Hybrid Sensor Based Fuzzy Clustering Neural Network Classification for Human Activity Recognition

Ramtin Aminpour[1] and Elmer Dadios[2]

***Abstract*—IThe smartphone is going to become an all-purpose gadget for the human life and all of them at least armed with accelerometer sensor. In this study, the fuzzy c-means has been considered in the ANFIS model to produce the fuzzy inference system (FIS) to make the classification with the neural network algorithm to detect the six major human activities. The data were taken in real life with the accelerometer sensor of a smartphone. The results of the experiments show that the 97.2% accuracy could be acceptable in the field of study and the clustering structure could make the simulation more robust and faster.**

***Keywords:* Fuzzy clustering, Neural network, Human activity recognition**

I. Introduction

Human activity recognition is widely used in humancomputer interaction, fitness tracking, and maintenance of elderly people [1]–[4]. The data from activities could be gathered by camera sensors, audio sensors, and embedded sensors [5]. Nowadays, smartphones are personal importance in the societies. All of the smartphones have internal sensors to collect data with low power consumption and powerful processors. One of the most useful embedded sensors of the smartphones is the accelerometer which could be used to collect extensive data on human activities [6].

In this study, a Neuro-Fuzzy inference system combined with the fully-connected layer neural network has been used to classify the human activities. Integration of neural networks and fuzzy logic systems could be a hybrid approach to the model of a system. The study of the architecture is shown in Figure 1.

II. Related Work

Applications of computational intelligence have been used in many fields based on neural network, fuzzy logic, genetic algorithm, and hybrid approaches of these algorithms. NeuroFuzzy has been proposed by Jang [7] with the concept of integration with human and learning capability of the structure of the neural network. Neuro-Fuzzy systems could be powerful solutions in many applications [8], [9].]. Neural network and fuzzy logic are dynamic with the ability of parallel processing to approximate the input and output functions.

One of the problems of fuzzy design is the difficulty to determine the number of rules and also the number of membership functions of every rule. Hybrid algorithms can optimize the systems to the trade of this problem [10], [11]. Hybrid algorithms have been used for fine-tuning and learning of parameters of the neural network and fuzzy logic. Lin [12] proposed a Takagi Sugeno (TS) type of fuzzy model with a hybrid learning algorithmic rule. The approach was used to modify the mean and the deviation of the membership functions. A combined Takagi Sugeno type Neuro-Fuzzy system has been done with the bee colony algorithm for parameter optimization [13].

A comparative study for classification of ECG signals with MultiLayer backPropagation learning (MLP) has been done by Ozbay [14]. They introduced a Fuzzy Clustering Method (FCM) based neural network, which shows faster and better accuracy to compare of ordinary MLP architecture.

Kim et al. [15] have developed the FCM algorithm for the color clustering problems. Mingoti [16] performed a clustering algorithm based on Self-Organizing Map (SOM) neural network and FCM and they found that the performance of the algorithm was improved in the presence of outliers. A hybrid study of Support Vector Machine (SVM) and FCM for gene dataset has been done

[1] Ramtin Aminpour, Department of Electronics and Communications Engineering, De La Salle University, Manila, Philippines (email: ramtin aminpour@dlsu.edu.ph)

[2] Elmer Dadios, Department of Manufacturing Engineering and Management, De La Salle University, Manila, Philippines (email:elmer.dadios@dlsu.edu.ph)

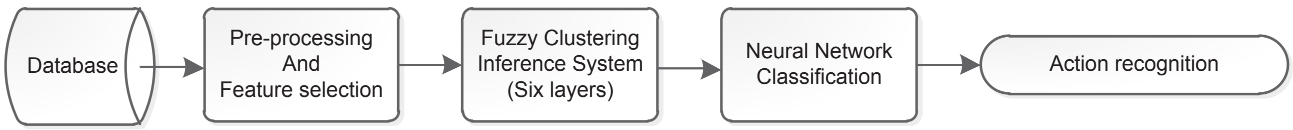

Fig. 1. Architecture of the FCM neural network model

by Mukhopadhyay [17]. Aydilek [18] proposed a hybrid approach of Genetic Algorithm (GA) with FCM and SVM to estimate missing values and optimization of the size of a cluster.

The hybrid algorithm could be an optimal way of a solution for system design. The learning algorithm of Neuro-Fuzzy is based on a steep descent optimization like the backpropagation algorithm. Similar to other gradient methods, steep descent optimization cannot prove to converge to the global solution. On the other hand, the parameters of the membership functions cannot be tuned in and modified. In these situations, optimization with hybrid algorithms could give an efficient result.

III. DATASET DESCRIPTION AND FEATURE EXTRACTION

An Android smartphone has been used to collect the data in this study. The accelerometer has been collected the data with a sample frequency rate of 50 Hz from seven adult persons to detect six activities of walking, jogging, running, jumping, using stairs, and standing. The smartphone was placed in the front pocket of the volunteers. Each activity was repeated five times during a period of 30 seconds. After collecting the data, pre-processing of the data by a low-pass filter has been done to clean the raw data from missing data, noise reduction, and outlier detection.

To detect the activities, proper feature set must be extracted from the raw data. A sliding window with the length of 2.5 seconds is used to separate the data. The acceleration sensor of the smartphone has three dimensions in which four features from time domain and two features of frequency domain have been extracted. In total 18 features have been selected to extract from X, Y, and Z axes of the accelerometer. These features are shown in Table I. In the Table x_i are the features, N is the total number of features, and FFT is the Fast Fourier Transform of the features.

The data might have a different scale because of the gait, the height and the weight of volunteers. For this reason, the data must be normalized to zero means before using into the classification algorithm.

TABLE 1
FEATURES EXTRACTION FROM ACCELEROMETER OF SMARTPHONE

Features	Math explanation	
Mean Absolute Value	$\frac{1}{N}\sum_{i=1}^{N} x_i$	(1)
Variance	$\frac{1}{N}\sum_{i=1}^{N} (x_i - \overline{x})^2$	(2)
Root Mean Square	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}$	(3)
Skewness	$\frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^3}{\sigma^{3/2}}$	(4)
Dominant frequency	$Max(FFT)^2$	(5)
Energy	$\sum(FFT)^2$	(6)

$$f_{normalized(i)} = \frac{f_{raw(i)} - \mu}{\sigma} \tag{7}$$

Here μ is mean and σ is the standard deviation of the features data. All the raw data replaced with normalized data to build the features matrix.

IV. CLASSIFICATION MODEL ARCHITECTURE

The structure of the adaptive neuro-fuzzy framework model (ANFIS) consists of input variables and output variables with a Takagi-Sugeno type of rule-based. The type of this network is an adaptive, multi-layer, and feed-forward [7]. The rule sets are evaluated by linguistic variables, a linear combination between input values, and a constant parameter which is employed to obtain the result of the rules.

In the first layer of this network, input variables are mapped into fuzzy sets through the process of fuzzification and generate membership grades with a membership function such as triangular or sigmoid. The next layer is working as a fuzzy conjunction to combine the fuzzy sets on each input. Another layer calculates the ratio of the rule that fire to the sum of all firing strength and then multiplied by the function of TKS fuzzy rules and extract the sum of all outputs of each rule. Finally, the crisp fuzzy output is calculated during the process of defuzzification by the weighted average method.

The ANFIS has two types of parameters, linear parameters on the consequent part and nonlinear parameters in the commence part. To optimize these variables, ANFIS has several strategies such as gradient descent, steepest descent, and hybrid technique [7]. In the consequent part, the output of each layer is transferred toward the last layer and the parameters are adjusted by the least squares method. In the premise part, the error signals are transferred to the first layer and update the parameters by the gradient descent method. The processes are done with the limited number of iterations during the epochs. The error between the output and also the target goes to minimize by weight adjustment of the connections throughout the learning method [19].

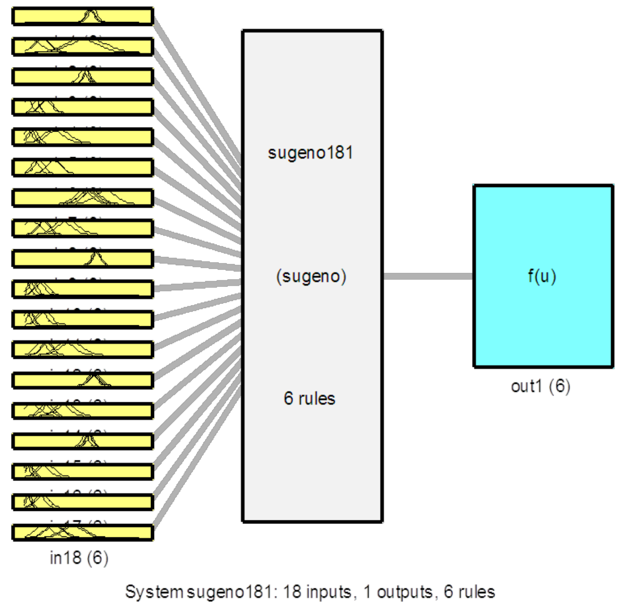

Fig. 2. Sugeno neuro fuzzy clustering model

The Sugeno Neuro-fuzzy clustering for this study is shown in Figure 2.

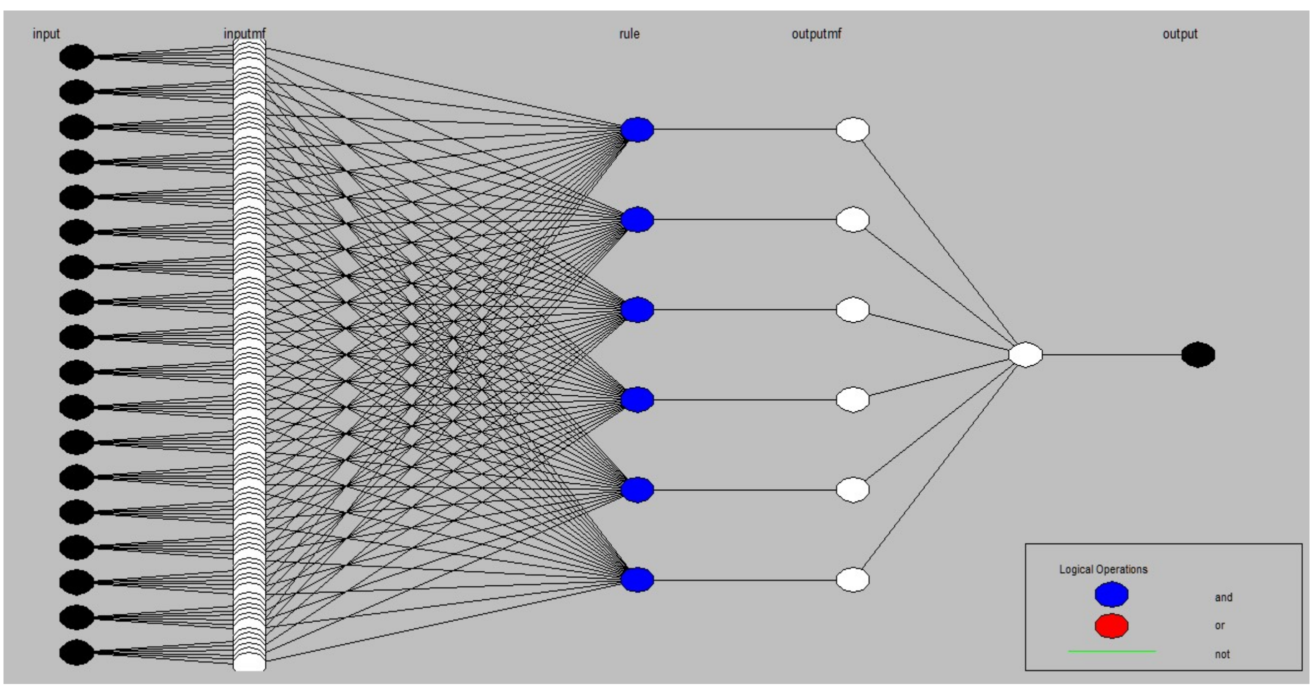

Fig. 3. ANFIS structure model

A. ANFIS Model Building

In this study, the data have been separated into three parts. Seventy percent have been used during the training of the algorithm, 15% as a checking data to prevent of the over-fitting of the model, and remaining 15% for testing of the model to check the predicted ability of the algorithm. During the training phase of FCM, the parameters are determined automatically in the specific epochs to minimize the checking error. Samples of the dataset for walking and running activities are given in Table II.

There are three methods to generate the fuzzy inference system (FIS) structure in ANFIS, grid partition, subtractive clustering, and fuzzy c-means clustering [20]. The fuzzy clustering method and the neural network which have been used as a classification are explained below. Because of six activities, the simulation has six different outputs. The ANFIS structure of one of the outputs of this study is shown in Figure 3.

B. Fuzzy Clustering Method

Fuzzy inference system (FIS) could be generated by fuzzy c-means (FCM) clustering. The FCM structure can generate the rules from the behavior of the data and determine the number of rules and membership functions of the input and output variables of the algorithm. The number of clusters can be set in the FCM algorithm. The bigger cluster radius generates fewer clusters and fewer rules during the process of generating FIS. In the Takagi Sugeno structure, the membership functions for input and output are set with Gaussian and linear, respectively.

The steps of a fuzzy clustering algorithm are as follows [21], [22]:

1) Initialize the number of clusters.
2) The fuzzification step which is selecting a metric Euclidean norm and the weighting metric.
3) Initialize the cluster prototype and iterative counter.
4) Calculate the partition matrix.
5) Update the fuzzy cluster centers.
6) If the norm of cluster centers was smaller than epsilon then stop the algorithm otherwise, repeat step two up to four.

TABLE 2
SAMPLES OF DATASET FOR TWO ACTIVITIES

Walking$_x$	***Walking$_y$***	***Walking$_z$***	***Running$_x$***	***Running$_y$***	***Running$_z$***
–0.03	–1.2	–0.66	0.6	0.23	0.24
–0.03	–1.2	–0.66	0.1	0.37	0.11
0.05	–0.79	0.05	–0.33	–0.2	–0.18
0.41	–1.06	0.16	–0.33	–0.2	–0.18
0.41	–1.06	0.16	1.36	–1.32	1.26
–1.27	–1.5	–0.15	–1.25	–1.99	0.22
–0.45	–0.18	–0.07	–0.13	–0.01	0.04
–0.45	–0.18	–0.07	–0.13	–0.01	0.04
–0.5	–0.64	0.44	0.81	–1.99	–0.55
0.06	–1.05	–0.59	0.81	–1.99	–0.55

TABLE 3
THE CONFUSION MATRIX OF ACTIVITIES FOR CLASSIFIER

Activity	**Walking**	**Jogging**	**Running**	**Hopping**	**Using stairs**	**Idle**
Walking	2991	64	5	0	33	5
Jogging	16	1784	32	2	0	2
Running	11	19	1531	9	5	0
Hopping	24	8	2	14	1366	8
Using stairs	24	8	2	14	1366	8
Idle	3	0	0	0	8	1679

The feature data have been grouped into six clusters to distinguish the six activities of the target. Six features are extracted from each axis of the accelerometer. In total, 18 features are used to detect the activity of each class. As a result, in this study, 108 fuzzy membership functions are generated to distinguish the output activities. Some samples of fuzzy membership functions for the first output of the target are shown in Figure 4, Figure 5, and Figure 6. The Gaussian membership functions have been chosen automatically by fuzzy inference system (FIS) in contrast with the fuzzy logic algorithm.

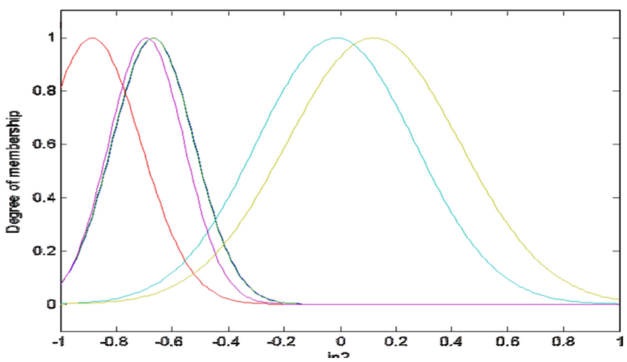

Fig. 4. Fuzzy membership of Input 2 for the first class

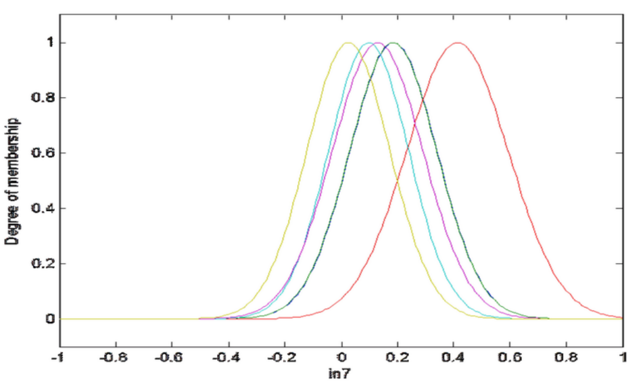

Fig. 5. Fuzzy membership of Input 7 for the first class

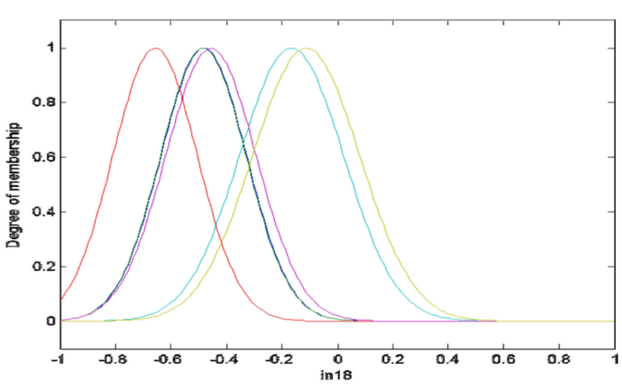

Fig. 6. Fuzzy membership of Input 18 for the first class

V. Experiment and Analysis of Results

To detect the activities the features data have been clustered to the number of activities by the fuzzy clustering algorithm. In the next step, the output of FCM has passed through a full node connection neural network to classify the human activities. The pattern recognition network has 18 neurons in the hidden layer, the training function of the network has been selected by Levenberg-Marquardt, and the performance function was chosen by mean square error. The features data of FCM have been divided randomly in the training ratio of 70%, the validation ratio of 15%, and the remained 15% for the test of the algorithm.

The result of confusion matrix and ROC curve are shown in Table III and Figure 7 respectively. The ROC curves which are closer to the left part of the plot have better classification accuracy. The confusion table shows that the most confused about activities are between jogging and walking, and using stairs and walking. The simulation shows that the accuracy of this classification is 97.2%. The output performance of the algorithm is shown in Figure 8. In the performance of the simulation, after 30 epochs the training stopped due to an increase of validation error against the minimum mean square error (MSE) parameter. The confusion table of the classifier shows that maximum errors are between jogging with walking, running with jogging, and using stairs with walking activities.

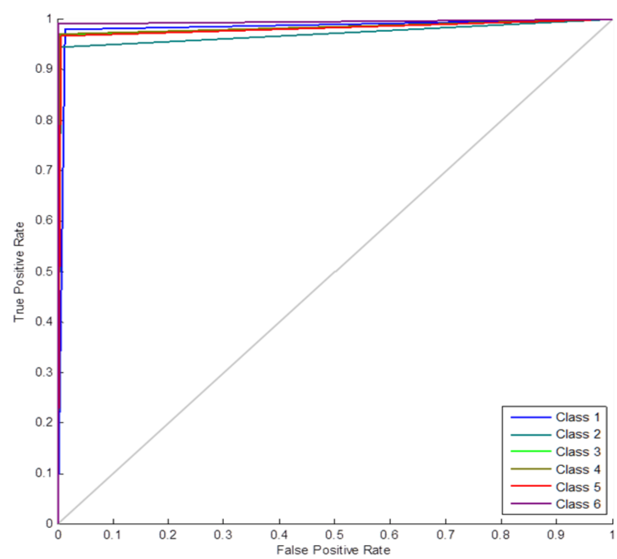

Fig. 7. ROC curve of classification

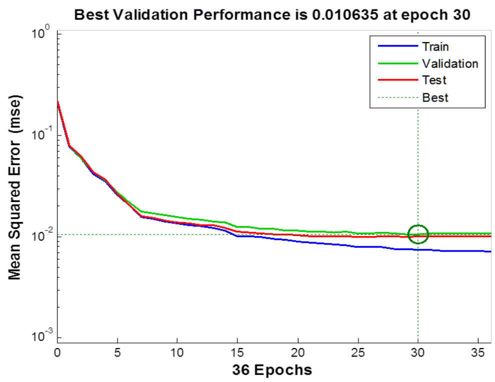

Fig. 8. Performance of simulation model

VI. Conclusion and Future Work

In this study, the hybrid fuzzy clustering with the neural network algorithm is used to classify and recognize the human activities. The fuzzy c-means is used to generate the fuzzy inference system to develop the ANFIS based method.

Using the hybrid fuzzy cluster algorithm proves that the developed ANFIS model is more robust and faster than classic algorithms with an acceptable accuracy to compare of related works in the relevant area.

In the future works, the hybrid Fuzzy Clustering Neural Network algorithm could be compared to another type of hybrid fuzzy cluster algorithms such as Ant colony optimization, Differential evolution, or Particle swarm optimization.

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