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ORIGINAL ARTICLE

Telemonitoring of Daily Activity Using Accelerometer and Gyroscope in Smart Home Environments

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Abstract
Wearable sensors in the smart home environment have been actively developed as assistive systems to detect behavioral anomalies. Smart wearable devices incorprated into daily life can respond immediately to anomalies and process and dispatch important information in real-time. Artificially intelligent technology monitoring of the user's daily activities and smart home ambience is especially useful in telehealthcare. In this paper, we propose a behavioral activity recognition framework which uses inertial devices (accelerometer and gyroscope) for activity detection within the home environment via multi-fused features and a reweighted genetic algorithm. The procedure begins with the segmentation and framing of data to enable efficient processing of useful information. Features are then extracted and transformed into a matrix. Finally, biogeography-based optimization and a reweighted genetic algorithm are used for the optimization and classification of extracted features. For evaluation, we used the "leave-one-out" cross validation scheme. The results outperformed existing state-of-the-art methods, achieving higher recognition accuracy rates of 88%, 88.75%, and 93.33% compared with CMU-Multi-Modal Activity, WISDM, and IMSB datasets respectively.

Keywords Daily life activity recognition · Local binary pattern · Mel frequency cepstral coefficients · Optimization algorithm · Reweighted genetic algorithm

1 Introduction

Advances in sensor technologies allow us to revolutionize the resident's daily life routines in indoor environments. Nowadays, embedded sensors are used in home environments to record frequent activities and to monitor physiological movements in order to avoid serious injuries [1, 2]. A smart home environment can learn to determine an individual's health and safety status, perform certain acquisitions, and make decisions in real-time [3, 4]. Accurate assessment and pertinent responses to continuous monitoring via Human Activity Recognition (HAR) systems can provide 24/7 care and support rehabilitation, surveillance, medical diagnosis, fitness therapies and disability support services.

In recent decades, different approaches have been implemented for HAR using wearable and video sensor devices. Video sensors provide reasonable results but they impose several limitations such as restricted movement, privacy issues, and changes in light conditions. By contrast, our work exploits the benefits of wearable sensors. In [5], Hussain et al. proposed a system to detect activity patterns by analyzing statistical features based on k-nearest neighbors. In [6], Guo et al. presented a feature solving strategy along with three basic classifiers to discriminate between a resident's activities. In [7], Dias and Cunha designed a model that monitors the health status and fitness of people using textile and wearable sensors. The above approaches provide good solutions in the HAR domain with some limitations such as the requirement of a large number of sensors, and unidirectional feature patterns. A novel method is needed to overcome such limitations and to improve the quality of the subject's life at home.

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In this paper, we propose novel multi-fused features of the Gaussian mixture model, and a reweighted genetic algorithm to classify human activities within the smart home environment. These fused features consist of a 1D local binary pattern (LBP), principal component analysis (PCA), Phase Stretch Transform (PTS), Mel Frequency Cepstral Coefficients (MFCC), and Gaussian Mixture Model (GMM) which drastically increases the performance of HAR. Moreover, optimization and classification algorithms are performed using biogeography based optimization (BBO) and a reweighted genetic algorithm (rGA). The implemented model was evaluated over CMU Multi-Modal, WISDM, and IMSB datasets. The experimental results show that our proposed methodology outperformed conventional methodologies in terms of performance.

The rest of this paper is organized as follows. The complete system methodology, presented in Sect. 2, consists of preprocessing, feature extraction, optimization, and classification. Section 3 describes an experimental setting, description of datasets, and performance results. Finally, Sect. 4 presents the conclusion and future work.

2 Proposed HAR Model

This section presents a detailed description of the monitoring of daily life activities which is intended to accurately predict complex patterns of behaviour. This is done by the extraction, optimization, and classification of novel features. Initially, the proposed system preprocesses the data of complex activities ranging from fitness/exercise and routine kitchen activities to life-log activities within the smart home environment. These collected data are segmented into 5 s window size and then filtered out using the Kalman filter. In the second step, five different features are extracted from time and frequency domains. Subsequently, in the last step, the extracted features are optimized and classified using biogeography-based optimization and a reweighted genetic algorithm. The architectural flow of the proposed methodology is depicted in Fig. 1.

2.1 Data Preprocessing and Noise Removal

In this step, preprocessing is done using a Kalman filter on the collected data to remove inconsistencies from the framed data as shown in Fig. 2. This filter acts as an optimal estimator which extracts parameters of interest from inaccurate, indirect, and uncertain observations [8]. The filtration is performed by reducing the mean square error in the signal and predicting the maximum likelihood of the current signal from the previous signal. It is defined as;

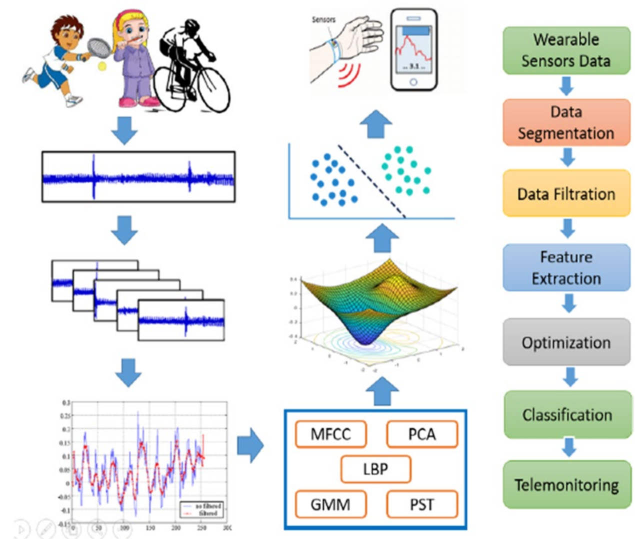

Fig. 1 The system architecture of the proposed HAR model

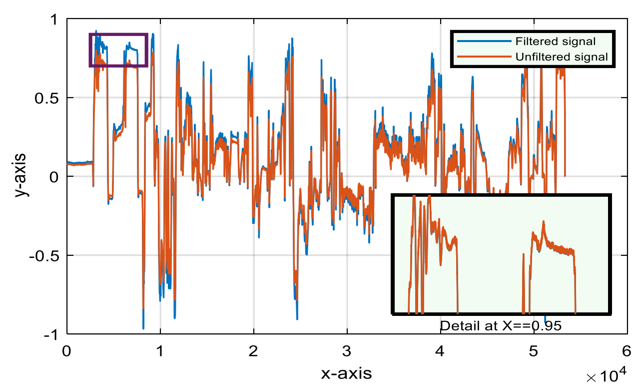

Fig. 2 Filtration of signal using Kalman filter

$$Kalman(sig) = (st)(sig - 1) + (M)(vec) + pn \tag{1}$$

In the above equation, *st* is the state transition model which is applied to the previous signal *sig-1*. Moreover, *M* represents the control input model that is applied to the control vector *vec* and *pn* where *pn* represents the process noise of the signal that is calculated from zero mean and covariance.

2.2 Multi-Fused Feature Extraction

After signal analytics, we transformed pre-processed data into significant multi-fused features. These features include Mel frequency features (MFCC), Gaussian mixture model (GMM), Local Binary Pattern (LBP), Principal Component Analysis (PCA), and Phase Stretch Transform (PST) features. The complete features extraction methodology is depicted in Algorithm 1.

```
Algorithm 1: HAR based Multi-fused features extraction
Input: F: accelerometer and gyroscope files directory
Output: Y: Multi-fused features for smart home activities.
/* Filtering and noise removal */
for 1: length(F)                 /* read all sensors data */
    [X] = extract_file(F)   /* extract files from directory */
    [FA] = filter(X, kalman filter) /* apply filter on data */
    [WIN]=segment(FA)   /*apply segmentation on data*/
    for i=1: WIN            /* Extract points*/
        [lbp_acc, lbpg] = LBP(FA)   /*extract local binary
                                     pattern*/
        [pca_acc, pca_gyro] = PCA(FA)   /*extract
                            principal component analysis*/
        [pst_acc, pst_gyro] =   PST(FA)   /*extract phase
                                     stretch tranform*/
        [mfcc_acc, mfcc_gyro] = MFCC(FA) /*extract
                        melfrequency cepstral coefficients*/
        [gmm_acc, gmm_gyro] = GMM(FA)   /* extract
                               gaussian mixture model*/
    end
end
/* combine all above calculated features into one matrix*/
  Y= combine_features(lbp_acc, lbp_gyro, pca_acc,
     pca_gyro, pst_acc, pst_gyro, mfcc_acc, mfcc_gyro,
     gmm, acc, gmm_gyro)
return Y
```

2.2.1 Mel Frequency Cepstral Coefficients Feature

Mel-Frequency Cepstral Coefficients (MFCCs) is mostly used in speech processing to analyze the speech resolution on low frequency. The calculated spectra of speech are mapped to a Mel scale which is used to calculate frequency band energies. The speech and inertial signal share similar energy distribution in lower frequencies therefore $MFCC_s$ can be applied for feature extraction in daily life activities recognition. MFCCs calculate the power spectrum by first taking the Fourier transform of the signal to find the power of the spectrum. The calculated spectrum is then mapped onto the Mel scale using overlapping windows. Finally, the log of the power is calculated on Mel frequencies and is taken to the discrete cosine transform. The resultant MFCCs represents the spectrum's amplitude (see Fig. 3).

$$MFCC(sig) = \sum_{i=0}^{n} g_n \mathrm{Cos}[pi/n(i+0.5)k] \tag{2}$$

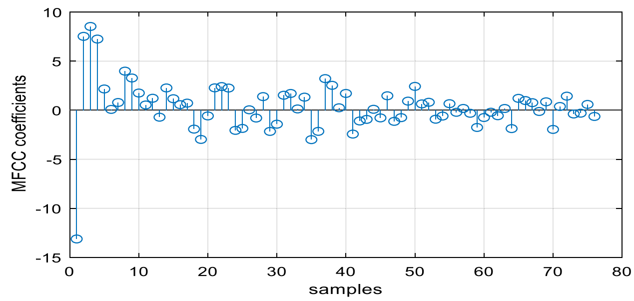

Fig. 3 MFCCs applied over wearable signals

$$sig(k) = \left\{ \begin{array}{l} sig(i), k = k_i \\ 0, other\, k \in [0, N-1] \end{array} \right\}$$

where g_n is the total number of sample signals in each frame, i is the current sample of the signal, and n represents total samples of the current frame. To get the coefficient of the signal, each critical band of the MFCCs signal sig is individually calculated and defined by k. MFCCs features are highly uncorrelated due to the discrete cosine transform. So, if the observed signal is equal to the desired signal then the signal values in the covariance matrix [9] are taken as MFCCs coefficients, otherwise, the signal values are assigned zero. Here, k_i is the index of the observed signal.

2.2.2 Gaussian Mixture Model (GMM)

Gaussian Mixture Model (GMM) is applied to the preprocessed data to find covariance, mean, and weight vectors which are used to model the clusters N of the dataset. The vector is calculated by using the maximum likelihood estimation of a given signal. After that, the weight vector is measured using an iterative maximization method to find the maximum probability. Finally, GMM covariance measures the deviation of two samples in the current signals. These parameters are calculated as;

$$GMMmean(sig) = \left(\sum_{i=1}^{n} s_i + \dots\dots\dots\dots + s_n \right) / n \tag{3}$$

$$GMMwr(sig) = \left[1 + \left(s_{i+1} - s_i \right) / s_i \right]^2 \tag{4}$$

$$GMM\mathrm{cov}(sig) = \sum_{i=1}^{n} \left(s_i - \mu_x \right) \left(s_{i-1} - \mu_y \right) / (n-1) \tag{5}$$

where $_i$ represents the index number, s_i and s_{i-1} are the current and previous samples of a frame respectively. In addition, the μ_x and μ_y are the means of accelerometer signals and of gyroscope signals, respectively. Finally, n represents the total number of samples. $GMM_{mean}(sig)$, $GMM_{wr}(sig)$, and $GMM_{cov}(sig)$ represents mean, weight vector and covariance of current GMM coefficients. GMM coefficients are calculated on a signal as shown in Fig. 4.

2.2.3 Local Binary Pattern

In Local Binary Pattern (LBP), the middle value from the samples is selected as a threshold and all other samples are compared against the selected threshold. If the sample of the frame is less than the threshold, the value is set to 0; otherwise, the value is set to 1. Finally, all the binary values are converted to decimal values (see Fig. 5).

LBP gives one decimal value against each frame which is defined as;

$$Binary(sig) = \begin{Bmatrix} 1, s >= threhold \\ 0, s < threshold \end{Bmatrix} \tag{6}$$
$$LBP(sig) = Decimal(Binary)$$

where s is the sample of the signal in the current frame and *threshold* is the center value of the frame. *Binary(sig)* represents the binary representation of a current sample. Moreover, *LBP(sig)* is the calculated local binary pattern of the current signal. The LBP algorithm is applied to an "eating soup" activity as shown in Fig. 6.

2.2.4 Principal Component Analysis (PCA)

PCA is a technique that uses the orthogonal information of signals to examine the interrelation of samples in the current frame. It combines the samples of a frame in a specific way so that we can retain the variables having a minimum average square distance and drop the rest of the variables. The first step is to calculate the center of the data by subtracting mean μ from each attribute x_i so that the origin is in the center of the data as shown in the following equation.

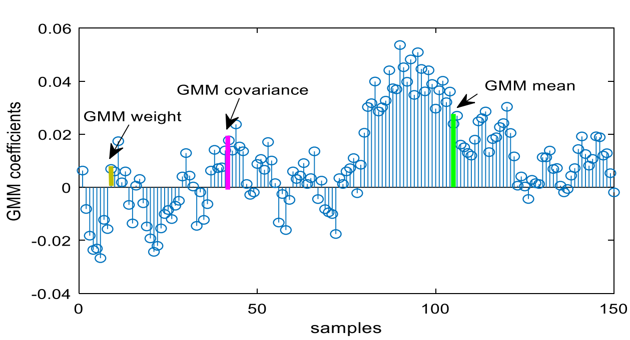

Fig. 4 Coefficients of GMM covariance mean and weight vectors

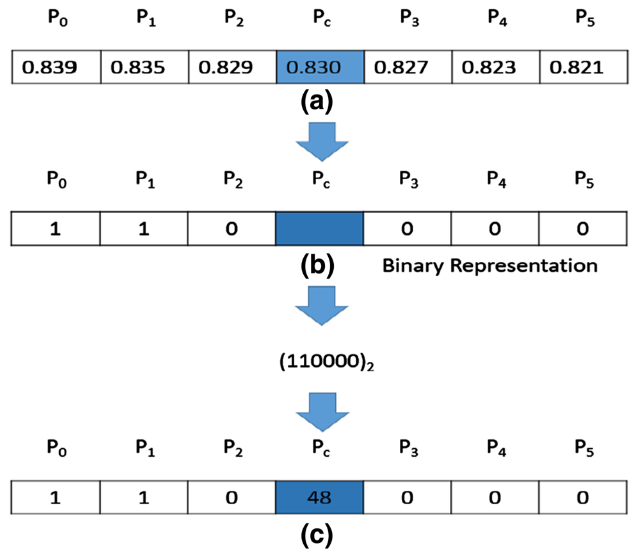

Fig. 5 LBP is applied to 7 samples value. First, the signal is divided into segments as in (**a**). In **b** the middle sample Pc is selected as a threshold value for associated values P_0, P_1,…, P_5. Finally, in (**c**) the resultant LBP code is converted into decimal representation

$$PCA(x) = x_i - \mu \tag{7}$$

Next, the covariance is calculated to find out positive or negative correlations between the numbers of attributes as shown below;

$$\mathrm{cov}(a_1, a_2, a_3, \ldots, a_n) = \frac{1}{n}\sum_{i=1}^{n} x_{a1},\ x_{a2}, \ldots, x_{an} \tag{8}$$

The covariance matrix result is multiplied by its transpose. Covariance matrix has two important features which are variance and covariance of the data. So, eignvectors e and eigenvalues λ represent data direction (covariance) and its magnitude (variance) respectively. Finally, the best-fitted eigenvalue and corresponding lambda are selected,

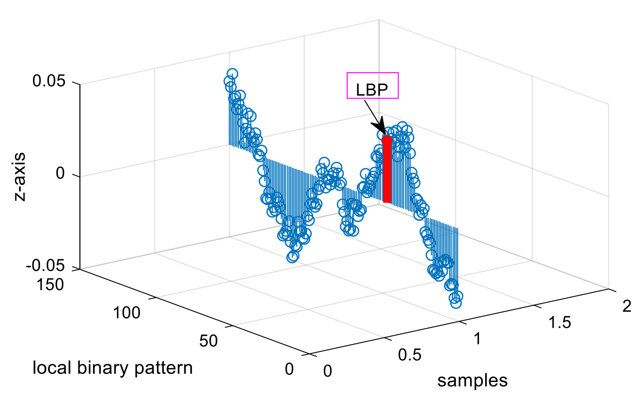

Fig. 6 The LBP of eating soup activity

which give greater eigenvector as shown in the following formula.

$$\sum e = \lambda e \tag{9}$$

Then, eigenvector is transformed into a new subspace to generate PCA coefficients as shown in Fig. 7.

2.2.5 Phase Stretch Transform Feature

In Phase Stretch Transform (PST), the preprocessed data is passed through a smoothing filter and then converted into the frequency domain. The transform's output is a phase in the spatial domain. The amount of phase selection depends on the amount of frequency to fetch high/low-frequency values. The threshold value of phase stretch transform is calculated through an iterative method. It is an approximated mean which is calculated from the maximum and minimum values of the range of the signals that give the best possible results. In our case, the optimum value of the threshold is 0.002. Thus, the phase of the signal greater than 0.002 is set to 1 and otherwise it is set to 0. The PST is defined as;

$$PST(sig) = FFT\left[K(sig) \bullet L(sig)\right] \bullet FFT\left[B(sig)\right] \tag{10}$$

where *FFT* is the Fast Fourier Transform of the frequency response of *L(sig)* and a warped phase *K(sig)*. On the other hand, *B(sig)* is the output of the phase signal. *PST(sig)* represents the Phase Stretch Transform of the current samples. The calculated PST is shown in Fig. 8.

2.3 Biogeography Based Optimization (BBO)

Biogeography Based Optimization is a heuristic algorithm which exhibits excellent optimization performance. The algorithm is implemented on the concept of the natural distribution of species (i.e. signal). These species distribute themselves in different habitats which are relatively independent of each other. The environmental suitability of species depends on the value of the Habitat Suitability Index (HSI) [10]. The higher value of HSI leads to higher suitability for species and vice versa. Similarly, species living in habitats with lower HSI values try to move to habitats having higher HSI values. Therefore, individuals, iteratively exchange information about immigration and emigration rates based on HSI values to build candidate solutions as shown in Fig. 9. The BBO algorithm first randomly initializes *N* number of vectors. Each vector is evaluated and then follows mutation and migration steps to reach minima [11].

The BBO algorithm is divided into the following steps;

a. Initialize BBO parameters that include emigration rate, maximum emigration rate, migration rate, maximum migration rate, species count, and so on. These parameters are necessary to convert the solution of vectors into habitats and to Suitability Index Variables (SIVs).
b. After initializing parameters and habitats, a mapping is done between the emigration rate, number of species, and immigration rate based on the predicted value of HSI.

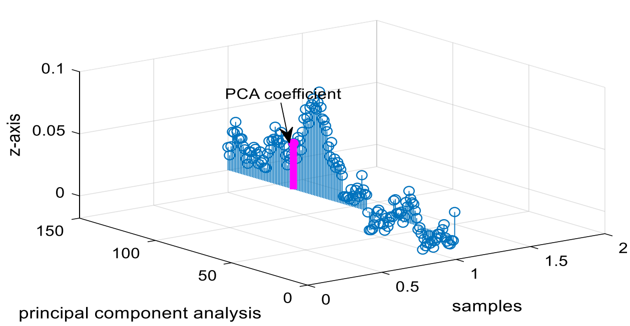

Fig. 7 PCA of wearable signal coefficients

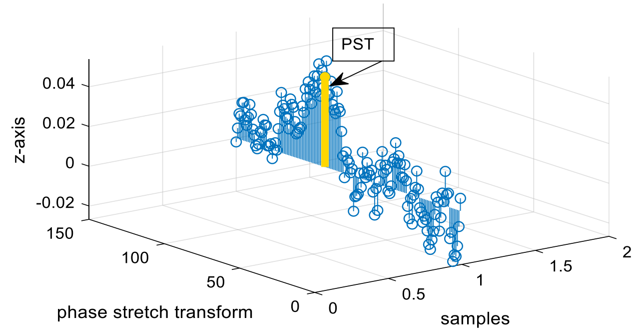

Fig. 8 Phase stretch transform coefficient of wearable signal

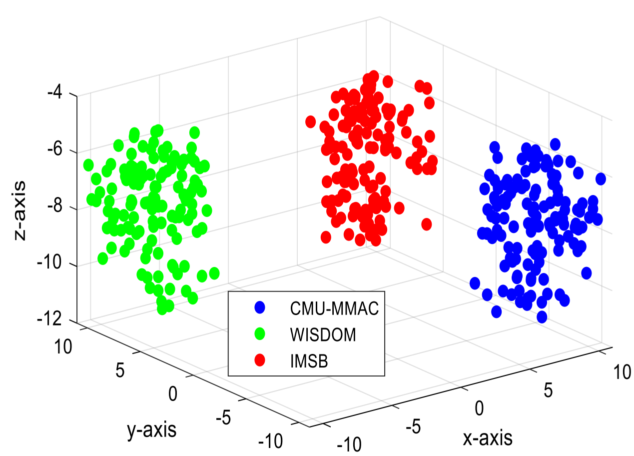

Fig. 9 Biogeography based optimization is applied to three different HAR datasets

c. Then, migration is done to modify the SIV of the selected habitat.
d. Finally, the mutation is done on the counted value of species, which includes increasing or decreasing the probability of the species count.
e. The loop is repeated from step c for a fixed number of iterations.

2.4 Classifier: Reweighted Genetic Algorithm

For activity classification, we introduced a modified version of the state-of-the-art [12] genetic algorithm (GA). The proposed reweighted genetic algorithm (rGA) is divided into two phases, namely, reweighted feature selection and classification. In the first phase, optimized features are pooled together and assigned a weight by using a support vector machine and random forest classifier. In the second phase, resultant output is classified into different human activities as defined in Algorithm 2.

Algorithm 2: Re-weighted Genetic Algorithm for Classification
Input: OF: Optimized features
Output: CF: Classified pattern for smart home activities.
/* Codebook generation and pattern matching */
for 1: row /* read all sensors data */
for 1: col /* Extract points*/
[CC] = Crossover_pattern (OF) /* calculate crossover chromosomes*/
[GM] = Mutation (cross_chrm) /*calculate global maxima*/
[OC, WC] = Duplicate (OF) /*divide into original and weighted chromosomes*/
[CB] = Fitness (WC, CC) /*generate codebook*/
[CF] = Classification (OC, GM) /*extract classified features*/
end
end
/* return classified features*/
return CF

Initially, rGA starts by taking optimized features and applying crossover and mutation techniques. In the crossover function, the optimized features are represented as chromosomes in a subspace known as population. A mutation is then applied to the crossed chromosomes to increase the diversity of chromosomes and provide a methodology for escaping from local optimum. Finally, resultant chromosomes are

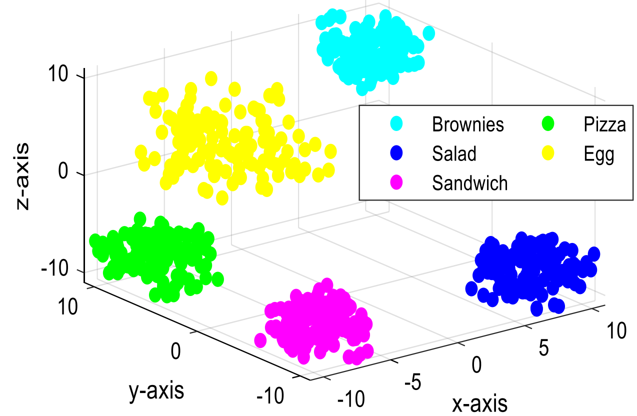

Fig. 10. 3D plot of rGA classification over CMU-MMAC dataset

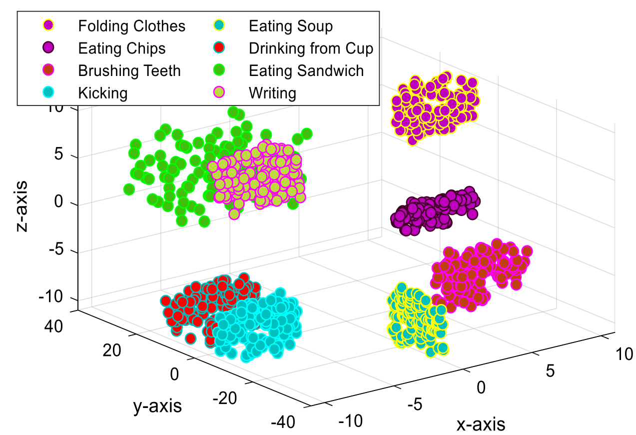

Fig. 11. 3D plot of rGA classification over WISDM dataset

duplicated and weights are assigned to them so that prominent features get assigned by better weight.

$$Cross_{Opt}(f) = \sum_{n=1}^{N} O_{f1}, O_{f2}, \ldots\ldots, O_{fn} \times O_{f1}, O_{f2}, \ldots\ldots\ldots, O_{fn} \quad (11)$$

$$Mut_{Opt}(f) = O''_{f1}, O''_{f2}, O''_{f3}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots, O''_{fn1} \quad (12)$$

where O_{fl} is the optimized feature of BBO. *Cross* and *Mut* is the crossover and Mutation function applied to the biogeography based optimized features, respectively.

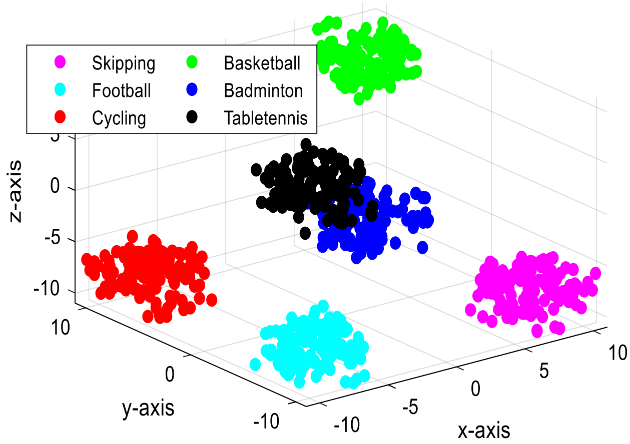

Fig. 12. 3D plot of rGA classification over IMSB dataset

These rGA patterns are then inserted into codebook patterns. These patterns are classified by finding a maximum matching cluster from the codebook. The classification results of CMU-MMAC, WISDM, and IMSB datasets are depicted in Figs. 10, 11, 12.

3 Experimental Results and Analysis

3.1 Experimental Setting and Datasets

To observe the training/ testing performance [13] of the proposed HAR system for smart home environments, we applied the leave-one-out cross-validation (LCV) method.

In CMU-MMAC (CMU-Multimodal Activity Database) [14], the dataset is taken from many other modalities besides accelerometer and gyroscope sensors. In this paper, only accelerometer and gyroscope sensor data are used. The sensors are located all over the human body including upper arms, forearms, right and left calves, abdomen, thighs, and wrists. There are five different food preparation activities including *brownies, salad, sandwiches, pizza, and eggs,* which are performed within a kitchen environment.

WISDM (Wireless Sensor Data Mining) dataset [15] is collected using an accelerometer and gyroscope on a smartphone and smartwatch. A smartphone is placed in a pocket and the smartwatch is placed on the dominant hand. A total of 51 subjects performed 18 different activities from which only eight activities are selected i.e. *folding clothes, eating chips, brushing teeth, kicking, eating soup, drinking from a cup, writing, and eating sandwiches*, for the evaluation of our smart home proposed methodology.

The self-annotated IMSB (IM-Sporting Behaviors) dataset [16] contains collective data from accelerometer and gyroscope sensors. These sensors are attached at three different locations: the knees, back, and wrists. This dataset includes fitness/sports exercises, i.e. *skipping, football, badminton, basketball, cycling, and table tennis*.

Table 1 Recognition accuracy over CMU-MMAC dataset

Activity	BR	SL	SD	PZ	EG
BR	**8**	0	1	0	1
SL	0	**10**	0	1	0
SD	1	0	**9**	0	0
PZ	0	1	0	**8**	1
EG	0	0	1	0	**9**
Mean recognition accuracy = 88%					

BR brownies, *SL* salad, *SD* sandwich, *PZ* pizza, *EG* egg

3.2 Experimental Result and Evaluation

We examined the performance of the proposed methodology over three challenging datasets CMU-MMAC, WISDM, and IMSB. Our final application is installed on smart phones to monitor sporting behaviors and daily life activities. The purpose of testing the application on a smart phone is to analyse the model in real-time. This model can be used in medical applications by first testing the model on a health monitoring dataset. This model can determine whether the person needs external help. Depending on the situation, the smart phone can automatically alert pre-assigned caregivers. It can also be used to give advice (e.g. exercise more) or to reassure the patient, based on the sensor and environmental data. The system achieved recognition accuracy rates of 88%, 88.75%, and 93.33%, respectively. The accuracy rates are presented in the form of a confusion matrix as shown in Tables 1, 2, 3.

An extensive number of experiments were performed on three datasets that give significantly improved results against state-of-the-art methods as shown in Table 4.

4 Conclusion

In this paper, we developed an effective HAR framework for a smart home environment via multi-fused features and a reweighted genetic algorithm. These features include MFCC, GMM, LBP, PST, and PCA, to select the optimal data. BBO with rGA is used to optimize, train, and recognize different types of daily life activities. Our proposed system outperforms others in terms of accuracy at 88%, 88.75%, and 93.33% over CMU-MMAC, WISDM, and IMSB datasets, respectively. In real-world applications, our proposed

Table 2 Recognition accuracy over WISDM dataset

Activity	FC	EC	BT	KC	ES	DC	WR	ED
FC	**9**	0	0	0	0	0	1	0
EC	0	**10**	0	0	0	0	0	0
BT	0	1	**9**	0	0	0	0	0
KC	1	0	0	**9**	0	0	0	0
ES	0	1	0	0	**8**	0	0	1
DC	0	1	0	0	0	**9**	0	0
WR	1	0	**0**	0	0	0	**9**	0
ED	0	1	0	0	1	0	0	**8**
Mean recognition accuracy = 88.75%								

FC folding clothes, *EC* eating chips, *BT* brushing teeth, *KC* kicking, *ES* eating soup, *DC* drinking from cup, *WR* writing, *ED* eating sandwich

Table 3 Recognition accuracy over IMSB dataset

Activity	SK	FB	BD	BB	CY	TT
SK	**10**	0	0	0	0	0
FB	0	**8**	1	1	0	0
BD	0	0	**9**	0	1	0
BB	0	0	0	**10**	0	0
CY	0	0	1	0	**9**	0
TT	0	0	0	0	**0**	**10**
Mean recognition accuracy = 93.33%						

SK skipping, *FB* football, *BD* badminton, *BB* basketball, *CY* cycling, *TT* table tennis

Table 4 Comparison of the proposed system with state-of-the-art methods

Methods	Mean accuracy (%)		
	CMU-MMAC	WISDM	IMSB
Support vector machine [17]	69.8	–	–
Random Forest [18]	–	75.9	–
k-Neighbors [19]	–	77.8	–
HMM-MIO [20]	71.2	–	–
Proposed method	**88**	**88.75**	**93.33**

system should perform well for the recognition of daily life activities in indoor smart home/office/hospital environments.

In the future, we plan to improve statistical features by adding different techniques. We will also develop our dataset to include complex activities, especially data for children and data for Parkinson's disease patients.

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