OUTLIER DETECTION IN WIRELESS SENSOR NETWORK BASED ON TIME SERIES APPROACH

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

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AUGUST 2019

ABSTRACT

Sensory data in Wireless Sensor Network (WSN) is not always reliable because of open environmental factors such as noise, weak received signal strength or intrusion attacks. The process of detecting highly noisy data and noisy sensor node is called outlier detection. Outlier detection is one of the fundamental tasks of time series analysis that relates to predictive modeling, cluster analysis and association analysis. It has been widely researched in various disciplines besides WSN. The challenge of noise detection in WSN is when it has to be done inside a sensor with limited computational and communication capabilities. Furthermore, there are only a few outlier detection techniques in WSNs and there are no algorithms to detect outliers on real data with high level of accuracy locally and select the most effective neighbors for collaborative detection globally. Hence, this research designed a local and global time series outlier detection in WSN. The Local Outlier Detection Algorithm (LODA) as a decentralized noise detection algorithm runs on each sensor node by identifying intrinsic features, determining the memory size of data histogram to accomplish effective available memory, and making classification for predicting outlier data was developed. Next, the Global Outlier Detection Algorithm (GODA) was developed using adaptive Gray Coding and Entropy techniques for best neighbor selection for spatial correlation amongst sensor nodes. Beside GODA also adopts Adaptive Random Forest algorithm for best results. Finally, this research developed a Compromised Sensor Node Detection Algorithm (CSDA) as a centralized algorithm processed at the base station for detecting compromised sensor nodes regardless of specific cause of the anomalies. To measure the effectiveness and accuracy of these algorithms, a comprehensive scenario was simulated. Noisy data were injected into the data randomly and the sensor nodes. The results showed that LODA achieved 89% accuracy in the prediction of the outliers, GODA detected anomalies up to 99% accurately and CSDA identified accurately up to 80% of the sensor nodes that have been compromised. In conclusion, the proposed algorithms have proven the anomaly detection locally and globally, and compromised sensor node detection in WSN.

DEDICATION

This thesis is lovingly dedicated to my parents, my supportive wife, and my brother and sisters for their support, encouragement, and constant love have sustained me throughout my life.

ACKNOWLEDGEMENT

In preparing this thesis, I was in contact with many people, researchers, academicians, and practitioners. They have contributed towards my understanding and thoughts. In particular, I wish to express my sincere appreciation to my main thesis supervisor, **Professor Dr. Samad Haji Ismail**, for encouragement, guidance, critics and friendship. I am also very thankful to my co-supervisor **Dr. Hassan Chizari** for his guidance, advices and motivation. Without their continued support and interest, this thesis would not have been the same as presented here.

ABSTRAK

Data sensor dalam Rangkaian Sensor Wayarles (WSN) tidak selalunya boleh dipercayai kerana faktor persekitaran terbuka seperti bunyi bising, penerimaan isyarat yang lemah atau serangan pencerobohan boleh berlaku. Proses mengesan data dan sensor yang sangat bising dipanggil pengesanan data pencilan. Pengesanan data pencilan merupakan salah satu tugas asas analisis siri masa yang berkaitan dengan pemodelan ramalan, analisis gugusan dan analisis sekutuan, dan banyak dikaji dalam pelbagai bidang selain WSN. Cabaran pengesanan data pencilan pada WSN adalah apabila perlu dilaksanakan dalam sensor yang mempunyai keupayaan komputeran dan komunikasi yang terhad. Selain itu, hanya terdapat beberapa teknik pengesanan data pencilan dalam WSN tiada algoritma untuk mengesan data pencilan pada data sebenar dengan tahap ketepatan yang tinggi secara setempat dan juga pemilihan jiran berkesan untuk pengesanan kolaborasi global. Dengan yang demikian, tujuan kajian ini adalah untuk mereka bentuk teknik pengesanan data pencilan setempat dan global secara siri masa untuk WSN. Algoritma Pengesanan Data Pencilan Tempatan (LODA) yang dicadangkan adalah algoritma pengesanan bunyi yang terdesentralisasi yang dijalankan pada setiap nod sensor dengan mengenal pasti ciri dalaman, menentukan saiz memori histogram data untuk menetapkan keperluan memori berkesan, dan membuat pengelasan untuk meramal data pencilan. Seterusnya, Algoritma Pengesanan Data Pencilan Global (GODA), dibangunkan menggunakan Teknik Penyesuaian Kelabu Adaptif dan Entropi untuk pemilihan hubung kait ruangan di antara nod sensor. Di samping itu, GODA juga mengguna pakai algoritma Hutan Rawak Adaptif untuk hasil terbaik. Akhir sekali, kajian ini juga mencadangkan Algoritma Pengesanan Nod Sensor Terkompromi (CSDA), sebuah algoritma terpusat yang diproses di stesen pangkalan untuk mengesan nod sensor terkompromi tanpa mengira penyebab anomali. Untuk mengukur keberkesanan dan ketepatan algoritma, satu senario menyeluruh telah disimulasikan. Data bising telah disuntik ke atas data dan nod sensor secara rawak. Hasil kajian menunjukkan LODA mampu mencapai 89% ketepatan dalam meramal data pencilan, GODA mampu mengesan data pencilan sehingga 99% ketepatan, dan CSDA mampu mengenal pasti dengan tepat sehingga 80% nod sensor terkompromi. Sebagai kesimpulan, algoritma yang dicadangkan telah membuktikan pengesanan anomali secara tempatan mahupun global, dan pengesanan nod sensor dikompromi dalam WSN.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACF	–	Auto-Correlation Function
ACVF	–	Auto-Covariance Function
ADOD	–	Adaptive Distributed Outlier Detection
AIC	–	Akaike Information Criterion
ANN	–	Artificial Neural Network
AR	–	Auto Regressive
ARFIMA	–	Autoregressive Fractionally Integrated Moving Average
ARIMA	–	Autoregressive Integrated Moving Average
ARMA	–	Auto Regressive Moving Average
BIC	–	Bayesian Information Criterion
BN	–	Bayesian Network
CART	–	Classification and Regression Tree
CSDA	–	Compromised Sensor node Detection Algorithm
ED	–	Event Detection
GODA	–	Global Outlier Detection Algorithm
kNN	–	k-Nearest Neighbor
LODA	–	Local Outlier Detection Algorithm
LSA	–	Local Search Algorithm
PACF	–	Partial Auto Correlation Functions
PCA	–	Principal Component Analysis
PoI	–	Phenomenon of Interest
QoS	–	Quality-of-Service
RF	–	Random Forest

SARIMA	–	Seasonal Autoregressive Integrated Moving Average
SPE	–	Spatial Process Estimation
SVM	–	Support Vector Machine
WSN	–	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

1.1 Overview

Wireless sensor networks are sensor network technologies which are widely deployed on environmental monitoring, atmospheric monitoring, process monitoring, material sensing, security applications, etc. These networks operate on collective networking and computing of individual sensors based on their physical sensing properties and processing capabilities. Sensors nodes, cooperatively communicate and relay aggregated data to the main network control system for further processing and acting (Kobo *et al.*, 2017). In this regard, these sensors, must have an ability to conform to the collective networking functionalities as governed by their respective network policies. In WSNs, sensor nodes can be randomly deployed, in essence allowing opportunities for applications even in inaccessible areas. This feature about sensor networks, allows the possibility of deploying a large number of sensors over intuited areas for as long as communications can be established and sustained among these sensor nodes. A WSN consists of, but not limited to; a WSN server, routers, switches, sensor nodes, etc. depending on the design setup as required for its purpose (Mathews *et al.*, 2018).

Basically, each sensor node comprises sensing, processing, transmission, mobilizer, position finding system, and power units. Sensor nodes coordinate among themselves to produce high-quality information about the physical environment. Sensor field can be considered as the area in which the nodes are placed. Sensor nodes are the heart of the network. They are in charge of collecting data and routing this information back to a sink. A sink is a sensor node with the specific task of receiving, processing and storing data from the other sensor nodes. Sinks are also known as data aggregation points. A Task manager also known as base station is a centralized point of control within the network, which extracts information from the network and disseminates control information back into the network. The base station is either a laptop, a workstation or a server (Shaik and Shakeel Ahamad, 2018) .

Wireless sensor networks can be used in a wide range of applications, such as structural and environmental monitoring, habitat monitoring, health monitoring, military surveillance, weather detection and underwater acoustic. This wide range of applications presents various design, operational and management challenges for WSN (Mohamed *et al.*, 2017). There are broad range of WSN applications, which can be categorized according to their goal, interaction pattern, or reporting time. The goal of the application can either be sense, or sense and react. When the goal of the application is sense only, nodes collect sensed data, and send them to the sink node sense and react applications; on the other hand, nodes interact with the environment, and take action based on the sensed data, such as home automation applications. In For both categories, the reliability and accuracy of the data are important to ensure that the decision making based on the sensor data received from the environment is accurate. Data collection techniques are applied for collecting the aggregated data from the testbed and transmitting them to the sink station. If these data are lost or jumping during transmission, it will inevitably lead to the unreliable or error results. Therefore, the completeness and accuracy for scientific data are so important in decision- making. Nevertheless, in actual data collection scenario, data loss is so common (Li *et al.*, 2019).

Data measured and collected by WSNs is often unreliable. The quality of data set may be affected by noise & error, missing values, duplicated data, or inconsistent data. The low cost and low quality sensor nodes have stringent resource constraints such as energy (battery power), memory, computational capacity, and communication bandwidth. The limited resource and capability make the data generated by sensor nodes unreliable and inaccurate. Especially when battery power is exhausted, the probability of generating erroneous data will grow rapidly. On the other hand, operations of sensor nodes are frequently susceptible to environmental effects. The vision of large scale and high density wireless sensor network is to randomly deploy a large number of sensor nodes (up to hundreds or even thousands of nodes) in harsh and unattended environments. It is inevitable that in such environments some sensor nodes malfunction, which may result in noisy, faulty, missing and redundant data. Furthermore, sensor nodes are vulnerable to malicious attacks such as denial of service attacks, black hole attacks and eavesdropping, in which data generation and processing will be manipulated by adversaries (Abukhalaf *et al.*, 2016).

1.2 Problem Background

Outlier detection is the process of finding data objects whose behavior are highly varying from expectation. It is considered to be one of the fundamental tasks of data mining. In Wireless sensor networks, outliers can be defined as those measurements that significantly deviate from the normal pattern of sensed data. Due to various reasons that includes fault in sensors, communication error etc., wireless sensors tend to generate outliers. The presence of outliers in a dataset leads to a biased outcome and erroneous conclusions, when the data is further analyzed. Identifying outliers before data analysis helps improvise the quality of data. Identifying outliers in univariate data and multivariate data have to be dealt differently. Most of the outlier detection techniques applied on univariate data rely on the assumption that there is an underlying distribution of the data, which is assumed to be identically and independently distributed. When dealing with multivariate data, identifying outliers becomes difficult, when each variable is considered independently. Only when multivariate analysis is performed and there is correlation between the considered considered variables, outlier detection is possible (Mathematics, 2017).

When type of data is considered the outliers can be classified as local and global outliers. Local outliers Taking the point that are recognized in wireless sensor network at individual sensor nodes, techniques for reducing communication overhead and maintaining scalability of network with proper determination of outliers is important. Many event detection applications, for example, vehicle following, surveillance and monitoring can be done using local outlier detection. Local outlier identification has two variations in wireless sensor network. One variation is that historical values are used for determining the wrong or faulty value in the given sensor network. Another option is adding historical reading of their own; where the value of neighbor is taken to determine the value is proper or not i.e. the anomaly is based on the feedback from the neighbor node. When compared with the second approach the first one lags as it doesn't provide that much accuracy and robustness in the detection of outliers. Global outliers are popular as they have global perspective and also they draw more attention as they focus on the complete characteristics of WSN instead of working locally like local outlier. On basis of different network architecture, different type of identification can be done on many nodes. All the data collected id transmitted to sink node in the centralized architecture. It delay the response time very much and cause a lot of communication overhead. Cluster head collect the data and identifies outlier in cluster based approach. It has better response time and energy consumption as compared to the former one (Goyal and Munjal, 2015).

Identifying what has caused the outlier in sensor data is an important task. Potential sources of outliers in WSNs include noise & errors, actual events, and malicious attacks(Sun *et al.*, 2018). Distinguishing between sources of outliers is a vital matter which in turn gives an insight on how to handle the detected outlier. Generally speaking, if the detected outlier is an error or noisy data, it should be removed from the sensed data to ensure high data quality and accuracy; and to save energy consumption by eliminating communication load. Otherwise, if the outlier is caused by an event (e.g. fire or chemical spills), eliminating the outlier will lead to loss of important hidden information about events, which may have undesired penalty. However, many researches tend to deal with outliers and events as similar conditions by treating events as some sorts of outliers (i.e. events are one of the causes of outliers). Due to the fact that there exists spatio-temporal correlation among neighboring node readings, this observation enables us to distinguish between events and errors. This is based on the fact that noisy measurements and sensor faults are likely to be stochastically unrelated, while event measurements are likely to be spatially correlated(Fawzy *et al.*, 2013a).

Outlier detection is an important aspect of data mining, where the main objective is to identify anomalous or unusual data from a given dataset. Outlier detection is interesting because it involves automatically discovering interesting and rare patterns from datasets (Ahmed *et al.*, 2014; Huang *et al.*, 2017). Outlier detection has been widely studied in statistics and machine learning, where it is also known as outlier detection, deviation detection, novelty detection, and exception mining. Outliers are important because they indicate significant but rare events, and they can prompt critical actions to be taken in a wide range of application domains. For example, an anomaly in an MRI image may indicate the presence of a malignant tumour (Ahmed *et al.*, 2016). Similarly, abnormal behaviour in a credit card transaction could indicate fraudulent activities, an unusual traffic pattern in a network could mean that a computer is hacked or under attack, e.g., using worms and Denial of Service (DoS) attacks (Marchette, 2001).

1.3 Problem Statement

The quality of data collected by sensor nodes is affected by anomalies that occur due to various reasons, such as node failures, reading errors, unusual events, and malicious attacks. Therefore, anomaly detection is a necessary process to ensure the quality of sensor data before it is utilized for making decisions. Thus, an outlier detection algorithm is required to determine inconsistencies and possibly to filter them to enhance the quality of the sensor reading data (Zhu and Hua, 2015). As far as the technique categories, statistical techniques, data mining, and computational intelligence are employed most widely.

De Paola *et al.* (2015) presented an Adoptive Distributed Outlier Detection (ADOD) algorithm to identify, in a WSN, the faults in the data. As per the needs of the application, the effective classification, efficiency and communication can be improved in ADOD. The better collaboration of the nodes, which can occur through effective classification, results in outlier identification. If this collaboration is low, efficiency and communication get affected. This algorithm, utilizing constrained Pareto optimization, resolves the problem of contradictory objectives of improving classification, efficiency and communication at the same time. A set of Bayesian Networks (BNs) distributed over the WSN undertakes the task of outlier identification. A spread of the structure of all the BNs over a set of collaborating sensor nodes is present. The technique presented by us is new due to the dynamic creation of the collaborating set in the presence of limitations and variations in the observed physical phenomenon. Despite their many advantages, such as flexibility, one of the main drawbacks of this technique is the it can, however, deal with continuous variables in only a limited manner.

A new pattern-based anomaly classifier was proposed (Araya *et al.*, 2017). The Collective Contextual Anomaly Detection using Sliding Window (CCAD-SW) architecture distinguishes abnormal energy consumption patterns by overlapping SWs of smart buildings. To improve the potential of CCAD-SW, another framework was proposed called Ensemble Anomaly Detection (EAD). It elects classifiers on the basis of majority voting, and it is deployed by combining pattern-based and prediction-based anomaly classifiers to incorporate diversity among classifiers. This existing method is useful in many applications but they still cannot identify certain types of anomalies (Jiang *et al.*, 2014).

Zhang *et al.* (2015), presented an acceleration technique for object detection using CNN for very deep networks. The authors highlighted the importance of machine learning in WSN applications. WSNs are prone to faults and failures because of the multiple reasons discussed above. Authors in Miao *et al.* (2018), an online distributed method was proposed to handle the streaming data in WSNs. The approach was based on One-Class Support Vector Machine (OCSVM) to detect anomalies over networks and to get a decentralized cost function. Instead of kernel functions, they used a random approximate function. For approximate dimensions, a sparse constraint is also added in the decentralized cost function. After that, SGD is used to minimize the cost functions and derive two distributed sets of rules. This algorithm contributed to achieving high true positive and low misdetection rates.

In general, these researchers present anomaly detection methods in WSNs, which mainly consider detection accuracy and communication complexity of the algorithm. However, the computational complexity of the algorithm is less taken into account. In this study, a new method of anomaly detection is proposed in view of the computational complexity and can achieve comparable accuracy and less communication cost.

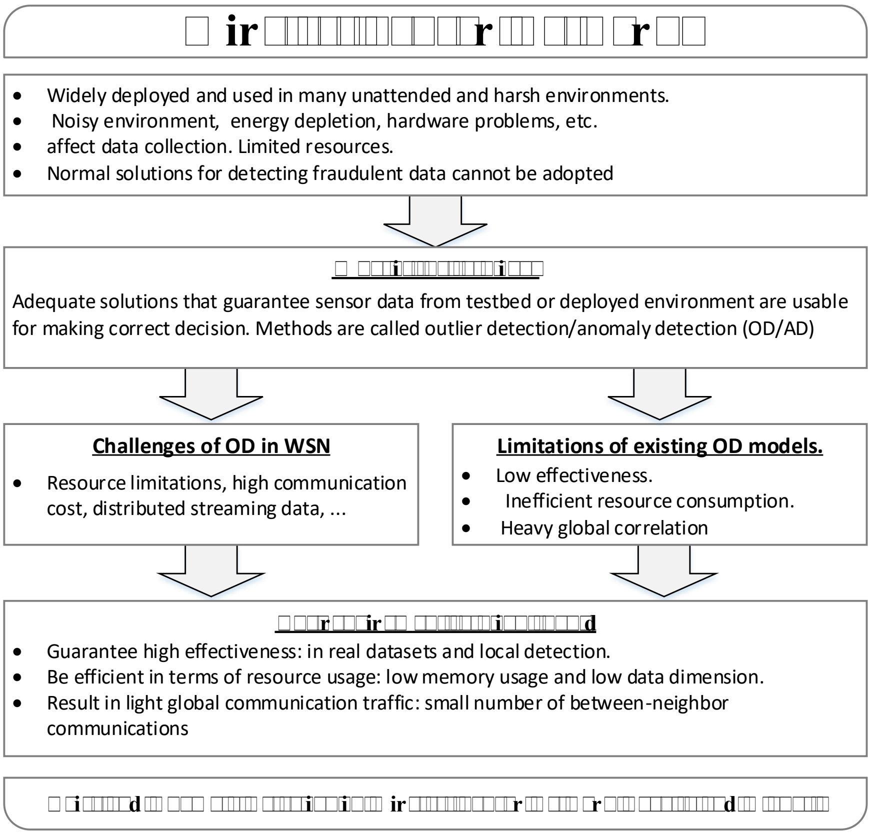

Figure 1.1: Scenario leading to the research problem.

Therefore, based on the above explanation there is a lack of an algorithm with time series consideration for detecting outlier in sensory data locally. Moreover, there are several studies for outlier detection globally but not considering to the time series concept and selecting the weighted neighbor as collaborative sensor node.

Figure 1.1 shows an overview of this study and the factors that lead to the problem of outlier detection in WSNs. Furthermore, Chapter 2 explains the details of WSNs and outlier detection challenges.

The combination of time series and WSN has attracted much attention. Numerous methods have been proposed to monitor numerical streams, including time-series indexing and sequence-pattern discovery. However, as stated in some research, these methods are not suitable for real-time monitoring streams and introduce an overhead in terms of resource consumption and computation. Therefore, the authors propose a method to monitor numerical streams and determine the lag correlation between them. This method can manage reasonably sized data streams incrementally, quickly, and with small resource consumption (Berjab *et al.*, 2018).

Use of formal time series analysis in sensor networks has been reported by several researchers. Using time-series modelling to decide the confidence levels for future samples, and skip the future readings if the values are likely to be accurate enough. However, this requires substantial processing (adjusting time series models continuously for each new sample), and it requires full rate sampling for some time after skipping samples. At best, it reduces the number of required samples by less than 50%. Some researches have used ARIMA modelling for the smoothing of noisy data and for interpolating missing data samples in a series, but again has not analysed the best sample rate to provide accurate data interpolation (Bhandari *et al.*, 2017).

1.4 Research Questions

As mentioned outlier detection plays a very important role in determining correct and reliable data in WSNs. Therefore, many algorithms are exist for resolving the outlier detection problem in WSNs. Some algorithms can detect outliers very accurate. However, they are consider the Multi-level approach of outlier detections. Which means detection outlier on sensor node locally and also use neighbors to identifying outlier globally based on time series approach as well as identifying compromised sensor node. Thus, the specific research questions of this study are as follows.

(i) How can noise be observed bottom-most level, at the sensor node itself, that termed as local detection using efficient features and the smallest possible memory size?

  a) Which smart features are effective for detecting noisy data at each local sensor?

  b) How can the window size for local noise detection that uses an appropriate memory size be determined?

c) How can noisy data be predicted at each sensor node?

(ii) How can noise be collaborative detected amongst sensor nodes, or intermediate level, that termed as global detection using best neighbor selection and effective features?

a) How can the best number of neighbors for collaboration be selected?

b) How can the best neighbor for spatial correlation be selected?

c) Which smart features are effective for collaboration with the selected best neighbors?

d) How can the noisy data in sensor readings be detected globally based on the extracted features ?

(iii) How can identify compromised sensor nodes centrally at the Base Station?

a) How can the features that can be used for detecting anomalous sensor nodes be determined?

b) How can the best combination of features for detecting sensor nodes having anomalous sensor data be determined?

c) How can compromised sensor nodes be detected in an entire network and marked as faulty sensor nodes ?

1.5 Research Aim

The aim of this research is to design and develop an outlier detection technique for WSNs that can detect noisy and outlier's data locally on sensor nodes while maintaining minimal amount of memory. It is further enhanced with time series analysis in smart selection amongst the neighborhood sensors for collaborative global detection environment. Ultimately, compromised sensor nodes are detected centrally at the Base Station for high accuracy solution.

1.6 Research Objectives

Based on the research questions, the research objectives of this study were as follows.

(i) To design and develop an independent outlier detection algorithm that runs on each local sensor node of a WSN with consideration of the nodes intrinsic features.

(ii) To design and develop a collaborative time series based global outlier detection algorithm to be applied amongst sensor nodes in a WSN.

(iii) To design and develop a centralized time series based outlier detection algorithm on base station of a WSN for detecting compromised sensor nodes regardless of specific cause of the anomalies.

1.7 Research Scope

The assumptions and limitations of this research study are as follows.

(i) The dataset used in this research was provided by the Intel Berkeley Research Laboratory (IBRL, 2004). It is a benchmark real dataset that has been used widely in many outlier detection studies.

(ii) Sensors were assumed to have sufficient energy and storage to perform the simulation.

(iii) The network structure was assumed to be static and the sensors to be homogeneous and time synchronized, as are those used in previous studies.

(iv) This study does not include response actions when outliers and anomalous sensor nodes have been detected.

1.8 Significance of This Study

This study is significant for the following reasons.

(i) The quality of data collected by WSN applications is very important for subsequent analysis and decision-making procedures. Therefore, anomalous measurements must be detected to support correct decision making.

(ii) Security concerns related to WSNs motivated this research study, because the number and types of attacks are increasing. Given that attacks are considered a source of outliers and anomalies, the detection of these types of outliers and anomalies helps the network survive and operate as expected.

(iii) The WSN lifetime is also affected by the design of efficient outlier detection methods, which was one of the sub-considerations of this research.

The findings of this research are expected to lead to the development of the proposed outlier detection model in different fields for various applications, such as the monitoring of abnormal phenomena in agriculture and health care, environmental monitoring, and many more. Figure 1.2 demonstrate development phases of proposed model.

1.9 Summary of Research Contribution

The main contribution of this study is locally and globally detecting outliers, as well as anomalous sensor nodes, in WSNs, that efficiently utilizes the limited resources of WSNs. The main contributions are provided by the design and development of the following components, as shown in Figure 1.3.

(i) An efficient local outlier detection algorithm that provides accurate predictions and utilizes small amounts of resources.

(ii) An algorithm that uses spatial correlation with neighbors to detect outliers globally and selects the best neighbors.

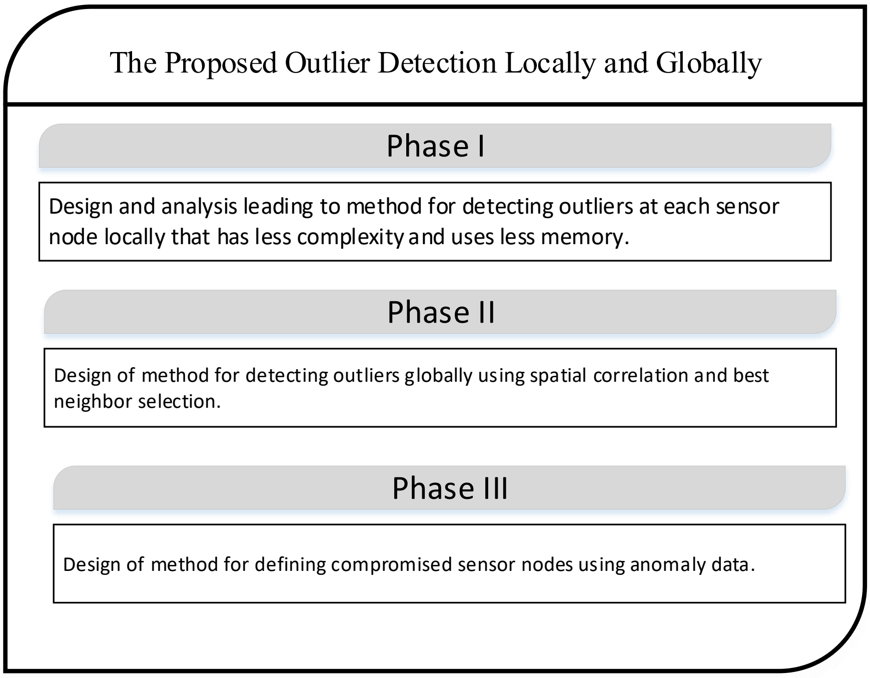

Figure 1.2: Phases of development of proposed model and algorithm

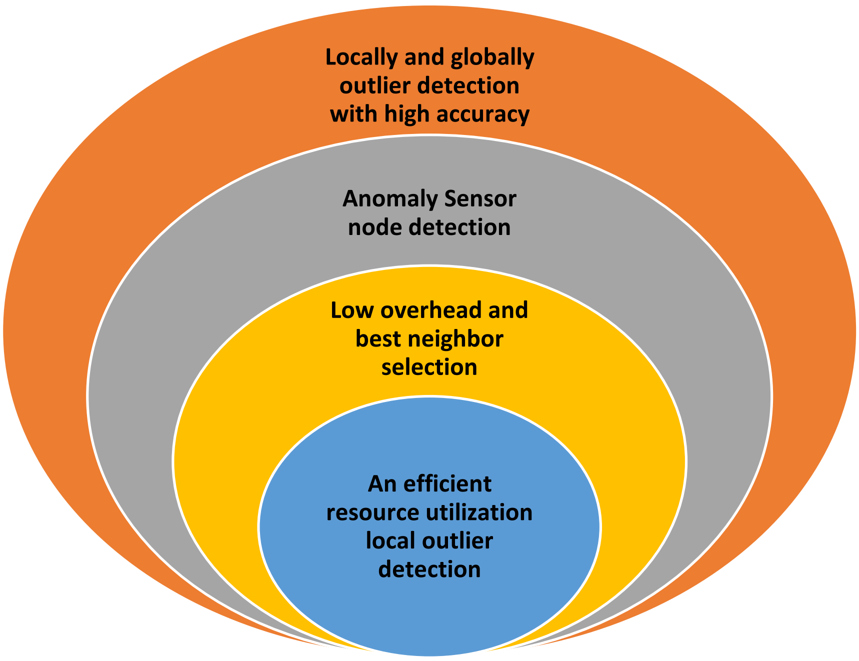

Figure 1.3: Hierarchical diagram for implementing the proposed algorithm

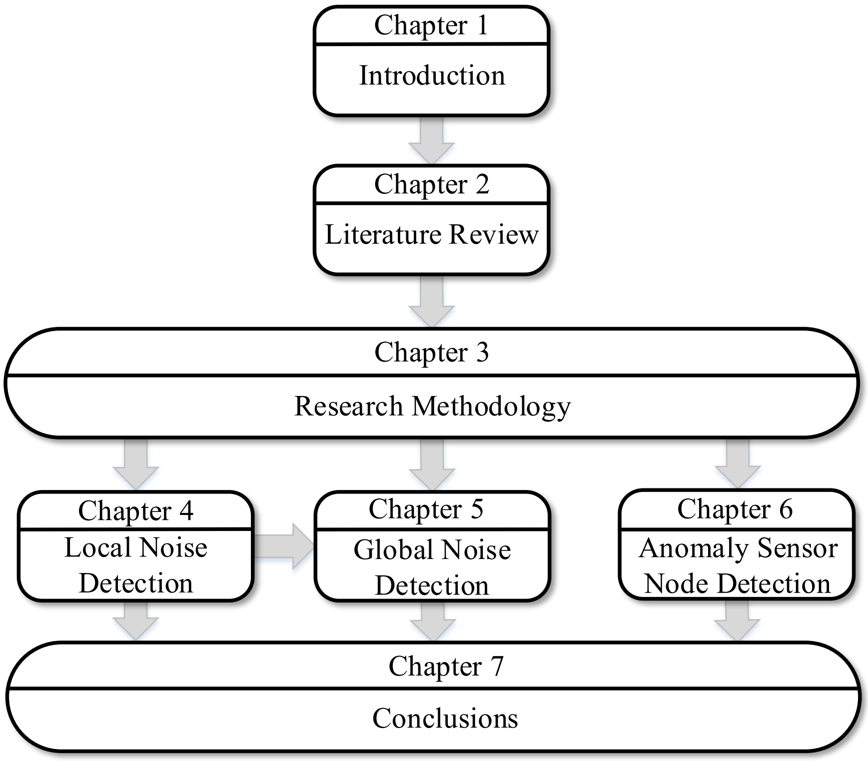

Figure 1.4: Thesis organization

(iii) An outlier detection algorithm that can report compromised sensor nodes.

1.10 Thesis Outline

This thesis consists of seven chapters, organized as shown in Figure 1.4. In Chapter one, the research study is introduced and an overview of the thesis is presented. In Chapter 2, work related to this research study is reviewed and existing techniques are explained and compared. In Chapter 3, the methodology used to achieve the main goal, which is noise detection in time series in sensor data of WSNs locally and globally, is described. Chapter 4 discusses data cleansing and important features for detecting noise locally while considering the necessity of low memory usage. In Chapter 5, a method for distributed noise detection that uses a novel neighbor selection algorithm to increase the detection accuracy globally is described. In Chapter 6, a method is proposed for anomalous sensor node detection at the base station to detect compromised sensor nodes and thus allow reliable decision making at the sink. Chapter 7 summarizes the study and concludes this thesis. It also includes suggestions for possible future studies on the detection of outliers in WSNs.

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LIST OF PUBLICATIONS

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2. Asadi, S., Abdullah, R., **Safaei, M.**, & Nazir, S. (2019). An Integrated SEM-Neural Network Approach for Predicting Determinants of Adoption of Wearable Healthcare Devices. *Mobile Information Systems*, 2019. https://doi.org/10.1155/2019/8026042. **(Q3, IF: 1.63)**

Indexed Journal

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1. **Safaei, M.**, & Ismail, A. S. H. (2012, February). SmartSim: Graphical sensor network simulation based on TinyOS and TOSSIM. In *2012 Third International Conference on Intelligent Systems Modeling and Simulation* (pp. 611-615). IEEE. https://doi.org/ 10.1109/ISMS.2012.19. **(Indexed by SCOPUS)**