# APPLICATION-SPECIFIC THINGS ARCHITECTURES FOR IOT-BASED SMART HEALTHCARE SOLUTIONS

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Human body is a complex system organized at different levels such as cells, tissues and organs, which contributes to 11 important organ systems. The functional efficiency of this complex system is evaluated as health. Traditional healthcare is unable to accommodate everyone's need due to the ever-increasing population and medical costs. With advancements in technology and medical research, traditional healthcare applications are shaping into smart healthcare solutions. Smart healthcare helps in continuously monitoring our body parameters, which helps in keeping people health-aware. It provides the ability for remote assistance, which helps in utilizing the available resources to maximum potential. The backbone of smart healthcare solutions is Internet of Things (IoT) which increases the computing capacity of the real-world components by using cloud-based solutions. The basic elements of these IoT based smart healthcare solutions are called "things." Things are simple sensors or actuators, which have the capacity to wirelessly connect with each other and to the internet. The research for this dissertation aims in developing architectures for these things, focusing on IoT-based smart healthcare solutions. The core for this dissertation is to contribute to the research in smart healthcare by identifying applications which can be monitored remotely. For this, application-specific thing architectures were proposed based on monitoring a specific body parameter; monitoring physical health for family and friends; and optimizing the power

budget of IoT body sensor network using human body communications. The experimental results show promising scope towards improving the quality of life, through needle-less and cost-effective smart healthcare solutions.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

# CHAPTER 1

# INTRODUCTION

## 1.1. Health and Human Body

From an engineering perspective, the human body can be defined as a combination of multiple subsystems where each component of the subsystem needs to function smoothly. This complex system, the human body, is organized at different levels such as cells, tissues and organs, which together contribute to 11 important organ systems. Figure 1.1 shows the anatomy of the human body.

A imbalance in any of these organizational levels can affect the equilibrium of the entire system. The overall functional efficiency and stability of this system is evaluated as health. The World Health Organization (WHO) defines human health as a state of complete physical, mental and social well-being [1]. Advancements in technological and medical research, coupled with increased awareness about health and hygiene, have resulted in an increase in life expectancy of individuals [37]. However, the increasing costs of medical treatments and ever increasing population, is causing major healthcare inequality in terms of geographical limitations, economic status, lifestyle etc. [42]. Due to these inequalities, there exists a vast gap between the group of people that strive to contribute to the human well-being, and people who are in need of these resources.

## 1.2. Significance of Smart Healthcare

A smart solution for a smart city is a combination of one or more intelligent components that helps in improving the living standards of its citizens [45, 44, 29]. Components of a smart solution may include sensing elements such as sensors and actuators, computational elements such as processors, workstations, servers etc., connected to each other to perform ubiquitous computing. Smart transportation, smart buildings, smart energy, smart governance, and smart healthcare are notable components of smart city solutions [46]. With an aim towards improving the healthy living of citizens, smart healthcare plays a significant role in a smart city. The costs involved in treating chronic diseases have been constantly

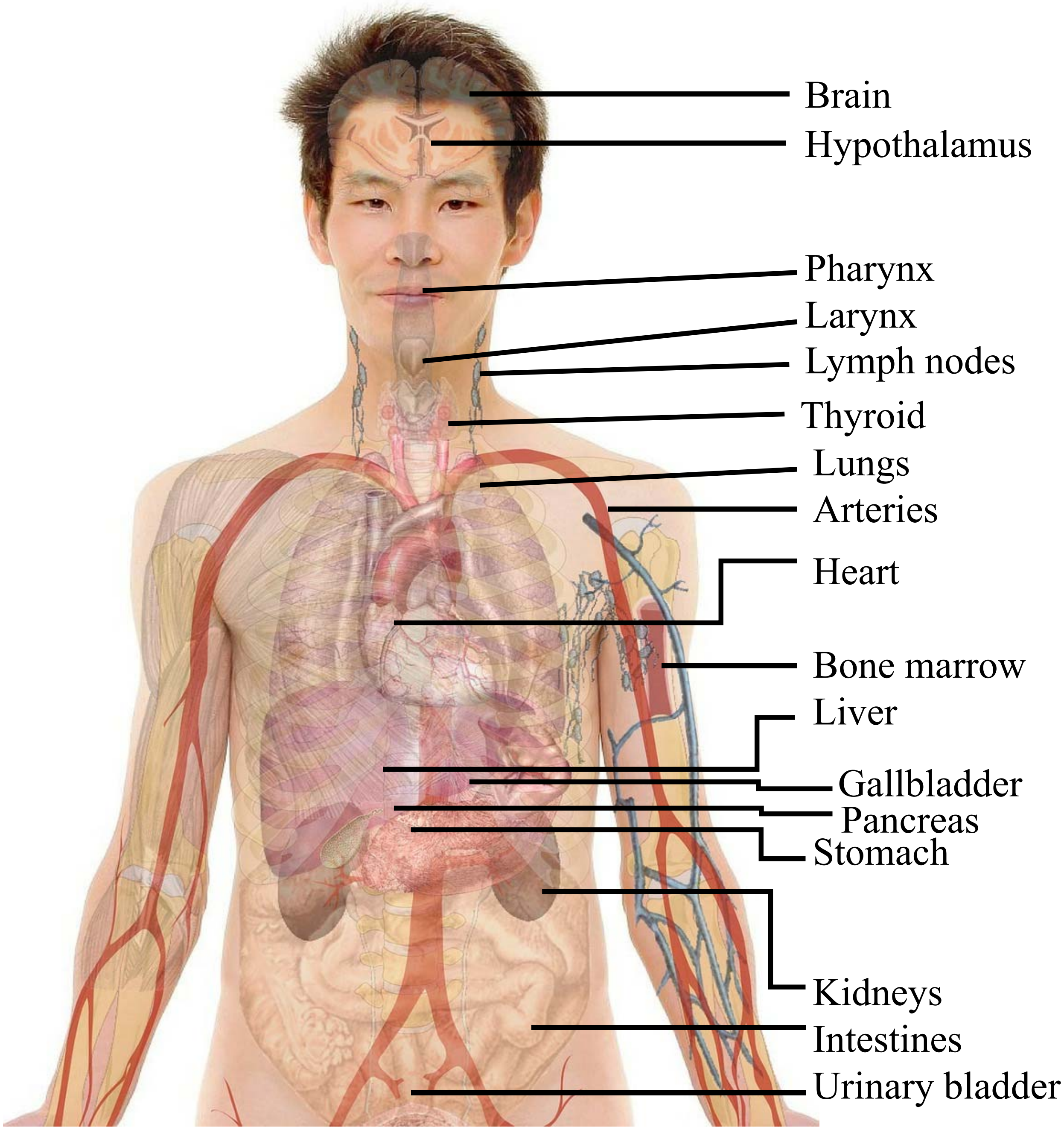



Figure 1.1: Anatomy of the human body (Image Courtesy of Creative Commons, pixabay.com).

increasing. By 2025, this cost is expected to increase to a total of 60 % of total healthcare costs. In addition to this, the healthcare inequalities amongst individuals require any healthcare solution to enhance remote assistance. This has been the driving force for traditional healthcare applications shaping into smart healthcare solutions. Figure 1.2 shows the difference between traditional healthcare and smart healthcare.

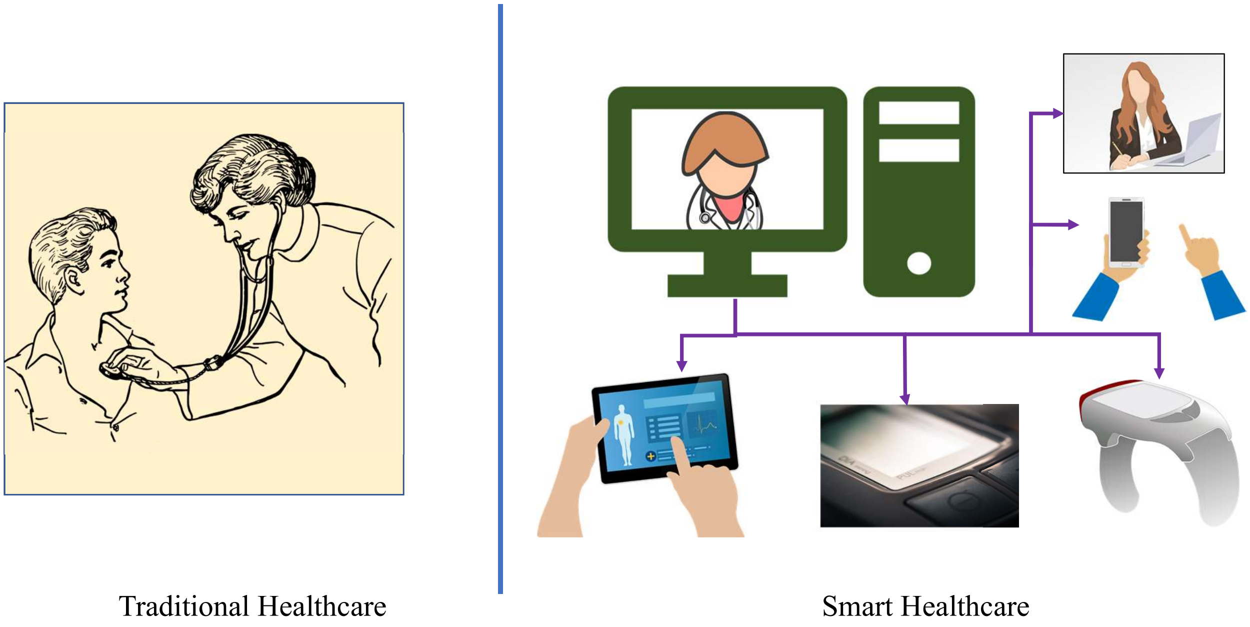



Figure 1.2: Difference between traditional healthcare and smart healthcare (Image Courtesy of Creative Commons, pixabay.com).

In recent days, the concentration of research in healthcare is on continuous monitoring solutions which aim in preventing major chronic diseases. One of the key aspects of smart healthcare is its ability to keep users health-aware. It helps users to manage emergency situations and improves the quality of their lives. By deploying smart healthcare solutions the available resources are best utilized to their maximum potential. By providing the ability for remote assistance, smart healthcare reduces the overall healthcare costs.

Figure 1.3 shows a classification of smart healthcare based on design aspects and commercial aspects. In terms of design aspects, connectivity technologies contribute more towards faster data transfer, power budget and size of the solution. Irrespective of the application, any component in the smart healthcare architecture requires a wireless protocol to be used for facilitating remote assistance. Depending upon the range and proximity of the devices placed, the connectivity technologies are chosen. The medical devices used in the smart healthcare design can be classified based on whether the device is placed on the human body or is a stationary medical device used in creating a smart environment. Body sensors are mainly designed for physiological monitoring. Wearables such as smart watches, activity trackers, smart clothing, and wearable cameras are designed with a focus on obtaining one or more physical parameters from the human body. These wearables are designed either for a single condition such as activity monitoring, drug delivery system [48], or a cluster of multiple conditions such as fitness monitoring, assisted living etc. [2]. Ingestible sensors involve devices which can be swallowed in order to monitor the human body from the inside. On the commercial perspective, smart healthcare can be classified based on the end-user market and system management.

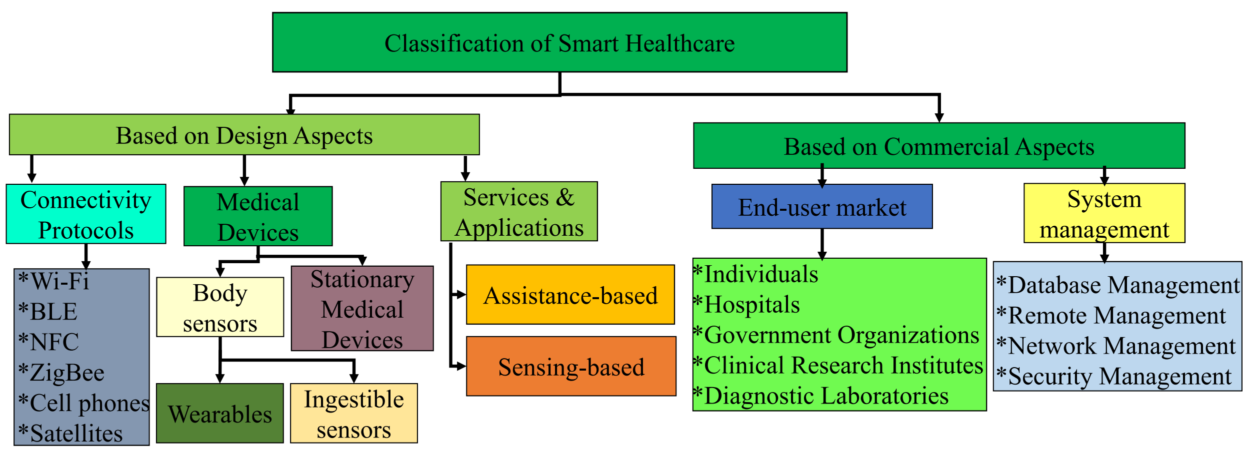



Figure 1.3: Classification of smart healthcare.

In the present digital era, most of the smart healthcare solutions can be categorized as connected health, which is a collective term for subsets such as assistance-based applications, and sensing based applications. Assistance-based applications include telemedicine and e-medicine which help users find resources to educate themselves, enhance self-care, provide feedback to the user, and complement it with remote-care. Assistance-based healthcare solutions help the users receive feedback from the clinicians whenever required. Sensing-based applications require a sensing element such as a sensor or actuator to monitor a parameter, either continuously or periodically, depending upon the application. The role of connected health in sensing-based applications is primarily determined by the end user market. For example, in designing a blood pressure monitor, the cost, area, power and overall architecture varies depending upon the end-user market. In a hospital scenario, a blood pressure monitor would be connected to the main database maintaining health records, whereas a blood pressure monitor designed for individual use must be of smaller form factor to be placed in the body as a wearable device. This end-user market defines the economy of smart healthcare.

## 1.3. Internet of Things Trends in Smart Healthcare

The Internet of Things (IoT) helps the real-world electronic components of smaller form factor to perform advanced computing using cloud-based solutions. It makes these real-world components self-sufficient and gives them the benefit of remote-access and faster data sharing [47]. Sensors are simple electronic devices which convert a physical quantity such as temperature, humidity, proximity, light intensity etc., into numerical values [55]. With advancements in technology, portable electronic devices such as phones, tablets, and smart watches, are embedded with multiple sensors which help in sensing many physical parameters. IoT based solutions store these numerical quantities of the physical parameters in the cloud where meaningful interpretation to this data can be obtained. Due to the faster data sharing and ability to be self-sufficient, the IoT has has been widely used in transportation, healthcare, agriculture, energy conservation, building construction, and surveillance [31]. Any healthcare solution starts from identifying a healthcare application, towards which the product can be further developed. The IoT offers a multitude of benefits and advanced solutions which make it an integral component of many smart healthcare applications. Smart healthcare solutions based on the IoT range from diagnosing chronic diseases to efficient management of pharmacy inventories [70]. The confluence of research in smart electronic systems combined with medical science has made IoT based smart healthcare a billion dollar industry. Figure 1.4 illustrates the different aspects of the IoT in smart healthcare.

IoT-based smart healthcare solutions help in reducing the distance between doctor and patient and make healthcare more affordable and attainable. With enormous potential

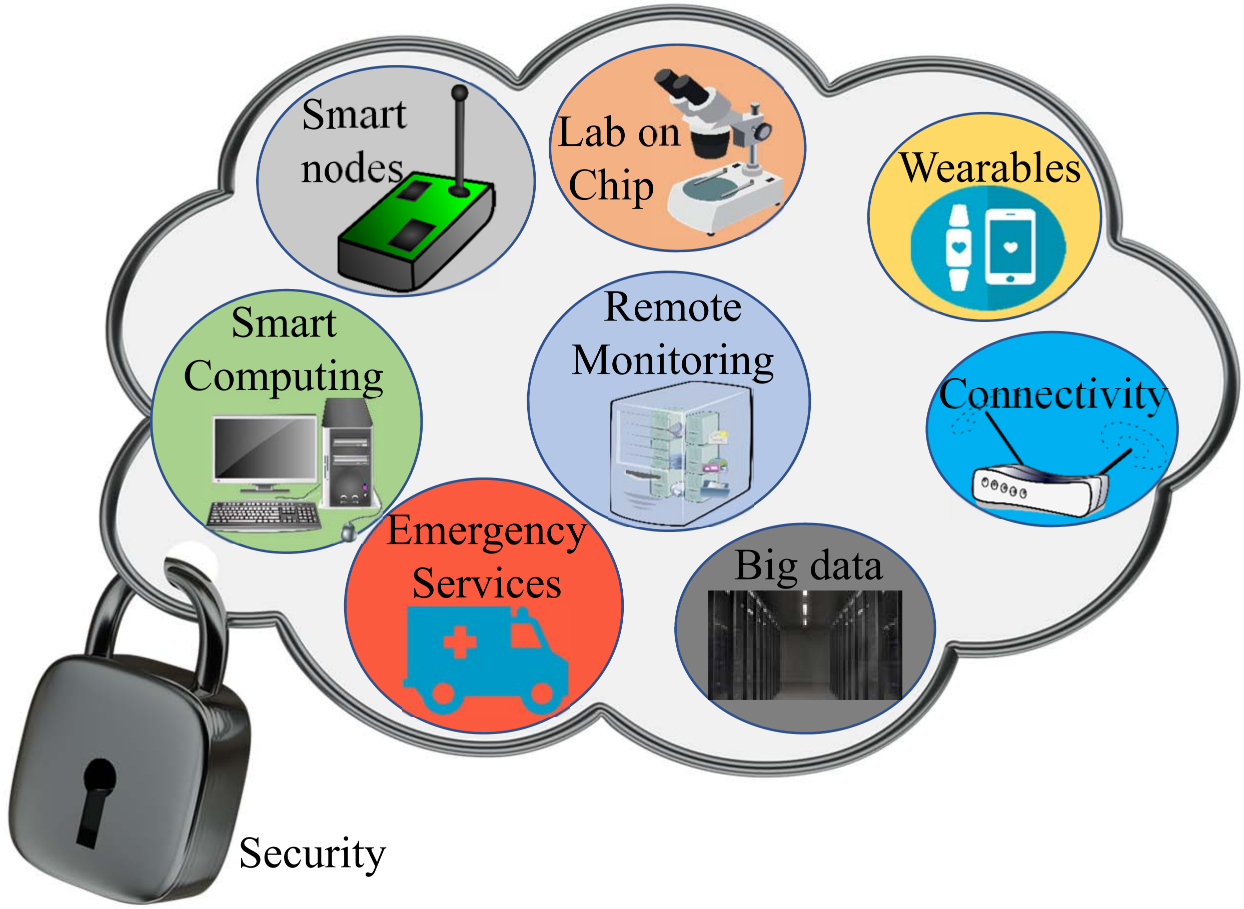



Figure 1.4: Internet of Things for smart healthcare.

benefits, the IoT has made many biomedical applications very diverse, which makes it to be redefined as the "Internet of Everything" [43]. Improving quality of life through remote assistance and helping users be health-aware, are the key driving factors of smart healthcare solutions. Certain applications involve non-diagnosis based solutions, such as inventory monitoring where IoT based solutions help in organizing drugs efficiently, maintaining digital health records, and offering healthcare assistance through tele-services.

## 1.4. Motivation for this Dissertation

The motivation for this dissertation is to contribute to the research in smart healthcare by identifying applications which can be monitored remotely. In pursuit of this, a body parameter was identified to be monitored to improve the quality of life through the IoT.

Following this research, a solution to monitor and analyze the physical health of family and friends is proposed. Further, a method to address the increasing power budget in a body sensor network was analyzed for IoT based smart healthcare. Following are the background for the motivation of this dissertation

### 1.4.1. Basal Body Temperature Monitoring through the IoT

The basic elements of the human body are cells which depend on the body environment for healthy function. This process of keeping the body environment stable in terms of body temperature, water content, oxygen level and chemical content, is called homeostasis. One of the important factors to keep the body environment under control is human body temperature, which tells if the body is functioning normally or not. This human body temperature is controlled by a gland in the middle of the brain, called hypothalamus. With respect to homeostasis, the hypothalamus sends signals, as a chemical called pyrogen, which help in maintaining the body temperature. For example, when the hypothalamus senses that the body is very hot, it sends signals to the sweat glands and when it senses that the body is too cold, it sends signals to the muscles to shiver.

Human body temperature gives direct insights on the metabolic and hormonal health of an individual. It also helps in understanding if there are any underlying issues. Though the ideal human body temperature may vary amongst different individuals, the healthy temperature range, in medical terms, is 97° Fto 99° F. Body temperature keeps varying throughout the day depending upon when the body is active and when it is at rest. The lowest human body temperature acquired during sleep is known as Basal Body Temperature (BBT). Monitoring this BBT over a period of time, helps us understand the functioning of glands, organs and relevant underlying disorders, which can be directly related to metabolic rate.

### 1.4.2. Human Activity Monitoring for Smart Families

A healthy lifestyle can be achieved by maintaining a healthy diet and remaining physically active. A person's physical health can be evaluated by the amount of exercise they get. Maintaining a regular exercise schedule is directly related to reducing cardiovascular risk factors such as bad cholesterol, insulin sensitivity, blood pressure, and body weight. Wearables such as smart watches, and activity monitoring pedometers, aim in monitoring the physical health of individuals. Understanding the physical health of the family and friends can help in keeping us health aware.

### 1.4.3. Energy Efficient Architectures using Human Body Communication

A body sensor network, also known as a body area network, is made up of sensors or wearables connected to each other wirelessly. Any smart healthcare component is embedded with multiple functionalities. These functionalities can be implemented as a single wearable or as a body sensor network. With increase in computing complexity, it is important to have stringent power budget both at the device level and in the entire network. One of the most significant contributors to power consumption in an IoT device is the wireless protocol. Depending upon the design and application, it is necessary to choose appropriate wireless protocols to keep the overall power dissipation minimal. Human body communication (HBC) is a low power wireless data communication technology which can help in developing energy efficient body sensor networks.

## 1.5. Organization of this Dissertation

The organization of this dissertation is given in Figure 1.5. The current industry trends in IoT based smart healthcare and the different services and applications for smart healthcare are discussed in Chapter 2. In Chapter 3, the importance of maintaining a healthy body temperature is discussed, followed by a novel architecture to monitor basal body temperature using the IoT. The proposed architecture can be used as a wearable to obtain accurate BBT values. Chapter 4 aims in proposing a feature based solution for activity monitoring. The proposed solution helps in identifying unique features for each individual and keeps the concerned people informed. Chapter 5 aims in optimizing the power budget of the IoT body sensor network using human body communication. The proposed methodology can help in implementing an energy efficient body sensor network. Chapter 6 concludes this dissertation followed by a few pointers for future research.

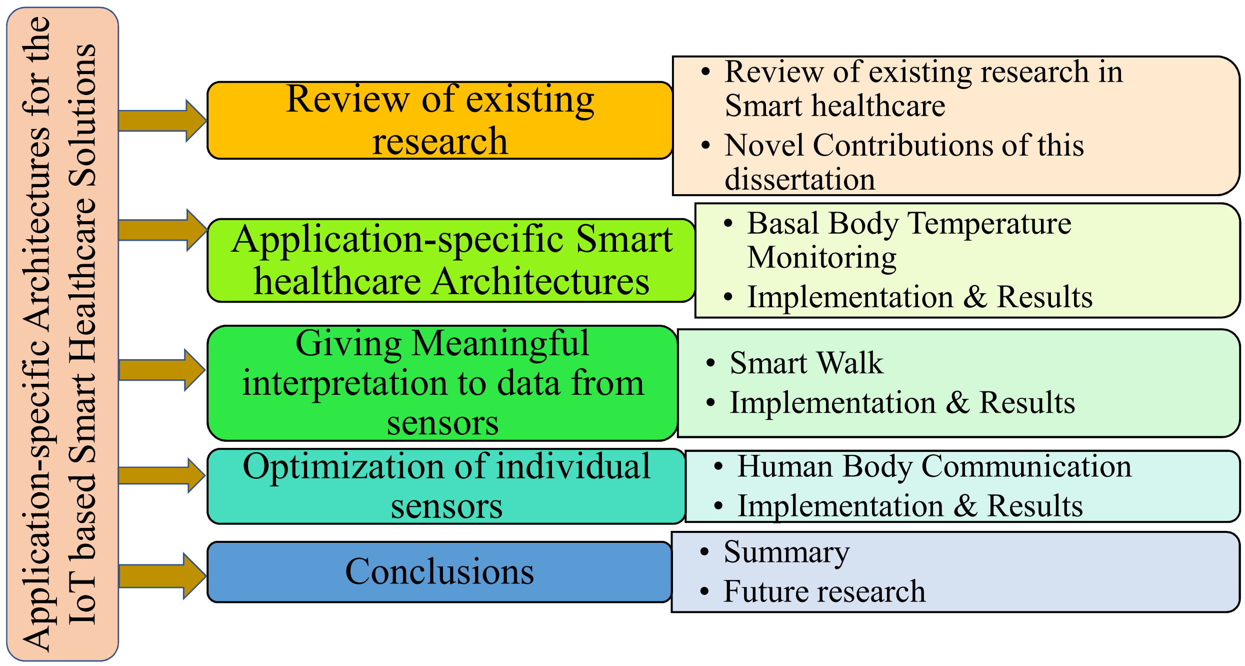



Figure 1.5: Organization of this dissertation.

# CHAPTER 2

## PRIOR RESEARCH IN SMART HEALTHCARE

IoT based smart healthcare solutions cover a wide spectrum. Possible applications can range from vital sign monitoring in newborns to assisted living in elderly, with a primary focus on improving quality of life. The design considerations for these devices vary depending upon the cost, functionalities and sophistication of the application. From the sensor IC design to a complete product development, research in smart healthcare is an intersection of VLSI, embedded systems, biomedical engineering, machine learning, Artificial Intelligence and cloud computing [64]. The related literature survey for this dissertation includes design considerations such as requirements, attributes, security aspects and services and applications for which the smart healthcare based architectures are designed. In addition to this, a thorough analysis of the current industry trends in smart healthcare and overall evolution of wearables is discussed in this chapter.

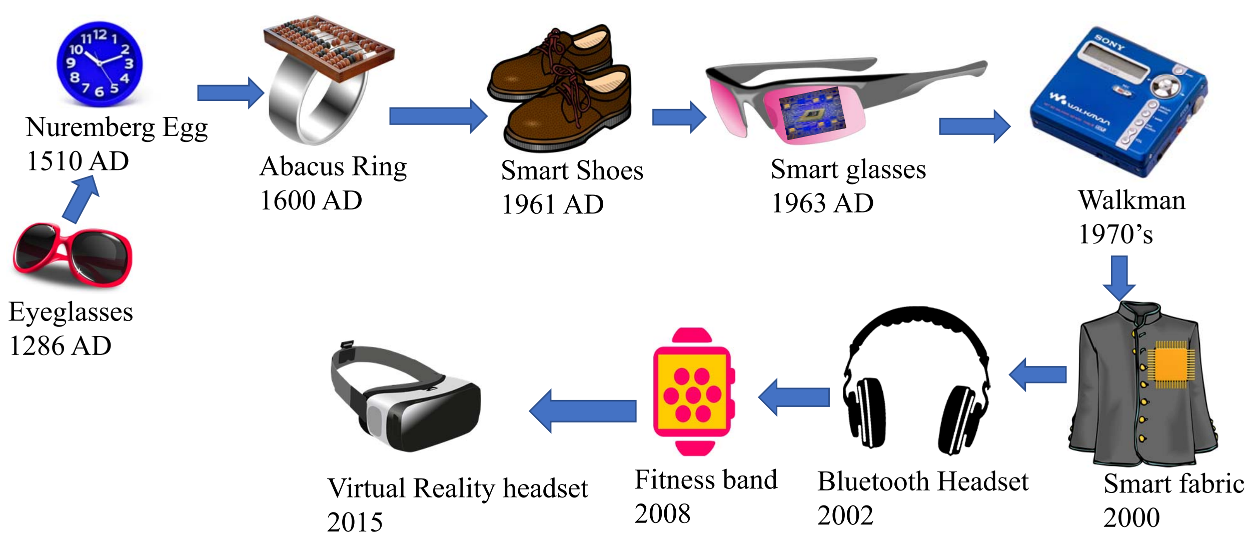



Figure 2.1: Evolution of wearables (Image Courtesy of Creative Commons, pixabay.com).

## 2.1. Evolution of Wearables

The basic elements of smart healthcare are wearables, which help in improving the quality of life. Wearables have evolved from simple portable structures to very advanced devices. Figure 2.1 depicts the evolution of wearables from 1286 AD to the present. The first evidence of one such wearable, which changed the lives of millions of people, is the invention of eyeglasses in 1286 AD. This important life-changing invention was followed by wearable clocks, known as the Nuremberg Egg in 1510 AD. These wearable clocks have been evolving every year from wrist watches to a computer-on-watch in the modern world. A computation based wearable called the Abacus Ring, which served as a portable calculator, was invented in the 17th century. The first sensing based wearable was invented during the 1960's. This wearable was in the form of smart shoes which served as a timing device. In the same decade, eye glasses embedded with video capabilities were invented. The first portable audio device, Walkman invented in the 1970's, was a game-changing invention in the music industry. A smart conducting fabric that supports other portable devices such as mobile phones, mp3 player and headsets was invented in 2000. The first wireless headset based on Bluetooth connectivity was invented in 2002. Though the year 2014 was regarded as the year of wearables, the first evidence of a fitness band to monitor the activity and amount of calories burned, was in 2008. The most recent important invention in wearable technology is the virtual reality headset which was first commercially available in 2015. With every passing year, the computational complexity of the wearables is increasing constantly. Eyeglasses have evolved into the virtual reality headset, portable clocks have evolved into smart watches with the ability to compute as fast as smart phones. Researchers have been constantly working towards developing advanced wearable technologies that can contribute to improving the quality of life.

## 2.2. Design Considerations of Smart Healthcare Architectures

Due to the wide range of problems that can be addressed using IoT-based smart healthcare solutions, the design considerations for developing a smart healthcare architecture can be categorized based on the requirements, components, security aspects, services and applications for which the architecture is designed.

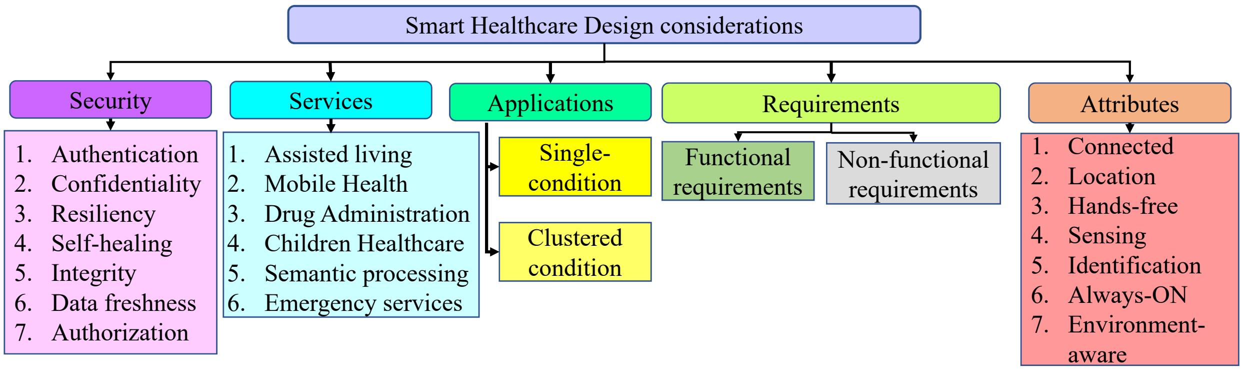



Figure 2.2: Design considerations of smart healthcare.

### 2.2.1. Requirements for Smart Healthcare Design

The design requirements for smart healthcare architectures can be broadly categorized as functional and non-functional requirements. Functional requirements help in addressing the functional implementation of the smart healthcare architecture. These requirements might include the sensitivity of the sensors, form factor of the devices, frequency and range of operation, etc. For example, the use of temperature sensors in a smart healthcare application might vary from clinical grade sensors for obtaining human body temperature to industrial grade temperature sensors for inventory management. On the other hand, non-functional requirements are generic. Nonfunctional requirements help in determining the quality of healthcare system. This type of requirement can be classified into performance and ethical requirement. The performance aspect is inter related to the functional requirements which contribute towards the power budget, cost of the design, system reliability, enriched user experience, smaller form factor, ability to inter operate across different platforms, ease of deployment, popularity of the smart healthcare system to offer continuous support, scalability of the system to upgrade to newer versions and technologies, ambient intelligence, and ample connectivity since the prime motive of designing a smart healthcare device is to ensure medical service promptly.

### 2.2.2. Components for Smart Healthcare Architectures

Perspectives of smart heathcare vary widely amongst different researchers and industries based on the chosen goal to be achieved. Smart healthcare architectures are made up of components that can be categorized as sensors or actuators which can be defined as any analytical device that records a biological event; computing devices ranging from wearables to PDAs such as smart phones, laptops, tablets; data storage elements which include any component with a memory element attached to it; and networking components such as routers, wireless components, switches, link sensors, base stations and so on. Healthcare monitoring systems are built based on sensors such as temperature sensors, ECG, blood pressure, blood glucose, EMG, heart rate, SpO2, gyroscope, motion sensors, accelerometers and so on. The accuracy and precision of these sensors may vary depending upon the application. Memories play a very important role in smart healthcare since they help in recording the sensing events, which is the main step towards further processing the obtained data. Storing information is the most important function of these systems. Data storage components in a smart heathcare network cover a broader spectrum starting from embedded memory on the sensing devices to big servers that are used to handle big data analytics. Based on the severity of the problem addressed, the sophistication of the components varies.

### 2.2.3. Security Aspects of Smart Healthcare

Security aspects of the smart healthcare architectures are authentication of the devices in the smart healthcare network; maintaining confidentiality of the user information; ability to heal itself in case of a security attack [4]; freshness of the data to be able to remain updated on the passwords and availability of data to authorized users. In addition to taking security measures in the software, hardware-assisted security is also important to develop robust systems. One method of implementing hardware-assisted security is through physical unclonable functions (PUFs) which are unique to each hardware [81], [80]. The PUF acts as a biometric for hardware that helps in maintaining the integrity of the network.

### 2.2.4. Services and Applications Available through Smart Healthcare

In this era of ubiquitous healthcare platforms, healthcare services are available to everyone. In the healthcare perspective, services can vary from push-notifications on the healthcare mobile App to cross-connectivity protocols required for connected devices. Modifications in already existing healthcare systems might help in integrating these systems in smart healthcare. In addition to being secure and fast, these services should also be easily accessible to the patient. Context-aware services use the current location of the user to provide additional services. This could be used in mobile or wearable sensors. For example, based on the information received from the sensor, the walking trail can be tracked to analyze the number of miles covered. In some cases where the user needs to call an ambulance or a paramedic, the required assistance can be provided based on the geographical data obtained from the user. Embedded context prediction (ECP) provides a framework with appropriate mechanisms which can be used to build context aware systems. Context aware systems can operate in ubiquitous environments [23]. Semantic processing is a behavior of the human brain to understand color, pattern, objects etc. based on the context that helps in deeper processing. For example, when a familiar word is heard, our brain processes its meaning based on our semantic memory which involves common knowledge. In smart healthcare, the use of semantics and ontologies has led to a service called semantic medical access (SMA). This helps in processing ubiquitous data available in the medical cloud and providing emergency services by integrating the services [61] [79]. Wireless body area networks (WBANs) are the basic components of community healthcare monitoring. Community healthcare monitoring helps in creating a network around the local community. Multiple WBANs constitute a community healthcare network and multiple community healthcare networks constitute a cooperative network. A community healthcare network might include schools, residential areas, hospitals etc. which helps in providing energy efficient monitoring in rural areas. Child healthcare is another important service to be provided by the healthcare professionals and the government. Analyzing food patterns, emotional or mental behavior patterns are significant areas of concern. IoT-based smart heath care systems aiming at educating and empowering hospitalized children is proposed in [74]. A specific architecture for getting assistance in respiratory problems in smart cities has been proposed in [53]. Significant amongst numerous other services provided by smart healthcare is drug administration and reaction. In todays world, some people trust search engines more than the healthcare professional, which leads to one of the bad practices, self-medication. In such scenarios, if the patient has consumed a drug which he/she is allergic to, then immediate assistance needs to be provided. This can be achieved by intelligent pharmaceutical systems [83] with sufficient information about the patient and their allergic profile. Applications of smart healthcare start from fitness monitoring on one end of the spectrum to vital sign monitoring in hospitals. Smart healthcare systems are composed of sensors or actuators which are interconnected wirelessly. These networked sensors help in collecting a wide range of information based on physical, cognitive and behavioral processes from different persons, across a building or a locality. Based on the application, the quality of health care systems is improved with additional machine learning algorithms and artificial intelligence. The wide range of applications can be grouped into inter-body sensing, intra-body sensing and environmental management [39], [63]. Intra body sensing applications refer to those which help in monitoring multiple vital signs. For example, in fitness tracking through a smart watch, along with parameters such as number of calories burned, steps taken, active hours etc., it is also important to track the pH sensitivity of the sweat, oxygen intake of the body, heart rate monitoring, etc. In order to meet the competitive smart healthcare market, the industries are trying to incorporate as many sensors as possible to offer ubiquitous sensing. Heart rate monitoring and remote ECG monitoring through wearables have offered cost effective solutions in smart healthcare [62]. In smart watches, it is also necessary to keep a track of the previous monitoring analysis. Algorithms that incorporate cognitive and behavioral process are being deployed in these sensors to identify patterns. Such patterns from various users can help researchers and industries to develop models that can be used in treating a condition better. This method of creating models based on monitoring systems from different users can be grouped into inter body sensing. Examples for this group of applications can be again selected from fitness monitoring through smart watches where, with the emergence of virtual reality, these applications are used to set a walking or hiking trail. Creating sensitive and responsive digital environments has made the smart healthcare domain a multi and inter-disciplinary research area [84]. Mobile applications that are associated with wearables learn from the users, reason about their intentions of using the device and help them plan in achieving their fitness goals [3]. A web based food journal has been proposed in [4], which assists the users in maintaining healthy eating habits. Environmental management applications help in establishing communication between the hospital and the patient. Monitoring the first responders health status in an endemic or epidemic outbreak, getting ambulance assistance in case of emergency, developing evacuation schemes for disaster management in hospitals, maintaining active databases to ensure correct delivery of organs/blood to the user in need, and ensuring accurate billing of surgical procedures through RFID tags are some of the significant applications in environmental management.

#### 2.2.5. Attributes of Smart Healthcare Designs

The first and foremost significant attribute for smart healthcare design is that it needs to be connected. With the architecture varying from a sensing device to large servers, it is important that the flow of data across these architectures is not interrupted. In wearable designs for smart healthcare, the location of the user needs to be monitored to provide environment aware services. Detecting the location of the user is also important in design of emergency services and ambient assisted living, which also requires that the architecture remains environment-aware. Seamless architectures are always on demand amongst the consumers which makes the design of hands-free architectures an important attribute. Other important attributes of smart healthcare architectures involve accurate sensing, identification of each component, remaining always-ON or service-ready in the smart healthcare network.

Figure 2.3: Ubiquituous computing in the smart watch (Image Courtesy of Creative Commons, pixabay.com).

2.3. Industry Trends in Smart Healthcare

The scope of smart healthcare products has expanded its horizons and has been predicted to be a 57.85 Billion USD market by 2023. With considerable ongoing research and a scope to address new issues, entrepreneurs and well-established industries are competing at their best with remarkable creativity. Smart syringes, smart pills and smart RFID cabinets are gaining everyones interest in the smart healthcare domain. RFID has been widely used for infection safety, radiology and control infections such as TB [6]. The electronic health record is the most significant product of smart healthcare which has given an altogether new perspective for addressing big data issues. These products fall across different verticals such as health data and storage, monitoring and treatment and inventory management. Body worn sensors with Internet-connected smartphones have been revolutionizing the medical research. These body worn sensors are used for physiological monitoring, i.e. monitoring and recording a persons vital signs such as blood pressure, temperature, heart rate and so on, activity monitoring, i.e. using MEMS based sensors to measure muscular activity, movements and posture, interconnecting multiple body area networks to perform large scale physiological monitoring. In the present digital health revolution, Intel is leading the list with their Digital Health Foundation. The company is constantly coming up with innovative technologies for data analytics, assistive technology and improving the home environment for the elderly population. Notable amongst their innovations is "Collaborative Cancer Cloud Platform" which employs cloud based cancer research through Intels Ignition Labs. At IBM, research has been carried out on pattern recognition, analysis of data such as physiological signals or images and genome based personalized medicines. IBMs Watson, an artificial intelligence computer system, can look at the content of the patients health record and process the medical information faster, to provide better health care models. IBM has partnered with Apple, Johnson and Johnson and Medtronic to continue their digital health research in a large scale. Google has a dedicated life sciences division to develop and research new technologies in digital health. Qualcomm Life helps in capturing the medical device data and integrates it to the nearby database partner through a wireless medical device and secures the information. This platform offered by Qualcomm provides a high range of system interoperability and security. Microsofts "Connected Health Platform" helps in offering digital health services through desktop frameworks. Microsoft Lync is used by doctors to offer medical services to patients in rural areas. Samsung has a 50 million USD investment in digital health through their Digital Health Initiative which is a collaboration of smart sensors, algorithms and data processing techniques through open source hardware and software platforms. Apple has an open source framework, ResearchKit, which aids researchers to develop apps that can facilitate medical research. On the retail front, Amazon offers a unified healthcare platform where the users can access all the healthcare information, availability of latest products, health insurance and "on-demand" services. Wearables, especially in the form of smart watches or bands, have been revolutionizing the market. Notable products include

Fitbit, moov, Proteus, Pebble Time, Withings AliveCor Health monitor, Beddit and so on. These wearables have multiple functionalities such as tracking sleep, blood pressure, diabetes, fitness measurement, baby monitoring and so on. Along with the entrepreneurs and established industries, many research and educational organizations are also actively working on smart healthcare.

## 2.4. Novel Contributions of this Dissertation

The following are the novel contributions of this dissertation

- A novel IoT based architecture for monitoring Basal Body Temperature (BBT) autonomously is proposed in Chapter 3.
- A novel support vector machine based BBT analysis engine has been proposed.
- The proposed novel BBT monitoring architecture helps in analyzing the underlying disorders identifiable by BBT.
- A novel framework to monitor the physical health of family and friends is proposed in Chapter 4.
- A feature based dynamic human activity monitoring algorithm has been proposed to monitor the physical health of family and friends.
- The proposed algorithm uses a dynamic calibration module that improves the accuracy of the proposed human activity monitoring algorithm.
- A novel decision table based human activity learning model is developed based on human activity features that are unique to each individual.
- A novel ambulatory monitoring Body Area Network based on human body communication is proposed in Chapter 5.
- A novel low power design of the proposed ambulatory monitoring Body Area Network based on frequency selective baseband transmission is implemented using Simulink®.

# CHAPTER 3

# IMPROVING QUALITY OF LIFE THROUGH BASAL BODY TEMPERATURE (BBT) MONITORING

This chapter presents a system for accurate monitoring of basal body temperature for thyroid function monitoring [65].

## 3.1. BBT Monitoring through the IoT: A Broad Smart Health Perspective

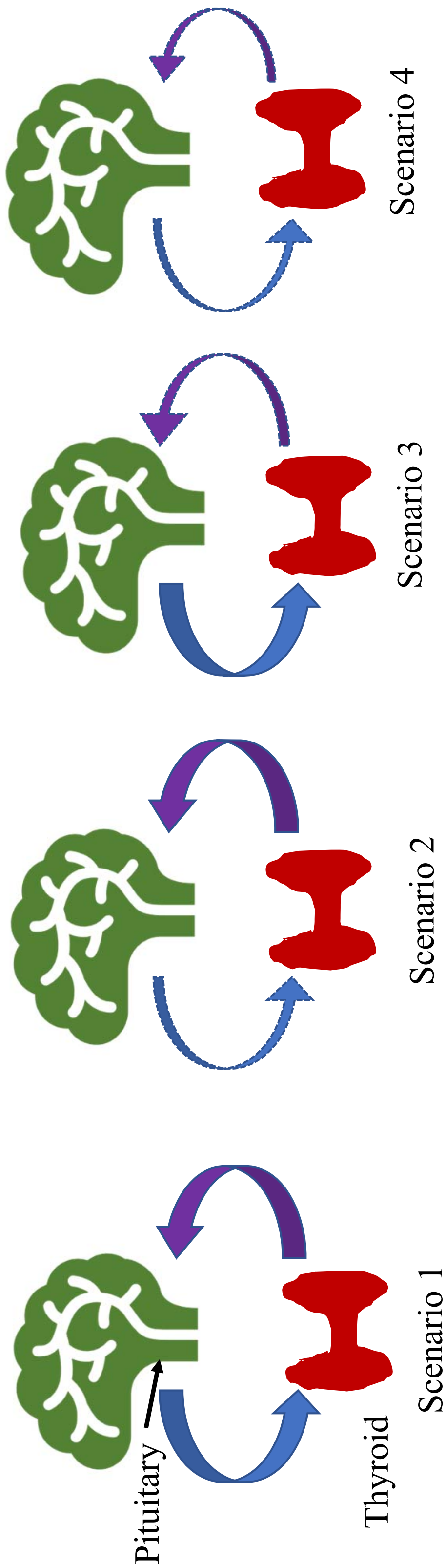
### 3.1.1. Background

The endocrine system is one of the most important body systems. It is comprised of hormone-secreting glands. Hormones are chemical substances that acts as a messenger along the blood stream to coordinate functions of different body systems. The primary glands of the endocrine system are the hypothalamus, the pituitary, the thyroid, the parathyroid, the adrenals, the pancreas, the pineal gland and the reproductive organs. The hypothalamus, which is also responsible for metabolism and body temperature, acts as a neural control for these glands. The hypothalamus also secretes a hormone to control the pituitary gland, which is the most important endocrine gland. The thyroid, an important endocrine gland, is responsible for healthy metabolism and heart functioning. The pituitary gland secretes the Thyroid-Stimulating Hormone (TSH), which stimulates the thyroid to secrete a hormone called thyroxine (T4). Depending upon the level of T4 in the blood, TSH is generated by pituitary gland, stimulating the thyroid gland to produce more or reduce the amount of thyroid hormone. The Thyrotropin-Releasing Hormone (TRH) regulates the production of TSH. The imbalance of thyroid hormones affects metabolism, muscle strength and development of fetus in pregnant women. The secretion of thyroid hormones and related thyroid diseases are illustrated in Figure 3.1. This chapter aims in understanding the function of the thyroid gland based on the variation in BBT. To achieve this, an IoT based architecture is proposed to monitor BBT accurately. Since the primary motive of the proposed architecture is to continuously monitor BBT, one can also use this for fertility assessment, weight loss and healthy lifestyle management. In some situations where blood hormone levels might be normal, the under functioning of the thyroid causes weight issues, depression, etc. The proposed basal body temperature monitor can help identify such underlying disorders in advance.

### 3.1.2. BBT Monitoring Sensor Design Considerations

Smart healthcare architectures range from devices like lab-on-a-chip to artificial organs which can be placed in the body. The basic block diagram involved in designing a sensing-based smart healthcare monitoring system is shown in figure 3.2. The ideal components of this architecture include a sensor or a sensing module for data acquisition, a processor unit to obtain the information and process it, a transmitting/receiving unit to send/ receive the data obtained and a memory to store the information until connected to the collection terminal. For BBT monitoring, a temperature sensor module is used as a sensing module in the architecture. The values are stored in non-volatile memory. The power module, which is used to power up the system, consists of a battery source. The communication module can be varied based on the requirements. For example, a bluetooth or IEEE 802.11 protocol can be used to help the sensing module communicate with the base station. Data transfer between the base station and the sensing module can also be achieved with the help of a USB port, when there is lack of Internet access. In order to produce sensing modules with smaller form factors, the RF antenna can come in handy: it can remain static when not used and can be easily powered up based on the requirements.

An ideal BBT sensor needs to be portable, consume low power and have a user friendly interface to make it a device that can be used by people of all age groups. It is necessary to be portable since it has to be worn by the patient throughout the night, so that the device records the temperature continuously. Since BBT monitoring can be effective only when the temperature is recorded one or two hours before the person wakes up or in some cases immediately after a person wakes up, it is necessary to record the temperatures continuously, in which case the device needs to operate in low power modes to give it a longer lifetime. Hence, to be power efficient, the proposed architecture is designed with that constrain in mind. In such an architecture, the wireless modules are power hungry since they




| Condition | Normal (Scenario 1) | Hyperthyroidism (Scenario 2) | Hypothyroidism Primary (Scenario 3) | Hypothyroidism Secondary (Scenario 4) |
|---|---|---|---|---|
| TSH | Normal | Low | High | Low |
| T4 | Normal | High | Low | Low |

Figure 3.1: Functions of the thyroid gland.

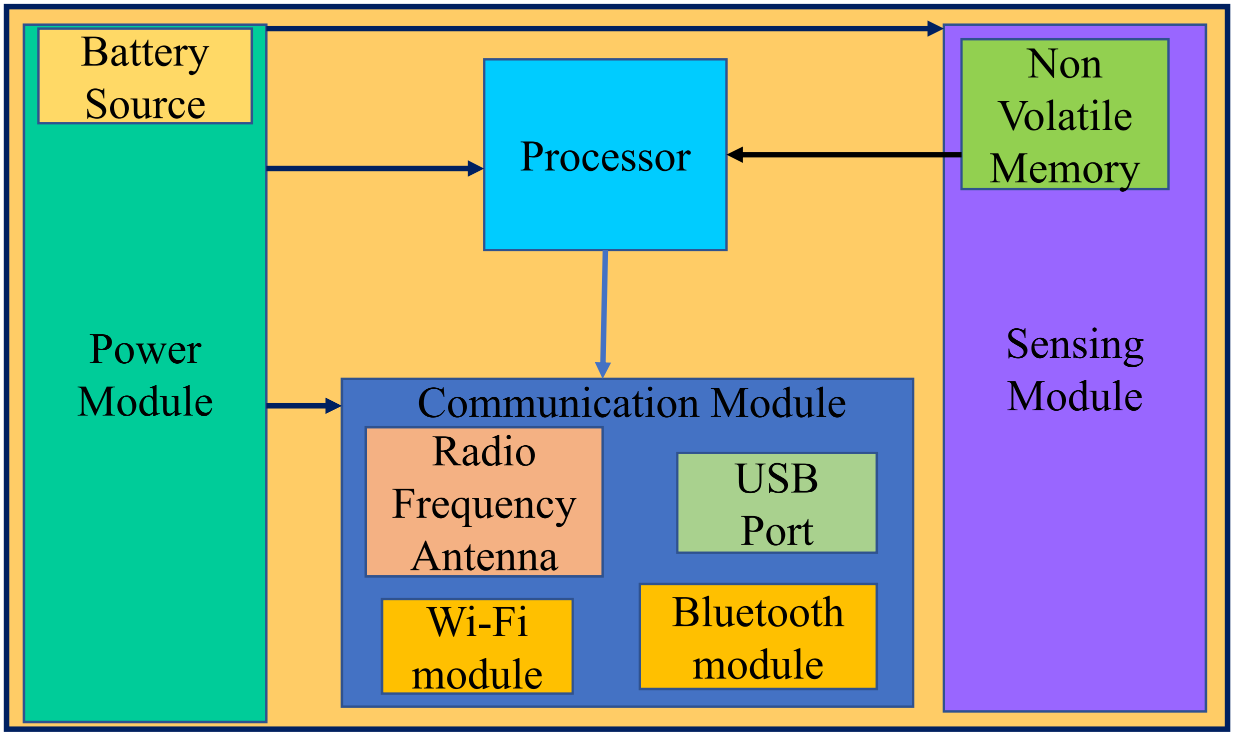



Figure 3.2: Basic architecture for smart health monitoring.

continuously transmit/receive signals. By using the proposed architecture, the temperature sensor, which is the primary element to obtain temperature values, is being employed for a longer period of time whereas the power consuming modules are used only when required.

## 3.2. Related Prior Research

An IoT architecture for temperature measurements using 4G health applications based on IPV6 connectivity has been demonstrated in [24]. An FPGA based fall detection system has been proposed in [54]. In this system, a wireless wearable sensor platform, SHIMMER is used to detect the fall. The architectures proposed use off-chip memory. SHIMMER is a low power wireless sensor used for many biomedical applications such as temperature detection, fall detection [11] etc. The functionalities of SHIMMER can be expanded by using additional daughter boards. In designs where off the shelf components are being used, SHIMMER gives wider flexibility. Wearable monitoring sensors have been demonstrated in [38], [75], and [76]. In [38] a wearable monitoring device has been proposed for temperature and heart rate monitoring. Similarly, in [35] a wearable temperature sensor for passive and semi-passive applications has been reported. In this application the on-chip temperature sensor uses power from the RF analog front end to operate and the off-chip sensor is battery powered. An energy efficient front end for wireless temperature sensor architecture has been proposed in [76]. The temperature sensor proposed is embedded in a passive RFID tag and is manufactured with 180 nm technology. In [75] a passive wireless sensor module has been proposed with an external temperature sensor and Analog to Digital Converter (ADC) where distilled water is used as the temperature sensing material.

### 3.3. Design of the Proposed BBT Monitoring Sensor as an IoT Component

In the proposed monitoring system, the temperature sensor module along with the non-volatile memory are used as an *in vitro* component, i.e. it is placed on the body of the person throughout the night to obtain temperature values. The temperature acquisition is done with the help of the oscillator block as shown in Figure 3.3. The variation in oscillating frequency is compared with the frequency of the system clock and the temperature is calculated. The complexity can be significantly reduced when the time delay is compared instead of frequency. The difference in delay in the clock pulse and the oscillator output is calculated with the help of a binary counter. The output of the counter is written to the memory of the digital block. This information can be transmitted using the wireless module present in the sensor design. With the help of a wireless module, many such sensors are connected to the sensor network, which helps to make the diagnosis easier at the physician's end. The proposed monitoring system as an IoT component consists of a patient's module and a doctor's module, i.e. the patient's end consists of the sensor along with additional components for data logging, while at the doctor's end the data acquisition system along with the error correction mechanism is deployed. All the important components of the proposed architecture are briefly discussed below.

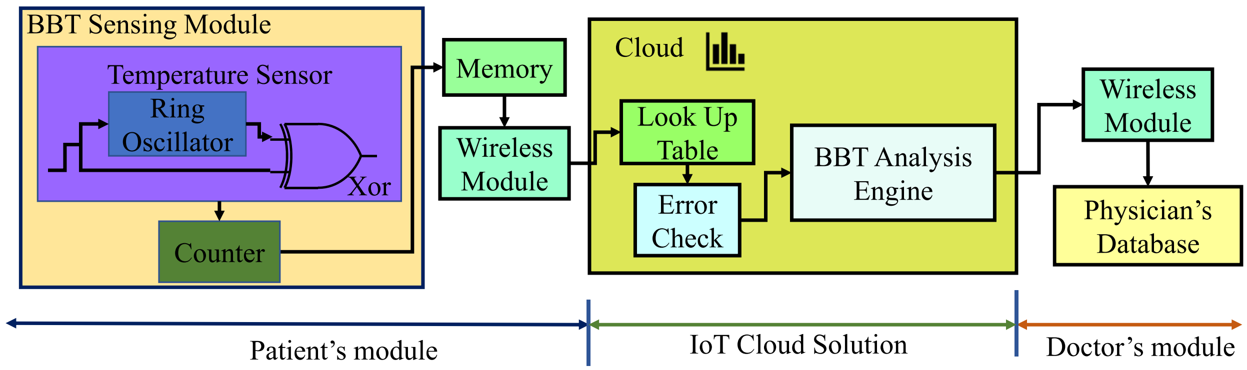



Figure 3.3: Architecture of BBT monitoring sensor as an IoT component.

### 3.3.1. BBT Monitoring Sensor: Patient's Module

The temperature acquisition for the BBT monitoring sensor is done by using a ring oscillator. A ring oscillator is designed using an odd number of inverters and can be used to monitor human body temperature variation [73]. In order to achieve oscillation, the ring must provide a $2\pi$ phase shift and have unity voltage gain at the oscillating frequency. The oscillation frequency $f_{\mathrm{osc}}$ is given by:

$$f_{\mathrm{osc}} = \frac{1}{N_{\mathrm{stage}}(T_{\mathrm{pd,LH}} + T_{\mathrm{pd,HL}})}, \tag{1}$$

where $\mathrm{N_{stage}}$ is the number of stages in the ring oscillator and the propagation delays $\mathrm{T_{pd,\ LH}}$ and $\mathrm{T_{pd,\ HL}}$ are given by:

$$\begin{aligned} T_{\mathrm{pd,LH}} &= \frac{-2C_L V_{\mathrm{Th,p}}}{K_p(V_{\mathrm{DD}} - V_{\mathrm{Th,p}})^2} + \\ & \quad \frac{C_L}{K_p(V_{\mathrm{DD}} - V_{\mathrm{Th,p}})} \ln \frac{1.5V_{\mathrm{DD}} + 2V_{\mathrm{Th,p}}}{0.5V_{\mathrm{DD}}} \end{aligned} \tag{2}$$

$$\begin{aligned} T_{\mathrm{pd,LH}} &= \frac{2C_L V_{\mathrm{Th,n}}}{K_p(V_{\mathrm{DD}} - V_{\mathrm{Th,n}})^2} + \\ & \quad \frac{C_L}{K_p(V_{\mathrm{DD}} - V_{\mathrm{Th,n}})} \ln \frac{1.5V_{\mathrm{DD}} + 2V_{\mathrm{Th,n}}}{0.5V_{\mathrm{DD}}}, \end{aligned} \tag{3}$$

where$V_{\mathrm{DD}}$ is the power supply and $V_{\mathrm{Th,n}}$ and $V_{\mathrm{Th,p}}$ are the threshold voltages of the NMOS and PMOS, respectively. $C_L$ is the capacitive load to the oscillator and $K_p$ is a model parameter depending on the transistor oxide capacitance and the carrier mobility in the channel.

The threshold voltage $V_{Th}$ is very sensitive to temperature fluctuations. The oscillating frequency variation is inversely proportional to temperature fluctuation, i.e. as the temperature increases the oscillating frequency decreases and the time period increases. This is used to calculate the variation of temperature based on the oscillating frequency. Ring oscillators can vary widely based on the design and application they are being used. Figure 3.4 shows different common inverter architectures. The basic inverter and the current starved with symmetrical load architectures have high frequency deviations in terms of temperature variations while the current starved with output switching architecture has the lowest sensitivity. The relative frequency deviation ratio between the architectures in (a) and (b) in Figure 3.4 is estimated to be around 5:1.

Instead of using complex components such as op-amps and integrators, a simple XOR gate is used to measure the difference in temperature. The basic architecture is shown in Figure 3.5. The variation in width of the oscillator output based on the increase/decrease of temperature is sensed with the help of the XOR gate, as the other input to the gate is the pulse generator, which has defined pulse width. The oscillating frequency produced by the ring oscillator is compared with the system clock with the help of a counter. A 10-bit counter is designed using JK flip flops. The oscillating frequency is given by the clock pulse and the system clock is given as an input to the counter. Since an XOR gate is already used to compute the delay of the pulse in the thermal sensor, a less complex circuit can be employed to analyze the temperature variation. The acquired BBT sensor values are stored in memory for further processing.

The wireless module is the key factor that determines the energy efficiency of the system. If the wireless module is switched on throughout the night it can affect power consumption to a great extent and would also heat up the system which would lead to erroneous temperature values. Zigbee and other IEEE protocols such as IEEE 802.15.4, IEEE 802.11, and Bluetooth are commonly used for sensor network applications. Low power Wi-Fi also increases battery lifetime. Currently, many power saving mechanisms can be used to reduce the power dissipation of the wireless module. IEEE 802.11 power save (PS) mode is a power

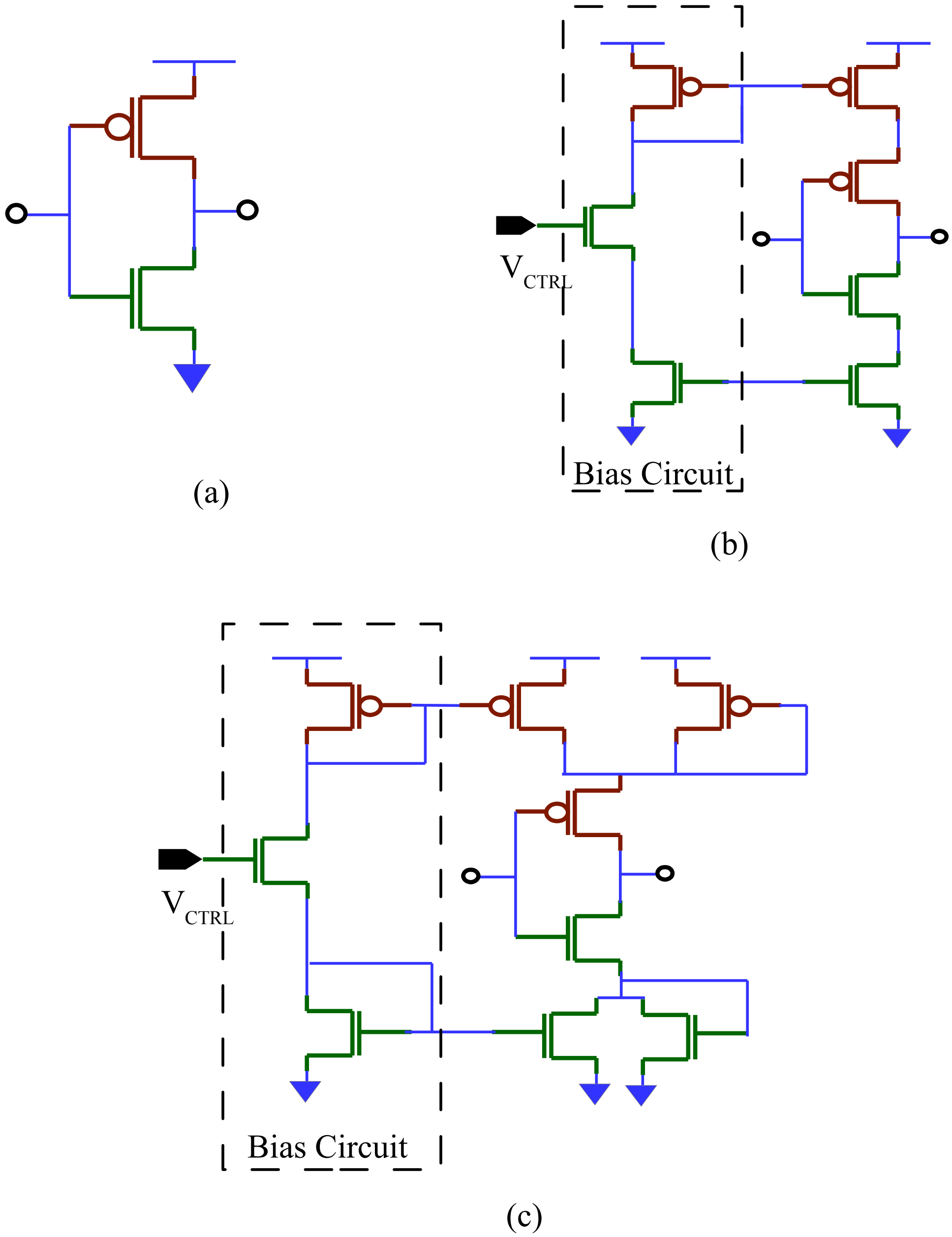



Figure 3.4: Inverter: (a) Basic type; (b) Current starved with output-switching; (c) Current starved with symmetrical load.

saving mechanism that allows mobile stations to turn off both transmitter and receiver when not in use. Since in this application we need to only transmit the temperature values along with the time stamp once a day, Bluetooth is used as the wireless module in the system.

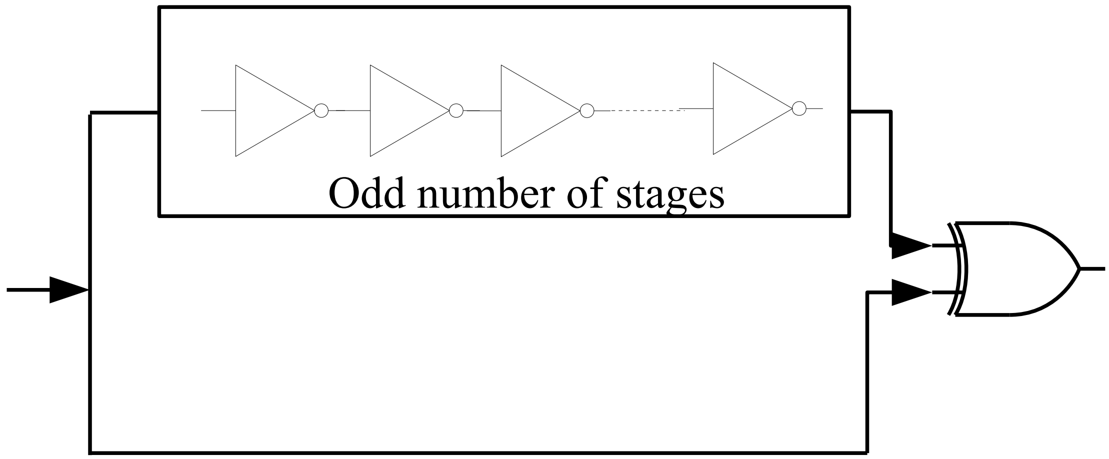



Figure 3.5: Thermal sensor using a ring oscillator and an XOR gate.

### 3.3.2. BBT Monitoring Sensor: IoT Cloud Solution

An IoT cloud-based solution helps in faster computation and easy deployment. A look-up table approach helps in reducing the computational complexity to an array indexing operation. This helps in obtaining results which are more accurate and reliable. Several tests are performed using the design and the calibrated values are defined in the look-up table. The output value is the temperature value derived from the deviation in frequency for different temperatures. In this design, the look-up table is used at the output of the counter to map the number of counts to calibrated temperature values. The normalized temperature values are given as input to the error checking engine which helps in determining the accuracy of the whole system. Depending upon the output of the error checking engine, the patient's data are further processed using the BBT Analysis Engine. In the event of higher error range, the BBT sensing module is triggered again to obtain the BBT values. The input data received from the user are processed by a dynamic Support Vector Machine (SVM) engine. Figure 3.6 demonstrates the flow of data along the SVM engine.

SVMs are an example of supervised learning where the learning algorithm is used to analyze data and recognize patterns [72]. SVMs can be classified into linear and non-linear based on the input kernel. When a set of data is given and is to be separated by a single feature, then the hyper plane to be defined is one-dimensional; when the data is to be

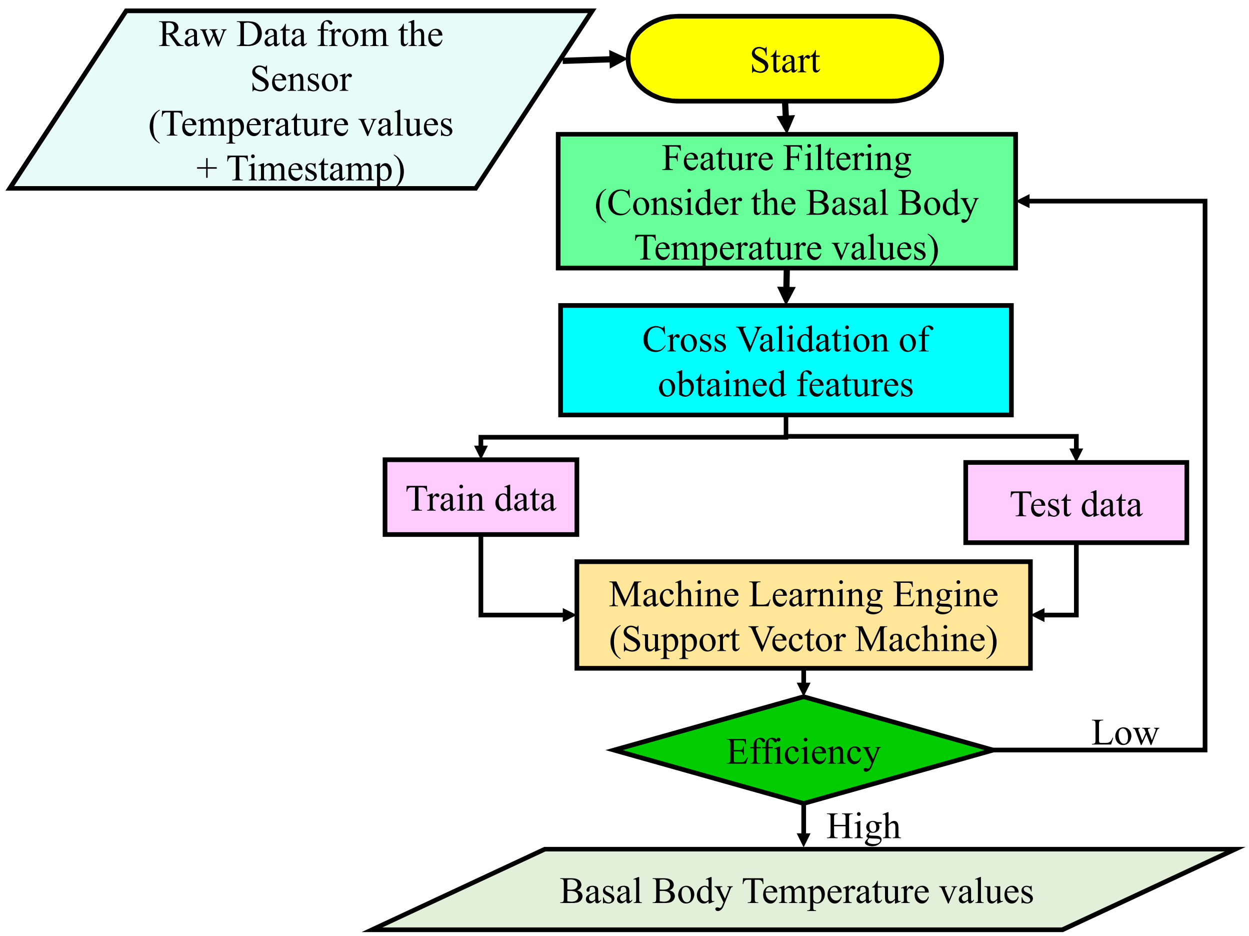



Figure 3.6: Support vector machine based BBT analysis engine.

separated based on 2 features then the hyper plane is two dimensional (line). SVMs classify data without modeling a probability distribution.

The temperature data are assigned to a group and are classified into good or bad data. After being assigning in a group, the data are segregated into training data and test data with the help of cross validation. The "holdout" value is varied depending upon the efficiency required by the doctor. For example, if the holdout value is 0.4, then 60% of the data are considered for training the SVM engine and 40 % are considered for testing it. After classifying the test and train data, the SVM classifier is trained using the "svmtrain" block. The output of this is used to further classify the test set. The efficiency of this engine is measured with the help of two parameters: efficiency and class performance. The "classperf" function helps in evaluating the performance of the classifier. The train and test blocks help in printing the segregated data in separate files which can be optional. This dynamic engine helps in classifying the data irrespective of the size of the input data by using dynamic blocks. By setting a threshold to the output of this engine, we can discard the BBT data if the efficiency is too low and a new set of values can be taken from the user.

#### 3.3.3. BBT Monitoring Sensor: Doctor's Module

At the doctor's end, the BBT values analyzed using the IoT based cloud are received and logged into the database. Based on the obtained information, the doctor can further continue the current treatment or, in case of critical situations, the patient can be called to the health facility for further tests.

### 3.4. Implementation and Validation of the BBT Monitoring Sensor

Figure 3.7 shows the flow of data across different modules in the proposed design [65]. The implementation of the modules in both patient and doctor's ends is presented in detail in the following subsections.

#### 3.4.1. Simulation Level Validation

In general, various ring oscillator architectures have been used as temperature sensors. In this research, we have analyzed the performance of the basic ring oscillator architecture and current starved ring oscillator with balanced load, which is very sensitive to temperature variation. The efficiency is decided based on the stability of frequency over the temperature range and power dissipation. Since the basal body temperature varies by a very small margin, a wider time period over this temperature range is the most important deciding factor. Four architectures and their performance were analyzed based on stability over the temperature range of interest. These are: ring oscillator with 9 stages, 13 stages and 17 stages and a current starved ring oscillator of 5 stages with balanced load. Figure 3.8 shows the implementation of the 5 stage current starved ring oscillator architecture with balanced load where each stage was designed based on Figure 3.4(c). This architecture is very sensitive to temperature variations and hence is ideal for temperature sensing applications. The initial

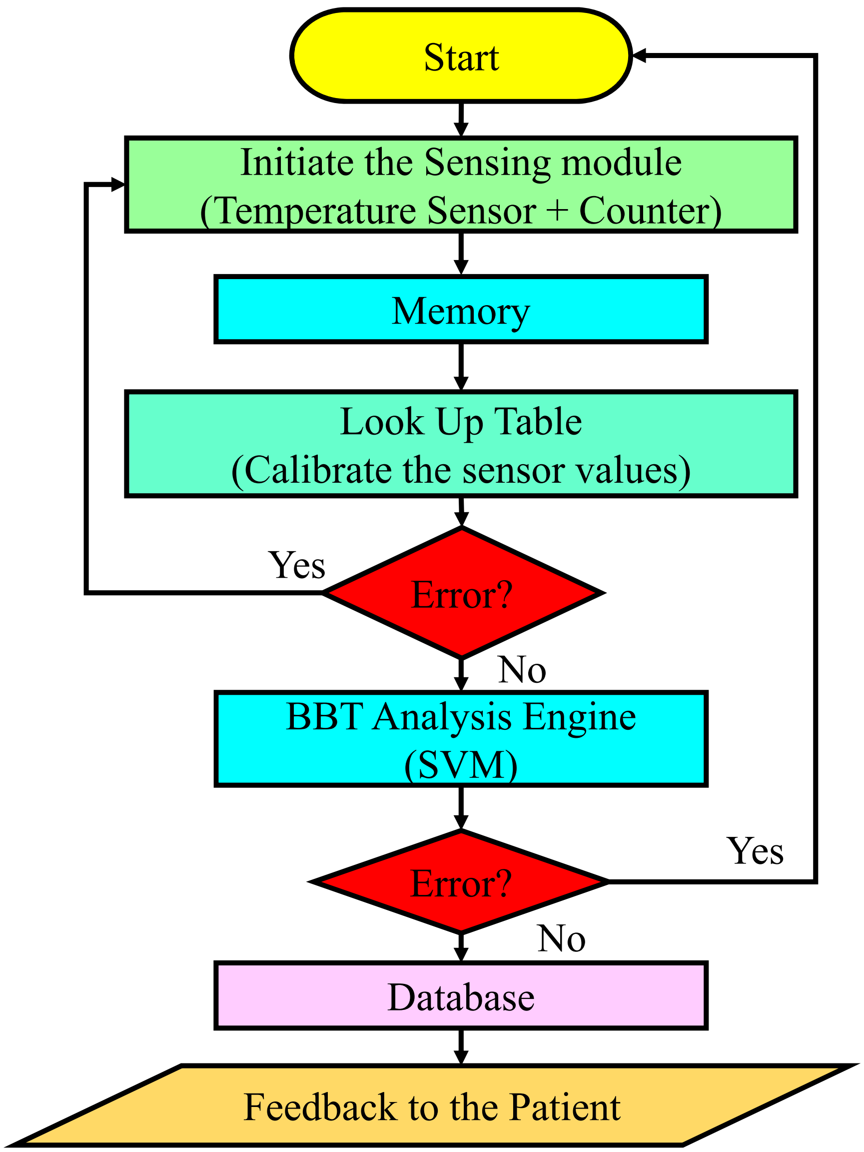



Figure 3.7: Flow diagram of data flow across the modules.

stage of the inverter is supported by a biasing circuit which consists of a PMOS and 2 NMOS transistors. The control voltage is given through the NMOS. Subsequently, based on the requirements, more stages are added with each inverter supported by a balanced load. In Simulink®, the architecture is designed with the help of Simscape® elements present in the Simulink® library. Implementing the system by using subsystem blocks helps in adding additional stages easily. This helps in making the variations required and adding as many blocks as required without having to alter the architecture for every simulation. In Simulink® , the voltage and current are interpreted as physical signals. In order to analyze the changes in these physical signals, it is important to convert the physical signal to a Simulink® signal. This is done with the help of S-PS and PS-S converters available in the Simulink® library. The variation in the output based on the temperature variation is inspected with the help of a scope block.

The simulation results of the thermal sensor for four different architectures are tabulated in Table 3.1. The temperature dependence feature is modeled for performing temperature analysis. By varying the temperature values, the corresponding variation in frequency is observed by using the "bilevel measurement" feature in the scope block. Since the human basal body temperature value is of very small dynamic range, the temperature values are varied for a smaller range and the corresponding variations are observed. The values obtained are plotted as a graph using the plot function and it is observed that as the temperature increases, the oscillating frequency decreases and the propagation delay increases, as shown in Figure 3.9. Due to the switching activity of each transistor, it is required to have simulation time as short as possible. Since the human body temperature varies only between 35-38° C, the results of this range are tabulated. The sensor was calibrated for 25-45° C. The temperature sensor was designed based on Figure 3.5. The output of the ring oscillator was given to the counter.

As temperature increases, the time period increases and the frequency decreases. When the time period is long, it becomes easier to analyze even the slightest variations in temperature. As can be seen in Table 3.1, for a thermal sensor with 9 stage ring oscillator, as the temperature increases, the count increases only by 1 unit, whereas in a 17 stage ring oscillator, for each unit increase in temperature, the normalized count increases by around 4-5 units. This helps in better analysis of the basal body temperature variation as the temperature range is of very small margin and it helps in obtaining better resolution. The 13 stage ring oscillator and current starved ring oscillator have almost the same amount of variation in the normalized count for each unit of temperature variation. For example, at 37° C, it can be observed that the time period variation of the 9 stage ring oscillator is around 200 ps whereas for the 17 stage ring oscillator, the time period is increased to almost

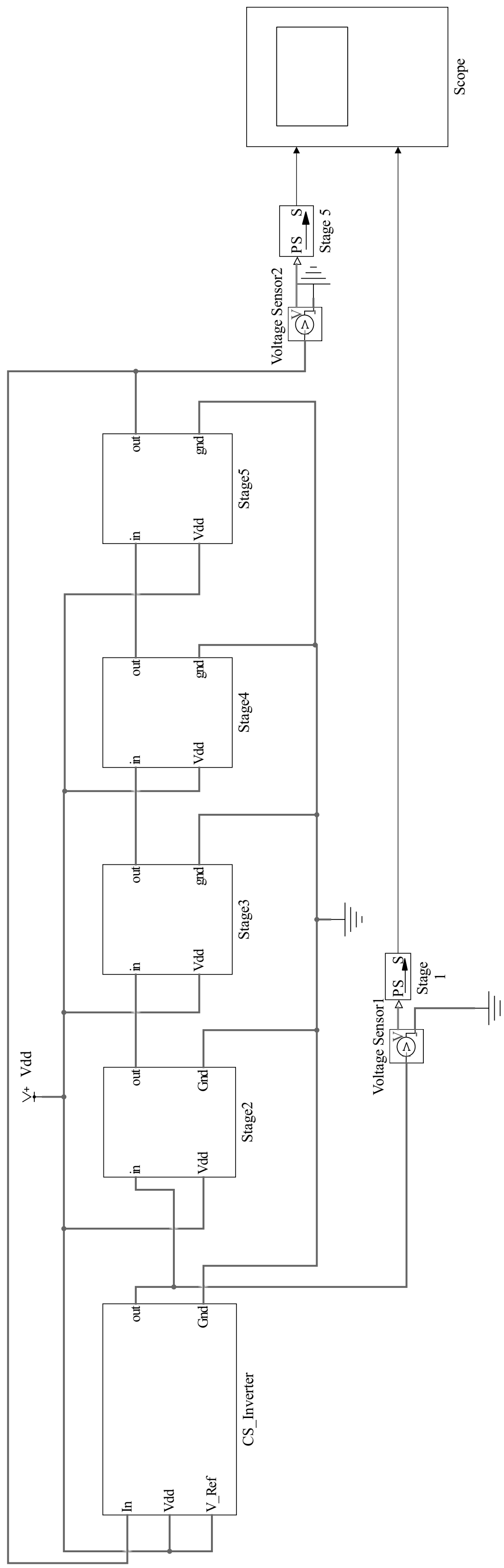



Figure 3.8: Simulink® implementation of current starved ring oscillator with balanced load.

Table 3.1. Frequency and time period values for various temperatures.

| | RO 9 Stage | | | RO 13 Stage | | |
|---|---|---|---|---|---|---|
| Temp $^oC$ | Normalized Count | Time Period (ns) | Frequency (MHz) | Normalized Count | Time Period (ns) | Frequency (MHz) |
| 35 | 62 | 7.328 | 90.73 | 86 | 11.172 | 86.042 |
| 36 | 63 | 7.646 | 90.436 | 88 | 11.650 | 85.84 |
| 37 | 64 | 7.837 | 90.168 | 90 | 12.168 | 85.182 |
| 38 | 65 | 8.115 | 89.971 | 92 | 12.781 | 84.625 |
| 39 | 66 | 8.471 | 89.654 | 94 | 13.206 | 84.136 |
| 40 | 67 | 8.887 | 89.342 | 96 | 14.012 | 83.517 |
| | **RO 17 stage** | | | **CS RO 5 Stage** | | |
| Temp $^oC$ | Normalized Count | Time Period (ns) | Frequency (MHz) | Normalized Count | Time Period (ns) | Frequency (MHz) |
| 35 | 120 | 15.105 | 64.273 | 71 | 11.622 | 79.931 |
| 36 | 125 | 15.92 | 63.61 | 73 | 11.65 | 79.452 |
| 37 | 129 | 16.874 | 62.994 | 76 | 12.168 | 79.116 |
| 38 | 134 | 17.36 | 62.13 | 79 | 12.781 | 78.516 |
| 39 | 139 | 18.103 | 61.213 | 81 | 13.206 | 78.038 |
| 40 | 145 | 18.907 | 60.214 | 84 | 14.012 | 77.759 |

900 ps for the same temperature. Similarly, it can be observed that the frequency decreases by around 300 KHz when the temperature is increased from 36° C to 37° Cin the 9 stage ring oscillator whereas the frequency decreases by around 700 KHz for the 17 stage ring oscillator. It can be observed from Figure 3.9 that, though initially the time period of the 13 stage ring oscillator and the current starved ring oscillator vary by a small margin, when

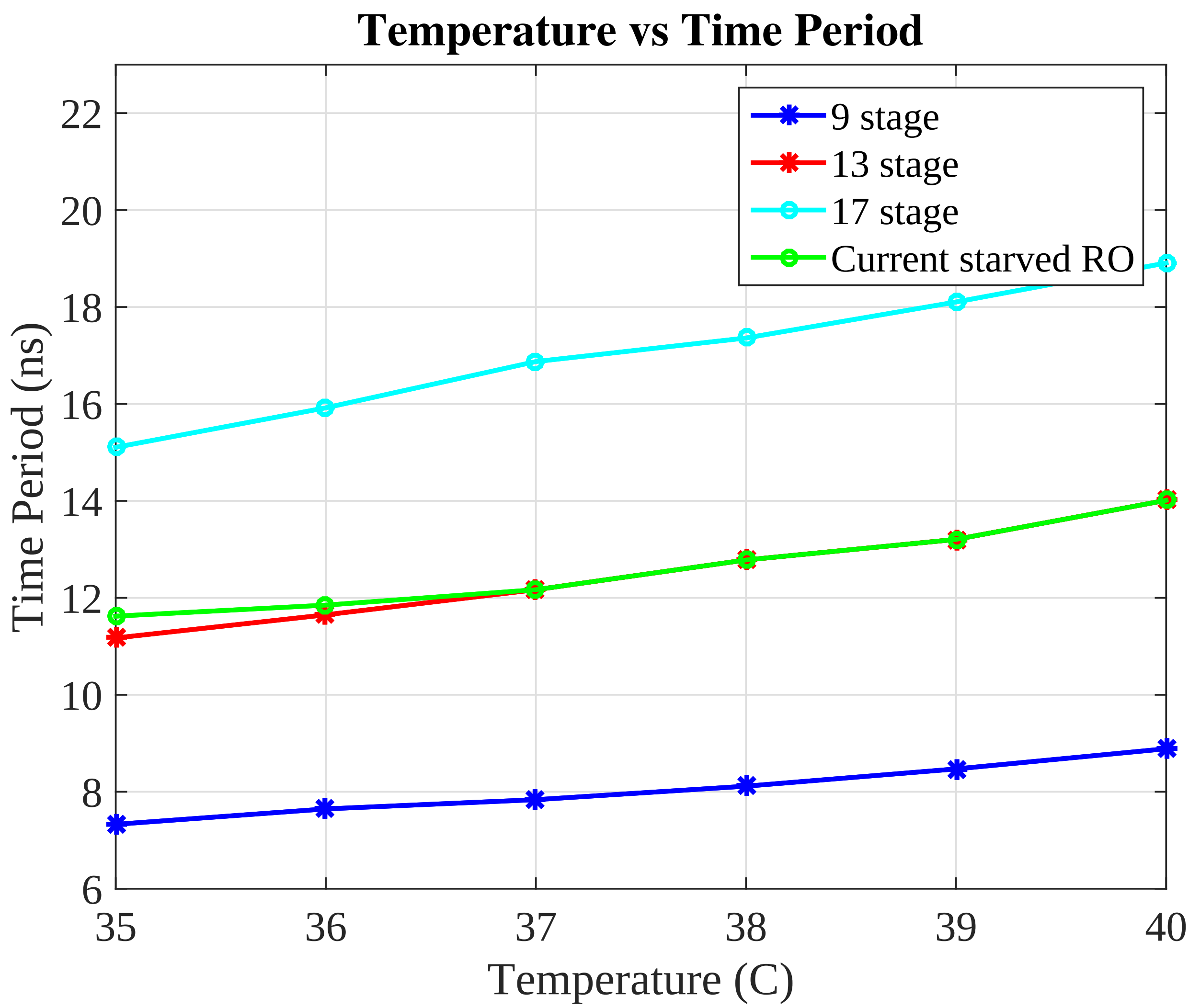



Figure 3.9: Time period vs. temperature for different sensor architecture simulations in Simulink®.

the temperature increases from 35° C to 36° C, the variation in time period is almost the same as the temperature gradually increases. This explains the reason for observing almost identical amounts of variation in the normalized count in the required temperature range. Figure 3.9 also shows that for each temperature, as the number of stages varies, the time period values also keep increasing. For the 9 stage ring oscillator, the time period range is 7-8 ns and it can be seen that the range increases when more stages are added. It can also be seen that the higher the number of stages, the better is the variation range in the temperature. Similarly, in Figure 3.10, it is observed that as the temperature increases, the frequency decreases. For the required temperature range, the frequency range is 60-64 MHz for the 17 stage ring oscillator temperature sensor, whereas for the same temperature range the frequency range for the 9 stage oscillator is 89-91 MHz. Therefore with more stages added in the thermal sensor, better values are obtained both in terms of frequency and time period. Unlike the time period variation, the frequency ranges of the 13 stage ring oscillator and the current starved ring oscillator with 5 stages, are in different range.

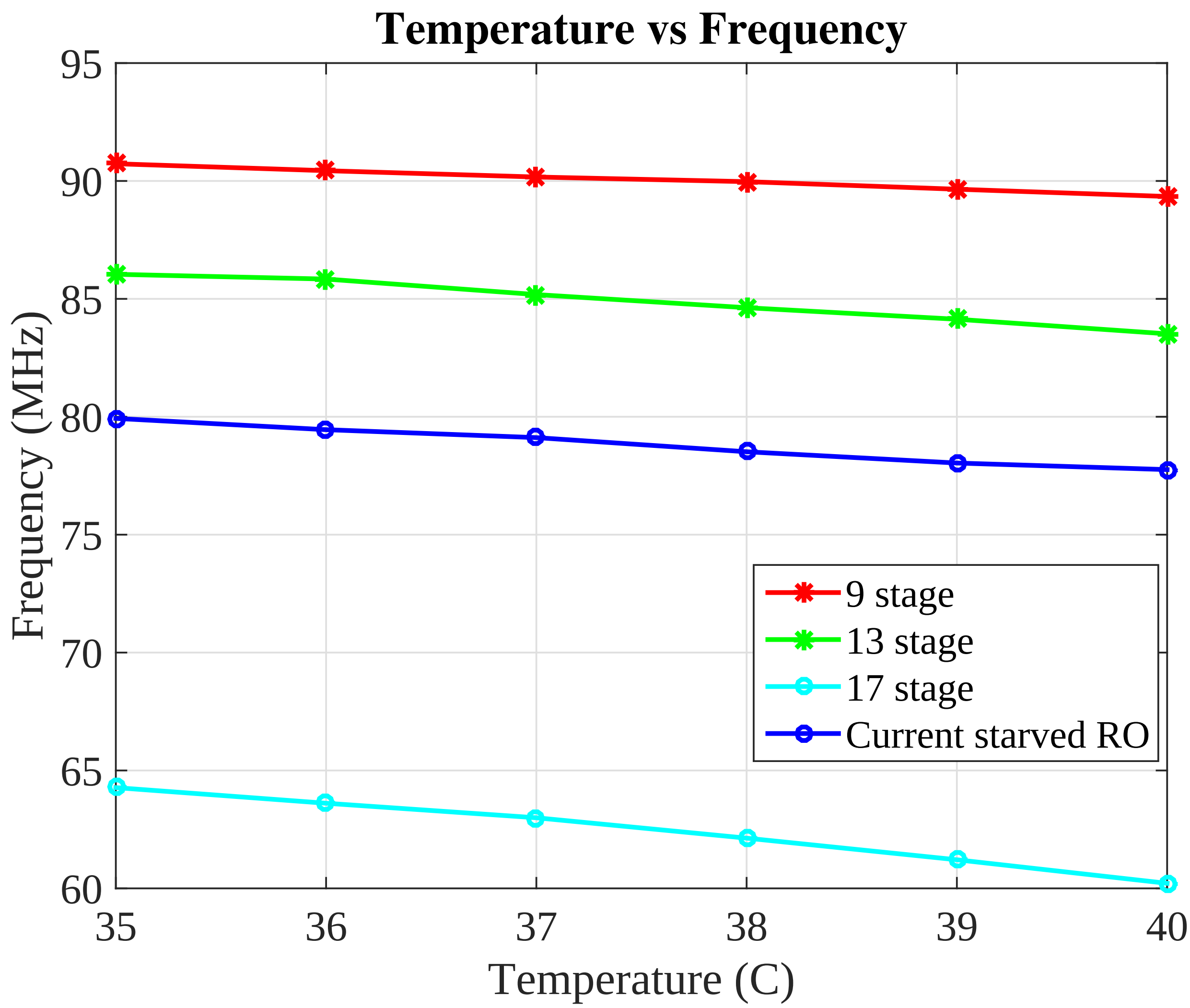



Figure 3.10: Frequency vs. temperature for different sensor architecture simulations in Simulink®.

In this work, the output of the ring oscillator is compared with the pulse generator or clock. These two signals are XORed before transmission. When adding many stages to the ring oscillator based on the requirements, there exists the possibility of having non linearity in the output. When comparing with the pulse generator output, there are more chances for misinterpreting a smaller peak value as an actual rising edge and missing out on a rising or falling edge due to various other reasons such as jitter, etc. Hence two different methods of obtaining the oscillator output are used: the raw output of the oscillator and a normalized output for both time period and frequency based on the variation in temperature. The comparison of raw output data and normalized values can be seen in Table 3.2.

From the output values, it can be inferred that the normalized output gives better values and more linearity in analyzing the temperature variation. In Figure 3.11, the time period of oscillator output and normalized time period with the help of a look-up table are plotted. In this plot it can be observed that at each temperature variation, there is more linearity in the normalized output. When the temperature increases from 35 to 36 ° C, for the 17 stage ring oscillator temperature sensor the time period or normal oscillator output varies by around 700 ps whereas the normalized output varies by almost 1 ns. This helps in avoiding misinterpretation of noise values as actual oscillator output. Thus in order to improve efficiency, the values obtained with the help of the look-up table are used as input to the XOR gate where the other input comes from the pulse generator. Figure 3.12 shows a three-dimensional analysis of time period and frequency values for the temperature range of 35-40° C.

### 3.4.2. Learning Model of the BBT Analysis Engine

In order to prototype an IoT module with both sender and receiver modules, the BBT analysis engine is deployed in the IoT cloud. The temperature sensor values obtained from the patient's end were given as input to the error checking module. The input given to the SVM engine is raw data. The SVM engine dynamically assigns group values based on the input values. The raw data along with group information are fed as input to the cross validation block. The cross validation block helps in dividing the data into training and test data. Based on the holdout value, the percentage of data for training and testing purposes is decided. The training and test data are fed as input to the SVM engine which

TABLE 3.2. Normalized frequency and time period values along with raw data for 13 stage and 17 stage ring oscillator temperature sensors.

| | RO 13 Stage | | | | | |
|---|---|---|---|---|---|---|
| Temperature $^oC$ | Time Period (ns) | Frequency (MHz) | Oscillator Output Time Period (ns) | Oscillator Output Frequency (MHz) | Normalized Time Period (ns) | Normalized Output Frequency (MHz) |
| 35 | 11.172 | 86.042 | 28.64 | 36.90 | 27.811 | 37.487 |
| 36 | 11.650 | 85.84 | 29.673 | 35.812 | 29.844 | 36.627 |
| 37 | 12.168 | 85.182 | 31.97 | 34.916 | 30.962 | 35.957 |
| 38 | 12.781 | 84.625 | 32.711 | 33.829 | 32.882 | 34.865 |
| 39 | 13.206 | 84.136 | 34.621 | 32.876 | 34.317 | 33.591 |
| 40 | 14.012 | 83.517 | 35.231 | 31.279 | 36.421 | 32.297 |
| | **RO 17 Stage** | | | | | |
| Temperature $^oC$ | Time Period (ns) | Frequency (MHz) | Oscillator Output Time Period (ns) | Oscillator Output Frequency (MHz) | Normalized Time Period ns | Normalized Output Frequency (MHz) |
| 35 | 15.105 | 64.273 | 43.995 | 22.73 | 38.309 | 26.103 |
| 36 | 15.92 | 63.61 | 44.691 | 22.376 | 39.876 | 25.078 |
| 37 | 16.874 | 62.994 | 45.52 | 21.968 | 40.99 | 24.815 |
| 38 | 17.36 | 62.13 | 45.92 | 21.187 | 41.423 | 23.929 |
| 39 | 18.103 | 61.213 | 46.876 | 20.978 | 42.719 | 22.209 |
| 40 | 18.907 | 60.214 | 47.542 | 20.512 | 43.644 | 21.913 |

helps in classifying the input into good and bad data. The efficiency is decided based on total efficiency and class performance. Class performance is used to evaluate performance of

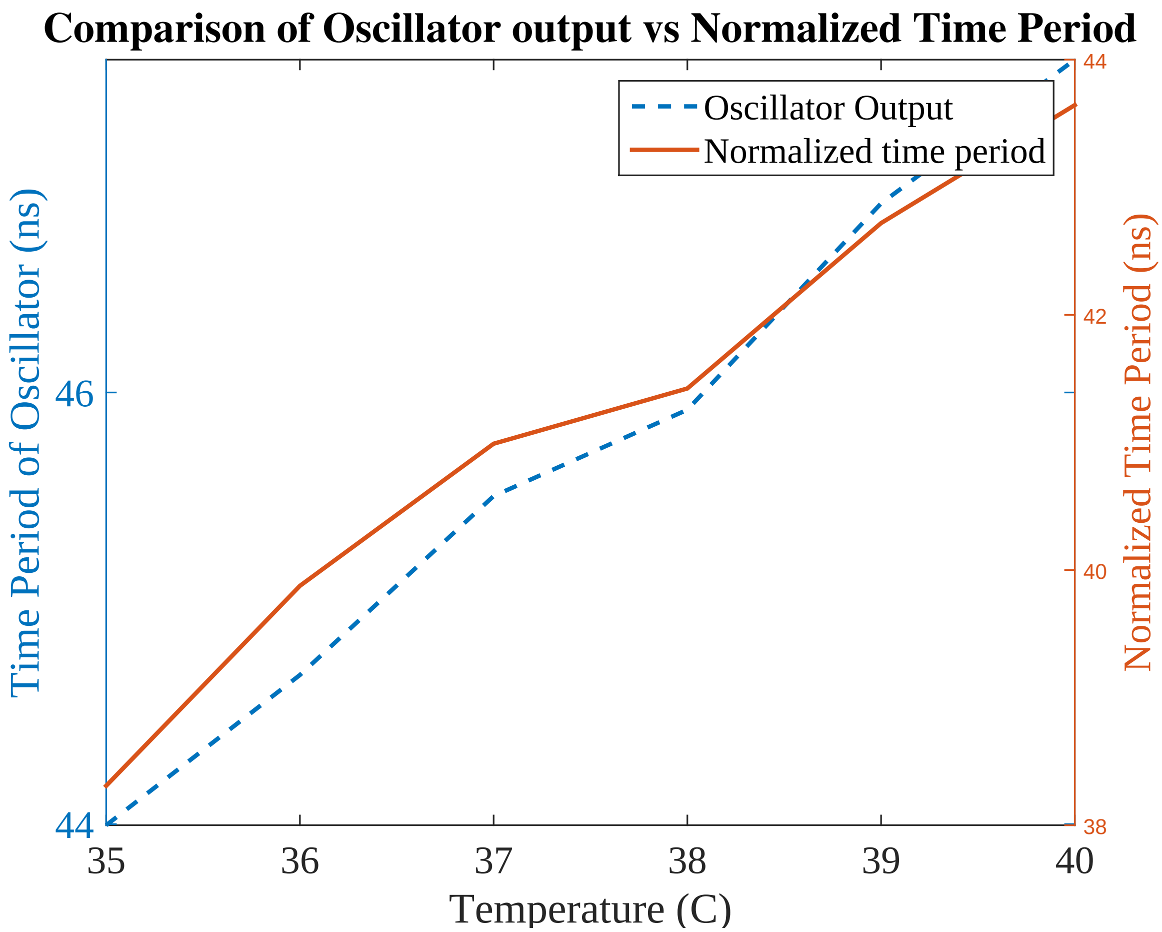



Figure 3.11: Comparison of oscillator output vs. normalized time period for 17 stage temperature sensor in Simulink®.

a classifier. In Table 3.3, the total efficiency of the classifier is tabulated. The classifier was simulated many times and the average values were tabulated. The error checking method showed an efficiency of 98.08% when 70% of the data were considered for training and 30% for testing the error checking engine. The Simulink® block diagram of the error checking engine is shown in Fig. 3.13.

### 3.4.3. Characterization of the Sensor Module

In Table 3.4, the characterization data of the sensor are tabulated. The number of transistors increases with the number of stages: for the 9 stage ring oscillator, 20 transistors are required since the first stage of inverters is replaced by a NAND gate for better stability.

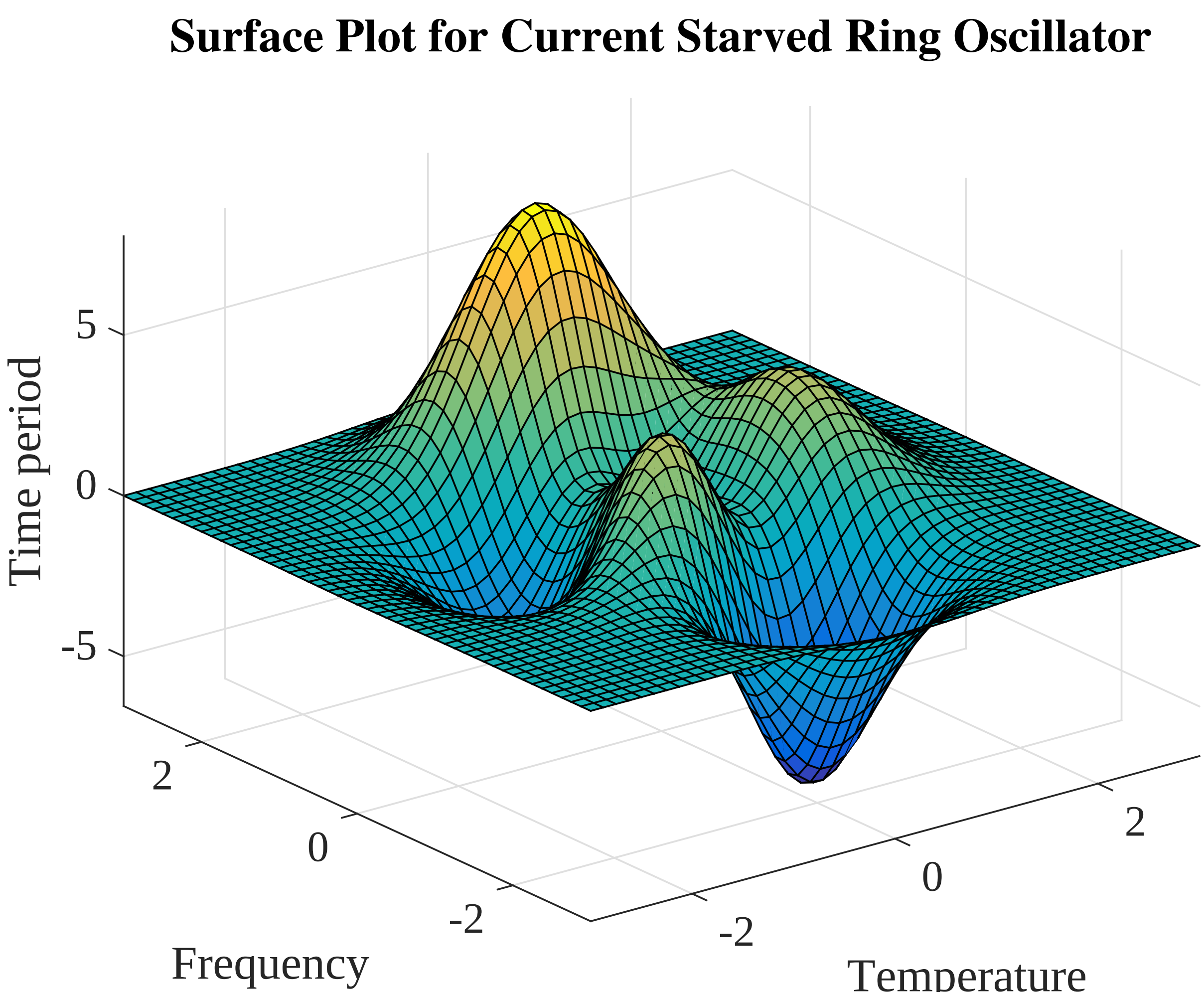



Figure 3.12: Surface plot for time period and frequency values in the current starved ring oscillator.

TABLE 3.3. Efficiency of the BBT analysis engine.

| Holdout value | Efficiency (%) |
|---|---|
| 0.4 | 98.08 |
| 0.5 | 97.93 |
| 0.6 | 97.64 |
| 0.7 | 97.32 |

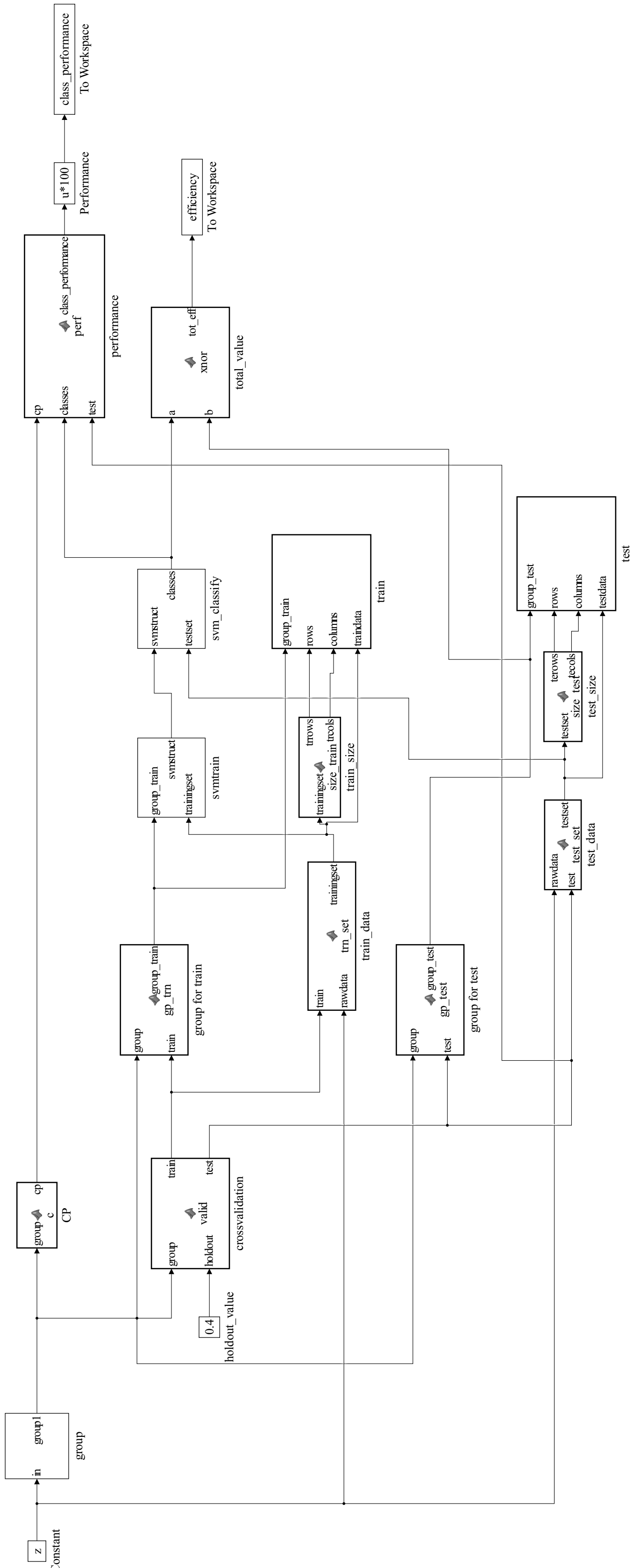



Figure 3.13: BBT analysis engine in Simulink®.

The current starved ring oscillator with balanced load requires more transistors, in spite of just using 5 stages. This is because extra transistors are required for providing the balanced load. The time period varies between 7 ns to 19 ns based on the number of stages. As more stages are used in the ring oscillator architecture, the time period range increases. Similarly, based on the architecture, the frequency range also varies from 60 MHz to 91 MHz. The average time period variation per $^oC$ is 200 ps for the 9 stage ring oscillator whereas it varies up to 900 ps per $^oC$ for the 17 stage ring oscillator. The time period variation is around 450 ps per $^oC$ for both the 13 stage ring oscillator and a 5 stage current starved ring oscillator with balanced load. The variation of normalized count per $^oC$ increases as the number of stages increases. To compare the values of different architectures, the simulations were performed over a time period of 100 ns.

TABLE 3.4. Characterization table for different sensor architectures.

| | Temperature Sensor Architectures | | | |
|---|---|---|---|---|
| | RO 9 Stage | RO 13 Stage | RO 17 Stage | CS RO 5 Stage |
| No. of Transistors | 20 | 28 | 36 | 33 |
| Time Period range (ns) | 7.320-8.90 | 11.150-14.05 | 15.100-18.910 | 11.600-14.05 |
| Frequency range (MHz) | 89.300-90.750 | 83.500-86.050 | 60.200-64.300 | 77.700-79.950 |
| Average Time Period (ps) / $^o$C | 200 | 450 | 900 | 450 |
| Average Frequency (KHz)/ $^o$C | 200 | 450 | 900 | 450 |
| Normalized Count / $^o$C | 1 | 2 | 2 | 4 |
| Simulation Time (ns) | 100 | 100 | 100 | 100 |
| Power supply | 1.5 V | 2 V | 2 V | 2 V |

The temperature sensor architecture was simulated and the normalized count values were used to calibrate the sensor. These values were used in the look-up table to check for errors. Table 3.5 shows a comparison of power dissipation of our ring oscillator architecture with already existing research. In [59], an injection locked oscillator was used to improve the linearity and the total power dissipation was observed to be 2.88 mW. A CMOS based PTAT oscillator was designed as temperature sensing module in [56] and the total power dissipation was observed to be 0.9 $\mu$W . In [35, 15], the sensor was designed for temperature sensing using a passive RFID tag and the power dissipation was observed to be 3 $\mu$W and 5.1 $\mu$W, respectively. In [52], a temperature to current generator was proposed for smart temperature analysis and the power dissipation was measured to be 2 mW. A 9 stage ring oscillator was considered for power dissipation comparison, which shows a 23 % power reduction compared to previous work of temperature sensor implementation.

Table 3.5. Comparison of related research in temperature sensor design.

| Temperature Sensor Research | Power | Research Techniques |
|---|---|---|
| W. Shin [59] | 2.88 mW | Injection Locked Oscillator |
| Z. Shenghua [56] | 0.9 $\mu$W | PTAT Oscillator |
| Y. Liu [35] | 3 $\mu$W | CMOS embedded EEPROM process |
| J. Park [52] | 2 mW | Cascode Structure |
| N. Cho [15] | 5.1 $\mu$W | BJT based Temperature sensor |
| **This research** | 0.560 $\mu$W | Ring Oscillator |

# CHAPTER 4

# HUMAN ACTVITY MONITORING FOR SMART FAMILIES

This chapter presents an accurate piezoelectric based accelerometer sensor design for tracking physical activity [66].

## 4.1. The SmartWalk System in the IoT: A Broad Perspective

### 4.1.1. Significance

Human physiological monitoring can be defined as the monitoring of vital parameters that aid in the normal healthy function of human body. Traditionally, these vital physiological signs are being monitored under a clinical environment with the assistance of stationary medical devices such as bedside monitors, telemetry systems etc. Monitoring the physiological signals a on daily basis using a wearable can be more applicable and easy to use. By continuous monitoring and accumulating such data over a period of time, doctors can help in predicting future health problems. In sophisticated designs, machine learning algorithms are used to analyze these parameters and give better predictions.

Sensors used to acquire the physiological signals are very generic. Identifying the required features for the design application is a very crucial step in designing a monitoring system. For example, an accelerometer is a simple electromechanical device that measures the acceleration forces based on orientation. Figure 4.1 shows the basic working principle of accelerometers. In a 3-axis accelerometer, the orientation of the human body is considered with respect to 3-axes such as $x$-axis, $y$-axis, and $z$-axis. The $x$-axis, also known as the roll-axis is used to measure the side direction, i.e. when the person under observation is twisting or turning. The pitch-axis, i.e. the $y$-axis is used to evaluate if a person is moving forward or not. The $z$-axis is used to measure the vertical direction of the person, such as leaning forward or backward. With the help of these small electromechanical devices, multiple monitoring solutions in various disciplines can be considered. Significant applications of accelerometers include protecting hard drives in laptops, analyzing the screen orientation of mobile phones, the positioning of drones, vibration analysis in air conditioners, flush detection, package monitoring etc. In smart healthcare, some important applications of accelerometers include the performance of swimmers with respect to arm movement, monitoring bionic limbs or artificial organs, counting the number of steps taken, fall detection, etc. Hence depending upon the application, the appropriate features need to be extracted. In this chapter a

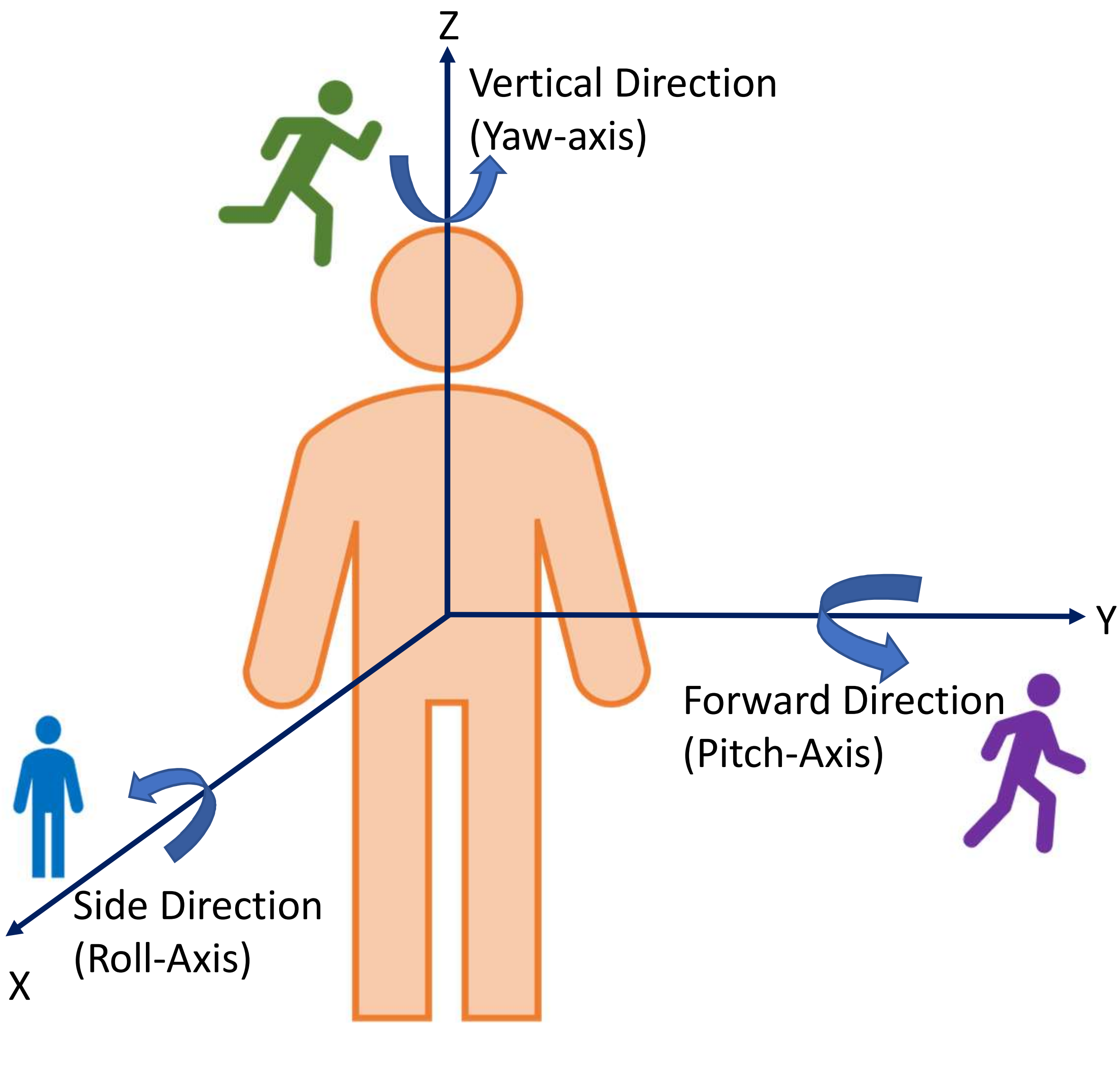



Figure 4.1: Working of a 3-axis accelerometer.

feature based human activity monitoring algorithm for improved efficiency is proposed. The proposed system is validated by using hand-held devices.

4.1.2. Design Considerations

The design phase of a smart healthcare monitoring system can be broadly divided into a data acquisition phase and a data analysis phase. Figure 4.2 shows the significant steps involved in the design phases of any health monitoring system. Identifying the appropriate application for which the wearable is designed, sensor calibration, and integration of sensors are some of the significant steps involved in the data acquisition phase whereas filtering, feature extraction, detecting appropriate features, and noise cancellation are the steps involved in the data analyzing phase. Any monitoring system designed to obtain health data contains one or more sensors to obtain the required data and algorithms to convert these raw signals into meaningful values. The overall efficiency of the system can be evaluated only when both the data acquisition and data analysis phases are carefully designed.

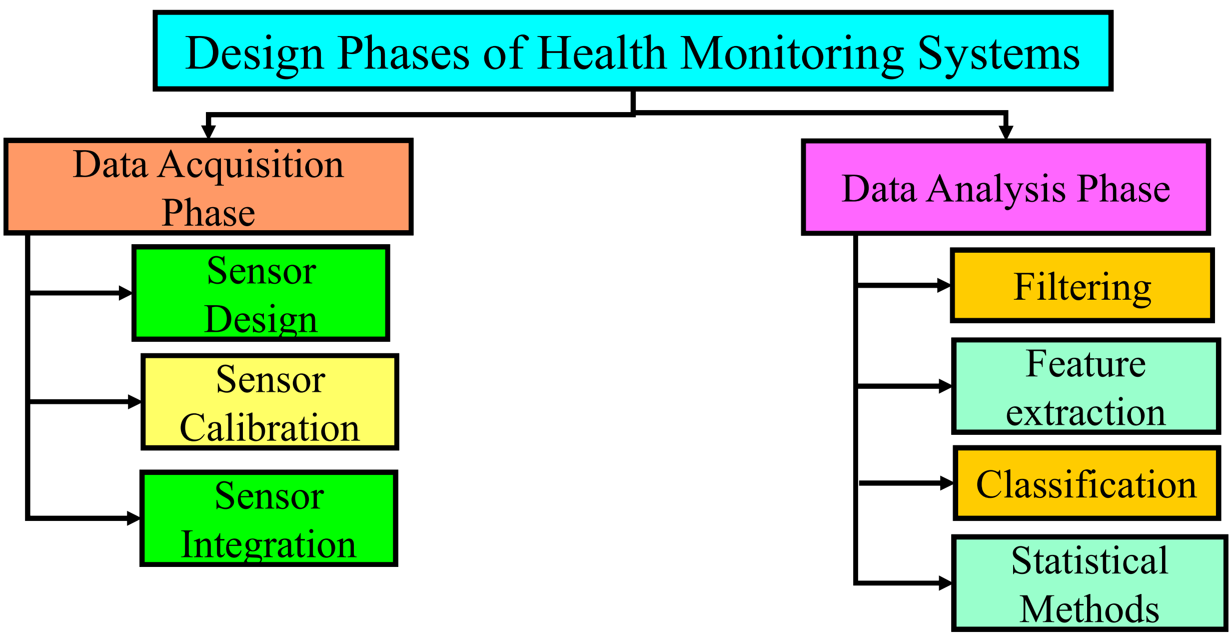



Figure 4.2: Design phases involved in health monitoring systems.

Figure 4.3 shows the framework of the Smart Walk system though the IoT. The framework contains four significant blocks or phases such as a data acquisition phase using the sensor system, a data processing phase using the algorithms, sharing the information to the concerned people and providing assistance to the users, as required. The design phases in this framework are the data acquisition and algorithm design phases. For the data acquisition phase, the sensors considered are accelerometers available through smart phones, wearables and smart watches. In order to achieve data processing using algorithms, 3 main phases are considered: the data preprocessing phase which includes analyzing all the acquired data continuously for a given period of time; the application of filtering techniques to enhance the required signals and remove the unwanted noise; and the detection phase which is done based on the variation of obtained signal values with respect to a set threshold or zero crossing events. The detection phase in the design can be done either manually or through machine learning algorithms, which have higher accuracy in detecting patterns. For this research the accelerometer data are being processed through machine learning algorithms and the classifier efficiency is evaluated.

## 4.2. Related Prior Research

Physical health monitoring was initially done using pedometers that consist of 3-axis accelerometers [28]. These accelerometers help in analyzing human walking, which is also called the gait. Using the data obtained from these pedometers, both walking and jogging actions were monitored [57]. Step length estimation and human step detection are generally done by using peak detection methods or cross correlation methods. A model for detecting step length based on Kalman filtering and the cross-correlation method is proposed in [27] and [33]. Monitoring human activity based on the physical health of the person by using a peak detection method is proposed in [16]. Peak detection can be done by a mere fixed threshold method as proposed by researchers in [41] and [71], which has the major drawback of low accuracy as the threshold varies amongst individuals [25]. In terms of wearable designs, the position of sensors in the human body and the type of wearable also plays an important role in accuracy. For gait monitoring, a shoe based design has been proposed in [26] whereas a smart phone based solution has been proposed in [34]. On the algorithm design, a zero-velocity update method which works on the idea that after every single step the person comes to a neutral position, has been proposed in [68] and [10]. A gait analysis system based on variation of parameters with respect to both time and space has been proposed in [7].

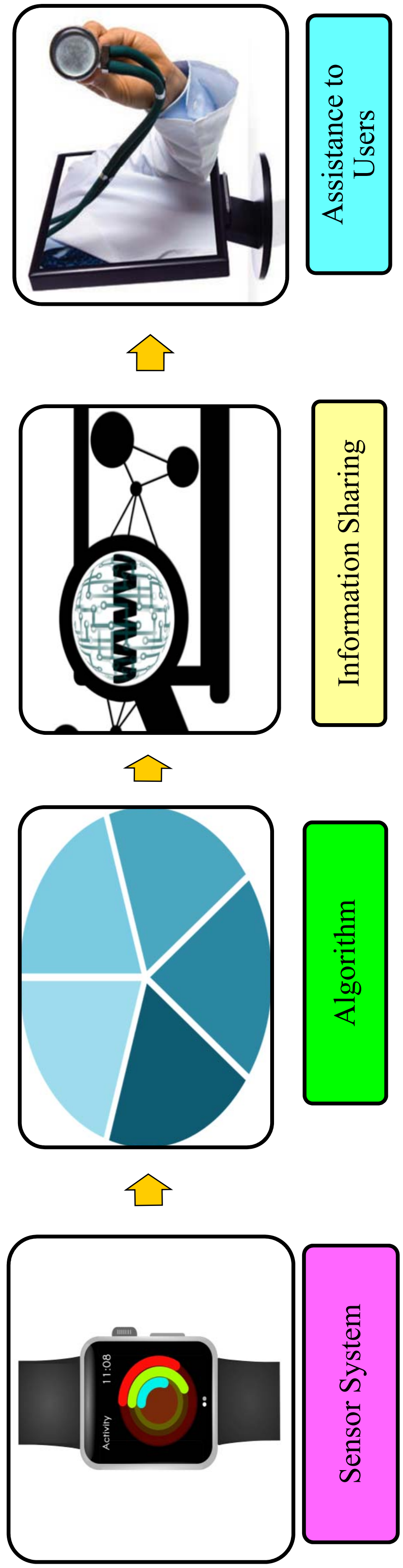



Figure 4.3: Framework of the SmartWalk system (Image Courtesy of Creative Commons, pixabay.com).

## 4.3. System Level Design of the SmartWalk System

The system level design of the SmartWalk system can be broadly divided in three sections: sensors for data acquisition, feature extraction to calculate the learning parameters, and the design of a human activity monitoring algorithm for step detection and step length estimation. Figure 4.4 shows the datapath involved in the sensor design for the smart walk system. The data acquisition is done using a 3-axis accelerometer. The inputs to the feature extraction module are 3-axis values based on which features such as signal energy, correlation, kurtosis, skewness, and maxima and minima, are extracted. By using the extracted features, the step length, step detection and distance traveled by a person are computed. Periodically, the calibration of this sensor system is done based upon which of the features are extracted.

### 4.3.1. Sensor Design

Accelerometers help in analyzing the position and velocity of the object with respect to gravity, i.e. they measure the rate of change of the velocity of an object. The output of the accelerometer is in G-forces (g) or in meters per seconds squared. One G-force is equivalent to 9.8 meters per seconds squared. Based on the requirement of these g values, the sensing axes of accelerometers vary widely. Accelerometers in general can be broadly classified based on the sensing technologies and the sensing axis, as shown in figure 4.5.

Based on sensing technologies, they can be classified into three main categories: capacitive MEMS, piezoresistive and piezoelectric. Capacitive accelerometers are of smaller size and can be easily mounted on devices. The variation in capacitance changes of a seismic mass are studied under acceleration values. Piezoresistive accelerometers, as the name indicates, provide an equivalent resistance value for variation in acceleration. They are used in applications which require wider bandwidth of G-force values. On the other hand, piezoelectric accelerometers produce an electric charge proportional to the acceleration values. They are used in applications which require high level of sensitivity. As piezoelectric accelerometers produce an electric charge, the method of producing this equivalent charge can be either charge based or voltage based. Charge based accelerometers, also known as charge mode accelerometers, are capable of operating in extreme environments. Voltage mode Internal

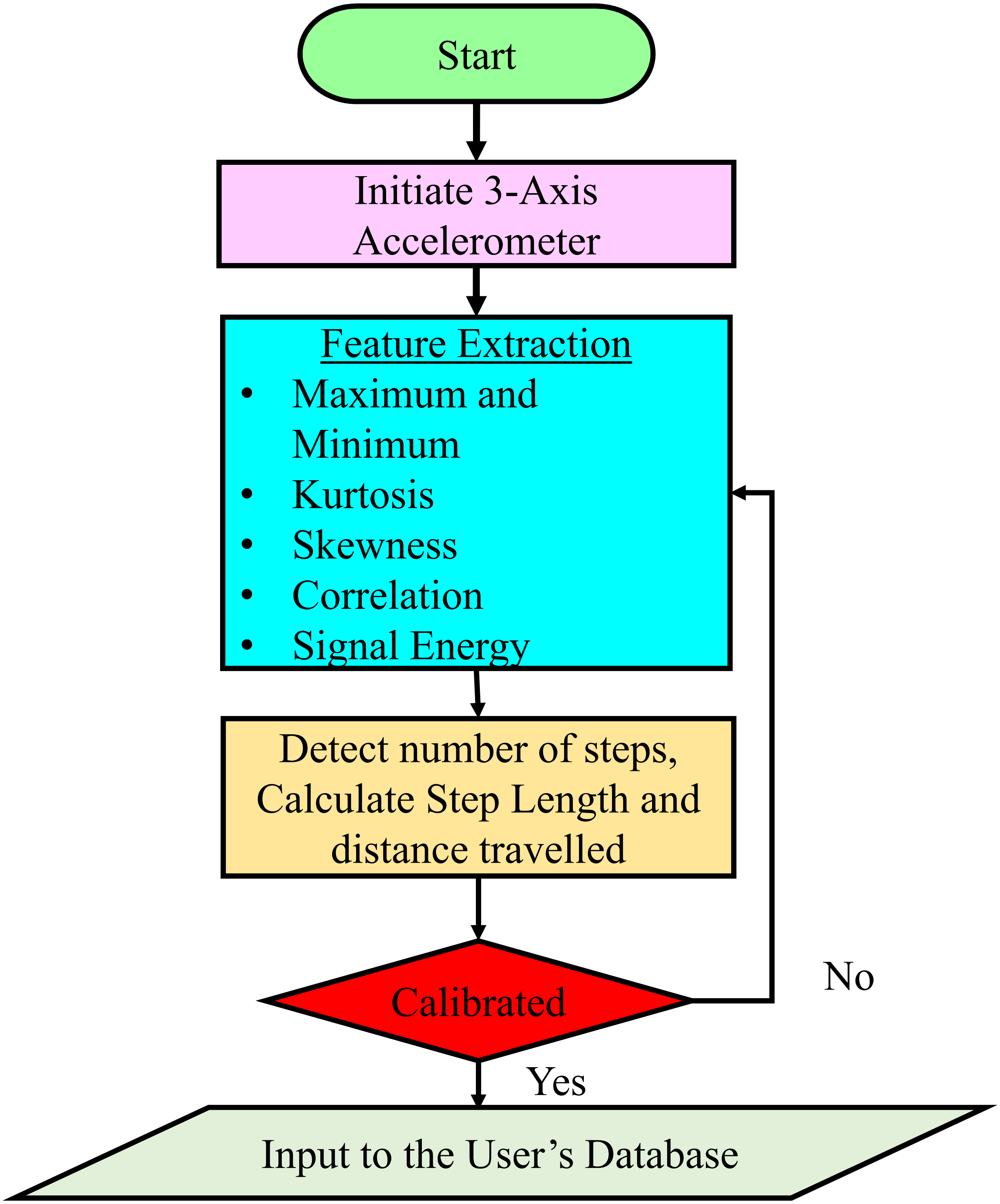



Figure 4.4: Datapath for efficient parameter estimation.

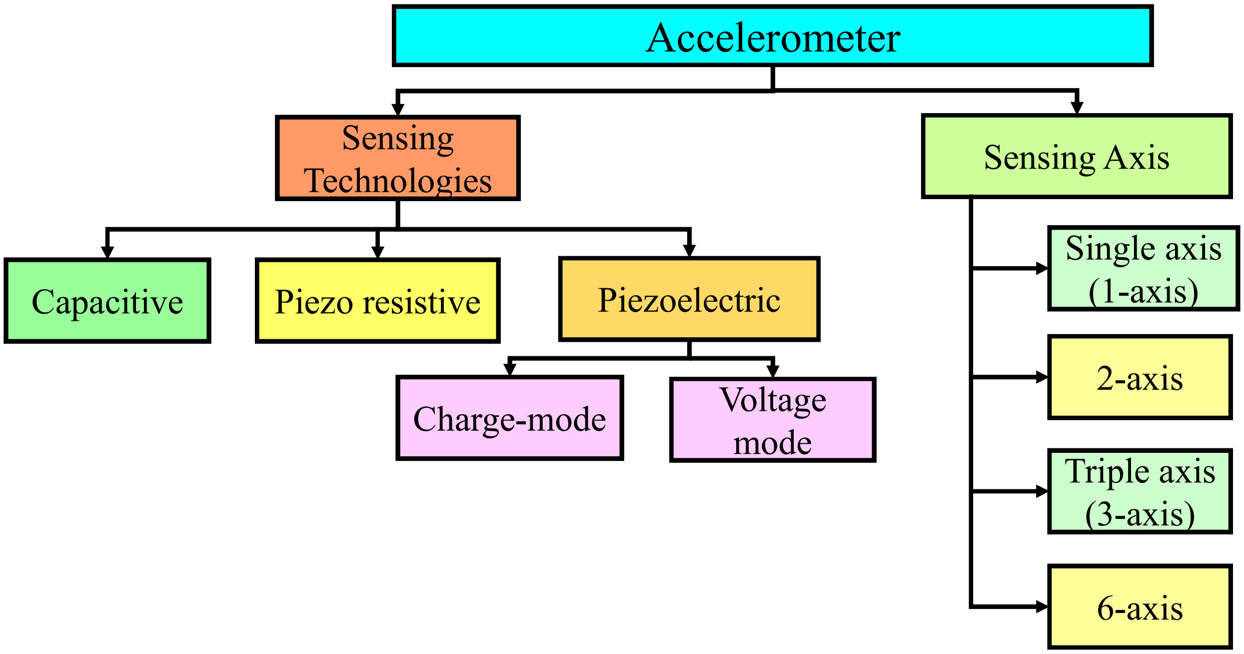



Figure 4.5: Classification of accelerometers.

Electronic Piezoelectric (IEPE) accelerometers are widely used in mobile devices due to their light weight and easy integration.

Based on the sensing axis, accelerometers are designed to sense up to 6 axes. Single axis accelerometers are used to sense acceleration with respect to a single axis. They are widely used in automotive applications which require very high G-force values. Two-axis accelerometers produce medium G-force values and are used to detect acceleration with respect to 2 axes. They are used in both automotive and industrial applications which require positioning, shock detection etc. 3-axis accelerometers produce low-g range values and are used in a wide range of applications due to their accuracy. With an ability to detect changes in motion along 3 axes, these accelerometers are used in applications such as medical, home appliances, navigation devices, and augmented reality. Recently, 6-axis accelerometers are gaining very high popularity due to their high-resolution and low-power design. The 6-axis designs are usually made up of a combination of a 3-axis accelerometer along with a 3-axis gyroscope or 3-axis compass, which provides better stability.

### 4.3.2. Feature Extraction for Data Analysis

The widely used accelerometer for healthcare applications based on hand held devices is a 3-axis piezoelectric accelerometer. This indicates changes in twisting or turning ($x$-axis), leaning ($y$-axis) and movement against gravity ($z$-axis). In order to study the variation of these axis values with respect to the orientation, the tilting angle of an individual axis needs to be calculated. For better understanding, it is important to analyze these axis values through meaningful parameters, known as features. The significant features of accelerometer values are: skewness, which is used to measure if the data are symmetric; kurtosis, which is the measure of peakedness and flatness in the signal; signal energy, which is measured as the area between the signal curve and time axis; maxima and minima of the signal in the given frame; zero crossing of the given data along the time series; and mean and standard deviation of the sensor values [17]. By studying the sensor values as these features, a pattern in variation of human activity is analyzed. using which the human activity monitoring algorithm can be designed.

### 4.3.3. Human Activity Monitoring Algorithm

In order to monitor human activity, at first the difference between the idle state and moving state needs to be detected. This is done with the help of human step detection. After differentiating the idle and moving state, the length of the steps taken is calculated to identify the features unique to different individuals. Hence, the human activity monitoring algorithm was designed by considering human step detection and step length estimation. Figure 4.6 shows the basic steps involved in detecting human steps. Human step detection or activity detection cannot be obtained by mere change of direction obtained through accelerometer values. The number of steps taken are used for calculating the difference between the walking and standing phases. To avoid interference of noise and actually capture the steps, a robust algorithm to analyze the zero crossing events needs to be considered, as the energy and velocity of each step varies amongst individuals. The noise of the accelerometer value is removed by converting the sensor values to scalar values, which is done by squaring the axis values and summing them together. Based on these scalar values, the threshold for steps is decided by taking the average value of the crossing events and accordingly the number of steps are computed.

The length of each step taken is unique to each person and varies depending upon the energy and walking capability of the person. The human step length estimation is done by calculating the approximate distance from heel to heel. This is measured from the initial point of contact of one heel to the next heel. Human step length estimation varies linearly in accordance to the walking frequency and accelerometer variance as follows:

$$StepLength = \alpha . f + \beta . v + \gamma, \tag{4}$$

where $f$ denotes walking frequency, $v$ denotes the variance of the accelerometer and $\alpha, \beta$ and $\gamma$ are pre-learned parameters which influence step length. Analyzing the right parameters for $\alpha, \beta$ and $\gamma$, influences the accuracy of the algorithm.

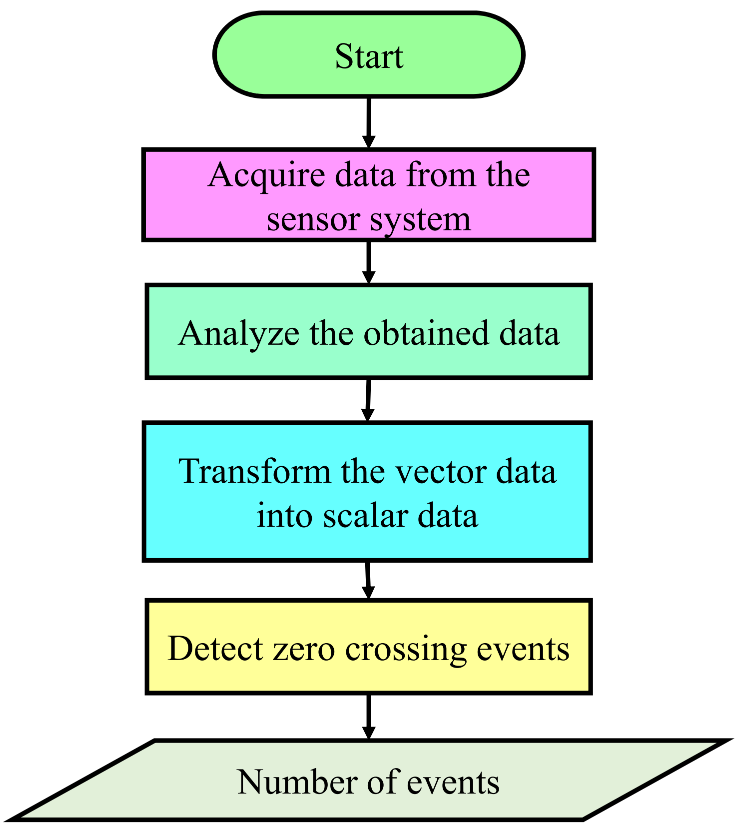



Figure 4.6: Algorithm for human step detection.

### 4.4. Implementation and Validation of SmartWalk system

The proposed SmartWalk system aims in creating a feature based human activity monitoring algorithm which can help in monitoring the physical health of family and friends [66]. The proposed system is validated by building a learning model based on the features extracted from a hand held device such as a smart phone, and a user interface was created to display this data to authorized users.

#### 4.4.1. Human Activity Learning Model

Any learning model can be evaluated based on its efficiency to learn from the training data and implement the mechanism on the test data. To evaluate the efficiency of the proposed human activity detection method, a public database consisting of human activity data detected from a smartphone were considered from Kaggle. This public database of 10291 instances were grouped into six categories such as walking, sitting, walking upstairs, standing, walking downstairs and laying. Figure 4.7 shows the distribution of the total amount of data obtained from the smartphone based sensor grouped into 6 activities. The learning model can be proved efficient only with the right choice of learning parameters. One standard parameter cannot be considered as a feature in developing all the learning models, as the purpose of the feature varies. For example, the purpose of computing minima and maxima from the accelerometer values is to characterize different movements whereas zero crossings are computed to differentiate between walking and running. To analyze a common feature for identifying and classifying 6 activities in the dataset, kurtosis, minima and maxima were considered.

The human activity database from the smartphone was divided into train and test datasets. This was converted into an ASCII text file called, Attribute-Relation File Format (ARFF), which contains the list of instances and its corresponding attributes. ARFF files contain header and data sections. ARFF files help in defining the relation between the dataset with respect to the attributes. This ARFF file is given as input to the machine learning design suite called WEKA [22], [18]. This contains tools to preprocess the data and visualize the classifier's performance, thus helping in faster prototype development.

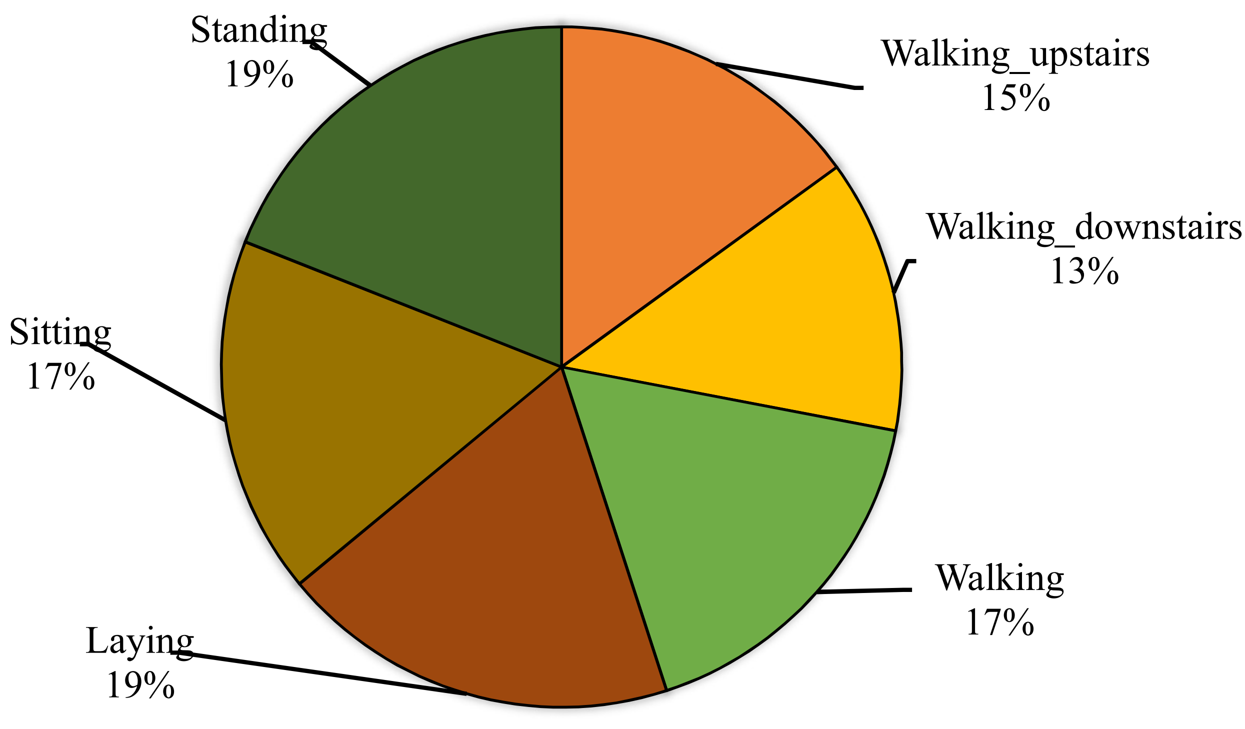



Figure 4.7: Total number of input instances grouped under 6 activities.

Figure 4.8 shows the analysis of kurtosis values in WEKA. The top 3 sub columns represent the $x$ axis, $y$ axis and $z$ axis, respectively. The 3 subcolumns in the second row indicate the data grouped based on activity, score and kurtosis values. Unlike sitting, standing and laying, the kurtosis values are higher for walking upstairs and downstairs, as the peakedness of the signal is high. For the same reason, the classification of kurtosis values for sitting, standing and laying are not high, since there are fewer distinctive peaks in that case. From this analysis, it can be observed that kurtosis is ideal for detecting walking related activities such as walking upstairs or walking downstairs. After evaluating kurtosis as a feature, different classifiers were used to build a better activity learning model. The performance of different classifiers along with their error values and correlation coefficients are tabulated in Table 4.1. Regression based models help in modeling the relationship between a scalar variable and an explanatory variable. A multilayer perceptron maps input data to the corresponding output data. An M5 rules based classifier implements a divide

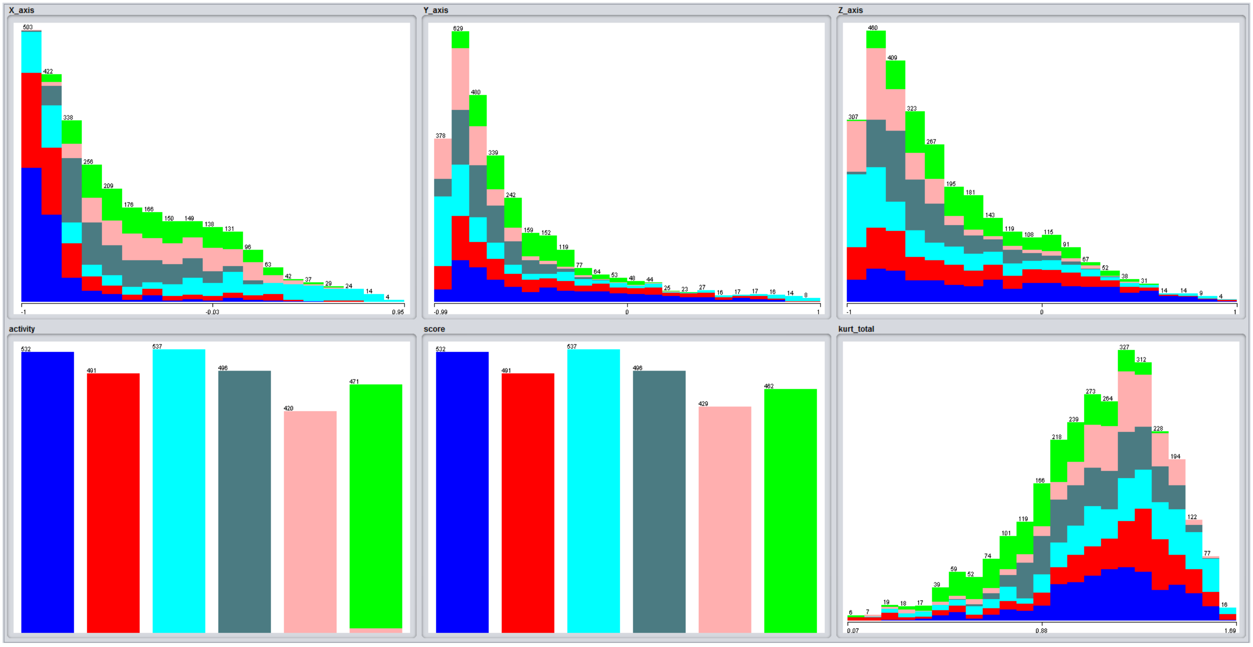



Figure 4.8: Kurtosis analysis in WEKA.

and conquer approach. It can be observed that in developing a learning model based on kurtosis, M5 rules, multilayer perceptron and decision table based classifiers had relatively better correlation coefficient, in comparison to the other classifiers which had a very high error rate. Figure 4.9 shows the performance of the classifier with respect to kurtosis as a feature.

In evaluating the performance of a classifier for a learning model based on minima and maxima, the decision table, bayesian network and multiple layer perceptron based classifiers had smaller error percentage than the other classifiers. The performance of different classifiers is shown in Table 4.2.

4.4.2. Experimental Validation

Based on the feature analysis for human activity monitoring, it can be observed that for the kurtosis and maxima and minima as features, a learning model built using decision tables and a multilayer perceptron would perform better. Since the data used for evaluating the classifiers were from a hand held smart phone, a similar setup was used to validate this observation. For validating the classifiers' performance, the test data were obtained from

Table 4.1. Classifier evaluation for kurtosis values using WEKA.

| Classifiers | Correlation Coefficient | Mean absolute error | Root mean squared error | Relative absolute error | Root relative squared error |
|---|---|---|---|---|---|
| SMO Regression | 0.7795 | 0.1029 | 0.1956 | 44.8049 % | 67.68 % |
| Gaussian Process | 0.7979 | 0.1146 | 0.1742 | 49.90% | 60.28 % |
| M5 Rules | 0.9741 | 0.0409 | 0.0657 | 17.82 % | 22.72 % |
| Decision Table | 0.9263 | 0.0619 | 0.11 | 26.94 % | 38.07 % |
| Linear Regression | 0.7979 | 0.1142 | 0.1741 | 49.71 % | 60.27 % |
| Multilayer Perceptron | 0.9645 | 0.0597 | 0.0868 | 26.00 % | 30.03 % |
| Additive Regression | 0.9273 | 0.0856 | 0.111 | 37.26 % | 38.41 % |

Table 4.2. Classifier evaluation for minimum and maximum accelerometer values using WEKA.

| Classifiers | Mean absolute error | RMS error |
|---|---|---|
| Input Mapped Classifier | 0.0014 | 0.0018 |
| SMO | 0.222 | 0.3089 |
| Decision Stump | 0.2234 | 0.3342 |
| Simple Logistic | 0.0437 | 0.0587 |
| Decision Table | 0.0015 | 0.0002 |
| Bayes Net | 0.0009 | 0.3309 |
| Multilayer Perceptron | 0.0012 | 0.0016 |

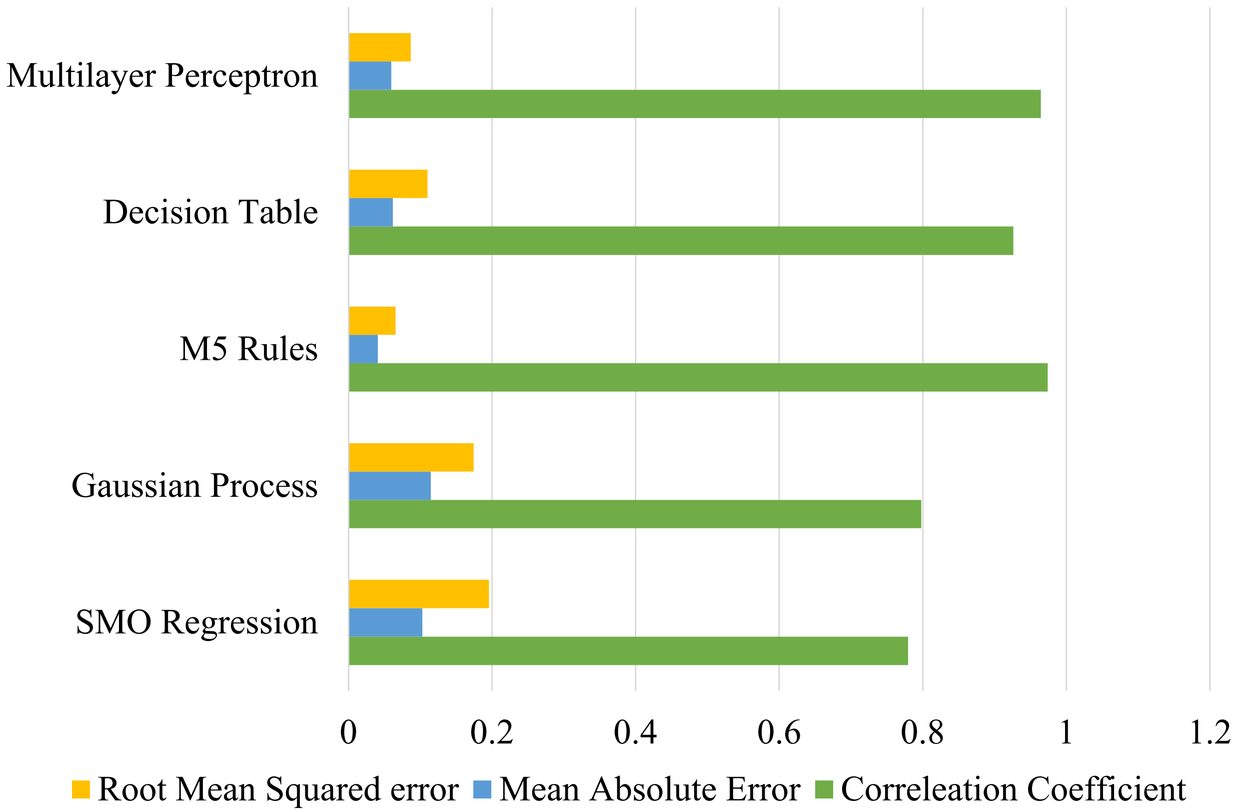



Figure 4.9: Human activity monitoring classifier evaluation using kurtosis as a feature.

hand held accelerometer mounted on a commercially available sensor board, the Educational Boosterpack MKII. This sensor board was integrated with the 32 bit microcontroller TI MSP432. Figure 4.10 shows the data acquisition module used to obtain the test data. The 3 axis analog accelerometer on the Boosterpack can be accessed through the pins J3.23, J3.24, J3.25 for the $x$, $y$, and $z$ axes, respectively. With the help of this experimental setup, walking, standing and sitting data were obtained from 3 different subjects.

To differentiate the walking activity from standing and sitting values, kurtosis was observed as a feature. Figure 4.11 shows the kurtosis values of the obtained test data from the hand held device. Since standing and sitting only varies the data along a single axis, the kurtosis varies significantly for walking, in comparison to sitting and standing. To classify between the sitting and standing postures, the maxima and minima of the $z$-axis are taken

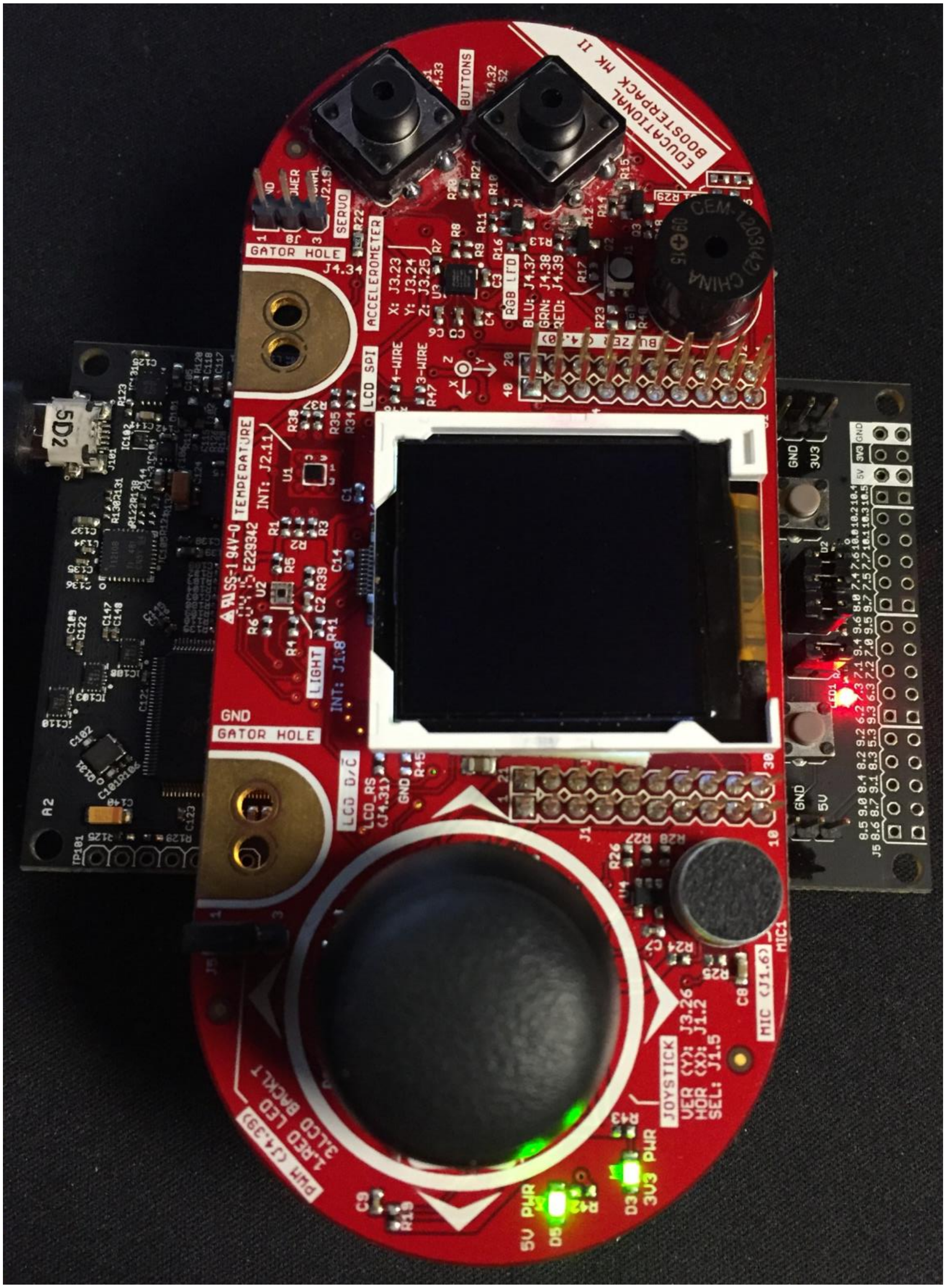


Figure 4.10: TI MSP432 integrated with the sensor board, Educational BoosterPack MKII.

into account. It can also be observed that the features vary significantly among different individuals. This is because some may take a longer step, contributing to the peak in kurtosis, whereas some may take smaller steps.

The performance of the proposed feature based human activity monitoring algorithm is

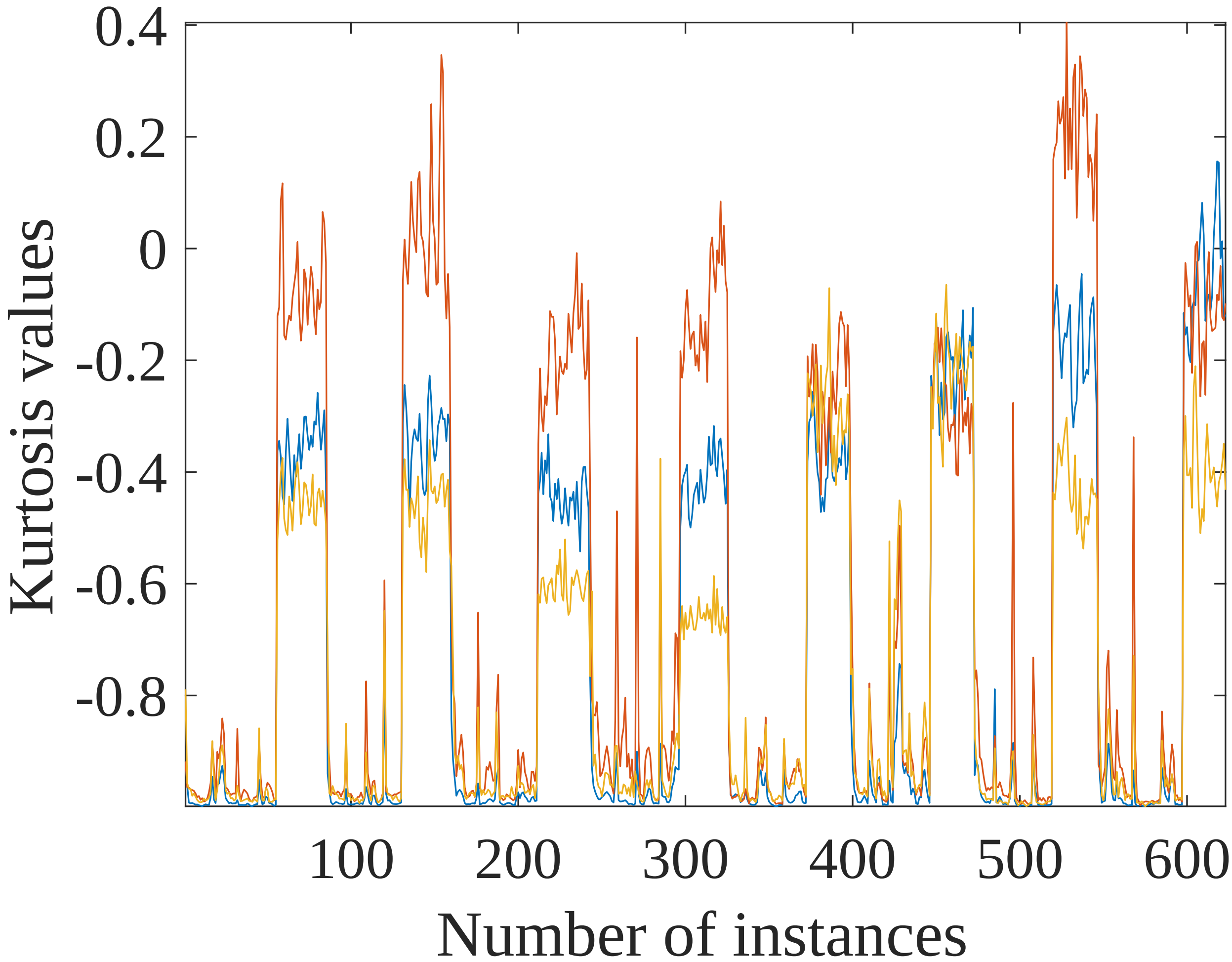



Figure 4.11: Kurtosis values in different postures such as sitting, standing and walking obtained from 3 different subjects.

compared with the results of the dynamic algorithm proposed in [13], and the awareness algorithm proposed in [58]. Table 4.3 shows this performance comparison. It can be observed that, the worst case accuracy of the proposed feature-based algorithm provides 97.9 % efficiency in computing the step length.

Table 4.4 shows the characterization of the proposed SmartWalk system based on the

Table 4.3. Performance comparison with existing results.

| Research Works | Method | Features considered | Activities | Accuracy (%) |
| --- | --- | --- | --- | --- |
| Shin et al [58] | Awareness algorithm of movement status | Step length and total walking distance | Walk and run | 96 |
| Chien et al [13] | Dynamic algorithm | Number of steps taken | Walking, jumping and jogging | 95 |
| This Work | Feature based human activity monitoring algorithm | Step detection and step length estimation | Walking, sitting, standing | 97.9 % |

feature based human activity monitoring algorithm. The SmartWalk system was validated with the help of the TI MSP432 launchpad integrated with the sensor board, Educational Booster Pack MKII. The launchpad was programmed with the help of the open source tool, Energia and MATLAB®, and the data analysis was done with the help of classifiers built using WEKA. It was observed that for the classifier based on the decision table, the worst-case accuracy was 97.9 % . The output of the obtained data was displayed using the user interface as shown in Figure 4.12.

Table 4.4. Characterization of SmartWalk system.

| Characteristics | Specifics |
|---|---|
| Sensor system | TIMSP432 launchpad integrated with Educational Booster Pack MKII |
| Operating Frequency | 48 MHz |
| Sensor data acquisition tool | Energia and MATLAB |
| Data Analysis Tool | WEKA |
| Sample Dataset | 10291 instances for analysis and 623 instances for validation |
| Classifier | Decision Table |
| Accuracy (Worst case) | 97.9 % |

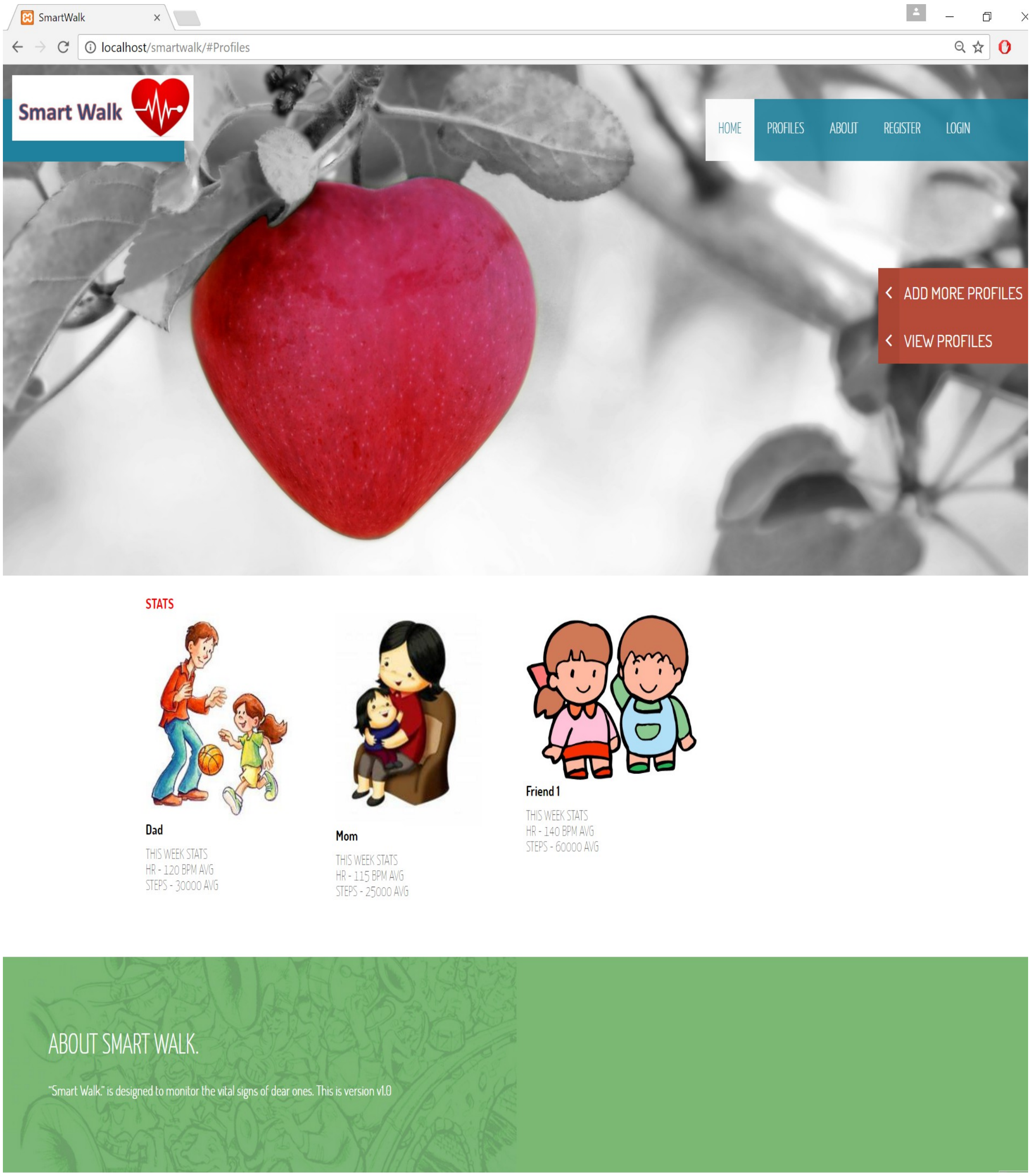



Figure 4.12: User interface to display the human step values.

# CHAPTER 5

# ENERGY EFFICIENT ARCHITECTURES USING HUMAN BODY COMMUNICATION

This chapter presents an architecture for an ambulatory health monitoring system using a body coupled communication channel [67].

## 5.1. Human Body Communication in the IoT: A Broad Perspective

### 5.1.1. Background

Wireless Sensor Networks (WSNs) are made up of groups of sensors that are dedicated to sense, record and monitor a physical condition. The main advantages of WSNs are the ability they provide in collecting and organizing data at a centralized location. A body area network, also known as BAN, is formed by a group of small sensors placed around or inside the body. For sensors to be connected in a wireless sensor network or a wireless body area network, a connectivity technology such as Bluetooth, Wi-Fi, RF etc. is required. In a wireless network of sensors, the maximum power dissipation is due to the wireless component which deploys protocols for linking the sensors, transporting data across and creating an IP for each of these networks. Figure 5.1 shows the different layers of the network and their corresponding protocols.

In smaller intelligent devices such as wearables, communication methods such as optical communication, radio wave communication, sound or electric medium of communication, magnetic field of communication and body coupling have been used [20]. Unlike sound and radio wave communication, optical communication has a limitation with non line-of-sight communication. Non line-of-sight communication is used in places where the transmitter and the receiver are not placed in a straight path. Sound wave and magnetic wave communication based modules cannot be minimized to smaller form factors. Body coupling communication, which considers the human body as a communication channel, supports non line-of sight, multiple link and low-power communication in body area networks.

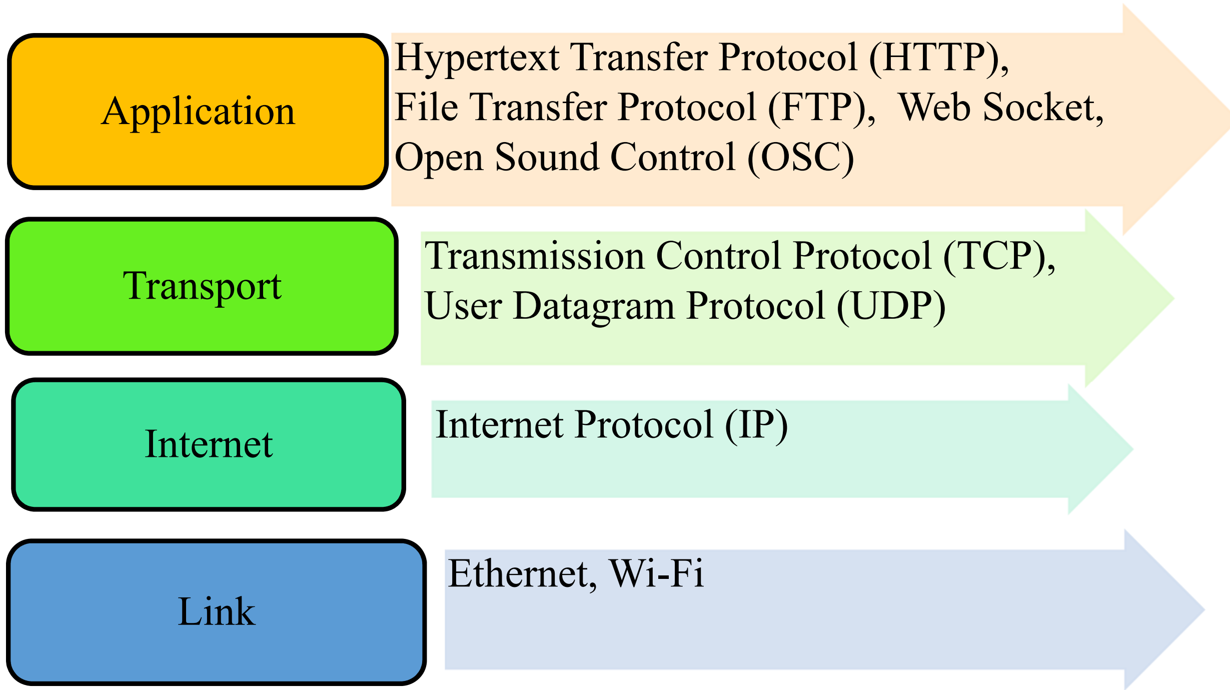



Figure 5.1: Different layers of the network and their corresponding protocols.

The human skin consists of 3 layers, namely the epidermis, the outermost layer; the dermis, the layer of skin beneath the epidermis; and the hypodermis, which is made up of fat and connective tissue. Figure 5.2 shows the anatomy of the human skin. The sensors or wearables for the body area network are placed on the epidermis layer which has a conductive tissue under it. By passing electric current at appropriate frequencies, the human body acts as a conducting medium. Though there is a limitation in the amount of current that be passed through the human body, this method of communication is being widely supported due to their simplicity of the design. This simple and effective method of communication with the human body acting as the communication channel is called human body communications (HBC). This can be achieved by creating a potential difference across two points in the body, where the electrode does not have to be present exactly over the sensors, i.e. the human body acts as a capacitor in between these electrodes. This helps in deploying a master-slave architecture with more passive components and fewer active components. This helps in reducing the overall power budget of the body area network. HBC based architectures have

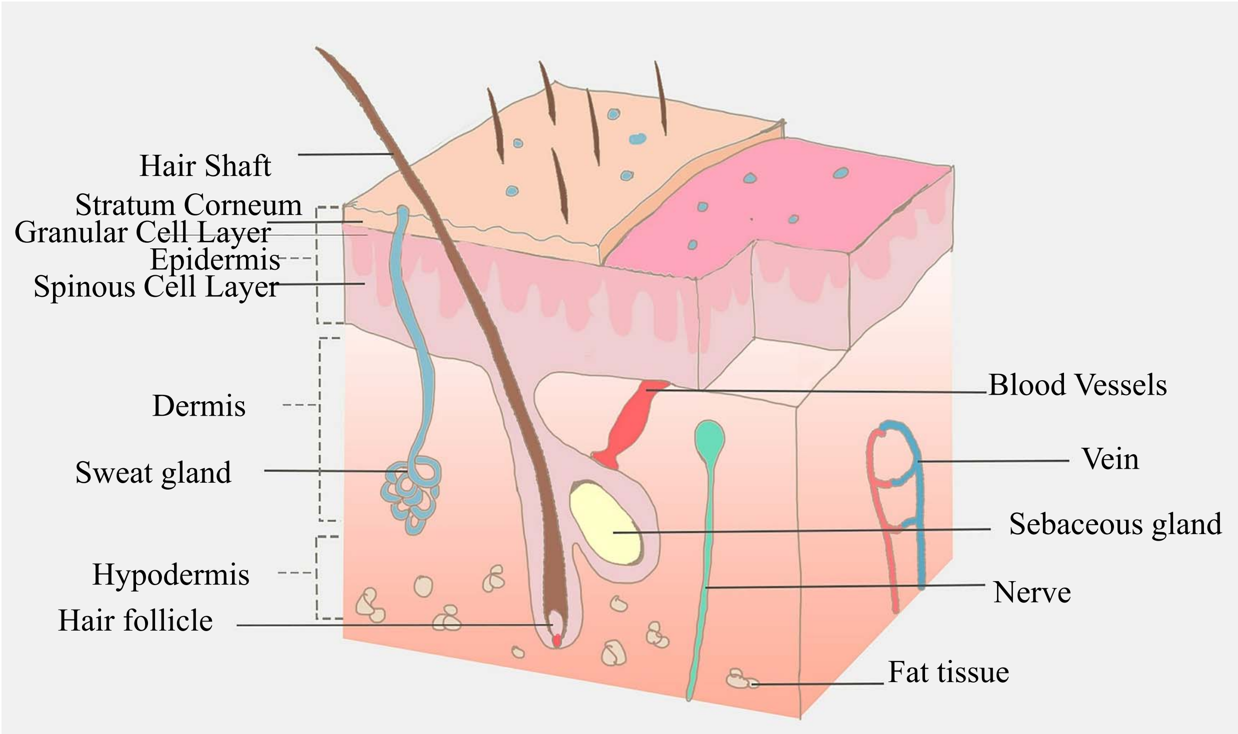



Figure 5.2: Anatomy of the human skin (Image Courtesy of Creative Commons, pixabay.com).

been used in generating unique security keys, also known as Physical Unclonable Functions (PUFs) [80], [82]. Figure 5.3 shows the different area networks that can be implemented to facilitate the communication. Though a smart healthcare architecture may involve any of the mentioned area networks, the area network related to sensing physiological parameters called Body Area Network or Body Sensing Network (BSN) plays a very important role.

### 5.1.2. Design Considerations

In this research we propose an ambulatory monitoring body area network which uses human body communication. In implementing a simple body area network with the human body as communication channel, the design considerations are the power budget of the overall network, heat dissipation, non line-of-sight communication, amount of electricity that can be passed through the skin to activate the electrodes, frequencies at which the sensors need to operate, performance of the network, and the form factor of each and every component.


Figure 5.3: Different types of area networks.

In Figure 5.4, a transceiver model for human body communication is presented. It can be observed that the human body can be modeled as capacitors in series with spreading resistance, leading to high pass filters.

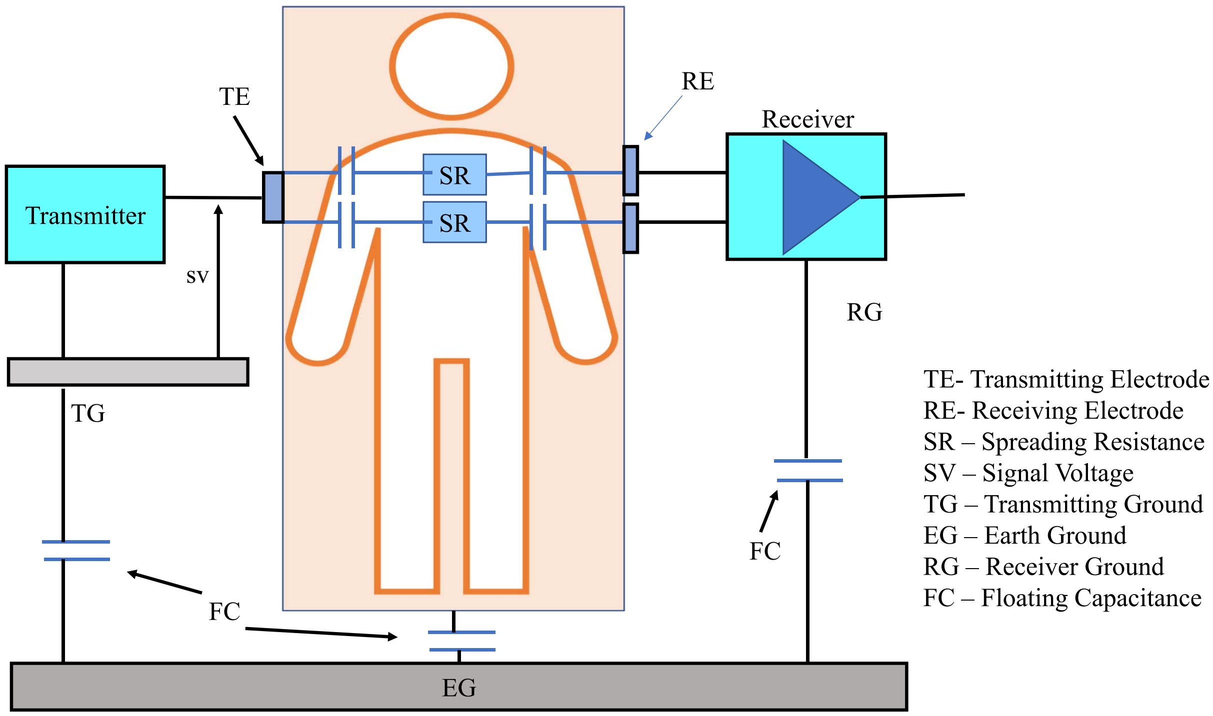



Figure 5.4: Transceiver model for human body communication.

## 5.2. Related Prior Research

The very first idea of a personal area network was discussed in [85]. Modeling the human body channel can be done by using galvanic coupling, which is achieved by applying differential signals in both transmitter and receiver [51], [21]; capacitive coupling, which is achieved by inducing an electric field using the electrode [19]; or electro-optic sensors [60]. Body coupled communication implemented using a potential difference is discussed in [8]. An analysis on the variation of the potential difference across different tissues in body coupled communication has been discussed in [78]. A master-slave intra-body network architecture with the human body as a conductor is proposed in [30]. Body Area Networks that are built using low power radios [69] have been used in smart textiles that contain sensors and wires embedded in them [40]. Body Coupled Communication (BCC) [9] used in BAN helps in avoiding inconvenience through wires [12].

## 5.3. Proposed Ambulatory Monitoring Body Area Network

An ambulatory monitoring system is intended to monitor the physical health of a person. It helps in monitoring the walking capabilities of a person. With respect to the application for which the ambulatory monitoring system is designed, the number of sensors integrated varies. In a monitoring system designed for the elderly, the sensors might range from thermal sensors, blood pressure monitoring, eye movement and fall detection. In a monitoring system designed for an active individual, in addition to using sophisticated sensors for heart rate monitoring, steps taken and so on, the design needs to be of smaller size like a wrist watch. Figure 5.5 shows the proposed ambulatory monitoring system. The proposed system consists of an array of sensors which communicate amongst each other through the human body channel. The proposed BAN is in the form of master-slave architecture, where the array of sensors act as slaves and transmit the sensed values to the base station. The sensing values are transmitted through body coupled communication (BCC) or frequency selective baseband transmission (FSBT). As the input resistance varies, the corner frequency varies accordingly and the gain of the the BCC channel is changed, i.e, if the input resistance increases, the corner frequency decreases and the gain of the BCC channel is increased. In the base station, a multiple in multiple out (MIMO) system is deployed to modulate and encode the input message, which is to be transmitted through the MIMO channel. The output of the MIMO channel is fed into the Encoder block which encodes the input message using an orthogonal space-time block code at varying rates depending upon the number of transmission antennas used. The encoded output is transmitted through the MIMO channel. The 6 fading channel is implemented using either Rayleigh or Rician fading channel.

### 5.3.1. Array of Sensors

The proposed BAN aims in detecting falls along with temperature monitoring. The array of sensors in the proposed ambulatory monitoring BAN consists of a temperature sen-

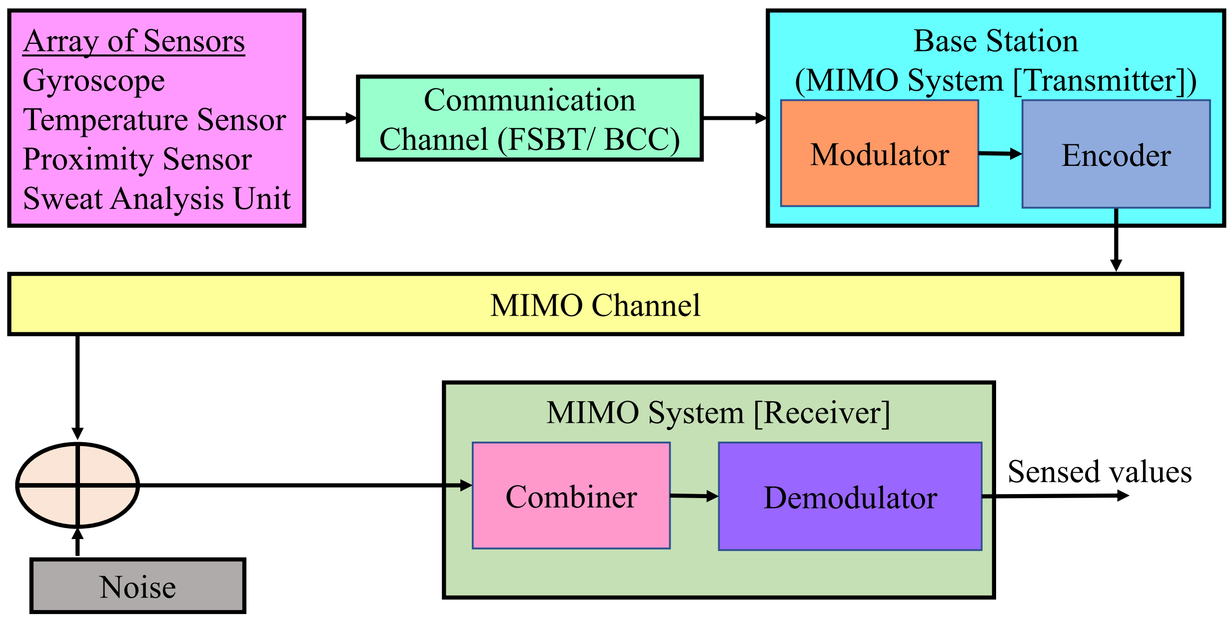



Figure 5.5: Datapath across the ambulatory monitoring body area network.

sor, to monitor the temperature variability; a proximity sensor to identify the position of the sensor and the object; a gyroscope to understand the orientation of the user; and a sweat analysis unit. The temperature sensor is designed using ring oscillators followed by a digital counter. A $2\pi$ phase shift is required to achieve oscillation and unity voltage gain in the ring oscillator frequency. The proximity sensor helps in detecting the presence of nearby elements. Also known as a simple distance sensor, the proximity sensor helps in tracking the distance between the object and the sensor. By using the sensing distance, the proximity sensor detects an object in the given radial offset $R$.

The gyroscope helps in understanding the orientation of the object that uses it. In the proposed BAN, the gyroscope is used to analyze if the patient and sensor are in the desired orientation. A gyroscope consists of a vibrating mass which experiences a small force when displaced from its original path. The gyroscope uses capacitance to sense this displacement and outputs a proportional number of counts. A block level diagram of the gyroscope sensor is shown in Fig. 5.6. In this design, the vibrating mass is designed under MEMS Gyro dynamics and static bias, and outward noise is added along with the output. The scale factor helps in converting the output to proportional number of counts.

The human blood contains eight essential minerals, namely iron, sodium, zinc, calcium, potassium, selenium, sodium and magnesium. In addition to these minerals, the level of glucose and sodium in the blood should be at optimal levels to maintain healthy life. By analyzing the sweat of a person, the mineral composition of the blood can be analyzed. The acid and alkaline levels in sweat can be measured using pH sensitive sensors, which measure the potential difference between the reference and test electrodes. This can be achieved using an operational amplifier which evaluates the difference between the inverting and non-inverting inputs.

5.3.2. Communication Channel

Human Body Communication can be considered as a method of transmitting and receiving data through the body. To facilitate data transfer, continuous modulation schemes are used in HBC. Though continuous modulation helps in transferring data, it does not support the touch and play mechanism. Low power radios and BCC have almost the same efficiency and give more flexibility for the user. The data rate of BAN varies from 10 Kbps to 10 Mbps. A low power BAN based on HBC can be met only when no RF/IF components are used in the specified frequency band. This can be achieved by using frequency selective channel, where the frequency selectivity is a relationship of input and output described as a convolution between input and impulse response. Walsh codes help in implementing Frequency Selective Baseband transmission (FSBT). A Walsh (Hadamard) code consists of an $M_n$ matrix where $n$ is an even integer. It has all 1s and 0s such that all rows differ from each other by exactly $1/2n$ positions. In Figure 5.7 the transmitter and receiver of FSBT is demonstrated. The 64 Walsh code matrix is divided into 4 subgroups by using the corresponding index. In the transmitter, the input is given to the serial to parallel block which divides the input into 4 subgroups. These 4 signals are given as input for the FSBT Modulator, where the input is spread using a 64 Walsh code in the frequency spreader. Since the human body has high attenuation, the input to the receiver is considered with additive

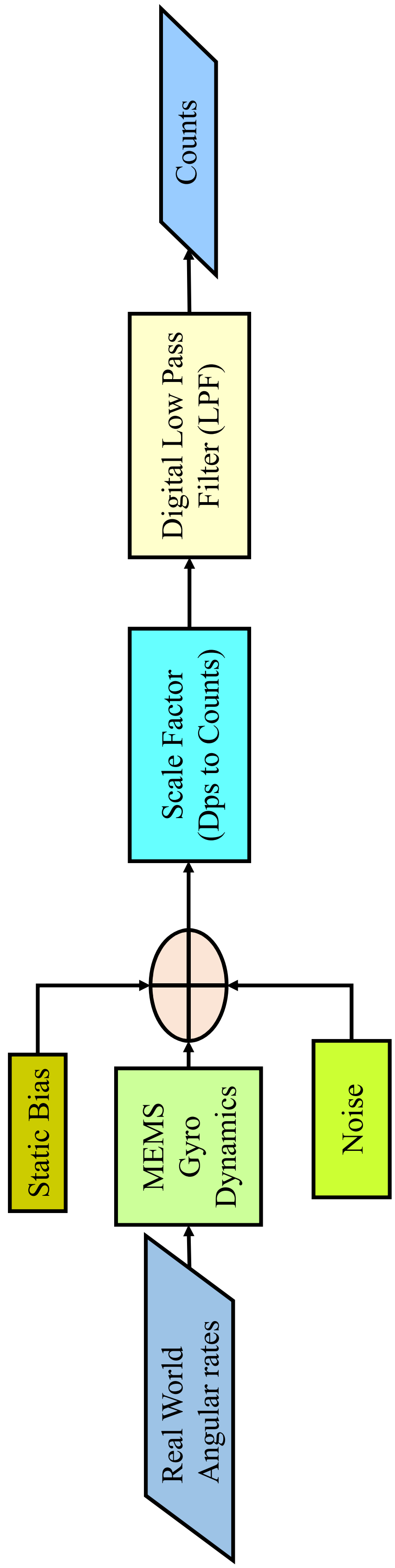



Figure 5.6: Block diagram of a simple MEMS based gyroscope.

noise and intrinsic channel with attenuated symbol. The demodulation is done by adopting the maximum likelihood detection method.

Body Coupled communication can be designed by considering the human body as a single circuit, an electrostatic component or as a waveguide to pass the electromagnetic waves. In considering the human body as a circuit, a reference wire is used along the length of the wire. Body communication achieved through electrostatic coupling can be done by relying on the earth as ground. In this case, the human body is considered as a biological conductor between the transmitter and receiver end. In modeling such a biological conductor, a capacitor is said to exist between the body and the ground. This can be achieved by placing one electrode on the skin and leaving the other electrode floating, such that a forward path is created between the attached electrode and a return path is created from the ground to the floating electrode [36]. Figure 5.4 shows the different body communication methods. Another method of body coupling is considering the human body as a waveguide for passing electromagnetic waves. This method, also known as galvanic coupling [77] considers almost zero dependence with respect to the external environment. In order to make the human body a waveguide, two transducers are used at both the transmission and receiving end. The galvanic coupling method is considered in intra body communication through wearables and implantable devices, due to its robustness. But it has the drawback of working efficient only in smaller distances and limits the transmission rate as it is directly in contact with the skin and passing high signals at the transmission end can be harmful for the user. In an experimental setup, a simple body communication channel can be implemented as a pair of high pass filters in the case of capacitive coupling and in galvanic coupling method as a channel which would only exhibit one high pass filter.

## 5.4. Implementation and Validation of Ambulatory Monitoring Body Area Network

The simulation level modeling of the proposed ambulatory monitoring BAN based on human body communication was done using Simulink® [67]. Fig. 5.8 shows the implementation of the gyroscope in Simulink®. Since the real time data would have some bias and noise added to it, a constant bias value is added to the output of the sensing module. The

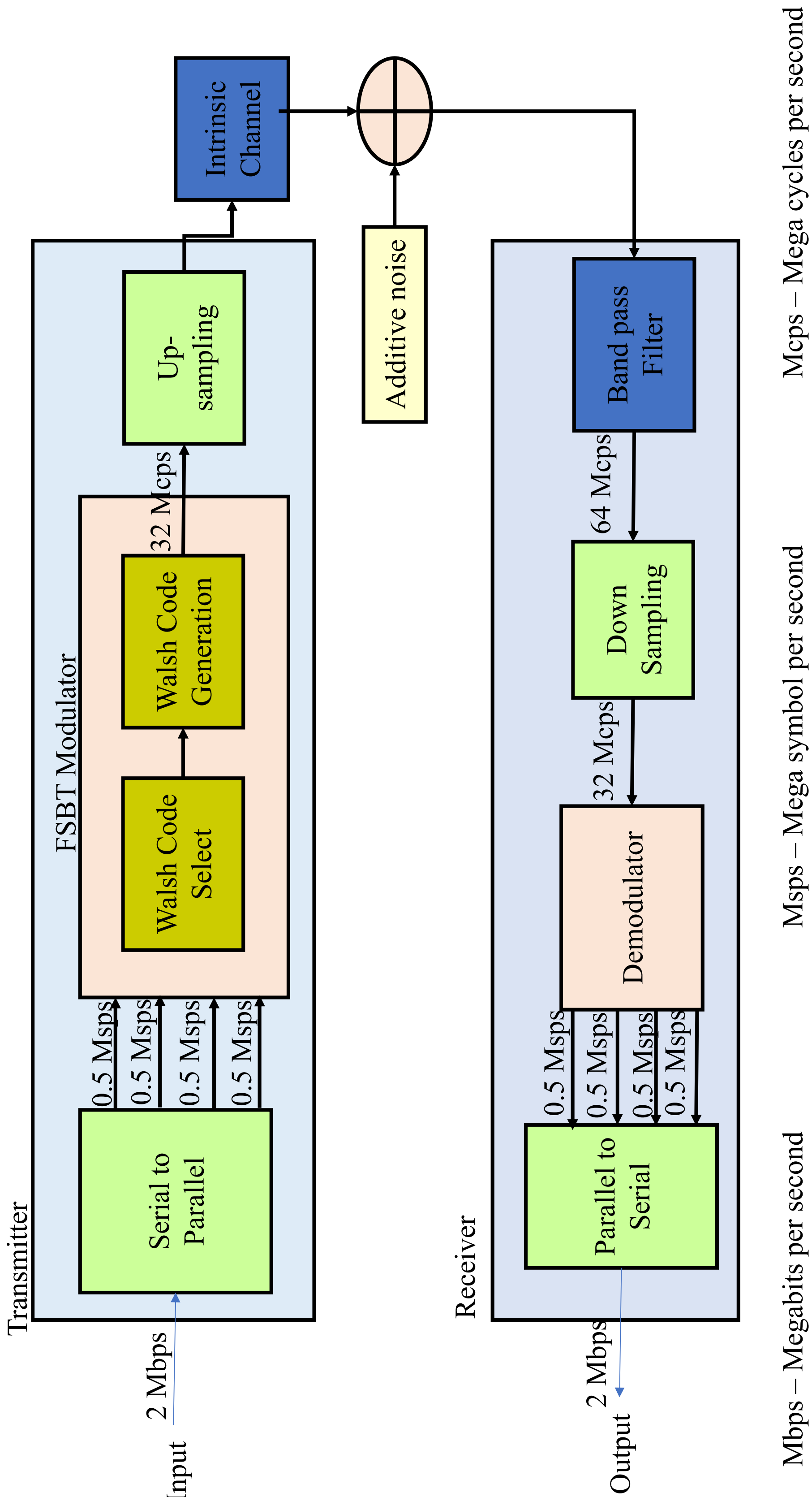



Figure 5.7: HBC block diagram with FSBT modulator.

computed gain is then sent along the low pass filter, which helps in obtaining the required gyroscope values. Similarly, the other sensors involved in the ambulatory monitoring BAN, namely the temperature sensor, the sweat analysis unit and the proximity sensor were modeled using Simulink® and the output of these sensors was considered for transmission across the BAN.

Fig. 5.9 shows the system level modeling of the human body as an electrostatic component, i.e. via capacitive coupling. This model of the human body as a spreading resistance has the advantage of setting the corner frequency of the high-pass filter and the passband level. The input resistance is directly proportional to the level of passband and gain of the body channel such that as the input resistance increases, the corner frequency decreases which in turn increases the gain of the body channel.

Some amount of white noise added along the sensor values for better readability such that even minor changes in the sensor values can be captured. Figure 5.10 shows the output of the gyroscope sensor module along with white noise. The added noise is filtered and removed at the receiving end. The band pass filter helps in such filtering of unwanted signals, as it passes through only signals within a fixed frequency range. The output of the band pass filter used along the HBC implementation can be observed in figure 5.11.

Body Coupled Communication has the advantage of non-line of sight path which indicates that the electrodes need not to be placed in the same point of contact. To model this at the system level, a continuous probability distribution called Rayleigh distribution was considered. In the case of FSBT, where a line-of-sight communication path is required, a Rician distribution, which is a probability distribution with potentially non-zero mean is considered. In the FSBT modulator, the encoded signal is given as input to the combiner along with white noise. The output of the combiner is again fed into the demodulator which demodulates the signal at the output. A 64 Walsh code which can be used for human body communication is shown in Fig. 5.12.

The frequency spectrum was analyzed with the help of the spectrum analyzer block in Simulink®. The performance of HBC in FSBT implementation is evaluated based on

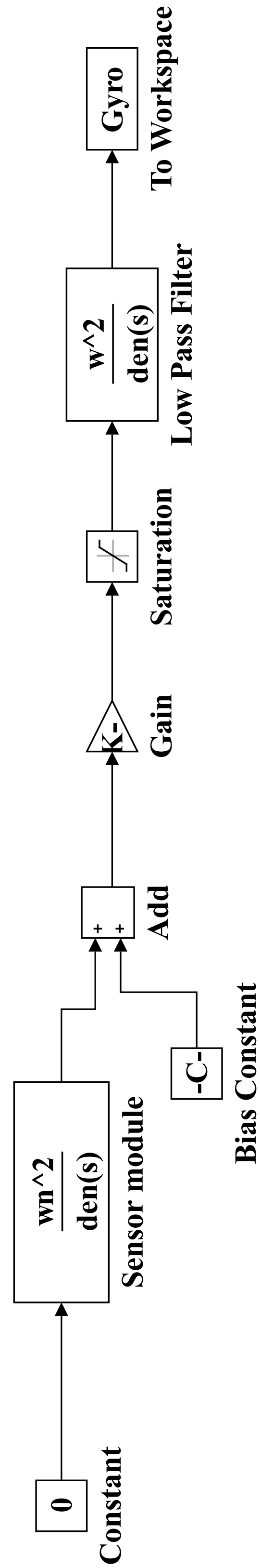



Figure 5.8: Gyroscope block diagram in Simulink®.

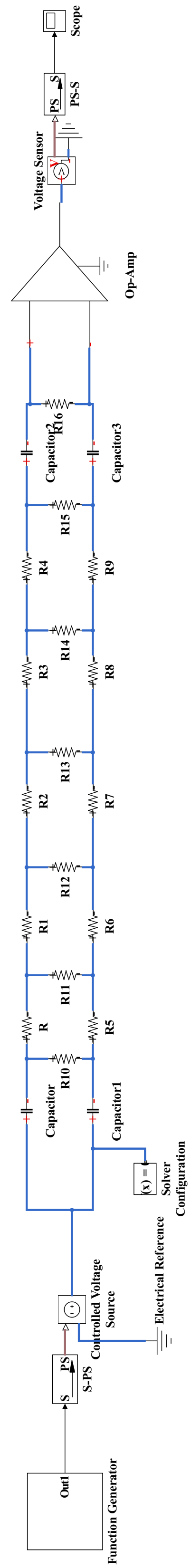



Figure 5.9: Body modeled as a spreading resistance. The transmitter and receiver are capacitively coupled to the body.

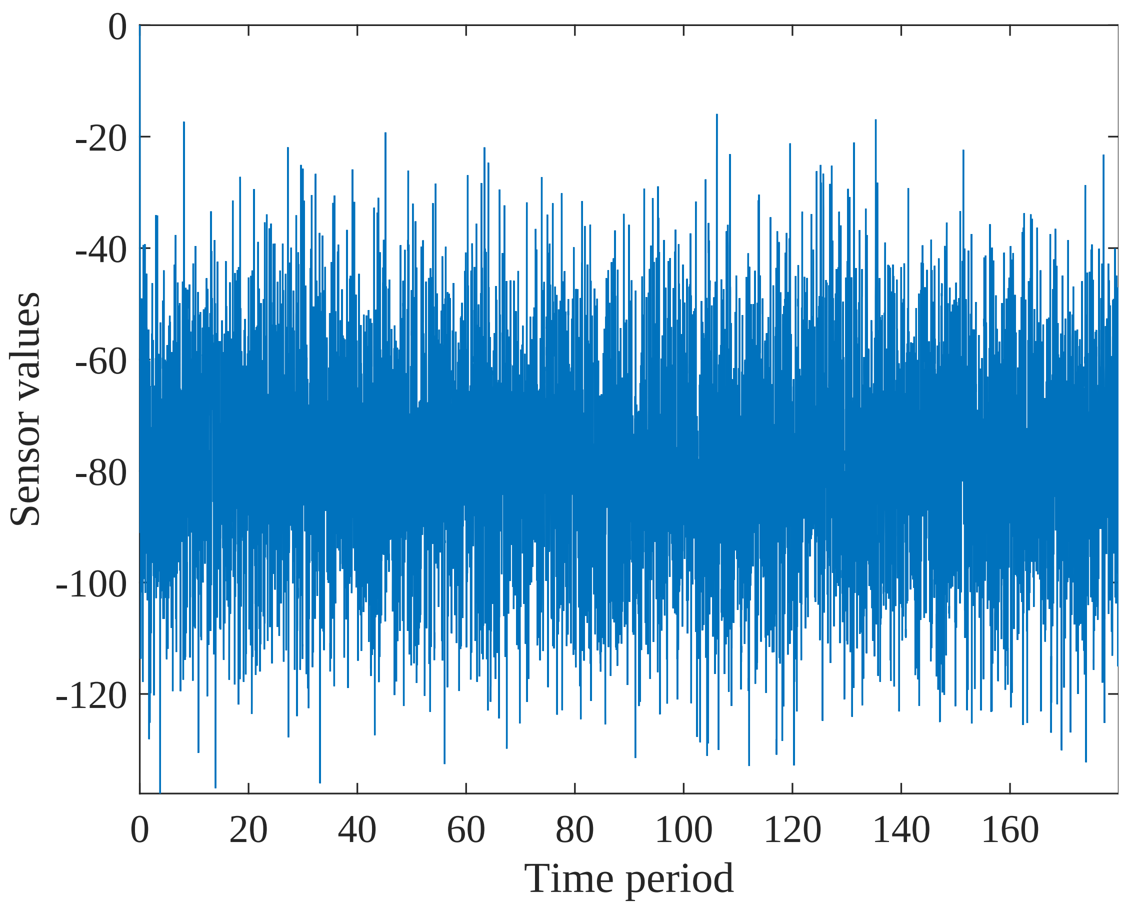



Figure 5.10: Output of gyroscope sensor module with white noise.

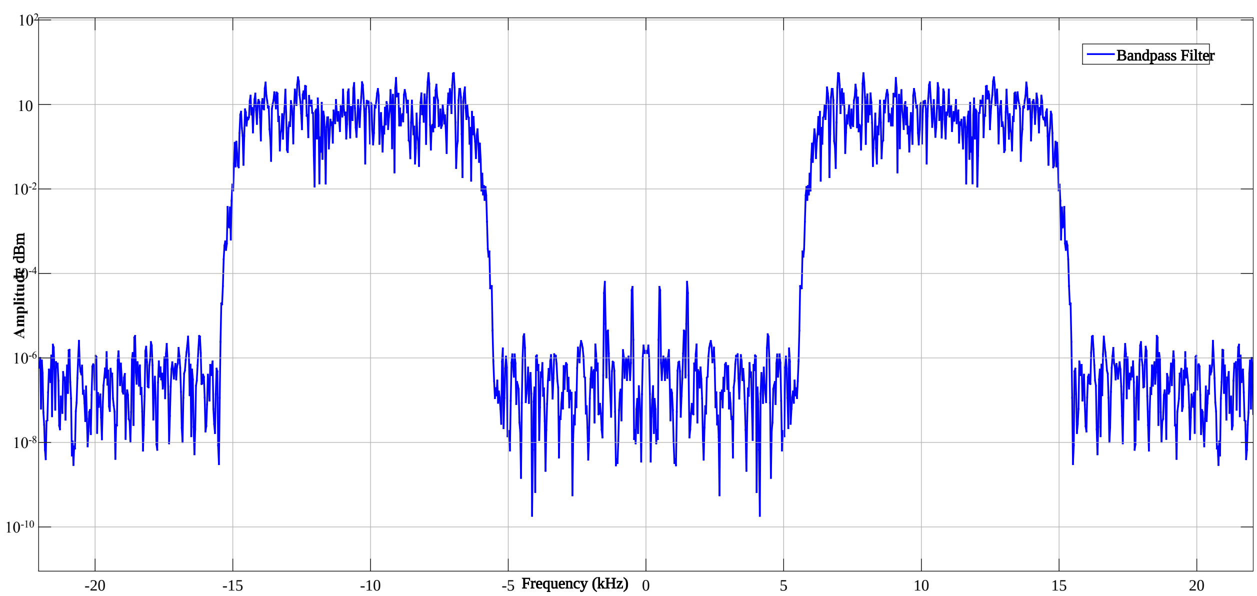



Figure 5.11: Frequency spectrum after BPF in HBC implementation.

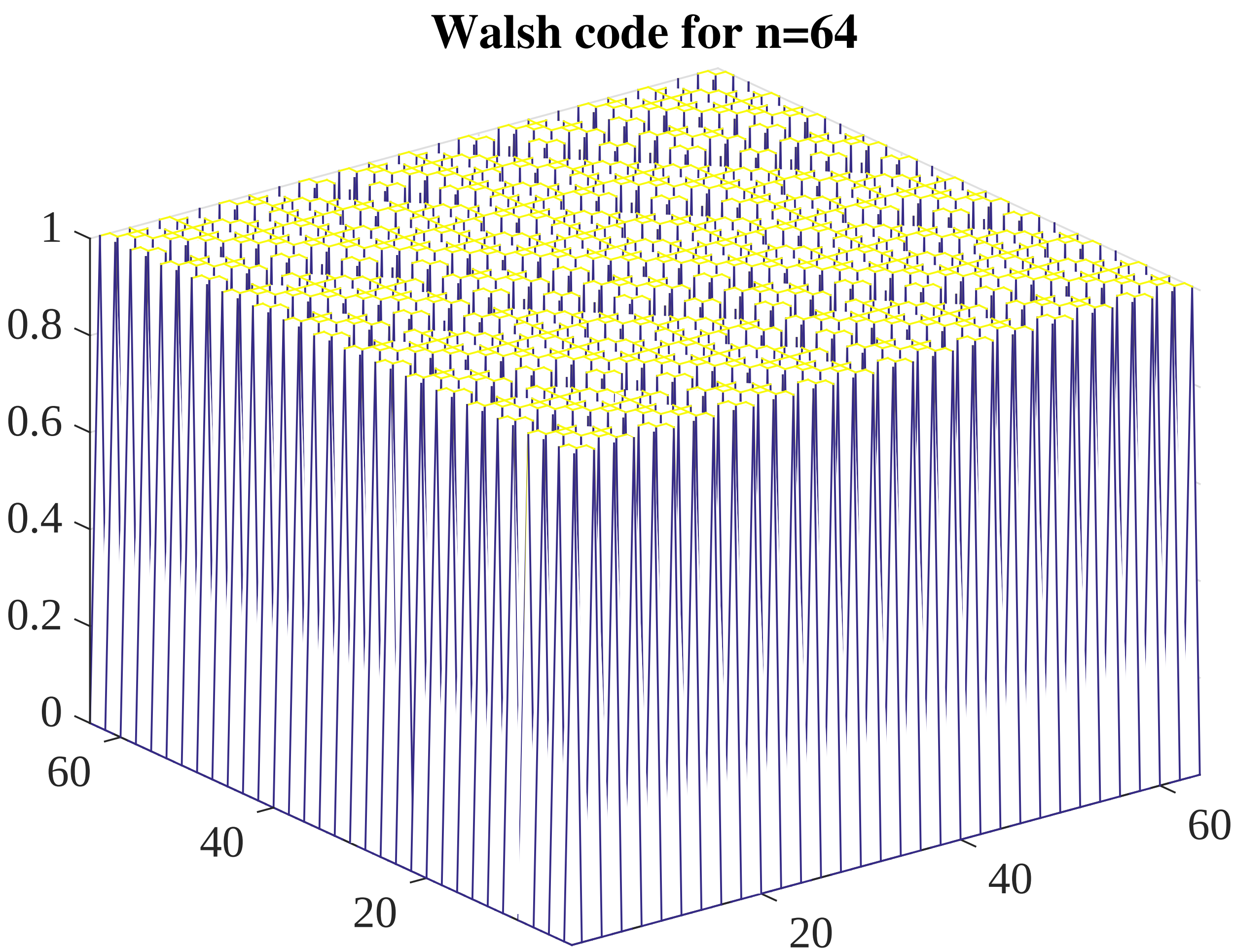



Figure 5.12: A mesh of Walsh code for $n$=64, i.e. $M_{64\times64}$ of all 1s and 0s.

Average Signal to Noise Ratio and Bit Error Rate. A surface plot of the performance analysis is shown in Fig. 5.13.

When body coupled communication was implemented using resistance and capacitance, the channel gain was estimated based on the transmitter frequency. Fig. 5.14 shows the BCC channel gain for capacitively coupled human arm model for input resistance $50\,\Omega$ and $250\,\Omega$. The frequency was varied from 10 MHz to 100 MHz. It can be observed that as the input resistance was increased, the gain increased but the slope gradually decreased, thus indicating variation in corner frequency. Table 5.1 lists the methods used in implementing the ambulatory monitoring body area network. It can be observed that power consumption was 3.14 mW which implies a 31 % power reduction compared to the related research work

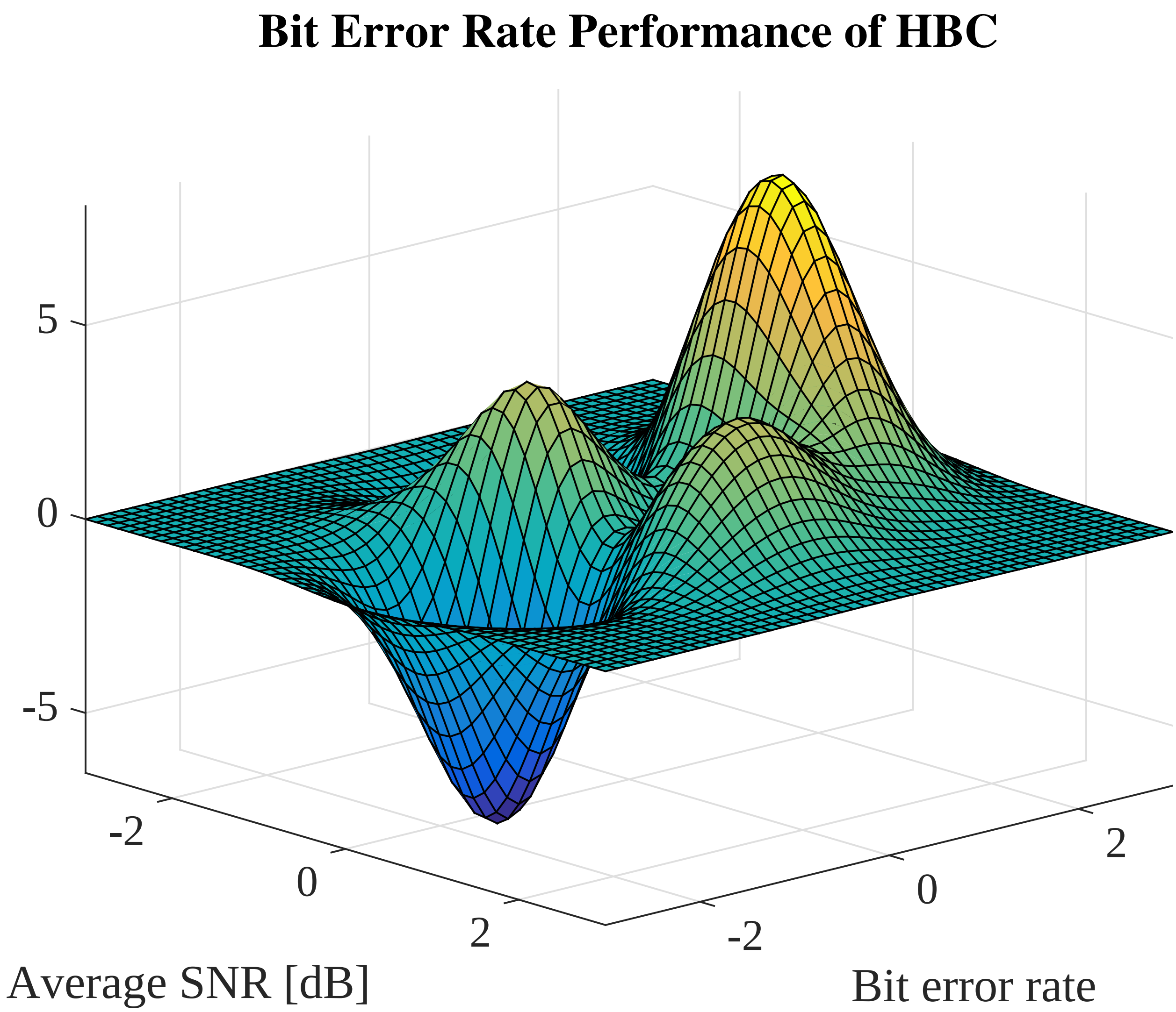



Figure 5.13: Performance of HBC with FSBT.

in [14].

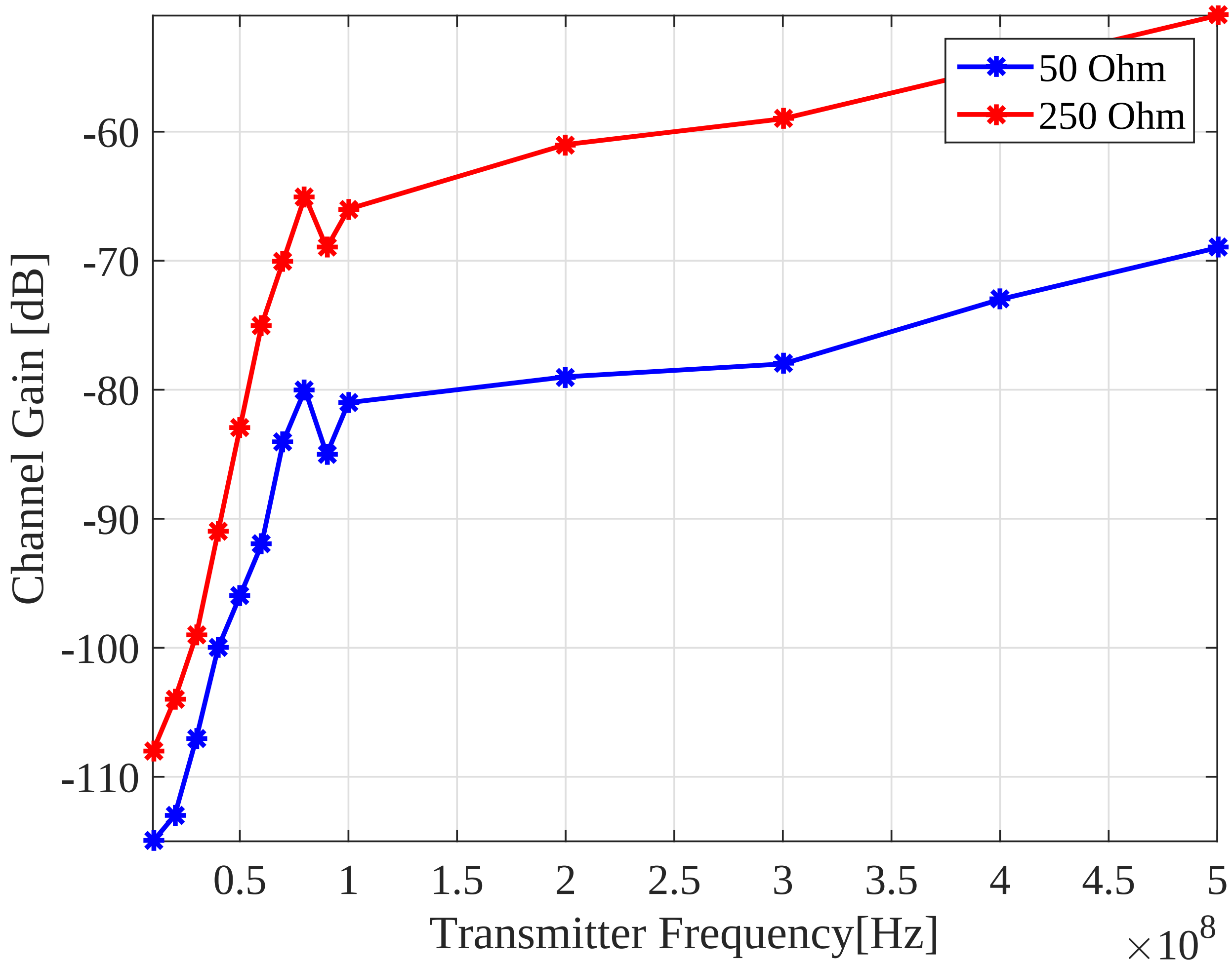



Figure 5.14: Frequency response for BCC channel.

TABLE 5.1. Characterization table of the proposed ambulatory monitoring BAN.

| | |
|---|---|
| Frequency Band | Frequency Selective Baseband |
| Spreading | Frequency Selective Walsh Modulation |
| Communication Environment | Intra Body Communication |
| MIMO Encoder | Orthogonal Space Time Block Code |
| MIMO Channel | Rayleigh distribution |
| MIMO Combiner | Orthogonal Space Time Block Code |
| Walsh Code Size | 64 |
| BCC coupling method | Capacitively coupled |
| Frequency range of Operation | 1- 100 MHz |
| Power Consumption | 3.14 mW |

# CHAPTER 6

# CONCLUSIONS

## 6.1. Summary

This dissertation proposed 3 application-specific “thing” architectures for Internet-of-Things (IoT)-based smart healthcare solutions.

In Chapter 3, a novel IoT based Basal Body Temperature (BBT) monitoring architecture is proposed. The proposed architecture was developed as an IoT component. By implementing different architectures for temperature monitoring, it was observed that better linearity and wider range of time period and frequency range can be observed at the expense of more transistors. Since a higher number of stages implies more transistors, it can also be inferred that the switching activity increases and so does power dissipation. Hence on getting higher precision in the temperature sensor, a major trade off is power dissipation. In addition to energy efficiency, the overall system efficiency was also taken into consideration. In the system level implementation of the BBT temperature sensing module, a 23 % power reduction was observed.The efficiency of the support vector machine based BBT Analysis engine was observed as 98 %. Future research involves hardware software co-simulation of the BBT monitoring system. This would help in obtaining real time values that would help in calibrating the sensor. Further, this research can be extended to real time implementation of IoT based smart healthcare monitoring sensors to identify various underlying disorders.

In Chapter 4, a framework for a human activity monitoring system to keep track of physiological health of friends and family is proposed. The proposed feature-based human activity monitoring algorithm is dynamically calibrated based on the learning parameters. The proposed method improves the accuracy in detecting human activity and helps in identifying features unique to each individual. In case of abnormality in these values, the systems calibration can be checked. The proposed algorithm is validated using an experimental setup. The decision table based classifier on the data acquired from the sensing module yielded a 97.9% efficiency, in the worst case.

In Chapter 5, a low power communication method for an IoT based ambulatory monitoring body area network is proposed. The proposed ambulatory monitoring system was implemented based on FSBT and BCC in Simulink®. The proposed method reduces the power budget but increases the attenuation. It was observed that the main advantage of using HBC is that it does not require any additional RF components. It was also observed that in independent touch-based applications, FSBT plays an important role and BCC is very important in inter-sensor communication.

## 6.2. Future Directions of the Proposed Research

Needle-less and cost-effective healthcare solutions are important to bridge the gap between healthcare inequalities. The human body is a complex system which has various parameters indicating the normal functioning of this system. Future directions of this research would involve identifying more body parameters which can be used to monitor the physiological health. With enormous funding and increasing attention towards the smart healthcare domain, there are numerous products and applications available for users. Future research involves developing consumer electronics such as wearables to monitor underlying disorders using body parameters. As a multi-dimensional research area built using millions of tiny devices, the future directions of this research need to be focused towards developing secure, reliable smart healthcare architectures. In the smart healthcare system it is important to have a very good trade-off of security, energy consumption, and response/smartness [5, 32]. The future research of the research proposed in this dissertation should be in that direction. Smart healthcare systems, particularly when operated by battery, need to optimize energy, peak power, and power fluctuation to increase battery life significantly [49, 50].

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