Thesis for the Degree of Doctor of Philosophy

EVOLUTIONARY LEARNING MODELS FOR INDOOR AND OUTDOOR HUMAN ACTIVITY RECOGNITION

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by

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Dedicated to my parents

Muhammad Ibrahim and Ruqia Bano.

For their immense support and encouragement.

Abstract

Human activity recognition is an emerging field of research that enables a large number of human-centric applications including healthcare, human-computer interactions, robotics, and supporting aging society etc. The aim of this research is to support an aging society and active lifestyle by providing personalized services and assistance for performing their daily life activities. In order to recognize the human activities, it is important to ensure that the sensing technology is seamlessly integrated with users environment and unobtrusive. Embedded sensors technology is one of the acceptable solution for sensing the indoor environment without disturbing the inhabitant privacy. Similarly, smartphone is one of the best choices to monitor the outdoor environment without adding the extra burden of wearing sensors.

Many researchers have designed a variety of models to recognize the indoor and outdoor activities. Nevertheless, despite of this progress, the current activity recognition models are not adequate for practical use in the real world applications for a number of reasons. One of the most notable problem in the existing models is the low accuracy, which is due to the domination of major activities over the minor activities and the associated ambiguities with these activities. During the training phase of the existing models, minor activities are not properly learned; therefore, accuracy may be decreased. In addition, the non-deterministic nature of activities (activities are performed differently due to different lifestyles, cultures, and mental and physical differences) also contributes to the decrease in classification accuracy.

To overcome the aforementioned problems, novel evolutionary learning models for indoor and outdoor activities are proposed in this dissertation. For indoor activities, we introduce a novel Evolutionary Ensembles Model (EEM) that values both minor and major activities by processing each of them independently. It is based on a Genetic Algorithm (GA) to handle the non-deterministic

nature of activities. It has the ability to embed activity representation structure information such as location, value or sensor type and produce reliable results from small datasets. This learner generates a human-understandable rule profile to ensure a certain level of confidence for the performed activities. For outdoor activities, a novel Evolutionary Fuzzy Model (EFM) is proposed to measure the ambiguities associated with the dynamic activities and relax the domain knowledge constraints which are imposed by domain experts during the development of fuzzy systems. Based on the time and frequency domain features, we define the fuzzy sets and estimate the natural grouping of data through expectation maximization of the likelihoods. A GA is investigated and designed to determine the optimal fuzzy rules.

We have conducted extensive experiments to demonstrate the effectiveness of the proposed learning models on real-world datasets collected from smart homes and smartphone. We have also shown that our evolutionary learning models outperform the state-of-the-art activity recognition approaches. At the end of the thesis, we discuss limitations and some possible directions for future work and extensions.

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Chapter 1

Introduction

1.1 Overview

Over the last few years, activity recognition has become an active research area due to the wide range of human centric-applications. For instance, the emerging demographic change towards an ageing population is introducing drastic changes into our society. Nursing homes and care facility units are renowned solution for elderly people. A person who lives in these units becomes depress due to the lack of independence. Aging society demands a reliable solution to stay active for a long time, prevent social isolation and assistance for performing daily life activities independently in their own homes. Smart home and smartphone are conceived as one strategy to provide a level of independence at homes and improve their quality of life without disturbing their privacy [1] [2] [3]. It provides a platform to reduce the health expenditures and burden of health care professionals. Furthermore, it also helps the family members to track the performed activities of inhabitants when they are outside from home.

Another useful application area for activity recognition is to monitor the lifestyle [4] [5]. Because the modern life style tends to involve in more sedentary jobs, while there are growing evidences showing the relationship between common health problems such as diabetes, cardiovascular, insomnia or obesity [6]. They often follow well-defined exercise routines (walking, jogging, running, or cycling) as a part of their treatment. In the physicians prescription, lasting duration is the most important metric that measures the amount of the activity [7]. Accurate information about the duration of activities is helpful for the practitioners as well as for subjects to compliance their activity routines according to the prescription. Therefore, the activity recognition may also identifies whether the individual has any difficulty in following the routines or not.

Besides the elder care support and lifestyle monitoring applications, activity recognition has been considered as a core component for home automation and office [8] [9], and security and surveillance [10]. It may also be applicable to the emergency situation by detecting the critical activity such as fall detection [11]. Due to the numerous potential applications activity recognition has been gaining increasingly interest from the enterprises as well [12], [13]. Researchers have used a wide variety of cameras such as stereo, 3D, and infrared to recognize the activities. To recognize the human activities automatically in a seamless manner, ubiquitous sensor technology and learning models are the key components to provide robust services and open platform to build applications over the activity recognition layer as shown in Figure 1.1.

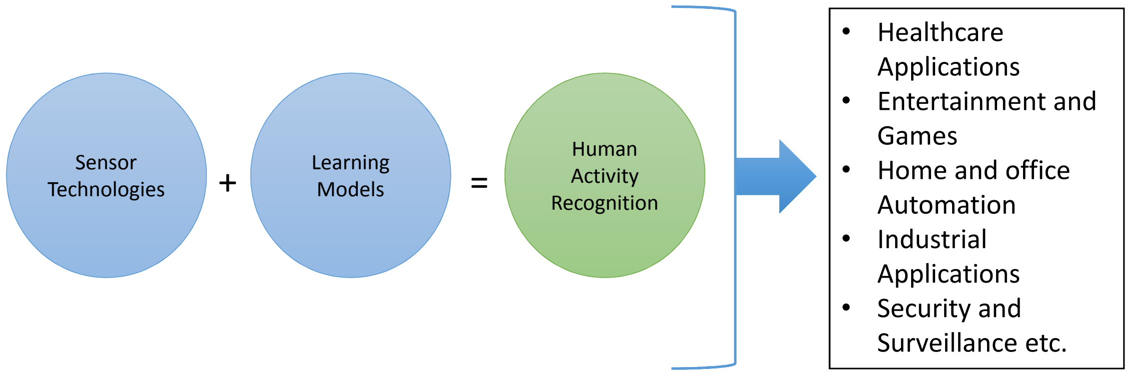


Figure 1.1: Activity recognition module with services

The nomenclature of sensing technology is divided into video cameras [14], wearable sensors [15], and embedded sensors [16]. Each has its own advantages and disadvantages. The subsequent paragraphs provide more detail about each approach.

Video Camera-based Activity Recognition: Video camera are the one of the possible source to recognize the human activities [17] [18]. Researchers have used a wide variety of cameras such as stereo, 3D and infrared to recognize the activities. This approach is easy to be used in the public places where camera can be installed at fixed positions. The best usage of this technology is closed circuit tv (CCTV) safety cameras to keep the track of public spots like metropolitan centre squares, roads, shops, and stations etc. In such systems, the video-based approach is a better choice because the camera can provide more comprehensive information about the user activities. However, video cameras are not practical to recognize the indoor daily life activities due to privacy, day/night vision problems, large storage space for recording streams, and complex environments. For instance we cannot put the videos camera into bedroom due to privacy reasons and mostly inhabitants do not want to monitor directly.

Wearable Sensor-based Activity Recognition: Wearable sensor-based approaches are personalized systems to recognize the activities [19] [20] [15]. It is not affected by the interaction of multiple users. A rang of wearable sensors include accelerometer, gyroscope, electrocardiogram (ECG), and skin conductance response (SCR) etc. Among different kinds of wearable sensors, accelerometer is the commonly used one to monitor the outdoor daily life activities which requires repetitive motion of the body. For examples: walking, running, and exercising. Furthermore, it has low cost, low power consumption and its strong capability in recording the motion of the body for both static and dynamic state of the user. But, still this solution is obtrusive and requires users to wear the sensor devices.

Embedded Sensor-based Activity Recognition: Embedded sensors is an acceptable solution for sensing the environment without disturbing inhabitant privacy and adding an extra burden of wearing sensors [16]. It is an acceptable and the most suitable solution for indoor activities. These sensors can monitor the environment continuously and require no dependent action on the user part to operate. However, they are infrastructure dependent and cannot monitor the outdoor activities. Also, difficulties can be faced when more than one inhabitants in the home. A comparison of these sensing technologies based on different parameters, is presented Table 1.1.

Characteristics	Video sensors	Wearable sensors	Embedded sensors
Indoor	Yes	Yes	Yes
Outdoor	Yes	Yes	No
Privacy concerns	Yes	No	No
User freedom	Yes	No	Yes
Multiple user confusion	Yes	No	Yes
Deployment	Complicated	Easy	Complicated
Storage space	Large	Small	Small

Table 1.1: Comparison of sensing technologies

1.2 Motivation

From the above analysis, it can be seen that simple sensors is one of the acceptable solution for indoor and outdoor activities. In order to recognize the indoor activities, several steps are required to build the environment. First step is to select an environment (e.g., Smart home) and sensor type that will be deployed. Second step is to identify the objects and proper location where these sensor will be deployed for sensing the environment. Third step is to define a reliable communication protocol to send the data over the server machine. All these steps are related to build a physical environment. On the other hand, in order to learn the performed activities several challenges exists to build a robust learning model that can represent the true mapping between the sensing layer and recognized activities. The most noticeable is the domination of major activities and non-deterministic nature of activities because same activities are performed differently due to different lifestyles, cultures, mental and physical differences. Particularly, in case of outdoor activities, motion of the body is involved and wearable sensor (e.g., accelerometer) is a good choice to recognize the activities. In present days, current generation of the smartphone is an alternative solution to the wearable devices because it contains many diverse and powerful embedded sensors. The smartphone includes accelerometer, magnetometer, gyroscope, proximity, ambient light, GPS, and cameras. Furthermore, it is one of the best choices for activity recognition due to its unobtrusive characteristics, high storage capacity and computation, low energy consumption and programmable capabilities. On the other hand, it increases the number of challenges due to unobtrusive characteristics and ambiguities associate with outdoor activities.

Therefore, our motivation is to take the advantages of the assistive technologies of smart home and smartphone for making human activity recognition more significant. We proposed novel learning models to solve the domination issues of major activities over the minor activities, non-deterministic nature, and ambiguities associated with indoor and outdoor activities. The proposed evolutionary learning models have proved itself robust and helpful to recognize the performed activities more accurately.

1.3 Problem Statement

Many researchers have designed a variety of models to recognize the indoor and outdoor activities through smart homes and wearable sensors. They have greatly contributed in research community, however, some of the challenges that still need to be overcome are:

- the domination of major activities over minor activities,
- the non-deterministic nature of the activities,
- unobtrusiveness of devices,
- handling ambiguities associated with motion of the body related activities, and
- lack of availability of learning models to work well for small datasets.

Indoor human activity recognition using embedded sensor in a smart home is presented with a number of challenges. Firstly, activities of daily life can be carried out with high degree of freedom in relation to the way and the sequential order they are performed. Individuals have different lifestyles, habits or abilities and have their own way of performing the activities. Though activities usually follow some kind of pattern but there are no strict constraints on the sequence of the actions. For example, to prepare a meal firstly turn on the stove and then place a saucepan on the stove, or vice versa. Such phenomena happen in almost all daily life activities. The wide range of activities and the variability and flexibility in the manner in which they can be performed require an approach to handle the situation. Secondly, data sparsity is also an issue in smart home activity recognition because the size of the training data is relatively small in comparison with the other machine learning datasets. It is due to the nature of daily life activities where some activities are performed more often as compared to the others. For example, meal preparation, bathing are the more frequent activities as compared to laundry or cleaning home. Current researches on activity recognition have mainly focused on the use of probabilistic and statistical methods that are not sufficient to handle the above situations.

Rule learning classifiers are an alternative to learn the target concept in the form of explicit rules [21] [22]. The use of rule sets as knowledge representation also makes them very competitive in terms of interpretability and produce the results to make inferencing. In activity recognition knowledge representation is very complex due to a large number of performed activities. Increasing the number of daily life activities means that some advanced techniques is required to generate the rules to handle the complex representation. Genetic based machine learning is one of the way to search the rules and provide a way to handle this kind of situation [21]. It is one of the efficient mechanism based on natural evolution and allows efficient searches over complex search spaces. It use the essence of the mechanisms of heredity and evolution, extracting these processes from the specific context of genetics. By using these concepts, it is possible to design adaptive method for activity recognition. In our method, we search most suitable representation of the feature vector with higher associated measures of performance. We maintain a population with their associated performance measures and repeatedly applying idealized genetic operators to produce optimal results without trapping into local minimum.

In case of outdoor human activity recognition, it is usually associated with the motion of the body. Various kind of sensors are used for outdoor activity recognition such as accelerometer, GPS, video and others. Among these, accelerometer is one of the most useful sensor to assess the activities. The prime reason for using accelerometer is its highly reliable in detecting the motion of the body. Moreover, they are available in small sizes and at a low-price. Accelerometer sensor is highly sensitive and generate lots of ambiguity and noise to recognize the activities. For instance, walking and jogging or upstairs and downstairs followed in the same action sequence. As a result in the classification, it is not being able to distinguish such activities to a sufficient degree. Furthermore, variation of actions done by different people to perform these activities decrease the accuracy rate. Proper handling of these variations requires an accurate model for clearly distinguish the activities.

However, most of the existing methods such as decision trees [23], Bayes classifier [24], and Bayesian networks [25] suffer from accuracy and reliability problems as well as performance degrades further when fewer training instance are available for minor classes. Besides these issues, some methods require long training times and significant amount of parameter tuning such as HMM [16] and Neural Network [26]. A fuzzy inference system can be an alternative to distinguish the user motion patterns because of its ability of decision making. The selection of fuzzy inferencing is based on the characteristic of data, its easiness of understanding, flexibility, and tolerance of imprecise sensory data to classify different activities. In order to recognize the activities, we proposed evolutionary fuzzy approach which can distinguish temporal sequence information but also be tolerant to variation of actions done by different people. Fuzzy logic base classification are known with the ability to absorb data differences by learning and has been successfully shown to be effective in video-based activity recognition studies [21]. The challenging part in the fuzzy inference system is to properly define the membership functions and fuzzy rules which can solve activity recognition problem more accurately.

1.4 Proposed Concept

Our proposed concept is based on the evolutionary learning models to recognize the indoor and outdoor human activity recognition. We proposed a unified framework that is capable to learn the daily life activities and process it according to the sensory input source. In case of smart home environment, we developed evolutionary ensemble model to recognize the indoor activities. In case of outdoor activities, accelerometer sensor of the smartphone is utilized and fuzzy theory is applied to deal with the ambiguities related to the motion of the body. Figure 1.2 shows the proposed framework.

In the first step, temporal sensory data is pre-processed to remove the un-necessary data. In case of indoor activities, different sensors in smart home environment sensed the data and stored into log files along with time stamp over the server. In order to learn the activities; unnecessary information is removed in preprocessing step like removing the multiple header lines from sensory and annotation data log files. Then features are extracted according to the sensory input source and learn the activities in respective components of the unified framework. The detail of each component is described in the Chapter 4.

1.5 Contributions

This dissertation focuses on the solution of major challenges associated with the indoor and outdoor activities. It is applicable to diverse environments and provides technically rich learning models. It is possible to configure the system by an end-user with little knowledge. We proposed

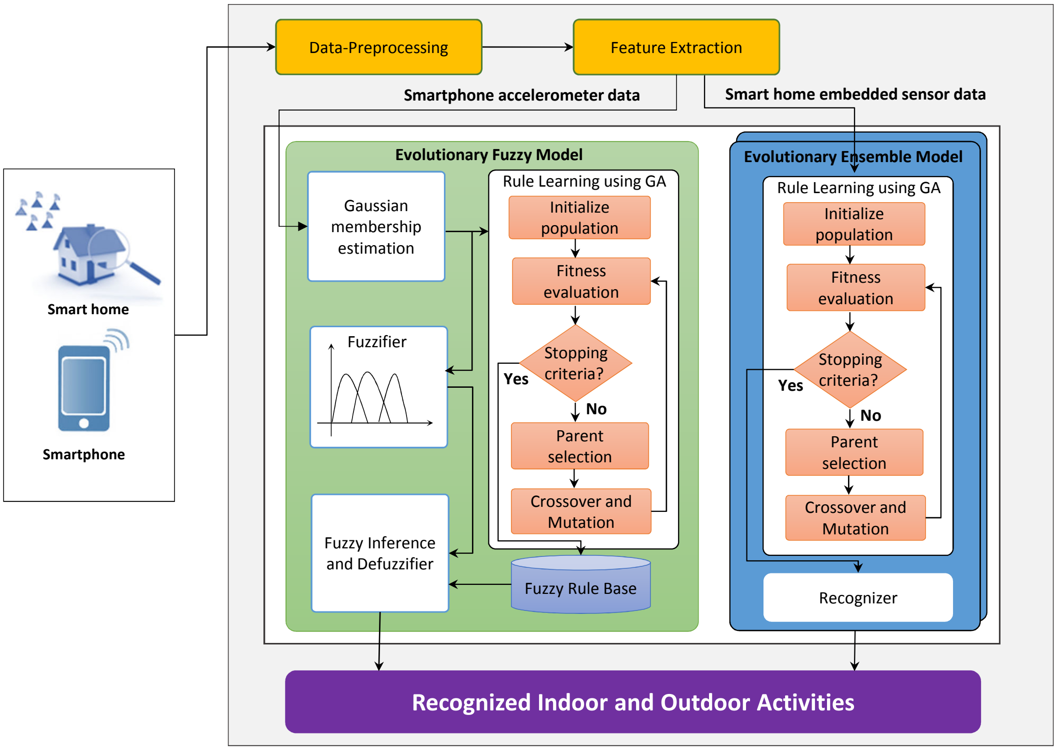


Figure 1.2: Unified framework for indoor and outdoor activity recognition

a novel learning model (i.e., EEM) to recognize indoor human activities by designing a Genetic Algorithm (GA) based evolutionary ensemble learners that has better accuracy than the existing state-of-the-art methods. We introduce a method to process the information independently by giving equal importance to minor and major activities; hence, the problem of few occurrences of minor activities can be solved. Our proposed model has the ability to embed activity represenation structure, which produce reliable results from small datasets and generate human understandable activity rules. For these reasons, our EEM model has the potential to work with real world applications. For outdoor activities, we proposed a novel evolutionary fuzzy model (i.e., EFM) to deal with the ambiguities of dynamic patterns of human activities by defining fuzzy sets. The most common strategy for defining the fuzzy sets is by using human experts or by trial-and-error [19]. However, domain experts cannot be expected to provide optimal membership values for activity recognition problems. This situation becomes more complex when the number of inputs and outputs increases, which ultimately increases the number of fuzzy rules. Our proposed EFM solves the aforementioned problems by introducing an estimation method for membership functions to determine the natural grouping of data over a pre-specified number of fuzzy sets. We solve the problem of defining the fuzzy rules by introducing an evolutionary method called Genetic Algorithm (GA). The GA is an optimization algorithm that provides a better way to define optimal fuzzy rules over poorly understood and irregular search spaces. Consequently, our model relaxes the imposed constraints of the domain experts knowledge and becomes more robust and reliable in complex situations. An empirical evaluation shows that the proposed model is successful at recognizing dynamic activities by utilizing a smartphone accelerometer.

We have conducted extensive experiments to demonstrate the effectiveness of our proposed learning models on real-world datasets collected from smart homes and smartphone. We have also shown that our evolutionary learning models outperform the state-of-the-art activity recognition approaches.

1.6 Structure of the Dissertation

This dissertation is organized in the following structure.

- **Chapter 1 - Introduction**: In this chapter a brief introduction of human activity recognition and its nomenclature is illustrated to recognize the indoor and outdoor activities. We discuss the limitation of existing learning models and current challenges in the activity recognition domain. At the end, an overview of the contributions made is provided.

- **Chapter 2 - Related Work**: Chapter 2 gives an overview of the related work in the area of activity recognition. We briefly discuss about the available sensor technology and learning models for indoor and outdoor activity recognition. Furthermore, we provide a general architecture of activity recognition system and review different application domains to show the applicability of human activity recognition.

- **Chapter 3 - Preliminaries**: Chapter 3 presents preliminaries that are used in this dissertation to provide a quick overview of evolutionary methods. More specifically, methods, schemes and systems discussed in this chapter provide the building blocks for our proposed evolutionary learning models.

- **Chapter 4 - Indoor activity recognition**: Chapter 4 explains the proposed evolutionary ensemble model for indoor activity recognition in smart home environments. We formulate the problem into mathematical form and then explained the learning model from data acquisition to recognition phase of the performed activities. Empirical evaluation and results are discussed to illustrate the performance of the model.

- **Chapter 5 - Outdoor activity recognition**: Chapter 5 presents the evolutionary fuzzy model for outdoor physical activity recognition using smartphone accelerometer. We explained the data acquisition mode and detail of the proposed model to recognize the dynamic physical activities. Furthermore, we also provide the detail of parameter estimation and experimental comparisons to show that our model performs well as compared to existing counterparts.

- **Chapter 6 - Conclusion and future directions**: Chapter 6 concludes the dissertation along with the main contributions. The future directions for this research work are also mentioned in this chapter, which can be an intresting subject for further research in human activity recognition domain.

Chapter 2

Related Work

In this chapter, first we discuss about the existing sensor technologies for activity recognition and then well-known existing models and their limitations are overlooked. At the end, the applications of human activity recognition are focused. However, stronger emphasize is given to the learning models because they are the main focuses of this dissertation.

2.1 Sensor Technology for Human Activity Recognition

Sensor technology plays an important role to recognize the activities as discussed in Section 1.1. Roughly, human daily life activities are categorized into indoor and outdoor. Indoor activities are related to the interaction of human with the objects. For example, cooking, grooming, and taking medicines etc. In case of outdoor activities, they require the motion of the body like walking, jogging or running etc. Such activities are recognized by the body attached sensors to get the activity patterns. In this section we specifically discuss the best available technologies for indoor and outdoor activity recognition.

2.1.1 Indoor Activity Recognition

In order to recognize the indoor human activities, smart homes are considered as one of the best solutions. These homes are perceived as intelligent environment to monitor the interaction with different objects and collection of low-level sensory data. There are a number of sensors available to sense the environmental attributes, as shown in Figure 2.1.

These kind of sensors can be used to recognize the indoor human activities; however, it should be noted that environmental sensors such as temperature, humidity, gas/water flow etc. may not be comprehensive enough for activity recognition. On the other hand, audio/video sensors are not

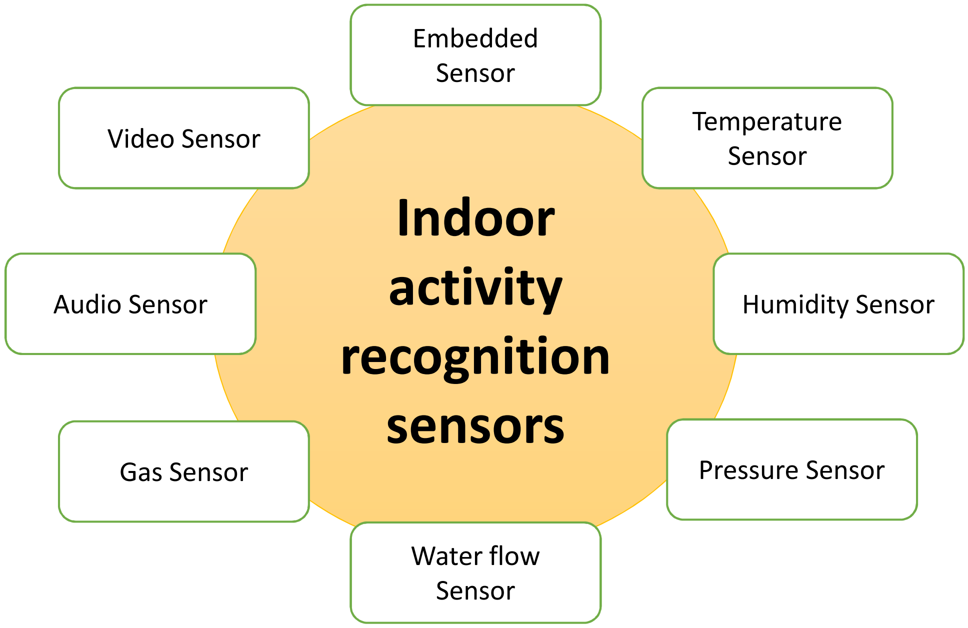


Figure 2.1: Available sensors to sense the indoor environment

acceptable solution as discussed earlier. Therefore, they are often compensated by state changed embedded sensors. Simple sensors can often provide powerful clues about activity. For instance, opening the fridge door, turning on the stove and exhaust fan. Collectively these clues strongly provide the information about the cooking activity. Sensors are integrated into the architecture of the home and build a true environment of ubiquitous sensing technology. It sense the environment 24 by 7 and logs the sensory data. This low-level sensory data is processed to detect the performed activities for high level applications and services delivery. To generate the real datasets for activity recognition, volunteers are requested to live in these smart homes and perform the daily life activities in a usual manner. Many research groups from all over the world developed several smart homes such as CASAS and MavHome [27] at Washington State University, Aware Home [28] at Georgia Tech University, Adaptive House [29] at University of Colorado, House_n [30] at Massachusetts Institute of Technology (MIT), and House A [16] at Intelligent Systems Laboratory. In the above mentioned smart homes most of them use embedded sensors technology to recognize the daily life activities. The need for the development of such technologies is the demand for active aging, reduction of healthcare cost, and the individuals remain independent in their own homes.

These days, activity recognition in home environment is available at commercial level such as: Quiet Care Systems [31] and e-Neighbor [32].

2.1.2 Outdoor Activity Recognition

Outdoor human activity recognition is usually associated with the motion of the body. Various kind of sensors are used for outdoor activity recognition as shown in Figure 2.2. Among these, accelerometer is one of the most useful sensor to assess both static and dynamic activities. The reason for using accelerometer is that it is highly reliable in detecting the motion as well as tilt positions. Moreover, they are available in small sizes and at a low-price. Due to these reasons, they are superior as compared to other sensors. Underneath concept of accelerometer is to measure the acceleration due to movement and capabilities of responding to acceleration due to gravity. These two factors are most important for any physical activity recognition system [33]. Often additional sensors are included such GPS sensors, heart rate sensors, gyroscopes and compasses [34] [35].

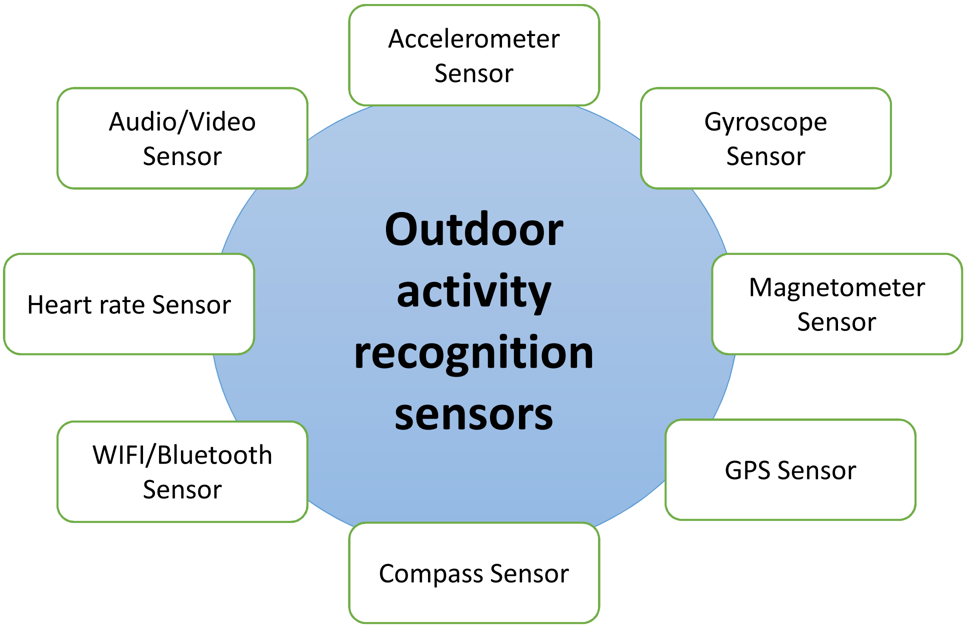


Figure 2.2: Available sensors to sense the outdoor environment

In the last few years, many researchers developed different activity recognition systems that are based on implanted accelerometers in special shirts, bracelets or belts to recognize the both static and dynamic physical activities [22] [36] [37]. In the static category, postures of the body are mainly focused which include sitting, standing or lying down and the transitions between them. These activities are helpful to monitor risky situations and detect falls, particularly for elderly people. In dynamic category, motion of the body is integral to these activities such as walking, running, or climbing stairs. Wearable sensor-based solutions are obtrusive because people might forget to wear them, or find them uncomfortable to wear. In this situation, an alternative solution to wearable devices is current generation smartphones to recognize dynamic activities. The smartphone is equipped with a number of built-in sensors, including accelerometer, magnetometer, gyroscope, proximity, ambient light, GPS, and cameras. Compared to using body-worn sensors, it is one of the best choices for physical activity recognition due to its unobtrusive characteristics, high storage capacity, computation power, low energy consumption and programmable capabilities.

2.2 Architecture of an Activity Recognition System

In this section, we briefly explain the activity learning models for human activity recognition. In activity recognition, signal processing and activity models are the most important in learning phase as illustrated in the block diagram , shown in Figure 2.3.

In the first step, temporal sensory data is pre-processed and features are extracted by a selected method. In second step, data is divided into training data for learning phase and testing data for testing and validation phase of the model. In third step, activity models learn the activities by providing training data and store the models parameter. In the final step, the learned model is tested over the test data to evaluate its performance. For indoor and outdoor activities, heterogeneous type of sensors are used to recognize the activities. Due to this reason, signal processing and activity models may be different while the other steps remains the same. In the following sections we focus on these two parts of activity learning models.

2.3 Learning Models for Indoor Activity Recognition

In this section, we discuss about the signal processing methods and activity models for embedded sensors in the smart home environment to recognize the indoor activities.

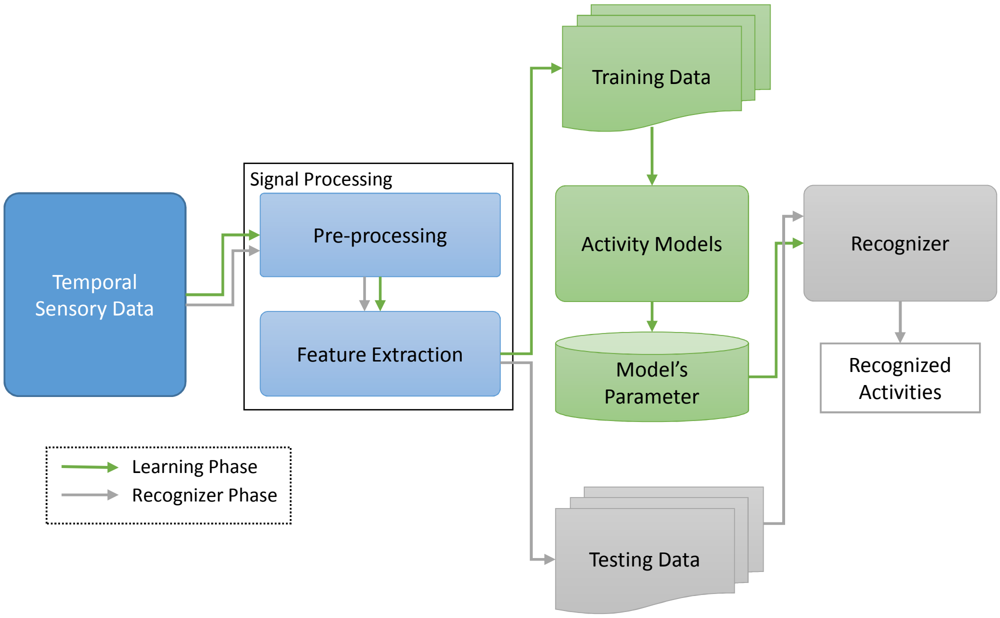


Figure 2.3: Block diagram of an activity recognition system

2.3.1 Signal Processing

Pre-processing step: In the literature, three common approaches are adopted to process the sensor streams as shown in Figure 2.4 [23]. We illustrates each of them as follows:

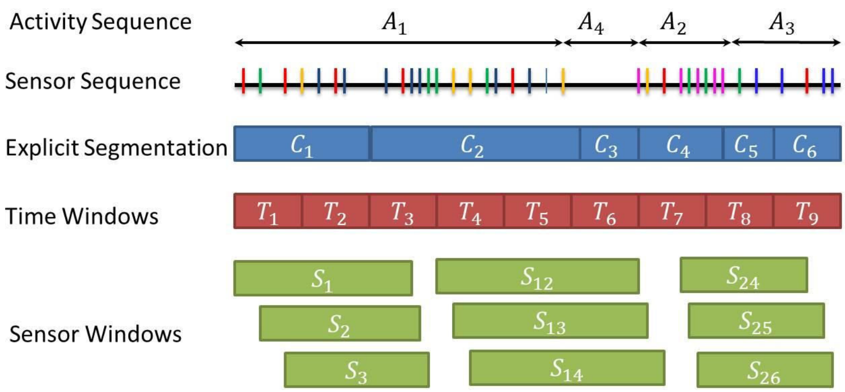


Figure 2.4: Three common approaches to process the temporal streaming of data

- **Explicit segmentation**: This method is based on the cluster of sensor streams. It is a two step process. Firstly, data is segmented on the basis of closely occurred sensors sequences. In the second step, this explicit segmentation is used for recognizing the activities. This method can segment the sensory data streams but it is not true for all cases to map an individual segment or group of segment for the performed activity. Figure 2.4 shows the mapping of activity sequence A_1, A_2, and A_3 with explicit segmentation of $C_1, ..., C_6$. Usually, during the training phase of the activity learning models these explicit segmentation parts are used. Due to this reason, learning models recognize the performed activities with low accuracy during the recognition phase.

- **Time-based windowing**: In this approach, stream of temporal sensory data is divided over the constant time stamp regardless of the start and end time of the performed activity. Computationally, this technique is less expensive as compared to the explicit segmentation. It is useful when system obtained the data continuously over a specific period of time. Many researcher used this for accelerometer and gyroscope sensors to breakdown the temporal streams of data. The amount of time interval is usually selected by the analyzing the activity nature and obtained result after the learning phase. In case of embedded sensors, even though nature of the sensor data is temporal but depends on the interaction of the human. In Figure 2.4, during the time interval T_6 no sensor event is fired. Technically, these sensors do not have a constant sampling rate. To handle this situation, some heuristic based methods are developed to extend the activity occurring in the previous time intervals to the current time interval.

- **Sensor event-based windowing**: In this approach, streams of sensor data is divided into the sequence windows containing equal number of sensor events as shown in Figure 2.4. It is evident that the windows appear to vary in their duration. This is fine considering that during the performance of activities, multiple sensors could be triggered, while during silent periods, there will not be many sensor rings. This method too has some inherent drawbacks. For example, consider the chunk S_26, in Figure 2.4. The last sensor event of this chunk corresponds to the beginning sensor event of activity A_4. There is a significant time lag between this event and its preceding sensor event. The relevance of all the sensor events in this chunk on the last event might be small if the time lag is large. Thus treating all the sensor events with equal importance will not be a good approach. To avoid this kind of issues, Intille [24] explicitly incorporate the activity duration for event-based window approach. They defined variable size of feature windows by defining one feature window per activity. This feature window is equal to the duration of the performed activity carried out by the subject. Thus, if M is the number of activities to recognize, there were M different feature windows with lengths $L_i, ..., L_m$. The duration or length L_i for each feature window was the average duration for each activity calculated from all the activity labels generated by experience sampling method (ESM) and indirect observation.

Feature Extraction: It is a highly domain specific technique to map the raw sensory data to some other representation space with the objective to recognize the performed activities more easily. For simple state change embedded sensors, feature vectors are extracted from the temporal sensory data that is active sensor and time information at a specific period of time as discussed above.

2.3.2 Activity Models

Activity recognition based on sensory data is a challenging task due to complex environments and noisy data. The state-of-the-art and most popular activity recognition techniques are based on probabilistic models such as Hidden Markov Models (HMM) [38], Conditional Random Fields (CRF) [39], Naive Bayes classifier [24], and some other classification methods [40] [41] [42].

Kasteren *et al.* [16] recognized the daily life activities by using Hidden Markov Model (HMM). HMM is a probabilistic function of Markov chains based on the first order Markov assumption of transition. In activity recognition, hidden state is human activities and HMM recognizes activities from both sensor observation and previous activity according to the first order Markov chain. However, HMM is also a generative, directed graph model [43]. Generative model means that observation data is randomly generated. In other words, it should enumerate all possible random cases in the model. Directed graph is used to capture order between states. Therefore, a generative and directed graph model in activity recognition implies that it should find all possible sequences of observations. However, many activities may have non-deterministic natures in practice, where some steps of the activities may be performed in any order. Missing an observation or an order will cause the HMM to produce errors in the model. Another popular probabilistic model is the conditional random field (CRF). By holding the Markov property in CRF gives us the linear-chain CRF. The HMM and linear-chain CRF have been successfully applied in activity recognition [16] [44].

Tapia *et al.* [24] chose Bayesian classifier to detect the daily life activities. Bayesian classifiers make strong and often clearly incorrect assumptions that each class attribute is independent given the class. They also assume that all attributes that influence a classification decision are observable and represented. For these reasons, they are sometimes assumed to perform poorly in real domains. On the contrary, however, experimental testing has demonstrated that naive Bayes are surprisingly good classifiers on some problem domains, despite their strict independence assumptions between attributes and the class. Kautz *et al.* [25] used Bayesian network classifier to track the daily activities of residents in an assisted living community. The algorithm can distinguish different activities such as asleep and having meals solely based on noisy information about the location of the residents and when they move. Even though Bayesian network show some promise, they may not scale to environments that contain hundreds of sensors, particularly if real-time recognition of activity is a goal.

An alternative approach that has been explored by Maurer *et al.* [23], employed decision trees to learn logical descriptions of the activities. This approach offers the advantage of generating rules that are understandable by the user. Similarly, Chen *et al.* [40] introduces a knowledge-driven approach to real-time, continuous activity recognition based on multi-sensor data streams in smart homes. The approach goes beyond the traditional data-centric methods for activity recognition in three ways. Firstly, it makes extensive use of domain knowledge in the lifecycle of activity recognition. Secondly, it uses ontologies for explicit context and activity modeling and representation. Thirdly, it exploits semantic reasoning and classification for activity inferencing. The limitation of such method is to define explicit representation of each context in the ontologies and their association based on domain knowledge.

A number of difficulties and limitations remains with these approaches. The learning capability of probabilistic models depends on the observation of activity class distribution (the observed state) and the transitions between adjacent activities (transitions between states). Existing methods are unable to model activity representation structure such as location, value or sensor type.

Furthermore, they require sufficient data to produce reliable results. Minor activities are skipped during the learning phase due to their few occurrences in the dataset. Therefore, probabilistic models are treated as a black box for recognizing activities; this is impractical for crucial applications such as healthcare.

Evolutionary techniques as learning classifiers have successfully solved some well-known problems, such as function approximation, general prediction, classification and data mining tasks [45] [46] [47]. Matthew *et al.* [48] proposed an extended version of learning classifier and utilized GA to produce generalizations over the space of all possible condition-class combinations. Kuncheva *et al.* [49] used a GA to design the classifier fusion system and determined that, as a learner component, GA outperforms other classifier models. Also, GA has been successfully used as a learner to select optimal genes for analyzing DNA microarrays [50]. On the other hand, in ensemble learning paradigm, n individual learners are trained using machine learning algorithms [51]. This solves the problem in which a single learner suffer from statistical, computational, and representational problems. Statistical problems arise due to high variance in the data that excessively increase the size of the search space. Computational problems occur when the training data is computationally intractable and can get stuck in local optimum. Representation problems cause biasness for learning algorithms. Both theoretical and empirical studies of ensemble learning show higher accuracy in real world applications such as spam email filters, character recognition, text categorization, face recognition, computer-aided medical diagnosis, and gene expression analysis [48].

2.4 Learning Models for Outdoors Activity Recognition

Outdoor activities are usually monitored by body worn sensors or a smartphone which is most likely to be with a user during the outdoor activities. In this section, we specifically illustrate the pre-processing, feature extraction steps for accelerometer sensor and activity models for outdoor activity recognition.

2.4.1 Signal Processing

Pre-processing step: In the case of triaxial accelerometer data, pre-processing can be one of many different kinds such as applying smoothing function, orientation issues, or streaming temporal data by applying windows technique.

- **Smoothing Function:** A triaxial accelerometer measure the acceleration of the user and returns an estimated real-value of the acceleration along x, y, and z axes in a 3D coordinate system. The raw accelerometer data potentially has two issues. First, the acceleration data is sensitive in nature and it may generate noise. To reduce such noise, smoothing functions are applied such as low-pass and high-pass filter. In low-pass filters, signals are filtered and made smoother that are less dependent on short changes. While high-pass filter eliminate the gravity component and take into consideration only the isolated sudden changes in acceleration. In order to apply these functions, one should be careful because sometimes small amount of changes are vanished which are important for certain cases. So the decision whether to apply or not a smoothing function depends on the proper analysis and intended application.

- **Orientation Issues:** The orientation of the accelerometer sensor has an impact on the values of each axis. Many researchers distinguished user motion activities by attaching accelerometers in known positions and orientations on the users body. The change in orientation may produce unsatisfactory results due to different value of x, y and z axis. While other researchers remove the impact of orientation through computing the magnitude of all three axis. In this situation, directional information is lost. Another useful method has been proposed by Mizell [52] to solve the orientation issue and estimate the gravity force by components from the available acceleration data.

- **Streaming Temporal Data:** The accelerometer sensor continuously sense the data over a constant rate (i.e., Hz). The stream of temporal data is divide into data segments over a defined time interval to identify useful patterns. Each data segment over the specified time interval is known as window. If the widows have some data samples as intersection, then this technique is named as overlapping sliding windows.

Feature Extraction: In case of accelerometer sensory data, a large variety of feature extraction schemes are proposed to recognize the activities associated with the motion of the body. These features are categorized into three broad types.

- **Time Domain:** Time domain features are directly derived from a window of acceleration data and simple statistical features. Most common features are mean, variance, standard deviation, median, percentile etc.

- **Frequency Domain:** In case of frequency domain features, the window of sensor data must first be transformed into the frequency domain and then features are calculated. For instance, the energy feature is calculated by applying the Fast Fourier Transformation (FFT) to find the quantitative characteristics of the data over a defined time period.

- **Wavelet Domain**: In wavelet domain, both time and frequency characteristics are analyzed. The original time-domain signal is initially decomposed into a coarse approximation and detail information. With wavelet decomposition, the half-band filters are designed to enable perfect reconstruction of the original signal and to avoid aliasing effects. In subsequent levels of decomposition, the approximation signal from the previous level is split into a second approximation and a detail coefficient. This process is repeated to the desired decomposition level [53].

2.4.2 Activity Models

For outdoor activity recognition, several studies exist which focus on the usage of accelerometer signals and analysis of motion patterns in the activity recognition domain. Lara *et al.* [54] introduced a mobile platform for real-time human activity recognition. Their system is composed of a wearable device and a Bluetooth-enabled Android phone; experiments were performed in a sequential fashion which recognized walking, running, and sitting activities. They analyzed the C4.5 tree family classification algorithm and produced acceptable results; however, the recognized activities comprise on a small group of activities and quite distinguishable from each other. The performance of the decision tree decreased in case of large group of activities.

Wang et al. [26] detect five different human walking patterns using a multilayer neural network classifier. They obtained classification accuracies 92% for these five activities. Their neural network classification on new subjects data is decreased (i.e., 88.54%). Specifically, there was a 25.4% drop in the detection of slope-up walking. The reason behind the decrease in accuracy is the learning capabilities in activity recognition domain. It learns the activities over the existing training data with minimum error that become less flexible to the variation of new subject action pattern.

Ravi *et al.* [55] reported the results of their study for a small group of dynamic activities using a single triaxial accelerometer worn near the pelvic region. Four features were extracted from the accelerometer data (i.e., mean, standard deviation, energy, and correlation). In order to perform the classification task, they analyzed the performance of base-level classifiers and meta-level classifiers on two subjects, and achieved high accuracy. The sampling frequency was 50 Hz and window size was 5.12 seconds. They used the Plurality Voting classifier but complication may arise while increasing the number of subjects as well as dynamic activities.

Preece *et al.* [56] analyzed statistical and wavelet-based features for classifying dynamic activities using accelerometers mounted to waist, thigh, and ankle as well as their combinations. They reported a similar level of accuracy in case of time/frequency or wavelet features when the accelerometer was mounted on the waist. However, for both ankle and thigh mounted sensors, the time/frequency domain features significantly outperformed the wavelet features. They used an instance-based classification algorithm, Nearest Neighbor, to recognize the activities and concluded that frequency-based features accurately classify activities. They obtained remarkable classification accuracy with ankle and thigh mounted sensors, using a sampling frequency of 64 Hz for their experiments.

Helmi *et al.* [19] proposed a fuzzy inference system to classify a small group of human activities by extracting three features: peak to peak amplitude, standard deviation, and correlation between the axes. They collected three subjects data by attaching the triaxial accelerometer to their waists with a sampling rate of 22 Hz. The fuzzy rules and the membership functions of this fuzzy system are defined manually based on the experiences of domain experts.

Dempster-Shafer theory is recognized as an effective approach to handle the uncertainties [57]. It is an alternative to Bayesian networks that is designed to combine the evidence. Rather than computing probabilities of propositions, it computes probabilities that evidence supports the propositions. It is consider as a fusion-based method to combine the evidence from multiple sources of information that may yield a more reliable decision. Such information fusion has become highly popular for many applications related to image processing and computer vision [58] because it improves the quality of a decision by decreasing uncertainty and imprecision and increasing the amount of global information [59]. In case of outdoor activity recognition domain, single source of information (i.e., accelerometer sensor of smartphone) is used that limits the applicability of Dempster Shaffer theory.

2.5 Applications of Activity Recognition

In this section, we discuss the application point of view to highlight some important application domains that rely on activity recognition. We discuss healthcare, energy-efficient power management, entertainment and games, industrial, and security and surveillance application areas. In these applications, we presented that the automatically detected activities can play a significance role to provide useful services.

2.5.1 Healthcare Applications

Besides the healthcare application discussed in Section 1.1, activity recognition can play a significant role in the risk and prevention domain. For instance, patients with diabetes, cardiovascular disease, insomnia or obesity often follow effective physical activity plan or routines like walking, jogging, running or cycling as a part of their treatment. In the physicians prescription, lasting duration is most important metric that measures the amount of activity [7]. Accurate information about the duration of activities is helpful for the practitioners as well as for subjects to compliance their activity routines according to prescription. Furthermore, physical activity recognition may also identifies whether the individual has any difficulties to follow the routines.

Another useful application is Active Lifestyle. It is a proactive approach to adopt healthy lifestyle in our daily routines. For instance, daily exercise, diet, sleep and social relationships are the wellbeing indicators. A progressive health effects can be observed if they are well managed.

Activity recognition system can recognized the amount of exercise, sleeping patterns and provide the dietary information when it detects user is preparing dinner. In 2011, European commission funded a mega project to find out the sustainable lifestyles. The goal of this project is to come up with the future scenarios for more sustainable lifestyles and began by taking stock of existing knowledge on sustainable lifestyles. Through this initial research, they identified the challenges and barriers to more sustainable living today, as well as promising trends, drivers and opportunities to encourage more sustainable ways of living in the future [60].

2.5.2 Entertainment and Games

The adoption of activity recognition in entertainment and sports is faster than other domains because accuracy and privacy is less crucial as compared to healthcare domain. In [61], a wearable sensor based system is introduced to notice the dance performance and correct the moves latterly. Keyl *et al.* [62] recognize the cricket batting strokes based on sequences of body and bat postures. In their system, they capture the motion of a batsman playing a stroke. Which is then compared to known strokes provided by the classification. A feedback is provided which outlines how well the selected stroke was played. In sports field, numerous commercial systems are available that are based on activity recognition technology. The K-Vest 3D technology [63] improves golf skills through its use of biofeedback. It is an all-in-one capture, analysis and training solution that allows golf instructors to measure swing efficiency and movement patterns with real-time training experiences that improve swing faults in less time.

The most recent popularity in game control is Microsoft Kinect [64] to develop interactive game and activity recognition is the core component to reflect the physical movement into a virtual character. With Kinect, thousands of businesses and developers are creating applications that allowing their customers to interact naturally with computers by simply gesturing and speaking.

2.5.3 Home and Office Automation

In recent years, sensor technology have offered new and exciting opportunities to increase the smartness of devices within the home and offices. Activity recognition systems can provide active support to such systems in terms of efficient utilization in home appliances [65] [66] and office resources.

2.5.4 Industrial Applications

Another area of research on human activity recognition is the industrial zones where it can play a significant role to prevent mistakes, make the work faster and more efficient, automate the assembly parts of automobiles and shorten the training process of workers. Furthermore, it is providing the services over the wearable sensor devices for the workers and helping them by supporting in production, maintenance, health care, and emergency rescues. Another typical work in this area published in [67], the system records activity data using wearable and environmental sensors for recognizing the worker activities in car manufactory.

The work in [68] is based on activity recognition by attaching the computing devices and multiple sensors onto different parts of the assembly the system that can recognize the actions of the user and determine the current stat of the assembly. They explained their system over the IKEA PAX wardrobe application. Similarly, aircraft assembly [69] other on-site tasks [70] [71] demonstrates a genuine utility of wearable systems.

2.5.5 Security and Surveillance

In security and surveillance, activity recognition plays an important role in traffic flow analysis, military security, patrolling of country borders, surveillance of forests for fire detection and patrolling of highways and railway for accident detection. Furthermore, observation of people and vehicles in public places to prevent theft and robbery. The most common sensor technologies includes CCD cameras, thermal cameras and night vision device [72]. Now-a-days, a lot of visual technologies is used for security and surveillance purposes which ultimately require a lot of manpower to monitor all these cameras. There is a need to develop intelligent visual surveillance that should work well as the numbers of cameras exceed the capability of human operators to monitor them.

Nour *et al.* [73] present an intelligent video-surveillance framework for event recognition in crowded scene to detect the abnormal human behavior. They addresses four main challenges: behavior understanding in crowded scenes, hard lighting conditions, multiple kinds of input sensors, and contextual-based adaptability to recognize the active context of the scene. As final output of the system, an alarm or notification will be generated, in case of detection of abnormal behavior according to certain criteria. PRISMATICA [74] is a proactive integrated system for ambient intelligence in public transport environments. It extract the meaningful information from the geographical spread sensor by using computer vision techniques. Similarly, Vu [75] have developed an audio-video event recognition system for public transport security. The aim is to provide a solution for the automatic surveillance in public transport vehicle (e.g. trains and metros) by analyzing human behaviors based on audio-video stream interpretation.

2.6 Summary

In this chapter we began our investigations with the sensor technologies for indoor and outdoor human activity and general architecture for recognizing the activities. We discuss the signal processing and activity models to learn the activities. Finally, we discuss some of the applications the applications where indoor and outdoor activity recognition has great impact on valueable services.

Chapter 3

Perliminaries

This chapter presents a brief overview of evolutionary learning and fuzzy systems that provide the building blocks for evolutionary framework. Several evolutionary learning paradigms have been developed that is quiet long to provide a complete review of all of these. We provide a good flavor of these approaches to make a rich ground for evolutionary learning models that are investigated in this thesis as potential solutions to activity recognition problems.

3.1 Evolutionary Learning

The concept of evolution is a hot topic of debate and active area of research from the last centuries. In different disciplines such as plants, chemical, stellar or man-made systems, evolution has different interpretations [76]. In computer engineering discipline, it draws inspiration from biological mechanism of evolution such as Darwins theory. It is also known as evolutionary computation and widely applied to a variety of problems, ranging from practical applications in industry and commerce to leading-edge scientific research. Darwins theory based on the natural selection or survival of the fittest concept. According to this, in the population only those individuals are more likely to survive, who has the best characteristics while others are passed away over the time. On a computer, evolutionary processes can be simulated at speeds thousands of times faster than real-time. Evolutionary computational model search a problem space by evolving a population of individuals, each of which represents a solution to the problem. By simulating the biological process of natural selection, survival of the fittest and reproduction operators best solutions are obtained over the time and adapted to the specific problem. There are many components of nature that contribute in biological evolution. However, evolutionary search process is influenced by the following main components.

- **Representation**: To solve the problem through evolutionary algorithm, first problem is encoded into a form of chromosomes. In chromosome, each attribute is known as genes. Once representation has been done in the form of chromosome then evolution search take place.

- **Population**: It is a process to collect the potential solutions based on chromosomes. After getting the population, it is evolved in the search process to get the best one and poor ones are removed.

- **Fitness Function**: During the search process, a function is required to evaluate the quality of individuals in the population. It is known as fitness function, or survival strength of individuals.

- **Parent Selection**: It is a way to promote the best individuals and responsible to improve the quality of the population. It selects the individuals from the population to apply the reproduction operators for creating the new offspring.

- **Reproduction Operators**:Recombination and mutation operators are applied over the selected parents to create the new offspring.

This process can be iterated until some stopping condition is satisfied. Common conditions are length of time, fitness evaluations, or fitness stops improving over the generations. Each iteration is referred as a generation.

3.1.1 Paradigms of Evolutionary Algorithms

The different ways in which the evolutionary algorithm components are implemented, result in different evolutionary computation paradigms [76].

- **Genetic Algorithms**: This is the most popular paradigm of evolutionary computation which model genetic evolution. In GA individuals were represented by binary strings or real-valued strings.

- **Genetic Programming**: It is considered as a variation of the genetic algorithms. Individuals are various kind of programs consisting data structures and functions represented by trees.

- **Evolutionary Programming**: The paradigm is derived from the simulation of adaptive behavior in evolution and developed to evolve finite-state machines. It usually use mutation operation and self-adaptation parameters of mutation.

- **Evolution Strategies**: In evolution strategies, each individual is represented by genetic building blocks and a set of strategy parameters that models the behavior of that individual in its environment. It applies both reproduction operators but main focus on mutation and mutations are accepted only in successive cases.

- **Differential Evolution**: It is similar to genetic algorithms, differing in the reproduction mechanism used. It differs significantly in the sense that distance and direction information from the current population is used to guide the search process. Differential Evolution operates better on fitness surfaces which are flat.

- **Cultural Evolution**: It is based on the principles of human social evolution [77]. The performance of the evolutionary algorithm can be improved if domain knowledge is used to bias the search space. Domain knowledge serves as a mechanism to reduce the search space by pruning undesirable parts of the solution space, and by promoting desirable parts.

- **Coevolution**: It is known as the competitive evolution to save an individuals. In this process, win of one spices means the die of others. In the next generation, each species changes in response to the actions of the other species during the previous generation. Furthermore, it has two types of coevolution that is competitive and cooperative.

In this dissertation, we mainly evolve genetic algorithm for the evolution learning process. The subsequent section focuses in more detail on genetic algorithm.

3.2 Genetic Algorithms

Genetic algorithms are considered as a first algorithmic models to develop and simulate genetic systems [76]. John Holland [78] was a pioneer researcher to apply the evolution concept computationally. GAs are simulated on a set of individuals and stochastic operators are applied over the consecutive generation for solving a problem. Each individual is represented by bit-string and consider as a point in a search space and a possible solution. The flow of standard GA is shown in Figure 3.1 and details about the operators are given below:

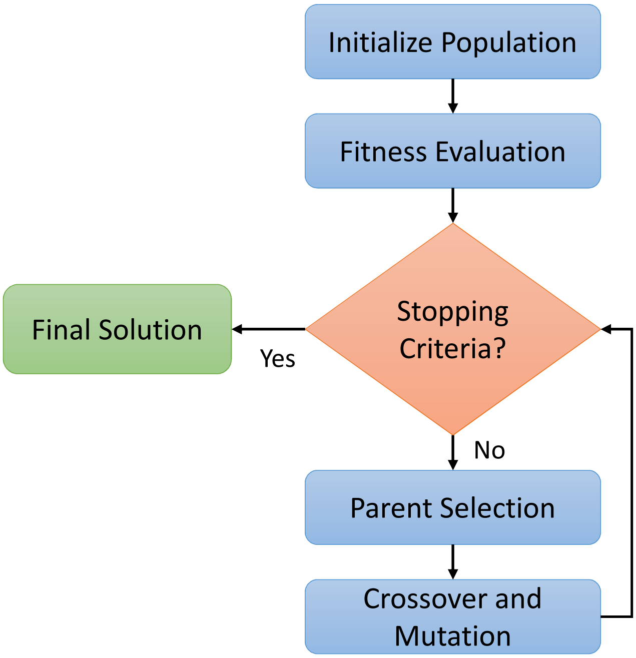


Figure 3.1: Process of Genetic Algorithm

3.2.1 Encoding

In order to solve the problem through genetic algorithm, it is important to transform in to gene representation (i.e., Chromosome). The process of transformation is called encoding. There are many methods of encoding, the common ones are binary encoding, real encoding, etc. The method chosen depends on the problem at hand. A good encoding scheme is also a most important factor for the performance of $GA's$. A binary encoded chromosome is represented in Figure 3.2.

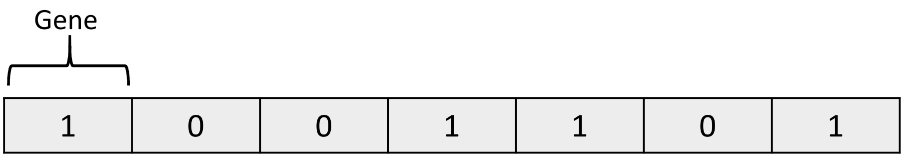


Figure 3.2: Choromosome encoding

The position of 0 or 1 in the chromosome represent a particular characteristic to the problem.

3.2.2 Crossover

Crossover operator is applied to create the new offspring from the selected chromosomes known as parents. During the crossover operation, information is exchanged between the participants and new offspring is created which has the features of both parents. There are following ways to exchange information.

- **One-point crossover**: It exchange the information between the parents and transform into offspring by selecting the random crossover point known as cut-point. After cut-point genes value are swapped to create new offspring as show in Figure 3.3.

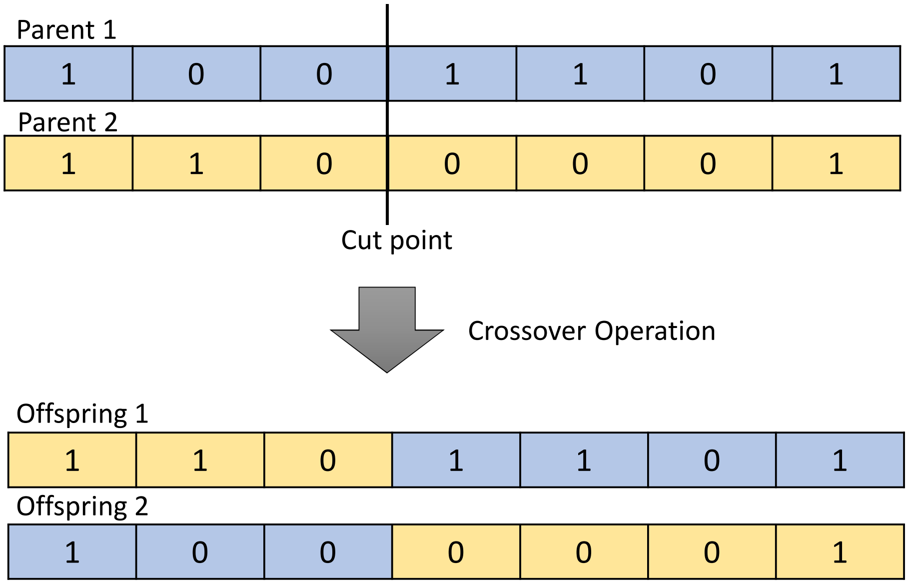


Figure 3.3: One-point crossover

- **Two-point crossover**: In two-point crossover, randomly two cut-points are selected and information is exchanged between the parents to create the new offspring as shown in Figure 3.4.

- **Uniform crossover**: In uniform crossover, parents exchange the information over the bit-swapping probability. For instance, if p = 0.5 then it means that each gene has equal chance

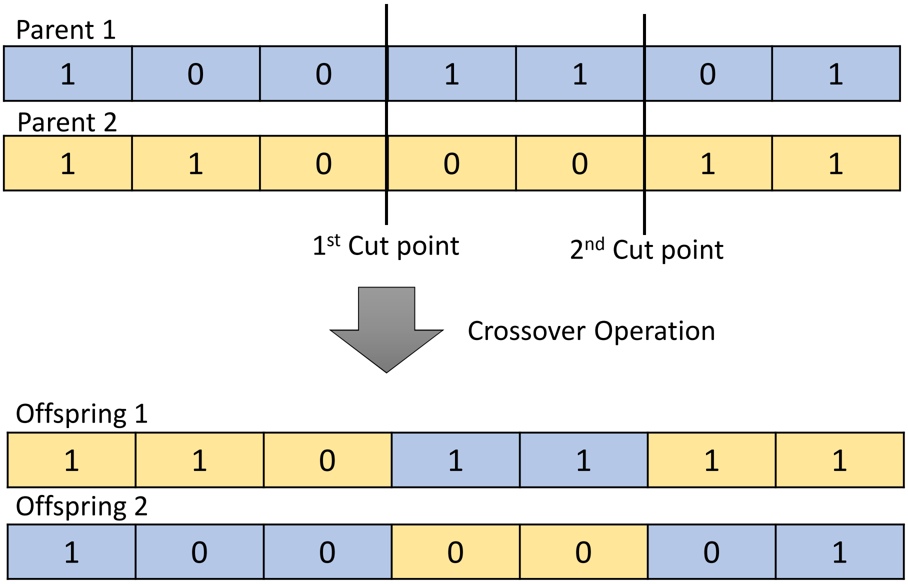


Figure 3.4: Two-point crossover

to be swapped as shown in Figure 3.5.

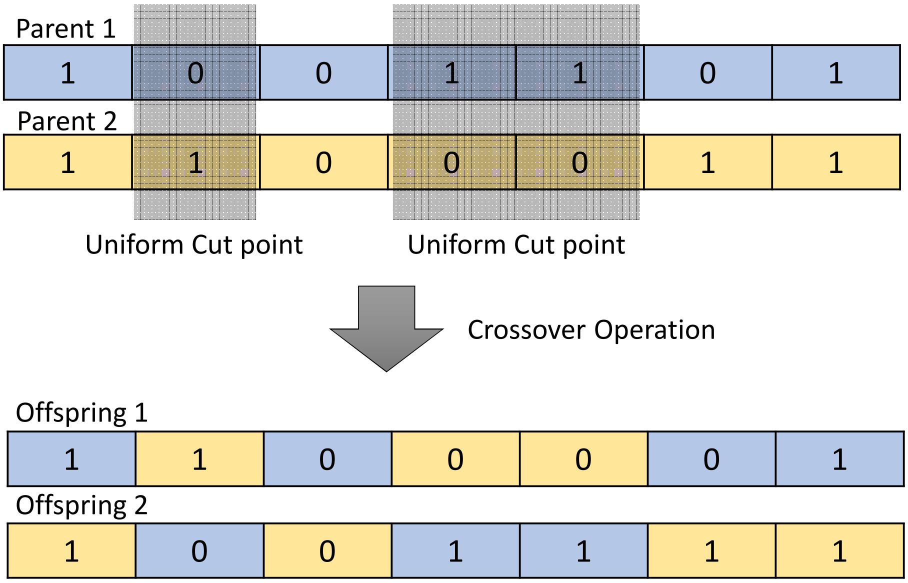


Figure 3.5: Uniform crossover

3.2.3 Mutation

This operator is applied to add the diversity in the genetic characteristics of population. In simple term, it introduces the new genetic material into existing individuals. Mutation is applied at a certain probability to produce a mutated offspring. For binary representation, following mutation operators are developed [76]:

- **Uniform Mutation**: In this operation genes are selected over a certain probability and its value are flipped because of binary representation as shown in Figure 3.6.

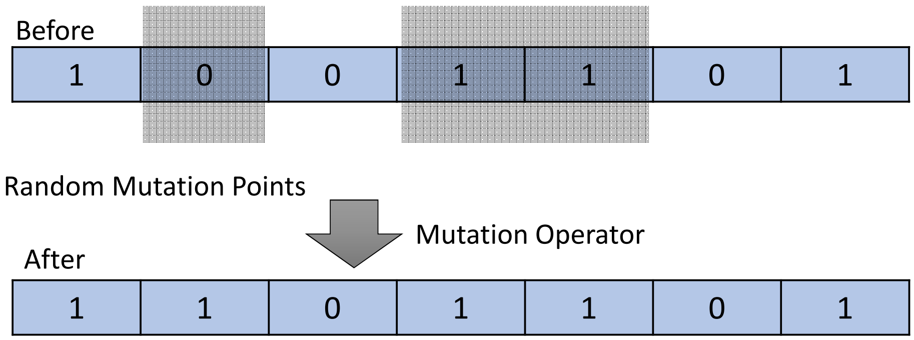


Figure 3.6: Random mutation

- **Inorder Mutation**: In this operation, two mutation points are randomly selected and only the bits between these mutation points undergo random mutation as shown in Figure 3.7.

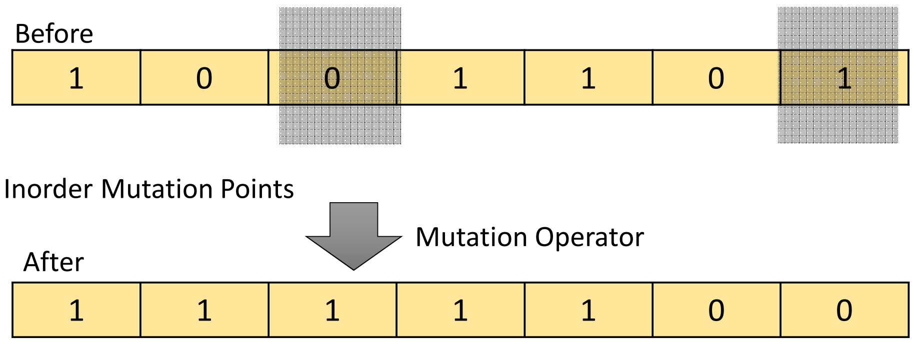


Figure 3.7: Inorder mutation

- **Gaussian Mutation**: For binary representations of floating-point decision variables, the bit string that represents a decision variable be converted back to a floating-point value and mutated with Gaussian noise [79].

3.2.4 Selection

The main objective of the selection is to step forward towards the better solution by selecting the individuals from the current population. These selected parents are used for creating the new offsprings. Selection process is directly related to the survival of the fittest concept of the Darwins theory. It is operated by following different ways;

- **Random Selection**: In random selection, each good and bad individual has equal probability to survive in the next generations. During random selection no fitness information is used to select the parents.
- **Proportional Selection**: In this selection, a probability distribution is created over the fitness and individuals are selected by sampling. The most common methods for sampling is roulette wheel and stochastic universal sampling. First, roulette wheel is created by normalizing the fitness values to the certain portion of the wheels and samples are chosen by spinning the wheel. There is a probability that best may not be selected during the spinning of the wheel. In stochastic universal sampling is based on the fitness proportionate selection which exhibits no bias and minimal spread. It chooses several solutions from the population by repeated random sampling.
- **Tournament Selection**: In tournament selection, a group of individuals are selected randomly and performance of selected individuals is compared to get the best from the group.
- **Rank-based Selection**: It uses the rank ordering of the fitness values to determine the probability of selection and not the fitness values themselves. This means that the selection probability is independent of the actual fitness value. Therefore, ranking has the advantage that a highly fit individual will not dominate in the selection process as a function of the magnitude of its fitness.
- **Boltzman Selection**: Boltzmann selection is based on the thermo dynamical principles of simulated annealing [76].

3.2.5 Stopping Conditions

Evolutionary operators are iteratively applied until a stopping condition is satisfied. The following conditions can be used to stop the process when:

- reach to the maximum number of generation,
- no improvement is observed over a number of consecutive generations,
- there is no change in the population, or
- an acceptable solution has been found.

3.3 Evolutionary Learning Classifiers

Evolutionary learning classifier systems are robust machine learning techniques that evolved rules to provide a plausible, human readable, model of the unknown system. In such systems, problem is converted into rule like structures and evolved through evolutionary algorithms such as genetic algorithm. The evaluation of these rules are done by basic reinforcement learning algorithm. John Holland is consider as the pioneer of learning classifier system because he did a lot of extensive research on biological inspired genetic algorithms and consequently introduced the learning classifier system as a cognitive systems framework [80].

Later on, it successfully applied to a wide range of areas such as medicine, computer science, machine learning, engineering, operation research, and parallel implementation. Some impressive example such systems that are applied in real-world scenarios are classification tasks [81] [82], large-scale data mining problems [46], robot control [83], medical [84] and intrusion detection [51] among others. Moreover, studies on real-world problems show that rule learning paradigms are competitive in comparison to other non-evolutionary learning algorithms in terms of predictive accuracy.

In order to understand the classifier functionality, it is divided into following three components.

- Transforming the problem into rule-based structures that contain the

  If $condition_1, condition_2, ..., condition_n$ *then Action.*

First part contains the conditions of the system while second part is the appropriate action that is based on these conditions.

- Applying computational search technique such as GA to evolve the population to search the new rules that will be better and more generalized than the existing one.
- Evaluation mechanism that are based on reinforcement learning techniques to assign utilities to existing rules, and guiding the search for better rules.

3.3.1 Approaches to Build the Model

There are two most popular method Michigan and Pittsburgh approach to build evolutionary classifier system, while later on hybrid and other models are also constructed to build the systems.

- **Michigan Approach** In the early days, first evolutionary classifier system was cognitive systems [80] developed at university of Michigan. The later implementations for other application areas are same as implemented first time so it becomes the standard framework to develop the evolutionary classifier systems. It is named as Michigan approach where a set of rule population is created and GA is applied to the whole population for getting the good rules. In this approach, individual rule compete for offspring generations and the whole evolved population is consider as a complete solution. Furthermore, this approach is typically applied to more complex tasks and provide online learning abilities, while it can also apply to offline problems as well [85].
- **Pittsburgh Approach** Smith from the University of Pittsburgh [48] introduced an alternative implementation of evolutionary learning classifier system that also adopted to develop many other systems. This approach is different from the Michigan approach in terms of problem solution structure. In Pittsburgh approach, it evaluates and evolves multiple populations, which compete with each other for reproductions. The final solution to the problem is the best individual of the population. Furthermore, this approach suffers from heavy computational cost and cannot do online learning [85]. An early advantage of the Pittsburgh approach came from its credit assignment scheme, where reward is assigned to entire rule-sets as opposed to individual rules [86].

3.4 Fuzzy System

Fuzzy logic system is introduced by Lotfi Zadeh [87] and based on fuzzy sets and fuzzy relations. It can be seen as an extension of set theory, where degree of vagueness is represented by membership functions between the range of [0, 1]. In order to make a fuzzy system, linguistic variables and terms are defined for the problem in hand. Membership functions and rule base are created to response the system during the testing phase. Once a fuzzy system is build then in first step input data is converted into fuzzy values using membership functions. In second step, on the basis of membership values, rules are evaluated in the rule base. It may possible to fire more than one rule for the given input data. In such situation, results of each rule is combined by certain operators to make an inference. Finally, this inference is converted again into non-fuzzy values output. Details of fuzzy set theory is given as follows:

3.4.1 Linguistic Variables and Hedges

Linguistic variables model the uncertainties of the natural language and define the input and output of the system. Furthermore, it is decomposed into linguistic terms and hedges. For example, the phrase, when walking is very fast, it will most probably jogging. In this example, fast is linguistic term and very is hedge to define the intensity of the object.

3.4.2 Membership Functions

Membership functions are used to convert the input data into fuzzy values known as fuzzification process. Similarly, output of the fuzzy system is fuzzy value that is converted in to crisp value used membership functions known as Defuzzification process. An important characteristics of fuzzy logic is that a numerical value may belong to multiple set at the time. There are different forms of membership functions such as triangular, trapezoidal, piecewise linear, Gaussian, or singleton as shown in Figure 3.8.

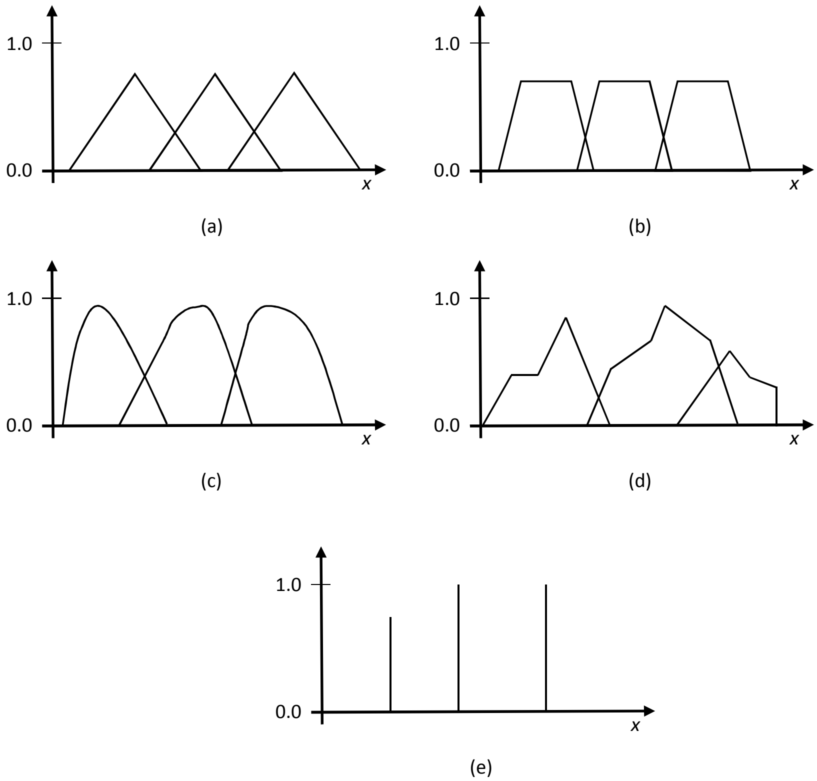


Figure 3.8: Membership functions (a) Triangular (b) Trapezoidal (c) Guassian (d) Piecewise linear and (e) Singleton

3.4.3 Fuzzy Rules

The dynamic behavior of the fuzzy system is characterized by a set of linguistic fuzzy rules and controlled the output variable. The general format of a fuzzy rule is:

If (conditions) then (action)

System action is based on the number of conditions and collectively have an impact for certain action. These rules are based on the knowledge and experience of a human expert within that domain.

3.4.4 Fuzzy Set Operations

The evaluations of the fuzzy rules and combination of the results of the individual rules are performed using fuzzy set operations. The operations on fuzzy sets are different than the operations on non-fuzzy set. Let A and B are the membership functions for fuzzy sets A and B.

- **Equality of fuzzy sets:** Two fuzzy sets A and B are equal if and only if the sets have the same domain, and $\mu_A(x) = \mu_B(x)\ \forall x \in X$
- **Containment of fuzzy sets:** Fuzzy set A is a subset of fuzzy set B if and only if $\mu_A(x) \leq \mu_B(x), \forall x \in X$. That is, $A \subset B$.
- **Complement of a fuzzy set (NOT):** Let $\bar{A}$ denote the complement of set A. Then, for all $x \in X, \mu_A(x) = 1\mu_{\bar{A}}(x)$
- **Intersection of fuzzy sets (AND):** The intersection of two-valued sets is the set of elements occurring in both sets. Operators that implement intersection are referred to as t-norms. The result of a t-norm is a set that contain all the elements of the two fuzzy sets, but with degree of membership that depends on the specific t-norm. A number of t-norms have been used, of which the min-operator and the product operator are the most popular [76]. If A and B are two fuzzy sets, then
  Min-operator: $MIN\{\mu_A(x), \mu_B(x)\}, \forall x \in X$
  Product operator: $PROD\{\mu_A(x)\mu_B(x)\}, \forall x \in X$.

- **Union of fuzzy sets (OR):** The union of two-valued sets contains the elements of all of the sets. The same is true for fuzzy sets, but with membership degrees that depend on the specific union operator used. These operators are referred to as s-norms, of which the max-operator and summation operator are most frequently used:
  Max-operator: $MAX\{\mu_A(x), \mu_B(x)\}, forallx \in X$
  Summation operator: $SUM\{\mu_A(x) + \mu_B(x)\mu_A(x)\mu_B(x)\}, forallx \in X$
  The mostly-used operations for OR and AND operators are max and min, respectively.

3.4.5 Defuzzification

The firing strengths of rules represent the degree of membership to the sets in the consequent of the corresponding rule. Given a set of activated rules and their corresponding firing strengths, the task of the defuzzification process is to convert the output of the fuzzy rules into a scalar, or non-fuzzy value [76]. There are different algorithms for defuzzification too. The mostly-used algorithms are listed in Table 3.1.

Table 3.1: Defuzzification algorithms

Operation	Formula
Center of Gravity	$U = \frac{\int_{min}^{max} u\mu(u)du}{\int_{min}^{max} \mu(u)du}$
Center of Gravity for Singletons	$\frac{\sum_{i=1}^{p}[u_i\mu_i]]}{\sum_{i=1}^{p}[\mu_i]}$
Left Most Maximum	$U = inf(u^{'}), \mu(u^{'}) = sup(\mu(u))$
Right Most Maximum	$U = sup(u^{'}), \mu(u^{'}) = sup(\mu(u))$

3.5 Summary

Recent advances in technology have created a demand for automatic problem-solving as well as an increase in the complexity of problems humans are trying to solve. Algorithm design cannot keep up, and there is a need for general algorithms that can be applied to a wide range of problems and still deliver acceptable. Evolutionary computing can fulfill this need by providing automated solutions with acceptable solutions. In this chapter, we discussed significant advances of the learning classifier system including representations, computational models and successful applications.

In comparison to other machine learning techniques, the advantages of LCSs have become more pronounced: (1) rule-comprehensibility and thus knowledge extraction is straightforward; (2) online learning is possible; (3) local minima are avoided due to the evolutionary learning component; (4) distributed solution representations evolve; or (5) larger problem domains can be handled.

Chapter 4

Proposed Unified Framework for Activity Recognition

This chapter presents the proposed unified framework for indoor and outdoor activities. Activity recognition becomes a challenge due to the learning phased complications. Unlike the conventional methods that are unable to handle the complex situations with high class-accuracy, our framework is able to distinguish the different activities with high accuracy.

4.1 Evolutionary Ensemble Model for Indoor Activity Recognition

The proposed evolutionary ensemble model recognize the indoor activities performed in a smart home environment. To date, the state-of-the-art and most popular activity recognition techniques are based on probabilistic models like Hidden Markov Models (HMM) [38], Conditional Random Fields (CRF) [39], Bayesian Networks [24] and some other classification methods [40] [42]. However, a number of difficulties and limitations remain with these approaches. The learning capability of probabilistic models depends on the observation of activity class distribution (the observed state) and the transitions between adjacent activities (transitions between states). In case of embedded sensor, existing methods are unable to model the activity representation structure such as location, value or sensor type. Furthermore, they require sufficient data to produce reliable results. Minor activities are skipped during the learning phase due to their few occurrences in the dataset. Therefore, probabilistic models are treated as a black box for recognizing activities; this is impractical for crucial applications such as healthcare. To overcome the limitations of existing work, we propose an alternative state-of-the-art evolutionary ensembles model.

4.1.1 Mathematical Formulation

Let $\Omega = \{S_1...S_n\}$ be a set of n embedded sensors, e.g., {stove-sensor, refrigerator-sensor, microwave-sensor, door-sensor etc.} characterized by m attributes $a = [a_1, ..., a_m]^T$, where a_i includes sensor value, location and identity, to express the changes in the smart homes. In order to recognize the performed activities, we divide the daily life activities into a set of c classes $C = \{C_1, ..., C_c\}$. For each ensemble node (en), search space is defined as $S = (c, [S_{1a}, ..., S_{na}])$ where S_{ia} can be a sensor with all attributes. Similarly, rule space is defined as $R = (c, [S_{1a'}, ..., S_{na'}])$ where $S_{ia'}$ can be a sensor with all attributes and sensor value may be a "don't care term". An evolutionary ensemble learner (EL) for class c is a mapping from search space (S) to rule space (R) and is defined as:

$$\mathrm{EL}^{c}_{en} : S \rightarrow R \tag{4.1}$$

The output of $c-$evolutionary ensemble learners (EL_{en}) is aggregated on the central node (cn) as a Rule Profile (RP) and depicted as:

$$RP_{cn} = \sqcup_c EL^{c}_{en} \tag{4.2}$$

The proposed EEM for activity recognition is illustrated in Figure 4.1.

4.1.2 Data Preprocessing

In activity recognition, data preprocessing is an important step before applying any machine learning technique [88]. In the case of sensory data, preprocessing can be one of many different kinds, such as normalization of continuous values, handling missing values and streaming temporal data. In EEM, streaming temporal data is preprocessed using the event-based method. Each activity occurrence requires explicit mapping to sensor event time slices. In the dataset, performed activities starts and end time is recorded as a ground truth in an annotation file. Embedded sensors generate signals according to the subject interactions and maintain a log file with attributes start time, end time, sensor id and sensor value. We pick each performed activity time from annotation file and find all associated sensor instances from the log file to obtain training instances.

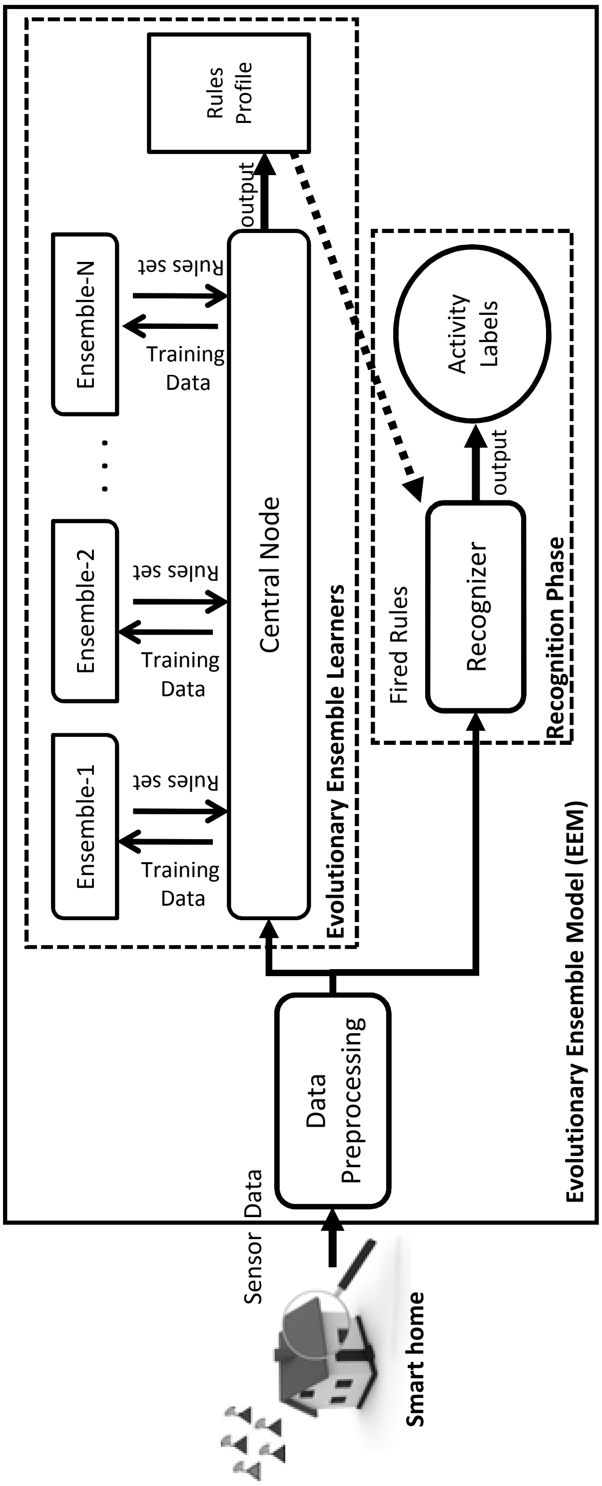


Figure 4.1: The evolutionary ensemble model (EEM)

4.1.3 Evolutionary Ensemble Learners

Evolutionary ensemble learner is the training phase of EEM. It consists of ensemble nodes to learn the activities, central node for providing training data and combines the output of each ensemble to make a rule profile.

4.1.3.1 Ensemble Nodes

After date preprocessing step, we divide the training dataset into disjunctive subsets. Each subset belongs to a unique class that is treated as a single population in our proposed approach. The population is processed by its own GA, which is capable of handling interruptions and non-deterministic activity sequences with a mutation operator and designed encoded chromosome. To train the model we encode chromosome and apply stochastic operators of the GA in the EEM as given in the subsequent subsections.

4.1.3.2 Encoding

The well-known Michigan approach [89] is used to encode the sensor values, type and locations. Every sensor in the home environment is treated as a single gene; a set of genes is a chromosome that presents a single activity rule. Each activity rule consists of two portions. The antecedent portion is the logical combination of sensor values in the form of $sensor\_value_1 \cap sensor\_value_2 \cap sensor\_value_3, ..., sensor\_value_n$, and the subsequent portion represents the activity class C_i . The size of the activity rule is fixed depending on the number of deployed sensors in a smart home. The encoding scheme is shown in Figure 4.2.

	Stove Sensor	Microwave Sensor	Fridge Sensor	Dishwasher Sensor	Freezer Sensor	Light Sensor	.	.	.	*n*-sensors	Activity Class
value	1	1	0	1	1	1	.	.	.	n	4
locus	1	2	3	4	5	6	.	.	.	n	-

Figure 4.2: Activity rule encoding

In Figure 4.2, n bits represent the sensors values, and the rightmost bit (i.e., 4) shows the activity class label. The locus of each bit provides information about the sensor location. For instance the value 1 at locus 2 represents the microwave sensor state in the kitchen.

4.1.3.3 Selection

Ranking-based selection [88] is implemented when the whole population is sorted from best to worst according to the ranked fitness values. In the proposed solution, each pair of parent selections incorporates low fitness activity rules with the best fit activity rules. After ranking, one parent is randomly selected from the top 50% of the ranked population, while the other is randomly selected from the remaining population. This guarantees exploration of the whole search space for producing better offspring in the next generation.

4.1.3.4 Crossover

Crossover is performed on the selected parents to create the new offspring. A dynamic single point crossover is applied as a reproduction operator. The cut point is decided on the basis of Augmented Feature Vector (AFV) which is calculated after each iteration (i.e., generation). The objective is to find generalized rules by identifying the most important sensors for a particular activity. It helps to avoid redundant offspring in the next generation. AFV is calculated by aggregating all the individual sensor values in the current population. The aggregated value for each sensor shows its overall importance. For example, in Figure 4.3, the sensors at locus 2 and 9 have high aggregated value compared to the others. We decide to apply a dynamic cutpoint after the most important sensor values in order to carry the best portion of the activity rule to the next population. We adopt the fittest replacement mechanism to every iteration of the GA so that the entire generation is replaced with a new population by retaining the best fit in the last generation.

4.1.3.5 Fitness Function

After creating a new population, the next step is to measure the quality of the activity rules. We evaluated the fitness of each individual rule using reinforcement learning. The fitness function F

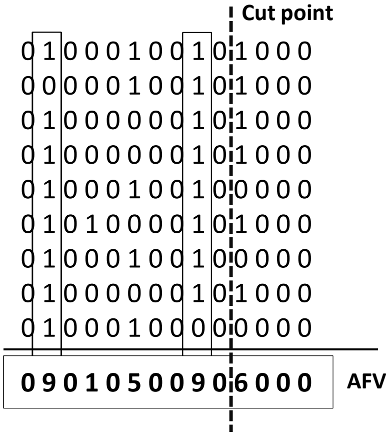


Figure 4.3: AFV calculation and dynamic cutpoint operator

evaluates the candidate rules on the basis of a reward and payoff mechanism [40] as follows:

$$\mathrm{F} = \sum_{i}^{n}\sum_{j}^{m}[reward(ActivityRule_i|SearchSpace_j) - payoff(ActivityRule_i|SearchSpace_j)] \tag{4.3}$$

$$Where, reward = \begin{cases} 1 & \text{if } ActivityRule \equiv SearchSpace \cap classLabel \equiv Correct, \\ 0 & \text{otherwise} \end{cases}$$

$$payoff = \begin{cases} -1 & \text{if } ActivityRule \equiv SearchSpace \cap classLabel \equiv Incorrect, \\ 0 & \text{otherwise} \end{cases}$$

In equation 4.3, accuracy-based fitness function is defined to find optimal score of activity rules. In fitness score of activity rule, reward of $+1$ is added for correct classification and payoff of -1 is deducted in case of incorrect classification of each training instance.

4.1.3.6 Mutation

The proposed approach inaugurates the diversity in activity rules to increase the fitness of individuals. The mutation operator assigns a "don't care" term$--$a value between $0, 1$ and -1 $--$on randomly selected genes of the activity rule. Interruption of sensor events is handled by introducing these don't care terms.

The stopping criterion for EEM is either a fixed number of generations or all training instances passed correctly. Later in the experiments and discussion section, we discuss the number of generations and the size of the population. The pseudocode for an ensemble node is depicted in Algorithm 1.

Algorithm 1: Ensemble Node Learner

Input : C − Crossover rate
λ − Mutation rate
G − Number of generations
μ − Population size
Output: SRS − Specific Rule Set
Node Learner

- $p = rand(\mu)$
- **while** $!(max(G) \parallel convg(G))$ **do**
  - $fitness = fRankFitness(p)$
  - **if** $!(fitness)$ **then**
    - **for** $m = 1 : (\lfloor p(C) \rfloor)$ **do**
      - $pOne = rand(upper(p/2))$
      - $pTwo = rand(lower(p/2))$
      - $AFV = fAugFeatVec(p)$
      - $Offspring = fcrossover(pOne, pTwo, AFV)$
      - $mut = rand(\lfloor p(\lambda) \rfloor)$
      - $SRS = offspring(mut)$

Algorithm 2: Central Node Processing

Input : $X(1..M)$ − Training Data
Output: $RP(1..N)$ − Rule Profile
Central Node Processing

- $ensemble\,[] = unqiue(actClass(X))$
- **for** $m = 1 : length(ensemble)$ **do**
  - $x = X(ensemble\,[m])$
  - $EL = fEnsNodLearn(C, \lambda, G, \mu, x)$
  - $RP[m] = EL$

Algorithm 3: Rule Conflict Resolving

Input : $RP(1..M)$ − Rule Profile
Output: $CRP\,(1..N)$ − Compact Rule Profile
Rule Conflict Resolving

```
activityClass [] = unqiue(actClass(RP))
for m = 1 : length(activityClass) do
    uRP [:, m] = unique(activityClass(m));
    rCount [m] = [activityClass(m)length(uRP [:, m])];
CRP = uRP []
for i = 1 : length(CRP) do
    scanRule = CRP(i)
    for j = 1 : length(CRP) do
        if isequal(scanRule(i), CRP(j)) then
            if rCount [i] > rCount [j] then
                CRP [] = delete(CRP [i])
            else
                CRP [] = delete(CRP [j])
```

4.1.4 Central Node

A specific rule set from n ensemble nodes is aggregated on the central node to create the activity rule profile described in Algorithm 2. It may have redundant and conflicting rules due to the overlapping region of the search spaces. So, we explicitly removed the duplicate rule instances. The problem of conflicting rules is resolved by giving priority to minor search spaces (i.e., minor activities) over major search spaces (i.e., major activities) as shown in Algorithm 3.

4.1.5 Recognition Phase

This phase recognizes activities based on sensor observation and activity rule profiles. For a particular set of sensor observations, rules are fired to recognize activity class labels. In the special case when more than one rule is fired, then conflicting class labels are resolved by majority voting. The pseudocode for the recognition phase is given in Algorithm 4.

Algorithm 4: Recognizing the activities

Input : $RP(1..M)$ − Rule Profile
$TD(1..N)$ −Test Data
Output: ACL Activity Class Label
Recognizing the activities
for $m = 1 : length(RP)$ **do**
  if $m = 1 : length(RP)$ **then**
    $voteList\,[] = vote + 1$

4.1.6 Summary

Accurate activity recognition and understandable output are very important for many practical and healthcare applications. Nevertheless, the current approaches to activity recognition do not handle the problems of major/minor activities and their non-deterministic nature. To solve these problems, we investigated an evolutionary technique with the ensemble paradigm. We proposed a novel model to distinguish major and minor activities and address their non-deterministic nature. The model is evaluated on three publically available smart home datasets (i.e., Chapter 5.), and the optimal parameters for indepth investigation are determined.

4.2 Evolutionary Fuzzy Model for Outdoor Activity Recognition

In case of outdoor activities, we proposed evolutionary fuzzy model, which utilizes the embedded accelerometer sensor of commercial smartphone for recognizing outdoor activities. Motion of the body is integral to the outdoor activities such as walking, running, or cycling etc known as dynamic activities. A few studies can be found in literature which investigate dynamic activities using single or multiple accelerometers [45] [51] [38]. To recognize dynamic activities using a smartphone accelerometer sensor, it is a big challenge due to the limitations of a single accelerometer instead of multiple accelerometers and subtle differences among dynamic activity patterns. For example, walking and jogging or jogging and running are different groups of activities; however, it is difficult to define sharp boundaries between them. We propose a novel Evolutionary Fuzzy Model (EFM) for outdoor activities to measure the ambiguities associated with dynamic activities and relax the domain knowledge constraints which are imposed by domain experts during the development of fuzzy systems. Based on the time and frequency domain features, we define the fuzzy sets and estimate the natural grouping of data through expectation maximization of the likelihoods. A GA is investigated and designed to determine the optimal fuzzy rules. The practical solution to the outdoor activity recognition problems is expected to be our evolutionary fuzzy model, due to its utilization of smartphones and natural way of handling ambiguities. The proposed architecture of evolutionary fuzzy model for dynamic activity recognition is illustrated in Figure 4.4. It consists of three major components: (1) Data collection: collection of the raw signals from the accelerometer sensor as an activity observation (2) Features extraction: extraction of the representative features to recognize the activities (3) Activity learner and recognizer: learning the activities during the training phase and recognizing the performed activities in the testing phase. The detail of each component is given in the subsequent sections.

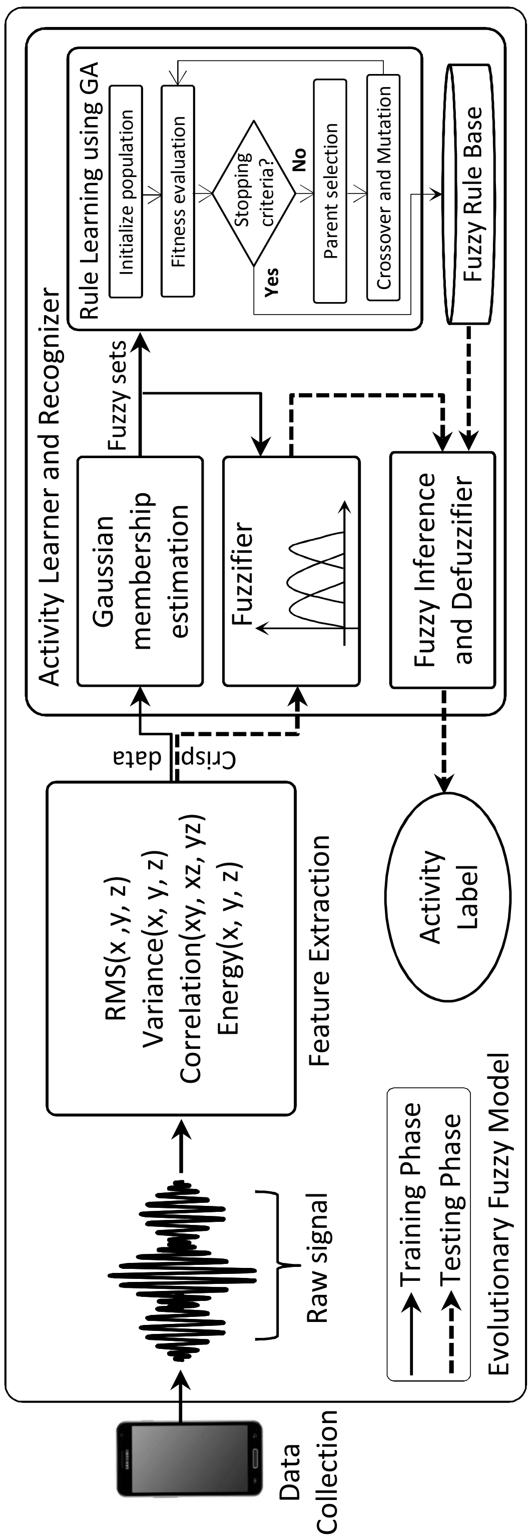


Figure 4.4: The detailed view of the evolutionary fuzzy model

4.2.1 Smartphone Accelerometer and Data Collection

The smartphones used in this research were Samsung Galaxy S and Google Android OS version Gingerbread. To collect the activities dataset, 10 healthy adult subjects (7 male and 3 females) of different ages, heights and weights were participated in this study. The characteristics of the subjects are shown in Table 4.1. Seven common dynamic activities were selected as the basic activities of daily life to be recognized - walking, jogging, running, cycling, going up stairs, going down stairs, and hopping. The selection of these activities was based on healthcare applications and is required for our u-lifecare research project [90]. Each subject was requested to perform these activities in a natural manner (without fixed duration or sequence).

	Min	Max	Mean	Std. Deviation
Age (year)	22	32	27.18	3.3710
Height (cm)	167	180	173.6	4.7806
Weight (kg)	48	92	64.8	13.3553

Table 4.1: Characteristics of the participants

The smartphone was placed in the front pant pocket regardless of its orientation to record the activities. A pant pocket location is an acceptable solution from the users point of view, if the user wishes to use the smartphone for activity recognition. Furthermore, intended activities depend on motion patterns of the legs. Each subject recorded the activities on different days at various locations without researcher supervision by using our application shown in Figure 4.5.

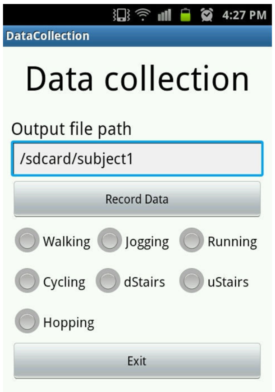


Figure 4.5: Dataset collection applications

Other studies claim that 22Hz$\sim$100Hz of frequency is suitable to classify different physical activities [7] [22] [36] [56] [91]. In this study, we analyzed and recorded the data at 50Hz, which is a suitable sampling rate for recognizing dynamic activities with acceptable accuracy. We collected approximately 16 hours of data over the two months. A representative data stream of accelerometer data for each activity is shown in Figure 4.6 to understand the difficulty of recognition.

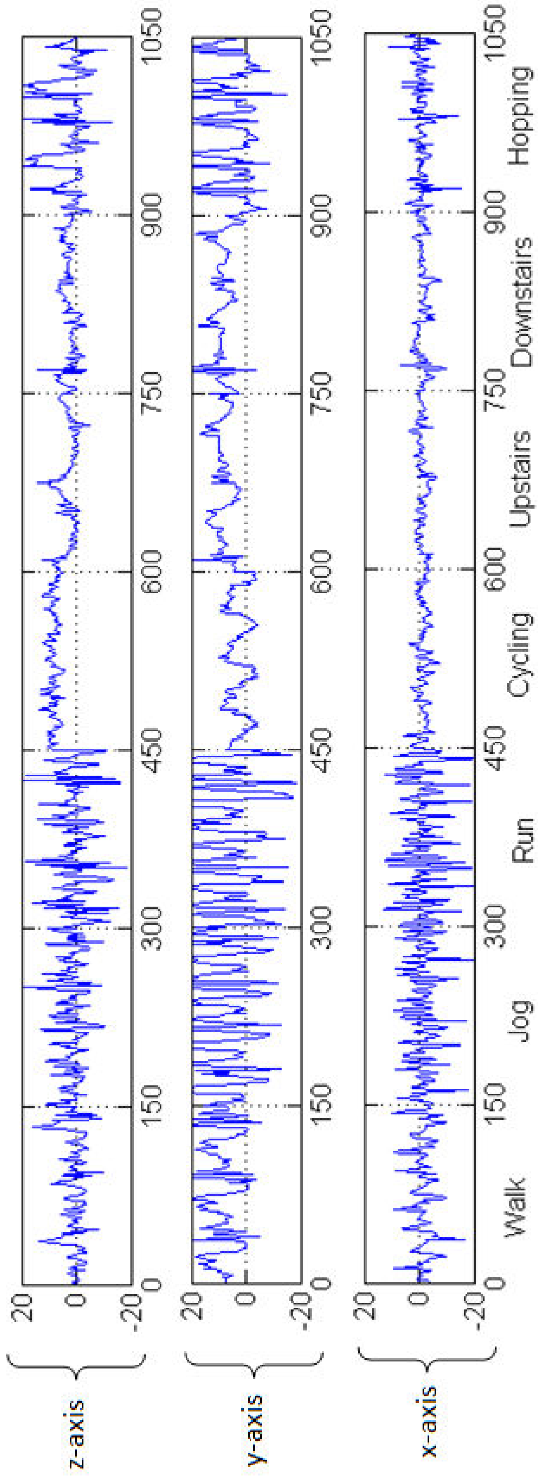


Figure 4.6: Representative raw signals of activities

In Figure 4.6, going up and down stairs are almost the same along the x-axis, while hopping and running activities are ambiguous along the y and z axes. Similarly, jogging and running activity signals are slightly different from one another. To distinguish these minor differences in the data for performed activities, we investigate suitable feature extraction methods for dynamic activities.

4.2.2 Features Extraction

An accelerometer sensor generates time series signals that are highly fluctuating and oscillatory in nature. It is difficult to recognize the activities using the raw signals. Feature extraction is a highly domain-specific technique that defines a new attribute using the signals to reduce computational complexity and to enhance the recognition process. In the past, many complex feature extraction techniques such as Principal Component Analysis (PCA) followed by Linear Discriminant Analysis (LDA) [92] and wavelet features [56] were used; however, they are computationally expensive and difficult to implement. Many researchers show that simple and low cost computational features are able to achieve high accuracy [56] [91]. First, we solve the orientation issue of acceleration data suggested by Mizell [52] and then extract the following time and frequency domain features to recognize dynamic activities:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{4.4}$$

$$\delta^2 = \frac{1}{n}\sum_{i=1}^{n} x_i - \bar{x} \tag{4.5}$$

$$Corr(x_i, x_j) = \frac{Cov(x_i, x_j)}{\delta_i \delta_j} \tag{4.6}$$

$$E = \frac{1}{n}\sum_{i=1}^{n} |FFT_i|^2 \tag{4.7}$$

In equation 4.4, the Root Mean Square (RMS) is a statistical time domain feature to measure the central tendency of varying quantity. Variance is dispersion metric to measure the data spread for different activities and is calculated by equation 4.5. The correlation feature in equation 4.6 illustrates the interrelationship among data and is helpful to differentiate simple from complex movements. For example, we can differentiate walking from going up stairs and down stairs. The walking activity usually involves changes in one dimension, whereas going up stairs and down stairs involves changes in more than one dimension. Similarly, in equation 4.7, the energy feature is calculated by applying the Fast Fourier Transformation (FFT) to find the quantitative characteristics of the data over a defined time period. It represents the stress of the signal and indicates the dynamics of the motion. The selections of these features are subject to the nature of the selected activities and collectively have high impact on the intended activities. No single feature is able to consistently perform better for all activities. All these features are computed for three-dimensional accelerometer data with a no overlapping sliding window method over a time interval of three seconds.

4.2.3 Activity Learner and Recognizer

Fuzzy systems with evolutionary techniques are being successfully used to model human-like thinking, measure ambiguities and do not demand an accurate mathematical model [93] [94] [95] [96] [97]. For these reasons, they provide a reasonable alternative approach to classical learning methods. Our proposed model learns the activities by defining the fuzzy sets and mapping the input feature space to the output through fuzzy rules. Membership functions are defined by maximizing the likelihood through an expectation maximization algorithm. We design an evolutionary method GA to learn the optimal fuzzy rules. The details of membership function estimation and rule learning are given in subsequent sections.

4.2.3.1 Fuzzifier

Fuzzification is the process of changing real scalar features into fuzzy values over the defined fuzzy sets. A fuzzy set is defined by a membership function that is graded between 0 and 1. In this study, we defined 12 fuzzy input variables: RMS, variance, covariance, and energy (i.e., 12 inputs = 4 (features per axis) for each of the three axes (x, y, z axes)). Theoretically, each fuzzy variable can have many fuzzy sets, but the most commonly used numbers are three, five, seven or nine [93]. We divide each fuzzy input variable into five fuzzy sets: very-low, low, medium, high, and very-high with a Gaussian membership function. The parameters of the Gaussian membership functions are estimated as follows.

4.2.3.2 Gaussian Membership Function Estimation

Statistical methods are an alternative to the construction of membership values utilizing training activity data. We assume that the acceleration pattern of an activity has a Gaussian-like distribution. We present this assumption in Figure 4.7. Although the assumption is not always true, it is reasonable since most activities have a fairly consistent mean value of the distinguishing features.

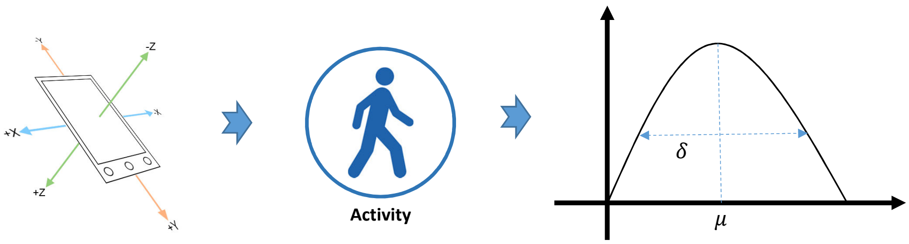


Figure 4.7: Assumption: acceleration pattern of an activity has a Gaussian-like distribution

In the proposed method, numbers of Gaussian distributions are equal to the number of defined fuzzy sets, and initialization is done by finding the range and dividing it into equal parts. To estimate the parameters of each Gaussian distribution, an Expectation-Maximization (EM) algorithm [98] is applied to maximize the likelihood over the training data as follows:

In this section, we present details of the parameters for Gaussian membership estimation for expectation maximization algorithms, which are used for computing μ_k and δ_k. The log-likelihood of the observed data $Y = \{Y_m\}, m = 1, ..., M$ is calculated as:

$$l(\Theta) = \sum_{m=1}^{M} logp_{mix}(Y_m|\Theta) \tag{4.8}$$

Expectation Step $(E - step)$

$$p_{mix}(Y_m|\Theta) = \sum_{k=1}^{K} p(Y_m|\theta_k) w_{mk} \tag{4.9}$$

and

$$\sum_{k=1}^{K} w_{mk} = 1 \tag{4.10}$$

To fit an observed set of data points $\{Y_m\}$, the mixing portion $''w''_{mk}$ and the components $''K''$ that generated each data point $''Y''_m$ is unknown. The objective is to find the parameter vector $\theta_k = [\mu_k, \theta_k]$. Inserting equation 4.9 into equation 4.8 gives,

$$l(\Theta) = \sum_{m=1}^{M} log \sum_{k=1}^{K} p(Y_m|\theta_k) w_{mk} \tag{4.11}$$

For Expectation step, use Jensen's inequality,

$$l(\Theta) \geq \sum_{m=1}^{M} \left[\sum_{k=1}^{K} w_{mk} logp(Y_m|\theta_k) \right] \Rightarrow E[log(p(Y_m|\theta_k))] \tag{4.12}$$

At the Maximization step $(M - step)$

$$\nabla_{\theta k} \sum_{m=1}^{M} \sum_{l=1}^{K} w_{mk} logp \left(Y_m | \theta_l\right) \tag{4.13}$$

At maximum, the partial derivations w.r.t all parameters vanish:

$$\nabla_{\theta k} l \left(\Theta\right) = \sum_{m=1}^{M} \frac{w_{mk}}{p \left(Y_m | \theta_k\right)} \nabla_{\theta k} p \left(Y_m | \theta_k\right) \tag{4.14}$$

In order to find the parameters of accelerometer data, our problem is similar problem of one dimensional Gaussian mixture, where we do not know the variances or mixture portions either. The parameter vector is $\theta_k = [\mu_k, \theta_k]$ is computed as:

$$p \left(Y_m | \theta_k\right) = \frac{1}{\sqrt{2\pi\delta_k^2}} exp \left\{ - \frac{\left(Y_m - \mu_k\right)^2}{2\delta_k^2} \right\} \tag{4.15}$$

The Expectation step is easily defined by inserting equation 4.15 into equation **??**. For Maximization, inserting equation 4.15 into 4.14 and taking the derivative w.r.t μ_k gives,

$$0 = \frac{\delta}{\delta_{\mu k}} l \left(\Theta\right) = \sum_{m=1}^{M} \frac{w_{mk}}{p_k \left(y_m | \theta_k\right)} * \frac{1}{\sqrt{2\pi\sigma_k^2}} exp \left\{ - \frac{\left(y_m - \mu_k\right)^2}{2\delta_k^2} \right\} * \frac{-2 \left(y_m - \mu_k\right)}{2\delta_k^2} = \sum_{m=1}^{M} w_{mk} \left(y_m - \mu_k\right) \tag{4.16}$$

$$\mu_k = \frac{\sum_{m=1}^{M} w_{mk} y_m}{\sum_{m=1}^{M} w_{mk}} \tag{4.17}$$

Taking the derivative w.r.t δ_k

$$\frac{\partial}{\partial \delta_k} l\left(\Theta\right) = \sum_{m=1}^{M} \frac{w_{mk}}{p_k\left(y_m|\theta_k\right)} * \frac{1}{\sqrt{2\pi\delta_k^2}} exp\left\{-\frac{\left(y_m-\mu_k\right)^2}{2\delta_k^2}\right\}\left[-\frac{1}{\delta_k}+\frac{\left(y_m-\mu_k\right)^2}{\delta_k^3}\right] \tag{4.18}$$

$$= \sum_{m=1}^{M} \frac{w_{mk}}{p\left(y_{m|\Theta_k}\right)}\left[-\frac{1}{\delta_k}+\frac{\left(y_m-\mu_k\right)^2}{\delta_k^3}\right] * p\left(y_m|\Theta_k\right) \tag{4.19}$$

$$\Rightarrow \sum_{m=1}^{M} w_{mk}\left[\frac{-\delta_k^2+\left(y_m-\mu_k\right)^2}{\delta_k^3}\right] = 0 \tag{4.20}$$

$$\delta_k^2 = \frac{\sum_{m=1}^{M} w_{mk}\left(y_m-\mu_k\right)^2}{\sum_{m=1}^{M} w_{mk}} \tag{4.21}$$

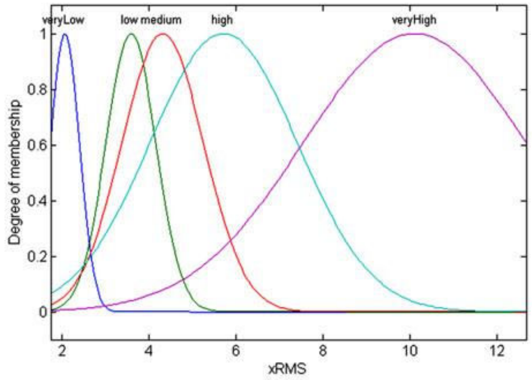
$$\delta_k = \sqrt{\frac{\sum_{m=1}^{M} w_{mk}\left(y_m-\mu_k\right)^2}{\sum_{m=1}^{M} w_{mk}}} \tag{4.22}$$

Equations 4.17 and 4.22 are required parameters for the Gaussian membership function. After estimation, we obtain the parameters: center (μ_k) and standard deviation (δ_k) for each fuzzy set as shown in Table 4.2.

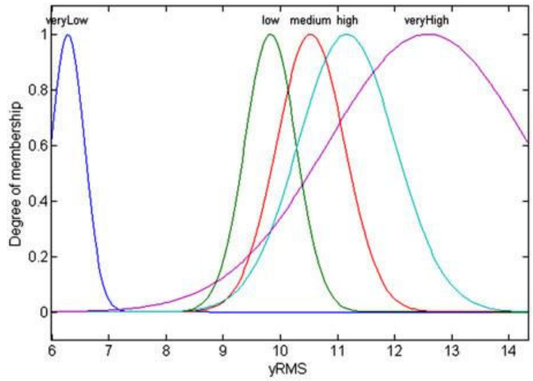
Parameter Estimation		μ_x	δ_x	μ_y	δ_y	μ_z	δ_z
RMS	Very low	2.0806	0.3311	6.2331	0.2867	2.5325	0.2764
	Low	3.6014	0.5759	9.7983	0.4489	3.5286	0.3247
	Medium	4.3237	0.9352	10.5287	0.5916	4.1769	0.9129
	High	5.6829	1.6944	11.1824	0.8412	4.6374	1.1508
	Very high	10.0838	2.5517	12.5821	1.7337	7.5937	1.7096
δ^2	Very low	2.164	0.8859	9.0882	3.6385	1.03	0.7101
	Low	9.4408	2.6224	20.1302	4.0457	5.857	1.3976
	Medium	13.1113	3.5358	26.613	7.1513	9.7751	2.5971
	High	25.8409	9.701	70.5636	10.0789	22.3297	8.8136
	Very high	82.031	34.5779	92.6388	15.0831	44.6485	20.7813
$Corr\,(x_i, x_j)^2$	Very low	-0.3585	0.0855	-0.3844	0.076	-0.4061	0.0694
	Low	-0.0462	0.103	-0.1854	0.0797	-0.1372	0.0775
	Medium	0.023	0.1112	0.0865	0.1119	0.0067	0.093
	High	0.1509	0.1613	0.2507	0.1424	0.1531	0.1593
	Very high	0.4391	0.2539	0.4138	0.211	0.3982	0.1851
E	Very low	14.623	3.7203	22.5516	4.7044	16.344	2.4627
	Low	29.0289	3.944	43.6205	4.8321	23.2049	4.5916
	Medium	31.0961	5.305	49.4905	5.9332	30.1824	6.7669
	High	45.6145	9.9425	66.0577	6.8354	41.65	8.7217
	Very high	70.3286	16.7727	74.1976	15.804	65.2823	13.0504

Table 4.2: The parameter estimation of membership functions

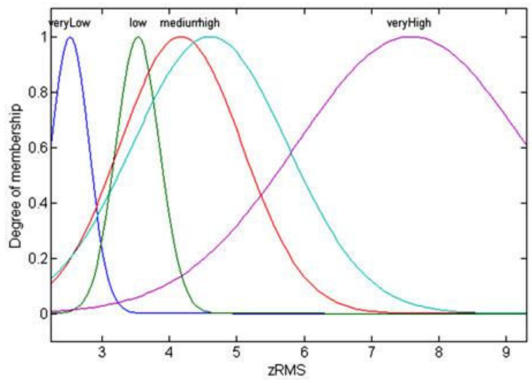
Figure 4.8 and 4.9 represents the fuzzy sets of the statistical features defined over the estimated parameters. It employed for analyzing the effect of statistical features drawn from our proposed Gaussian membership function estimation method (i.e., as shown in Table 4.2). It specified the degree of membership between the value of statistical feature along each axis and fuzzy sets.



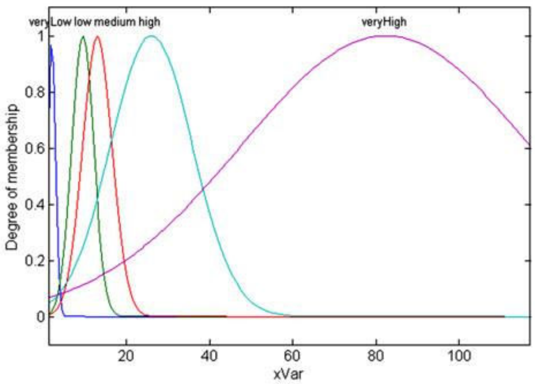
(a) Estimation of RMS (x-axis)



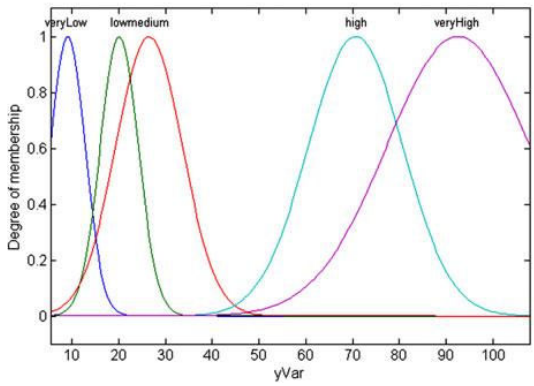
(b) Estimation of RMS (y-axis)



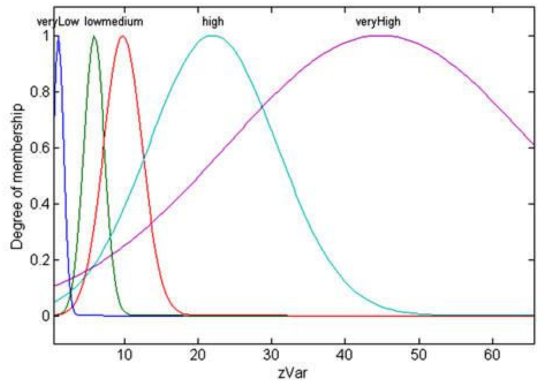
(c) Estimation of RMS (z-axis)



(d) Estimation of δ^2 (x-axis)

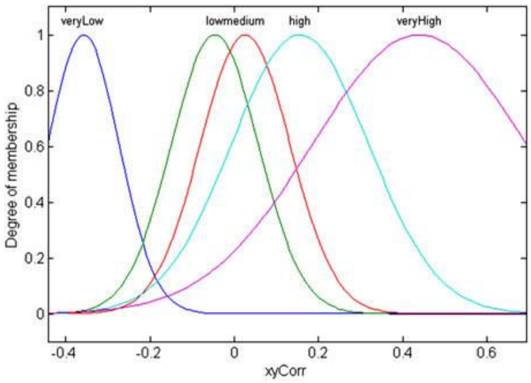


(e) Estimation of δ^2 (y-axis)

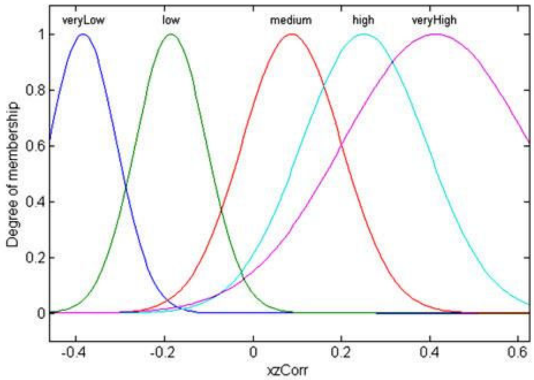


(f) Estimation of δ^2 (z-axis)

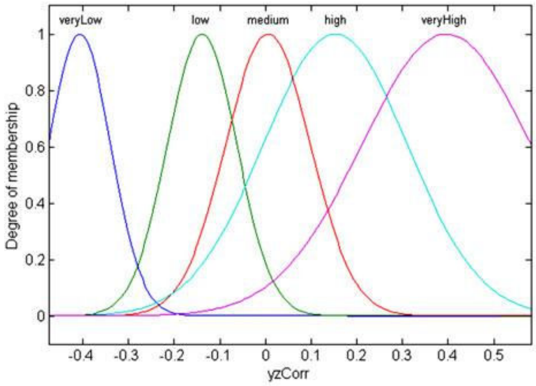
Figure 4.8: (a) The number of fuzzy sets estimation



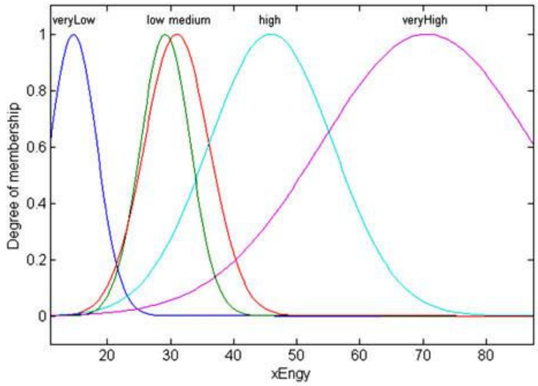
(h) Estimation of $Corr$ (xy-axis)



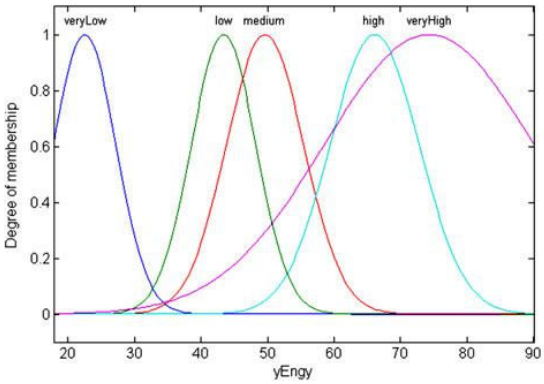
(i) Estimation of $Corr$ (xz-axis)



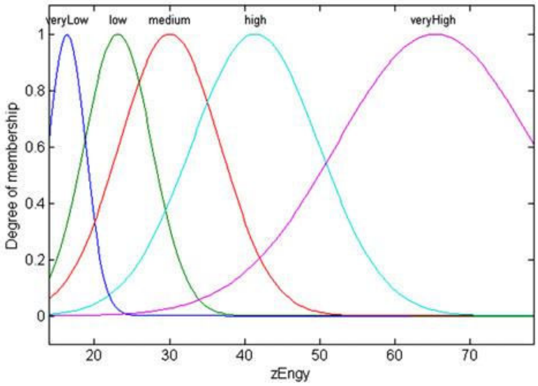
(j) Estimation of $Corr$ (yz-axis)



(k) Estimation of E (x-axis)



(l) Estimation of E (y-axis)



(m) Estimation of E (z-axis)

Figure 4.9: (b) The number of fuzzy sets estimation

4.2.4 Rule Learning using the Genetic Algorithm

In evolutionary methods, GA has the ability to learn *if-then* rules based on a survival of the fittest mechanism. The important consideration is representing the problem as a chromosome structure and applying stochastic operators. We designed the representation strategy and stochastic operators of the GA in the EFM as follows:

4.2.5 Representation

The well-known Michigan approach [89] is used to encode the features and treat them as a single gene. A set of genes is a chromosome that presents a single activity rule. Each activity rule consists of two portions. The antecedent portion is the logical combination of fuzzy sets and fuzzy operators in the form of$fuzzy_value_1 \cap fuzzy_value_2 \cap fuzzy_value_3, ..., fuzzy_value_{12}$ and the consequent portion represents the activity label. Each fuzzy variable-defined linguistic value of the fuzzy set is mapped onto a value 1-5 to represent each of the five terms and 0 for the "don't care" term. Chromosome encoding is shown in Figure 4.10.

xRMS	yRMS	zRMS	xVar	yVar	zVar	xyCorr	xzCorr	yzCorr	xEnergy	yEnergy	zEnergy	Activity label
1	5	0	2	4	0	4	5	1	4	2	1	6

Figure 4.10: Chromosome encoding of the activity rule

4.2.6 Fitness Function

The representation scheme encodes the problem into the integer-genotype, and the fitness function measures the quality of the solution. The fitness function is problem-dependent so we evaluated the fitness of each individual rule using reinforcement learning. The fitness function "F" evaluates the candidate rules on the basis of a reward and payoff mechanism [88] as follows:

$$\text{F} = \sum_{i}^{n} \sum_{j}^{m} [reward(ActivityRule_i | SearchSpace_j) - payoff(ActivityRule_i | SearchSpace_j)] \tag{4.23}$$

$$Where, reward = \begin{cases} 1 & \text{if } ActivityRule \equiv SearchSpace \cap classLabel \equiv Correct, \\ 0 & \text{otherwise} \end{cases}$$

$$payoff = \begin{cases} -1 & \text{if } ActivityRule \equiv SearchSpace \cap classLabel \equiv Incorrect, \\ 0 & \text{otherwise} \end{cases}$$

In equation 4.23, the accuracy-based fitness function is defined to find the optimal score of the activity rules. In the fitness score of the activity rule, a reward of $+1$ is added for correct classification, and a payoff of -1 is deducted for incorrect classification of each training instance.

Algorithm 5: Rule Learning using the Genetic Algorithm

Input : C $-$ Crossover rate
λ $-$ Mutation rate
G Number of generations
μ $-$ Population size
Output: OFR $-$ Optimized Fuzzy Rules
Rule Learner
$p = rand(\mu)$
while $!(max(G) \parallel convg(G))$ **do**
$fitness = fRankFitness(p)$
if $!(fitness)$ **then**
for $m = 1 : (\lfloor p(C) \rfloor)$ **do**
$pOne = rand(upper(p/2))$
$pTwo = rand(lower(p/2))$
$Offspring = fcrossover(pOne, pTwo)$
$mut = rand(\lfloor p(\lambda) \rfloor)$
$OFR = offspring(mut)$

4.2.7 Stochastic Operators

Ranked-based selection [26] is implemented when the whole population is sorted from best to worst according to the fitness value. After ranking, one parent is randomly selected from the top 50% of the ranked population, while the other is randomly selected from the remaining population. This guarantees exploration of the whole search space for producing better offspring in the next generation. Crossover is performed on the selected parents to create new offspring. A dynamic single point crossover is applied as a reproduction operator. We adopt the fittest replacement mechanism to every iteration of the GA so that the entire generation is replaced with a new population by retaining the best fit in the last generation. The proposed approach also inaugurates diversity in activity rules by using a uniform mutation operator. It assigns a “don’t care” term−−a value of 0 or any other membership value−−on randomly selected genes of the activity rule. The stopping criterion for GA is either a fixed number of generations or correct passage of all training instances. Later in the experimental and discussion section, we discuss the convergence and stochastic operator’s parameters. The pseudocode for rule learning is depicted in Algorithm 5.

Due to a large number of activities and overlapping regions in the search spaces, some conflicting rules may be generated. The conflicting rules have the same antecedent conditions but lead to different class labels. Therefore, we had to choose one from two or more conflicting rules in each class. We chose the rule that was supported by a maximum number of training examples. After the rules are generated, they are stored into the rule repository for the recognition phase. Once the fuzzy rule base is established, EFM is able to recognize the performed activities by mapping the actual input feature values to the output values by means of inferencing and the defuzzification process.

4.2.8 Fuzzy Inference and Defuzzification

Fuzzy inference is a logical process by which new facts are derived from the known facts by applying the inference rules. A set of rules are fired during the fuzzy inference. In order to draw conclusions from a set of rules, a method is required to produce an output from a collection of rules. In the proposed EFM, the output of each rule is aggregated by an implication method that is based on a union operator. The output of fuzzy inferencing is a fuzzy set. The process of converting the fuzzy output into a scalar value is called defuzzification. We applied the fuzzy Centroid method that is most commonly used and is very accurate [76]. In this method, each membership function is clipped at the corresponding strengths of the activated rules. The centroid of the composite area is calculated, and the horizontal coordinate is used as the output of our evolutionary fuzzy model. The complete pseudocode for an EFM training and recognition phase is depicted in Algorithm 6 and 7, respectively.

Algorithm 6: Evolutionary Fuzzy Model (Training Phase)

Input : S(x,y,z) − Accelerometer Raw Signals
Output: [dGuassianInputMF, RuleGeneration] − Membership Function and Fuzzy Rules
Activity Learner
  for $m = 1:3$ **do**
    $featVector = [rms(S(m)), var(S(m)), cor(S(m)), energy(S(m))]$
    $MFEstimation(\mu, \delta) = fComputeDistribution(featVector(m))$
    $dGuassianInputMF = MFEstimation(\mu(m), \sigma(m))$
  $RuleGeneration = fGALearner(dGaussianInputMF, C, \delta, G, \mu)$

Algorithm 7: Evolutionary Fuzzy Model (Testing Phase)

Input : S(x,y,z) − Accelerometer Raw Signals
Output: ACL − Activity Class Label
Activity Recognizer
  $featVector =$
  $[rms(S_x, S_y, S_z), var(S_x, S_y, S_z), cor(S_{xy}, S_{xz}, S_{yz}), energy((S_x, S_y, S_z))]$
  $findMFValue = dGuassianInputMF(featVector)$
  $firedRules = RuleRepository(findMFValue)$
  $unionImplication = firedRules$
  $defuzzification = centroid(unionImplication)$
  $ACL = defuzzification$

4.2.9 Summary

The proposed model utilized the embedded accelerometer sensor of a commercial smartphone to recognize outdoor activities. Outdoor activity recognition becomes a challenge due to the use of a single accelerometer and vague class boundaries. We proposed a novel evolutionary fuzzy model to measure the ambiguities between imprecise decision boundaries. Unlike the conventional methods that are unable to handle complex situations with high class-accuracy, this model is able to distinguish outdoor activities. Our model relaxes domain expert knowledge constraints and estimates the membership function through a statistical method. EFM is evaluated on a comprehensive group of activities, and results are shown in Chapter 5.

Chapter 5

Evaluation and Results

This chapter presents the evaluation and results of proposed unified framework for indoor and outdoor human activity recognition. We also compared our propose learning models with the state-of-the-art methods and performed experiments show significant imporvement in recognized activities. It is expected that evolutionary learning models would be a practical solution as compared to existing counterparts.

5.1 Indoor Activity Recognition Results

In this section, we present the results to evaluate and validate the evolutionary ensemble model to measure the accuracy level of recognized activities and investigate the feasibility of the EEM for the indoor activity recognition domain.

5.1.1 Data sets Description

The experiments are performed on three smart home datasets, two from MIT's House_n [24] and one from ISL [16]. For MIT's House_n, datasets were recorded in two apartments by deploying 77 and 84 sensors on everyday objects. Two volunteers performed daily life activities for two weeks. The details description of the datasets and annotation method can be found in [24]. ISL data was collected from 14 binary sensors attached to the doors, cupboards, refrigerator, and toilet. A volunteer performed common household activities for 28 days. In Table 5.1 and 5.2 characteristic of MIT Activity Data Subject 1 (MITADS1), MIT Activity Data Subject 2 (MITADS2) and ISL dataset are shown. The Num column shows activities count, Time column shows the time in seconds and Sensor column shows generated sensor events.

Activity	MITADS1			MITADS2		
	Num.	Time	Sensor	Num.	Time	Sensor
Toileting	85	128185.70	4084	40	60494.48	1599
Washing dishes	7	10534.42	274	21	31796.88	713
Preparing breakfast	14	21307.70	645	18	27511.95	702
Preparing lunch	17	25940.10	784	20	31006.33	733
Preparing dinner	8	12385.05	329	14	21538.88	549
Preparing a snack	14	21308.83	715	16	24214.25	581
Preparing a beverage	15	22850.68	599	-	-	-
Dressing	24	36033.93	1038	-	-	-
Bathing	18	27546.28	848	-	-	-
Grooming	37	55969.00	1682	-	-	-
Cleaning	8	12319.98	223	-	-	-
Doing laundry	19	28950.58	945	-	-	-
Going to work	12	17997.03	584	-	-	-
Taking medication	-	-	-	14	21183.23	590
Watching TV	-	-	-	15	23223.25	667
Listening to music	-	-	-	18	28469.97	701

Table 5.1: Characteristics of the annotated activities in the House_n smart home

Activity	Num.	Time	Sensor
Idle	-	3507.27	38
Going out	33	17304.78	83
Toileting/toilet downstairs	114	198.78	388
Bathing	23	219.80	52
Sleeping/going to bed	24	12335.25	173
Prepare breakfast	20	55.65	122
Prepare dinner	10	325.03	125
Get a drink	20	17.75	62

Table 5.2: Characteristics of annotated activities in the ISL smart home

5.1.2 Performance Measures

In order to evaluate our model, the three standard metrics of precision, recall, and F-measure are used as performance measures. They are calculated using the values of the confusion matrix [99] and computed as:

$$Precision = \frac{1}{Q}\sum_{i=1}^{Q}\frac{TP_i}{NI_i} \tag{5.1}$$

$$Recall = \frac{1}{Q}\sum_{i=1}^{Q}\frac{TP_i}{NG\,i} \tag{5.2}$$

$$F - Measure = \frac{2 \cdot precision \cdot recall}{precision + recall}. \tag{5.3}$$

Where Q is the number of performed activities, TP is the number of true positives, NI is the total number of inferred labels and NG is the total number of ground truth labels.

5.1.3 Experiments and Discussion

The model has been implemented in MATLAB 7.6. The configuration of the computer is an Intel Pentium(R) Dual-Core 2.5 GHz with 3 GB of memory and Microsoft Window 7. We split the dataset using the leave one day out approach; therefore, the sensor readings of one day are used for testing and the remaining days for training. We evaluated different crossover rates to determine the optimal accuracy point. It is obvious from Figure 5.1 that 0.4 is closer to the optimal parameter as compared to others. We analyzed the effect of the mutation rate with different values and discovered the optimal point at 0.005, as shown in Figure 5.2. Small values of mutation make the solution stable, and values greater than 0.005 do not improve the accuracy. We analyzed different generation sizes for the convergence of EEM and observed a stable point after 125 generations, as no more significant improvements were found after this point, as shown in Figure 5.3. Similarly, we analyzed different sizes of population, ranging from 30 to 60 and found the optimal point at 35, as depicted in Figure 5.4. On the basis of the above analysis, we determined the optimal parameters as 0.4 crossover, 0.005 mutation, 125 generations and 35 population size. The results of our experiments are summarized in Tables 5.3, 5.4 and 5.5.

In Table 5.3, the result of the proposed EEM is presented in a confusion matrix for the MITADS1 dataset. The activities Going out, Bathing and Grooming are recognized with 100% accuracy. The most confusion takes place during the Preparing a snack and Cleaning activities. These were recognized correctly half of the time but misclassified for the remaining occurrences. In the

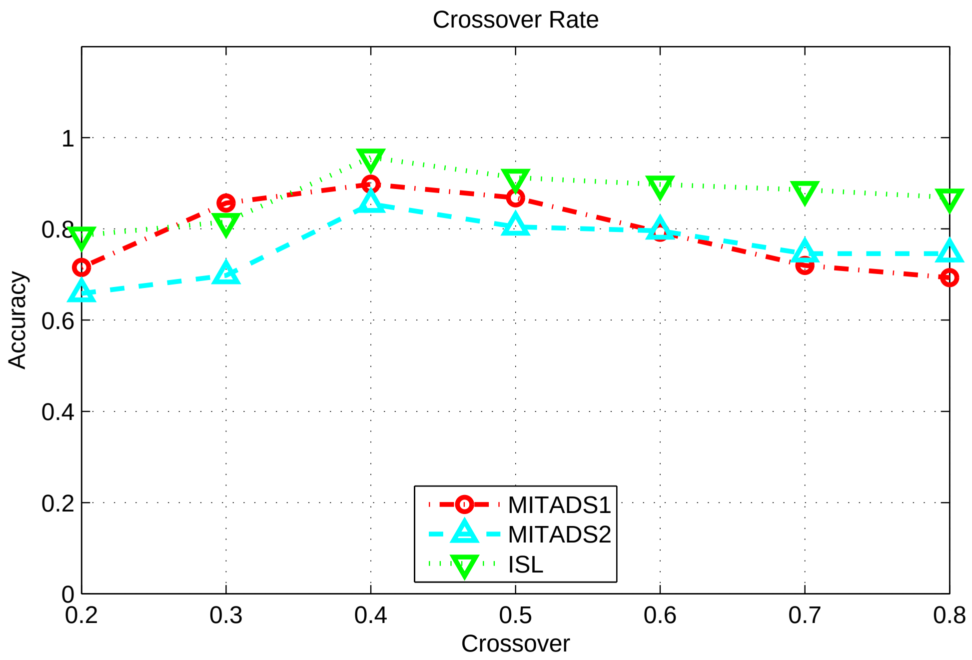


Figure 5.1: Effect of crossover values

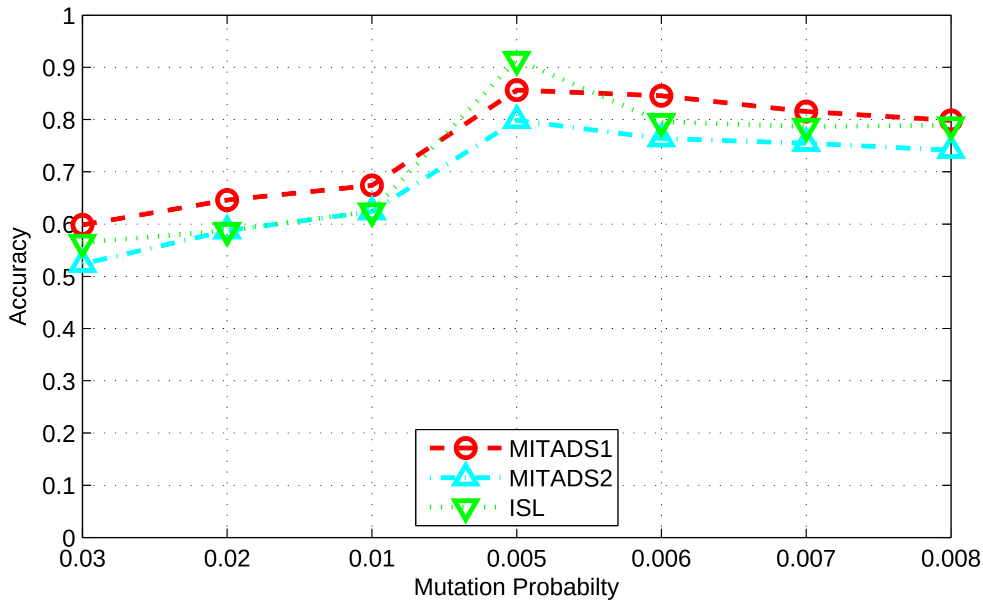


Figure 5.2: Effect of mutation values

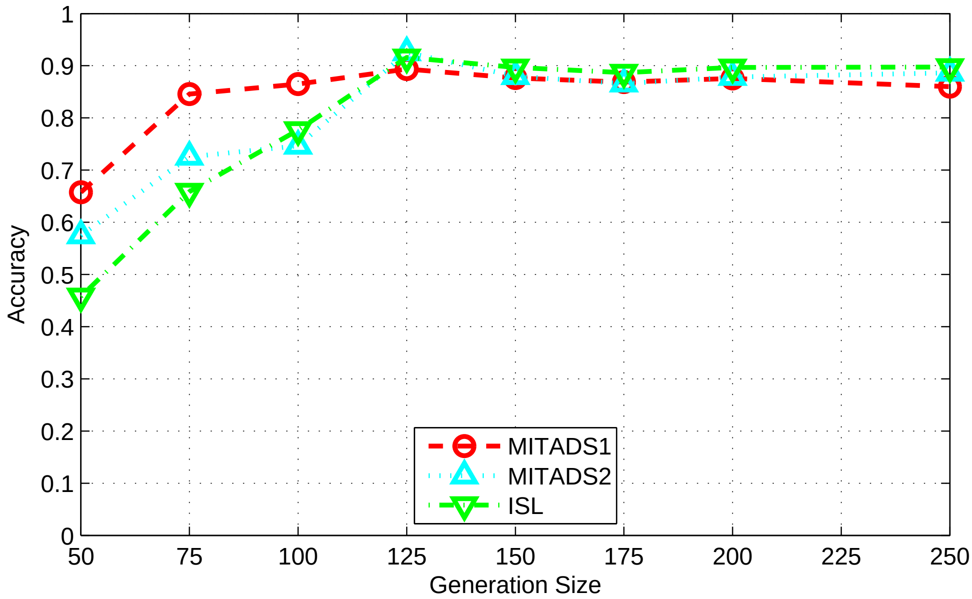


Figure 5.3: Effect of number of generations

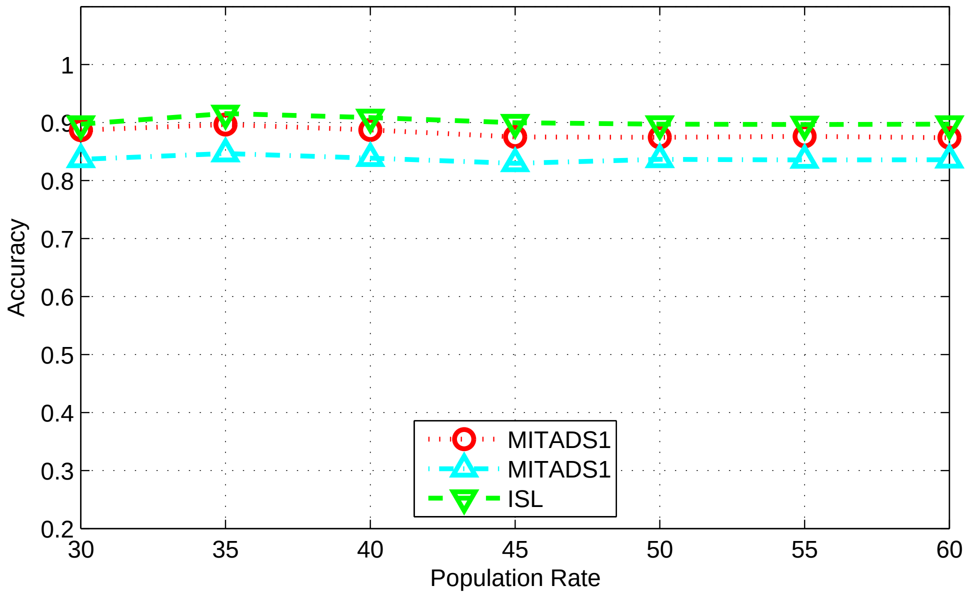


Figure 5.4: Effect of population size

case of MITADS2, Preparing Breakfast and Watching TV are recognized with the highest accuracy, while the worst recognized activity is Preparing a snack, which is correctly classified seven times and confused with other activities nine times, as shown in Table 5.4.

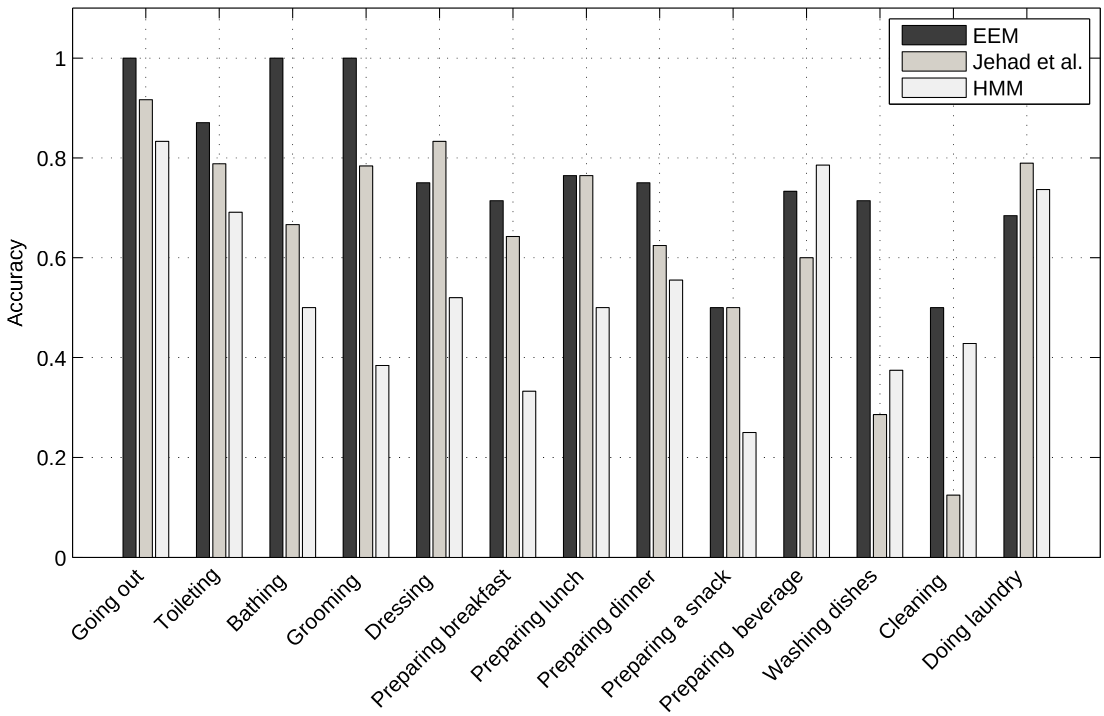


Figure 5.5: The MITADS1 activity recognition results

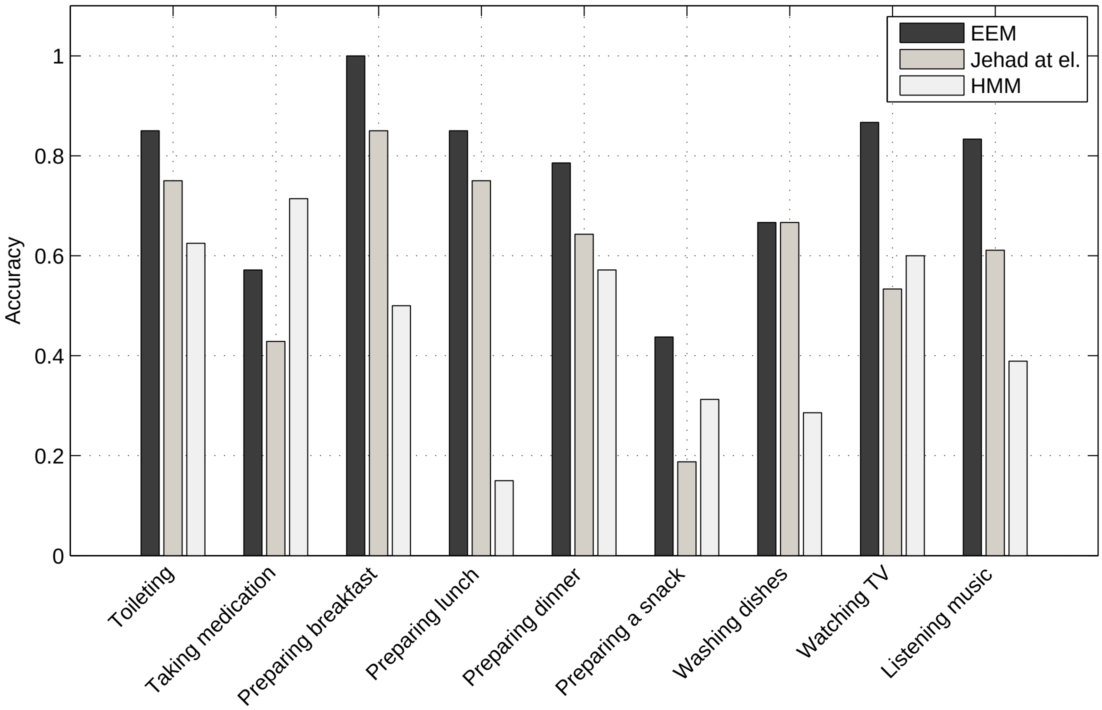


Figure 5.6: The MITADS2 activity recognition results

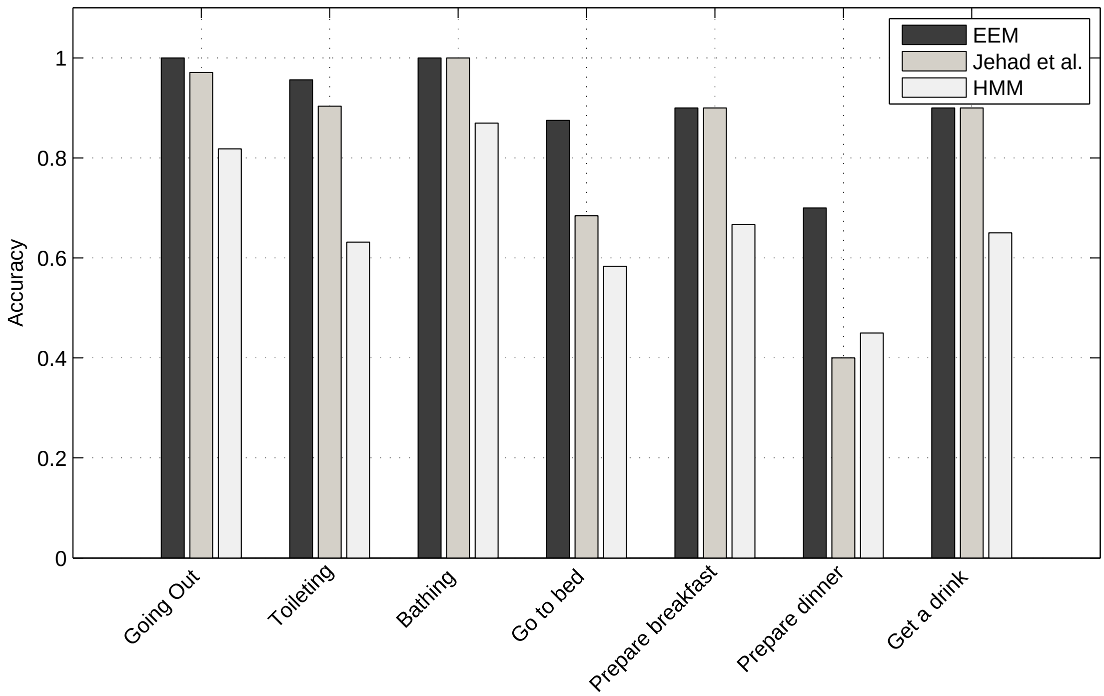


Figure 5.7: The ISL activity recognition results

Activity	Going out	Toileting	Bathing	Grooming	Dressing	Preparing breakfast	Preparing lunch	Preparing dinner	Preparing a snack	Preparing beverage	Washing dishes	Cleaning	Doing laundry
Going out	12	-	-	-	-	-	-	-	-	-	-	-	-
Toileting	-	74	5	1	-	-	-	-	2	1	-	2	-
Bathing	-	-	18	-	-	-	-	-	-	-	-	-	-
Grooming		-	-	37	-	-	-	-	-	-	-	-	-
Dressing	-	1	2	1	18	-	-	-	-	-	-	-	2
Preparing breakfast	-	-	-	-	-	10	-	-	1	3	-	-	-
Preparing lunch	-	-	-	-	-	1	13	3	-	-	-	-	-
Preparing dinner	-	-	-	-	-	-	-	6	2	-	-	-	-
Preparing a snack	-	-	-	-	-	2	2	3	7	-	-	-	-
Preparing beverage	-	2	1	-	-	1	-	-	-	11	-	-	-
Washing dishes	-	-	-	-	-	-	-	-	-	-	5	2	-
Cleaning	-	-	-	-	-	-	-	-	-	-	2	4	2
Doing laundry	-	2	2	-	-	-	-	-	-	1	1	-	13

Table 5.3: The confusion matrix of recognized activities in the MITADS1 smart home

Activity	Toileting	Taking medication	Preparing breakfast	Preparing lunch	Preparing dinner	Preparing a snack	Washing dishes	Watching TV	Listening music
Toileting	34	1	-	-	-	1	1	1	2
Taking medication	2	8	-	-	1	1	2	-	-
Preparing breakfast	-	-	18	-	-	-	-	-	-
Preparing lunch	-	-	1	17	-	2	-	-	-
Preparing dinner	1	-	1	1	11	-	-	-	-
Preparing a snack	1	5	-	2	1	7	-	-	-
Washing dishes	3	2	-	-	-	-	14	2	-
Watching TV	1	-	-	-	-	-	1	13	-
Listening music	2	1	-	-	-	-	-	-	15

Table 5.4: The confusion matrix of recognized activities in the MITADS2 smart home

Activity	Going out	Toileting	Bathing	Go to bed	Prepare breakfast	Prepare dinner	Get a drink
Going out	33	-	-	-	-	-	-
Toileting	-	109	4	1	-	-	-
Bathing	-	-	23	-	-	-	-
Go to bed	-	3	2	19	-	-	-
Prepare breakfast	-	-	-	-	18	7	-
Prepare dinner	-	-	-	-	3	2	-
Get a drink	-	-	-	-	1	1	18

Table 5.5: The confusion matrix of recognized activities in the ISL smart home

Dataset	Model	Precision	Recall	F-Measure	Accuracy
MITADS1	EEM	0.7515	0.6909	0.7199	0.7678
	Jehad et al.	0.6668	0.6401	0.6532	0.6401
	HMM	0.5308	0.5321	0.5314	0.5303
MITADS2	EEM	0.7721	0.7624	0.7672	0.7623
	Jehad et al.	0.6550	0.6204	0.6372	0.6022
	HMM	0.5015	0.4587	0.4792	0.4608
ISL	EEM	0.8997	0.9044	0.9020	0.9044
	Jehad et al.	0.8264	0.8065	0.8163	0.8226
	HMM	0.7130	0.6575	0.6843	0.6670

Table 5.6: Precision, Recall, F-Measure and Accuracy

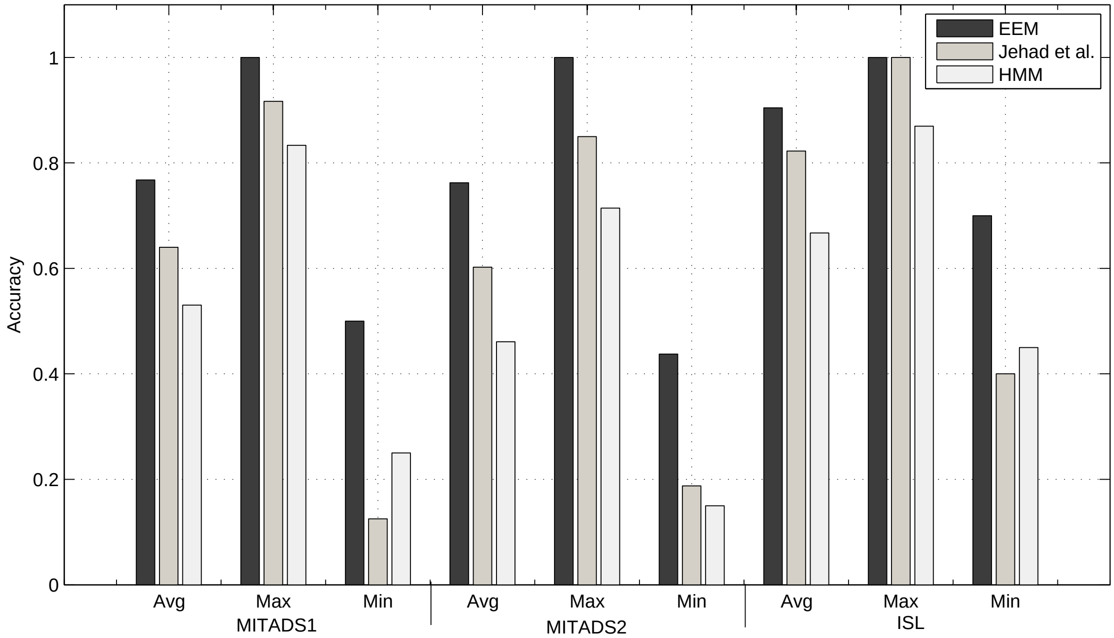


Figure 5.8: Accuracy comparison (Avg, Max and Min)

5.1.4 Summary

In all of the experiments, an approximately 6-30% higher accuracy is observed. Experimental results demonstrated that handling the issues – discussed in chapter 4 – consistently increased accuracy for each considered activity. In this study, only a single inhabitant is considered at a time; therefore complications may arise due to the presence of several residents in a home.

This limits the applicability of this model at present; however, the generic nature of training and implementation will lead to the success of EEM for conceivable complex situation. Our future plan includes handling multiple residents and recognizing interleaved and parallel activity under the framework of evolutionary ensembles.

5.2 Outdoor Activity Recognition Results

In this section, we present the results to evaluate and validate the EFM in order to measure the accuracy level of recognized activities and to investigate the feasibility of Gaussian membership estimation in the outdoor activity recognition domain.

5.2.1 Data sets Description

The smartphones used in this research were Samsung Galaxy S and Google Android OS version Gingerbread. To collect the activities dataset, 10 healthy adult subjects (7 male and 3 females) of different ages, heights and weights were participated in this study. The characteristics of the subjects are shown in Table 4.1. Seven common dynamic activities were selected as the basic activities of daily life to be recognized - walking, jogging, running, cycling, going up stairs, going down stairs, and hopping. The selection of these activities was based on healthcare applications and is required for our u-lifecare research project [90]. Each subject was requested to perform these activities in a natural manner (without fixed duration or sequence). The smartphone was placed in the front pant pocket regardless of its orientation to record the activities. A pant pocket location is an acceptable solution from the users point of view, if the user wishes to use the smartphone for activity recognition. Furthermore, intended activities depend on motion patterns of the legs. Each subject recorded the activities on different days at various locations without researcher supervision

5.2.2 Performance Measures

The three standard metrics of precision, recall, and F-measure are used as performance measures. They are calculated using the values of the confusion matrix [99] and are computed as:

$$Precision = \frac{1}{Q}\sum_{i=1}^{Q}\frac{TP_i}{NI_i} \tag{5.4}$$

$$Recall = \frac{1}{Q}\sum_{i=1}^{Q}\frac{TP_i}{NG_i} \tag{5.5}$$

$$F-Measure = \frac{2 \cdot precision \cdot recall}{precision + recall}. \tag{5.6}$$

Where Q is the number of performed activities, TP is the number of true positives, NI is the total number of inferred labels and NG is the total number of ground truth labels.

5.2.3 Experiments and Discussion

A set of experiments was conducted to evaluate the performance of the proposed model. The accelerometer data under consideration included both indoor and outdoor activities of different human subjects. EFM was implemented in MATLAB 7.6. The configuration of the computer was an Intel Pentium(R) Dual-Core 2.5 GHz with 3 GB of memory and Microsoft Windows 7. We split the dataset using the '10-fold-cross-validation approach and evaluated different parameter values for GA in order to determine the optimal points. On the basis of our analysis, we determined the optimal parameters to be 0.8 for crossover, 0.1 for mutation, 55 for population, and 500 for generation. In order to calculate the feature vectors from the raw signals, no overlapping-sliding windows take placed over the accelerometer data, which had a length of 150 data samples (about 3 sec). Within a window, root mean square, variance, correlation and energy features were extracted from each axis of the signal. Then, these values were fuzzified by finding the membership values

Activity	Crisp Output
Walking	0.00-0.29
Jogging	0.30-0.45
Running	0.46-0.60
Cycling	0.61-0.80
Downstairs	0.81-0.86
Hopping	0.87-0.90
Upstairs	0.91-1.00

Table 5.7: Activity recognition from the crisp output

Activity	Walking	Jogging	Running	Hopping	Cycling	Up stairs	Down stairs
Walking	6585	145	5	-	-	-	-
Jogging	4	3628	56	-	-	-	-
Running	3	25	2572	-	-	-	-
Hopping	2	24	14	990	21	-	22
Cycling	-	19	14	11	2819	10	22
Up stairs	9	5	2	15	6	1084	48
Down stairs	10	6	2	14	9	20	572

Table 5.8: The confusion matrix of activity recognition

for the fuzzy input variables. Applying the fuzzy operators to the different parts of the antecedents, implication, aggregation, finally produced a crisp output. Table 5.7 shows how the activity can be recognized using the crisp output. The results of our experiments are summarized in Tables 5.8 and 5.9.

In Table 5.8, the recognition results of the proposed EFM are presented in a confusion matrix. The activities ‘walking’, ‘jogging’ and ‘running’ are recognized with high accuracy. They are sometimes slightly confused with each other but never confused with other activities. It shows the effectiveness of the EFM to deal nicely with the dynamic activities. The most confusion takes place during the ‘up stairs’ and ‘down stairs’ activities, but these complex activities were recognized accurately more than 90% of the time. In the case of the individual subject, ‘walking’, ‘jogging’, ‘running’ and ‘cycling’ activities were recognized with high accuracy, as shown in Table 5.9. We demonstrated a single day activity routine of a person with a ground truth and recognized activities, as is shown in Figure 5.9.

Subjects	Walking	Jogging	Running	Hopping	Cycling	Up stairs	Down stairs	Avg.
Subjects 1	0.9958	0.9947	0.9714	0.8596	0.9932	0.9152	0.9012	0.9473
Subjects 2	0.9452	0.9673	1.0000	0.9382	0.9930	1.0000	0.8889	0.9618
Subjects 3	0.9958	0.9947	0.9821	0.8596	0.9932	0.9491	0.9012	0.9537
Subjects 4	0.9736	0.9934	1.0000	0.9459	0.9430	0.8739	0.9230	0.9504
Subjects 4	0.9734	0.9618	0.9852	0.9444	0.9671	0.9145	0.9125	0.9513
Subjects 6	0.9452	0.9673	1.0000	0.9496	0.9930	1.0000	0.8888	0.9634
Subjects 7	0.9901	1.0000	0.9810	0.8260	0.9967	0.9056	0.8235	0.9318
Subjects 8	0.9945	0.9869	1.0000	0.8765	0.9449	0.8956	0.9491	0.9496
Subjects 9	0.9736	0.9934	1.0000	0.9459	0.9430	0.9159	0.9230	0.9564
Subjects 10	0.9734	0.9618	0.9852	0.9444	0.9671	0.8974	0.9125	0.9488

Table 5.9: Individual subject activity recognition accuracy

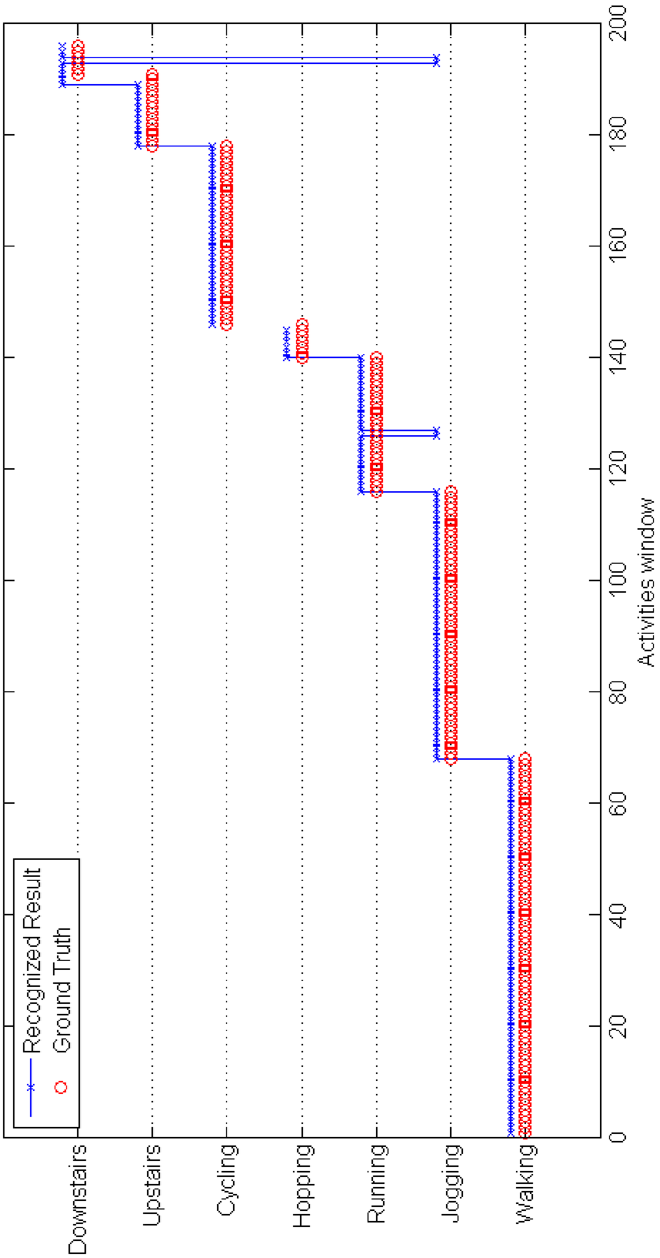


Figure 5.9: A single day recognized activities routine

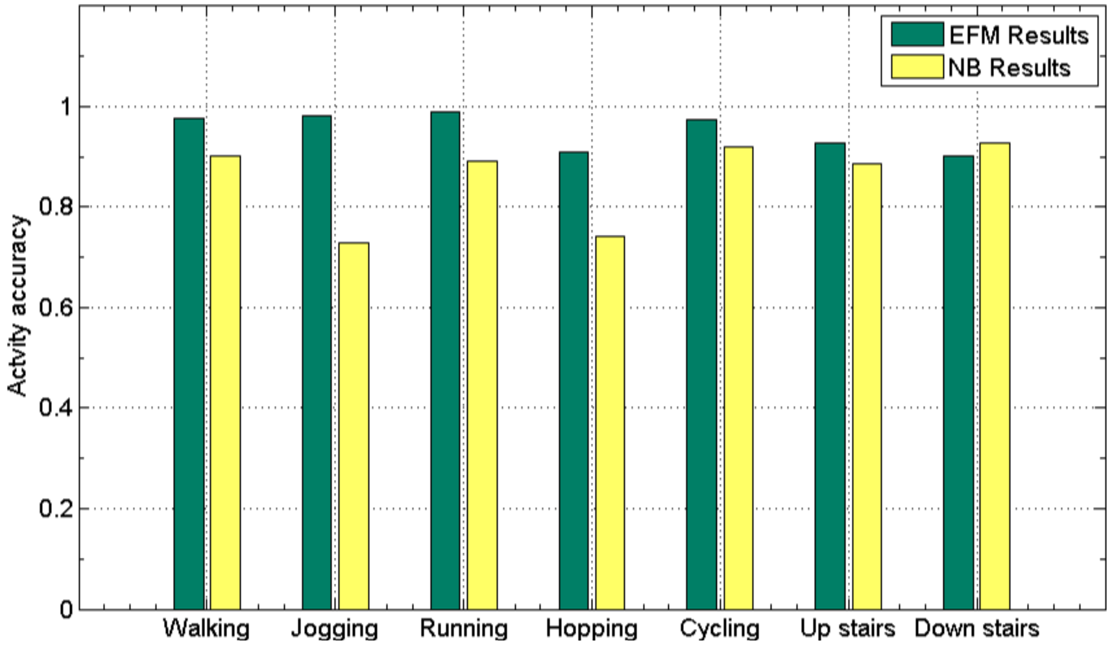


Figure 5.10: Comparison of individual activity classification accuracy

Figure 5.9 illustrates the smooth recognition rate of the performed activities with ground truth. In the whole day, our system confused running and going down stairs with jogging one time. Two recent previous studies were identified that are similar to our work in terms of recognizing the same dynamic activities or using a fuzzy inference system as a classification method. Preece et al. [56] studied the same set of dynamic activities, but their experimental setup was different. They collected the data using multiple accelerometers mounted on different body locations so that their results are not directly comparable to our study. However, we achieved an almost same level of accuracy by utilizing the embedded accelerometer in the smartphone and overcoming the limitations of a video-based annotation method. Our method is more realistic for annotating the performed activities, and unobtrusive device selection makes our model superior to the existing one. Helmi et al. [19] proposed a model that is based on a fuzzy inference system to recognize with quite high accuracy a small group of activities including moving forward, jumping, going up stairs and going down stairs. They defined the membership functions and fuzzy rules with the help of domain expert knowledge along with a trial and error-based strategy to refine the fuzzy boundaries so direct comparison of classification is not possible. However, our model relaxes the domain expert knowledge conditions. EFM is able to estimate the membership functions through a statistical method and fuzzy rules using a GA optimization algorithm.

The classification accuracies reported in Tables 5.8 and 5.9 represent the confusion between the activities and the average recognition of activities across all subjects. To validate and investigate EFM further, we compared it with one of the most reliable and powerful techniques, the Naive Bayes (NB) classifier. Our dataset activities classes are imbalanced due to some activities that appear much more frequently than others. Class-accuracy [16] is the primary way to evaluate the performance of an activity classifier rather than using time slice accuracy. For instance, the total instances of 'walking' were 6736 and total instances of going 'down stairs' were 636 in our dataset. If a classifier correctly classified 6585 instances of 'walking' (accuracy = 97.75%) and 400 instances of 'going down stairs' (accuracy = 62.89), then the time slice accuracy would be 94.75%, whereas the class-accuracy would be 80.32%, since walking is more frequent than downstairs activity. Therefore, we reported the class-accuracy results in Figures 5.10 and 5.11 and kept all the data settings unchanged. This comparison shows that a remarkable improvement in terms of accuracy was achieved compared to the state-of-the-art method.

As can be seen from Figure 5.10, our EFM model achieves significant improvement for all recognized activities except the down stairs activity in comparison to NB. We achieved remarkable improvement for the comprehensive group of dynamic activities including 'walking', 'jogging', 'running', 'hopping' and 'cycling' as compared to existing methods. Our proposed model recognized the activity correctly most of the time, but probability-based methods did not perform very well in all cases. It can be seen from Figure 5.11 that our proposed model EFM shows stable results, with high maximum, minimum and average class-accuracy. On the basis of the confusion matrix presented in Table 5.8, we computed three performance measures: precision, recall, F-measure, as shown in Table 5.10. The EFM performed better for all three measures. Besides the precision and recall, we further perform the non-parametric Wilcoxon Signed-Ranks Test [100] for rigorous comparison to detect the differences between the existing and our proposed model behavior. The p-value is computed (i.e., p-value = 0.0313) for the pairwise comparison concerning EFM. It shows our model achieves a significant improvement over the existing Naive Bayes method with a level of significance $\alpha = 0.05$.

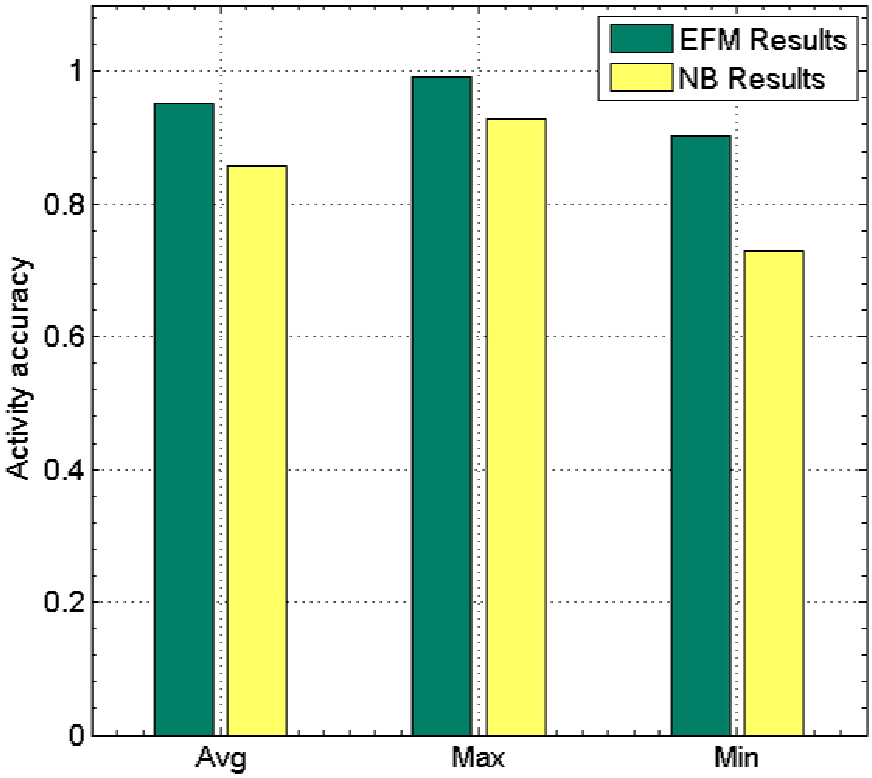


Figure 5.11: Class-Accuracy comparisons (Avg, Max and Min)

Model	Precision	Recall	F-Measure	Class-Accuracy
EFM	0.9551	0.9540	0.9545	0.9534
NB	0.8350	0.8619	0.8482	0.8921

Table 5.10: Precision, Recall, F-Measure and Class-Accuracy

5.2.4 Summary

The proposed evolutionary fuzzy model is evaluated on a comprehensive group of dynamic activities. In every experiment, approximately 9% higher class-accuracy was observed and p-value < 0.05. Experimental results demonstrate that handling the issues – discussed in chapter 4 – consistently increased the overall accuracy. In this study, fixed position of a smartphone is considered; therefore, complications may arise due to different positions. This limits the applicability of this model at present; however, the generic nature of training and implementation will lead to the success of EFM for conceivable complex situations. Our future plan includes handling position-independent recognition by deriving novel features using the proposed framework.

Chapter 6

Conclusion and Future Directions

This chapter concludes the research carried out in this dissertation. The subsequent sections summarizes the contributions made in this dissertation to the area of indoor and outdoor human activity recognition. In the end, we conclude this study with potential future directions that can be explored to extend the research carried in this dissertation.

6.1 Conclusion

Human activity recognition is an emerging field of research that enables a large number of human-centric applications. Therefore many researchers have been investigating their time and efforts in proposing practical solutions for activity recognition. So far two of the most important challenges in the area of activity recognition are how to obtain good recognition results from the simple sensor and how to construct learning models which are able to resolve the ambiguities between the human activities.

In this dissertation, the first challenge is addressed by proposing an evolutionary ensemble model to learn the activities more accurately. The advantage of this method is the ability to process the major and minor activities independently and works well over the small datasets. Regarding to the second challenge, to solve the ambiguities issues associated with the outdoor activities. Existing fuzzy models are not able to define the membership functions automatically nor fuzzy rules. In this work, we overcome this limitation by assuming that acceleration pattern of an activity has a Gaussian-like distribution. Although the assumption is not always true but it is reasonable. Since, most of the activities have a fairly consistent mean value around the distinguishing features. We define the number of Gaussian distributions equal to the number of defined fuzzy sets. Initialization is done by finding the range and dividing it into equal parts and then estimate the natural grouping of data through expectation maximization algorithm. Fuzzy rules are defined by our proposed genetic algorithm (GA).

With the above proposed solution, this dissertation technically contributes novel learning models for solving the discussed problem in human activity recognition domain.

6.1.1 Evolutionary Ensemble Model (EEM)

The proposed model is based on ensemble learners and take the advantage of genetic algorithm simultaneously. Previous approaches do not consider the activity representation structure, just utilized the sensor events sequence. We consider the activity representation structure that can provide more vital information for better human activity recognition. More importantly, the proposed method overcome the limitations of the previously proposed algorithms. Hence it produces much better recognition accuracy in comparison with the existing one.

6.1.2 Evolutionary Fuzzy Model (EFM)

The proposed model in this dissertation relax the domain knowledge constrains to define the fuzzy sets and rules. We measure the ambiguities associated with the motion of the body related activities by analyzing and estimating the natural grouping of data. All the necessary algorithms for training and inferencing the model are presented in chapter 5.

6.2 Future Directions

In this dissertation, we contributed to the area of indoor and outdoor human activity recognition. Two stage methodologies were proposed that are based on evolutionary algorithms. These methodologies provide a robust learning models in human activity recognition domain. Besides the achievement, we also pointed out the limitations of our solution, which require further research effort to be solved completely.

- For Indoor activity recognition, only a single inhabitant is considered at a time. One of the possible direction is to handle the multiple residents and recognize the indoor activities under the framework of evolutionary learning models.

- In outdoor activity recognition study, we consider fixed position of a smartphone. Complications may arise due to different positions.

- The generic nature of training and implementation will lead to the success of EFM for conceivable complex situations. Our future plan includes handling position-independent recognition by deriving novel features using the proposed framework.

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Appendix A

List of Publications

International Journal Papers:

[1] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee, and Young-Tack Park, "EFM: Evolutionary Fuzzy Model for Dynamic Activities Recognition using a Smartphone Accelerometer", In Journal of Applied Intelligence - Springer (SCI, IF: 1.853), ISSN:1573-7497, 2013.

[2] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee, and Young-Koo Lee, "EEM: Evolutionary Ensembles Model for Activity Recognition in Smart Homes", In Journal of Applied Intelligence - Springer (SCI, IF: 1.853), ISSN:1573-7497, 2012.

[3] Iram Fatima, **Muhammad Fahim**, Sungyoung Lee, and Young-Koo Lee, "A Unified Framework for Activity Recognition-based Behavior Analysis and Action Prediction in Smart Homes", Journal of Sensors - MDPI (SCIE, IF: 1.953), EISSN:1424-8220, Vol. 13(2), 2013.

[4] Iram Fatima, **Muhammad Fahim**, Sungyoung Lee, and Young-Koo Lee, "Analysis and Effects of Smart Home Dataset Characteristics for Daily Life Activity Recognition", Journal of Supercomputing - Springer (SCI, IF:0.917), 2013.

[5] Iram Fatima, **Muhammad Fahim**, Sungyoung Lee, and Young-Koo Lee, "MODM: Multi-Objective Diffusion Model for Dynamic Social Networks using Evolutionary Algorithm", Journal of Supercomputing - Springer (SCI, IF:0.917), 2013.

[6] Maqbool Hussain, AsadMasood Khattak, Wajahat Ali Khan, Iram Fatima, Muhammad Bilal Amin, Zeeshan Pervez, Rabia Batool, Muhammad Amir Saleem, Muhammad Afzal, **Muhammad Fahim**, Muhammad Hameed Saddiqi, Sungyoung Lee, and Khalid Latif,

"Cloud-based Smart CDSS for Chronic Diseases", In Journal of Health and Technology - Springer, ISSN: 2190-7188, 2013.

[7] Iram Fatima, Sajal Halder, Muhammad Aamir Saleem, Rabia Batool, **Muhammad Fahim**, Young-Koo Lee and Sungyoung Lee, "Smart CDSS: Integration of Social Media and Interaction Engine (SMIE) in Healthcare for Chronic Disease Patients", The Journal of Multimedia Tools and Applications (SCIE, IF:1.014), 2013.

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International Conference Papers:

[9] **Muhammad Fahim**, Le Ba Vui, Iram Fatima, and Sungyoung Lee, "A Sleep Monitoring Application for u-lifecare using Accelerometer Sensor of Smartphone". Published in 7th International Conference on Ubiquitous Computing and Ambient Intelligence, Carrillo - Guanacaste (Costa-Rica), 2013 (Accepted).

[10] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee and Young-Koo Lee, "Activity Recognition Based on SVM Kernel Fusion in Smart Home". Published in International Conference on Computer Science and its Applications, Jeju, Korea, Springer-Verlag Lecture Notes in Electrical Engineering Vol.203, 2012.

[11] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee and Young-Koo Lee, "An Evolution of Fusion Over Smart Homes". Published in International Ambient Assisted Living Association Summit, Bilbao, Spain, Jun 27-29, 2012.

[12] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee and Young-Koo Lee, "Daily Life Activity Tracking Application for Smart Homes using Android Smartphone". Published in 4th International Conference on Advanced Communication Technology (ICACT'12),Phoenix Park, Pyeongchang, Korea, Feb 19-22, 2012.

[13] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee and Young-Koo Lee, "Activity Recognition: An Evolutionary Ensembles Approach". Published in 13th ACM UbiComp Workshop SAGWare, Beijing, China, September, 2011.

[14] **Muhammad Fahim**, Iram Fatima, Sungyoung Lee and Young-Koo Lee, "A Multi-Strategy Bayesian Model for Sensor Fusion in Smart Environments". Published in 5th International Conference on Computer Sciences and Convergence Information Technology, Seoul, Korea, November 2010.

[15] Iram Fatima, **Muhammad Fahim**, Rabia Batool, Muhammad Aamir Saleem, Young-Koo Lee, Sungyoung Lee, "CDSS: Integration of Social Media Interaction Engine (SMIE) in Healthcare for Chronic Disease Patients", Published in International Conference on Advanced IT, engineering and Management (AIM 2013), Seoul, Korea, Feb. 21-23, 2013.

[16] Iram Fatima, **Muhammad Fahim**, Young-Koo Lee, and Sungyoung Lee, "Classifier Ensemble Optimization for Human Activity Recognition in Smart Homes", Published in 7th International Conference on Ubiquitous Information Management and Communication (ICUIMC IMCOM 2013), Kota Kinabalus, Malaysia, Jan 17-19, 2013.

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Domestic Conference Papers:

[21] **Muhammad Fahim**, M.H. Siddiqi, Iram Fatima, Sungyoung Lee, and Young-Koo Lee , "Daily Life Monitoring Application for Diabetic Patients using Android Smartphone". Published in 35th Conference of Korea Information Processing Society (KIPS), Jeju, Korea. 14 May, 2011.

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