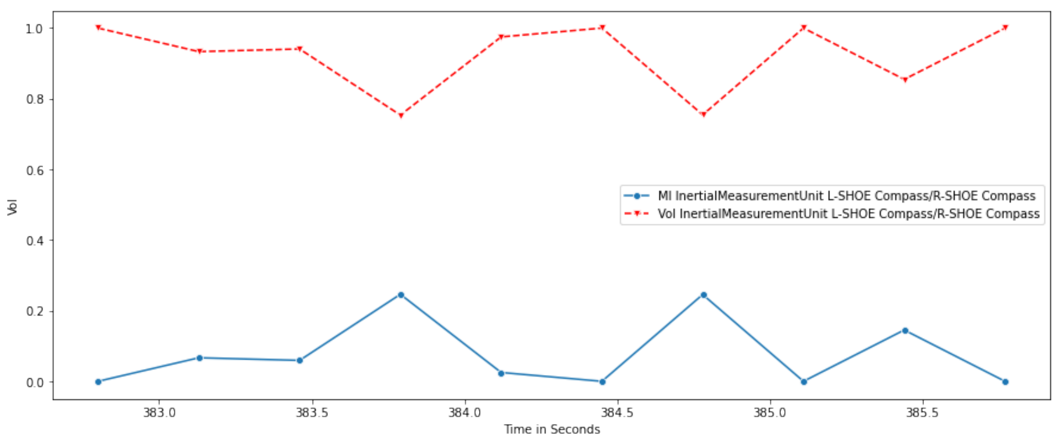


(c) *Sitting*

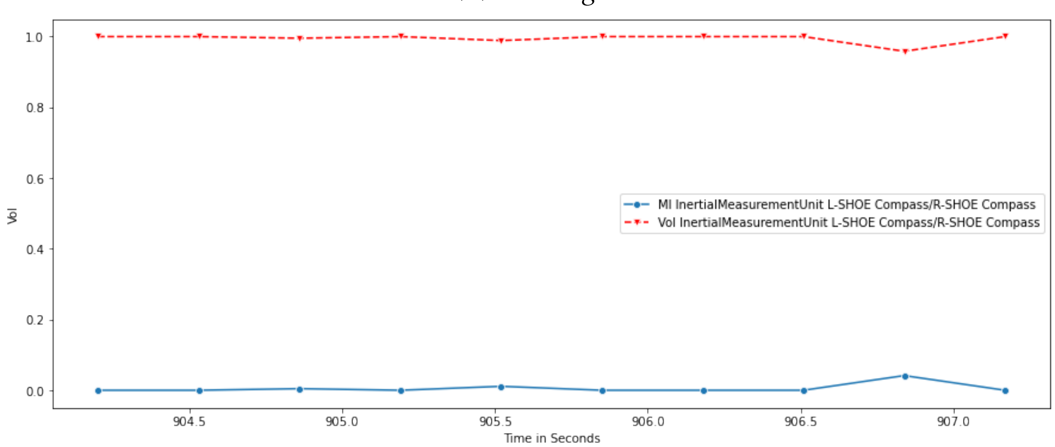
Figure 3.15: *VoI and MI of left lower arm and right lower arm IMU gyroscopes, when different activities were performed in different time windows*



(a) *Lying.*



(b) *Walking.*



(c) *Sitting.*

Figure 3.16: *VoI and MI of left shoe and right shoe IMU compass sensors, when different activities were performed in different time windows*

Chapter 4

Discussion

In this thesis, we have considered a publicly available activity recognition dataset called OPPORTUNITY dataset to study the correlation and mutual information of motion sensor signals. Our goal was to identify a reliable mechanism to prioritize the sensory data transmission in order to minimize the cost and bandwidth consumption without degrading the quality and the importance of a given piece of information. To achieve that, first we studied newly recognized concepts which are used for content aware data dissemination of smart communication networks called AoI and VoI. These concepts are already used in smart vehicular networks, underwater communication systems and other IoT applications for efficient data transmission over limited available resources. We realized this notion could be very useful in $IoMT$ or smart healthcare applications where the timely available accurate medical data is priceless.

AoI is simply the freshness of information, while VoI is the importance of data according to its use of the particular application context. We introduce several basic methods using signal processing techniques and Information theory to asses the value of information of sensor data, and based on that we suggest optimal transmission delay for each sensor.

In our data analysis, first we pre-processed the dataset and calculated the autocorrelation and cross correlation of sensor signals using selected data sample. Based on those results we proposed appropriate data transmission lags for each sensor and we suggested how to prioritize the data transmission when two or more sensors are highly correlated.

Our next method was to calculate the Mutual information of selected sensors while the test subject performed different activities. Afterwards we computed the VoI of those sensor data. Here we suggest that the higher the VoI, the higher the priority we should give to the particular sensor.

However, the preliminary methods and results of this thesis could be used as an initiative for further analysis using advanced algorithms to harness the VoI for efficient information distribution in $IoMT$.

4.1 Main findings

The sensors are transmitting data every 33 Milliseconds. Higher the autocorrelation value means that sensor data is, to some extent, redundant. In other words, a sensor at time T sends the same or very similar information of the signal that has already sent at time T-1. Due to redundant information or the signal with less VoI, the associated radio resources are wasted, and the cost, which we can think of as the bandwidth and storage required to send and store the signals, is increased. For instance, sending each signal 33 milliseconds has cost C = 1, and the VoI is nearly zero. Therefore, on full cost the VoI achieved is minimum. In order to avoid this and to provide maximum VoI, we will calculate appropriate time interval for each highly autocorrelated signal by analyzing the autocorrelation at different lags. When the autocorrelation values become less than 0.5, we suggest that this is the optimal time interval for transmitting a particular signal.

Looking at the suggested time intervals for the autocorrelated signals, it was noticed that most of the signals are sending valuable information at time interval equals to 5 seconds. By considering the optimal time interval as t; t=5 seconds (5000 milliseconds) while the original time interval as 0.033 (33 milliseconds), the cost can be cut off up to 152 times $(5000/33 = 151.5)$. This cost however can be enormous, considering there can be hundreds of such signals as in the case of the Opportunity dataset that we have used.

Let us now look at the cross correlation of one signal with the others at different T. The goal here is two dimensional. One thing we want to find is, the sensors that are highly correlated with one another and based on that, decide which one of them is more appropriate to transmit. This way we can reduce the cost and increase VoI by choosing the most efficient sensor. On the other hand we can find the optimal time interval using the autocorrelation analysis for the selected sensor (that will be in charge of the transmission) in order to further reduce the cost and increase the VoI.

By using MI, methods can be implemented to check the dependency of two signals and also check whether the information sent by two sensors are similar or can be derived by using only one signal. MI, by definition, quantifies the

”amount of information” obtained about one random variable by observing the other random variable.

We have used MI in conjunction with Pearson correlation to check the VoI we obtain by sending two signals at different T. Our results show that even at different delays, the VoI obtained by sending two signals is quite low, and both of the signals are highly correlated, moreover the MI of both signals is also high. Therefore, it is better to use only one of such signal at an optimal T to cut the cost and maximize VoI.

4.2 Limitations and future perspectives

The limitations of the study mostly arise because of the shortcomings of the data. It includes the unavailability of real-life data. The data used for the study were acquired from a lab environment simulating real-life situation, however, such data do not necessarily mimic the real-world situations. For instance, the dataset have very limited updates for some activities, such as walking. As a result of that, two problems occurred, one of which is class-imbalance while the other is little variance. Even for these kinds of activities, the data are gathered in a closely monitored atmosphere. Therefore, the yielded data do not necessarily reflect the real-world situation. The dataset do not indicate any real cost values related to the sensor data transmission such as bandwidth used, latency, etc. Therefore, we only managed to make assumptions in terms of cost. Had there been the real costs associated with each update, more analysis would have been possible in this area. The performed analysis, therefore, includes the assumption of the costs involved. Hence, imaginary values have been suggested in this area. Another limitation of the work is that the dataset used has the sensors worn by a subject all over its body. The jacket and other apparels worn by subject has tightly setup sensors, and also the environment is tightly monitored, therefore, there is very little chance that the sensors outputs readings other than expected readings. In contrast, the wearable sensors in real-world situation have a good chance of misplaced location. Therefore, calculating VoI on the basis of Age of Information on such situations is missing in the included analysis. The Future work should include the collection and analysis of a real-world dataset which should be rich enough to give results that can help in the decision-making process. In such dataset, the cost should be associated with the updates. Some of the indicators for cost can be bandwidth required to make each or some updates, the approximate consumption of battery to make some updates, the storage capacity to require the updates, etc. Moreover, there should be lesser and more appropriate sensors used for the collection of such dataset. More importantly, the dataset should be collected by keeping in mind the analysis of VoI. Future works on this field should include the improvement of existing techniques and also the research of new and different approaches. These approaches should include finding VoI using the Pearson correlation, auto-correlation, MI, Entropy, and Information Gain. An ensembles model of such different techniques can be more accurate and more useful for such analysis. Another shortcoming of this work, and possible improvement for future research, could be the investigation of more advanced methods, e.g., based on machine learning, to estimate the correlation among signals, and assess the VoI based on that. There are many different possibilities to use these for the calculation of VoI and associated variables. Some of these works, for example, can include the use of Regression Models to predict the VoI.

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