AN EFFICIENT FUZZY FUSION-BASED FRAMEWORK FOR SURVEILLANCE APPLICATIONS IN WIRELESS MULTIMEDIA SENSOR NETWORKS

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ABSTRACT

AN EFFICIENT FUZZY FUSION-BASED FRAMEWORK FOR SURVEILLANCE APPLICATIONS IN WIRELESS MULTIMEDIA SENSOR NETWORKS

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Previous advances in Information Technologies and especially in Micro Electro-Mechanical Systems, have made the production and deployment of tiny, battery-powered nodes communicating over wireless links possible. Networks comprised of such nodes with sensing capability are called Wireless Sensor Networks. The early deployment aim was to use these nodes only in a passive way for indoor applications. These kinds of early nodes had the ability to sense scalar data such as temperature, humidity, pressure and location of surrounding objects. However, recently available sensor nodes have higher computation capability, higher storage space and better power solutions with respect to their predecessors. With these developments in addition to scalar data delivery, multimedia content has become the core focus. A wireless sensor network with multimedia capabilities is called Wireless Multimedia Sensor Network. There has always been a trade-off between accuracy and energy-efficiency in these new generation networks because of their resource-constrained nature.

In this thesis we introduce a new approach to address this trade-off in Wireless Multimedia Sensor Networks. Although a number of previous studies have focused on various special topics in Wireless Multimedia Sensor Networks in detail, to the best of our knowledge, none presents a fuzzy multi-modal data fusion system, which is light-weight and provides a high accuracy ratio. Especially, a multi-modal data fusion system targeting surveillance applications make it inevitable to work within a multi-level hierarchical framework. In this thesis, our primary focus is on accuracy and efficiency by utilizing our framework. Along with the fuzzy fusion framework, a new fuzzy clustering algorithm, namely Multi-Objective Fuzzy Clustering Algorithm (MOFCA), is introduced and evaluated in detail as well.

Keywords: wireless multimedia sensor networks; fuzzy clustering and classification; hierarchical data fusion; surveillance applications; evolving networks

ÖZ

KABLOSUZ ÇOKLU-ORTAM DUYARGA AĞLARDA GÖZETLEME UYGULAMALARI İÇİN BULANIK FÜZYON-TABANLI ETKİN ÇATI

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Bilgi teknolojileri ve özellikle Mikro Elektro-Mekanik Sistemlerdeki geçmiş ilerlemeler, kablosuz bağlantılar üzerinden haberleşen küçük ve pille çalışan düğümlerin üretim ve konuşlandırılmasını mümkün kıldı. Algılama kabiliyeti olan bu tip düğümler içeren ağlara Kablosuz Duyarga Ağlar denilmektedir. İlk konuşlandırma amacı, bu düğümleri sadece iç ortam uygulamaları için pasif şekilde kullanmaktı. Bu tip düğüm noktalarının ilk sürümleri sıcaklık, nem, basınç ve çevreleyen nesnelerin yerleri gibi sayısal verileri algılama kabiliyetine sahipti. Ancak son zamanlarda görülen algılayıcı düğümler, ilk sürümlere kıyasla, daha yüksek hesaplama kapasitesi ile depolama miktarına ve daha iyi güç besleme çözümlerine sahiptir. Bu gelişmelerle birlikte, sayısal veri iletimine ilave olarak çoklu-ortam içeriği ana odak noktası oldu. Çoklu-ortam kabiliyetine sahip kablosuz duyarga ağlara, Kablosuz Çoklu-Ortam Duyarga Ağ denilmektedir. Kaynak kısıtlılıkları nedeniyle bu yeni jenerasyon ağların doğruluk ve enerji-etkinliği arasında her zaman bir denge var olmuştur.

Bu tezde, Kablosuz Çoklu-Ortam Duyarga Ağlardaki bu dengeye hitap eden yeni bir yaklaşımı tanıtıyoruz. Her ne kadar birkaç geçmiş çalışma Kablosuz Çoklu-Ortam Duyarga Ağlardaki çeşitli özel konulara detaylı olarak odaklanmış olsa da, bildiğimiz kadarıyla, hiçbiri az-maliyetli ve yüksek doğruluk oranı sağlayan bulanık çoklu-modalite veri füzyon sistemini sunmamaktadır. Özellikle, gözetleme uygulamalarını hedef alan çoklu-modalite veri füzyon sistemleri hiyerarşik bir çatı içerisinde çalışmayı kaçınılmaz kılmaktadır. Bu tezde ana odak noktamız, çatımızı kullanarak doğruluk ve etkinliğin her ikisi üzerindedir. Bulanık füzyon sistemi ile birlikte, Çok-Amaçlı Bulanık Kümeleme Algoritması (ÇABKA) adında yeni bir bulanık kümeleme algoritması da tanıtılmış ve detaylı olarak değerlendirilmiştir.

Anahtar Kelimeler: kablosuz çoklu-ortam duyarga ağlar, bulanık kümeleme ve sınıflandırma, hiyerarşik veri füzyonu, gözetleme uygulamaları, evrim geçiren ağlar

dedicated to ***my beloved wife and family*** *who were always praying for my success and also worked hard to bring me up to who I am today...*

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ALGORITHMS

LIST OF ABBREVIATIONS

2D	Two Dimensional
A	Ampere
ADC	Analog-to-Digital Converter
AML	Approximate Maximum Likelihood
AOI	Area-Of-Interest
BFC	Binary Fuzzy Classification
C	Class
CH	Cluster Head
CHEF	Cluster Head Election using Fuzzy
CIS	Communication Information Systems
CMOS	Complementary Metal-Oxide Semiconductor
COA	Center of Area
COG	Center of Gravity
Coor	Coordinate
COTS	Commercial-off-the-Shelf
CPU	Central Processing Unit
DBCP	Density-Based Clustering Protocol
DECA	Density-based Energy-efficient Clustering Algorithm
DEED	Distributed Energy-Efficient self-Deployment
DOA	Direction-of-Arrival
Dof	Depth-Of-Field
EAUCF	Energy Aware Unequal Clustering with Fuzzy
EECS	Energy Efficient Clustering Scheme
EEUC	Energy-Efficient Unequal Clustering
EMD	Empirical Mode Decomposition
FC	Fusion Center
FND	First Node Dies
FoV	Field-Of-View
F/NAR	False/Nuisance Alarm Rate
GPS	Global Positioning System
GPSR	Greedy Perimeter Stateless Routing
HNA	Half of the Nodes Alive
HEED	Hybrid Energy-Efficient Distributed
Hz	Hertz
IDT	Interdigitated Transducer
IR	Infra-Red

IT	Information Technologies
j	Joule
LS	Least Square
LEACH	Low Energy Adaptive Clustering Hierarchy
LND	Last Node Dies
m	Meter
MASON	Multi-Agent Simulator of Neighborhoods
MATLAB	Matrix Laboratory
MB	Megabyte
MBR	Minimum Bounding Rectangle
MEMS	Micro-Electro Mechanical Systems
MMC	Multimedia Card
MOFCA	Multi-Objective Fuzzy Clustering Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MUSIC	Multiple Signal Classification
NAND	Not AND
NOR	Not OR
N/A	Not-Applicable
pH	Power of Hydrogen
PIR	Passive Infra-Red
PpS	Pulse per Second
QoS	Quality-of-Service
RF	Radio Frequency
SNR	Signal-to-Noise Ratio
SPI	Serial Peripheral Interface
TPGF	Two Phase geographical Greedy Forwarding
TRE	Total Remaining Energy
UAV	Unmanned Air Vehicle
V	Volt
XL	Extra Large
XS	Extra Small
WiPIR	Wireless PIR
WMSN	Wireless Multimedia Sensor Network
WSN	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

Surveillance has always been an important task for human beings either for protecting a precious asset or gathering information from the surrounding environment. However, things to be monitored are increasing with a huge rate due to the changing requirements day by day. As a result, it becomes difficult for individuals to do this task by some manual techniques. It is also difficult to do this job even by using computer technologies, which are usually placed on sheltered indoor environments. To be able to fulfill such requirements, a need for a technology that can do the required job by providing efficient results with a high accuracy ratio even in outdoor environments has emerged, wireless multimedia sensors.

Recent technological advances in Communication Information Systems (CIS) and especially in MEMS (Micro Electro-Mechanical Systems) have made the production and deployment of tiny, battery-powered nodes (units) which communicate over wireless links possible. These nodes have several parts including a radio-transceiver, a micro controller, an electronic circuitry for interfacing with the compounds, and a power supply. Upon completing the successful production of the wireless nodes, these nodes are geared with the sensors demanded by the application area. Figure 1.1[1] depicts the components of a wireless sensor node. A Wireless Sensor Network (WSN) is comprised of such units at varying numbers, where each single unit is connected to one or generally several units.

In this thesis, an efficient fuzzy fusion-based framework designed specifically for surveillance applications in wireless multimedia sensor networks is proposed. Along with the framework, a new fuzzy clustering algorithm which is implemented as part

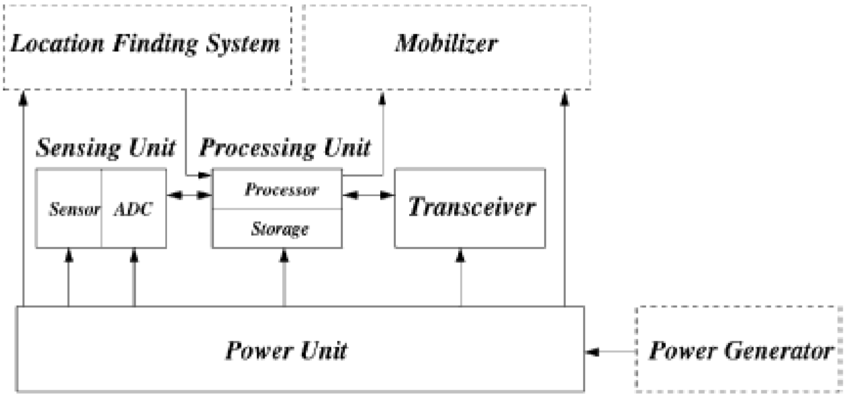

Figure 1.1: Components of a wireless sensor node [1].

of the framework for WSN clustering is also introduced and evaluated in detail.

Performance of the introduced fuzzy clustering protocol is reasonably better than its competitors and according to the obtained experimental results, which will be presented in Chapter 3 in detail, it is a candidate algorithm to be implemented in any WMSN application. Proposed fuzzy fusion-based framework which implements the introduced fuzzy clustering algorithm considers both energy and accuracy aspects while its performance scales well. Our framework provides high classification accuracy while preserving energy consumption for surveillance applications by the use of fuzzy multi-modal data fusion architecture. Overhead caused by the use of data fusion system is insignificant when considered together with the accuracy aspect.

In the following sections, the rapidly increasing use of WSNs and its derivative, Wireless Multimedia Sensor Networks (WMSNs), are discussed by presenting the usage areas and capabilities. At the end of the chapter, the road map of this thesis and the motivation behind it will be provided.

1.1 Wireless Sensor Networks

Actually what leverage the idea of WSNs is the production of tiny sensor nodes and the collaborative effort among them [1]. A sensor node (unit) may be in varying sizes. A WSN includes a large number of sensor nodes deployed either densely or in a sparse way either inside the phenomenon or around it at some distance. The deployment position of the nodes can be engineered according to the needs or can be randomly, especially in harsh or hostile environments. An early deployment aim was to use these sensors in a passive way for indoor applications. These kinds of early nodes had the ability to sense scalar data such as temperature, humidity, pressure, and location of surrounding objects. Initially, these nodes had little computation capability and storage space and their only use was to transfer scalar data to the necessitated places, which are generally the base stations (sinks). For these reasons, this kind of WSNs is mainly used for indoor applications. However, recently available sensor nodes have higher computation capability, higher storage space, and better power solutions with respect to their predecessors and their primary usage area has shifted from indoor to outdoor applications. From this perspective, the main usage area consists of military applications, environmental measurements, and chemical instance processing together with disaster relief. Through the technological advances and enforced by the user requirements, in addition to scalar data delivery, multimedia content delivery has become the core focus, which has given birth to the WMSNs.

1.2 Wireless Multimedia Sensor Networks

Wireless Multimedia Sensor Network (WMSN), consists of different kinds of nodes that are equipped with various types of sensing units. They measure not only scalar data, which can be transmitted through low-bandwidth channels and in a delay-tolerant manner, but also still images, audio and video streams, which require high-bandwidth channels. A reference architecture of a WMSN is presented in Figure 1.2[2].

WMSNs have started to appear as a result of the combination of low-power communication infrastructure with low-cost multimedia content providers such as CMOS (Complementary Metal-Oxide Semiconductor) imaging cameras and microphones. With the addition of these technologies, this derivative of WSNs now has the capability to store, process, correlate, and fuse multimedia content. Bearing in mind the power that comes through the data fusion, WMSNs consist of rich application areas such as environmental monitoring, healthcare delivery, object detection, localization, tracking applications, industrial process controls, and surveillance applications.

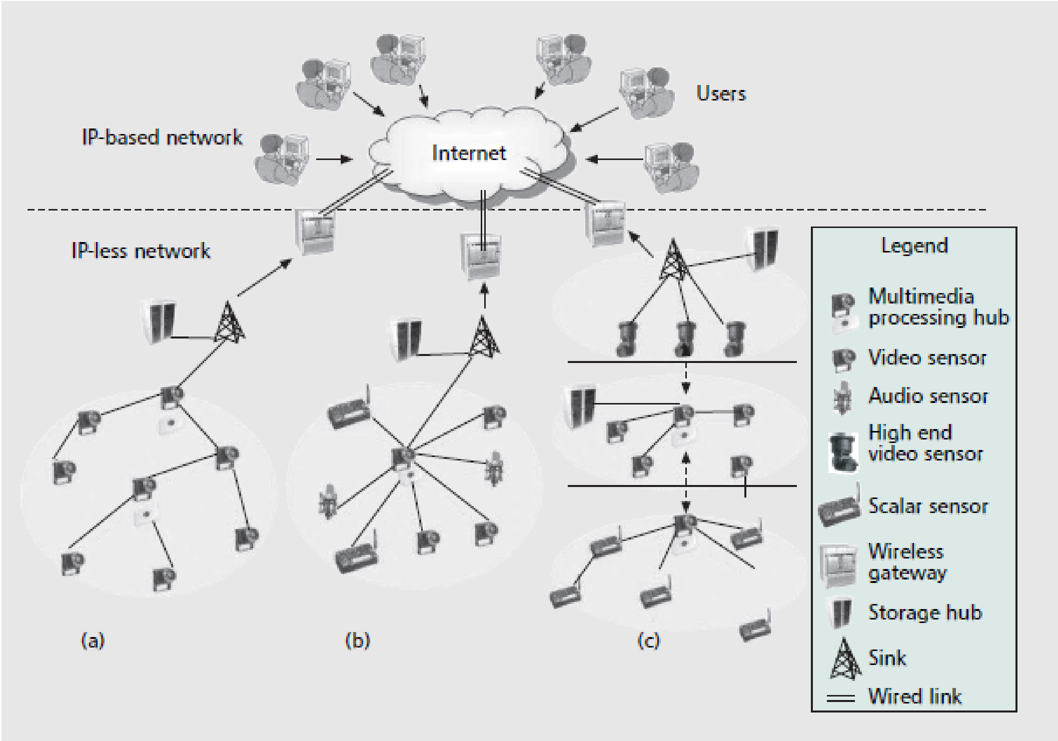

Figure 1.2: A reference architecture of a WMSN [2]: a) Single-tier flat, homogenous sensors, distributed processing and centralized storage b) Single-tier clustered, heterogeneous sensors, centralized processing and storage c) Multi-tier, heterogeneous sensors, distributed processing and distributed storage.

1.3 Challenges in WMSN Applications and Multimedia Streaming

As always do, each gain comes with a cost enforcing the decision maker to rethink the pros and cons of the subject in question. This is also valid for WMSNs. Initial design and process models thought for WSNs is not suitable for WMSNs due to the characteristics of the multimedia content. For this reason network layers and the requirements demanded for each layer has to be rethought for the WMSN context. Hardware requirements of the multimedia nodes diverge greatly from that of a scalar node. Constrained computation capability, storage capacity and short-endurance battery power are among the main disadvantages faced in WMSNs. In addition to hardware constraints, network architecture poses great obstacles for WMSNs. Demanded QoS (Quality of Service) levels and real-time or near real-time data transmission requirements are among the prevailing obstacles that need to be addressed.

Data storage and management issues in WMSNs are other pitfalls in the area. Restricted hardware resources of sensor nodes impede most general storage management issues to be implemented on multimedia sensor networks. For this reason, there are two general approaches to overcome this difficulty. One of them is for the sensor nodes to possess very little storage to be able to use the restricted energy sources efficiently and immediately transmit data to the sink and let the sink have the burden of long term storage and sensor data processing. The other approach is to design and implement a storage-centric sensor network as depicted in [3] in which, each sensor node should be equipped with energy efficient and high-capacity flash storage. In these arguments, the first one assumes (which is nearly always true) that sink may be positioned in a better, sheltered place where there is less constraint for processing power and storage capabilities. The second one assumes (also for some applications) that the energy consumption for the transmission of data is more than energy consumption for the storage of data. For the realization of the storage-centric networks, active and sleep-mode energy consumption of available flash-based storage options for sensor platforms are evaluated comprehensively to reduce the energy consumption by sensor data storage and presented in [4]. Characteristics of tested devices, flash energy consumption, sleep mode current and power-on energy consumption of the devices are given in Table 1.1-1.3, respectively. It is probable that new studies targeting WMSN storage issues will be hybrid approaches including the pros of each mentioned distinct approach.

Table 1.1: Characteristics of Tested Devices [4]

Type	Manufacturer	Capacity	Interface	Page Size (Byte)	Erase Block (Pages)
Serial NOR	Atmel	512 KB	SPI	256	1
Serial NOR	ST	512 KB	SPI	256	256
MMC	Hitachi	32 MB	SPI	512	16
NAND Flash	Toshiba	16 MB	8-bit bus	512	32
NAND Flash	Micron	512 MB	8-bit bus	2048	64

Table 1.2: Flash Energy Consumption (Energy per Byte (μJ)) [4]

	Read	Write	Erase	Bulk Erase	Total
Atmel NOR	0.26	4.3	2.36	Not allowed	6.92
Telos NOR	0.056	0.127	N/A	0.185	0.368
Hitachi MMC	0.06	0.575	0.47	0.0033	1.108
Toshiba NAND (16MB)	0.004	0.009	N/A	0.004	0.017
Micron NAND (512MB)	0.027	0.034	N/A	0.001	0.062

Challenges in WMSN applications can be classified as being internal, external and

Table 1.3: Sleep Mode Current and Power-on Energy Consumption [4]

	Sleep Current μA	Power Up μJ
Serial NOR	2	0
Hitachi MMC	84	1130
Toshiba NAND	5	0

application level challenges. Internal challenges stem from the internal structure of the resource constrained tiny nodes. External challenges stem from the environmental effects on the nodes and application level challenges stem from the domain-specific usages. Resource (computation, memory and communication) restrictions, changing topologies and cruel ecological conditions, Quality of Service (QoS) necessities, data redundancy, erroneous packets and changing link capacity, security issues, large-scale deployment and ad hoc topologies, and integration with IP-based and other networks are mentioned as headlines of challenges in Industrial WSN applications in [5]. These challenges are also valid for WMSN applications since most Industrial WSN applications include multimedia content inherently.

Multimedia streaming requires high-bandwidth channels and timeliness. There are key challenges that have to be met for the stream coding and transport level. Key challenges for the video coding in the sensors are the low power and computational capabilities of the sensor nodes. Key challenges for the transport are the real-time requirements of the bursty video traffic that needs to meet the periodic play out deadlines of the video frames as well as several lossy wireless hops between the source and the sink [4].

Transmission of the multimedia stream from nodes to sink may contain static or dynamic holes, which are caused by the inefficient placing of the sensor nodes or the overlapping. A place where sensor nodes cannot cover because of the inability to deploy nodes suitably is called a static hole. Dynamic holes mean the overlapping of the streaming data in a densely deployed sensor node environment. Efficient and reliable transmission of the multimedia streaming data back to the base station is investigated. Two Phase geographical Greedy Forwarding (TPGF) routing algorithm for exploring single or multiple optimized node-disjoint hole-bypassing transmission paths are proposed and differences between TPGF and Greedy Perimeter Stateless

Routing (GPSR) are studied and presented in [6]. Since the transmission is in streams, this case consumes more energy when compared to scalar data transmission. The network should fulfill its task in order WMSN to be beneficial to the end user. For this reason, although the lifetime of the individual nodes looks relatively unimportant, it is crucial actually. To succeed in WMSN applications, mentioned hindrances must be overcome.

1.4 Road Map of This Thesis and Motivation Behind

As clearly stated in the abstract, the motivation behind this thesis is the trade-off between energy-efficiency and accuracy. Along the literature survey, most of the studies reviewed either focused on one or other. It's nearly an inherent belief that if someone gets better results for one, will have worse results for the other. In order to fulfill the gap between the two metrics-of-interest, this thesis proposes a fuzzy fusion-based framework. According to experimental evaluations done and obtained results, this framework has a high accuracy ratio while preserving energy consumption for wireless multimedia sensor networks.

This thesis begins with the essentials of WSNs and WMSNs. This part mostly addresses to an audience of novices to WSNs. Then, detailed preliminary information about challenges in WMSN applications and multimedia streaming are given. In Chapter 2, background of the area and related work are discussed. Starting with Section 2.1, sensor types used in WMSN applications and especially in our framework, of such as the Passive Infra-Red sensor (2.1.1), the seismic sensor (2.1.2), the acoustic sensor (2.1.3) and the camera (imaging) sensor properties (2.1.4), will be given. Afterwards, selected sample studies concerning sensor types that are employed in our framework are highlighted in (2.1.5). Importance of fuzzy set theory over crisp sets for WMSNs will be detailed in Section 2.2, and thereafter in Section 2.3 data (information) fusion usage in WSN and WMSN applications will be introduced.

This will lead us to Chapter 3 where a new fuzzy clustering algorithm, named Multi-Objective Fuzzy Clustering Algorithm (MOFCA), is introduced and described in detail. Since MOFCA is the clustering algorithm implemented in the fuzzy fusion-based framework which will be presented in Chapter 4, detailed analysis and experimental evaluation of the algorithm are also done in this chapter. At the end of the chapter, a brief summary before detailing into the framework will be provided.

Following in Chapter 4, description of the efficient fuzzy fusion-based framework which this thesis is based upon is presented. Presented are surveillance applications, popular scenarios used in those applications, and a number of framework components (4.1), system modeling (4.2), fuzzy clustering (4.3), data correlation (4.4), hierarchical data fusion (4.5), experimental evaluation (4.6), and computational complexity analysis (4.7). The discussion of all of the mentioned topics here provides the background necessary for understanding the experimental results of Chapter 4. Although some sections of these chapters are more targeted to readers with not much background on WMSNs and multi-modal data fusion, many important details about how they do cooperate with each other are mixed into more generic knowledge from the reference material of this thesis. At the end of the chapter, a summary is also provided.

Finally in Chapter 5, our conclusions and possible future work are stated. This chapter will contain a summary of important observations that were made through the thesis preparation and experiments done. This will conclude the thesis.

CHAPTER 2

BACKGROUND AND RELATED WORK

In this chapter, sensor types used in WSN and especially in WMSN context are investigated. Detailed information about sensors used in the framework and sample studies including these sensor types are highlighted. Thereafter, fuzzy set theory which is crucial for sensor clustering and data fusion system is presented. Finally, preliminary information about data fusion which will be detailed in Chapter 4 is given.

2.1 WMSN Sensor Types and Sample Studies

A sensor is a device or a converter which measures a quantity and converts it / respond to it as generating an electrical output signal which can be read by observers or instruments. For high-precision measurements, it is generally calibrated against known standards. A sensor's sensitivity indicates how much the sensor's output changes when the measured quantity changes [7]. Before elaborating into WMSN sensor types, a sample Zigbee Mote data acquisition board that can embed available sensor types is depicted in Figure 2.1. Over these kinds of boards, it is possible to embed different type of sensors and by this way, a wireless sensor node is constituted. There is a wide range of available sensors that can be used in wireless platforms including Passive Infra-Red (PIR), seismic, acoustic, pyro sensors and etc. Main classification among sensors depends on the working principle of the sensor as being an active or a passive device. Active sensor transducers generate electric current or voltage directly in response to environmental stimulation. Thermocouples and piezoelectric accelerometers can be stated as examples of this type. Passive transducers produce a change in some passive electrical quantity, such as capacitance, resistance, or inductance as a result of stimulation. The stimulus could be physical such as a changing pressure, temperature; could be chemical such as a particular gas concentration; could be biological such as the presence of a biological agent; and finally, it could also be electrical such as the strength of an electric or magnetic field or a changing conductivity [8].

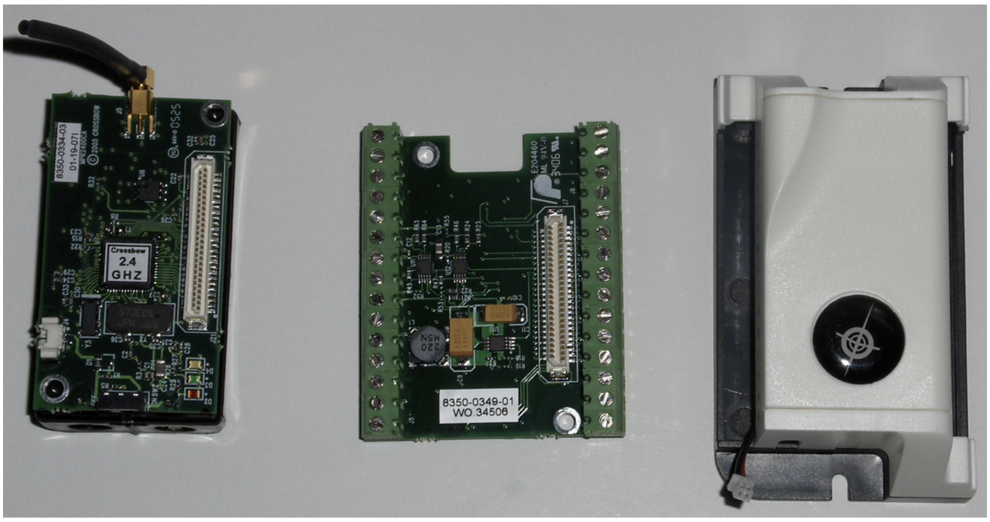

Figure 2.1: A sample Zigbee Mote data acquisition board.

As described in the previous paragraph, there can be different classifications of sensors and main classification depends on the working principle of the sensors. There are a broad variety of sensors including acoustic, vibration, chemical, moisture, flow, fluid, seismic, imaging, PIR, photon, thermal sensor classes, and so on. Since the energy consumption of the wireless nodes is crucial for the network lifetime, it will be a good choice to employ the types of sensors that require or consume the least available energy. In this respect, since passive sensors do not require external power source to work, it is preferable to use them in wireless energy-constrained environments. However, this choice also depends on the application area to be modeled; because only a subset of sensors is usable for different scenarios. In the following sub-sections, we detail and focus our view of sensors to those that are employed in most WMSN surveillance applications including our framework.

2.1.1 Passive Infra-Red (PIR) Sensors

This class of sensors senses motion (movement) within its range and view by measuring the disseminating radiation from the objects. They are small, inexpensive and low-power devices. For this reason they are suitable to be employed in WSN and WMSN applications. A sample PIR sensor is presented in Figure 2.2 [9]. They are often referred to as PIR, "Passive Infrared", "Pyroelectric", or "IR motion" sensors. Detection by these type of sensors takes place by capturing the broken field of a pre-defined normal temperature.

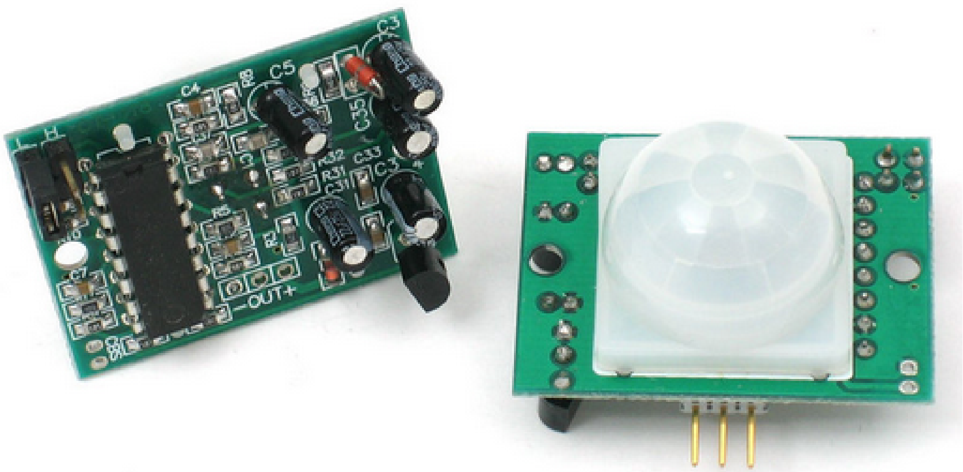

Figure 2.2: A sample Passive Infra-Red (PIR) Sensor [9].

PIRs are basically made of a pyroelectric sensor which can detect levels of infrared radiation. Every object emits some low level radiation, and the hotter the object is, the higher the emitted radiation is. The detection part of the sensor is actually split in two halves, because the thing looking to detect is the change in IR levels. The two halves are wired up so that they cancel each other out when there is no change in the measured IR levels. If one half measures more or less IR radiation than the other, the output will swing high or low according to the movement direction of the object. A sample drawing of a PIR response to a moving body is given in Figure 2.3[10].

A four-block PIR sensor diagram is depicted in Figure 2.4 [10]. The first block is for optical focusing of the IR radiation onto the PIR sensor. For this purpose, Fresnel lenses are preferred since they have lower thickness. The second is the sensing block. This block contains the real instrument that measures IR radiation. The third block is the amplifier block, which amplifies the output signal, and the last block is the

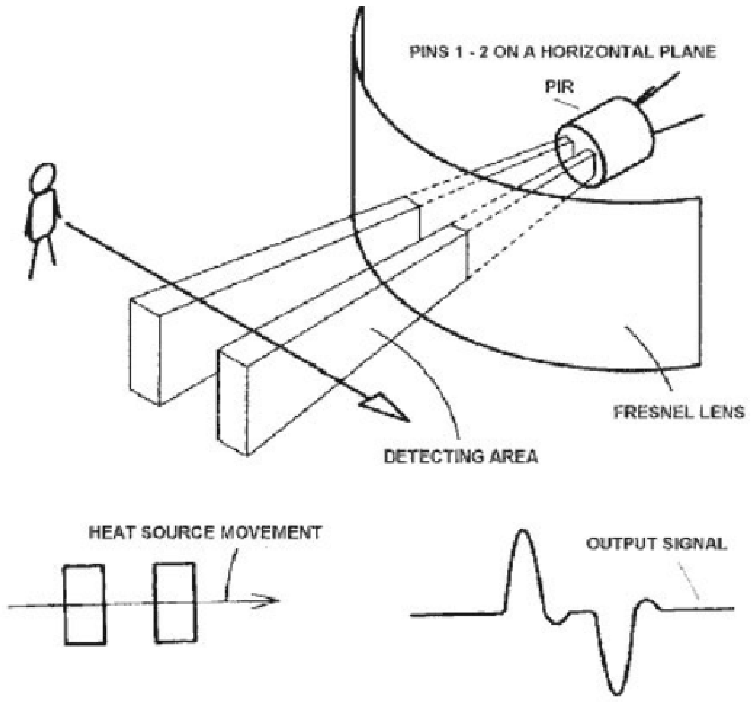

Figure 2.3: A drawing of PIR response to a moving body [10].

comparator block that gives the output voltage of either 5V for logic one or 0V for logic zero [10].

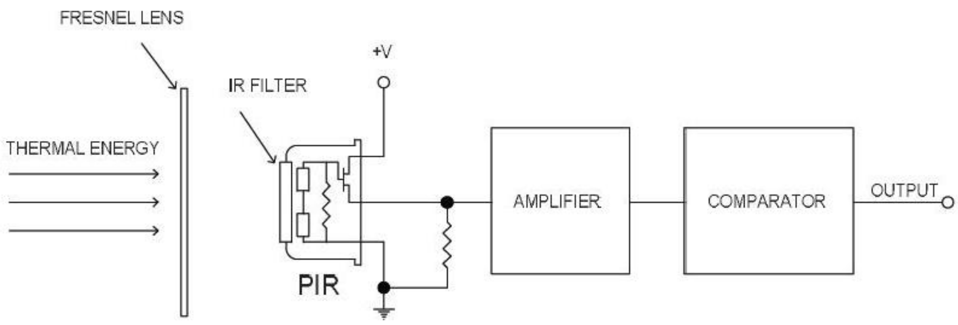

Figure 2.4: PIR Sensor Block Diagram [10].

Although PIR sensors are low power and low cost, pretty rugged, have a wide lens range, and are easy to interface with, they also have some pitfall such as PIRs won't tell us how many objects are around, what type of object is, or how close they are to the sensor. Also, when multiple targets enter the sensing field of a sensor from the both halves of the detection part at the same time, the generated signals cancel each other and there is a possibility that the detection will not occur.

2.1.2 Seismic Sensors

The second class of sensors used in WMSN applications is seismic sensors. These devices can sense seismic waves (vibrations) which are generated by activities on ground and underground. Seventy percent of generated seismic vibrations are transmitted by Rayleigh waves which spread on the surface of the world. In order to detect humans and vehicles, Rayleigh waves can be very useful because of the transmission direction [11]. Detection takes place by measuring the seismic signal. In order to use these sensors in applications such as surveillance which necessitates discrimination between object types, there are important parameters that need to be calculated. Among these parameters, step size and speed (or cadence), background noise, shoe type, presence of more than one target type, and ground and especially soil conditions are the most interesting ones. Three types of seismic sensors are used at present [12];

1) Geophones,

2) Piezoelectric acceleration sensors, and

3) Micro-mechanical silicone acceleration sensors.

Generally, the geophone sensor type is used as the seismic sensor in WSN and WMSN applications since they are more resistant to Doppler effects generated by environmental differences when compared to acoustic sensors. A geophone is a sensor type in contact with the ground surface which transduces its movements into electrical signals. Geophones have the ability to work in a passive way and possess higher detection ranges relative to other sensors [13]. A typical geophone sensor is depicted in Figure 2.5 [14].

In applications, generally two types of geophones are used: single-axis and three-axis geophones. Three-axis geophones have high bearing estimation error which is a bottleneck for this type. Single-axis geophones have the ability to respond to vibrations oriented only in the same direction as a sensor axis [15]. Because of this reason, single-axis geophones use triangulation method for path tracking applications.

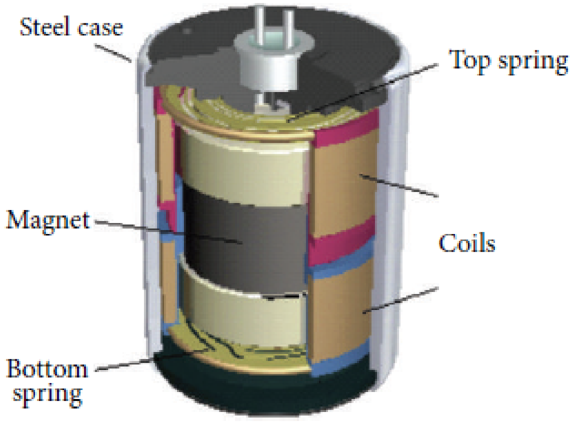

Figure 2.5: SM-24 Geophone, representative view and the unit [14].

2.1.3 Acoustic Sensors

This type of sensors are a class of Micro Electro-Mechanical Systems (MEMS) which rely on the modulation of Surface Acoustic Waves (SAW) to sense a physical phenomenon [16]. Sound waves are created by alternate compression and expansion of material at certain frequencies. The speed of sound depends on the medium through which the waves are traveling, and is often quoted as a fundamental property of the material. Nearly all acoustic wave devices and sensors use a piezoelectric material to generate the acoustic wave. SAW sensors transduces an input electrical signal into a mechanical wave which is easily influenced by physical phenomenon. This wave is then transduced to electrical signal again and changes in amplitude, phase, frequency or time-delay between input and output can be measured for detection. General structure of a surface acoustic wave sensor is depicted in Figure 2.6. A wireless surface acoustic wave sensor can be made by replacing the output Interdigitated Transducer (IDT) and by coupling the input IDT to a Radio Frequency (RF) antenna rather than a voltage source [17].

Typical SAW sensors operate from 25 to 500 MHz. One disadvantage of these devices is that Rayleigh waves are surface-normal waves, as a result SAW sensors are poorly suited for liquid sensing. When a SAW sensor is contacted by a liquid, the resulting compressional waves cause an excessive attenuation of the surface wave. Because a Rayleigh wave propagates along the surface of a material rather than through the bulk of the material, the energy of the wave is maximized at the surface. SAW sensors

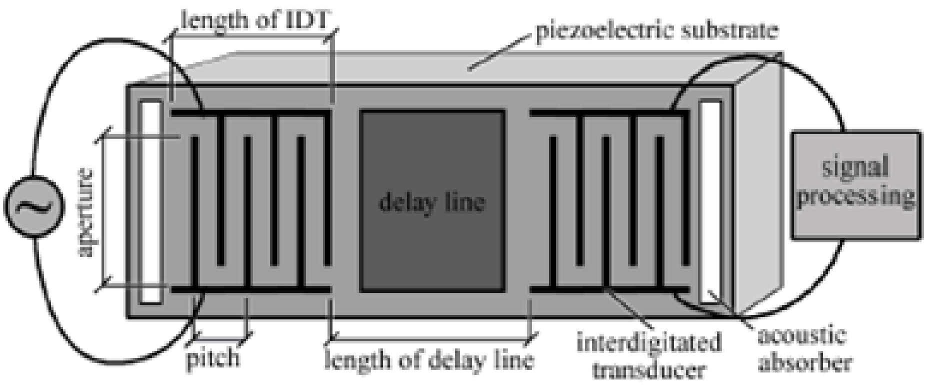

Figure 2.6: General structure of a SAW sensor [17].

make use of this principle. Commercially available Hydra acoustic sensor detection ranges by Selex ES Company are given in Figure 2.7 [18] to serve as an example of the detection range of an acoustic sensor.

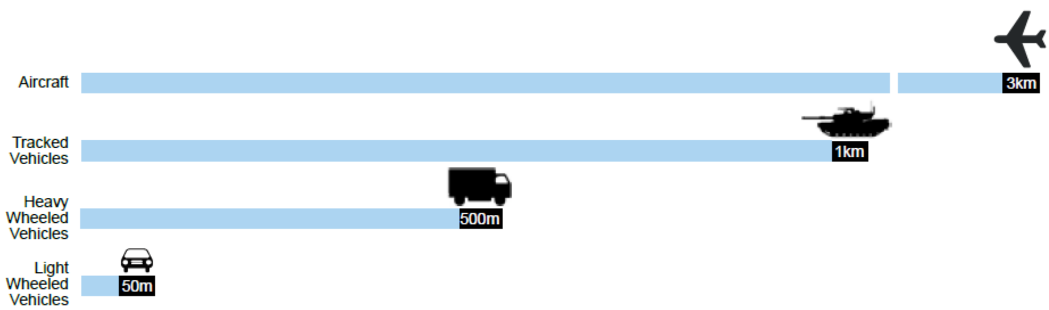

Figure 2.7: Hydra acoustic sensor detection ranges [18].

Some of the common applications of acoustic wave sensors according to [19] are:

1) Temperature Sensor (based on SAW delay line),

2) Pressure Sensor (SAW velocities as above),

3) Torque Sensor (compression & tension),

4) Mass Sensor (measuring thickness as particulate),

5) Humidity Sensor.

Other applications include measuring force, acceleration, shock, angular rate, viscosity, displacement, and flow, in addition to film characterization. The sensors also have an acoustoelectric sensitivity, allowing the detection of pH levels, ionic contaminants, and electric fields.

2.1.4 Camera (Imaging) Sensors

In accordance with the technological advances, cost of the visual data capture devices are getting cheaper every other day. Together with the increasing usage of these imaging devices in wireless environments, it is now possible to extract more detailed information from the environment. However, due to the characteristics and unique properties of the multimedia data and the resource constrained nature of WSNs, employing these imaging devices as sensors in WMSNs causes more challenges to be faced. Traditional multimedia system approach is not valid for use in WMSNs. In this regard, it is preferable to decide on what to transmit at the source since the processing cost is negligible when compared to communication cost. This type of sensors has the ability to capture and process streaming data (images and video). When attached to a wireless node, this data can also be sent to the required places for further analysis. In Figure 2.8, a sample deployment from the BWN research lab at Georgia Tech [20], Stargate board with an 802.11 card and a MICAz mote interfaced with a Logitech QuickCam Pro 4000 web cam. Cyclops [21], depicted in Figure 2.9, is a smart vision sensor that can be controlled by a low power micro-controller host. This picture shows Cyclops with an attached MICA2 Mote. As a result of these kinds of implementations, wireless nodes can process the captured images or video streams.

Figure 2.8: Logitech web cam interfaced with Stargate platform [20].

CMUCam3 is among one of the most commonly used imaging sensors [22]. It is a smart sensor having vision capabilities and used in different applications such as surveillance to which this thesis targets. Each node deployed with an imaging sensor

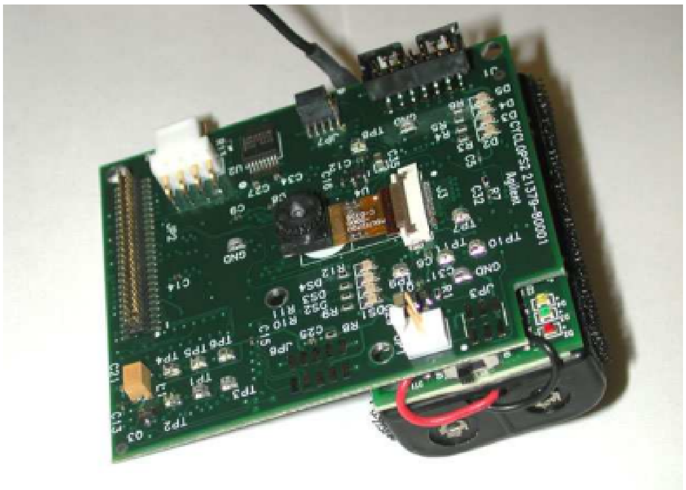

Figure 2.9: Cyclops with a miniature camera [21].

has a Field-of-View (FoV) and Depth-of-Field (DoF) values which denote the coverage of the sensor, as shown in Figure 2.10, in which imaging sensor can operate to capture and process an high-precision image or video. Because of these parameters, as opposed to seismic and acoustic sensors which have omni-directional coverage, imaging sensors have directional coverage as it is also the case for PIR sensors.

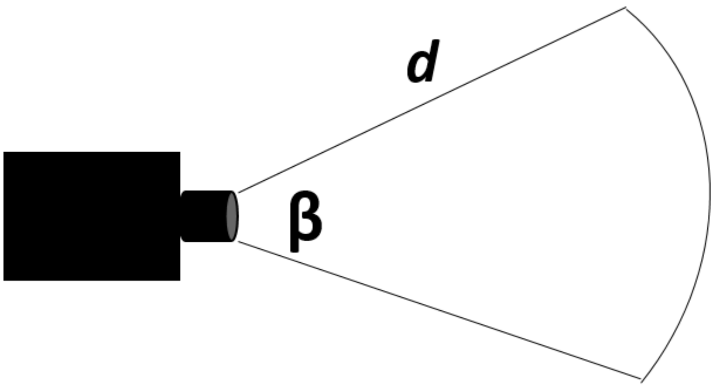

Figure 2.10: FoV (β) and DoF (d) parameters of an imaging sensor.

If the WMSN is deployed specifically for a surveillance application and is comprised of multimedia nodes which consist of camera sensors, area-of-interest (AOI) may have overlapped regions and holes (blind regions) as depicted in Figure 2.11 due to the node positioning and orientation. An overlapped region is an area which can be covered by more than one imaging sensor. A hole, or a blind region in this context, is an area which is not covered by any of the imaging sensors. In the figure, orange-colored areas are covered by more than one imaging sensor, white-colored areas are covered by only one sensor and black-colored areas denote the blind regions.

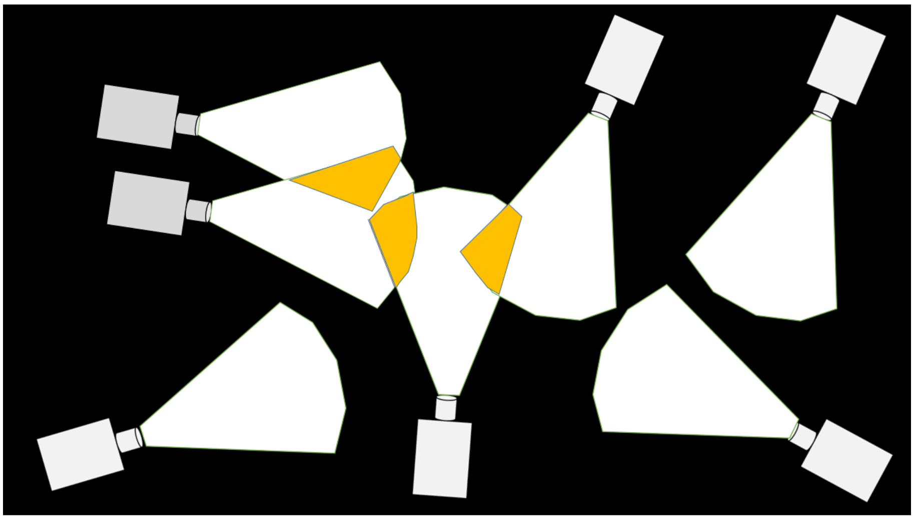

Figure 2.11: Coverage of the AOI according to imaging sensors.

2.1.5 Selected Sample Studies Concerning Sensor Types

In this subsection, selected sample studies dealing with sensor types used in WSN and WMSN applications are presented. These studies are generally single-modality researches. Studies consisting multi-modal information are presented in Section 2.3. In the context of PIR sensors; design and implementation of a wireless node including PIR sensors, called WiPIR, is given in [23]. This study explains how PIR sensors can be used for wireless sensor networks targeting surveillance systems, traffic control, and people or object tracking applications. In [24], PIR sensors are used for activity recognition with the aim of creating expert building systems that are capable of recognizing day-to-day activities of their inhabitants. By this way, authors think that this will enhance security by mining/flagging the outlier patterns in data. They also think that since these sensors only detect heat sources, they preserve much of the privacy of the occupants. This case is an example usage of PIR sensors for indoor environments. Surveillance tracking system using PIR motion sensors in WSN is studied in [25]. Here, authors first analyze the performance and the applicability of PIR sensors for security systems and then propose a region-based human tracking algorithm. According to [10], when PIR sensor circuitry is modified and analog signal is extracted and sampled instead of standard logical output, it is possible to develop human, pet and flame detection methods to be implemented on these new generation PIR sensors. Author describes the possible pros of the new sensing capabilities and implement a human motion event detection mechanism with lowered false alarm rates (FARs) through the use of these developed PIR sensors. The design of a sensor network platform for reliably detecting and classifying, and quickly reporting, rare, random, and ephemeral events in a large-scale and long-lived manner is studied in [26]. Here, together with other sensor types, authors design a PIR sensor for low-power continuous operation and include asynchronous processor wake-up circuitry.

In the context of seismic sensors; a data-driven personnel detection scheme using seismic sensors has been presented in [27]. According to the analysis done on the seismic data, authors stated that the seismic data shows the presence of non-linearity, which means that its current value cannot be determined by using past values. Moreover, as opposed to Wavelet and Fourier based techniques, which assume source linearity and stationality, Empirical Mode Decomposition (EMD) algorithm has been proposed to overcome the pitfalls of the aforementioned techniques. Other techniques that have been implemented to detect footsteps using seismic/acoustic sensors have been presented in the same study in a concise way. Seismic sensors developed by the company General Sensing Systems for footstep detection and other security applications have been tested and obtained results have been presented in [28]. Since seismic data can be storage intensive when sampled at high data rates, USB device usage as a storage medium in a WSN consisting of seismic sensors which monitor glaciers was implemented as part of the project in [29]. Comparison of geophones and accelerometers using laboratory and field data in the context of seismic sensing has been presented in [30]. According to the study done, if the sensor coupling is equivalent, the data quality is also equivalent.

In the context of acoustic sensors; by using a beam former, Multiple Signal Classification (MUSIC) algorithm has been proposed to classify multiple acoustic signals in [31] but this method needed high CPU cost, and thus proved to be inefficient for WSN applications. In another research, by applying the approximate maximum likelihood (AML) method to synchronized audio channels of each acoustic array for estimating the direction-of-arrival (DOA) of vocalizations, the location of the phenomenon is estimated in [32] by applying least square (LS) methods to DOA bearing crossings of multiple acoustic arrays to detect woodpecker locations. Unmanned Air Vehicle (UAV) usage as information-seeking data mule for the localization with sparse acoustic sensor network has been studied in [33] but since there is no direct connection among sensor nodes, we do not consider this study for our wireless multimedia sensor network applications. However, presented results are promising to be implemented in WMSN context. In the context of camera (imaging) sensors; design of a mote for distributed image sensing applications in wireless sensor networks was studied in [34]. In the study, requirements of an image sensor mote and currently available platforms are reviewed and presented extensively. As depicted in [35-37], image sensors have been considered in the past as data sources for surveillance and security applications. However, in these and most of the studies, wireless network only act as a medium which transfers the raw data (stream) to the base station (sink). Thereafter, in-network processing solutions have started to appear. These solutions were highly complex to embed in wireless nodes. As a solution to one of the known object localization problem, lightweight object localization with a single camera in wireless multimedia sensor networks was presented in [38]. According to the obtained experimental results, authors achieved promising accuracy without introducing a major energy consumption. Efficient and accurate object classification from video frames in WMSNs has been studied in [39]. Here authors describe the efficiency of the method considering the extracted effective features and accuracy by using a genetic algorithm whose memory requirements is minimal.

2.2 Fuzzy Set Theory

Fuzzy sets are sets whose elements have degrees of membership to the sets. In classical set theory, the membership of elements in a set is assessed in binary terms, an element either belongs or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval [0, 1]. Fuzzy sets generalize classical sets, since the indicator functions of classical sets are special cases of the membership functions of fuzzy sets [40]. In fuzzy set theory, classical sets are usually called crisp sets. The fuzzy set theory can be used in a wide range of domains such as wireless sensor networks in which information is incomplete, imprecise, or vague.

Mathematical definition of the Fuzzy Set is given below in Eq. 2.1. In the equation, x denotes an element of the fuzzy set and $\mu(x)$ is the membership degree of the element to the set.

$$\bar{A} = \{x, \mu(x) \mid x \in X\} \tag{2.1}$$

As stated in [41], major goals of fuzzy sets are modeling of uncertainty, relaxation (generalization of dual logic), compactification (reducing the complexity of data to some degree), and meaning preserving reasoning by using linguistic approximation. In researches concerning WSNs and especially WMSNs, fuzzy set theory is often applied in classification, clustering, and data fusion related studies mostly by employing linguistic approximation. Those applications concerning the usage of this theory will be referred in the related chapters and sections of the thesis in detail.

2.3 Data (Information) Fusion

Data fusion is a technology used for the integration of multiple data, knowledge, or information representing the same entity into a coherent, accurate, useful state, so that this fused data is used to make better decisions or representations about the entity. It is an attractive technique since it helps us better understand the nature of the entity that we cannot do so by using any of the information source alone. The term "information fusion" is taken as a synonym for data fusion, or sometimes refer to the fusion of processed form of data.

Data Fusion is probably the most studied topic lately in the WSN and WMSN researches, since the data collection (gathering/aggregation) is the primary reason of these networks and the resource-constrained nature is the primary pressure over them. There are different definitions of data fusion but here we adapt the definition in [42]. With the use of fusion techniques, volume of data that needs to be transmitted and energy consumption because of this transmission can be reduced significantly. Moreover, this also extends network lifetime since the number of alive nodes will be more when compared to fusion-less aggregation techniques. Aggregation tree related algorithms and relevant processing methods in the context of data fusion are presented in [43]. One classification about data fusion is about the time when the data fused: early or late fusion. In early fusion, gathered data is fused as early as possible and then algorithms are applied to fused data to make a decision about the detection. However, in late fusion, first algorithms are separately applied to each data to decide what the detection is, and then the results are fused. So, early fusion is sometimes called the value fusion and late fusion is sometimes referred to as decision fusion. Detailed classification of aggregation techniques and information fusion for WSNs are presented in [44] and [45], respectively. Figure 2.12 presents and describes the flow of generic data fusion process. In the figure, red colored processes (fuzzification and defuzzification) may occur or not according to the chosen fusion methodology.

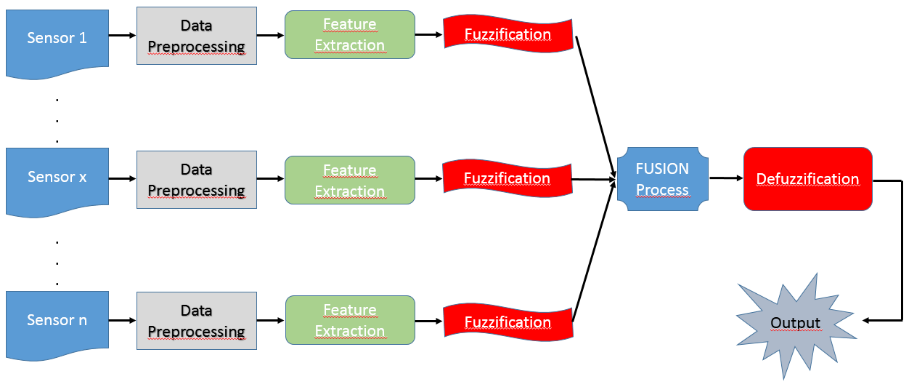

Figure 2.12: Flow of generic data fusion process.

Activity and event recognition, object localization and classification, moving target detection are among the prevailing application areas of data fusion. Bayesian data fusion for distributed target detection is studied in [46]. Here, authors describe a fusion center (FC) and sensor local decisions are fused at the FC. Cluster based data fusion, in which nodes form clusters and each cluster consists of a cluster head (CH) and several member nodes, is among the important data fusion methodologies [47]. According to [48], data fusion is effective in achieving stringent performance requirements such as short detection delay and low false/nuisance alarm rates (F/NAR), especially in the scenarios with low signal-to-noise ratios (SNRs) for real time detections. Since WMSN environment used for surveillance applications necessitates real time detection, it is obvious to use a fusion architecture for the aforementioned reasons.

CHAPTER 3

MOFCA: MULTI-OBJECTIVE FUZZY CLUSTERING ALGORITHM FOR WIRELESS SENSOR NETWORKS

Clustering is a useful method which can group sets of similar objects in a multidimensional space into so-called clusters. The objects that are member of a cluster are more similar to each other rather than to the objects in other clusters. The graphical representation of clustering is depicted in Figure 3.1, where part (a) shows the input objects to be clustered and part (b) presents the four discovered and output clusters as circles. The objects that are not assigned to any cluster are not more similar to any object in one cluster then in another cluster.

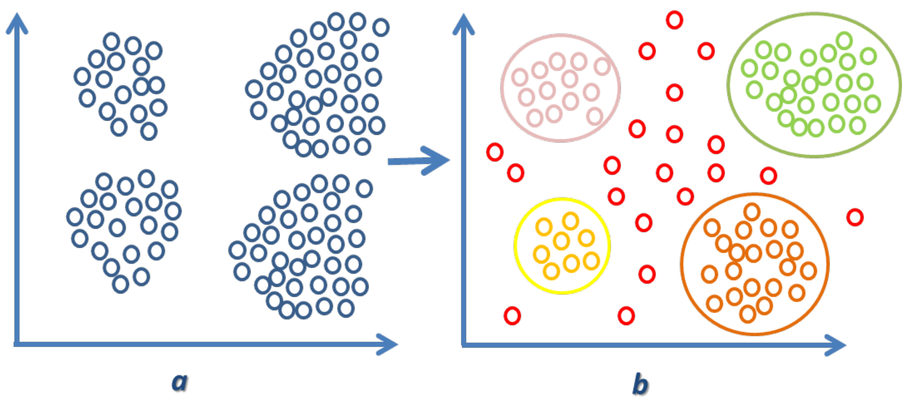

Figure 3.1: Graphical representation of clustering.

As seen from Figure 3.1, clustering greatly helps in binding together the objects of similar behavior. Actually, main idea behind clustering is that if a rule is valid for an object in one cluster it is also possible that the same rule is applicable to other objects in the same cluster since other objects in the same cluster are similar to it. In the following section, clustering phenomenon is introduced from the WSN perspective.

3.1 Introduction to Clustering Phenomenon in WSNs

Clustering is used as a means of efficient data gathering technique in terms of energy consumption in WSN context. In wireless networks, nodes (units) are geared with batteries which are not rechargeable in most of the cases. Recently, energy schemes of these nodes have gained much interest among researchers. This topic has been studied for many years, and [50] and [51] are among the recent studies and lately the trend is towards energy-harvesting nodes [52]. However, readily available commercial off-the-shelf (COTS) units may not use this technology and the deployed area may not allow the use of such available energy-harvesting methods. Because of all these reasons, decreasing energy consumption through energy-efficiency has been still one of the major goals [53]. In this respect, designing energy-efficient algorithms is crucial to extend the lifetime of sensor nodes.

In the WSN, sensor units can be grouped into small partitions which are called clusters. In each cluster, there is a cluster-head (CH), also sometimes called as the leader, which coordinates data gathering from the member units and transmission of the collected data to the sink. CH selection can be done in a centralized or distributed manner. Clustering in WSN assures stringent performance requirements even though when there are a large number of units [54] and [55]. It also improves the scalability of WSNs [56]. In addition to scalability of the network, route set up localization, communication bandwidth conservation by decreasing the relayed packets, reducing the rate of energy consumption and stabilization of the network topology are pros of clustering [57].

Since efficient CH selection can reduce energy consumption, the selection mechanisms have been studied thoroughly in the literature. Most of the available approaches utilize a two-step process, in the first step they select CHs with more remaining energy, and then in the second step they make a rotation among the member nodes to balance energy consumption. This case shows that these selection approaches take only the energy of the nodes into account, not the location and the density of the nodes yet. As a result of not considering the location of the deployed nodes, the *hotspots* problem arises in multi-hop WSNs. This problem is known as the early dying of the CHs that are close to the sink or over critical paths because of the heavy inter-cluster traffic relay. In an effort to overcome this problem, the unequal(uneven) clustering approach, which creates variable size of clusters based on the distance between CHs and the sink, has emerged. By utilizing such an unequal clustering methodology, clusters that are close to the sink are created in smaller sizes (service areas) when compared to the clusters that are further. In addition to the hotspots problem, the deployment locations of the nodes may change by redefined requirements or environmental effects. This type of networks is called *evolving networks* since they evolve over time. In this type of networks, initial distribution may look like a uniform one, however the final scene may resemble a non-uniformly distributed computing devices. As a result of this situation, the *energy hole* problem arises. This problem is known as the early dying of some close nodes around WSN which prevents data gathering. This variability in the node locations affects the density of the nodes over time. There are studies trying to address the energy hole problem by employing a non-uniform node distribution. However, most of the proposed clustering approaches do not take this situation into account either by the node-staticity assumptions or by uniform distribution of the nodes at the first phase. This distribution is especially crucial in heterogeneous WSNs when compared to their homogeneous counterparts since different sensing instruments have different ranges in which they can operate.

In this chapter, a Multi-Objective Fuzzy Clustering Algorithm (MOFCA) is introduced with the aim of prolonging the lifetime of WSNs and fulfilling the shortcomings of aforementioned approaches. MOFCA selects the final CHs via energy-based competition among the chosen tentative CHs which are initially determined by a probabilistic model. MOFCA is a distributed competitive protocol which focuses on assigning appropriate ranges to tentative CHs. Our proposed algorithm, MOFCA, utilizes three parameters; namely remaining energy, distance to the sink, and density of the nodes. Furthermore, in order to overcome the uncertainties inherent in the WSN environment, a fuzzy logic approach is utilized. To evaluate the performance of our approach, it is compared with the existing equal and unequal clustering mechanisms such as LEACH, CHEF, EEUC and EAUCF. A number of experiments are performed under predefined four scenarios. Obtained results show that MOFCA is a promising fuzzy clustering algorithm and performs better than all of the compared algorithms in the most of the scenarios. Because of these reasons, we employ MOFCA in our fuzzy fusion-based framework which will be presented in the next chapter.

The remainder of this chapter is organized as follows: in Section 3.2 background and related work about our algorithm with some domain information are presented. Then, our proposed clustering algorithm MOFCA is introduced and discussed in Section 3.3 and 3.4 in detail. Thereafter, our contributions are explored by evaluating the proposed algorithm and presenting the obtained performance results in Section 3.5. Finally, in Section 3.6, our conclusions and a brief summary are given.

3.2 Background and Related Work

Data gathering process deals with efficient data aggregation from deployed nodes. Clustering approaches in this sense provide energy-efficient infrastructure for the demanded task. The need for clustering emerges from the known requirements such as decreasing the number and size of data packets to be transmitted and providing efficient delivery mechanisms to these routed packets. This topic is even more crucial when considering the application types which include more multimedia streaming data every other day.

In the literature, there are various proposed clustering protocols for wireless networks. In the following paragraphs, key and discriminating features of the widespread clustering algorithms are stated. In order to help specify the key features of our proposed algorithm, it is useful to conceive what other available proposed algorithms do for clustering.

Low Energy Adaptive Clustering Hierarchy (LEACH) is a distributed protocol which promotes local decisions to select CHs [58]. It selects CHs based on probability model and then rotates CHs. This model is employed in order to balance energy consumption of the nodes throughout the network lifetime; otherwise selected CHs would consume more energy when compared to member nodes. In LEACH, CHs perform data compression before transmitting data to the sink. However, LEACH is not an efficient algorithm in terms of the network lifetime since it does not consider the distribution of sensor nodes and the remaining energy on each node.

Hybrid Energy-Efficient Distributed (HEED) algorithm is designed for multi-hop networks and node-equality is the primary assumption [59]. Two-phase parameter check is done to select CHs. In the first phase, remaining energy of a node is used for the probabilistic selection of the CHs. If a tie occurs in the first phase, second-phase parameters such as node degree, distance to neighbors, and intra-cluster energy consumption are applied to break the tie in the selection process.

Initialization of newly deployed sensor networks is studied in [60]. Here, the authors argue that good clustering can be computed efficiently even for the restricted network model and propose a probabilistic CH election algorithm. In their approach, the probability of each node being elected as a CH depends on the node connectivity (degree) and the main idea behind is that the nodes compete to become dominators. For this reason, algorithm tries to find a dominating set of nodes which are good candidates to be CHs.

Energy Efficient Clustering Scheme (EECS) is introduced for periodical data gathering applications in WSNs [61]. It is a LEACH-like protocol such that it utilizes node residual energy in the selection of constant number of CHs, however, in the cluster formation phase load is balanced among CHs. It is a distributed algorithm and the experimental results show that it performs nearly 35% more energy-efficient than LEACH.

Because of the uncertainties occurring in the WSN nature, increasing number of clustering algorithms [62], [63], and [67] make use of fuzzy logic to overcome the arising problems. For this reason, they are known as fuzzy clustering approaches. In these approaches, fuzzy logic is mostly employed to get a better combination of the applicable input parameters to obtain an optimal output, which is CH election in this context. In the fuzzy approach pursued by [62], the CH election occurs by considering three fuzzy descriptors in the sink which denotes this algorithm as a centralized one. Here; node centrality, node concentration, and residual energy of each node are the fuzzy input parameters.

Cluster Head Election using Fuzzy logic (CHEF) [63] is a similar approach to the proposed method in [62], but here CH election occurs in a distributed manner which does not necessitate the central control of the sink. Moreover, there is one less fuzzy descriptor. Residual energy of each node and local distance are the fuzzy input parameters of this algorithm.

Equal clustering approaches like the aforementioned ones suffer from the hot- spots problem in multi-hop WSNs. This situation is explained as the more energy consumption of the nodes that are close to the sink when compared to the further ones because of heavy relay traffic [53]. To overcome this problem, unequal (uneven) clustering approach has emerged. Main idea behind this methodology is to adjust the cluster sizes with respect to the distance between the CH and the sink. As a result, it is possible to distribute the energy consumption over the network by changing the effect of inter-cluster and intra-cluster work of the CHs according to their distances to the sink.

Energy-Efficient Unequal Clustering (EEUC) is a competitive uneven distributed clustering protocol. In the protocol, each node has a preassigned competitive radius and CHs are elected by local competition [64]. Competition radius decreases as the nodes approach the sink. In addition to being an uneven clustering protocol, this method is also a probabilistic approach since for every clustering round, a node probabilistically chooses to attend or not to the CH election competition. The term *round* points out the time interval between two successive clustering process.

Multi-objective solutions are introduced to the clustering phenomenon and Multi-Objective Particle Swarm Optimization (MOPSO) algorithm is among them. In the algorithm both number of clusters in an ad hoc network and energy consumption are tried to be optimized [65]. There are three parameters employed by this algorithm. These are the degree of the nodes, battery power consumption of mobile nodes and transmission power.

Density-Based Clustering Protocol (DBCP) is an improvement over LEACH on the basis of nodes' connectivity [66]. A metric of nodes' relative density is introduced for CH selection. By considering the alive neighbor nodes in certain round, the algorithm promotes that nodes in a dense area have larger probability to become a CH.

Energy-Aware Unequal Clustering with Fuzzy (EAUCF) algorithm is introduced to address the hotspots problem and extends the lifetime of WSNs. This algorithm utilizes randomized periodical rotation together with fuzzy logic, however, does not follow a pure probabilistic approach to elect final CHs and considers only the stationary nodes [67]. Fuzzy descriptors employed in the EAUCF are residual energy and distance to the sink of the tentative CHs.

Density-based Energy-efficient Clustering Algorithm (DECA) defines the density of each node and regards it as a crucial metric together with nodes' remaining energy [68]. These two metrics are employed to select CHs in the algorithm.

3.3 System Model

Before detailing into the proposed algorithm, properties of the system model that are used for experimental evaluation are given. Our assumptions for the system model are as follows:

- All units are identical.
- Units are deployed either manually in order to form a non-uniform distribution or randomly.
- The base station (sink) can be anywhere in the Area-of-Interest (AOI - boundaries of the WSN). It does not need to be located away from the AOI. However, it could also be out of the AOI.
- All units do not have to be stationary after the deployment phase. However, mobility meant here does not include the forceful change of the initial placement by remote control. It includes only the change in places which is caused by terrestrial movements such as erosion or displacement resulted by external objects. With the inclusion of this assumption, evolving networks are also targeted.
- Since mobility is assumed to be generated by external sources, it does not cause units to consume energy.
- When the units are deployed, they have the same energy level, and this battery-power is initially one (1) joule (j).

- Units are able to adjust transmission power with respect to the distance of the receiving units.
- Distance calculation between nodes is done considering the received signal level.

Representation of the energy dissipation model is as employed in [58]. Depleted energy measurement in transmitting or receiving l bit over a distance of d is done as in Eq. 3.1 and Eq. 3.2, respectively. E_{elec} = 50nJ/bit, ε_{fs} = 10pJ/bit/m^2 , ε_{mp} = 0.0010pJ/bit/m^4 and d_0 = 20 m. E_{elec} is the consumed energy per bit in the transmitter and receiver electronic circuitry and ε_{mp} is the energy disseminated per bit in the RF amplifier.

$$E^{TX}(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2, d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4, d \geq d_0 \end{cases} \tag{3.1}$$

$$E^{RX}(l) = E^{RX-elec}(l) = lE_{elec} \tag{3.2}$$

3.4 Algorithm Essentials

MOFCA is designed by considering two important factors: firstly it should be energy efficient in all employable scenarios and secondly lightweight enough to be implemented on real sensor hardware boards. It is a distributed unequal fuzzy clustering algorithm which makes use of local decisions for the determination of node competition radius and electing tentative and final CHs. There is no need for a central decision node (generally the sink) for the election process. Motivation behind the algorithm is to overcome the hotspots and evolving network situation occurring in WSNs while still achieving efficient results for the stationary distribution case. That is why, this algorithm is called a multi-objective solution for clustering problems. MOFCA considers three parameters, namely distance to the sink, node remaining energy, and the density of the node with the aim of estimating the competition radius for tentative CHs. In addition to these parameters, MOFCA also employs fuzzy logic in calculating competition radius. With the use of fuzzy input and output variables, uncertainties inherent in the WSN nature are handled in an effective manner. MOFCA is based upon a probabilistic model which is used for the election of tentative CHs and utilizes randomized periodical rotation. Our approach is multi-objective, since it reaches an efficient solution to the clustering phenomenon considering both the stationary and evolving networks. MOFCA employs remaining energy, distance to the sink, and density of the nodes, nearly all parameters considered so far, together with fuzzy logic in estimating competition radius. The flow of messages in MOFCA protocol together with the pseudo-code is explained in Algorithm 1. $Comp_i$, E_i , and S_i represent the competition radius, remaining energy and state of a particular sensor node i respectively.

Each unit generates a random number (μ in Algorithm 1) between the unit interval [0,1] in every round. If the generated number for a particular unit is not equal to or greater than the predefined threshold (Th), which depicts the ratio of the aspired tentative CHs, then that unit (i) becomes a tentative CH. Since MOFCA uses remaining energy, distance to the base station, and density parameters to calculate competition radius, this value changes dynamically in MOFCA. It is wise to adjust the competition radius of a CH while these input parameters are changing. If this radius does not change according to the values of the input variables, the unit's energy depletes rapidly. To get rid of this situation, MOFCA adjust the competition radius of each tentative CH accordingly. In order to handle uncertainty, computation of the radius is done by using predefined fuzzy rules. This process is depicted as line 8 in Algorithm 1. The fuzzy rules are given in Table 3.1. To be able to evaluate the rules, the Mamdani Controller [41] is employed as a fuzzy inference procedure and the Center of Gravity (CoG), also called the Center of Area (CoA), method is employed for the defuzzification process of the competition radius.

Algorithm 1: MOFCA Protocol

Input: A Non-Clustered WSN

Output: A Clustered WSN

Th ← Threshold value for becoming a tentative CH
S_i ← CLUSTERMEMBER
clusterMembers ← NULL
myCH ← This (self)
becomeTentativeCH ← TRUE
if *(μ <Th)* **then**
    By using three fuzzy input variables, generate crisp $Comp_i$
    Disseminate CandidateMessage (*Id*, $Comp_i$, E_i, d_i)
    On receiving CandidateMessage from node j
    if *($E_i < E_j$)* **then**
        becomeTentativeCH ← FALSE
        Disseminate CeaseElectionMessage(*Id*)
    else if *(($E_i = E_j$) and ($d_i \leq d_j$))* **then**
        becomeTentativeCH ← FALSE
        Disseminate CeaseElectionMessage(*Id*)
if *(becomeTentativeCH = TRUE)* **then**
    Disseminate CHMessage(*Id*)
    S_i ← CLUSTERHEAD
    On receiving JoinCHMessage(*Id*) from node j
    clusterMembers ← ADD(j)
    EXIT
else
    On receiving all CHMessages
    myCH ← the nearest CH
    Send JoinCHMessage(*Id*) to the nearest CH
    EXIT

Table 3.1: Fuzzy Rules in MOFCA Protocol

Distance to Base Station	**Remaining Energy**	**Calculated Density**	**Competition Radius**
Close	Low	Dense	12XS
Close	Low	Normal	11XS
Close	Low	Sparse	10XS
Close	Medium	Dense	9XS
Close	Medium	Normal	8XS
Close	Medium	Sparse	7XS
Close	High	Dense	6XS
Close	High	Normal	5XS
Close	High	Sparse	4XS
Medium	Low	Dense	3XS
Medium	Low	Normal	2XS
Medium	Low	Sparse	XS (Extra S)
Medium	Medium	Sparse	Small (S)
Medium	Medium	Normal	Medium (M)
Medium	Medium	Dense	Large (L)
Medium	High	Sparse	XL (Extra L)
Medium	High	Normal	2XL
Medium	High	Dense	3XL
Far	Low	Sparse	4XL
Far	Low	Normal	5XL
Far	Low	Dense	6XL
Far	Medium	Sparse	7XL
Far	Medium	Normal	8XL
Far	Medium	Dense	9XL
Far	High	Sparse	10XL
Far	High	Normal	11XL
Far	High	Dense	12XL

In the defuzzification, the fuzzy controller first calculates the area under the membership functions and within the range of the output variable, and then uses the Eq. 3.3 to calculate the geometric center of this area, where CoA is the center of area, x is the value of the linguistic variable, and x_{min} and x_{max} represent the range of the linguistic variable.

$$CoA = \frac{\displaystyle\int_{x_{min}}^{x_{max}} f(x) * x dx}{\displaystyle\int_{x_{min}}^{x_{max}} f(x) dx} \tag{3.3}$$

Three fuzzy input variables (descriptors) are used for calculating the CH competition radius. The first one is the distance to the sink. The fuzzy set defining this descriptor is depicted in Figure 3.2. The linguistic variables of this set are *close*, *medium* and *far*. A trapezoidal membership function is selected for *close* and *far*. However, triangular membership function is selected for *medium*.

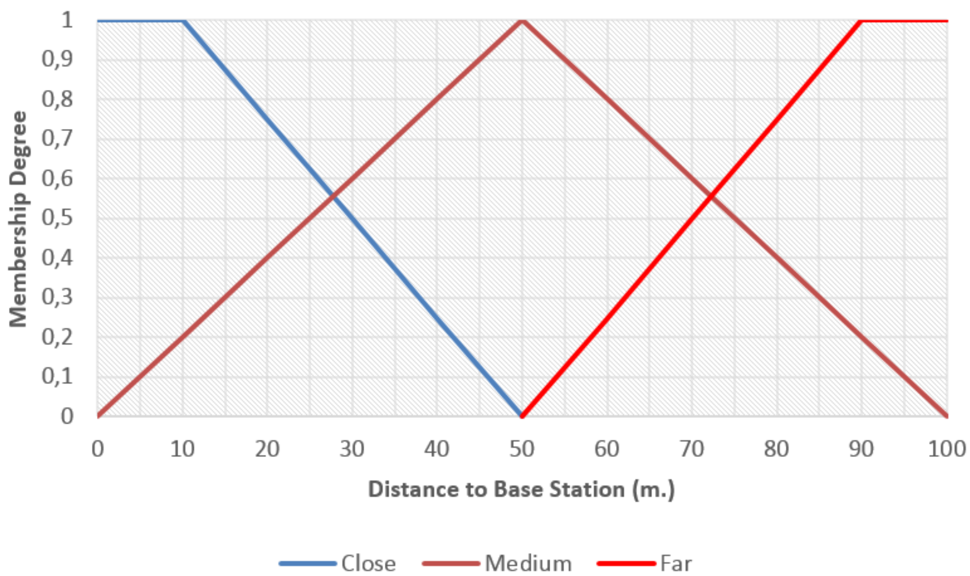

Figure 3.2: Fuzzy set defining the fuzzy input descriptor Distance to the Sink.

The remaining energy of the tentative CH is the second fuzzy descriptor. The fuzzy set defining this descriptor is given in Figure 3.3. This fuzzy set has *Low*, *medium* and *high* linguistic variables. A trapezoidal membership function is selected for *low* and *high*, whereas a triangular function is selected for *medium*.

The third fuzzy input descriptor is density of the tentative CH. The fuzzy set defining this descriptor is illustrated in Figure 3.4. *Sparse*, *normal* and *dense* are the linguistic variables of this fuzzy set. *Sparse* and *dense* linguistic variables have a trapezoidal membership function while *normal* has a triangular membership function.

In addition to other two fuzzy input variables which try to reach an energy-efficient solution, this variable adds robustness against changes in unit locations. This is achieved through tuning the competition radius according to the calculated density. This fuzzy variable helps tentative CHs which have higher unit density to compete for a larger radius. However, this is only true if we consider the distance to base station fuzzy variable having the values of *medium* or *far*. For the *close* value of this fuzzy vari-

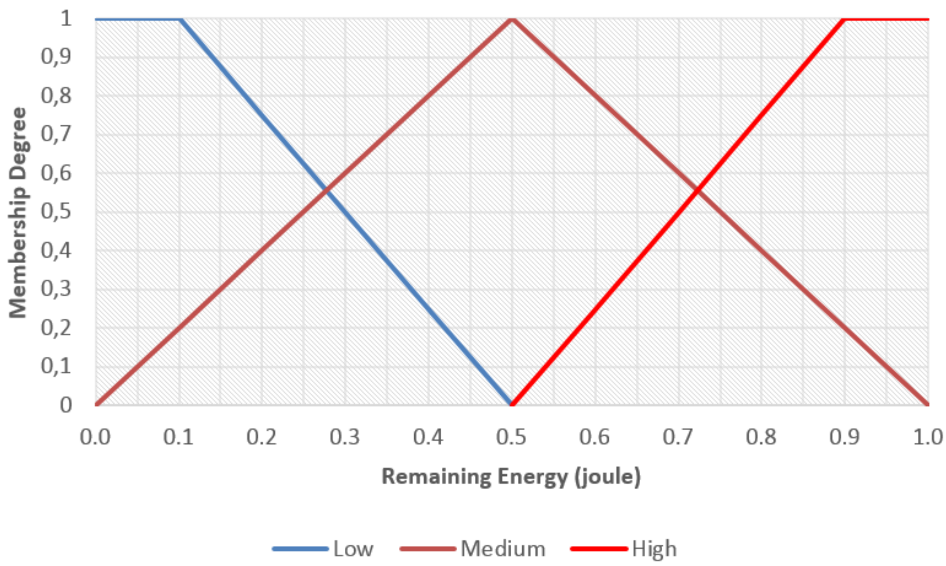

Figure 3.3: Fuzzy set defining the fuzzy input descriptor Remaining Energy.

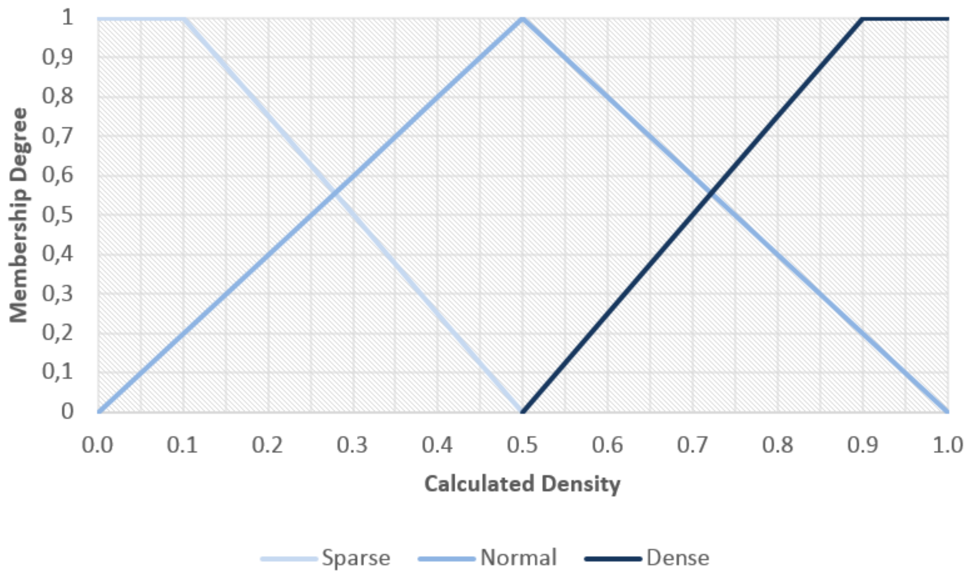

Figure 3.4: Fuzzy set defining the fuzzy input descriptor Density.

able, higher density means a smaller competition radius in order to decrease the service area of a CH. As a result of this tuning, clusters are formed more efficiently and the hotspots problem is alleviated. Moreover, for possible high-density areas in a non-uniformly deployed WSNs, it has an advantage that more units can become members of the elected nearest CHs and transmit to shorter distances. However, the vice-versa is also possible for some *deliberately formed* WSNs and, for this situation it exacerbates the efficiency metrics. By stating deliberately formed WSN, we imply the cases where most of the units are deployed around the corners of the quadratic shape of the AOI, the base station is nearly at the center of the AOI, and there are some high-energy units that are close to the base station and have *low* calculated unit densities in their competition ranges according to the units that are placed around corners. For this situation, MOFCA, by considering all fuzzy input variables, may elect a non-optimal CH and assign units to further tentative CHs. Although, this situation is tried to be addressed in fuzzy rules depicted in Table 3.1, experimental results are corroborating this condition. As a result of this situation, more energy might be consumed. However, this case is most probably not to be seen in any WSN that are not formed to exploit the effects of this situation. Densities of the tentative CHs (d_i) are calculated as in Eq. 3.4. A wireless unit knows the number of active units in its radius. However, for the calculation of node density parameter, a node needs to know the number of all active units in network (denominator in Eq. 3.4). Since the number of all active units may change at each round and it is not possible for a node to know its value, this value is broadcast to the WSN by the sink at the start of each round. Density fuzzy input variable in MOFCA is not employed as it is in DBCP. Higher node density in MOFCA means a bigger or smaller competition radius when electing tentative CHs while higher node density in DBCP means a greater probability for a node to become a CH.

$$d_i = \frac{Number\ of\ Alive\ Nodes\ in\ Radius}{Number\ of\ All\ Alive\ Nodes\ in\ Network} \tag{3.4}$$

The competition radius of the tentative CH is the only fuzzy output descriptor. Fuzzy set defining this fuzzy output descriptor is given in Figure 3.5. There are 27 linguistic variables which are very *12XS (extra small), 11XS, ... ,XS, small, medium, large, XL, ... , 11XL, and 12XL (extra large)*. *12XS* and *12XL* have a trapezoidal membership function. Triangular membership functions are employed for the remaining linguistic variables. The function in Figure 3.5 is not a symmetric triangular function as in previous figures. This is because the function in Figure 3.5 provides better results when employed in the simulation of scenarios. The fuzzy set for this output variable can also be tuned according to a specific scenario; however, we employ the same fuzzy set in all scenarios. If a particular tentative CH is located at the maximum distance to the base station (fuzzy input variable Distance to Base Station has the value of *far*), it has a full battery (fuzzy input variable Remaining Energy has the value of *high*), and calculated density in its region is high (fuzzy input variable Calculated

Density has the value of *dense*), then it has the maximum competition radius (fuzzy output variable Competition Radius has the value of *12XL*). On the contrary, if the remaining energy of a particular CH is near empty (fuzzy input variable Remaining Energy has the value of *low*), it is a close node to the sink (fuzzy input variable Distance to Base Station has the value of *close*), and calculated density in its region is high (fuzzy input variable Calculated Density has the value of *dense*) then it has the minimum competition radius (fuzzy output variable Competition Radius has the value of *12XS*). These extreme cases are colored in red in Table 3.1. The remaining possibilities fall between these boundaries.

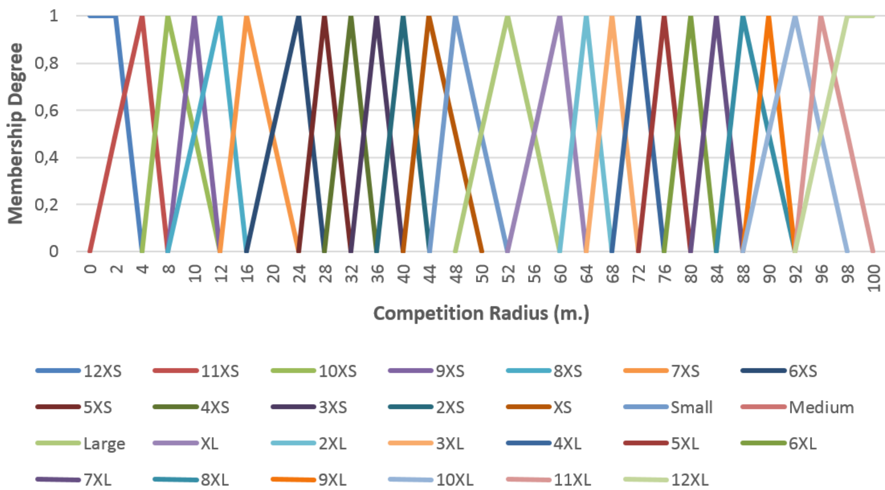

Figure 3.5: Fuzzy set defining the fuzzy output variable Competition Radius.

The *maximum competition radius* does not change for a particular WSN because either units are stationary in WSNs or the borders of the AOI are always known. The value of this parameter is advertised to the whole network by the sink. For these reasons, all units know this value beforehand. Relative competition radius of each unit can be calculated by using this parameter. The *maximum distance to the sink* does not change either, since the units are assumed to be stationary or only mobile in the AOI. Relative position of each unit to the sink can be determined by taking the maximum distance to the sink into consideration in the WSN.

Following the determination of the the competition radius of each tentative CH, the competition commences. Each tentative CH disseminates *CandidateCH* message to compete with other tentative CHs. This message is transmitted to the tentative CHs which are inside the maximum CH competition radius. It includes node information (*Id*), competition radius ($Comp_i$) , remaining energy level (E_i), and density (d_i) of the generating node. Remaining energy is the first key parameter in CH competition. If a tentative CH receives a *CandidateCH* message from another tentative CH which is in its competition range and the remaining energy of the generating node is greater than the remaining energy of the receiving node, then the receiving node cease the competition and disseminates a *CeaseElection* message. If a tie occurs in the remaining energy levels of the competing nodes, it is broken through the consideration of the calculated densities. If a particular tentative CH has the highest remaining energy level among the tentative CH which it receives a *CandidateCH* message from, or if it has the highest degree alive node density in its radius among equal-energy tentative CHs, then it becomes a CH.

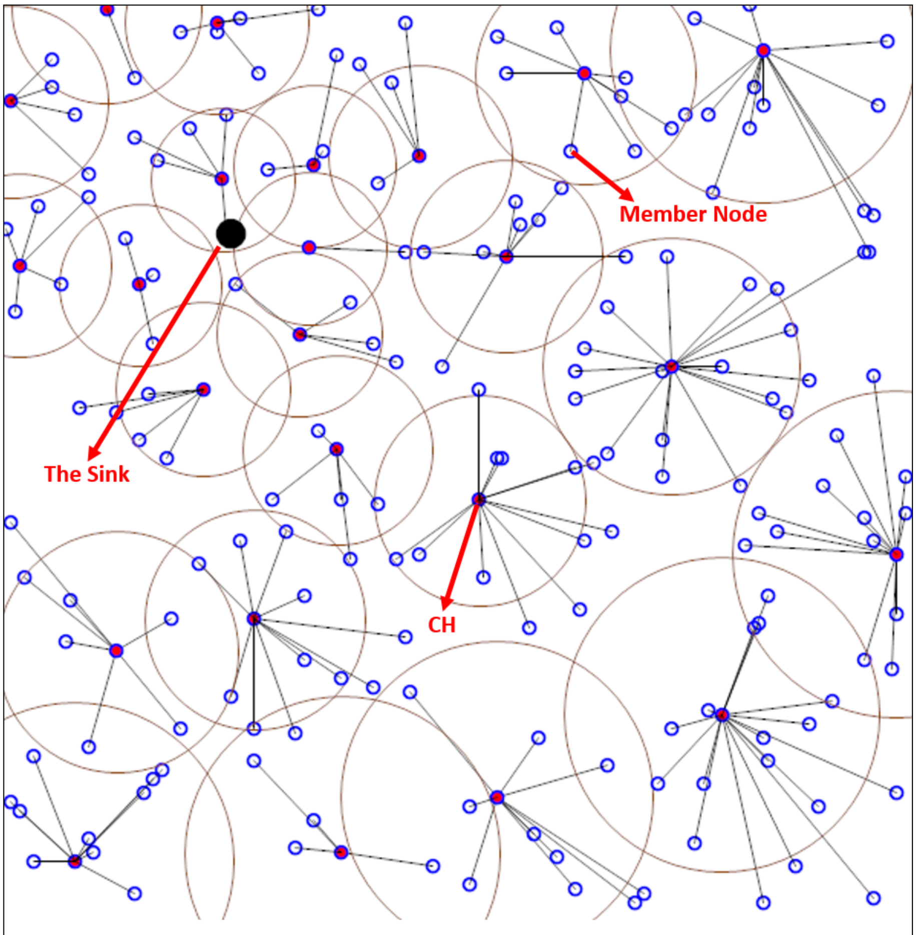

Figure 3.6: A WSN clustered by using our proposed MOFCA protocol.

With this competition, it is assured that no other CH co-exists in the competition radius of a particular CH and hereby, energy consumption over network is balanced. After election is completed, each sensor node not elected as one of the final CHs joins to the closest CH, as in most proposed clustering schemes. Figure 3.6 illustrates a part of the WSN which is clustered by using the proposed MOFCA algorithm. A total number of 200 wireless nodes are deployed to the AOI in this instance. The size of the AOI is 200m x 200m. The base station (sink) is colored in solid black with a larger size when compared to ordinary nodes, each CH is colored in solid red, and cluster member nodes are not filled with color. Node types are pointed out and service area (size/range) of the formed clusters are depicted in grey circles in the figure.

3.5 Experimental Evaluation

The obtained results of the simulations to analyze MOFCA are presented in this section. To assess the performance of the proposed algorithm, we compare it with the existing algorithms, namely LEACH, CHEF, EEUC, and EAUCF, in four different predefined scenarios in which there are two different cases with respect to the implemented routing protocol. These cases are the same for all scenarios which are direct transmission to the sink or multi-hop routing. Location of the sink has two varieties in the scenarios: either in AOI or out of the AOI. Node distribution is done either near-uniformly or non-uniformly by random or manual placement. By stating manual placement, we mean that nodes are distributed randomly into the selected areas which are chosen to form a non-uniform distribution type. Thus, we refrain from a setup which might provide an optimal scene for one algorithm but not for another. Total number of eight different set ups are tested. Scenarios detailed in the following subsections are chosen in an effort to test the impacts of node distribution type, routing protocol, and the location of the sink over protocols' energy-efficiency.

3.5.1 Experimental Setup and Performance Metrics

In all of the scenarios, CHs formed by LEACH algorithm forwards the gathered data to the base station via direct routing protocol and the desired ratio of CHs for this algorithm is set to 10%. Other algorithms employ either *direct* or *multi-hop* routing protocol depending on the selected case of the scenario. The α value of CHEF is set to 2.5 as in [63]. The optimal threshold value is calculated by using the equations in [63] and set as approximately 0.3 for 100 units and 0.21 for 200 units. For the EEUC

[61] and EAUCF [67] algorithms, threshold and coefficient values are set as defined in the original studies. For MOFCA, this value is set as 0.3. Outline of the predefined scenarios is as follows:

- In scenario 1, the sink is out of the AOI and units are deployed randomly to form a near-uniform distribution.
- In scenario 2, the sink is at the center of the AOI and units are deployed randomly to form a near-uniform distribution.
- In scenario 3, the sink is out of the AOI and units are deployed manually to form a non-uniform distribution.
- In scenario 4, the sink is at the center of the AOI and units are deployed manually to form a non-uniform distribution.

In depicted scenarios, CHs are elected and clusters are formed at each round. Then each CLUSTERMEMBER unit sends 4000-bit data to its CLUSTERHEAD. Each elected CH accumulates the received data with a defined ratio before transmitting to the base station. This accumulation ratio is set to 10% as employed in [63] and [67]. The size of data for a CH after accumulation is calculated by using Eq. 3.5 and Eq. 3.6. Here, S_{comp} depicts the value of compressed data, S_{rec} denotes the size of the received data from each CLUSTERMEMBER node, R_{acc} denotes the accumulation ratio, and N denotes the number of the cluster member nodes except CLUSTERHEAD in a particular formed cluster. Total of S_{comp} and S_{rec} denotes the size of the accumulated data, S_{acc} .

$$S_{comp} = (S_{rec} \times R_{acc} \times N) \tag{3.5}$$

$$S_{acc} = (S_{rec} + S_{comp}) \tag{3.6}$$

In order to test the effectiveness of our proposed algorithm, a set of experiments are conducted by using a WSN simulator[67]. This simulator is developed using the C# language and Microsoft .Net Framework 4.0, and is able to simulate the selected protocols in the same setup. However, simulations can also be done by using MATLAB

R2012b or MASON simulation libraries. The network is deployed on a 200m x 200m AOI and nodes deployed either to the selected to test the effectiveness, x_i and y_i coordinates manually or randomly. The initial energy of each node is modeled as 1 joule (j). All experiments are conducted on an eight-core Intel Xeon processor server running the Windows Server 2012 operating system. Every scenario is simulated 100 times to obtain more reliable and stable results and the average of the results are presented in the following subsection.

Metrics considered commonly to analyze the lifetime of the WSNs and efficiency of protocols are the First Node Dies (FND), the Half of the Nodes Alive (HNA), and the Last Node Dies (LND). According to these metrics [69], FND depicts a roughly calculated value for the round in which the first node (unit) of the network dies. This metric is useful for sparsely deployed WSNs and for the cases where the dying of a single node is crucial. However, for other cases, the dying of a single node is not so important. The WSN can still do its predefined duty without that first node being alive. Because there are so many cases that are not in the scope of the FND, the HNA metric is proposed to denote a roughly calculated value for the round in which half of the nodes die. This metric is especially useful when considering the coverage aspect of the AOIs by WSNs. The LND metric is also proposed to depict a roughly calculated value for the whole lifetime of the WSN. However, we follow the approach as stated in [67] such that most WSNs will be useless in most cases after half of the nodes die and employ the FND, HNA, and Total Remaining Energy (TRE) metrics to assess the performance of the compared protocols.

3.5.2 Performance Results

In the following four subsections, performance of MOFCA is evaluated according to the predefined scenarios. Obtained experimental results show that MOFCA outperforms the existing algorithms in the same set up in terms of efficiency metrics, which are FND, HNA, and TRE used for estimating the lifetime of the WSNs and efficiency of protocols. Evaluation of compared algorithms are done at the end of each scenario.

3.5.2.1 Scenario 1

In this scenario, the sink is out of the AOI and the nodes are deployed randomly to form a near-uniform distribution. The main idea behind choosing this scenario is to exploit the effects of the location of the sink and transmission type over near-uniform stationary distribution type among algorithms. A representative snapshot of the AOI in Scenario 1 is depicted in Figure 3.7.

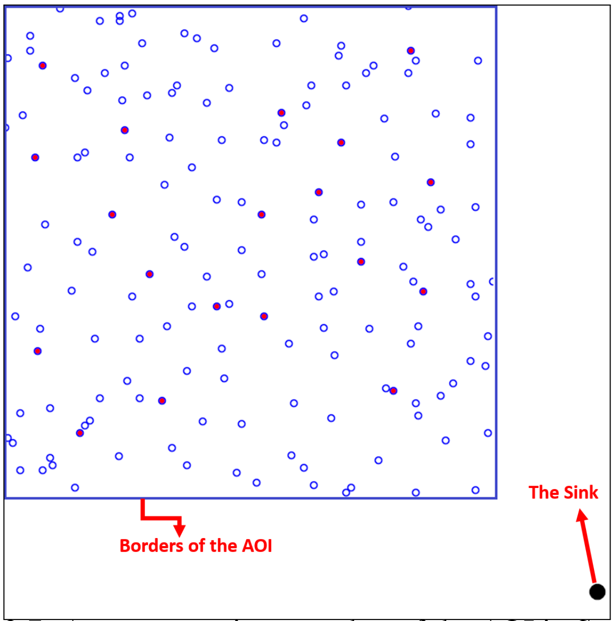

Figure 3.7: A representative snapshot of the AOI in Scenario 1.

CHs formed by the LEACH algorithm forwards the accumulated data to the base station with direct transmission in both cases. Other compared algorithms implement direct transmission in the first case, and the EEUC multi-hop routing protocol as depicted in [64] in the second case. Configuration applied in this scenario is depicted in Table 3.2.

Table 3.2: Configuration for Scenario 1.

Parameter	Value
AOI (Network Boundaries)	200m x 200m
Location of the sink	(250,250)
Number of deployed units	100
Data packet size	4000 bits
ε_{mp}	0.0010pJ/bit/m^4
E_{elec}	50nJ/bit
Aggregation ratio	10%

The experimental results of different cases are given in Table 3.3 and Table 3.4, respectively. The maximum competition radius for the EEUC, EAUCF and MOFCA algorithms in direct routing case are set as 80, 105 and 100m, respectively.

Table 3.3: Experimental Results of Scenario 1 (Direct Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	108	201	16.27
CHEF	75	209	17.54
EEUC	106	230	19.24
EAUCF	110	253	21.49
MOFCA	117	271	26.08

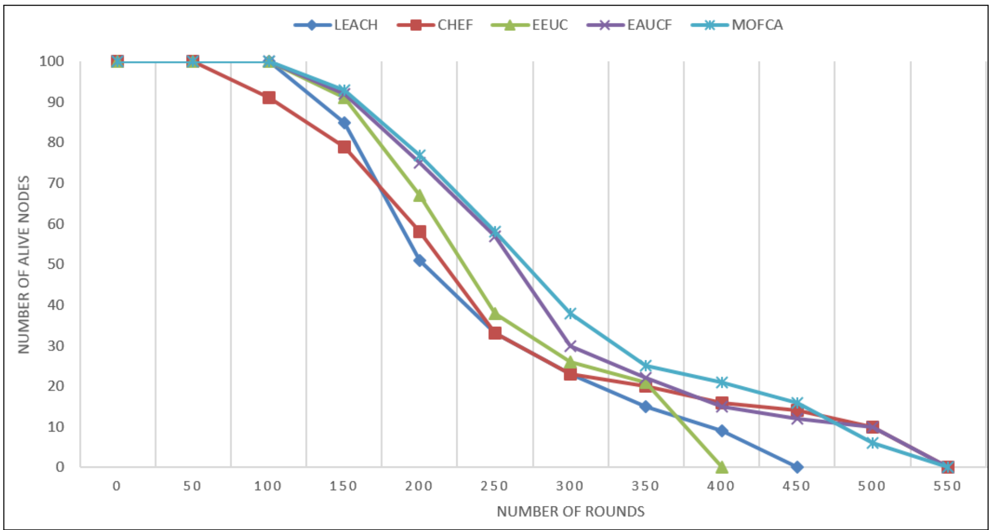

Figure 3.8: Dispersion of the active (alive) units with respect to the rounds (Scenario 1 direct routing case).

As can be seen from Table 3.3, our proposed MOFCA algorithm outperforms all other algorithms when considering all metrics. In this scenario, TRE is measured at round 200. Performance of CHEF is the worst when considering the FND metric; however, it performs better than LEACH if we consider the HNA metric. Dispersion of the active (alive) units with respect to the rounds for the first case is depicted in Figure 3.8. As can be seen from the figure, the starting point for the death of the deployed nodes in MOFCA occurs after all compared algorithms. Performances of LEACH and EEUC look like similar initially, however when considering the HNA metric, EEUC performs better than LEACH and CHEF both. Also the performance of EAUCF is close to MOFCA, and they pursue a parallel energy consumption phase; however, after the half of the node dies, EAUCF depletes TRE faster than MOFCA till nearly the last nodes. In this case, MOFCA performs 8% better than LEACH, 36% better than CHEF, 10% better than EEUC, and 6% better than EAUCF when considering the FND metric.

Table 3.4 depicts the multi-hop routing case for Scenario 1. The maximum competition radius for the EEUC, EAUCF and MOFCA algorithms in this case are set as 55, 60 and 70m, respectively. Our proposed MOFCA algorithm performs better than all compared algorithms when considering the FND, HNA, and TRE metrics. For the multi-hop routing case, performance of CHEF is similar to the first case. It is outperformed by all algorithms considering the FND metric. However, it performs better than LEACH considering the HNA metric. Dispersion of the active (alive) units with respect to the rounds for this case is depicted in Figure 3.9.

Table 3.4: Experimental Results of Scenario 1 (Multi-Hop Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	101	203	16.38
CHEF	77	221	35.13
EEUC	104	259	35.1
EAUCF	109	271	41.21
MOFCA	126	284	43.67

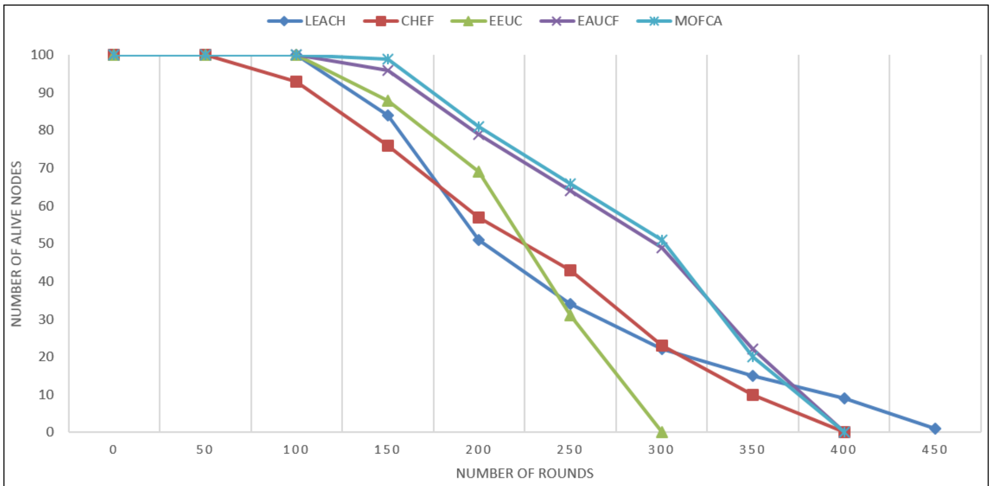

Figure 3.9: Dispersion of the active (alive) units with respect to the rounds (Scenario 1 multi-hop routing case).

As can be seen from the figure, death of nodes for MOFCA starts after all compared algorithms in this case, too. CHEF pursues a static decrease in TRE after the death of the first node differing from its performance in the first case. Other algorithms perform nearly the same when their performances are compared with their performances in the first case. In this case, MOFCA performs nearly 20% better than LEACH, 39% better than CHEF, 18% better than EEUC, and 14% better than EAUCF when considering FND and performs nearly 29% better than LEACH, 23% better than CHEF, 9% better than EEUC, and 5% better than EAUCF for the HNA metric.

3.5.2.2 Scenario 2

The sink is at the center of the AOI and the nodes are deployed randomly to form a near-uniform distribution in this scenario. As in scenario 1, the main idea behind choosing this scenario is to exploit the effects of the location of the sink and transmission type over near-uniform stationary distribution type among algorithms. A snapshot of the AOI in Scenario 2 is depicted in Figure 3.10.

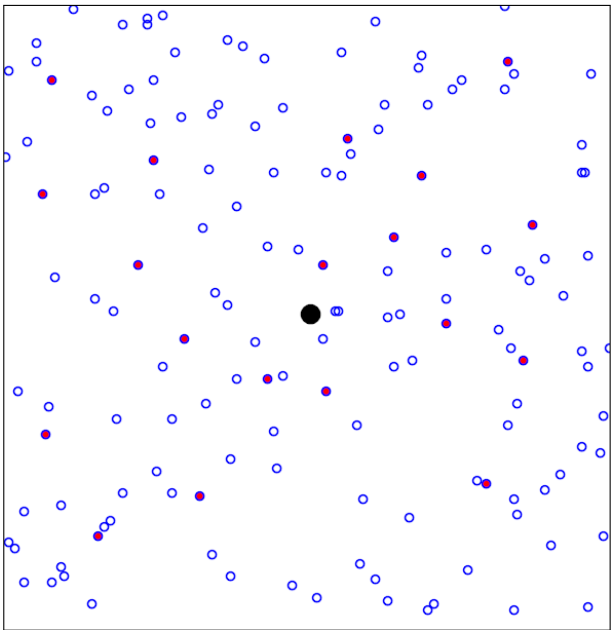

Figure 3.10: A representative snapshot of the AOI in Scenario 2.

CHs formed by the LEACH algorithm forwards the accumulated data to the base station with direct transmission in both cases. Other compared algorithms implement direct transmission in the first case, and the EEUC multi-hop routing protocol in the second case. Configuration applied in this scenario is depicted in Table 3.5.

The experimental results of different cases of this scenario are given in Table 3.6 and Table 3.7, respectively. The maximum competition radius for the EEUC, EAUCF and

Table 3.5: Configuration for Scenario 2.

Parameter	Value
AOI (Network Boundaries)	200m x 200m
Location of the sink	(100,100)
Number of deployed units	100
Data packet size	4000 bits
ε_{mp}	0.0010pJ/bit/m^4
E_{elec}	50nJ/bit
Aggregation ratio	10%

MOFCA algorithms in the direct routing case are set as 30, 60, and 65 m, respectively. TRE is measured at round 500 in the first case and at round 700 in the second case.

Table 3.6: Experimental Results of Scenario 2 (Direct Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	357	628	24.28
CHEF	440	773	37.48
EEUC	421	768	37.74
EAUCF	473	802	39.96
MOFCA	490	819	41.42

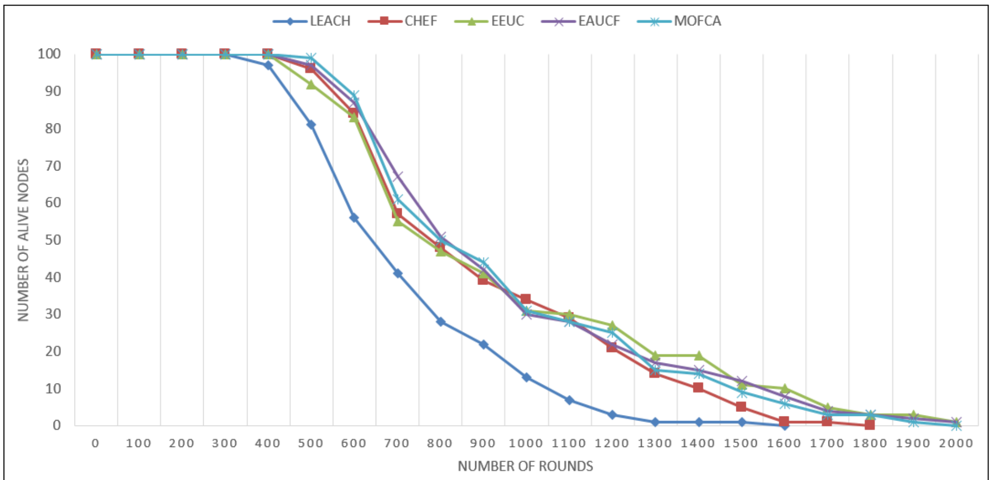

Figure 3.11: Dispersion of the active (alive) units with respect to the rounds (Scenario 2 direct routing case).

As can be seen from the Table 3.6, our proposed MOFCA algorithm outperforms all other algorithms when considering all metrics. Here, performance of the LEACH algorithm is the poorest most probably because it purely follows a probabilistic approach without considering the remaining energy levels of the nodes when selecting final CHs. CHEF outperforms LEACH and EEUC when considering the FND and HNA metrics, which is different from results of the first case of Scenario 1. By looking at this result, we may state that the location of the sink has a great impact over the performance of CHEF since this is true for both cases of this scenario.

Table 3.7: Experimental Results of Scenario 2 (Multi-Hop Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	360	624	8.53
CHEF	441	777	19.17
EEUC	424	769	20.14
EAUCF	487	816	20.82
MOFCA	479	837	20.94

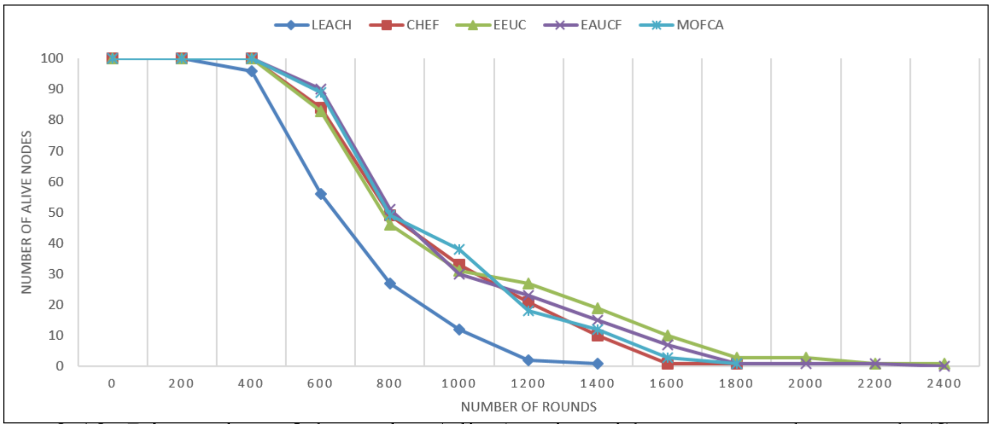

Figure 3.12: Dispersion of the active (alive) units with respect to the rounds (Scenario 2 multi-hop routing case).

Dispersions of the active (alive) units with respect to the rounds for both cases of this scenario are depicted in Figure 3.11 and Figure 3.12, respectively. Table 3.7 depicts the multi-hop routing case for Scenario 2. The maximum competition radius for the EEUC, EAUCF and MOFCA algorithms in the direct routing case are set as 30, 60, and 45 m, respectively. Although our proposed MOFCA algorithm performs better than all compared algorithms when considering the HNA metric, EAUCF performs better than MOFCA, which is an interesting result. After mining the results of this case, we come up with a situation that MOFCA creates less number of clusters initially than EAUCF does, because of the competition radius adjustment according to the values of the input variables which causes it to consume more energy initially. However, after some of the nodes die and the density of each node changes accordingly, MOFCA enters a more stable state, catches up EAUCF, and performs better than all of the other algorithms for the HNA and TRE metrics. The performance of LEACH is the worst in both cases. By looking at the decrease in number of alive sensors in the algorithms, it is correct to state that algorithms except LEACH pursue more or less similar executions. In this case, as stated, EAUCF performs 2% better than MOFCA for the FND metric, but MOFCA performs 25% better than LEACH, 8% better than CHEF and 11% better than EEUC for the same metric. Moreover, MOFCA performs better than all compared algorithms when considering the HNA and TRE metrics. Between MOFCA and its closest rival EAUCF, there is a 3% difference in HNA metric, as can be seen from Table 3.7.

3.5.2.3 Scenario 3

In this scenario, the sink is out of the AOI again, as in Scenario 1. However, the nodes are deployed manually to form a non-uniform distribution type. A representative snapshot of the AOI in Scenario 3 is depicted in Figure 3.13.

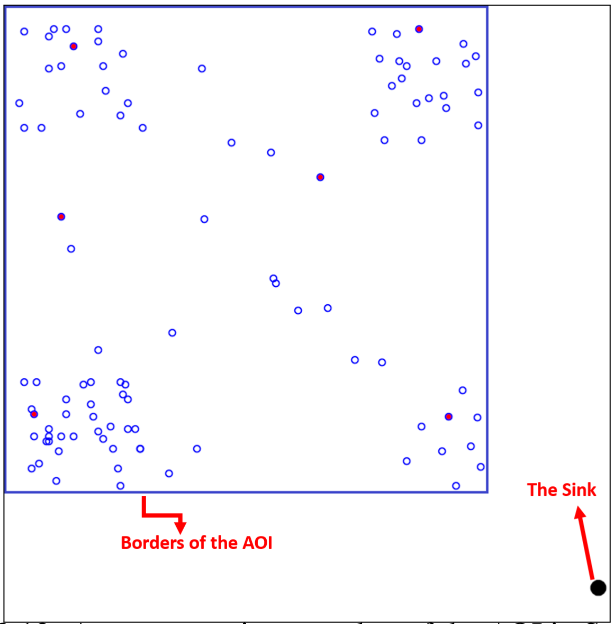

Figure 3.13: A representative snapshot of the AOI in Scenario 3.

Configuration of this scenario is the same as Scenario 1, so it will not be given here again. Main differences between Scenario 1 and Scenario 3 are the deployment and distribution types of nodes. Moreover, at each round location of the nodes are changed +/- 5m in x and y coordinates in order to simulate an evolving non-uniformly distributed network. The experimental results of different cases of this scenario are given in Table 3.8 and Table 3.9, respectively.

Table 3.8: Experimental Results of Scenario 3 (Direct Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	91	189	20.74
CHEF	76	159	15.90
EEUC	129	251	36.17
EAUCF	136	259	36.51
MOFCA	154	273	37.56

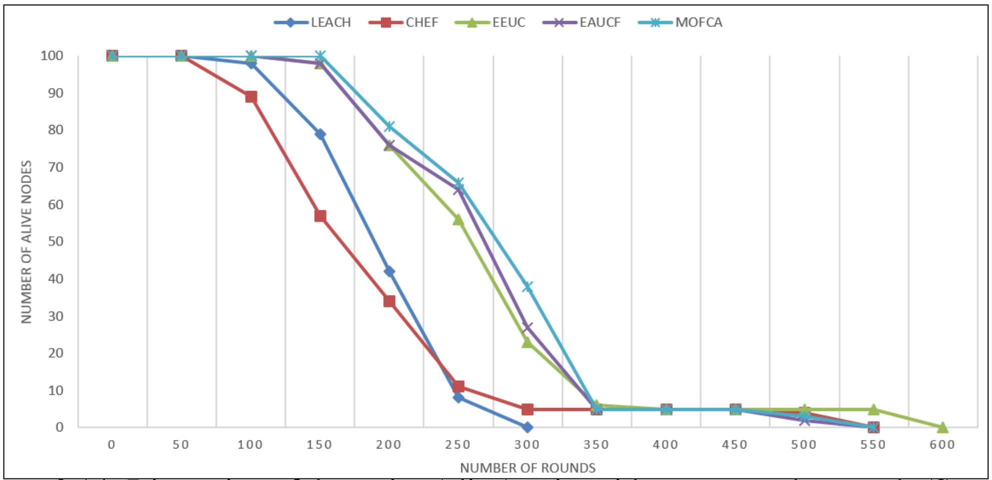

Figure 3.14: Dispersion of the active (alive) units with respect to the rounds (Scenario 3 direct routing case).

As can be seen from the Table 3.8, our proposed MOFCA outperforms all other algorithms when considering the FND, HNA, and TRE metrics. For the direct routing case, TRE is measured at round 150. Here, the performance of CHEF is again the poorest. Performances of EEUC and EAUCF are similar but EAUCF performs slightly better than EEUC. However, MOFCA outperforms all in an observable ratio as can be seen from the FND and HNA metric results. The proposed MOFCA protocol performs 41% better than LEACH, 51% better than CHEF, 19% better than EEUC, and 12% better than EAUCF for the FND metric. For the HNA metric, it is still the best performing algorithm on this set up; however, difference among MOFCA and compared algorithms decrease since the active units in MOFCA dies sharply faster than other algorithms after some round because it moves away from creating the necessitated number of clusters. Table 3.9 depicts the multi-hop routing case for Scenario 3. TRE is measured at round 100 for the multi-hop routing case. Proposed MOFCA protocol performs nearly 3% better than LEACH, 73% better than CHEF, 7% better than EEUC, and 8% better than EAUCF for the FND metric. It also performs better than compared algorithms for the HNA and TRE metrics.

According to the results of the both cases CHEF is the most sensitive algorithm to the transmission type. All algorithms except LEACH suffer in a great deal from the multi-hop transmission type considering the FND metric. However, if we consider the HNA metric, they are not affected from the transmission type as much as CHEF. Dispersions of the active (alive) units with respect to the rounds for both cases of this scenario are depicted in Figure 3.14 and Figure 3.15, respectively.

Table 3.9: Experimental Results of Scenario 3 (Multi-Hop Routing Case).

Algorithm	**FND**	**HNA**	**TRE(j)**
LEACH	88	189	43.50
CHEF	25	206	58.32
EEUC	84	254	67.47
EAUCF	83	261	68.50
MOFCA	90	268	70.34

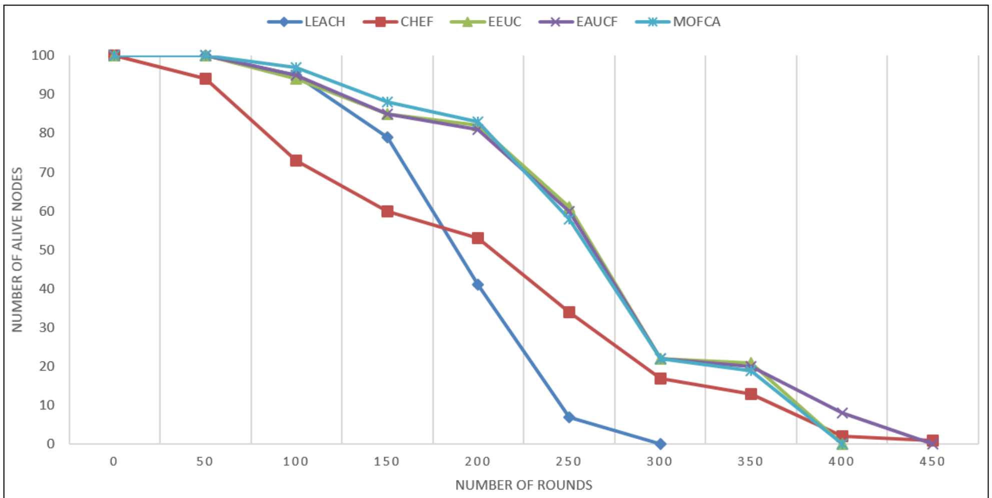

Figure 3.15: Dispersion of the active (alive) units with respect to the rounds (Scenario 3 multi-hop routing case).

As can be seen from the figures Figure 3.14 and Figure 3.15 both, if the sink is out of AOI, equal clustering algorithms suffer from this situation drastically. However, unequal clustering handles this situation in a much more effective manner.

3.5.2.4 Scenario 4

The base station is at the center of AOI and the nodes are deployed manually to form a non-uniform evolving distribution in this scenario. The main idea behind choosing this scenario is to exploit the effects of the location of the sink and non-uniform evolving distribution type together with transmission type over compared clustering algorithms. A representative snapshot of the AOI in Scenario 4 is depicted in Figure 3.16.

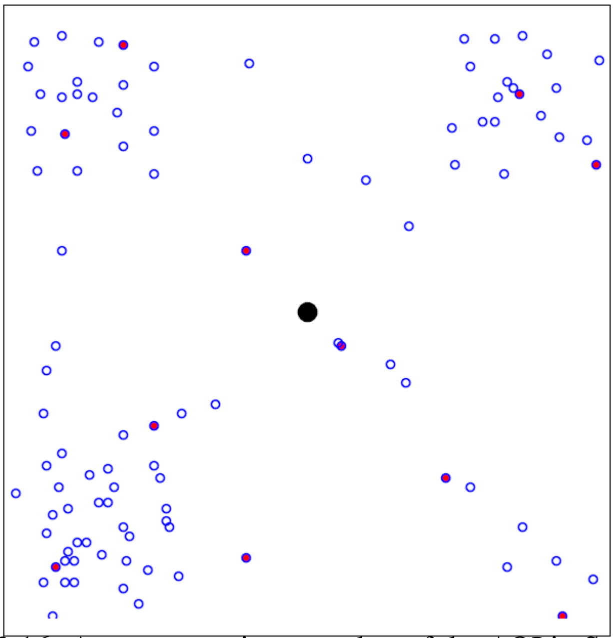

Figure 3.16: A representative snapshot of the AOI in Scenario 4.

Configuration of this scenario is the same as Scenario 2, so it will not be given here again. The difference between Scenario 2 and Scenario 4 are the deployment and distribution types of nodes. Moreover, at each round location of the nodes are changed +/- 5m in x and y coordinates in order to simulate an evolving network like in previous scenario.

Simulation results for different cases of this scenario are given in Table 3.10 and Table 3.11, respectively. As can be seen from the Table 3.10, proposed MOFCA protocol performs nearly 57% efficient than LEACH, 29% efficient than CHEF, 10% efficient than EEUC, and 8% efficient than EAUCF for the FND metric. TRE is measure at round 500 in both cases of this scenario. For the HNA and TRE metric, efficiency is still preserved in the direct routing case.

Table 3.11 depicts the multi-hop routing case for Scenario 4. In this case, MOFCA protocol performs nearly 53% efficient than LEACH, 22% efficient than CHEF, 10% efficient than EEUC, and 8% efficient than EAUCF for the FND metric. For the HNA and TRE metrics, efficiency is preserved like in the previous case. Dispersions of the active (alive) units with respect to the rounds for both cases of this scenario are depicted in Figure 3.17 and Figure 3.18, respectively.

Table 3.10: Experimental Results of Scenario 4 (Direct Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	217	599	18.93
CHEF	361	719	26.38
EEUC	453	835	38.18
EAUCF	464	837	38.85
MOFCA	502	873	38.91

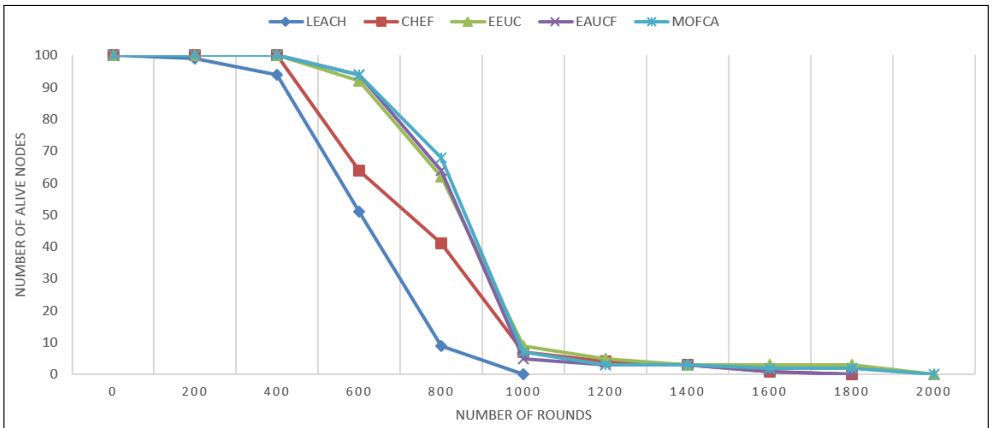

Figure 3.17: Dispersion of the active (alive) units with respect to the rounds (Scenario 4 direct routing case).

As in scenario 2, in Scenario 4 the location of the sink has also a great impact over the performance of CHEF for evolving network types. According to the experimental evaluations done among algorithms and obtained results, the MOFCA protocol outperforms all algorithms in all predefined scenarios except Scenario 2 multi-hop routing case which shows that this protocol is both energy-efficient and also robust against changes in the location of the nodes, which occur in evolving networks. In Scenario 2, multi-hop routing case, although the first node dies earlier than EAUCF, MOFCA performs better than EAUCF when HNA and TRE metrics are considered.

Table 3.11: Experimental Results of Scenario 4 (Multi-Hop Routing Case).

Algorithm	FND	HNA	TRE(j)
LEACH	220	599	19.24
CHEF	362	722	26.05
EEUC	418	806	38.43
EAUCF	426	822	38.67
MOFCA	461	847	39.83

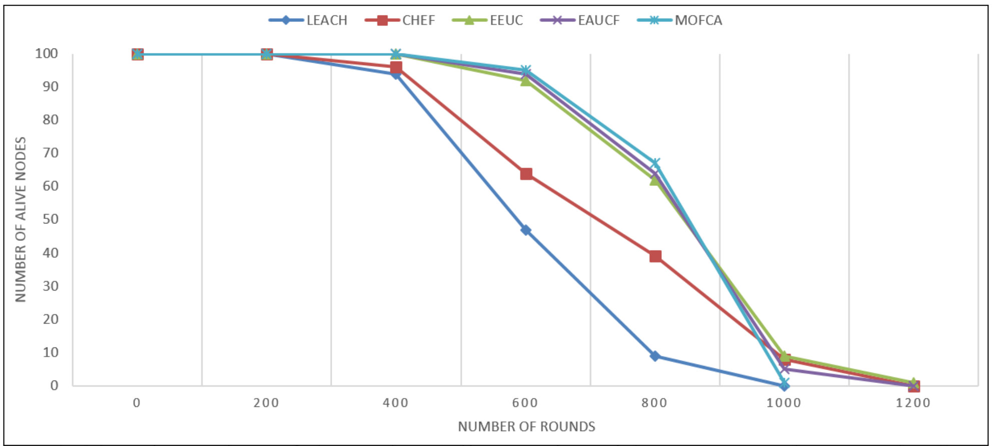

Figure 3.18: Dispersion of the active (alive) units with respect to the rounds (Scenario 4 multi-hop routing case).

3.6 Summary

If the obtained result sets of the predefined scenarios are analyzed and cross-comparisons are made, it can be concluded that the location of the sink has the uttermost impact on the CHEF protocol. So CHEF can be considered as a location-dependent algorithm of the sink. When the sink resides out of the AOI, it causes nodes to consume more energy because of transmission to longer distances. However, the increase in consumption for LEACH is affected less. The other algorithms are affected more or less the same way. When the impact of distribution type and stationary/evolving networks over protocols are to be investigated, it is realized that performance of EEUC gets closer to the performances of EAUCF and MOFCA under non-uniform evolving distribution type. Although EAUCF perform better than MOFCA for the FND metric under stationary near-uniform distribution type, it is not valid for the non-uniform evolving distribution type. If we compare the impact of direct transmission with EEUC multi-hop routing over protocols, it does not promote any bad performing algorithm to a better place or the vice-versa, which means that it has ignorable distinctive value.

In this chapter, we propose a multi-objective fuzzy clustering algorithm (MOFCA) which is not only energy-efficient but also distribution-independent for WSNs. Our proposed MOFCA algorithm considers remaining energy levels, distance to the sink, and density parameters in calculation of the cluster head competition radius while making use of fuzzy logic for overcoming the uncertainties occurring in the WSN nature. According to the evaluations done, it is an energy-efficient algorithm while its performance scales well.

CHAPTER 4

AN EFFICIENT FUZZY FUSION-BASED FRAMEWORK FOR SURVEILLANCE APPLICATIONS

This chapter is the core part of this thesis, because here we focus on a new approach for addressing the trade-off between accuracy and energy-efficiency of Wireless Multimedia Sensor Networks. Although a number of previous studies have focused on various special topics in Wireless Multimedia Sensor Networks in detail, to the best of our knowledge, none presents a fuzzy multi-modal data fusion system, which is light-weight and provides a high accuracy ratio. Especially, multi-modal data fusion targeting surveillance applications makes it inevitable to work within a multi-level hierarchical framework. In this chapter, we primarily focus on accuracy and efficiency by utilizing such a framework. In order to evaluate the performance of the proposed framework, a set of experiments is conducted and obtained results are presented. Comparison of the framework is done with the most employed setup. This setup, which we call *the baseline*, implements the same procedures till the data preprocessing step of our framework. However, from then on, it greatly diverges from the flow of our framework. Flowcharts of our proposed framework and the baseline are depicted in Figure 4.1 and Figure 4.2, respectively. In Figure 4.1 and Figure 4.2 both, node deployment, data correlation, data preprocessing steps occur in the same way. For this reason, they do not have any distinctive value and are not included in the efficiency comparison. However, clustering, data fusion, classification, and transmission steps occur in a different way and included in the evaluation.

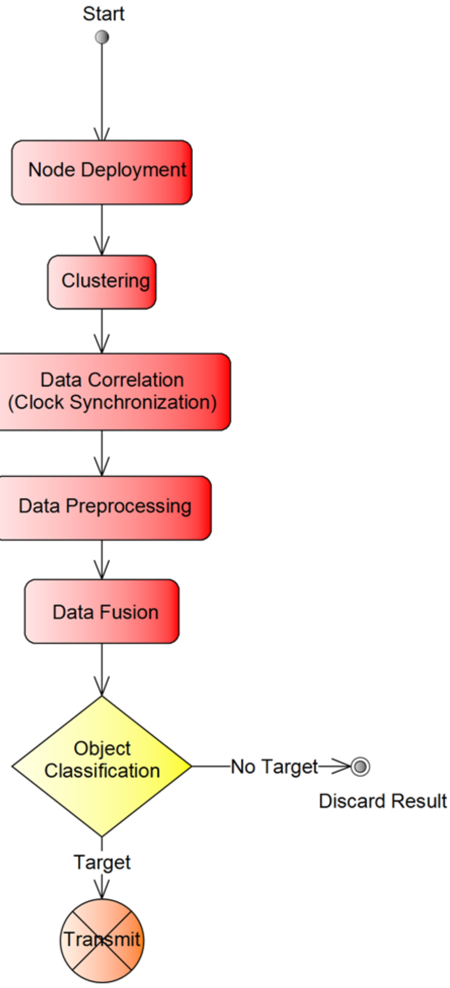

Figure 4.1: Flowchart of our proposed framework.

Previous advances in Information Technologies (IT) and especially in MEMS (Micro Electro-Mechanical Systems), have made the production and deployment of tiny, battery-powered nodes communicating over wireless links possible. As stated shortly in the first chapter, networks comprised of such nodes with sensing capability are called Wireless Sensor Networks (WSN). An early deployment aim was to use these sensors in a passive way for indoor applications. These kinds of early nodes had the ability to sense scalar data such as temperature, humidity, pressure and location of surrounding objects. Initially, these nodes had little computation capability and storage space and their only use was to transfer scalar data to the sink.

However, recently available sensor nodes have higher computation capability, higher storage space and better power solutions with respect to their predecessors and their primary usage area shifts from indoor to outdoor applications. With these develop-

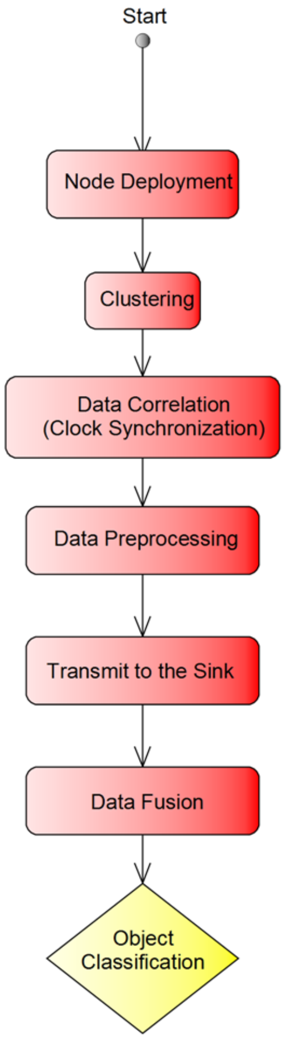

Figure 4.2: Flowchart of *the baseline*.

ments, in addition to scalar data delivery, multimedia content delivery has become the core focus. A wireless sensor network with multimedia capabilities, as often called Wireless Multimedia Sensor Network (WMSN), consists of different kinds of nodes that are equipped with various types of sensing units. They measure not only scalar data, which can be transmitted through low-bandwidth channels and in a delay-tolerant manner, but also still images, audio and video streams, which require high-bandwidth channels. Reference architecture of a WMSN is presented as Figure 1.2 [2] in the first chapter of this thesis. Our architecture for the data fusion framework is similar to the multi-tier (hierarchical) architecture which includes heterogeneous sensors and implements distributed processing. However, our system is adapted for the surveillance applications domain specifically. Proposed WMSN architecture for the data fusion framework is presented in Figure 4.3. In the figure, three popular sample scenarios for surveillance applications, namely area surveillance, path/trail surveillance and border/perimeter surveillance, are depicted. These scenarios are chosen in an effort to cover most of the implementation areas.

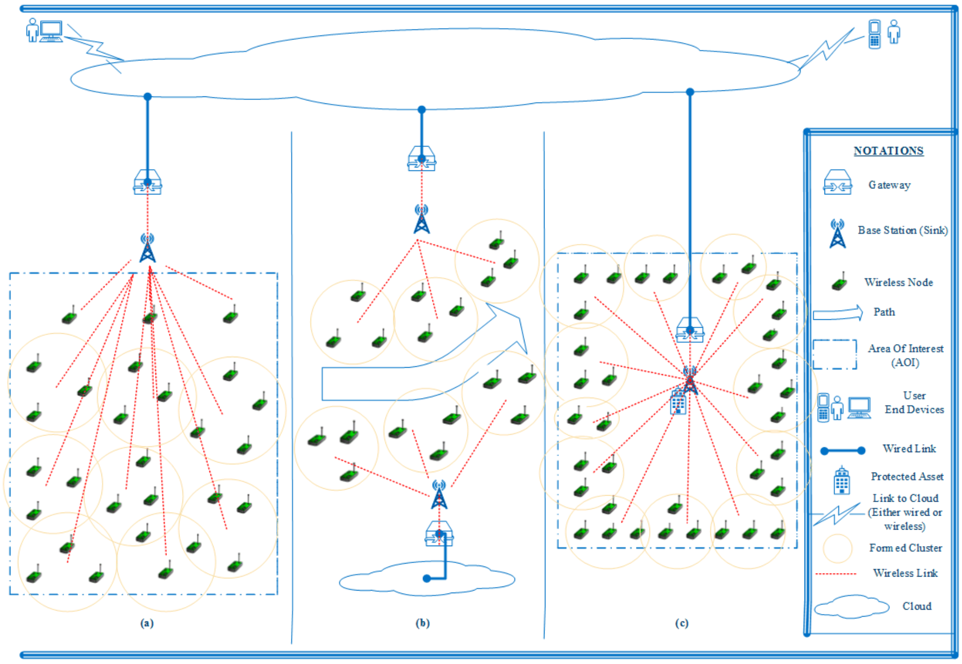

Figure 4.3: Proposed WMSN architecture for the data fusion framework. a) Area Surveillance b) Path/Trail Surveillance c) Border/Perimeter Surveillance.

4.1 Surveillance Applications and Framework Essentials

Surveillance applications probably are among the most implemented usage areas of WMSNs. Although it looks as if it is one of the military application types at first glance, more and more civilian implementations that consist of applications such as fire detection and city planning systems emerge every other day. In our thesis, we have chosen the area and border/perimeter surveillance applications as depicted in Figure 4.3 (a) and (c) to be modeled using our framework. In the AOI, we aim to detect objects and classify them as being human, animal, vehicle, or noise. In doing this, we make use of nodes which include PIR, seismic, acoustic, and camera sensors, about which we have provided the principles and selected sample studies in the second chapter of this thesis. These sensors could be placed on the same node, as well as on different nodes. The optimal subset of sensors to be employed for any specific application in any WMSN architecture, deployment algorithms, routing techniques, and security issues are beyond the scope of this thesis. We assume that all available sensor types (PIR, acoustic, seismic and camera) are present on any node. However, camera sensor placement could also be on a dedicated node assigned for this purpose. Our primary aim in this study is to achieve high classification accuracy while maintaining low energy consumption.

In order to be efficient in overall manner, each implemented step of the framework must also be efficient in its sole aspect. In the following sections, details about each implemented step of the framework are presented. Data preprocessing, data fusion, object classification, and transmission steps are highlighted all together in the Hierarchical Data Fusion section (4.5).

4.2 System Modeling and Network Deployment

Sensor node deployment has attracted much attention since it is directly connected with network coverage and lifetime. There has been extensive research about autonomous deployment schemes. Main idea behind these research is to provide multi-objective optimizations dealing with energy-efficiency, connectivity and quality of monitoring. System characteristics and assumptions made in the previous chapter for the fuzzy clustering algorithm are also valid for our framework. However, here more detailed view of a single wireless node and network deployment scheme is going to be provided.

WMSN deployment can be thought as being more complex when compared to WSN deployment, since most WMSNs consist of heterogeneous nodes with different capabilities. What makes the deployment a harder process is the difference in sensing, computation and communication capabilities of the nodes. So, in fact WSN deployment can also be a very tricky process when the nodes to be deployed differ on a large scale. However, in addition to this difficulty, there is also a gain in deploying heterogeneous nodes. Varying sensing ranges, computation and communication abilities make heterogeneous networks a precious tool for surveillance applications. An AOI of a single wireless node including various sensor types is depicted in Figure 4.4.

The network is manually deployed to the area so as to maximize the sensing coverage

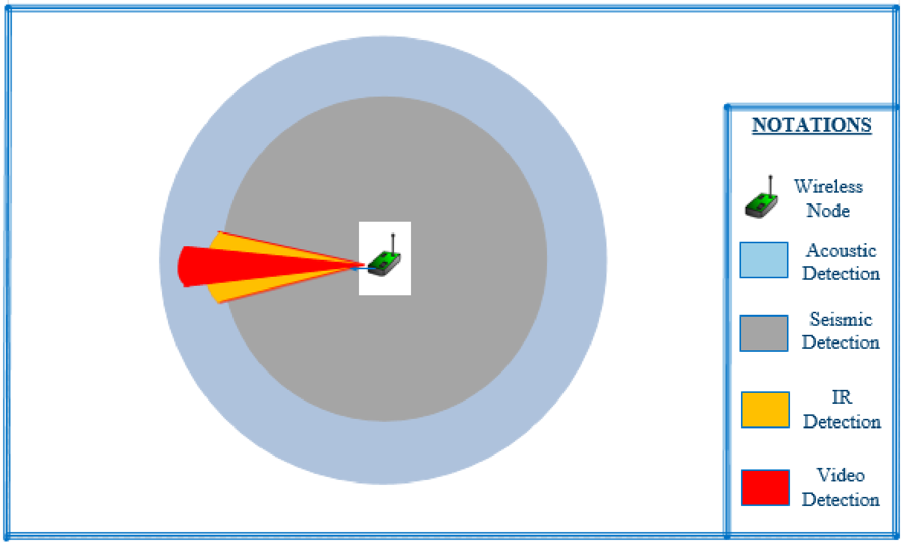

Figure 4.4: An AOI of a single wireless node including various sensor types.

in our framework. As stated in chapter 2, PIR and camera sensors have FoV (Field of View) and DoF (Depth of Field) values and they have a directed sensing range. However, as depicted in Figure 4.4, seismic and acoustic sensors have an omnidirectional isotropic range. We model the N-node network as an N-vertex undirected graph denoted by G, where V and E are its vertices (nodes) and edges (paths) as presented in Eq. 4.1 and Eq. 4.2, respectively. According to the positions of the nodes, 2D node deployment location (network topology) matrix is constituted by x_i and y_i values of the nodes as depicted in Table 4.1. Although we deploy nodes manually into the AOI because of its easiness in experiments, researchers considering the energy-efficient deployment scenario may follow the DEED (Distributed Energy-Efficient self-Deployment) algorithm as described in [70].

Table 4.1: 2D Node Deployment Locations (Network Topology).

N_Num	**1 2 ... N**
Coor. X (x_i)	x_1 x_2 ... x_N
Coor. Y (y_i)	y_1 y_2 ... x_N

$$G = (V, E) \tag{4.1}$$

$$V = \{1...N\} \tag{4.2}$$

4.3 Fuzzy Clustering

After nodes are deployed to the AOI, then the cluster formation process begins. Inappropriate CH choice can drastically increase the energy consumption and decrease the network lifetime. Because of this reason, it is crucial to choose the CHs and form clusters in an efficient way. In the light of recent advances and evaluations made on the energy consumption of the available algorithms, in our framework, we implement our proposed MOFCA (Multi-Objective Fuzzy Clustering Algorithm) protocol as the clustering algorithm, which is described and evaluated in detail in the previous chapter. For *the baseline*, implemented clustering protocol is LEACH. Since both the MOFCA and the LEACH protocols are explained and evaluated thoroughly at chapter 3, it should be clear that MOFCA handles the hotspots and energy hole problems more efficiently then LEACH considering the uniformly and non-uniformly deployed stationary and evolving networks in the same scenarios. For this reason, details of the algorithms are not going to be revisited here.

4.4 Data Correlation

Upon completing the network deployment and cluster formation steps, a crucial task in data fusion architecture must take place, namely clock synchronization of the deployed nodes. In sensing applications, time is a very important feature since AOI *evolves* over time. However, it is more critical when considering power management, transmission scheduling and data fusion applications in WMSNs. Data fusion depends on the spatial and temporal aspects of the sensor readings. In order to fuse sensor readings, correlated input items (signals/features) must first be identified, and this correlation must be made based on the capture time stamp or spatial aspects of the reading. Correlation based on the capture time stamp is among the possible choices. In addition to capture time stamp; space, time interval and spatio-temporal correlations are other leading approaches to provide a common frame to all nodes. In the literature, there are plenty of timing mechanisms proposed for WSNs. GPS (Global Positioning System) unit which has a PpS (Pulse per Second) output usage is one of the implemented synchronization mechanism as described in [33]. Detailed information about clock synchronization and use of signal processing techniques for accurate timing can be found in [71]. Pros and cons of each applicable method for time synchronization and detailed discussion about why WSNs necessitate special timing mechanisms can be found in [72]. However, in our study, we exploit virtual time stamps for both methodologies (our framework and *the baseline*) as described in [73] together with spatial information because of their ease-of-use and effectiveness in experiments.

4.5 Hierarchical Data Fusion

In the literature, there are abundant studies about how to fuse data. Some of them tried to be as accurate as possible, while others tried to save on energy consumption. There has always been a trade-off between energy-efficiency and accuracy. Bearing in mind this trade-off, we try to be as accurate as possible and maintain energy-efficiency in developing this framework. Both accuracy and efficiency come from our hierarchical usage of resources in good combination in WMSN.

According to [74], total energy consumption E can be modeled by Eq. 4.3, where E^{TX}, E^{RX}, and E^{CF} are total transmission cost, total reception cost and cost of hierarchical data fusion, respectively. E^{CF} consists of cost of data fusion and cost of object classification. With the aim of decreasing all of the above mentioned costs, we initially keep all the camera sensors and transmitters of nodes in sleep mode. They are treated as higher cost and power assets and are only made use of when a predefined threshold is exceeded after the initial level fusion in our proposed framework. By this way, E^{TX}, E^{RX}, and E^{CF} all decrease. We will explain this saving in detail in the evaluation section.

$$E = E^{TX} + E^{RX} + E^{CF} \tag{4.3}$$

The period of data sensing is called the collection (sensing) round t, and in our framework, as opposed to most of the studies, each node senses its range initially with its three sensors of available four. Moreover in our approach, again as opposed to most research, there is only one case, where second level asset (camera sensor) classified the detected object also as *object-of-interest*, which necessitates a transmission to CH and then to the sink for reactive measures to be taken. Until this time, radio transmitters in nodes except for CHs are also in sleep mode to reduce power consumption. By this way, we make use of the available resources in an hierarchical manner considering their energy consumption levels; because of which we call our methodology *Hierarchical Data Fusion*. In this subsection, we focus on all remaining steps of the flowchart of the framework, namely data preprocessing, data fusion, object classification, and data transmission.

Since our framework is designed specifically for surveillance applications, we classify detections to four main classes: *human*, *animal*, *vehicle* and *no detection* (noise, i.e. for discarding unnecessary and unreliable detections. In the experiments, we assume that the target (object) is in the range of all available sensors and human and animal objects do not exist together in the AOI.

Before the beginning of the detection process, background noise of each sensor in the AOI when there is no activity is measured and class signatures for interested targets are created for seismic and acoustic sensors. In preparing class signatures, initially we tried to fuzzy classify all detected signals, however we were not able to map input signals to fuzzy input and output variables as in [75]. Thereafter, we have made use of acoustic and seismic data properties for the initial level classification as described in [76] and [77], respectively. For the acoustic detection, acoustic signal is analyzed to determine the presence of a target by using Binary Fuzzy Classification (BFC) as described in [78]. Here, in what we differ lies in the target types and class label generation instead of evidences as the result of classification. In the first step of acoustic classification, after background noise is subtracted from the detected signal, a binary hypothesis test is made to classify the detection as *noise* or a *real signature*. If a signature is encountered, then in second level BFC, detection is either classified as group-one *vehicle* class, or group-two *human-animal* class. If the result of the second level BFC is group-two, then a third level BFC is done to assess whether detection belongs to *human* class or *animal* class. Each BFC is a Type-1 fuzzy logic rule based classifier. More detailed information about the methodology followed can be found in [78]. For the seismic detection, initially detected signal is segmented into 0.75

second windows and for each window a set of features which forms the *feature-vector* are extracted. A total number of 60 features are defined by using spectral technique (Fourier transform), statistical techniques (mean and variance) and entropy of the signal as described in [77]. By employing a supervised learning (since the source of the seismic signal is known), 20% of the *feature-vector* and the class labels are used for training the classifier. The rest of the *feature-vector* is utilized for detection of the class label of seismic activity. Finally, a simple decision-maker algorithm is implemented to enhance the probability of detection and reduce False/Nuisance Alarm Rate (F/NAR) as defined in [77]. Decision maker returns with the classification of the detected signal with the highest confidence result. The class signatures of *human* and *animal* are very close to each other, however class signature of *vehicle* is distinctly apart from both of them [79]. Since sensed time-series contain the signal itself and noise, it is intuitively probable that nodes closer to the target will provide better classification results as a result of high SNRs (Signal-to-Noise Ratio).For the passive infrared detection, PIR data is used as either 1 (presence of a target) or 0 (absence of a target). At the end, output for level-1 (initial level) fusion is generated. Defined threshold for the output of initial level fusion is the result of an object jointly classified as an *object-of-interest*.

If the initial level classification result is *human/vehicle*, then a trigger is sent to the camera sensor on the node to activate it; if not we simply discard the result. By this way, a higher cost asset is activated only needed and upper level decision can be made. For the second level classification, the camera sensor first detects the object. Then, two features from video frames, namely *Shape-Ratio* and *Speed*, are extracted by using MBR (Minimum Bounding Rectangle) of the detected object. Because our problem definition and our goals here are the same, in this second level classification, we follow the approach depicted in [39]. This approach is also suitable for our purpose since we manually deploy the network and know the coordinates of camera sensors for speed calculation. However, we differ in the action taken after classification. If the detected object is not classified as *human* or *vehicle* we do not activate the transmitter to send the result to the sink, rather, as we did in the first level classification, we discard the result. However, if vice-versa, we wake up the transmitter to send the result to the CH and to the sink by using two bits, which denote the class of object, for some reactive measure such as generating an alarm for human intervention to be taken. In this way, we not only classify objects with high accuracy, but also save on total energy consumption (E).

4.6 Experimental Evaluation

In this section, the obtained results of the simulations that are performed to evaluate our fuzzy fusion-based framework are presented.

4.6.1 Experimental Setup and Performance Metrics

To evaluate the accuracy and energy-efficiency side of our proposed framework, we compare it with the setup where sleep-and-wake up protocols are implemented in the same way for all sensors except camera sensors, however clustering methodology is chosen as LEACH which is the most representative clustering algorithm as depicted in [47]. All detections from any sensor modality from detecting node are sent to the CHs first and then CHs relay the acquired data to the base station for data fusion and object classification (decision making). As stated, we call this setup *the baseline* in order to compare our proposed framework with. In our framework, the detections are sent to the sink *if and only if* the detected object is classified as target.

In order to test the effectiveness of the proposed framework, a set of experiments are conducted by using MATLAB R2012b simulation libraries. As clearly described in previous sections, the object that needs to be classified is assumed to be in the range of all available sensors on the node and collaboration between nodes is not considered in this thesis. The initial energy of each node is modeled as 1 j. Depleted energy is measured according to Eq. 3.1 and Eq. 3.2. The communication range of each node is modeled as 60m and each node has the same type of transceiver unit. All experiments are conducted on an eight-core Intel Xeon processor rack server running the Windows Server 2012 operating system.

4.6.2 Performance Results

In our thesis, we have chosen the area (*Scenario 1*) and border/perimeter (*Scenario 2*) surveillance applications to be modeled, because we are not able to simulate more than one sink at the same time in our experiments.

After clusters are formed for compared methodologies in both application types, data correlation takes place. Thereafter, hierarchical data fusion is explored by testing the proposed framework for 642 instances which consisted of all four classes. In the proposed framework, there is no need to send a data packet to the sink when there is no *object-of-interest* in detections. Radio energy dissipation model is as employed in the previous chapter. Since there is no aggregation tree or no incremental fusion event when traversing the network over CHs, E^{CF} is only consumed at the detecting node in our framework. However, it is intuitively probable that cost of fusion is higher when the process takes place at the base station if it is located at a place where there are constraints on available resources, such as battery power. E^{RX} is consumed at the CH receiving the event and CHs that relay the result towards the sink. E^{TX} is also decreased by either discarding the uninteresting result (no target) or transmitting the result in two bits. By this way, total energy consumption E decreases when all its constituents decrease.

4.6.2.1 Scenario 1

For the *Area Surveillance* application, 2D node locations and clusters formed by the results of application of LEACH and MOFCA algorithms on the same set up are presented in Figure 4.5 and 4.6, respectively. The network is deployed on a 300m x 300m AOI and nodes manually deployed to the selected x_i , y_i coordinates. In the figures, CHs are marked with red dots (points), formed near cluster boundaries are depicted as black circles or lines, and the base station (sink) is located at (3, 11) and marked as bigger yellow dot (point) with label “1”. In this application type, the EEUC multi-hop routing protocol as depicted in [64] is employed for data transmission.

According to the experiments, level-1 and level-2 classification results obtained using our fusion-based framework for the area surveillance application are presented in

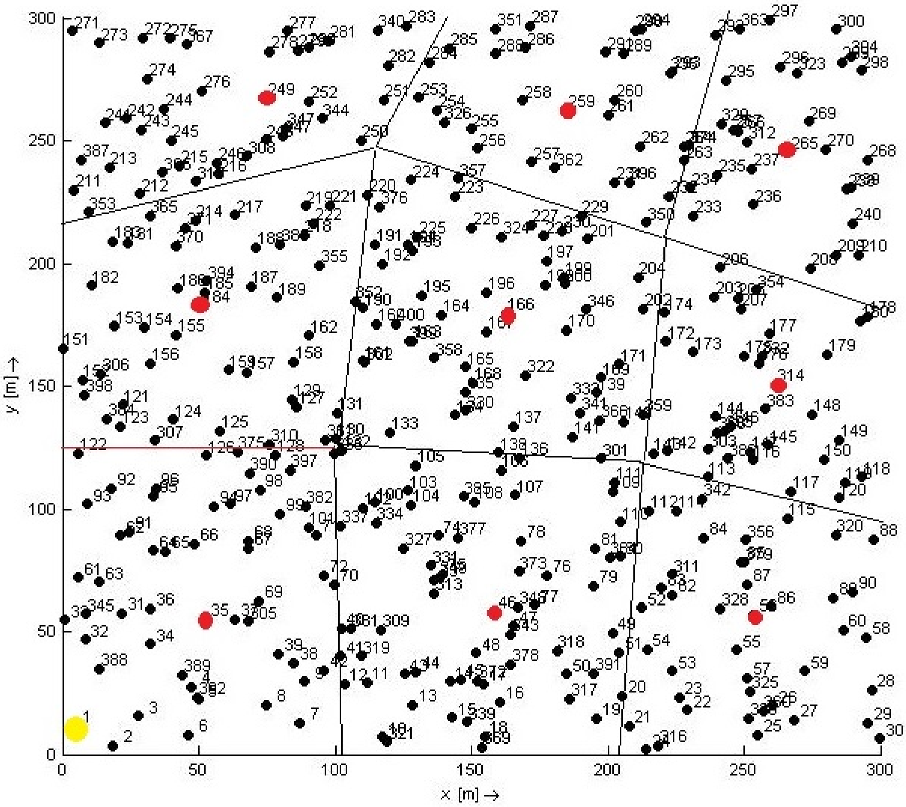

Figure 4.5: 2D node placement and clusters formed by the results of application of LEACH.

Table 4.2. (C0: *Human* class, C1: *Animal* class, C2: *Vehicle* class, C3: *Noise* class). Classes in rows denote the actual object classes and classes in columns denote the classification results. As can be seen from the table, our proposed framework has 95.4% classification accuracy for the *Human* class, 95.5% accuracy for the *Animal* class, 95.2% accuracy for the *Vehicle* class, and 100% accuracy for the *Noise* class. Average accuracy of our proposed framework is 95.6%. Moreover, in second level classification, misclassified 7 animals and 12 vehicles are classified correctly and do not require transmission for alerting the base station, this is where the efficiency part of the framework is exploited.

Object classification results of the baseline for the area surveillance application are depicted in Table 4.3. As can be seen from the table, *the baseline* has 96.4% classification accuracy for the *Human* class, 98.7% accuracy for the *Animal* class, 94.4% accuracy for the *Vehicle* class, and 94.5% accuracy for the *Noise* class. Average accuracy of *the baseline* is 96.2%. Although it looks as if *the baseline* performs better considering accuracy ratios when compared to our proposed framework, it will be

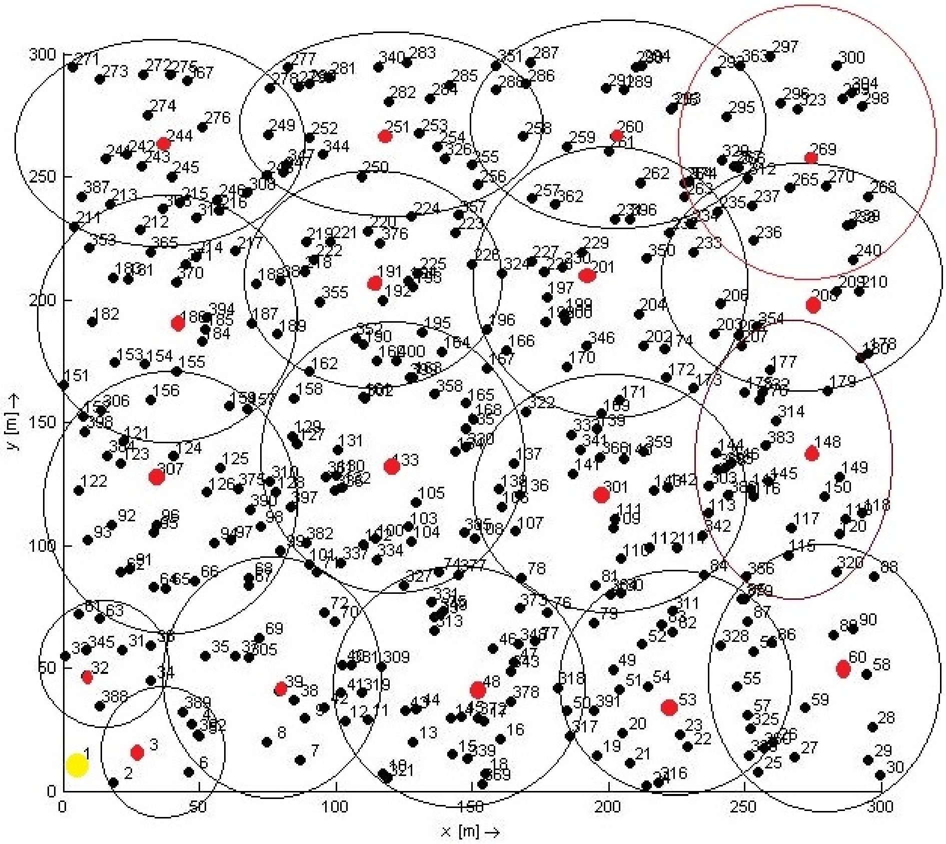

Figure 4.6: 2D node deployment and clusters formed by the results of application of MOFCA.

Table 4.2: Level-1 and Level-2 Classification Results Obtained using Our Framework for The Area Surveillance Application.

	Level-1 (Initial Level)				Level-2 (Higher Level)			
	C0	C1	C2	C3	C0	C1	C2	C3
C0	187	4	0	5	187	7	0	N/A
C1	7	149	0	0	N/A	N/A	N/A	N/A
C2	0	0	253	0	0	12	241	N/A
C3	0	0	0	37	N/A	N/A	N/A	N/A

much clearer after we present the efficiency comparison of them both for the area surveillance application.

Pros and cons of data fusion usage in the framework can be measured by evaluating the obtained experimental results. By this way, it is possible to present how much accuracy fusion process adds to the fusion-less state, and how much overhead it brings along. Accuracy add-on provided through data fusion for the area surveillance application is depicted in Table 4.4 while its overhead is presented in Figure 4.7.

Table 4.3: Object Classification Results of *The Baseline* for The Area Surveillance Application.

	C0	C1	C2	C3
C0	189	5	2	0
C1	2	154	0	0
C2	0	14	239	0
C3	0	2	0	35

Table 4.4: Accuracy Add-on Provided Through the Use of Data Fusion for The Area Surveillance Application.

Number of Instances	Fusion-Based Accuracy Ratios	Fusion-less Accuracy Ratios
100	96.2%	79.7%
200	94.9%	77.4%
400	95.1%	73.8%
642	95.6%	71.6%

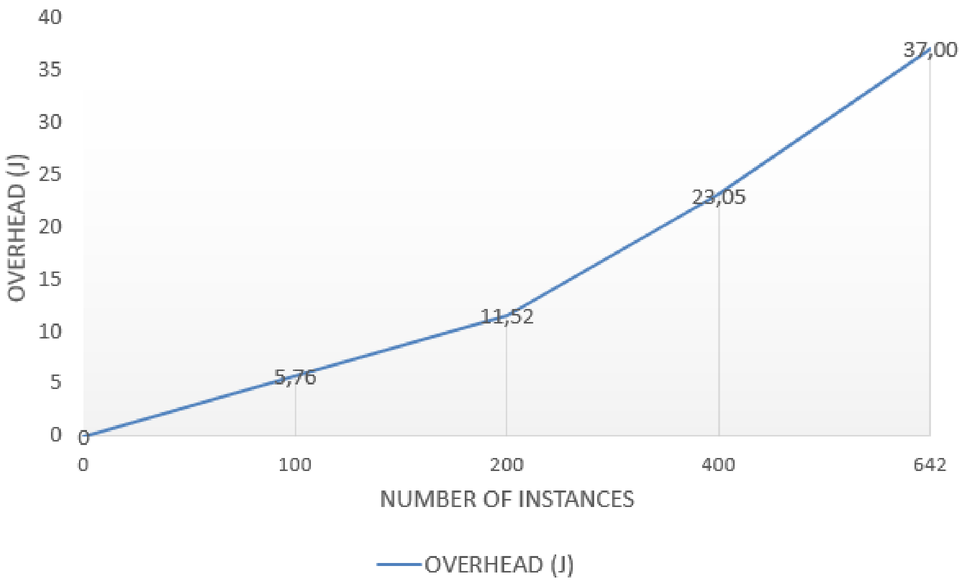

Figure 4.7: Overhead of data fusion with respect to the number of instances for the area surveillance application.

Total energy consumption of the compared methodologies with respect to the number of instances for the area surveillance application is presented in Figure 4.8. As can be seen from the figure, our proposed framework outperforms *the baseline* in terms of energy-consumption. Moreover, in-node hierarchical data fusion system performs 24.4% energy-efficient than the data fusion system that is occurring at the sink. Although efficiency comparison of the classification cost between compared methodolo-

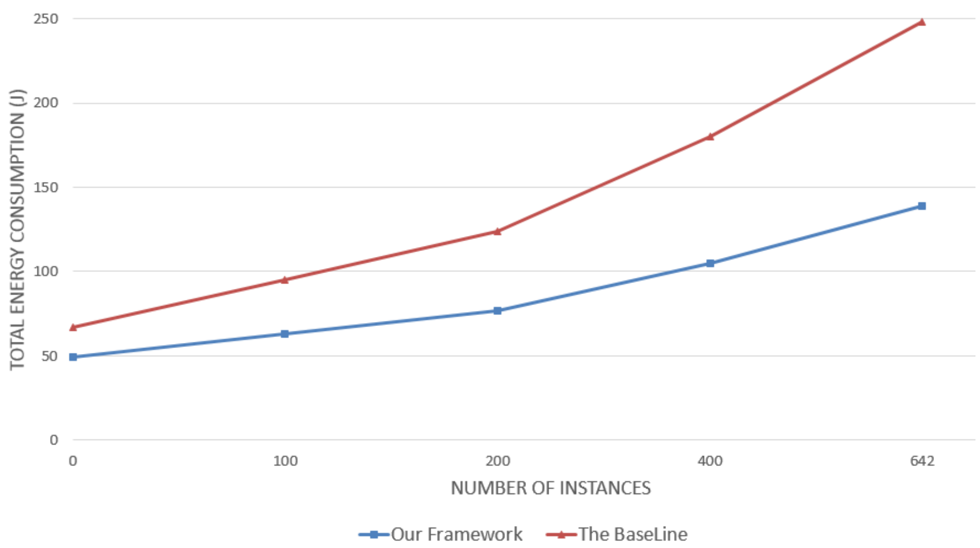

Figure 4.8: Total energy consumption of the compared methodologies with respect to the number of instances for the area surveillance application.

gies can be made, it has no distinctive value as such of the transmission cost. Since we relay the classification result of the object only when the object is a target class, we refrain from much of the transmission cost when compared with the baseline. That is why, our framework performs better as the number of instances grow.

4.6.2.2 Scenario 2

For the *Border/Perimeter Surveillance* application, the network is also deployed on a 300m x 300m AOI and nodes manually deployed to the selected x_i , y_i coordinates so as to form a non-uniform distribution, which is the case for border/perimeter surveillance applications. This is achieved through deploying the nodes to an outer strip of the whole AOI. In our simulations, the length of this strip is modeled as 50m, and the sink and the protected asset are located at the same place (150, 150) with marked as bigger yellow dot (point). 2D Node deployment locations for border/perimeter surveillance application are depicted in Figure 4.9. In this application type, direct routing protocol is employed for data transmission.

Level-1 and level-2 classification results obtained using our fusion-based framework for the simulation of the border/perimeter surveillance application are presented in Table 4.5. As can be seen from this table, our proposed framework has 92.3% classification accuracy for the *Human* class, 96.1% accuracy for the *Animal* class, 96%

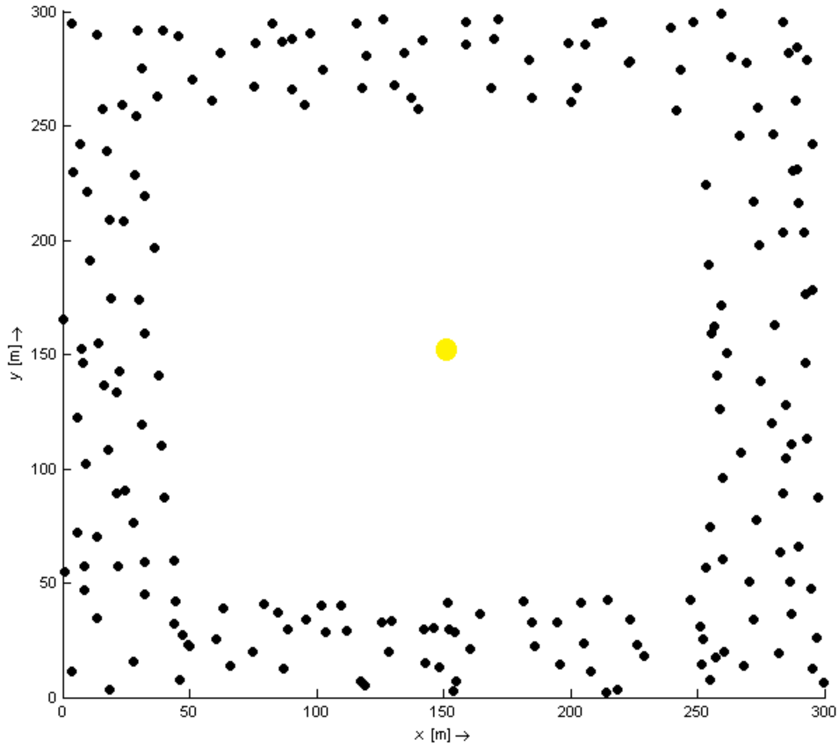

Figure 4.9: 2D Node deployment locations for border/perimeter surveillance application.

accuracy for the *Vehicle* class, and 100% accuracy for the *Noise* class. Average accuracy of our proposed framework is 96.04%. In second level classification in this application type, misclassified 6 animals and 10 vehicles are classified correctly and do not require transmission for alerting the base station.

Table 4.5: Level-1 and Level-2 Classification Results Obtained using Our Framework for The Border/Perimeter Surveillance Application.

	Level-1 (Initial Level)				Level-2 (Higher Level)			
	C0	C1	C2	C3	C0	C1	C2	C3
C0	181	9	0	6	181	6	0	N/A
C1	6	150	0	0	N/A	N/A	N/A	N/A
C2	0	0	253	0	0	10	243	N/A
C3	0	0	0	37	N/A	N/A	N/A	N/A

Object classification results of the baseline for the border/perimeter surveillance application are depicted in Table 4.6. As can be seen from the table, *the baseline* has 97.4% classification accuracy for the *Human* class, 98.7% accuracy for the *Animal* class, 95.2% accuracy for the *Vehicle* class, and 97.3% accuracy for the *Noise* class. Average accuracy of *the baseline* is 97.2%. However, after we evaluate the efficiency of both methodologies for border/perimeter surveillance application, we come across a similar situation which is presented for the area surveillance application.

Table 4.6: Object Classification Results of *The Baseline* for The Border/Perimeter Surveillance Application.

	C0	C1	C2	C3
C0	191	4	1	0
C1	2	154	0	0
C2	0	12	241	0
C3	0	1	0	36

Accuracy add-on provided through the use of data fusion for the border/perimeter surveillance application is depicted in Table 4.7. The overhead of data fusion is the same as the area surveillance application since the number of instances and the number of available sensors do not change. For this reason, it is not presented again.

Table 4.7: Accuracy Add-on Provided Through the Use of Data Fusion for The Border/Perimeter Surveillance Application.

Number of Instances	Fusion-Based Accuracy Ratios	Fusion-less Accuracy Ratios
100	94.5%	81.1%
200	93.9%	80.4%
400	93.7%	78.2%
642	96.04%	74.3%

Total energy consumption of the compared methodologies with respect to the number of instances for the border/perimeter surveillance application is presented in Figure 4.10. As can be seen from the figure, our proposed framework performs better than *the baseline* in terms of energy-consumption. As in the Scenario 1, our proposed algorithm MOFCA forms clusters more efficiently, which is showed in the previous chapter for non-uniformly distributed networks, and we refrain from transmission cost by applying our proposed *hierarchical data fusion* system in this scenario too. For this reason, obtained results of this scenario are complying with our expectations.

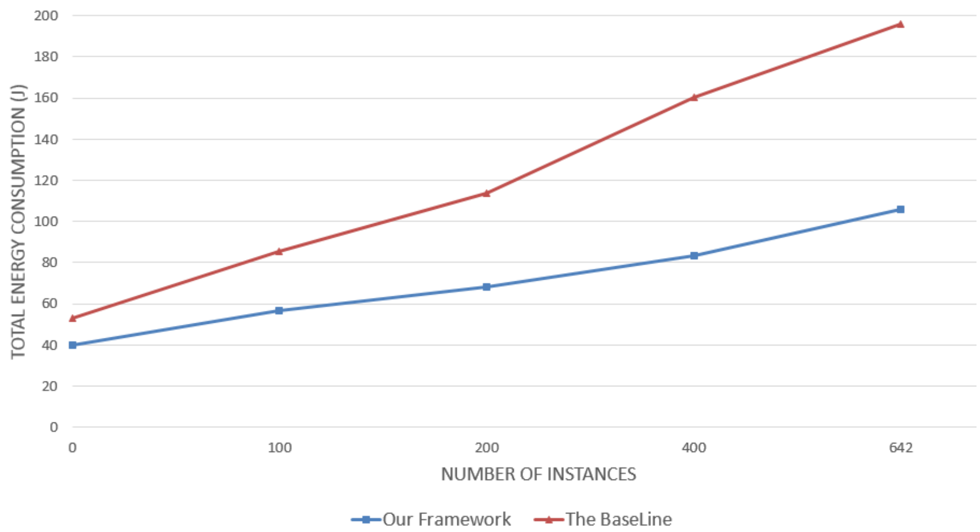

Figure 4.10: Total energy consumption of the compared methodologies with respect to the number of instances for the border/perimeter surveillance application.

4.7 Computational Complexity Analysis

Computational complexity of the framework consists of clustering, hierarchical data fusion and transmission processes. Lets assume that a total number of (n) nodes resides in the AOI.

The node clustering process requires comparing the residual energy levels of each node (i) with the remaining nodes ($n-1$) that are in its competition range for the election of a CH. Considering the non-uniform node distribution type, all available nodes might be in this range. For this reason, in the worst case, ($n^2 - n$) number of comparisons are done to elect CHs, which is $O(n^2)$.

If each of this (n) node has (k) scalar (seismic,acoustic, and PIR) sensors, these scalar sensors can detect (t) objects. A total number of ($k * t * n$) detections can occur and be fused. Since the fusion process occurs in each node and a simple decision maker algorithm is employed for this process, its computational complexity is O(1). As a result, complexity of the initial level classification is $O(k * t * n)$. After the fusion process, all detections could be classified as *object-of-interest* which necessitates a 2nd-Level classification in the worst case. Here, we employ the method described in [38], which requires calculating the similarity between the detection and each of the prototype objects in the classifier model for each feature. Considering that preferred features are one-dimensional, performing an Euclidian-distance calculation in order to find the similarities requires a constant time, which is O(1). Thus, assuming that (p) and (r) denote the feature count and the total number of prototypes respectively, the second level classification process is performed in $O(pr)$. Note that (p) is 2, (r) is 4 in our case. Hence, we can reduce the complexity to $O(r)$. Since $O(r)$ is consumed for each detection, computational complexity of the classification process is $O(r * O(k * t * n))$, which is $O(n)$. Moreover, this is also the computational complexity of the transmission process since in the worst case, all classification results may require a transmission to the sink.

For the computational complexity of the overall framework, we simply add the computational complexity of each constituent, finally which denotes $O(n^2)$.

4.8 Summary

In this chapter, we design and present an efficient framework of a multi-modal data fusion architecture specifically targeting surveillance applications by using higher cost assets in a hierarchical and corroborative way. The proposed framework considers both energy and accuracy aspects while its performance scales well.

Evaluations done on the accuracy and efficiency aspects clearly present that our proposed fusion-based framework pursues an energy-efficient operation while preserving classification accuracy. Although we have no chance to simulate the path/trail surveillance application in our thesis, we believe that if simulations are to be done for that case, results will be more or less the same, since it is intuitively probable that our framework should form clusters more efficient than the baseline and refrain from the transmission cost as in the previous scenarios.

Although the simulation results are promising, we believe that the accuracy of the framework would suffer because of the assumptions made (e.g., *animals* & *humans* not being present together at the AOI). For this reason, some further study should be done for real-world usability of this framework.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

In this thesis, an efficient fuzzy fusion-based framework which is designed specifically for surveillance applications in wireless multimedia sensor networks is presented. Along with the framework, a new fuzzy clustering algorithm is also introduced to be implemented in such a framework.

Performance of proposed MOFCA is reasonably better than the compared algorithms and it is a candidate algorithm to be implemented in any WSN application. As stated in the system model, MOFCA protocol includes stationary or mobile nodes. However, this mobility is simulated by the change of location of the nodes without causing energy consumption and we neglected the LND metric, which is usually not considered as important as the other parameters considered here. We believe that mobile sensor nodes should be considered as future work. For WSNs that are deployed dense-enough to provide high-availability to any sensor node, the other compared algorithms may be employed interchangeably on behalf of MOFCA.

The proposed fuzzy fusion-based framework considers both energy and accuracy aspects while its performance scales well. The framework provides energy-efficient operation while preserving high classification accuracy for surveillance applications by the use of fuzzy multi-modal data fusion architecture. Overhead caused by the use of data fusion system is insignificant if the accuracy aspect is considered. We simulate two popular scenarios out of available three in this thesis, since we are not able to simulate more than one sink at the same time in our simulations. Obtained simulation results for both scenarios show that our framework pursues a stable operation. It is intuitively probable that the framework will provide more or less similar results for the remaining scenario by forming clusters in an efficient manner and refraining from the transmission cost as in simulated scenarios.

Although the simulation results for the framework are promising, we believe that the accuracy of the framework would suffer because of the assumptions made. Simulation of the remaining scenario which requires the implementation of two sinks being present at the same time in the AOI can be a future study. Realization of this framework on real sensor hardware technologies and consideration of collaboration among neighboring nodes are among possible future studies.

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APPENDICES

.1 Comparison of the flowchart of our framework with the baseline.

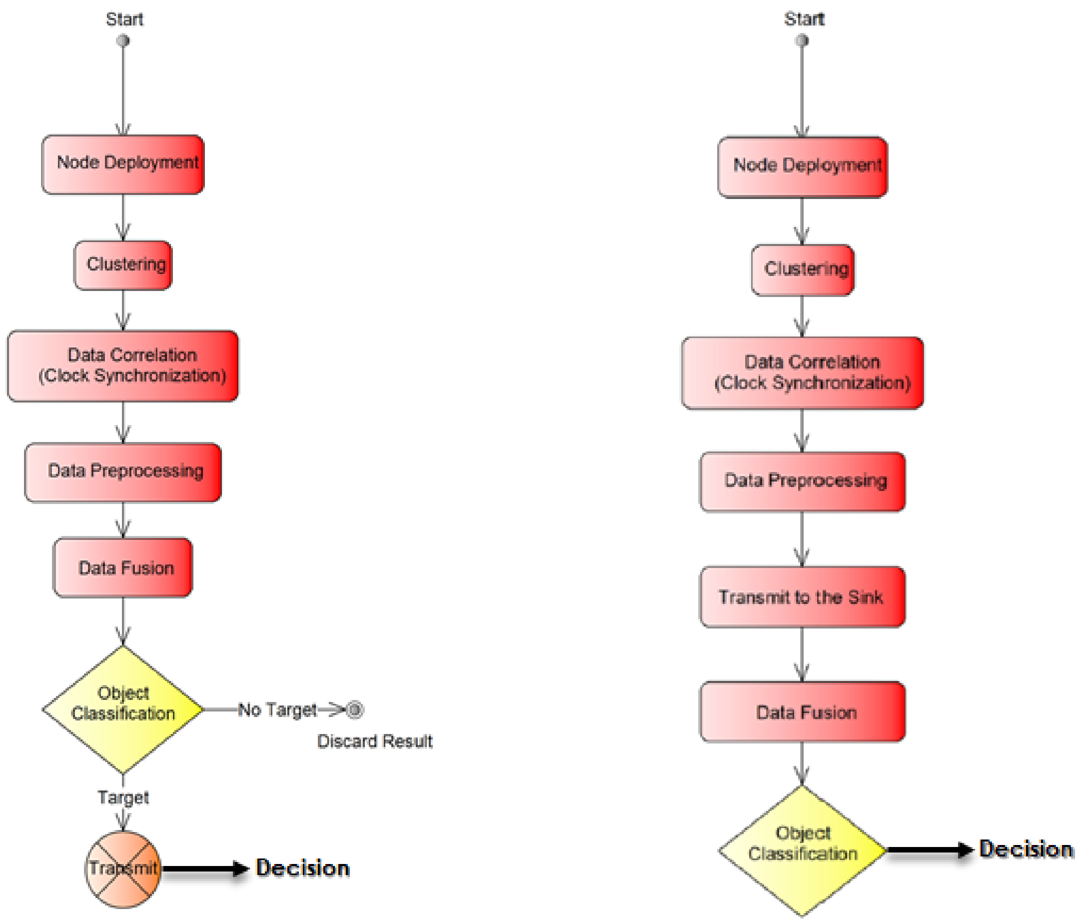

Figure .1: The part on the left depicts our framework, and the part on the right depicts *the baseline*.

.2 Hierarchical data fusion process.

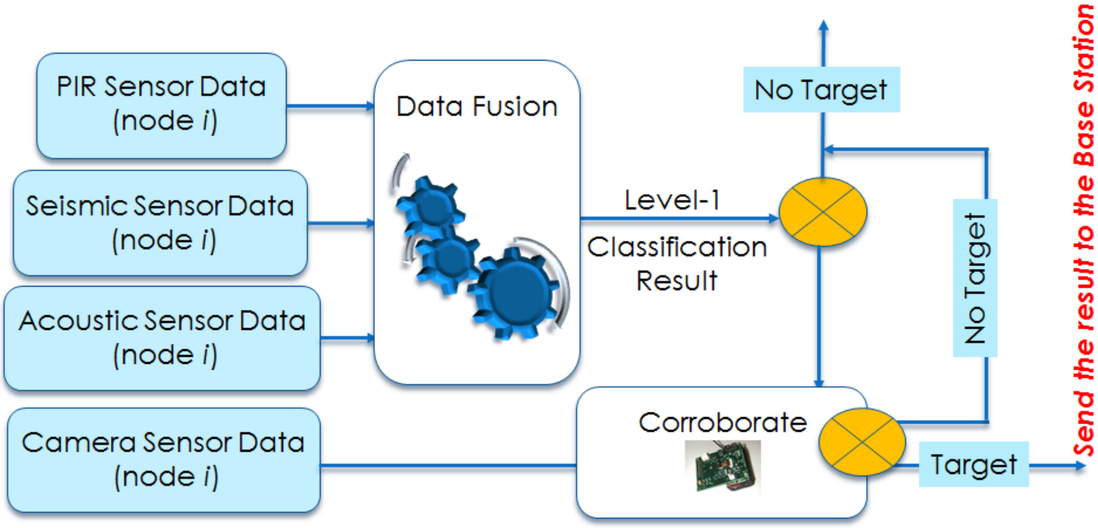

Figure .2: A representative view of the hierarchical data fusion process.