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EFM: evolutionary fuzzy model for dynamic activities recognition using a smartphone accelerometer

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Abstract Activity recognition is an emerging field of research that enables a large number of human-centric applications in the u-healthcare domain. Currently, there are major challenges facing this field, including creating devices that are unobtrusive and handling uncertainties associated with dynamic activities. In this paper, we propose a novel Evolutionary Fuzzy Model (EFM) to measure the uncertainties 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 Genetic Algorithm (GA) is investigated and designed to determine the optimal fuzzy rules. To evaluate the EFM, we performed experiments on seven daily life activities of ten human subjects. Our experiments show significant improvement of 9 % in class-accuracy and 11 % in the F-measures of recognized activities compared to existing counterparts. The practical solution to dynamic activity recognition problems is expected to be an EFM, due to EFM's utilization of smartphones and natural way of handling uncertainties.

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1 Introduction

Over the last few years, activity recognition using accelerometer signals has become an active research area due to its large number of potential applications including context-awareness, healthcare, and active lifestyle [1, 2]. For instance, patients with diabetes, cardiovascular disease, insomnia or obesity often follow well defined exercise routines (walking, jogging, running, or cycling) as a part of their treatment. Such human activities can be recognized by motion pattern analysis using wearable sensors, but this solution is obtrusive, and few users want to wear special shirts, bracelets or belts for that purpose [3–5]. Current generation smartphones are an alternative solution to wearable sensors due to their 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.

The nomenclature of accelerometer-based activity recognition is divided into static and dynamic categories. 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. Most of the research work has been done on static activities. Researchers have developed many probabilistic and machine learning approaches to identify a range of different activities from a body fixed accelerometer to the smartphone [5–9]. Motion of the body is integral to dynamic activities such as walking, running, or climbing stairs. A very small number of studies have investigated dynamic activities using single or multiple accelerometers [6, 10, 11]. To recognize dynamic activities using a smartphone accelerometer sensor 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. Classical probabilistic methods are unable to deal with such uncertainties [12].

The aim of this research is to recognize a comprehensive group of dynamic daily life activities. We proposed a novel evolutionary fuzzy model to deal with the uncertainties of dynamic patterns of these activities by defining fuzzy sets. The most common strategy for defining fuzzy sets is by using human experts or by trial-and-error [10]. 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 creating an evolutionary method called a 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 expert's 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.

2 Paper contribution and outline

Our contributions in this work are three-fold. First, we propose a novel evolutionary fuzzy model to deal with the uncertainties of dynamic activities and estimate membership functions by expectation maximization; hence, the problem of defining the input spaces can be solved. Second, GA is designed for optimal fuzzy rules without domain expert knowledge. Third, EFM performs well for dynamic activities and has superior accuracy to existing methods. In addition, we apply our proposed EFM to commercial smartphone-based activity recognition with a comprehensive group of dynamic activities that use an intensive activity dataset.

The rest of the paper is organized as follows. We briefly describe related works and their limitations in Sect. 3. In Sect. 4, we introduce our proposed EFM and its implementation for recognizing dynamic daily life activities. In Sect. 5, we analyze and evaluate our experimental results to validate our model. Finally, we conclude our paper in Sect. 6. We present details about the parameter estimation of membership functions in the Appendix.

3 Related work

There exist several previous studies on the usage of accelerometer signals and analysis of motion patterns in the activity recognition domain. Lara et al. [13] 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 the small group of activities and quite distinguishable from each other.

In [14] Ravi et al. 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. [6] analyzed statistical and wavelet-based features for classifying dynamic activities using accelerometers mounted to the 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. [10] 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 the three subjects' data by attaching the triaxial accelerometer to their waists with a sampling rate of 22 Hz. The fuzzy rules and

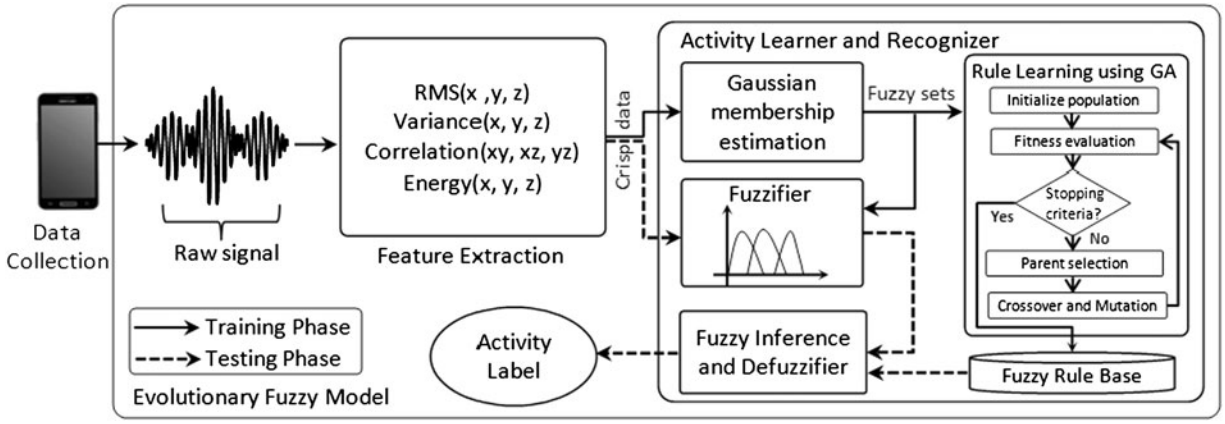


Fig. 1 The proposed architecture of the evolutionary fuzzy model

the membership functions of this fuzzy system are defined manually based on the experiences of domain experts.

In previous works, excellent approaches have been developed by researchers by varying the number of accelerometers, using different placements and considering different intended outcomes. For static as well as dynamic activities, some studies also reported on fuzzy theory [10, 15, 16] to recognize daily life activities; however, they required domain expert knowledge to develop the fuzzy systems or personal annotations to evolve the system. To overcome the limitations of existing work, we propose an alternative state-of-the-art evolutionary fuzzy model for recognizing dynamic activities using a smartphone accelerometer. We define the membership functions using a statistical method and investigate the suitability of GA as a rule learning classifier. Our proposed model has the ability to measure associated uncertainties and to generate fuzzy rules without expert domain knowledge. For these reasons, our EFM has the potential to work with real world applications.

4 Evolutionary fuzzy model

The proposed architecture of evolutionary fuzzy model for dynamic activity recognition is illustrated in Fig. 1. 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 details of each component are described in the following sections.

4.1 Smartphone accelerometer and data collection

The smartphones used in this research were Samsung Galaxy S and Google Android OS version Gingerbread.

Table 1 Characteristics of the participants

	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

To collect the activities dataset, 10 healthy adult subjects (7 male and 3 females) of different ages, heights and weights participated in this study. The characteristics of the subjects are shown in Table 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 [17]. 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 user's 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 Fig. 2. Other studies claim that 22 Hz–100 Hz of frequency is suitable to classify different physical activities [1, 3, 4, 7, 10]. In this study, we analyzed and recorded the data at 50 Hz, 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 Fig. 3 to understand the difficulty of recognition.

In Fig. 3, going up stairs 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 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) [4] and wavelet features [6] 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 [6, 10]. First, we solve the orientation issue of acceleration data suggested by Mizell [18] and then extract the following time and frequency domain features to recognize dynamic activities:

Fig. 2 Dataset collection applications

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

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

$$\mathrm{Corr}(x_i, x_j) = \frac{\mathrm{Cov}(x_i, x_j)}{\delta_i \delta_j} \tag{3}$$

$$E = \frac{1}{n}\sum_{i=1}^{n} |\mathrm{FFT}_i|^2 \tag{4}$$

In (1), 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 (2). The correlation feature in (3) 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 (4), 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.

4.3 Activity learner and recognizer

Fuzzy systems with evolutionary techniques are being successfully used to model human-like thinking, measure uncertainties and do not demand an accurate mathematical

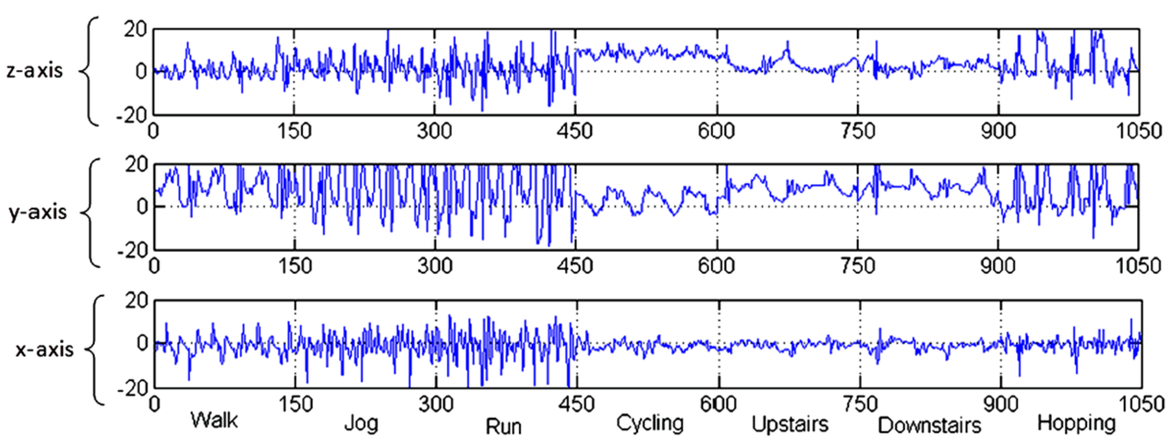


Fig. 3 Representative raw signals of activities

model [19–23]. 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.

4.3.1 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 [18]. 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.

4.3.2 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. Although the assumption is not always true, it is reasonable since most activities have a fairly consistent mean value of the distinguishing features. 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 [24] is applied to maximize the likelihood over the training data as follows:

$$p_k(Y_m \mid \mu_k,\ \delta_k) = \frac{1}{\sqrt{2\pi\delta_k^2}} \exp\left\{-\frac{(y_m-\mu_k)^2}{2\delta_k^2}\right\} \tag{5}$$

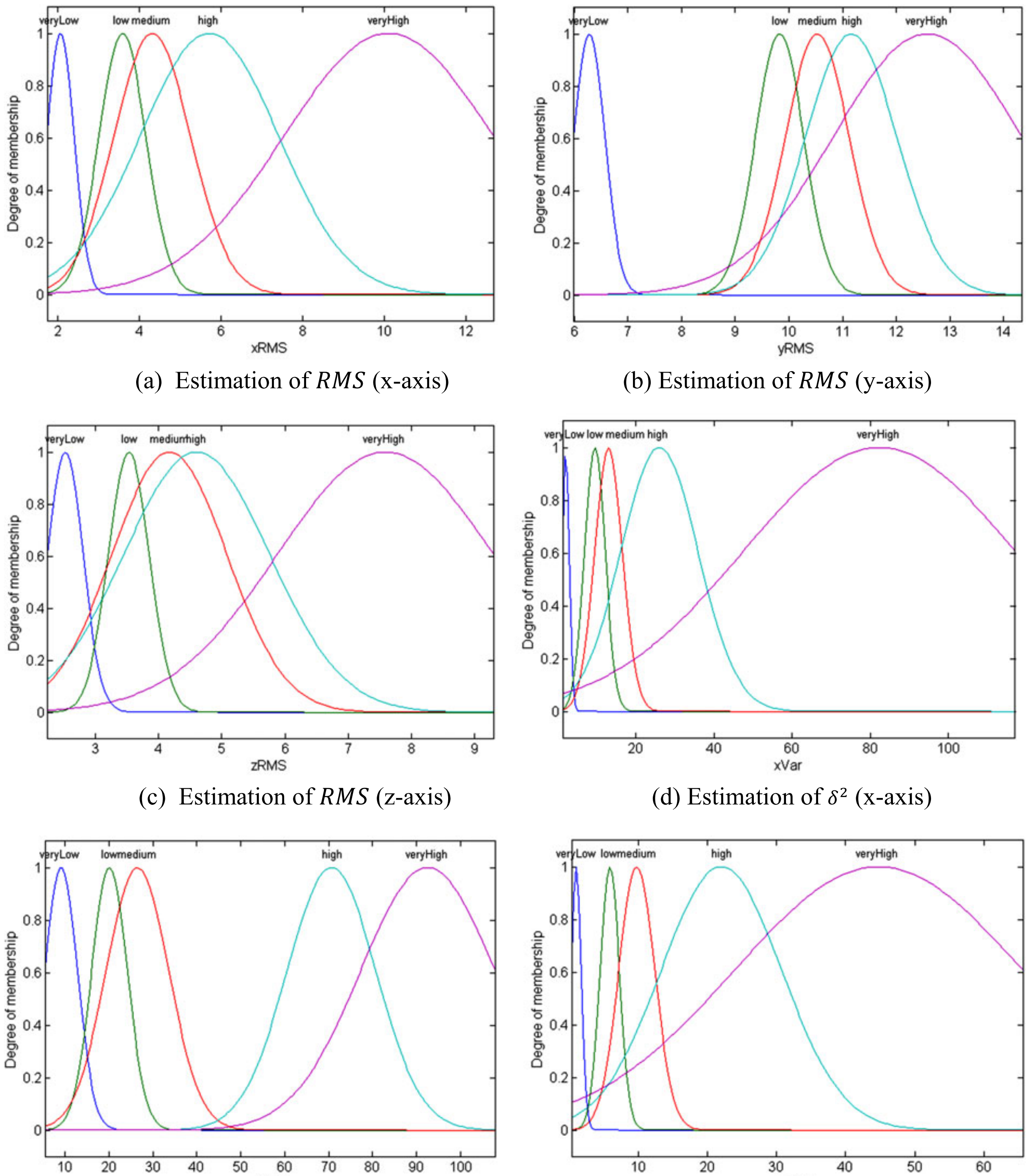
$$\mu_k = \frac{\sum_{m=1}^{M} w_{mk} y_m}{\sum_{m=1}^{M} w_{mk}} \tag{6}$$

$$\delta_k = \sqrt{\frac{\sum_{m=1}^{M} w_{mk}(y_m-\mu_k)^2}{\sum_{m=1}^{M} w_{mk}}} \tag{7}$$

Table 2 The parameter estimation of membership functions

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)[a]	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

[a] $(x_i, x_j) = (xy,\ xz,\ yz)$



(a) Estimation of RMS (x-axis)

(b) Estimation of RMS (y-axis)

(c) Estimation of RMS (z-axis)

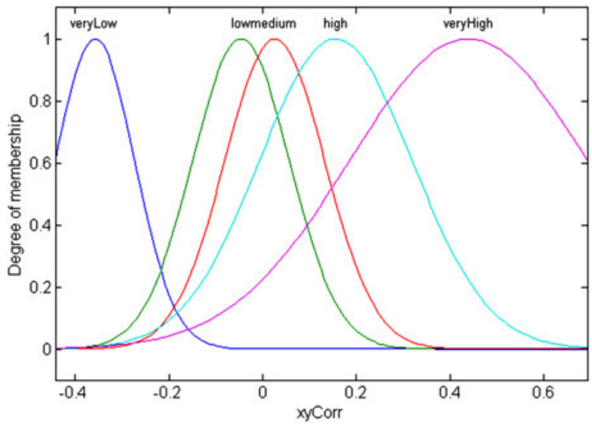
(d) Estimation of δ^2 (x-axis)

(e) Estimation of δ^2 (y-axis)

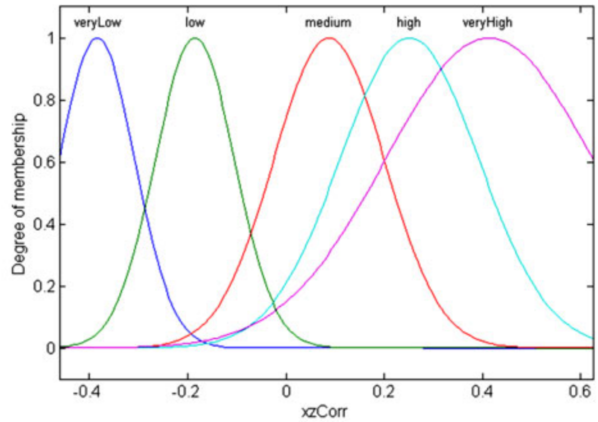
(f) Estimation of δ^2 (z-axis)

Fig. 4 The number of fuzzy sets estimation in EFM

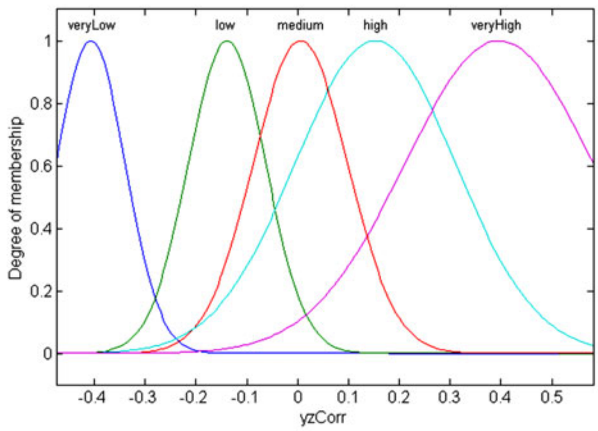
Details of the derivation of our defined parameters are presented in the appendix section at the end of this paper. After estimation, we obtain the parameters: center (μ_k) and standard deviation (δ_k) for each fuzzy set as shown in Table 2. Figure 4 represents the fuzzy sets of the statistical features defined over the estimated parameters. It is employed for analyzing the effect of statistical features drawn from our proposed Gaussian membership function estimation method (i.e., as shown in Table 2). It specified the degree of membership between the value of statistical features along each axis and fuzzy sets.



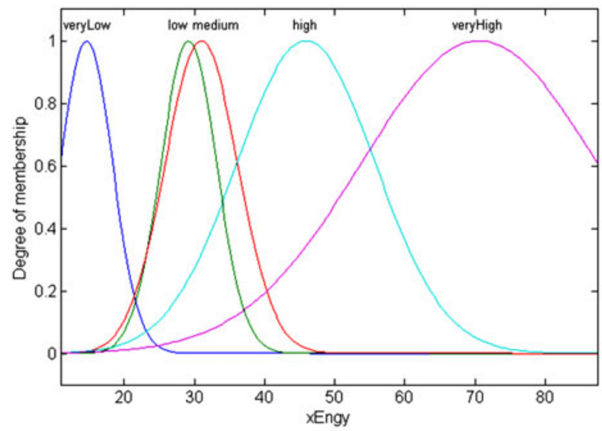
(h) Estimation of $Corr$ (xy-axis)



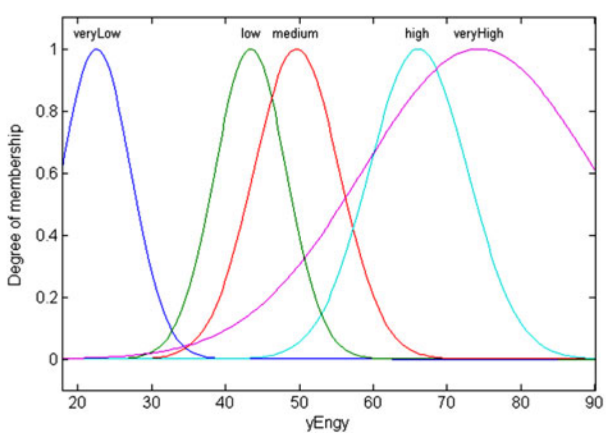
(i) Estimation of $Corr$ (xz-axis)



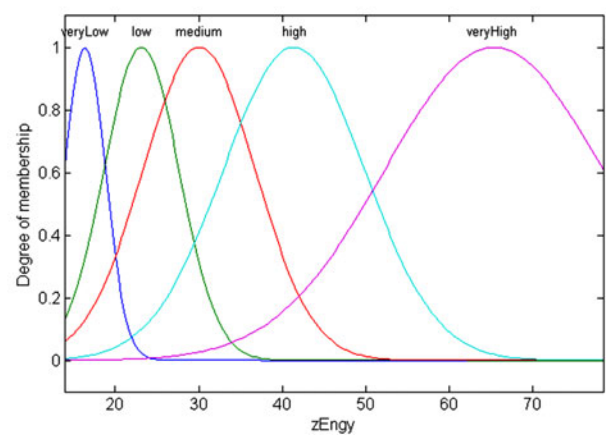
(j) Estimation of $Corr$ (yz-axis)



(k) Estimation of E (x-axis)



(l) Estimation of E (y-axis)



(m) Estimation of E (z-axis)

Fig. 4 (*Continued*)

4.3.3 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:

Representation The well-known Michigan approach [25] is used to encode the features and treat them as a single gene. A set of genes is a chromosome that presents a sin-

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

Fig. 5 Chromosome encoding of the activity rule

gle activity rule. Each activity rule consists of two portions. The antecedent is the logical combination of fuzzy sets and fuzzy operators in the form of fuzzy $\text{value}_1 \cap$ fuzzy $\text{value}_2 \cap$ fuzzy $\text{value}_3, \ldots,$ fuzzy value_{12}, and the consequent 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 Fig. 5.

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 [26] as follows:

$$F = \sum_{i=1}^{n} \sum_{j=1}^{m} \big[\text{reward}\ (\text{Activity rule}_i \mid \text{Search space}_j) - \text{payoff}\ (\text{Activity rule}_i \mid \text{Search space}_j)\big] \tag{8}$$

where

$$\text{reward} = \begin{cases} 1 & \text{if Activity rule} \equiv \text{Search space} \cap \text{classLabel} \equiv \text{Correct}, \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{payoff} = \begin{cases} -1 & \text{if Activity rule} \equiv \text{Search space} \cap \text{classLabel} \equiv \text{Incorrect}, \\ 0 & \text{otherwise.} \end{cases}$$

In (8), 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.

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

Algorithm 1 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 (μ)
   while (!max(G) || convg(G)) do
     fitness = fRankFitness(p)
     if !(fitness) then
       for m = 1: (⌊p(C)⌋) do
         pOne = rand(upper(p/2))
         pTwo = rand(lower(p/2))
         Offspring = fcrossover (pOne, pTwo)
         mut = rand(⌊p(λ)⌋)
         OFR = offspring(mut)
 end
```

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 1.

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.

4.3.4 *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

Algorithm 2(a) Evolutionary Fuzzy Model (Training Phase)

Input: *S(x, y, z)* – Accelerometer raw signals
Output: [*dGaussianInputMF, RuleGeneration*] – Membership functions and fuzzy rules

```
Activity Learner
    for m=1:3 do
        featVector = [rms(S(m)), var(S(m)), cor(S(m)), energy(S(m))]
        MFEstimation(μ, δ) = fComputeDistribution(featVector(m))
        dGaussianInputMF = MFEstimation(μ(m), δ(m))
    RuleGeneration =fGALearner(dGaussianInputMF, C, λ, G, μ)
end
```

Algorithm 2(b) Evolutionary Fuzzy Model (Recognition Phase)

Input: *S(x, y, z)* – Accelerometer raw signals
Output: *ACL* – Activity Class Label

```
Activity Recognizer
    featVector = [rms(Sx, Sy, Sz), var(Sx, Sy, Sz), cor(Sxy, Syz, Sxz), energy(Sx, Sy, Sz)]
    findMFvalue = dGaussianInputMF(featVector)
    firedRules = RuleRepository(findMFValue)
    unionImplication = firedRules
    defuzzification = centeroid(unionImplication)
    ACL = defuzzification
end
```

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 [27]. 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 Algorithms 2(a) and 2(b), respectively.

5 Evaluation and 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 activity recognition domain. 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 [28] and are computed as:

$$\text{Precision} = \frac{1}{Q}\sum_{i=1}^{Q}\frac{\text{TP}_i}{\text{NI}_i} \tag{9}$$

$$\text{Recall} = \frac{1}{Q}\sum_{i=1}^{Q}\frac{\text{TP}_i}{\text{NG}_i} \tag{10}$$

$$\text{F-Measure} = \frac{2\cdot\text{precision}\cdot\text{recall}}{\text{precision}+\text{recall}} \tag{11}$$

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 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 for the fuzzy input variables. Applying the fuzzy operators to the different parts of the antecedents, implication, aggregation, finally produced a crisp output. Table 3 shows how the activity can be recognized using the crisp output. The results of our experiments are summarized in Tables 4 and 5.

In Table 4, 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.

Table 3 Activity recognition from the crisp output

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

In the case of the individual subject, 'walking', 'jogging', 'running' and 'cycling' activities were recognized with high accuracy, as shown in Table 5. We demonstrated a single day activity routine of a person with a ground truth and recognized activities, as is shown in Fig. 6.

Figure 6 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. [6] 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. [10] 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

Table 4 The confusion matrix of activity recognition

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 Individual subject activity recognition accuracy

Subjects	Walking	Jogging	Running	Hopping	Cycling	Up stairs	Down stairs	Avg.
Subject 1	0.9958	0.9947	0.9714	0.8596	0.9932	0.9152	0.9012	0.9473
Subject 2	0.9452	0.9673	1.0000	0.9382	0.9930	1.0000	0.8889	0.9618
Subject 3	0.9958	0.9947	0.9821	0.8596	0.9932	0.9491	0.9012	0.9537
Subject 4	0.9736	0.9934	1.0000	0.9459	0.9430	0.8739	0.9230	0.9504
Subject 5	0.9734	0.9618	0.9852	0.9444	0.9671	0.9145	0.9125	0.9513
Subject 6	0.9452	0.9673	1.0000	0.9496	0.9930	1.0000	0.8888	0.9634
Subject 7	0.9901	1.0000	0.9810	0.8260	0.9967	0.9056	0.8235	0.9318
Subject 8	0.9945	0.9869	1.0000	0.8765	0.9449	0.8956	0.9491	0.9496
Subject 9	0.9736	0.9934	1.0000	0.9459	0.9430	0.9159	0.9230	0.9564
Subject 10	0.9734	0.9618	0.9852	0.9444	0.9671	0.8974	0.9125	0.9488

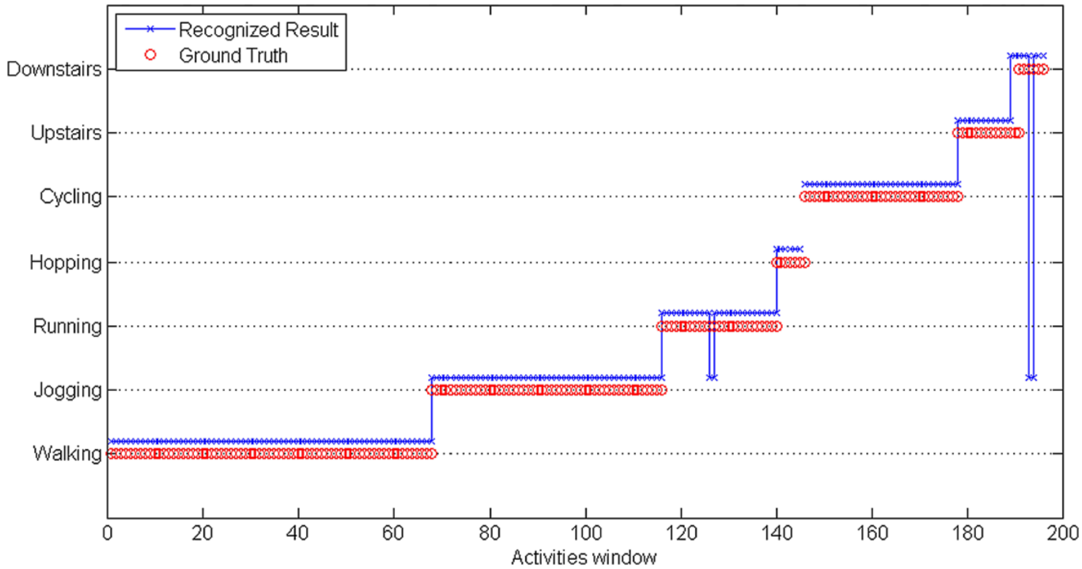
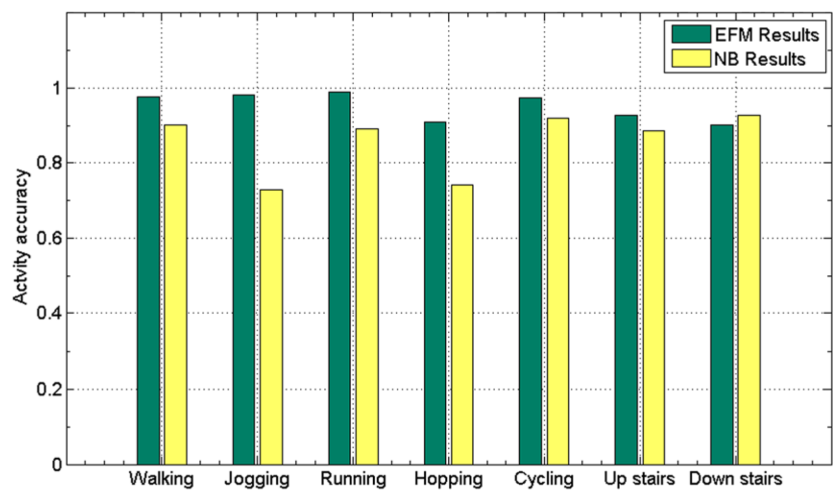


Fig. 6 A single day recognized activities routine

Fig. 7 Comparison of individual activity classification accuracy



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 4 and 5 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 Naïve Bayes (NB) classifier. Our dataset activities classes are imbalanced due to some activities that appear much more frequently than others. Class-accuracy [29] 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 Figs. 7 and 8 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 seen in Fig. 7, 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 pro-

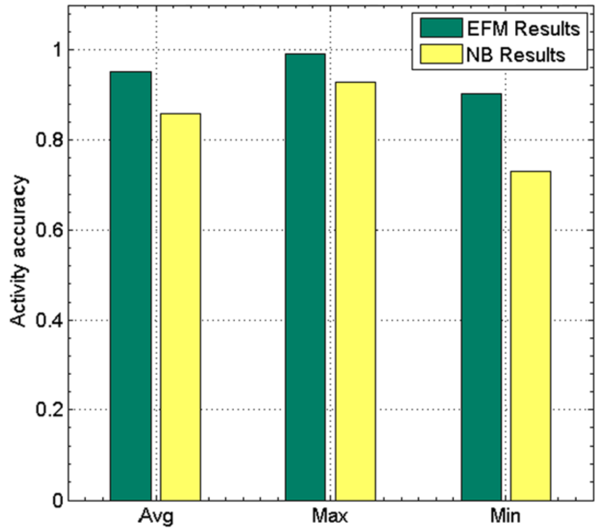


Fig. 8 Class-accuracy comparisons (Avg, Max and Min)

Table 6 Precision, recall, F-measure and accuracy

Model	Precision	Recall	F-Measure
EFM	0.9551	0.9540	0.9545
NB	0.8350	0.8619	0.8482

posed 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 Fig. 8 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 4, we computed three performance measures: precision, recall, F-measure, as shown in Table 6. The EFM performed better for all three measures. In addition to the precision and recall, we performed the non-parametric Wilcoxon Signed-Ranks Test [30] 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 Naïve Bayes method with a level of significance $\alpha = 0.05$.

6 Conclusion and future work

The proposed model utilized the embedded accelerometer sensor of a commercial smartphone to recognize dynamic activities. Dynamic 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 uncertainties 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 dynamic 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 dynamic activities, and the optimal parameters for in-depth investigation are determined. In every experiment, approximately 9 % higher class-accuracy was observed and p-value < 0.05. Experimental results demonstrate that handling the issues discussed above 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.

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Appendix

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 $Y = \{Y_m\}$, $m = 1, \dots, M$ is calculated as:

$$l(\Theta) = \sum_{m=1}^{M} \log p_{mix}(Y_m|\Theta) \tag{12}$$

Expectation Step (E-Step)

$$p_{mix}(Y_m \mid \Theta) = \sum_{k=1}^{K} p(Y_m \mid \theta_k) w_{mk} \quad \text{and} \quad \sum_{k=1}^{K} w_{mk} = 1 \tag{13}$$

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 $\theta_k = [\mu_k, \delta_k]$.

Inserting (13) into (12) gives,

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

For Expectation step, use Jensen's inequality,

$$l(\Theta) \geq \sum_{m=1}^{M} \left[\sum_{k=1}^{K} w_{mk} \log p(Y_m \mid \theta_k) \right]$$

$$\Rightarrow \quad E\left[\log\left(p(Y_m \mid \theta_k)\right)\right]$$

At the Maximization step (M-Step)

$$\nabla_{\theta_k} \sum_{m=1}^{M} \sum_{l=1}^{K} w_{mk} \log p(Y_m \mid \theta_l) \tag{14}$$

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

$$\nabla_{\theta_k} l(\Theta) = \sum_{m=1}^{M} \frac{w_{mk}}{p(Y_m \mid \theta_k)} \nabla_{\theta_k} p(Y_m \mid \theta_k) \tag{15}$$

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

$$p(Y_m \mid \theta_k) = \frac{1}{\sqrt{2\pi \delta_k^2}} \exp\left\{ -\frac{(Y_m - \mu_k)^2}{2\delta_k^2} \right\} \tag{16}$$

The Expectation step is easily defined by inserting (16) into (13). For Maximization, inserting (16) into (15) and taking the derivative w.r.t. μ_k gives,

$$\begin{aligned} 0 &= \frac{\partial}{\partial \mu_k} l(\Theta) \\ &= \sum_{m=1}^{M} \frac{w_{mk}}{p_k(y_m|\theta_k)} * \frac{1}{\sqrt{2\pi \delta_k^2}} \exp\left\{ -\frac{(y_m - \mu_k)^2}{2\delta_k^2} \right\} \\ &\quad * \frac{-2(y_m - \mu_k)}{2\delta_k^2} \\ &= \sum_{m=1}^{M} w_{mk}(y_m - \mu_k) \end{aligned}$$

$$\mu_k = \frac{\sum_{m=1}^{M} w_{mk} y_m}{\sum_{m=1}^{M} w_{mk}} \tag{17}$$

Taking the derivative w.r.t. δ_k

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

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

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

$$\delta_k = \sqrt{\frac{\sum_{m=1}^{M} w_{mk}(y_m - \mu_k)^2}{\sum_{m=1}^{M} w_{mk}}} \tag{18}$$

Equations (17) and (18) are required parameters for the Gaussian membership function.

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