ALGORITHMS FOR DETECTION OF PEOPLE CROWDS USING WIRELESS SENSOR NETWORKS

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Declaration

I hereby declare that this is my original work except for quotations which I have duly acknowledged. This research work has not been accepted for any degree and is not submitted for the award of another degree..

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Approval

The research work culminating into this thesis was conducted under my guidance and supervision .

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Dedication

This work is dedicated to all who in one way or another contributed to its successful completion.

Acknowledgements

With gratitude, I acknowledge the AfDB-HEST project scholarship enabled by Mbarara University of Science and Technology through the Faculty of Computing and Informatics that supported this work.

The PhD research journey is a journey through unknown rugged terrain. To soldier through the dark moments and ditches required another arm. Special thanks go to my research supervisors Dr Nabaasa Evarist and Dr Ariho Pius for their skilful direction. I am grateful for the flexibility, patience and tireless efforts of my doctoral team that comprised of doctors; Simon Kawuuma, Fred Kaggwa, and Richard Sembatys.

Codes failed to run, operating systems crashed, but my research colleagues at the Faculty of Computing and Informatics (FCI) *worked overtime unpaid.* I will always appreciatively look back on that. I remember behind the scene guidance from administrative desks in the Faculty of Computing and Informatics, the Directorate of Research and Graduate Training, and the Academic Registrars' offices.

Obbo Aggrey, 2023.

Abstract

People Crowds have attracted a lot of attention in recent decades. This can be attributed to the growth of the events industry that results in the damage of social services whenever people crowds are not controlled, the fear of negative effects of epidemics accelerated by uncontrolled people crowds such as high mortality rates and the breeding of political intolerance displayed through public demonstration. People crowds also comprise intelligent humans which means that they can possess the capability to bypass traditional crowd detection mechanisms. Their detection will therefore require special attention. On the other hand, advancements in microelectromechanical technologies that is used in the manufucture of sensors have led to the production of more effective lightweight sensor nodes with improved network coverage, and energy-efficient routing and aggregation protocols, resulting broadened the application domain of wireless sensor networks. Despite the above-mentioned dangers, coupled with technological advances, not much work has been done in the area of people crowds detection using wireless sensor networks. In this work, the researcher investigated the strengths and shortfalls of existing

crowd detection algorithms in relation to people crowds and developed algorithms for the detection of people crowds using WSNs. The developed People Crowd Detection (PCD) algorithms were simulated using MATLAB software and their performance analysed by establishing their complexities.The developed algorithms were of highest order O(n). The complexity indicated a fair performance while at the same time highlighting room for improvement. The conclusion made was that wireless sensor networks provide a basis upon which people crowds algorithms can be programmed and people crowds detected especially for resource-constrained environments.

Contents

Declaration ii

Approval iii

Dedication iv

Acknowledgments v

Abstract vi

List of Tables xiii

List of Figures xv

List of Equations xvi

Abbreviations xvii

1 Introduction 1

1.1 Background 1

1.2 Statement of the Problem 4

1.3 Research Objectives 5
1.3.1 Main Objectives 5
1.3.2 Specific Objectives 5
1.4 Research questions 6
1.5 Scope 7
1.6 Research Motivation 7

2 Review of Existing Crowd Detection Algorithms **10**
2.1 Introduction 10
2.2 Crowd Detection Approaches 13
2.2.1 Crowd Detection Through Radio Sensing 14
2.2.2 Wi-Fi based Crowd Detection 17
2.2.3 Crowd Detection Through Mobile Crowd Sensing . . . 21
2.2.4 Crowd Detection Through Crowdsourcing 23
2.2.5 Crowd Detection Using Wearable Tags 27
2.2.6 Crowd Detection Using Wireless Sensor Networks . . . 29
2.3 Algorithms in Wireless Sensor Networks 32
2.3.1 Distributed People Counting Algorithm using PIR Sensors 33
2.3.2 Crowd Density Estimation Using Wireless Sensor Networks 35
2.3.3 Crowd Density Estimation Using Cellular Phones . . . 41
2.3.4 People crowd detection in Train compartments. 43

3 Research Methodology 47

3.1 Introduction 47

3.2 Requirement Gathering - Method for objective one 49

3.3 Algorithm Design 50

3.4 Deployment of the developed algorithms 51

3.5 Analysis of Developed Algorithms 52

4 Research Results 54

4.1 Introduction 54

4.2 Crowd Detection Approaches 54

4.3 Crowd Detection Algorithms 55

4.4 Algorithms for People Crowd Detection 59

4.4.1 Design Requirements for People Crowd Detection . . . 60

4.4.2 People Crowd Detection Algorithms 73

4.4.2.1 Signal Generation Algorithm 73

4.4.2.2 Signal Decomposition Algorithm 74

4.4.2.3 Detection Algorithm 75

4.5 Implementation and Simulation 76

4.5.1 Simulation Set up 79

4.5.2 Simulation Parameters 82

4.6 Algorithm Analysis 87

5 Discussion of Results 90

5.1 Review of Literature on Crowd Detection 90

5.2 Design of People Crowd Detection (PCD) Algorithms 91
5.3 Deployment of People Crowd Detection (PCD) Algorithms . . 92
5.4 Analysis of the People Crowd Detection (PCD) Algorithm . . 92

6 Conclusions and Recommendations **94**
6.1 Conclusion 94
6.2 Research Contributions 95
6.2.1 Strength and shortfalls of existing crowd detection algorithms 95
6.2.2 Designing crowd detection algorithms 96
6.2.3 Deployment of people crowd detection algorithms . . . 97
6.3 Implication of the Research 97
6.4 Research Limitations 98
6.5 Recommendations 99

Bibliography **101**

A People Crowd Detection Algorithms **129**
A.1 **Detection Algorithms** 129
A.2 **MATLAB People Crowd Detection Algorithms** 130

B Comparative Analysis of Crowd Detection Approaches **132**

C Sensor node specifications **134**

D Publications **135**

D.1 **Publication 1** 135
D.2 **Publication 2** 135

E Approvals **136**

List of Tables

4.1 Comparative analysis of Crowd Detection Algorithms 57

4.2 Simulation parameters for Detection Algorithm 83

4.3 Simulation parameters for LEACH Protocol 83

B.1 Comparative analysis of Crowd Detection Algorithms 133

List of Figures

2.1 A generalized wireless sensor network 11

2.2 A depiction of crowd density estimation system using cellular technology 16

2.3 Deployment of a MAC address listening device 18

2.4 A depiction of the mobile crowd sensing layers 22

2.5 Crowdwatch Architecture 24

2.6 An RFID Pilgrim identification system 28

2.7 Subsystems of a sensor node 31

2.8 Crowd density mechanism 37

2.9 RSSI for different number of people 40

2.10 Generic cellular network. 41

2.11 Train side components of the train management system using ZigBee 45

3.1 Research Methodology 48

4.1 Wavelength, Amplitude and Frequency of a Wave 77

4.2 The process of ground detection from ground vibration 78

4.3 Classification of basic human physical activity 79
4.4 Underground deployment of WSN for People Crowd Detection 84
4.5 Signals received at the node. 85
4.6 Absolute frequencies of signals received at the node. 86

C.1 Hardware specifications of a geophone 134

E.1 National Council of Science and Technology Approval. 137

List of Equations

2.1 Probabilistic Model 12
2.2 Frequency domain in OFDM 19
2.3 Noise Vector 19
2.4 Frequency Domain Model 20
2.5 Variance Computation 20
2.6 People Crowd Count 33
2.7 Direction of motion 34
4.1 Fast Fourier Transform - 1 78
4.2 Fast Fourier Transform - 2 78

List of Abbreviations

AES	Advanced Encryption Standeard
AOA	Angle of Arrival
AP	Access Point
BS	Base Station
CCTV	Closed Circuit Television
CIAA	Confidentiality, Integrity, Authentication and Availability
CL-EKM	Certificate-less Effective Key Management
CSI	Channel State Information
CTP	Collect Tree Protocol
DARPA	Department of Advanced Research Project Agency
DES	Data Encryption Standard
DFA	Differential Fault Analysis
DSN	Distributed Sensor Network
ECC	Elliptic Curve Cryptography
FT	Fourier Transform
FFT	Fast Fourier Transform

FHSS	Frequency Hopping Spread Spectrum
HCS	Human-Centric Sensing
IoT	Internet of Things
LEAP	Location Encryption and Authentication Protocol
LTE	Long Term Evolution
MCD	Map Counter Dataset
MCS	Mobile Crowd Sensing
MCU	Micro-controller Unit
MIMO	Multi-Input Multi-Output
MNO	Mobile Network Operator
MS	Mobile Station
OFDM	Othogonal Frequency Division Multiplexing
PCS	People Crowd Sensing
PEM	Percentage of Elements
PCD	People Crowd Detection
PCSN	People Crowd Sensor Node
PIR	Passive Infra-Red Sensor
RF	Radio Frequency
RFID	Radio Frequency Identifier
ROI	Region of Interest
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
SIM	Subscriber Identity Module

SPINS	Security Protocol in Sensor Networks
SNEP	Sensor Network Encryption Protocol
TDOA	Time Difference of Arrival
ToA	Time of Arrival
UWSN	Underground Wireless Sensor Network
UMTS	Universal Mobile Telecommunication System
VPN	Virtual Private Networks
WAN	Wide Area Networks
Wi-Fi	Wireless Fidelity
WSN	Wireless Sensor Network

Chapter 1

Introduction

1.1 Background

The recent growth in the events industry, the global impact of disease pandemics [1], and the increasing number of stampedes and damages resulting from political upheavals and public demonstrations [2] have all but piqued interest in crowd detection research. On the other hand, the progress registered in microelectromechanical technologies has led to the manufacture of lightweight performing sensors and Wireless Sensor Networks (WSN). This has accelerated innovations in smart cities, smart homes and WSN applications. The developments present opportunities for the use of WSNs in people crowd-related applications.

Research interventions to address crowding problems have primarily relied on

either image-based or non-image-based approaches. Image-based approaches have, however, been reported to be affected by occlusion and are resource-intensive [3, 4, 5]. As a result, this study concentrated solely on alternatives to CCTV and non-video-based techniques. [6]. The goal was to provide a method for automatically detecting the presence of people crowds in an area of interest while utilizing the available resources. The findings of the research show related work in this area, and the ones considered closest to work include.

Mobile crowd sensing (MCS) is a class of sensing models in which individuals share data about an event or topic of mutual interest. Authors in [7] presented a survey of various mobile computing approaches. Because MCS typically requires multiple people to participate, participation may necessitate solicitation, and thus incentives or incentive models may become necessary. In practice, this approach may not be feasible for detecting out-of-control people crowds.

Radio Frequency Identifier (RFID) based sensing [8]does not detect people's presence but rather detects devices carried by people and uses these to determine the presence of people crowds. The Received Signal Strength (RSS) from communication infrastructure is used to detect the presence of people crowds. The limitation of these technologies, despite their low cost, is that they require individuals to have at least an RFID device or identifier. Indi-

viduals who are in having devices may intentionally turn them off or avoid them entirely when they realize they are being monitored invisibly. RFID technologies necessitate the use of relatively expensive readers.

Bluetooth was a widely used technology, particularly before the proliferation of smartphones. It continued to smartphones after smartphones became popular [9, 10]. However, Bluetooth laser-ranging technologies are deemed appropriate as an indoor solution and can not scale well for people crowds in urban cities. . The growing use of hotspots also presented an opportunity to focus on Wi-Fi technologies. And Wi-Fi technologies were used to monitor elderly people [11] and in people counting [42]. But Wi-Fi technologies are challenged by object occlusions and real-time processing requirements.

There continues to be consistent research in energy-efficient routing algorithms and data aggregation mechanisms in wireless sensor networks [13]. Together with developments in Micro-electromechanical (MEM) systems, it has led to the manufacture of lightweight energy-efficient sensors and less resource-intensive routing resulting. These all have resulted in more WSN-related applications. This research leveraged these developments to come up with algorithms for people crowd detection algorithms using WSNs. The outcome of the research was algorithms for people crowd detection using WSNs. The algorithms provide a blueprint for application and systems development. Based on the developed people crowds detection algorithms, crowd detection

systems or applications can be developed and employed by the police for surveillance purposes, local government in urban planning and event organizers for planning service delivery. It also acts as a stepping stone to further research in the area of people crowd management.

1.2 Statement of the Problem

People crowds are inevitable occurrences due to reasons ranging from religious pilgrimages, the growing events industry, mass motions due to wars and natural disasters, political rallies and of recently, the increase in disease pandemics. people crowds also include peaceful processions and demonstrations. If not detected early, uncontrolled crowds can lead to chaos and stampedes [14, 15], higher mortalities resulting from disease epidemics, robberies and difficulties in urban planning because of inadequate crowd statistics [16].

In addition, people crowds are normally spontaneous and unpredictable. This poses a challenge to many traditional crowd counting and estimation approaches. Due to their natural intelligence, people crowds can easily bypass many of the traditional approaches. Unfortunately, more emphasis has been directed towards technologies catering for non-people crowd detection such as vehicle classification [17] and real-time forest fire detection [18]. However, not much has been done in the area of people crowd detection. The dynamic

nature of people crowds coupled with the inherent shortfalls of wireless sensor networks highlights the need for special attention to enable the detection of people crowd presence using wireless sensor networks.

1.3 Research Objectives

Despite registered progress in WSNs and the pressing need to mitigate problems of people crowds not much has been done in the area of people crowds. This subsection presents the main objectives of the research and the steps that were followed to achieve them.

1.3.1 Main Objectives

The main objective of this research was to develop algorithms that would detect the presence of people crowds and using wireless sensor networks, route collected data to a base station for further analysis. The algorithms are to provide a procedural description of how people crowd presence is detected and act as a basis upon which people crowds detection applications and systems are developed.

1.3.2 Specific Objectives

The following specific objectives were identified:

i To asses the functionalities of existing crowd detection technologies and identify their capabilities and shortfalls in terms of the environment for which they were designed;

ii To design algorithms for people crowds detection based on the identified gaps and shortfalls of the existing algorithms;

iii To deploy the designed people crowd detection algorithms;

iv To analyse the performance of the developed algorithms.

1.4 Research questions

Four main research questions were established to guide the execution of the specific research tasks. The research questions were as follows:

1. What are the strengths and shortfalls of existing crowd detection approaches?

2. What are the shortfalls of existing sensor-based people crowd detection algorithms?

3. What are the design requirements for people crowd detection algorithms?

4. What software can be used to simulate people crowd detection?

1.5 Scope

In this research, the detection and routing algorithms were implemented on MATLAB. The coverage and communication ranges of the sensor nodes determine how much area will be covered by each sensor node, while the deployment algorithm is always used to extend the coverage area using multiple sensor nodes to create a wireless sensor network covering a much wider area. And vibrations generated by people crowds were simulated by generating random signals whose initial energy was 1 nJ each. A crowd in this work was defined as the number of people that falls within a defined range. This research is based on the principle that crowd size is directly proportional to the strength of the vibration it generates. To simulate crowd detection, vibrations were generated and a frequency range was defined to represent the people crowds. The number of people detected is dependent on the coverage and communication range of the individual sensor nodes.

1.6 Research Motivation

Despite progress in sensor technologies, there exist shortfalls in state-of-the-art solutions to people crowd detection using WSNs. This research identified major limitations in current literature and these relate to the fact that;

1. People crowds are spontaneous and unpredictable, presenting a challenge to traditional crowd detection approaches,

2. People are intelligent and can easily bypass or even destroy traditional detection systems and

3. Wireless sensor networks have known vulnerabilities of limited coverage, life span and physical security of individual sensor nodes.

Addressing the above-mentioned challenges calls for special effort. The result of this work is algorithms for the detection of people crowds. The algorithms present a procedural description of how a computational problem is solved. When the algorithms are programmed onto sensor nodes, they provide a basis upon which applications and systems can be developed for people crowd detection that in turn benefit in the following ways:

1. *Curb the effects of disease Epidemics.* The ability to detect crowds makes possible the control of their spread. This need was especially highlighted by the recent global effect of COVID-19. When data on the existence of people crowds are relayed to the base station, an appropriate course of action such as sending an emergency response team can help mitigate potential damages.

2. *Law and Order.* The popularity of mass movements means people crowds will develop spontaneously such as during sports events, music festivals and political demonstrations. And research shows that crowd members lose individual control and assume involuntarily movement [19]. This can become both a social and security threat. The

ability to detect crowd build-ups can go a long way in supporting both the police and the military in controlling crowds.

3. *Traffic Control.* Motor traffic is directly influenced by the number of pedestrians crossing and possible crowd build-ups on motor highways. This is especially true in areas where motor and pedestrian traffic share the same infrastructure. Therefore this research finds its way into motor and human traffic management.

4. *Management of Public Services.* Public facilities such as stadiums and conference halls are designed to meet a given capacity in terms of the number of people allowed in at a given point in time. Conformity with these regulations ensures efficient utilization of these resources. Early detection of people crowds minimizes accidents resulting from congestion and increases the life span of public facilities.

Chapter 2

Review of Existing Crowd Detection Algorithms

2.1 Introduction

This section introduces WSNs and people crowds. It then presents a review of work done in people crowd detection in the area of WSNs. The strength and shortfalls of the proposed approaches are discussed.

Wireless sensor networks are infrastructure-less wireless networks composed of spatially dispersed, dedicated sensor nodes or motes deployed to monitor physical phenomena as shown in Figure 2.1 below.

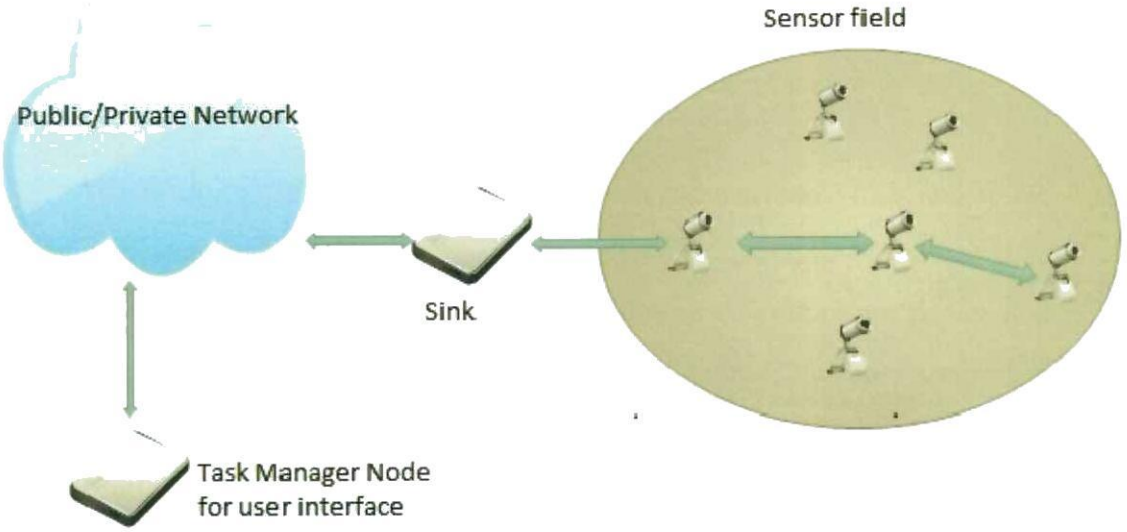

Figure 2.1: A generalized wireless sensor network

Sensor nodes collect data about a physical phenomenon and based on a defined threshold, forward collected data to a specialized node referred to as the sink for analysis. The sink node can be accessed remotely via Wide Area Network (WAN) or Virtual Private Network (VPN) connection.

The effectiveness of a wireless sensor network is dependent on the coverage of the respective sensor nodes. According to authors in [20], for a sensor node with sensing range R_n, circular coverage area A_s and located at point u, the deterministic sensing model that defines the probability $P(u, v)$ of sensing a target v_i in a sensing region is given in Equation 2.1 below.

$$P(u, v_i) = \begin{cases} e^{-\lambda d(u,v_i)^\alpha} & \text{if } d(u, v_i) \leq R_n \\ 0 & \text{Otherwise} \end{cases} \tag{2.1}$$

Where $d(u, v)$ is the Euclidean distance between u and v. λ and α are predetermined constants.

A crowd is considered a region corresponding to more than one person and with coherent and homogeneous motion [21]. While [22]defines a crowd as a large group of people with a common purpose such as in a political rally, sports event or rush hour on a busy street.

People crowds can be an indicator of a catastrophe such as a traffic jam, a political demonstration, an epidemic or even a political disaster that requires urgent intervention hence early detection. And crowds in urban cities can take the form of; i) individuals moving randomly, ii) individuals moving at pace in the same direction such as in a Christian procession, or iii) individuals stationed in one place. People crowds possess several characteristics that can be based on to detect their presence. These properties include footsteps vibration generated by people crowds, the effect of human bodies on Received Signal Strength (RSS), Channel State Information (CSI), and noise disturbances generated by riotous crowds. Different approaches have employed one or more of these. The next section provides an overview of the different human sensing categories. Their respective strengths and shortfalls when used for people crowd detection, especially in resource-constrained ur-

ban cities are highlighted. The focus was on technologies, methodologies and implementation of the notable approaches.

2.2 Crowd Detection Approaches

Crowd detection is the estimation of the number of people within a given area in real-time. Advanced detection of people crowds can protect both public and private property, and minimize potential injuries that could result from uncontrolled people crowds. Early detection can enhance the management of pedestrian traffic [23], and provide data for further forms of crowd analysis [74]. Human crowd sensing encompasses a range of technologies for the detection of human presence in an area the without intentional participation of subjects being detected. An insight into human-centric sensing modalities and approaches can enhance appreciation of the wave propagation generated by humans and people crowds that is important in the deployment of sensors and WSNs.

Of recent, crowd sensing and urban sensing surveys have been carried out [25, 26]. The various approaches to human sensing have been categorized as human-centric and crowd-centric, depending on the type of input detected. Crowd-centric sensing approaches, model the properties of a group of people, while human-centric approaches detect individuals. Human Centric Sensing (HCS) models have been used in personal security [27], health [28, 29] and

sports [30]. Crowdsensing approaches have also been classified as device-free and device-present. Device-free sensing is when no special equipment or cooperation is required from the subjects, while device-present crowd sensing requires that the individuals possess a special device. In this case, the term environment sensors are used to refer to sensor nodes/devices that capture information about their environment. However, many of these did not take into account challenges in many developing economies such as; the state of communication infrastructure and the chaotic nature of people crowds. For example, authors in [31] looked at activity recognition in smart homes based on the Internet of Things (IoT) sensor algorithm, and [40] discussed the challenges and opportunities of wireless human sensing for the smart IoT world. In this section, each of these approaches is analyzed concerning the above-mentioned constraints.

2.2.1 Crowd Detection Through Radio Sensing

Radio sensing is a sensing approach that is based on real-time processing of CSI information. Moving bodies and objects create a disturbance in electromagnetic waves. The disturbance then determines the value of the CSI. Unlike its counterparts such as the device present sensing, radio-based sensing does not require the cooperation of monitored subjects or subjects to be in possession, of a special device. Radio sensing detects the existence of people by measuring the RSS. Water which represents 70% of the human body absorbs part of the 2.4GHz radio signals resulting in a significant decay in

the RSS [33].

Sensing technologies that have employed RSS in real-time include:

- Array sensors
- Multi-Input Multi-Output (MIMO) sensors,
- Radio tomography, and
- Doppler sensors.

The array of sensors approach exploits the multiple antennas on a receiver to detect different aspects of human dynamics such as seating and falls [34]. While MIMO sensors are base on multiple propagation channels to detect people presence. In recent years, MIMO has transmitted large capacities at high speed using multiple antennas. Nishimori et al. in their work proposed an intrusion detection method using MIMO channels [35]. They analyzed the antenna arrangement suitable for MIMO sensing in indoor environments. Radio tomography on the other hand employs the multiple transceivers of radio waves focused towards a Region of Interest (ROI) or target. The presence of a person results in the absorption and reflection of propagated radio waves. Human detection is thus based on attenuation resulting through the links. The Doppler sensors compare the frequency of transmitted radio waves to the frequency of the received signals in detecting the speed and movement of a person. These have been used in speed guns. Doppler Effect has been proposed in fall detection [36]. Figure 2.2 below is a depiction of a crowd

density estimation system that has a base station and sensor nodes deployed to receive radio waves from cellular phones carried by people crowds. Collected data is forwarded to a remote server via a gateway or LTE technology to determine the existence of a people crowd.

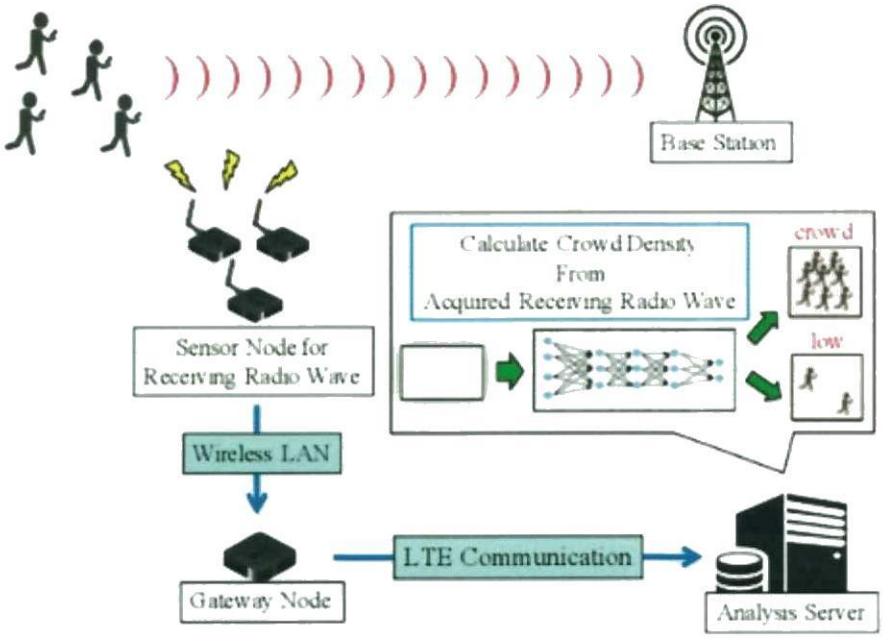

Figure 2.2: A depiction of crowd density estimation system using cellular technology

[37]

Conclusion

The limitation with radio sensing is that the approaches mainly assume device present sensing which requires persons to have radio devices. In addition, radio waves fade and are affected by noise. They also face interference in in-

door environments. In a study by Kostoff and others, evidence of the effect of 5G mobile technology on the human eye, and skin, and their adverse systemic effects were presented [39].

2.2.2 Wi-Fi based Crowd Detection

Wi-Fi-based crowd detection approaches exploit data available on Wi-Fi infrastructure to provide local crowd monitoring solutions. These solutions leverage the geospatial information collected by access points to enable real-time monitoring of people crowds. Popular crowd-counting approaches that have been used in crowd monitoring include approaches based on Channel State Information (CSI) [40, 41] and Received Signal Strength (RSS) [42]. In addition, probe requests used by smartphones nearby access points have been used to estimate people counts. Authors in [43] exploited device and Access Point (AP) addresses to estimate pedestrian count. The strong point with Wi-Fi-based sensing is that they are non-intrusive, free of occlusion and relatively cheaper because they utilize already existing infrastructure. Successful applications of Wi-Fi sensing have been shown in smart home activity sensing [44], pedestrian counting in urban traffic [45] and estimation and forecasting crowd counts [46]. Wi-Fi-based sensing has also been used in crowd monitoring [47]. The depiction in Figure 2.3 below has a Wi-Fi listening device that senses individuals with Wi-Fi-enabled devices in their possession. The devices access Wi-Fi networks via different Access Points (APs).

In crowd counting using Wi-Fi, a combination of both the ubiquity of Wi-Fi devices and the growth of Radio Frequency (RF) that is used in Wi-Fi has been employed in occupancy estimation using RF frequency. RF technologies are either device-based or device-free. In the context of device-free-free crowd counting, Received Signal Strength (RSSI) and Channel State Information (CSI) have been used to classify the number of people [49]. These make use of the identified relationship between several moving people and variations in both RSSI and CSI. In recent years, RSSI has been used in the detection of intruders [50]. Electronic frog employed dedicated Wi-Fi transmitters and receivers to estimate the number of pedestrians [51]. The operation of the Electronic frog is explained below.

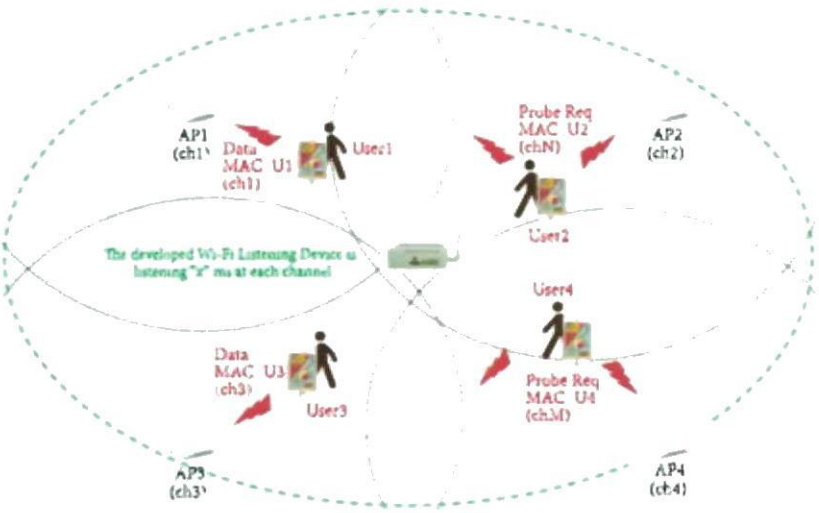

Figure 2.3: Deployment of a MAC address listening device [48]

To overcome the challenges of finding a stable monotonic function to characterize the relationship between crowd number and CSI, Wei et al. in their work proposed the use of a Percentage of non-zero Elements in a dilated matrix. The authors used the Percentage of Elements (PEM) in the dilated CSI matrix to indicate the crowd size. The PEM value keeps increasing up to a threshold saturation value at which point the presence of a crowd is assumed.

In practice, the transmitted signal is the same as signals received at the destination due to interferences during transmission. In Orthogonal Frequency Division Multiplexing (OFDM), the frequency domain was modelled as:

$$Y = HX + N \tag{2.2}$$

where Y and X are the receive and transmit vectors, with H and N as the channel matrix and noise vector H is estimated as:

$$\hat{H} = \frac{Y}{N} \tag{2.3}$$

For multiple signals reaching the receiver Y_i, the CSI is estimated as:

$$\hat{H} = \frac{Y}{X} = \frac{Y_0 + \sum_{i=1}^{n} Y_i}{X} = \hat{H}_0 + \frac{1}{X}\sum_{i=1}^{n} Y_i \tag{2.4}$$

The variance is computed on both sides of Equation 2.4 above:

$$D(\hat{H}) = \frac{n\delta^2}{X^2} \tag{2.5}$$

As the number of people and thus signals increases, the variance (δ^2) becomes smaller and the CSI value tends towards a threshold value that indicates people crowd presence.

Conclusion

Wi-Fi technologies are known to have limited range resolutions compared to other sensing technologies. In addition, Wi-Fi-based sensing faces multipath propagation and occlusion. And may not scale well with a big number of people. Many Wi-Fi systems are also only effective in controlled environments.

Wi-Fi sensing will also require a dense Wireless Access Point (AP) implementation. In addition, other Wi-Fi sensing challenges include privacy and security issues attributed to the many Wi-Fi applications that may be used for malicious purposes. Wi-Fi signals are sensitive to the coexistence of Wi-Fi sensing and networking that affects each other [52].

2.2.3 Crowd Detection Through Mobile Crowd Sensing

In the past few decades, the world has undergone a revolution from crowdsourcing models that involved the use of people crowds to collect data that could otherwise have been collected expensively using traditional methods. Mobile Crowd Sensing (MCS) paradigms emerged for the collection of smart city and Internet of Things (IoT) data. It leverages the extensive penetration of smartphones that possess several embedded sensors: GPS, cameras, accelerometers, light sensors and proximity sensors to form a large sensing system that can support several sensing applications. Examples of MCS applications include: gaming [53], hotspot identification [54], pilgrim tracking and identification [55], and public information sharing [56]. It has also been applied in Smart Social Distance (SSD) monitoring. The MCS model has taken the form of large reference analysers, street-level monitoring and participatory sensing. Unlike other traditional approaches, the MCS sensing framework is divided into levels that include crowd sensing, data collection, data transmission and application levels as shown in Figure 2.4 below.

Conclusion

An advantage of mobile crowd sensing is that they may not require specialized fixed sensor infrastructure and as a result are relatively cheaper. Unlike embedded systems, smartphones carried by humans are rechargeable and hence have a loosened power constraint. The varying radio ranges of

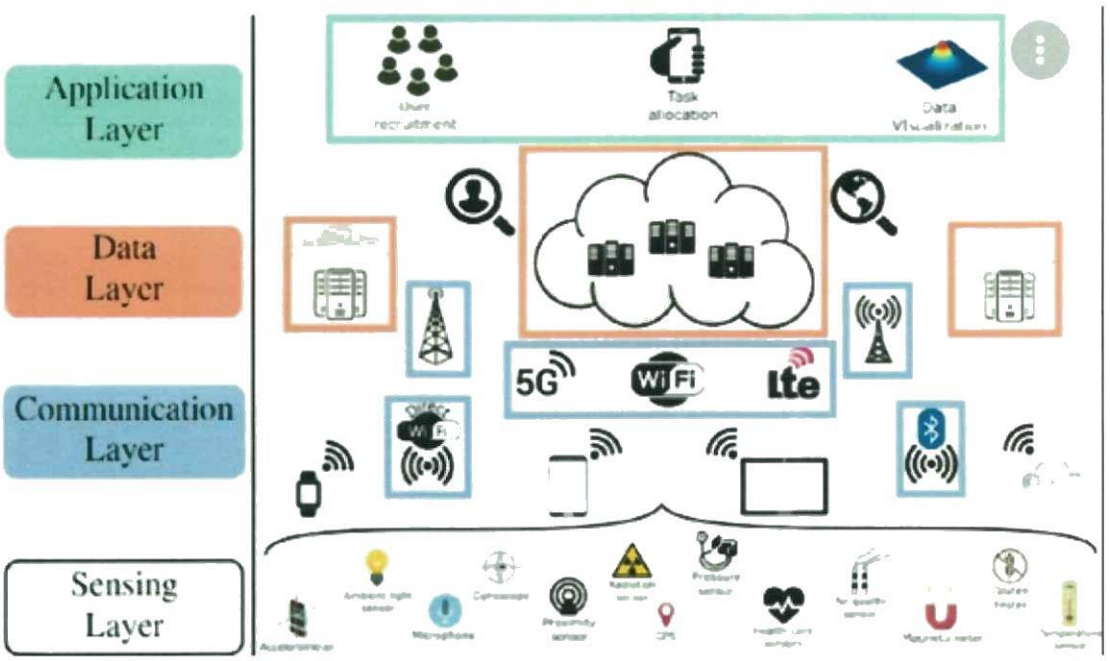

Figure 2.4: A depiction of the mobile crowd sensing layers [57]

different mobile devices however have a strong impact on the design and implementation of MCS systems. Several systems use a two-step process characterized by a first probing and then a processing stages that demand a portable and easy-to-deploy design to enable tracking of large crowds [58]. In addition, mobile sensing for large networks may not be achievable due to the high costs associated with a large number of sensing relay nodes. And although there has been a high penetration of smartphones, many people still use low-end mobile devices. As a result, it is hard to come up with an attractive incentive model for MCS.

2.2.4 Crowd Detection Through Crowdsourcing

Crowdsourcing technologies leverage information collected by individuals within a crowd [59]. Crowdsourcing involves obtaining information from a group of individuals via the internet. The individuals are sometimes given motivation in form of payments. It enables the sourcing of information from individuals with different skills and saves time. Crowd computing on the hand is defined narrowly as computer-mediated mediated computing by a huge number of computers behaving as a crowd with the sole objective of accomplishing the goal of enhancing computation. The computing functions are distributed among multiple dispersed computing devices. The multiple computing devices work together to accomplish tasks in a manner even comparable to a supercomputer.

Some cities have deployed smartphone-based crowdsourcing applications that

make use of information uploaded via cellular infrastructure to help manage crowds and associated city resources. An example is CrowdWatch [60]. Crowdwatch is a smartphone-based framework used in crowdsourcing people's behaviour and dynamics of a crowd from within the crowd itself. It achieves scalability and energy efficiency by offloading processing tasks to distributed devices.

CrowdWatch architecture employs hierarchical monitoring with nodes that can participate in different operating modes: Watcher, Sampler, Sensor or sleeping modes.

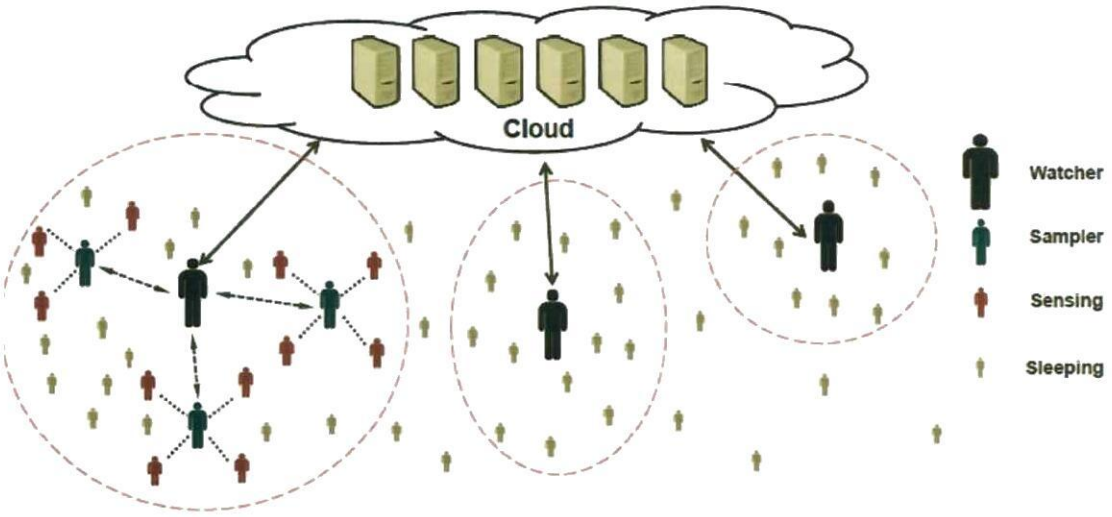

Figure 2.5: Crowdwatch Architecture [60].

A small group of watchers estimated to cover the whole crowd act as aggregators of information from other nodes within their Wi-Fi neighbourhoods

and each watcher targets several representative sample areas represented by a probabilistically selected sampler. The samplers collect sensing information from its domain or Bluetooth neighbourhoods and pass this information to the watcher which could be a gateway to the cloud servers. And to achieve energy conservation requirements, all the other nodes that are not actively participating go into sleeping mode.

The algorithm follows a probabilistic approach in determining which node becomes the watcher, sampler or sleeping sensor. Beacons are used for neighbour discovery, for informing regarding new nodes and for the existence of watchers and samplers already elected in any given domain. A contention-based approach is used during the selection of watchers with contention window size determining when the nodes can present their claims to become watchers.

Distant Wi-Fi connectivity is used for creating a dynamic backbone in the crowd while Bluetooth is used for local sampling and data collection by the sampler. During the crowd detection phase, the discovery protocol used does not require synchronization or the nodes to run at the same duty cycle. Sensing nodes send collected data to the samplers that will have entered the data collection phase. The samplers then aggregate data from multiple sensors and forward them to the watcher.

While this system boasts several advantages, they come with several limitations:

- Since information has to be uploaded to a server in the cloud, It means a

lot of resource requirements (Wi-Fi or cellular) in cases of simultaneous uploads by the many nodes.

- Reliance on the use of smartphones requires synchronization that is resource intensive in terms of energy consumption.
- Crowd behaviour is unpredictable - Sometimes crowds may form in an ad hoc manner
- Load balancing is also difficult to achieve in the absence of centralized coordination

Conclusion

CrowdWatch uses a distributed approach to mitigate challenges associated with the continuous upload of data to a central server because of the increasing number of phones that can be associated with big crowds. People crowds are however unpredictable. This makes it difficult and expensive to provide sufficient infrastructure coverage for detection. The practicality of CrowdWatch is also limited by the fact that humans are intelligent and it is much easier for them to bypass by avoiding phones. Users may require incentives to participate.

In a not-so-dense network, neighbour discovery by nodes with a high-duty cycle may not help in effecting appropriate resource utilization, while a low-duty cycle will take too long to detect crowds. To strike this balance, CrowdWatch enables some nodes to run at a higher duty cycle compared to others.

There is ongoing research on methods that can allow nodes to automatically adjust the duty cycle depending on the density.

2.2.5 Crowd Detection Using Wearable Tags

Wearable technology is a technology that uses electronic devices embedded on or worn by subjects of interest. The devices are powered by microprocessors and can send collected via wireless connectivity. The (Radio Frequency Identification (RFID) system constitutes of RFID tags, RFID readers, antennas and a computer used for connecting the readers. Their capability has put them at the forefront of IoT. RFID uses electromagnetic fields to automatically identify and track tags attached to the wearables.

There are three different ways of using a wearable multi-sensing device: human-centric, environment-centric and crowd-centric. Human-centric or people-centric sensing is intended for collecting data on personal traits such as movement and stress. The goal of environment-centric sensing is to capture information such as data on weather and pollution around a person. Finally, the third category emphasizes collecting spatial-temporal data on the behaviour of groups of people for example crowd density, and size. RFID-based crowd sensing systems include; the pilgrim tracking and identification system that used mobile phones in an area covered by a 3.5G network. They save data on mobile devices whenever there is internet outages [61, 69]. Figure 2.6 is a depiction of a pilgrim identification system by Mohandes.

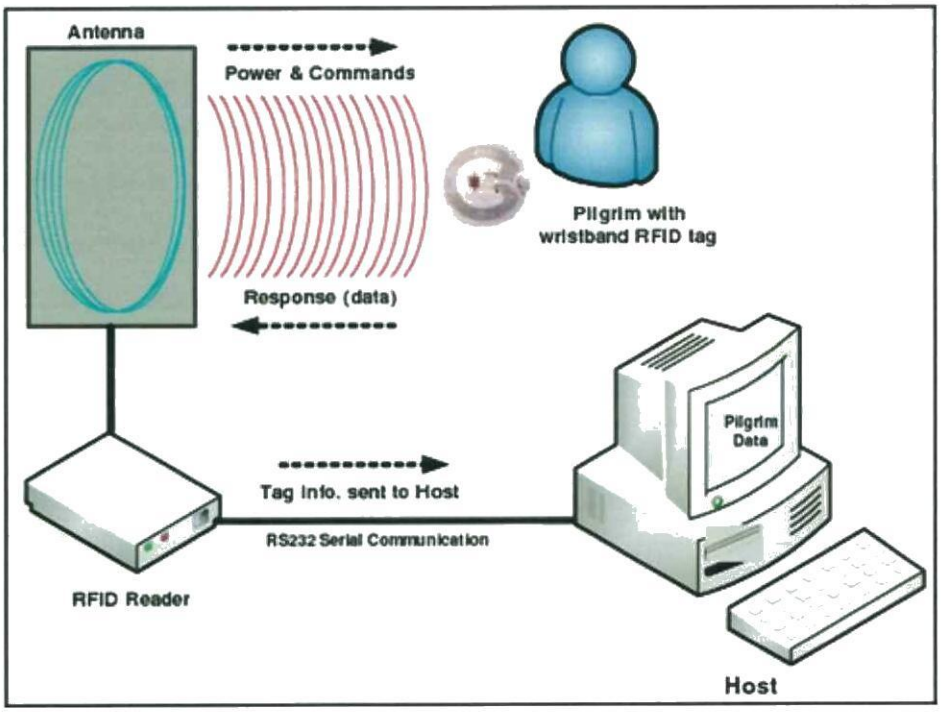

Figure 2.6: An RFID Pilgrim identification system
[70]

To overcome the challenges of power consumption, memory and structure of traditional wireless sensor systems, Bluetooth Low Energy (BLE) was proposed to mitigate the limitations of Bluetooth wireless sensor systems. Because BLE technology uses up to 40 2-MHz channels than standard Bluetooth and Frequency-hopping Spread Spectrum (FHSS), interference issues are relatively less. As a result, BLE technology will be practical whenever there is minimum data exchange, low battery life and implementations are expected to extend for longer periods. BLE is also relatively cheap.

Conclusion

A shortfall with RFIDs and other devise-based crowd monitoring approaches is that they may require consent from subjects. While out-of-bound crowds are very difficult to manage because of the RFID range limitations. The approach calls for additional crowd control mechanisms or a fusion of data from more than one sensor type to ensure effective crowd detection. In addition, although their prices have gone down over the years, the initial configurations are sometimes costly, difficult and time-consuming. Materials such as metal and liquid also negatively affect signal quality.

2.2.6 Crowd Detection Using Wireless Sensor Networks

Wireless Sensor Networks (WSNs) are a category of wireless networks that deploy group(s) of specialized transducers with communication infrastructure, intended to monitor, record and communicate results from diverse locations. The sensor nodes collect data on temperature, humidity, speed/ve-

locity, vibration, or even chemical concentration. Data collected is then used to monitor the environment of interest. Wireless Sensor Networks (WSNs) are one of the major innovations in the 21st century. From its inception as Distributed Sensor Network (DSN) designed for military intelligence by the Department of Advanced Research Project Agency (DARPA). They have however evolved to being used in infrastructure security, environmental habitat monitoring, industrial sensing and traffic monitoring using stealthy and wireless sensors [62] [71] [72]. The sensors (nodes) are placed across a Region of Interest (ROI) to route traffic towards the gateway node or sink. WSNs can be terrestrial, underground, underwater, multimedia or mobile WSNs [65]. They consist of nodes distributed along a sensing region to determine the presence of a target of interest. By capably measuring the presence or change in received signals, the sensor nodes can track or determine the existence of a target or groups of targets. The sensor nodes can be mobile such as used in mobile tracking. In addition, targets may traverse multiple sensing regions. This is of interest because sensor data has to be communicated to a processing point.

To enable data collection, processing and communication, a sensor node consists of four main subsystems [66] as shown in Figure 2.7 below. And these include:

1. *Computing subsystem/ Micro-controller Unit (MCU).* This is an electric circuit designed to interface between the sensor and an energy source. The MCU controls the sensor and manages the execution of

communication protocols.

2. *Communication Subsystem.* A radio transceiver with an internal antenna or connecting to an external one makes up the communication system. This component allows communication with neighbouring nodes.

3. *Sensing Subsystem.* This system comprises mostly sensors or actuators responsible for sensing environmental phenomena.

4. *Power Supply Subsystem.* This consists of a battery or an embedded form of energy harvesting feature.

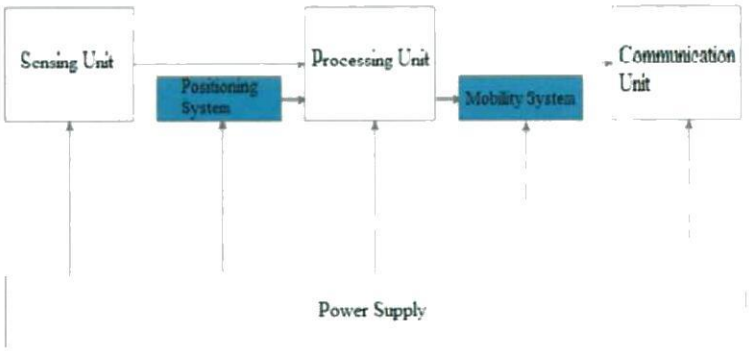

Figure 2.7: Subsystems of a sensor node

Growth in Micro-Electro-Mechanical Sensors(MEMS) technology has led to the production of lightweight and low-power sensors. This has resulted into:

- WSN that use efficient low-cost microprocessors and energy-efficient devices

- WSNs that can use operating systems and associated software that are simple, compact and energy aware.
- Support for energy efficient node organization, packet scheduling, location determination, time synchronizing, data processing, classification, identification, security and hence detection algorithms.

Conclusion

As a result of the above-mentioned developments, Wireless sensor networks present an opportunity for many supporting technologies and in-demand applications that can now be aligned to existing WSNs.

2.3 Algorithms in Wireless Sensor Networks

Wireless sensor networks are composed of an abundance of algorithms that include deployment, clustering, coverage and routing algorithms. And at a higher level, algorithms have been categorized as either centralized or decentralized algorithms [67, 68]. Centralized algorithms make use of a central hub that requires knowledge of the network to perform a task. While decentralized algorithms do not specify any central node or hub, rather each node maintains its local model and communicates collected data with its neighbours.

Without any particular order, the following subsections present a discussion of crowd-related algorithms and provide functionalities closest to that of this research. Also discussed are their strengths and shortfalls.

2.3.1 Distributed People Counting Algorithm using PIR Sensors

The distributed people counting algorithm employs distributed Pyro-electric Infrared Sensors (PIR) sensors around an ROI. People counting algorithms in conjunction with other algorithms are used to compute people crowd density which then is used to infer the existence of people crowds.

Pyro-electric infrared sensors emit a binary signal that indicates a movement or lack of movement. Signal frequency indicates the speed of motion, while signal phase shows the direction of movement. Distributed people counting employs multiple people counting sensors that record the number of entries and exits into and out of an area of interest to estimate the number of people. In distributed people crowd counting, a pre-defined set of sensors connect to a base station using radio waves. The observed space is of spatial area S_A, with predefined entry and exit points j. Each of the points is observed by a People Crowd Sensor Node (PCSN), C_j. The people crowd count, OCC is given by:

$$OCC_k = \sum_{i=0}^{n} \sum_{j=0}^{N} (C_{j,k,in} - C_{j,k,out}) \tag{2.6}$$

Given an estimation of the output signal as $VCC/2$ (Common Collector Voltage) when no movement is detected, the side of the motion, S is given

by:

$$S = \begin{cases} left & \text{if } s \geq \frac{VCC}{2} + v \\ right & \text{if } s \leq \frac{VCC}{2} - v \\ silent & \text{Otherwise} \end{cases} \tag{2.7}$$

Where v is the noise threshold above or below $\frac{VCC}{2}$.

According [158], the counting algorithm is developed from the basic count algorithm that has difficulty with performing counting in case of a queue. This approach takes a subsequent low-frequency peak as a different person passes through the line. While a change in amplitude shows a change in direction.

On the other hand, the kind of distortion caused by say four different persons could be similar to one caused by a slow-moving person. In this case, the researcher employs filters for the signal to include only low-frequency components.

Minimum time distance is defined to eliminate the possibility of having multiple peaks within a short distance and hence a false alarm.

To distinguish between a group of people standing within the sensor line of view and a person passing the line, an absolute distance of peaks in terms of signal amplitude is computed. That is $|s(t) - s(t-1)| \geq a_{min}$

The final count algorithm is as shown next.

1. Application of the low pass filter to reduce signal noise

2. Determination of signal peaks to identify the key points of the signal

3. Identification of patterns in the state of the string using regular expressions and counting the respective traversals while ignoring the peaks in case of a silent state.

conclusion

The distributed people counting using PIR sensors approach together with other people counting algorithms like the pedestrian counting systems [74] and estimation of building occupancy [159] are limited in people detection because:

1. They require a pair of well-aligned PIR sensors that will only generate people count which is less than required for people crowd detection.

2. They have to be placed at specified entry/exit points. This can only be possible when crowd entry and exit are limited only to a few restricted points or when the crowd already control.

2.3.2 Crowd Density Estimation Using Wireless Sensor Networks

Crowd density estimation using wireless sensor networks [160] builds on the concept that there exists a correlation between radio signal strength and crowd density. The effectiveness of conventional RSSI under an indoor envi-

ronment approach is negatively affected by reflection, refraction and diffraction caused by both human bodies and objects. The crowd density estimation algorithm uses a two-step process of detection and calibration as shown in Figure 2.8 below. In the detection stage, a Received Signal Strength Indicator (RSSI) is received and analyzed to determine the existence of signal disturbance. While during the calibration phase, the calibration mechanism sets a threshold value to reduce noise and deviations in detection. The effort is placed on reducing and eliminating errors. The WSN used the Collect Tree Protocol (CTP) where all nodes continuously send RSSI information containing packets to the sink.

Figure 2.8 reflects different crowd patterns in a WSN.

Detection Process

In the detection phase;

1. Time slots are determined in which RSSI readings are recorded.
2. Cells are created and for each of the created cells, a database is built in which RSSI readings during the different time slots are recorded.
3. And using the Fingerprint algorithm to determine whether the change in the created cell can is interesting or can be focused on.

The time slots are recorded such as

$$tm(t_0, t_1, t_2, ..., t_{m-1}, t_m)$$

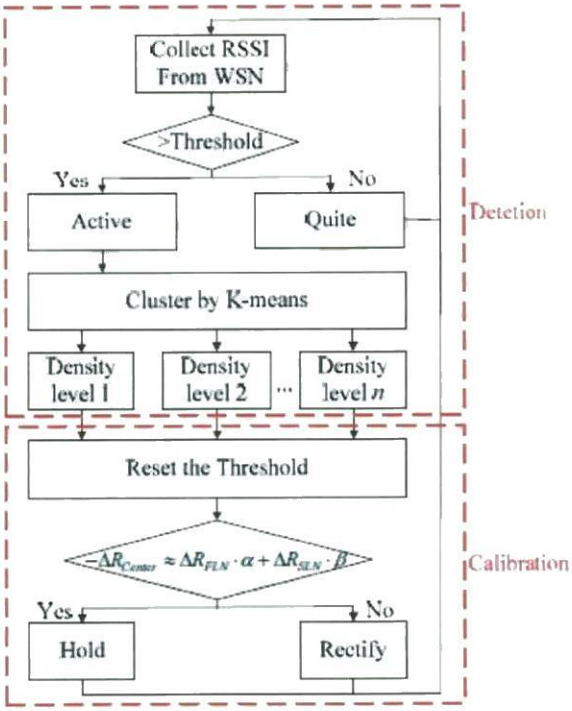

Figure 2.8: Crowd density mechanism [160].

.

Initially, the RSSI value is recorded for each cell as a vector as follows:

$$C_0(c_{01}, c_{02}, c_{03}, ...c_{0n})$$

. And the time slot t_m), it gives the vector

$$C_m(c_{m0}, c_{m1}, c_{m2}, ...c_{mn})$$

.

A predetermined threshold value $\Delta = T$ is then defined to determine whether the status is to be changed from quiet to active where the change is big enough for further analysis.

$$\Delta =\mid c_{mn} - c_{00} \mid > TdBm)$$

Using the two-step K-means algorithms, the approach first does the assignment step. In this step, each observation is assigned to the Voronoi-generated cluster with the closest mean.

Calibration Process

Taking into consideration the major factors in clustering accuracy - noise, determination of threshold value and the clustering algorithm, this approach introduced the use of a calibration algorithm.

Threshold is refined for each time slot. For t_m, $t_m(t_0, t_1, t_2, ...t_{m-1}, t_m)$ with the respective RSSI values are $RSSI_{t_m}$ to $RSSI_{t_{m-1}}$, the variance in each of

the subareas can take on the values:

$0 : \Delta < 10dBm$

$1 : \Delta > 10dBm$ and $RSSI_{t_m} > RSSI_{t_{m-1}}$

$-1 : \Delta > 10dBm$ and $RSSI_{t_m} < RSSI_{t_{m-1}}$

For sub-areas in the main area, the sum of RSSI variances is calculated. A positive-sum indicates an increase in variance while negative shows a fall in variance.

The total variance of the sub-areas is given by:

$RV\{n_1, n_2, ...n_k\}$ for $n_1, n_2, ...n_k$ sub-areas

And for each slot, the threshold is considered to be the maximum variation of the RSSI and is given by: $MaxRV\{n_1, n_1, ...n_k\}$

Figure 2.9 shows RSSI results for cases of no person, the presence of some people and a crowd. The increasing crowd is evidenced by increasing changes in RSSI readings.

Conclusion,

This approach has the advantage of having a better performance compared to camera-based approaches that come with high overhead in image processing and are made deficient by occlusion in crowded scenes. In addition, it can be re-used on already deployed WSNs and is low cost [160]. However

1. This technology was analyzed for small crowd sizes. The approach will however find challenges when with people crowds that develop build or break up rapidly from large people crowds.

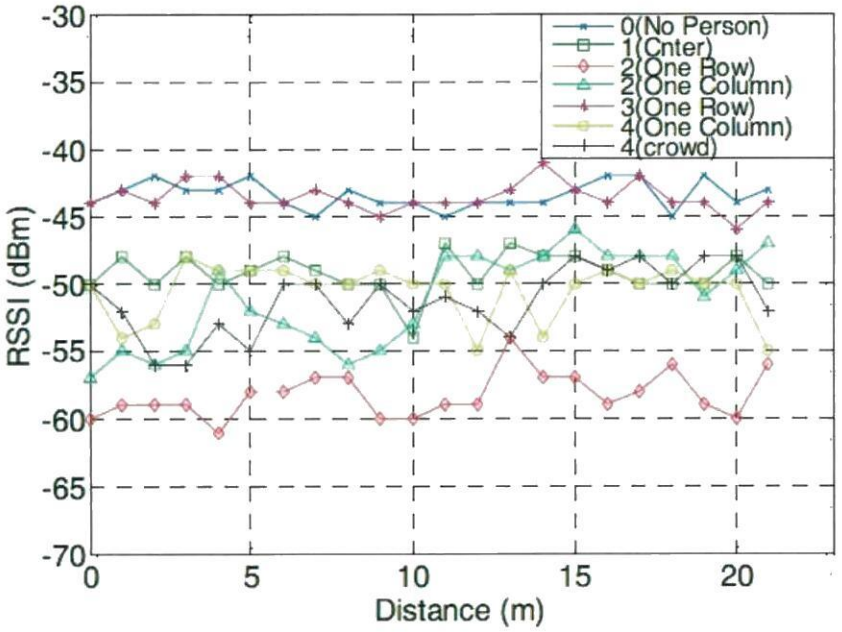

Figure 2.9: RSSI for different number of people [160].

2. It was initially designed for indoor deployment and as a result, there is no clear indication that it can be effective for outdoor environments.

2.3.3 Crowd Density Estimation Using Cellular Phones

A cellular network is a radio network normally distributed over land areas called cells, with each cell served by at least one transceiver also known as a Base Station (BS), Mobile Station a Mobile Station (MS)[161, 162]. Counters of the number of MSs observed in every cell and LAs are kept and tracked by the different Mobile Network Operators(MNOs) as illustrated in figure 2.10 below.

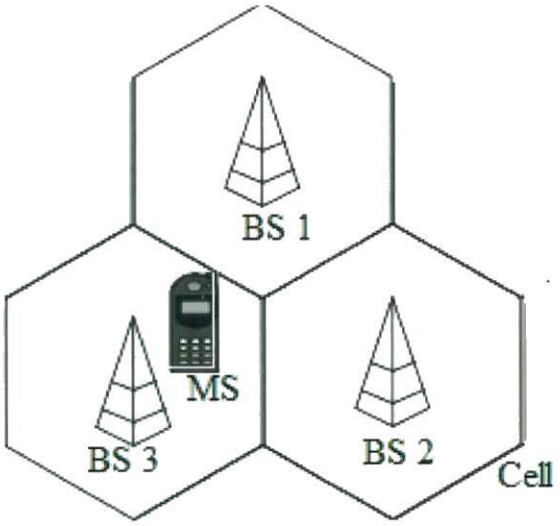

Figure 2.10: Generic cellular network.

A cellular network is a radio network normally distributed over land areas

called cells, with each cell served by at least one transceiver also known as a Base Station (BS), Mobile Station a Mobile Station (MS). Counters of the number of MSs observed in every cell and LAs are recorded.

People crowd detection using mobile phones is based on GSM (General System of Mobile Communications) and UMTS (Universal Mobile Telecommunications System) technologies, but can also be adopted by the LTE (Long Term Evolution). A hierarchy of intermediate data processing stages is employed with each MNO sending their map-counter Datasets (MCD). The MCD contains the number of MSs detected together with their corresponding map counters. Map-counter records for an MNO constitute the MCD datasets that are sent to a central entity and are denoted by S_m.

According to authors in [163], to estimate the total density D_T, optionally a union of all the individual MCDs is computed as

$$D_j = f(S_1, S_2, ...) = f(\bigcup_m S_m) \tag{2.8}$$

Where f is the data processing method kept and tracked by different Mobile Network Operators(MNOs) as illustrated in figure 2.10 below.

Conclusion

In terms of spatial and population coverage, this approach provides diversity across multiple MNOs. It also ensures the privacy of critical information

since map-counter records are aggregate data, not micro-data. Detection of people crowds will however be challenging because:

1. Mobile Stations today support more than just a single Subscriber Identity Module (SIMs). The approach will thus not give an accurate indication of the number of people in an area.

2. Mobile stations are either in idle or active state. Whenever an MS is in its idle state, it stays passive. And in its passive state and an MS will not transmit any signals, until there arise intentions to change to another cell. It is therefore difficult to have network detection of these nodes and hence people crowds.

3. Crowd density estimation involves the export of records between different Mobile Network Operators who may be governed by non-disclosure laws, on a business perspective this may be critical information to an organization.

2.3.4 People crowd detection in Train compartments.

The train transport network has over the past century been used as a relatively cheaper means of transport. As a result, trains that are made up of different compartments, sometimes get overcrowded. In addition, travellers only board and disembark from the railway station. To overcome this challenge crowd management via the ZigBee system was proposed by Prakash et al. [164]. It provided real-time information to passengers and managers

for proper planning and decision-making. The information provided among other things includes train running status and the estimated number of people in the train compartments.

Train Crowd Management is an example of the use of technology in providing information in advance to limit the effect of crow-related catastrophes.

This approach digitizes the mechanical system of a train to improve its effectiveness. It comprises a floor switch that is placed below the metal sheet of the train's compartment It is connected to the controller to give positive contact and eliminate the resistor from the circuit. This is the recommended way of handling power in newer electronic controllers. The Micro-switch is actuated by the physical environment i.e motion of the mechanical devices. A microcontroller 89s51 was used to transmit the information via ZigBee to the train station, where they are displayed on LCD monitors. The LCD monitors provide a visual impression of the state of the train compartments such as how crowded they may be and provisions that enable services like medical emergencies, theft or misuse notifications to passengers and the train management. Below, Figure 2.11 is an overview of the train side of the system.

Conclusion

Information provided in advance by the Train crowd management via ZigBee regarding the state of the train compartments to both the passengers and train management minimizes time wasted by passengers in locating free seats across the many compartments, while the train management team can

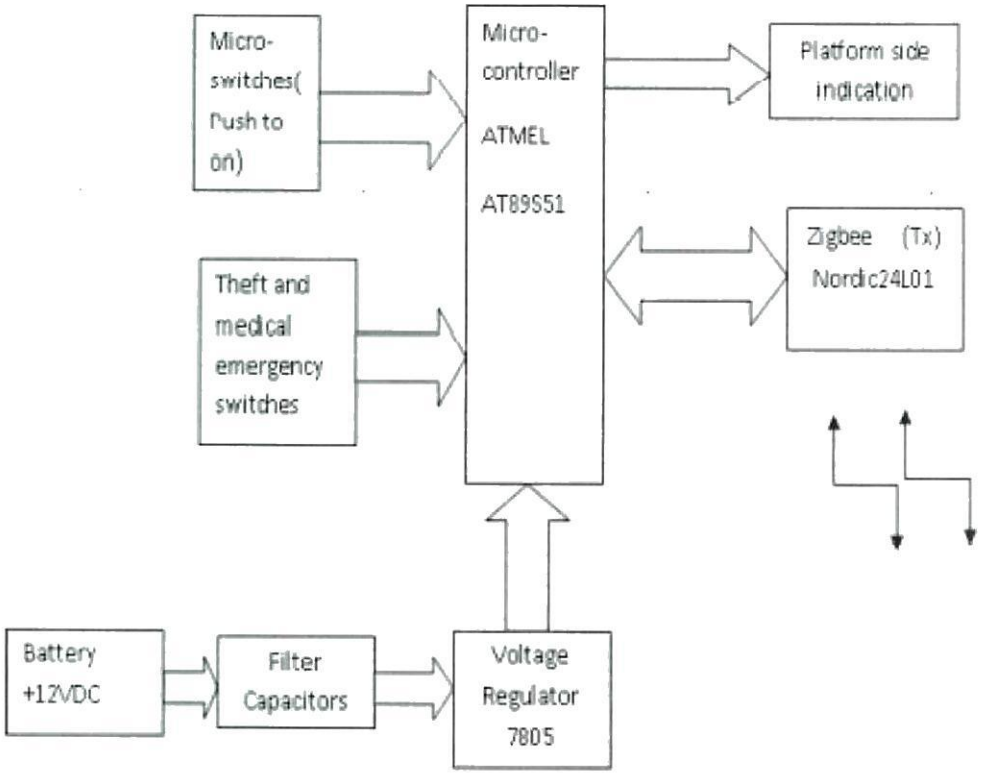

Figure 2.11: Train side components of the train management system using ZigBee

[164].

use them in making quick management decisions. The system is however considered complex and was initially designed for old-modelled mechanical trains.

Chapter 3

Research Methodology

3.1 Introduction

This chapter explains the research approach and strategy employed in understanding the research problem and exploring possible solutions to identified shortfalls.

There has been an ongoing philosophical debate among computer scientists concerning the methodological, ontological and epistemological questions. But computer science's greatest contribution is working with other scientists to find solutions in their various disciplines. Generally, research philosophies in computer science consider the ontology and epistemology of computational systems with a focus specifically on problems in problem specification, implementation and testing or verification. Guided by research questions and objectives discussed so far, the research methodology is borrowed from design

science research [165]. Design science addresses human problems through the creation of innovative artefacts. And Figure 3.1 below describes the research approach employed in this work.

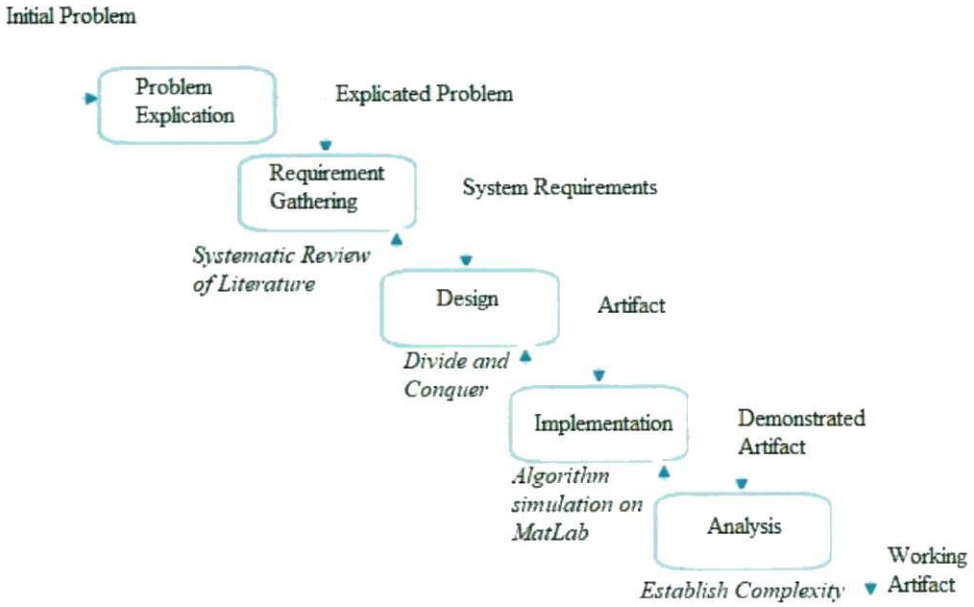

Figure 3.1: Research Methodology

Initially crowd problem was identified but later explicated as a people crowd problem. A requirement gathering was carried out to identify gaps in existing crowd-detection algorithms. This was followed by the design of algorithms based on the identified gaps, before implementation and analysis of the designed algorithms.

3.2 Requirement Gathering - Method for objective one

The first specific objective of this research was to identify existing algorithms for detecting people crowds and analyze the strengths and shortfalls of each. Below is how this objective was achieved.

The review was in the form of a background literature review. This was with the goal of not just delimiting the research problem and seeking new lines of inquiry, but also distinguishing between what has been done and discovering important variables relevant to the study. The review of the literature was broken down into the five major steps of searching, screening, full-text retrieval, data extraction and reporting [166]. Research questions informed the search strategy that involved a consideration of several academic journals published mainly in the past decade between 2010 and 2020, and a few before that. Initially, the review was on crowd-detection approaches where over 50 journal papers were reviewed. And given the unique nature of people crowds, the second stage narrowed the search to 8 journals related to people crowds detection algorithms. The review was performed to establish gaps and inconsistencies that may be found with existing crowd-detection algorithms. Overall, 85 literature sources that comprised electronic media, textbooks and appropriate information relating to people crowd detection were considered. The ultimate goal was to identify sufficient knowledge upon

which to conduct the research.

Requirement analysis involved defining and analyzing expectations of people crowd detection algorithms for resource-constrained environments. Factors requiring consideration for effective people crowd detection were presented. And the strengths and gaps of the current crowd-detection algorithms were meant to provide a basis upon which people's crowd-detection algorithms can be designed. In addition to identifying gaps in existing algorithms, requirement gathering involved determining methods and tools for crowd detection appropriate for environments with limited resources.

3.3 Algorithm Design

The second specific objective was to design algorithms for the detection of people crowds.

The main problem was broken down into smaller manageable problems and the problems were solved independently. As a result, the design approach employed was divide and conquer [167]. This approach breaks down the problem into specific workable sub-problems or tasks. The sub-problems are then 'conquered' by solving them recursively. Finally, the solutions to the sub-problems were combined to form an overall solution to the original problem.

The people crowd detection problem is broken down into smaller problems

of clustering, detection, routing, and fusion at the base station. This research focused mainly on the detection problem. And the algorithm design focussed on: problem description, analysis of the problem, development of a high-level algorithm, refining of the algorithm, and finally its review. As a first step, a description of the problem was formulated. During the second stage, the start and ending points of the problem were determined. And thirdly, high-level algorithms were formulated and finally reviewed. During each of these stages, an understanding of the dynamics of people crowds, and the environments for which they were designed was taken into consideration.

The divide and conquer approach supports parallelism and hence can allow developed algorithms to run on multiprocessor systems or different machines simultaneously.

3.4 Deployment of the developed algorithms

This research required the deployment of sensor nodes for the detection of people crowds. Because of expensive resource needs, the researcher simulated the detection of people crowds on simulation software. MATLAB is a programming platform designed specifically for engineers and scientists to analyze and design systems and products. MATLAB was chosen because:

- It allowed the researcher to generate random signals for analysis,
- It also supports the generation of code given the provided algorithms,

and

- MATLAB is a tested software that has been used by researchers over time.

3.5 Analysis of Developed Algorithms

The fourth objective of the research was to analyze the developed algorithms and to analyze their problem-solving capability in terms of space and time. To provide a theoretical estimation of the developed algorithms, the computational complexity theory was established. Complexity estimates the required resources for an algorithm to solve a defined task. Time complexity compares the effect of increasing input to an algorithm to the time required to accomplish the defined task, while space complexity relates the effect of increasing the input to the volume of memory required. Both time and space complexity are important, the best of each cannot however be achieved simultaneously. The choice of complexity depends on the situation and the need. For this reason, this research placed more emphasis on time complexity with the assumption that 1) for the development of applications and systems, developers will be more concerned about how first a request is serviced than how much space is required and 2) technological development has improved storage capabilities and yet many embedded systems have fixed hardware memory.

This work received approval from National Council of Science and Technol-

ogy. The approval letter can be found in Appendix E as Figure E.1

Chapter 4

Research Results

4.1 Introduction

This chapter presents a discussion of the details and f of the respective specific objectives in the research. The specific objectives were as follows: Reviewing current crowd detection algorithms, design of people crowd detection algorithms, simulation of people crowd detection algorithm and, analysis of the designed algorithm.

4.2 Crowd Detection Approaches

In Section 2.2, the different crowd detection approaches other than in the area of computer vision were presented. Despite their respective strengths, they were found to a good extent lacking as shown in Table B.1 under Appendix

B.

4.3 Crowd Detection Algorithms

The first objective was to identify the existing algorithms for the detection crowds and specify their capabilities and shortfalls in terms of the environment for which they were designed.

The ultimate objective was to determine whether existing crowd detection algorithms can effectively be deployed to detect people crowds. The algorithms were compared about how they measure up with parameters that have been considered invaluable in people crowd detection. From this research findings, several parameters that ensure effective people crowd detection were identified. These include;

1. *Ability to detect people crowds.* The algorithms examined were mainly non-people crowd detection algorithms with the ability to detect non-people crowds such as flocks, birds, and among other things vehicles. Most of these targets however are far less intelligent compared to human beings who are capable of bypassing detection.

2. *Outdoor deployment.* Although crowds can originate indoors, most crowd-related incidences are outdoors. It is therefore worth giving attention to outdoor crowd detection. Algorithms such as people counting algorithms only do the counting and are designed for indoor settings.

These are therefore considered less than appropriate for outdoor people crowd detection.

3. *Real-time Detection.* Within a relatively short time, crowds can run out of control. For this reason, is important to detect the crowds in advance. A real-time detection algorithm should be able to detect, predict and promptly report the existence or potential for a crowd build-up.

4. *Guaranteed participation.* For purposes of reducing costs incurred in providing incentives, and increasing trust in generated data, algorithms guaranteeing participation are preferred.

5. *Granularity.* Granularity provides a fair level of detail that enables the achieving of accurate results with less of false alarms.

Table 4.1 below is a comparative analysis of selected crowd detection algorithms.

Table 4.1: Comparative analysis of Crowd Detection Algorithms

No.	**Algorithm**	**Objective of the algorithms**	**Guaranteed Participation**	**Support for Outdoor**	**Granularity**	**Real-time**	**People Crowd-Detection**
1	Distributed People Counting-Algorithms using PIR Sensors	People Counting	Yes	No	Yes	Yes	No
2	Crowd Density Estimation Using Wireless Sensor Networks	Crowd density estimation	Yes	No	No	Yes	No
3	Crowd Density Estimation Using Cellular Phones	Crowd density estimation	No	Yes	Yes	Yes	No
4	Train Crowd Management Via ZigBee	Visualizing crowded compartments	Yes	No	Yes	Yes	No

- *The Distributed People Counting Algorithms Using PIR Sensors.* The People counting algorithm is a people counting algorithm capable of operating only under manageable indoor settings where entry and exit

points can be determined well in advance. Given the spontaneous nature of people crowds, it may not be practical in predicting and detecting people crowds.

- *Crowd Density Estimation Using Wireless Sensor Networks.* This approach did not necessarily put into consideration all aspects of people crowds such as in resource-constrained environments. In addition, it was initially designed for indoor application.

- *Crowd Density Estimation Using Cellular Phones.* The use of cellular phones requires that the phone be switched on. This will not be practical for intelligent humans who will opt out by switching off their phones or even leaving them behind during major events should they get to know of a possible tracking. People crowd detection here is also inaccurate in situations where phone subscribers possess multi-sim phones or carry more than one phone.

- *Train Crowd Management via ZigBee.* This approach is implemented in a well-managed indoor environment and cannot predict the formation of people crowds

Conclusion

Based on the results presented in Table 4.1 above, several works have been done in people counting and non-people crowd detection. Their algorithms have been developed with varying strengths and shortfalls. And as presented

in the table, they have been deployed mainly for non-people crowds and cannot effectively measure up to the requirements for people crowd detection. People crowd detection requires support for outdoor deployment, guaranteed participation and real-time support.

4.4 Algorithms for People Crowd Detection

This section addresses the second research objective of designing a people crowd detection algorithm. First, the design requirements for the detection algorithms. The design objective was mainly to come up with algorithms for people crowd detection in resource-constrained environments, especially in developing economies. The unique challenges therein relate to the dynamic nature of people crowds in developing countries and the shortfalls of WSNs. Limitations of WSNs have been highlighted in literature and they include dynamic topology, limited data rates, different traffic intensities, application-specific networking, energy constraints and time synchronization [75]. It is also evident that people crowds in developing countries can turn out to be both hard to control and violent. These factors emphasize the need for special attention in the design of people crowds detection algorithms in resource-constrained environments. In this section connectivity, scalability, security, performance and resource utilization are all discussed in the context of developing economies.

4.4.1 Design Requirements for People Crowd Detection

In WSNs, sensor nodes are deployed to collect data about a physical phenomenon in an ROI when deployed in an ROI. If not properly designed, they can turn out to be resource intensive, inefficient and insecure. In designing the people crowd detection algorithms the following factors were taken into consideration.

Connectivity. Although WSNs can work autonomously, for many applications, they require connectivity to either a Local Area Network (LAN), Metropolitan Area Network (MAN), global Internet or application-specific gateways to route sensor data for remote analysis. The Internet of Things (IoT) is a moving force for technology and describes an interconnection of objects and people embedded with sensors and software to exchange data. Integration of WSN applications to IoT has been seen as an enabler to achieving the apical of many applications. It is therefore inevitable. However, IoT is mainly implemented on TCP/IP, which has been perceived to be too resource-intensive for WSNs. This has inspired work in several enabling technologies that include:

- 6LoWPAN Gateway has been proposed to enable integration with IP

version 6. IPv6 is a fast emerging addressing protocol to mitigate IPv4 address exhaustion [76].

- Tiny TCP/IP is a configurable protocol stack that is known to occupy only a few kilobytes of code space and a few hundred bytes of memory space. It has therefore been proposed as an alternative to a fully-fledged TCP/IP [77].

- Micro SOA-model [78] is a model designed to integrate WSNs onto IP-based Networks or the Internet. It uses Mobile IP (MIP) and has been implemented to enable the movement of mobile devices across different networks while maintaining their IP addresses. It thus simplifies IP address management.

- Compression of XML and JSON messages reduces the resource overhead for devices with 48 KB of ROM and 10 KB of RAM.

- Spatial IP addressing [79] leverages the ability of sensor nodes to determine their location through localization which eliminates the extra overhead that would be required in address assignment. While header compression techniques, compress header information using simple pattern matching techniques in addition to utilizing only a small number of UDP ports for sensor datagrams. Application overlay routing reduces routing overhead by enabling attribute-based routing, while distributed TCP cashing (DTC) instead of relying on TCPs' resource intensive end

to end retransmission, requires only a local retransmission scheme to reduce energy consumption [80].

Overall, for relatively less developed economies, the fraction of the budget allocated to different government sectors cannot be relied upon to effectively provide all intended services. Connectivity options that minimize costs will logically be the ones of choice.

Scalability. A WSN is scalable if it can self-configure, is robust to topological changes and can easily accommodate additional sensor nodes. Scalability in WSNs has an integrated view that encompasses both software and hardware. Software scalability involves reliability in command dissemination and management of large volumes of data transfer and algorithms for their analysis. Hardware scalability on the other hand is determined by hardware capability to support network growth over time without necessitating replacement. It is dependent on the sensitivity and range of MEMS sensors, power usage and communication bandwidth of the radios. Hardware scalability is especially critical for environments realizing frequent environmental modifications. Recent works on the scalability of WSNs include Scalable Zigbee expansion solutions and efficient routing algorithms [81, 82]. These solutions, when incorporated into sensor networks, enable an increase in coverage that is inevitable for the ever-expanding urban cities and present opportunities for the detection of bigger numbers of people crowds.

Performance. The performance of a WSN is the measure of how well it runs and meets its intended objectives. It is evaluated based on several criteria. Optimizing network performance is necessary for reducing energy consumption in addition to network redundancy. To optimize performance, therefore, WSN designs and deployment aim at attaining the following:

- Minimizing energy consumption,
- Increasing node lifetime,
- Extending coverage, and
- Minimizing the number of nodes required.

Several techniques have been employed to achieve the above aims to enhance WSN performance and they include:
Clustering is a WSN topology management which involves the grouping of sensor nodes into clusters and electing a cluster head for each cluster, through which all traffic originating from the cluster is forwarded. Cluster-based WSNs provide more efficient network communication, allow for better topology management and hence are more energy efficient. Several works have been carried out in clustering. For example, work has been carried out in clustering of WSNs to increase network life span and minimize energy waste [83]. To improve network performance in people crowd detection, an

urban city can be subdivided into manageable clusters with respective cluster heads.

Also, critical to network performance, are the routing algorithms implemented. Provisioning of energy-efficient routing algorithms is inevitable in minimizing, packet loss, ensuring an end-to-end delivery and minimizing energy consumption proposed [84, 85]. There have also been efforts to make use of multiple paths [86], consider dynamics of the link between the source and destination [87], a combination of clustering and sink mobility [88] and employing type1 and type 2 fuzzy logic to minimize the burden imposed on cluster heads [89].

Formulations that will help achieve the above-listed objectives, compete with each other and only a trade-off solution can be achieved. For example, simple aggregation protocols may only be deployed in attack-free environments. The routing algorithm implemented will be highly dependent on the purpose of the detection.

Security. Secure communication capabilities are a key factor in most wireless communication including WSNs. Security of WSNs is different depending on the specific application of the network. For example, the security requirement for habitat monitoring can not be the same as that for crowd detection. However, they all try to adhere to the standard requirements of Confidentiality, Integrity, Authentication and Availability (CIAA). Although WSNs are considered self-healing, self-organizing and autonomous, the increased number of

WSN applications and requirements for data communications means sensor data can be vulnerable to several emerging network attacks. The limitations of computational capacity, limited energy, communication and memory of sensor nodes make it difficult to fully implement traditional security and privacy measures. In addition, the application of WSNs now extends beyond enclosed controllable environments. As a result, they can be vulnerable to attacks both on the communication channels and at the node level. Dener in his work classified these attacks as physical, link, network and transport layer attacks [90]. Given the critical nature of many sensor network applications, there is a need to address security issues associated with WSNs at all layers [91]. Ongoing work in the security of WSNs includes the design of low-cost sensors that are resistant to harsh environments, and fast and secure data flow. And existing security solutions in WSNs include the use of Encryption schemes, security protocols and Certificate less Effective Key Management (CL-EKM). While the focus on node-level solutions has aimed at minimizing unauthorized data injection during data aggregation and anomaly detection.

Encryption constitutes one of the most common tools used in the provisioning of security services in computer networks. The small memory, limited energy, and weak processors of wireless sensor nodes and the harsh environments in which nodes are deployed present problems in the implementation of traditional encryption schemes. Several encryption schemes have been proposed over time. Data Encryption Standards is a block cypher algorithm

that takes the plain text in blocks of 64 bits and converts them to ciphertext using keys of 48 bits. Its variants 3DES, DES-X were designed to counter the shortfalls of DES [95]. The Advanced Encryption Standard (AES) with 128, 192 and 256-bit sizes. And was considered more secure. The algorithms have however also been found to be vulnerable to various Differential Fault Analysis (DFA) [92, 93, 94] and are considered relatively slow. The blowfish algorithm is a symmetric-key block cypher that was designed to replace the DES. It was intended to provide a fast alternative to DES. And its complex key schedule makes the algorithm stronger. Compared to DES, it is secure for small-scale applications [96]. However, like DES, Blowfish is not a good fit for large-scale deployments. A trade-off option has to be taken.

Because WSNs are resource-starved, some researchers have resorted to trying to develop improved WSN protocols. Security protocols define the set of rules that determine how processes interact to provide a given security service [97]. And the goal of security protocols includes low power consumption, small code size and minimal computational complexity. Popular WSN security protocols include:

- Security Protocols for Sensor Networks (SPINS). It uses Sensor Network Encryption Protocol (SNEP), and μTESLA to provide for confidentiality and authenticated broadcasts in severely resource-constrained environments. SNEP has low communication overhead because it adds only 8 bytes per message, does not transmit counter values, offers au-

thentication and prevents eavesdropping. TinySec was designed as an improvement to the unfinished SNEP. TinySec is a link layer security protocol for WSNs implemented in the TinyOS release. It balances the trade-off between transparency, performance and security. TinySec also guarantees message authentication integrity and confidentiality. On the other hand, because of the resource limitation of sensor networks that prevent the implementation of traditional security mechanisms, μTESLA is a variant of TESLA that was proposed to mitigate the shortfalls of TESLA for application in WSNs. TESLA was designed for asymmetric communication and presents a costly alternative for WSNS. It stores one-way key chains and discloses a key for every packet. μTESLA uses a Message Authentication Code (MAC) together with a secret key to validate broadcasts.

- Location Encryption and Authentication Protocol (LEAP+) [98] - A key management protocol that supports four types of keys for each sensor node – a key shared with the base station, a pairwise key shared with another sensor node, a cluster key shared with multiple neighbouring nodes, and a global key shared by all the nodes in the network.

- Elliptic Curve Cryptography (ECC) is used in resource-constrained WSNs and at the same time information processing is required. A self-organizing algorithm using ECC consisting of certificate creation and hybrid key establishment to prevent impersonation-related attacks.

EEC is a key-based technique that uses pairs of public and private keys to decrypt and encrypt traffic respectively.

- MiniSec is a secure network layer protocol designed to ensure the security of WSN with minimum energy consumption. MiniSec uses an Offset Codebook (OCB) to offer authenticated encryption with only one pass over the message data instead of two passes for authentication and secrecy. It has two operating modes - single-source and multi-source broadcasts. A strong point with MiniSec is that it does not require padding because the ciphertext and plain text are all of the same length. It also minimizes transmission overhead because of strong replay protection and no need for the exchange of large counters.

- Link Layer Security Protocol (LLSP) [99] is an energy-efficient security protocol that provides for message authentication, access control and replay protection. It minimizes energy consumption while ensuring security. Its functionality has been compared to popular data link layer security protocols such as TinySec. It also employs Advanced Encryption Standards (AES) and Message Authentication Code (MAC) with Cipher Block Chaining (CBC) for message authentication. LLSP uses Feedback Shift Register (FSR) to minimize the overhead of forwarding counters with each packet while the authentication code of 4 bytes makes it harder to achieve the right MAC.

- ZigBee coordinates and distributes keys to devices requesting to join the

network. It plays the role of trust management that performs authentication, and network management for maintaining and distributing keys and configurations to enable end-to-end security. To provide appropriate security, ZigBee operates in residential and commercial modes for basic security in homes and commercial modes for high-security commercial applications.

- C-Sec Protocol has been considered the protocol of choice because it reduces energy consumption and because it hides header information, which makes it difficult to track the packets. The security algorithm is implemented in hardware and as a result, it is much faster. It also employs an efficient and secure AES-CFB encryption algorithm.

Certificate less effective Key Management (CL-EKM) is a public key-based scheme proposed for WSNs [100], while the Enhanced Certificate less Effective Key Management (ECL-EKM) was proposed to solve the management problems associated with both the symmetric and asymmetric key based schemes [101]. Certificate less key management schemes are designed to eliminate the need for certificate-based public key distribution and counter single point of failure characteristic of traditional key management schemes. These traditional schemes may find challenges when implemented for dynamic networks such as WSNs.

The current state of urban streets and road users in developing economies exposes sensor nodes to destruction and attacks by adversaries or disgruntled

individuals. While the exposure of sensor nodes makes them prone to false data injection and physical attacks. Data aggregation algorithms, therefore, need to be both efficient and resilient against compromise.

Resource Utilization. Nodes in WSNs are inherently resource-constrained in terms of communication bandwidth, processing speed and storage capacity. As a result, several approaches have been proposed to tackle the energy consumption problem of battery-powered nodes. These approaches include: radio optimization, data reduction, sleep/wakeup schemes, energy-efficient routing and energy repletion [102, 103].

Radio optimization approaches attempt to reduce energy dissipation resulting from wireless communication. To do this, research efforts have been invested in modulation schemes [104], power transmission [105, 106] and antenna direction [107, 108, 109].

Data reduction minimizes data that could have otherwise been delivered to the sink. Unnecessary samples and sensing tasks are reduced through appropriate aggregation schemes [110], data compression [111, 112, 113], network coding [114] and adaptive sampling [115]. In addition to reducing data traffic, these efforts also result in reduced network latency.

Sleep/wakeup schemes schedule radio state depending on network activity, while topology controls deploy redundant nodes to ensure space coverage. Some nodes of the WSN are deactivated while ensuring normal network coverage. This scheme is appropriate for networks that do not require the

activation of all nodes at the same time. Passive wake-up radios enable power-hungry nodes to be used for data transmission only.

Very important to the design of wireless sensor networks is network topology. For example, the determination of which sensor nodes should be closest to the sink. This is because nodes closest to the sink route have more traffic than any other on the WSN and hence have a higher energy depletion rate. Energy efficient routing protocols [116, 117] mitigate this challenge through the implementation of cluster architectures for both heterogeneous and homogeneous WSNs [118, 119]. When energy is used as a routing metric during route selection, preference can be given to sensors with more energy [120]. Other measures such as multipath routing [121], sink mobility [122], and relay node placement [123] can all be employed to improve network performance. Battery charging mechanisms have also been proposed to enable recharging of sensor batteries without human intervention [124]. Wireless charging makes possible wireless transfer of power between devices. The technique employs either electromagnetic radiation (EM) or magnetic resonant coupling. Magnetic coupling has been considered one of the most promising because of its higher efficiency with short ranges of several meters. Wireless charging fits the need for sensor deployments where it may not be possible to regularly have a physical connection with the nodes such as where nodes are embedded under concrete or below-ground surfaces.

Accuracy. The need for precision in many applications has inspired research

into the accuracy of positioning algorithms in WSNs. Node localization is for example used in determining the location of a node or subset of nodes. Published literature highlights the shortfalls and strengths of traditional positioning and localization algorithms. Traditional localization mechanisms include: Time of Arrival (ToA) [125], Time Difference of Arrival (TDOA) [126], Angle of Arrival (AOA) [127] and Received Signal Strength Indication (RSSI) [128]. RSSI algorithms have been considered the simplest and most cost-effective of the range-based positioning algorithms because it does not require additional dedicated hardware [129, 130]. RSSI-based approaches, however, trade off accuracy for low complexity and power saving.

Conclusion Their priorities will vary according to the different WSN applications. For instance, reliability might be critical for security-sensitive environments such as in the military and health where confidentiality is very essential. While traffic management may opt for speed than accuracy.

The designed algorithms include the people crowd detection algorithm in appendix A.1 and MATLAB detection algorithms (Appendix A.2).

The people crowd detection algorithm used frequency as the main parameter. A frequency range of 1.4 to 2.4Hz was used to emulate the frequency generated by people crowds. And any frequencies within the defined ranges are investigated to confirm the existence of people crowds.

The MATLAB people crowd algorithms were used in signal generation, converting received signals into their frequency components and detection of received frequency.

4.4.2 People Crowd Detection Algorithms

People crowd detection using wireless sensor networks encompasses detection of the people crowds by individual sensor nodes, routing of sensor data from the various nodes to the sink and data aggregation and fusion at the sink. This section describes the working principles of the detection algorithm together with the other supporting algorithms. The working principles in connectivity, coverage, connectivity and fusion are explained.

The detection problem is about how to determine the existence of people crowds in a Region of Interest (ROI). The choice of the detection algorithm is especially critical for regions with limited resources and where crowd movement is known to be spontaneous. In addition, people crowds are sometimes violent and hence the need to implement secure systems. To do this, the algorithm is implemented in underground sensor nodes. The sensor nodes are deployed to receive vibrations signals generated by people crowds, from which the various frequency components are obtained and used as a basis to predict the existence of people crowds.

4.4.2.1 Signal Generation Algorithm

This work involved designing algorithms for the generation of random signals, decomposition of received vibration signals into their frequency components and determination of whether the signals are within a specified range. All these algorithms are attached in Appendix A.2.

To generate random signals, MATLAB-enabled features were used to take

only the absolute values of the amplitude.

Signal Generation Algorithms

$$t = 0 : 0.001 : 5;$$

$$S_{max} = 15;$$

$$S_{min} = -15;$$

$$S = S_{min} + (S_{max} - S_{min}) * rand(1, length(t));$$

Where S_{max} was the maximum signal amplitude

4.4.2.2 Signal Decomposition Algorithm

To enable analysis, the generated ground signals had to be decomposed into their frequency components. Fourier transform is an algorithm that has been used by engineers and scientists to develop solutions to human problems. It decomposes a function into different components. Fast Fourier Transform (FFT) algorithm is a MATLAB-enabled version of the Fourier transform.

FFT was used to break the received signal into frequency components that were necessary for the analysis of the signals. This was done as shown below. Signal Decomposition Algorithm

$$F_s = 1/0.001$$

$$N = length(s);$$

$$Frequency = (0 : \frac{N-1}{N} * F_s;$$

Where F_s is the sampling frequency.

4.4.2.3 Detection Algorithm

People Crowd Detection(PCD) Algorithms

INPUT: Input signal $X(t_i)$, at time $t_{(i)}$ for all $i = 1, 2, ..., n$.. And l_i is the length of the signal.

OUTPUT: Frequency f_j for all $j = 1, 2, ..., n$.

Step 1: [Initialize $X(t_i)$]

Let $X(t_i)$ be Received Signal from a People Crowd.

Step 2: [By means of FFT, decompose $X(t_i)$ into the different Frequency

Components]

for $(X(t_i),\ 1 \leq i \leq n,\ i++)$

$f = fft(X(t_i), l_i)(\frac{2}{l_i})$

Step 3: [Analyze the Signals using the Frequency Components]

elseif $(f_j < 1.4)$

No Evidence of People Crowd

If $(1.4 \leq f_j \leq 2.4)$

Possibility of People Crowd Existence

elseif $(f_j \geq 2.4)$

Investigate Type of Crowd

Step 4: Return to Step 1

To detect people crowds, the developed PCD algorithm has to work in collaboration with other algorithms. Below is a description of the minimal requirements for the implementation of the PCD algorithm in people crowd detection.

4.5 Implementation and Simulation

This section presents a detailed description of the simulations and corresponding results generated. It is the result of the fourth objective of simulating people crowds detection. The details are as follows:

Harmonic waves are represented as a sine or a cosine function. For example Figure 4.1 below is a graph of the function $y(t) = Asin(2\pi\ ft + \varphi)$, where

f is frequency of the wave, φ is the angular velocity of the wave and time is t. The relationship between frequency and wavelength λ is such that $f = \frac{1}{\lambda}$

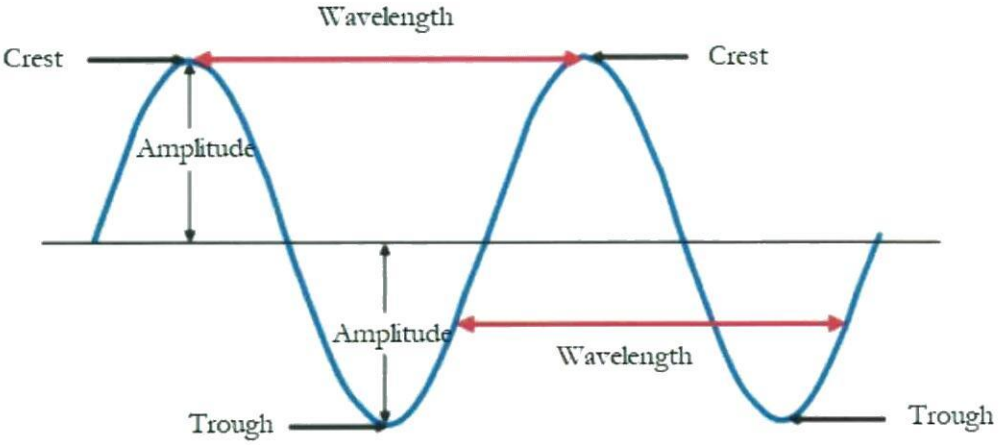

Figure 4.1: Wavelength, Amplitude and Frequency of a Wave

On the other hand, however, periodic waves such as vibrations generated by human movements 4.2 that are detected by can only be represented as a combination of multiple sine and cosine functions. For analysis purposes, therefore, the random signals generated were broken down into their harmonic components using a Fourier transform as shown in Equations 4.1 and 4.2 below.

$$X(t) = \frac{a_0}{2} + a_1 cos\omega t + a_2 cos2\omega t + ... + b_1 sin\omega t + b_2 sin2\omega t + ... \quad (4.1)$$

$$X(t) = \frac{a_0}{2} + \sum_{alln}(a_n cosn\omega t + b_n sinn\omega t) \tag{4.2}$$

Where:

$a_0 = \frac{\omega}{\pi}\int_0^{\frac{2\pi}{\omega}} x(t)dt = \frac{2}{\tau}\int_0^{\tau} x(t)\ dt$

$a_n = \frac{\omega}{\pi}\int_0^{\frac{2\pi}{\omega}} x(t)\ cos\ n\omega t\ dt = \frac{2}{\tau}\int_0^{\tau} x(t)\ cos\ n\omega t\ dt$

$b_n = \frac{\omega}{\pi}\int_0^{\frac{2\pi}{\omega}} x(t)\ sin\ n\omega t\ dt = \frac{2}{\tau}\int_0^{\tau} x(t)\ sin\ n\omega t\ dt$

Most literature on vibrations generated by people crowds have been in indoor environments. Related work has however been provided regarding the clas-

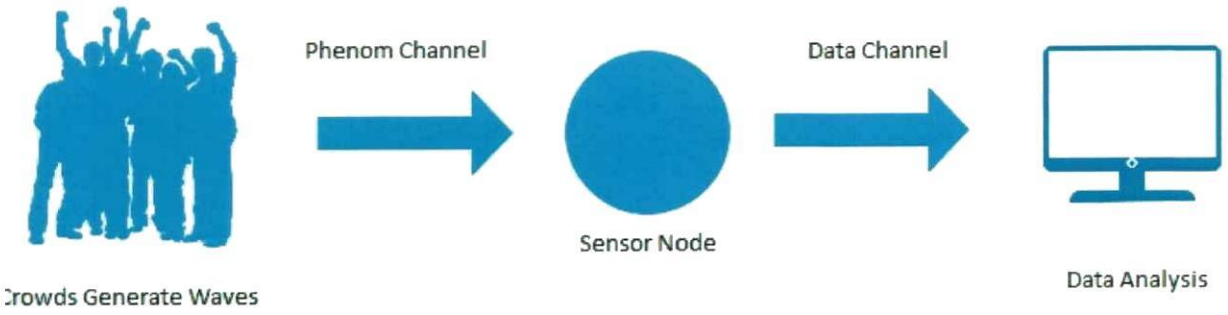

Figure 4.2: The process of ground detection from ground vibration

sification of vibrations resulting from basic human activities in stadiums as shown in Figure 4.3 below. This has been used in this work, the algorithm, however, provides the flexibility to adjust these values as new findings come out from the research. The figure shows that matching generates frequencies in the range of 1.4 to 2.4 Hz. Frequencies above this range represent more activity and can therefore still be analyzed for the existence of people crowds. In this research, therefore, the detection of people crowds is based on frequencies above 1.4Hz, while the amplitude shows the strength of the signal.

Type of activity	Full range Hz	Slow, Hz	Average, Hz	Fast, Hz
Marching	1,4-2,4	1,4-1,7	1,7-2,2	2,2-2,4
Run	1,9-3,3	1,9-2,2	2,2-2,7	2,7-3,3
Jumps	1,3-3,4	1,3-1,9	1,9-3,0	3,0-3,4

Figure 4.3: Classification of basic human physical activity [148]

4.5.1 Simulation Set up

Matlab is a matrix-based language that supports vectors and matrix-based operations that are fundamental for solving scientific and engineering-based problems. It enables matrix manipulation, plotting of functions, implementation of algorithms and interfacing with programs written in different languages. It has as a result been used by researchers in designing and analyzing systems and products. Although primarily intended for numeric computa-

tions, additional toolboxes and packages allow for multi-dimensional simulation and model-based design for dynamic and embedded systems.

Underground Wireless Sensor Networks employ three types of communication: underground to over ground, underground to underground and above ground to underground communications. An Underground Wireless Sensor Network (UWSN) is suggested because it addresses the security concern of node exposure. Challenges of node security and deployment complexity associated with people crowds detection in developing countries can be mitigated since the sensing nodes are out of view of the crowds. And deployment of UWSNs is relatively easy. They are also less affected by interference. A clustered WSN communication is preferred because, in addition to other advantages of clustering, it presents an opportunity for the subdivision of the ROI into manageable sectors. Network topology defines how various nodes, devices, and connections on a network are physically or logically arranged. WSNs support topologies that include: bus, star, ring, circular, meshed and grid topologies. The Grid topology has been considered an appropriate topology because it is energy efficient and its design enables functionalities with minimal maintenance requirements [150].

Localization in WSNs helps determine the location of sensor nodes. Work has been done to design, scalable, and efficient localization schemes [151, 152, 153, 154]. Time of Arrival (ToA) and Time Difference of Arrival (TDoA) is localization approaches that have high accuracy, high complexity, time synch and high power. On the other hand, RSSI-based estimators provide

low complexity, no time for synchronization, and low power but with low accuracy. Therefore whenever accuracy is not critical, RSSI is an approach of choice. With regAboutment considerations highlighted in Section 3 above, Tiny TCP/IP requires only a few kilobytes of code space and memory since existing infrastructure already supports the TCP/IP model.

Overall, the architecture takes into consideration the limited infrastructural resources that are characteristic of many developing economies. It also provides for scalability to allow later modifications and expansion since the extension of the WSN requires only minimal physical connectivity to the existing deployment. In addition, because UWSNs have most of the infrastructure underground, vulnerabilities resulting from exposure to sensing infrastructures are minimized. As a result, therefore, the proposed WSN presents a step towards achieving efficient detection of people crowds in resource-constrained environments.

To emulate ground vibrations generated by people crowds in an ROI, Matlab was used to generate random signals. Also for purposes of better visualization, three signals were later specifically generated and analyzed. Using Matlab's Fast Fourier Transform, the signals were transformed into the frequency domain for further analysis. The frequency range identifying people crowds was then visualized or filtered out as an indicator of people crowd presence. The Matlab algorithm can be found in Appendix C.

5.2 Simulation Parameters

atlab was used to simulate the people crowd detection algorithms. And generalization of the people crowds detection system deployment using SNs is illustrated in Figure 4.4 below. The goal was to design algorithms resource-efficient detection systems. The simulation parameters for de- tion, LEACH routing protocols and setup are as shown in Tables 4.2 and gure 4.3 below.

Table 4.2: Simulation parameters for Detection Algorithm

Parameter	**Value**
Frequencies	10, 8, 6
Amplitudes	6, 4, 2

Table 4.3: Simulation parameters for LEACH Protocol

Parameter	**Value**
Number of Nodes	50
Network Size	100 X 100
Location of Sink Node	150 X 150
Initial Energy of Normal Node	1 nJ
Probability of Cluster Head Selection	$5X10^{-2}$
Transmitter Energy per Node, E_{T_x}	$5X10^{-8}$ nJ/bit
Transmitter Energy per Node, E_{R_x}	$5X10^{-8}$ nJ/bit
Data Aggregation Energy, (E_{D_A})	$5X10^{-9}nJ/bit$
Amplification Energy(Efs) when $d < d_0$,	$1X10^{-11}$
Amplication Energy(Emp) when $d > d_0$	$1.3X10^{-15}$

Figure 4.5 and Figure 4.6 below are results of the simulation and show signals received and their absolute frequencies respectively. Performing a Fourier transform on the signals' allows for analysis of the signal's frequency component.

For physical implementation, node specifications are attached as Figure C.1 in Appendix C.1. The specifications in addition to the already discussed configuration parameters, highlight the major considerations when choosing between sensors from different sensors.

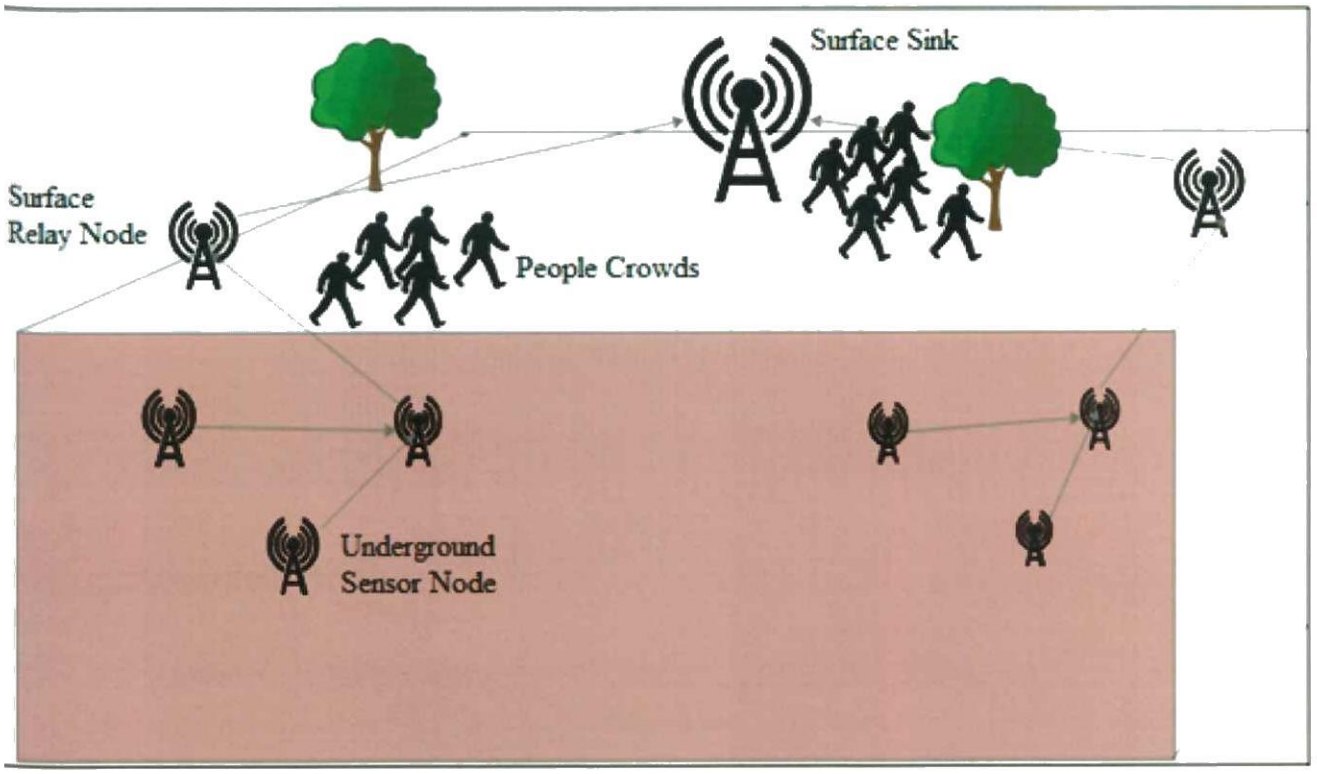

Figure 4.4: Underground deployment of WSN for People Crowd Detection

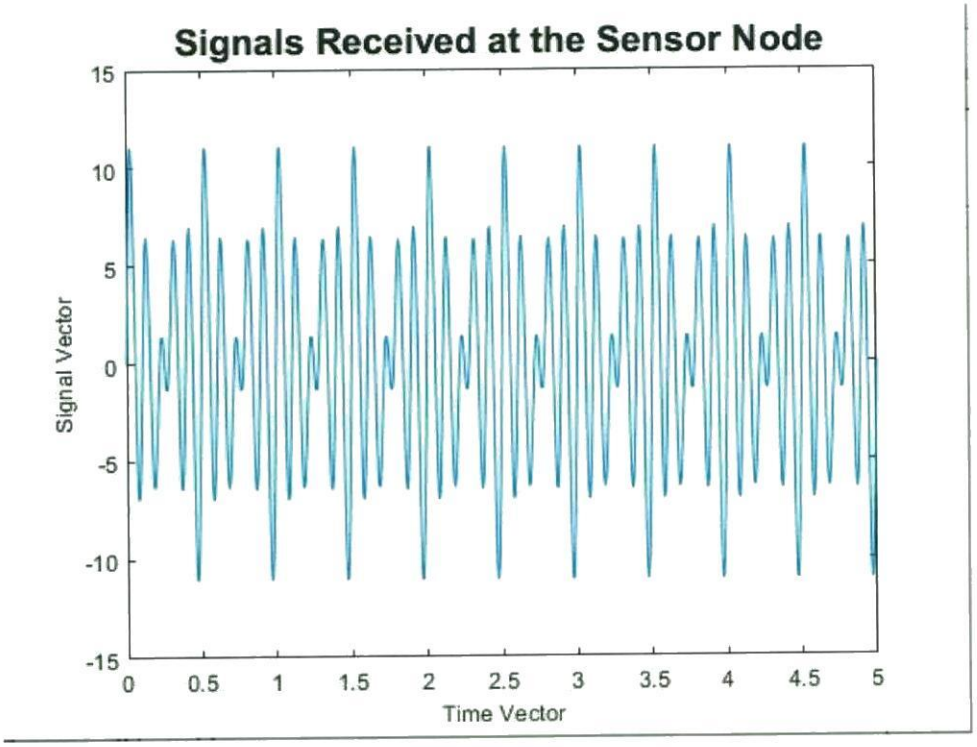

Figure 4.5: Signals received at the node.

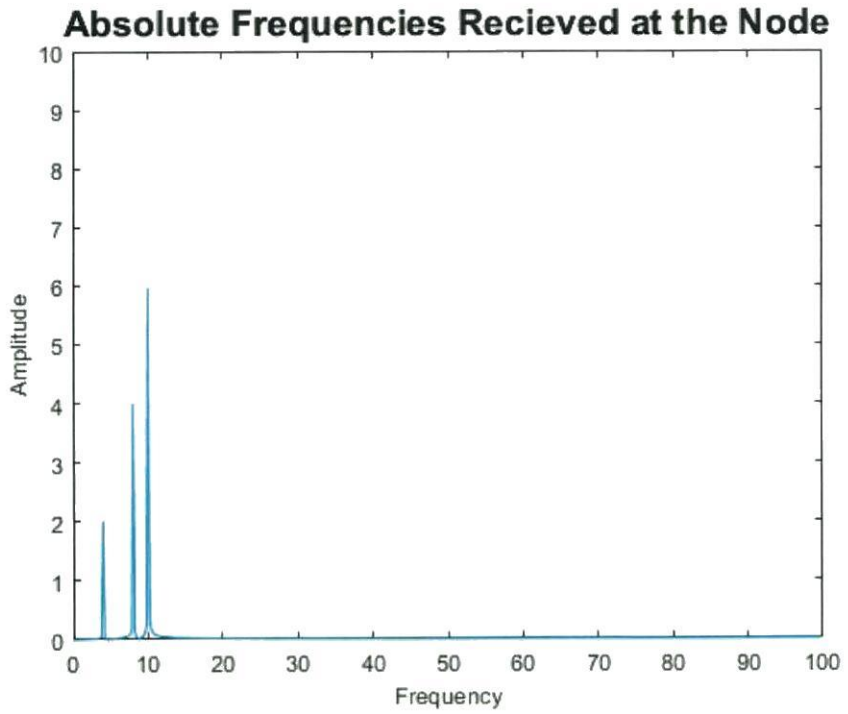

Figure 4.6: Absolute frequencies of signals received at the node.

4.6 Algorithm Analysis

The fourth objective of this research was to analyze the developed algorithms. To do this, the way the time is taken to run a task varied with increasing output was examined. This relationship is referred to as complexity.

Algorithmic complexity is a measure of how long an algorithm would take to complete given an input of size N. Complexity is usually in terms of time or space. In this work, time complexity has been used. Time complexity signifies the total time required for a program to run to completion. It provides an understanding of the best (Big ω), worst ($Big\ O$) and average(θ) run times of an algorithm.

The Big-O of a function $T(n)$, which is sometimes referred to as its upper bound and was opted for in this research, is given by:

$$O(f(n)) \tag{4.3}$$

$$iff, T(n) \leq C * f(n)$$
$$\forall\ n \geq n_0.$$

Where C is a constant and n_0 is the initial value of n.

The computed big O for the developed algorithm was for purposes of comparing it with future developed similar algorithms. And the rules used in coming up with the big-O notations were:

- All constants were ignored;
- Low-order terms were ignored when dominated by high-order terms;
- All constants, assignments and arithmetic operations, each had a big-O of 1.

Below are the worst-case runtimes of the designed algorithms.

Signal Generation Algorithms

$t = 0 : 0.001 : 5;$

$S_{max} = 15;$

$S_{min} = -15;$

$S = S_{min} + (S_{max} - S_{min}) * rand(1, length(t));$

Signal Decomposition Algorithm

$F_s = 1/0.001$

$N = length(s);$

$Frequency = (0 : \frac{N-1}{N} * F_s;$

Detection Algorithm

INPUT: Input signal $X(t_i)$, at time $t_{(i)}$ for all $i = 1, 2, ..., n$.. And l_i is the length of the signal.

OUTPUT: Frequency f_j for all $j = 1, 2, ..., n$.

Step 1: [Initialize $X(t_i)$]

Let $X(t_i)$ be Received Signal from a People Crowd.

Step 2: [By means of FFT, decompose $X(t_i)$ into the different Frequency Components]

for $(X(t_i),\ 1 \leq i \leq n,\ i++)$

$f = fft(X(t_i), l_i)(\frac{2}{l_i})$

Step 3: [Analyze the Signals using the Frequency Components]

If $(f_j < 1.4)$

No Evidence of People Crowd

elseif $(1.4 \leq f_j \leq 2.4)$

Possibility of People Crowd Existence

elseif $(f_j \geq 2.4)$

Investigate Type of Crowd

else

Return to step 1

Applying the rules above, to the designed algorithms, the Big O of the designed algorithms O(n). This shows that the performance of the algorithms is relatively reliable although they can still be improved.

And the complexity of the algorithm is n.

Chapter 5

Discussion of Results

Introduction

This section presents a discussion of the results obtained from this research which are presented below according to the specific objectives of the research.

5.1 Review of Literature on Crowd Detection

This work examined literature, especially within the past decade and a few and later than then. It involved an analysis of surveys on crowd detection algorithms and related work on people crowd detection. And based on the review of the various categories of crowd detection approaches, factors were identified for effective people crowd detection. These parameters as discussed

in Section 4.3 included the ability to: detect people crowds, support outdoor deployment, report real-time data, and guaranteed participation and granularity of the approach.

A review of existing people crowd algorithms was also specifically carried out however, results indicate that several research carried out on crowd detection were mainly on non-people crowds as indicated by the number of published works. On the other hand, a lot of efforts directed to people crow detection were concentrated in controlled environments such as indoor settings, environments with definite entry and exit points or just for a small number of participants. Many of these efforts also assumed the availability of adequate communication infrastructure, which is not necessarily the case in many areas.

5.2 Design of People Crowd Detection (PCD) Algorithms

The divide and conquer design methodology that was used, broke down the people crowd detection algorithms into algorithms for signal generation, decomposition and detection algorithms. Section 4.4.2 presented the different algorithms that became the focus of this research.

The divide and conquer design methodology was preferred because it makes the problem easier by dividing it into manageable sub-problems. The easy-to-solve problems are each solved individually and the different solutions are

combined to solve the original problem.

5.3 Deployment of People Crowd Detection (PCD) Algorithms

A vibration signal characteristic of people crowds was generated and decomposed into its various sine and cosine components using the Fourier Transform. Based on the various frequency components, a crowd existence was deduced as shown in Section 4.4.2.

The frequency values used were a result of work that showed frequency generated by a crowd in a stadium. With further research in this area, it is expected that information regarding the exact vibration generated by people crowds on an urban street shall soon be obtained with a higher degree of accuracy. The algorithm does not waste system resources to invest in traffic that may not be interesting, but will only give attention to traffic generating vibrations within a specified frequency threshold.

5.4 Analysis of the People Crowd Detection (PCD) Algorithm

An analysis of the PCD algorithm was carried out by establishing its complexity and specifically the worst-case scenario of the time complexity. Time

complexity was used since time remains an issue in many systems, while many strides have been made in provisioning memory or storage space.

The worst case scenario or upper bound was used instead of the best case and average case scenarios because it guarantees that the algorithms given any size of inputs, will finish in the indicated period. In addition, it is difficult to precisely determine the average case measurement.

To establish the algorithm complexity, the rules followed were as follows: constant terms were ignored, low order terms were also ignored whenever they were dominated by higher order terms, while the assignment and mathematical operations were allocated orders of one. And for a block of code, the big O for each line of the sequence is established before a sum for the whole sequence is obtained. The complexity of the PCD algorithm was thus established to be of order $O(n)$.

Chapter 6

Conclusions and Recommendations

6.1 Conclusion

This section presents the researchers' view about the detection of people crowds using wireless sensor networks and outlines aspects that require further investigations in Section 6.5.

From the discussion so far, people crowds are inevitable and their detection require special attention because of their spontaneous and dynamic nature. Accordingly, this work provided a solution for the detection of people crowds in the form of a people crowd detection system using wireless sensor networks. The results showed that the developed People Crowd Detection (PCD) algorithm detects people crowds based on vibration signals generated by the

crowds, offers a measure of system security by concealing sensor nodes from public view, and it presents a deployment option of minimum physical resources requirements. Hence the objectives of the research were achieved. However further investigations are necessary for the areas highlighted in the following subsection below.

6.2 Research Contributions

6.2.1 Strength and shortfalls of existing crowd detection algorithms

The findings from the research indicated that not much work has been done in the area of people crowd detection, especially using wireless sensor networks. While the existing detection algorithms and approaches were found to be either resource intensive or even not applicable for the detection of people crowds they were found to be spontaneous and unpredictable.

By examining existing approaches to people crowd detection, thereby identifying their shortfalls in the detection of people crowds, this work had both a societal contribution and contribution to the body of literature on requirements for the detection of people crowds. The identification of shortfalls and strengths addressed the first research objective.

6.2.2 Designing crowd detection algorithms

From the systematic review of literature, key design requirements for people crowd detection using wireless sensor networks were established as:

- Should be able to detect people crowds
- Should provision both indoor and outdoor deployment
- Should report real-time data
- Should guarantee participation
- Granularity to provide to a reasonable extent a modifiable level of detail.

Furthermore, the research presented design considerations for people crowd detection algorithms. The considerations as discussed in Section 4.4 include:

- Security
- Performance
- Resource utilization
- Scalability
- Connectivity

6.2.3 Deployment of people crowd detection algorithms

Many traditional crowd detection algorithms such as in image processing deploy visible crowd detection mechanisms that are visible to the human eye and may require pre-aligned deployment. This work leads to the deployment of underground sensor nodes that can detect vibrations generated by people crowds, are concealed from the public eye and hence are relatively more secure and protected from vandalism. As long as an area of interest is covered, all people crowds will be detected irrespective of their source or direction of flow. And finally, they have a relatively low resource requirement. Scalability and connectivity of the wireless sensor network are achieved through the appropriate implementation of coverage algorithms.

Various sensor nodes are manufactured by different vendors. The basic requirement for real-life deployment relates to communication range, sensing range and battery life.

6.3 Implication of the Research

This research presents an option for the detection of people crowds using wireless sensor networks in resource-constrained environments. The developed algorithms and by extension implemented people crowd detection systems can be used by security personnel to detect crowd build-ups well in advance before damage and destructions are realized.

The emergence of many disease pandemics that are airborne and contagious

emphasizes the increasing need to manage people crowds. Crowd detection systems can be employed to monitor people crowds in reducing the negative impacts of disease pandemics such as mortality rate.
The results of this work are a benchmark for the design of people crowd detection algorithms with better complexity and application.

6.4 Research Limitations

The major challenges in the research were as follows:

- In this work, all nodes deployed in the Matlab simulation have been assumed to have uniform working conditions. And that sensor radius is equal to the communication range. This is however not an ideal scenario in the real world.

- To simulate the frequency range generated by people crowds, results of work carried out in a stadium were used. Although it can be considered sufficient enough to highlight the crowd detection concept, it cannot be a perfect reflection of vibrations generated on a street or open grass.

- For generality purposes, LEACH was chosen as the routing protocol. There are however other routing protocols in wireless sensor networks. Hence the need to review other routing protocols.

Overall, results of the research show that people crowd detection using WSNs involved more than just the detection algorithms. Other algorithms that

required further investigation into people crowd detection include the base station algorithms and fusion algorithms.

6.5 Recommendations

The research examined current crowd detection algorithms and highlighted their strengths and shortfalls in the detection of people crowds, especially for resource-constrained environments characteristic of many developing economies. Despite advances in micro-electromechanical technologies and progress registered in the application of WSNs, not much has been done in the detection of people crowds using WSNs. This work provided the following recommendations:

Recommendation 1: In environments such as those characterized by less developed economies, deployment of wireless sensor networks is hindered by underdeveloped infrastructure and the nature of people crowds therein. Infrastructure deployment is not well planned and regularly undergoes modifications. While many people are usually unruly and not law-abiding, As a result, show little respect for public infrastructure. People crowd detection approaches and algorithms should therefore factor in these considerations when designing and developing people crowd detection systems.

Recommendation 2: Unlike crowds such as animal and vehicle crowds, people crowds are intelligent, spontaneous, dynamic and sometimes even uncontrollable and destructive. Existing crowd detection algorithms can there-

fore not be effectively deployed for people crowd detection. Hence, the need for special attention to people crowds detection.

Recommendation 3: In addition, despite registered progress in WSNs, crucial issues remain and require attention, especially in resource-constrained economies. These include the need for dense node deployment including regions that are sometimes hazardous and prone to failures, the broadcast nature of WSN communication, and the limited power, memory and computational capacity of sensor nodes. These factors need to be considered especially concerning people crowd detection.

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Appendix A

People Crowd Detection Algorithms

A.1 Detection Algorithms

INPUT: Input signal $X(t_i)$, at time $t_{(i)}$ for all $i = 1, 2, ..., n..$ And l_i is the length of the signal.

OUTPUT: Frequency f_j for all $j = 1, 2, ..., n$.

Step 1: [Initialize $X(t_i)$]

Let $X(t_i)$ be Received Signal from a People Crowd.

Step 2: [By means of FFT, decompose $X(t_i)$ into the different Frequency Components]

for ($X(t_i)$, $1 \leq i \leq n$, $i++$)

$f = fft(X(t_i),l_i)(\frac{2}{l_i})$

Step 3: [Analyze the Signals using the Frequency Components]

elseif ($f_j < 1.4$)

No Evidence of People Crowd

If ($1.4 \leq f_j \leq 2.4$)

Possibility of People Crowd Existence

elseif ($f_j \geq 2.4$)

Investigate Type of Crowd

Step 4: Return to Step 1

A.2 MATLAB People Crowd Detection Algorithms

Clearing and cleaning of workspace, close all windows and clear command window.

```
clear all;
clc;
close all;
```

Generation of Random Signals

```
t = 0:0.001:5;
smax = 15;
smin = -15;
s = smin + (smax-smin)*rand(1,length(t));
```

```
Fourier Transform to the Frequency domain
fs = 1/0.001
N = length(s);
Frequency = (0:N-1)/N*fs;

Function for detection of crowds based on the frequency range.
If the frequency is in the range of 1.2 and 2.4 MHz Record Frequency else
ignore
Plotting of results
figure
Magnitude = abs(fft(s));
Magnitude1 = abs(fft(s));
plot(Frequency, Magnitude1);
xlabel('Signal Samples', 'Fontsize',10);
ylabel('Absolute Frequency', 'Fontsize',10);
title('Simulation Results of Signal Frequencies generated by People Crowds','Fontsize',16);
```

Appendix B

Comparative Analysis of Crowd Detection Approaches

Table B.1: Comparative analysis of Crowd Detection Algorithms

Research work.	Strength	Shortfalls
Radio		
a. (Shibata, & Yamamoto, 2019)	1) Mitigates privacy issues	1) Are device-based 2) Require a labour-intensive training phase
b. (de Brito Guerra et al., 2019).	1) Accuracy in classification 2) Good performance	1)Lower data rates. 2) Device based. 3) Require labour-intensive training phase
c. (Ding et al., 2018).	1) Does not require RFID tags	1)Requires consent from subjects 2) Tags are still required within the area of interest 3) Require labour-intensive training
Wi-Fi		
a Frog Eye (Xi et al., 2014)	1) CSI is sensitive to environmental variation 2) Device free 3) Relatively accurate. 4) Scalable and 5) Reliable	1) High configuration and implementation cost
b. Wicount (Yang et al., 2018)).	1) Device free 2) Does not require a training phase. 3) Counts multiple people at the same time 4) High accuracy	1) Tested for crowds of up to 5 2) Is an indoor system 3) Require preplanned deployment.
c. Freecount (Zou et al., 2017). 2) Only requires commodity Wi-Fi routers	1) Device free 2) Tested for indoor environments	
d. Deepcount (Zhao et al., 2019).	1)Uses commercial Wi-Fi devices 2)High-accuracy results	1)To complex 2) Tested for closed environments 3)Tested for numbers of up to 5 people only
Mobile Crowd Sensing		
a. TransLIGHT (Sun et al., 2016).	1) Relatively cheaper deployment costs. 2) Also used in tourism, health and marketing drives 3) Provides open data for industries and other public bodies.	1) Devise-based 2) Requires motivation 3) Higher resource requirement 4) High number of vulnerabilities
b. SensorPlanet (SensorPlanet.org)	1) Presents a central test repository for information 2) Collects data from a wider scale	1) May requires querying different datasets 2) Data heterogeneity
c. Twitter (http://twitter.com/).	1) Has many subscribers. 2) Twitter APIs can retrieve the latest Twitter posts	1) Participants may require incentives. 2) Vulnerabilities resulting from open source languages 3) Unreliability of posts
Wearables (RFID, BLE, Bluetooth tags)		
a. (Weppner & Lukowicz, 2013).	1) Not so reliant on the number of devices.	1) Not all bluetooth devices are discoverable 2) Scan is limited only to about a 10m radius 3) Signal attenuation due to the signal absorption 4) Only a small proportion use bluetooth devices 5) User privacy may be at risk.
b. (Alhmiedat & Aborokbah, 2021).	1) Easy to deploy and maintain 2) Dependable and cheap.	1) May require guaranteed participation
c. (Galinina et al., 2018)	1) Provides aggregated data to users. 2) Provides redundancy of non-personal data 3) Enables quality assessment and reward sharing	1) Requires close proximity to charging terminal. 2) High infrastructural costs 3) Requires many devise-free mechanisms.
Crowd Sourcing)		
a. CrowdMonitor (Ludwig et al., 2015.).	1) Facilitates collection of both real and virtual data 2) Enables direct communication with data collectors 3)Minimizes data duplication	1) Inaccurate situational assessment by data collectors.
b. MTurk (Schmidt, & Jettinghoff, 2016).	1) Performs tasks meant for many people	1) High scepticism about the validity of data 2) Incentives necessary for participation
Wireless Sensor Networks)		
a. ExScal project (Arora et al., 2005).	1) Wider area coverage of approximately 3km 2)Wider coverage, accuracy and robust operation. 3) lower human operation and reliability.	1) Requires a dense deployment of sensor nodes
Sensor Fusion)		
a. Metro Sense Project (Eisenman et al., 2006).	1) Has a simplified service model 2) Enables large-scale people-centric sensing 3) Is low-cost, scalable and improved performance	1) Can have a sub-optimal process flow 2) High initial infrastructural requirements 3) Uses already existing infrastructure and services
b. mCrowd (Yan et al., 2009).	1) Encapsulates multiple crowdsourcing services 2) Maximizes on multiple crowdsourcing services.	1) Sub-optimal process flow for certain services

Appendix C

Sensor node specifications

	Values
Frequency	
Natural frequency	10 Hz
Tolerance	±2.5%
Maximum tilt angle for specified Fn	10°
Typical spurious frequency	>240 Hz
Distortion	
Distortion coil to case velocity with 17.78 mm/s (0.7 in/s) p.p.	<0.1%
Distortion measurement frequency	12 Hz
Damping	
Open circuit (typical)	0.25
Damping calibration-shunt resistance	1.339 ohm
Tolerance with calibration shunt	5%
Sensitivity	
Sensitivity	28.8 V/m/s (0.73 V/in/s)
Tolerance	±2.5%

Figure C.1: Hardware specifications of a geophone [155]

Appendix D

Publications

D.1 Publication 1

Obbo, A., Nabaasa, E. and Ariho, P., 2022. Human Sensing Meets People Crowd Detection–A Case of Developing Countries. European Journal of Technology, 6(1), pp.42-68.

Link: https://ajpojournals.org/journals/index.php/EJT/article/view/984/1106

D.2 Publication 2

Obbo, A., Ariho, P. and Nabaasa, E., 2022. Towards People Crowd Detection Using Wireless Sensor Networks. European Journal of Technology, 6(2), pp.32-48.

Link: https://ajpojournals.org/journals/index.php/EJT/article/view/1071/1180

Appendix E

Approvals



Uganda National Council for Science and Technology

(Established by Act of Parliament of the Republic of Uganda)

Our Ref: SIR31ES

20 March 2020

Obbo Aggrey
Mbarara University of Science and Technology
Mbarara

Re: Research Approval: **Algorithms for detection and management people crowds using wireless sensor networks**

I am pleased to inform you that on **20/03/2020**, the Uganda National Council for Science and Technology (UNCST) approved the above referenced research project. The Approval of the research project is for the period of **20/03/2020** to **20/03/2023**.

Your research registration number with the UNCST is **SIR31ES**. Please, cite this number in all your future correspondences with UNCST in respect of the above research project. As the Principal Investigator of the research project, you are responsible for fulfilling the following requirements of approval:

1. Keeping all co-investigators informed of the status of the research.
2. Submitting all changes, amendments, and addenda to the research protocol or the consent form (where applicable) to the designated Research Ethics Committee (REC) or Lead Agency for re-review and approval **prior** to the activation of the changes. UNCST must be notified of the approved changes within five working days.
3. For clinical trials, all serious adverse events must be reported promptly to the designated local REC for review with copies to the National Drug Authority and a notification to the UNCST.
4. Unanticipated problems involving risks to research participants or other must be reported promptly to the UNCST. New information that becomes available which could change the risk/benefit ratio must be submitted promptly for UNCST notification after review by the REC.
5. Only approved study procedures are to be implemented. The UNCST may conduct impromptu audits of all study records.
6. An annual progress report and approval letter of continuation from the REC must be submitted electronically to UNCST. Failure to do so may result in termination of the research project.

Figure E.1: National Council of Science and Technology Approval.