An ANFIS-based Human Activity Recognition using IMU sensor Fusion

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***Abstract*—Physical human activity is central to reducing the risk of many chronic diseases, thus it is considered vital to promoting healthy life styles. Also human Activity recognition (HAR) in recent times has found application in the explanations of the origin of complex diseases. In this paper an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based model is introduced for classification of daily living activities (ADLs) using data collected with a tri-axial Inertial Measurement Unit (IMU) sensor. Specifically, normalized data from the IMU axes within a specific window were considered to classify four chosen daily living activities (sit, stand, walk and run). The proposed ANFIS classifier were evaluated in terms of Root Mean Square Error (RMSE) over a variety of different ANFIS parameters and the results show that the selected activities are recognized well with an an overall accuracy rate of 98.88%.**

***Index Terms*—Human Activity Recognition, ANFIS, Sensor fusion, tri-axial IMU.**

I. Introduction

The use of various artificial intelligent tools in human gait recognition and several others human activities of daily living has been the focus of several research studies recently. This is because Human Activity Recognition (HAR) technologies are vital to promote healthy life styles and have the potential to offer explanations to the origin of complex diseases [1]. Moreover, other areas where HAR have found applications include Active and Assisted Living (AAL) systems for smart homes, monitoring and surveillance systems for indoor and outdoor activities, and tele-immersion (TI) applications [2].

Recently, various techniques have been studied to capture and classify human activities such as walking, sitting, lying down, standing and running conditions [3], [4]. These methods basically include image [5] [6] and non-image [7] based procedures. In image-based approaches multiple images of different classes of activities are taken as inputs to predict these activities. A comprehensive review of this approaches could be found in [8]. From user based evaluations, it was inferred that patients usually would prefer non-image based approaches because of privacy, convenience, and cost of equipment [9].

In view of the above, among several other sensor data, the use of IMU or accelerometer data in combination with artificial intelligent tools has enabled highly accurate classification of these human activities. For instance, a single input single output Fuzzy Inference System (FIS) for recognition of slow, medium and fast running conditions was proposed in [4]. This system was based on the hypothesis that if accelerometer data provides low, average or high Root Means Square (RMS) acceleration values then the inputs could be recognized as either slow, medium or fast conditions respectively. However, this system cannot be used to recognize activities where acceleration variation are not very distinct and or when using other sensor information rather than acceleration.

Fuzzy logic based HAR for the purpose of elderly home monitoring was the major focus in [10], where activities such as sleeping, exercising, bathing and several others were studied using inputs from different sensors. Although fuzzy logic implementation is always known for its simplicity, the case is not the same in the above because the model used a multiple input single output, and thus the number of rules becomes huge and consequently it will be difficult to correlate.

To overcome the complexity that comes with increased number of inputs and thus increased if-then rules, the use of Adaptive Neuro-Fuzzy Inference System (ANFIS) based HAR has been proposed and implemented. For example, a fuzzy computing model of activity recognition on Wireless Sensor Network (WSN) Movement Data for ubiquitous healthcare measurement was studied in in [3]. A FIS were used to model activities with distinct acceleration parameters and the ANFIS was used to model more indistinct activities. Thus, it can be concluded that ANFIS based activities classification performs better than the FIS based model in cases where non-linear sensor data are used. This is could be valid since the number of membership functions and the number of if-then rules will be enormous and usually the human is not able to accurately model this if-then based rules.

Although the aforementioned studies have illustrated the use of hand-crafted features over carefully selected sliding time windows extensively for FIS based systems; and a few others based on ANFIS for activity recognition, most of these studies have generally investigated the use of accelerometer data developed based on Single-Input and Single-Output (SISO) fuzzy model to classify human activities. Also the benchmark activity recognition based on end-to-end classification-style has received little attention in the literature. Hence, in this paper, we investigate the use of multiple inputs single output ANFIS based systems to classify sit, stand, walk and run ac-

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tivities and also consider benchmarking based on membership function performance. This recognition is achieved with the help of fusing the data comming from multiple sensors in the IMU together.

The rest of this paper is organized as follows, Section II discusses the proposed methodology involved in the recognizing the mentioned activities. In Section III, the ANFIS model and its implementation are described. Results and discussion are presented in Section IV. Finally, conclusions are presented in Section V.

II. Methodology

A three axes IMU sensor which is a combination of accelerometer, gyroscope and magnetometer was used in this study. Accurate and reliable data is key in the use of artificial intelligent tools. Hence, the optimal placement of accelerometers to acquire human activity data as studied and proposed in [11] is the waist or top of the sacrum. Therefore our sensor was placed at the waist or at top of the sacrum of the subject to classify one of the four chosen human activities as shown in Fig. 1.

In the context of the output from the sensor, the output variable **x** used in this study is a 3-dimensional vector comprising basically of acceleration (g, 3-axis), magnetic field (μT, 3-axis) and linear acceleration (m/s^2, 3 axis). The readings from the gyroscope were neglected because it does not contain distinctive features which can aid in the classification of the activities if interest. Time series data collected for each activity from this device at a sampling frequency of 100 Hz. Sit and stand data were collected for approximately 120 second each while walk and run data were collected for approximately 60 seconds and the time used for switching from one activity to the other were not taken into account. Figure 2 shows a graphical representation of the sensor output over a normalized time interval. As a form of data pre-processing, the magnetic field data was normalized over the range of the device. Then the root mean square (RMS) feature extraction metric was calculated from the 3D axes of each data set. These RMS values were calculated as proposed in [12].

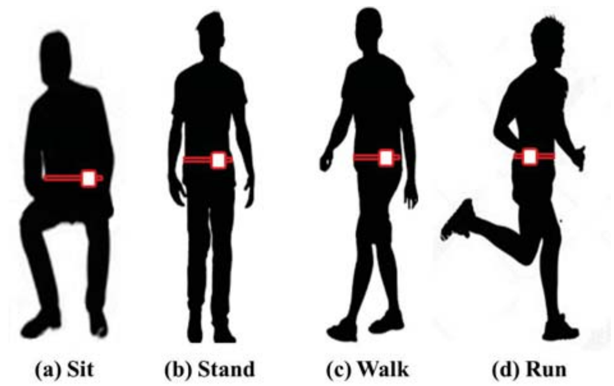
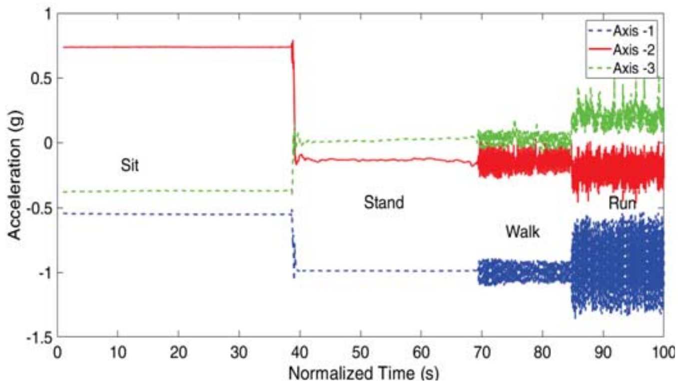
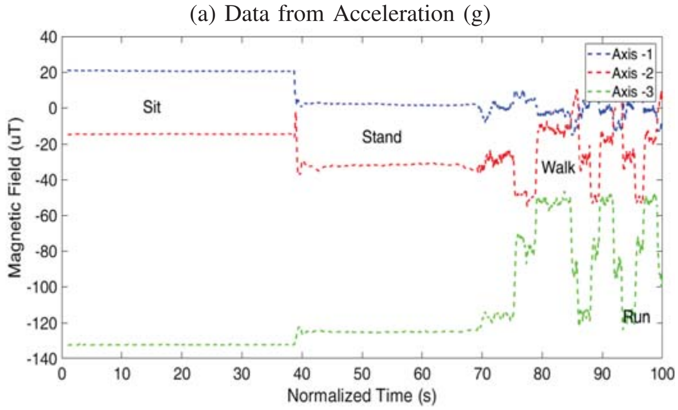


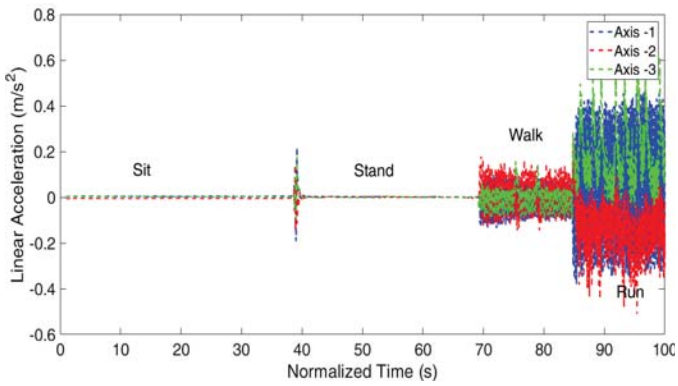
Fig. 1: Activities involved in this study. Red and white marks indicate the location of the IMU sensor.



(a) Data from Acceleration (g)



(b) Data from magnetic field (uT)



(c) Linear Acceleration

Fig. 2: Sensor data points

$$RMS = \sqrt{\frac{1}{N}(x^2 + y^2 + z^2)} \quad (1)$$

Where N is the number of axes, while x,y and z represent the Cartesian axes respectively. Furthermore, an average value of the RMS using a sliding window of 10 data points each without overlap was computed and this was used as the input to the system. The output Y are discrete labels corresponding to the studied activities, for which $Y \in [1;4]$ for four activities.

III. Adaptive Nuero-Fuzzy Inference System

ANFIS hybridizes the advantage of both FIS and neural network. ANFIS based HAR is a combination of the knowledge-based representation of the conventional Fuzzy logic rule-based approach with the learning capabilities of neural networks to predict and identify patterns of human activities and gait movement. It basically includes six layers which are input, fuzzification, rule antecedence, rule strength normalization, rule consequence and inference with de-fuzzification. Fig. 3 shows the processes involved in ANFIS, the fuzzification layer enables the allocation of input variables for an initial fuzzy set, and the antecedent layer constructs the nodes that represent the membership functions. During training, the antecedent

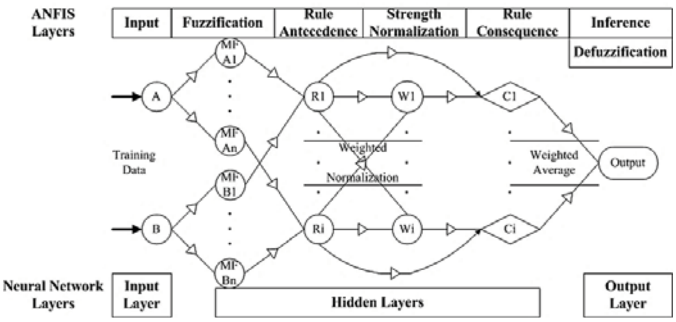


Fig. 3: General Overview of ANFIS model.

parameters will be modified with the fuzzy rules in the strength normalization layer iteratively until the root mean square error (RMSE) of the training sets are going steady. Then, the consequent layer combines them to determine the degree of the output. Thus, the rule-related layers above implicate the hidden layer with respect to the neural network. Finally, the node of inference layer computes the crisp output with defuzzification. In this study, Matlab ANFIS modeling, which is a sugeno takagi fuzzy based system was employed. The Modeling steps involves

1. Loading the training data, the data contains N +1 column where the last column contains the training data output.
2. Specify the structure and generate the FIS, this involves selecting the number of membership functions and their types.
3. Select the number of training epochs and train the ANFIS using Hybrid learning algorithm.

IV. Results and Discussion

The proposed ANFIS model for sit, stand, walk and stand human activity classification was Implemented using MATLAB installed on a computer with an Intel (R) core(TM) i7-4700MQ CPU running at 2.40 GHz using 6 GB of RAM, running Windows 10.

A. Activity Classification

In terms of activity classification, three membership functions(Generalized bell) for each of the three inputs were used to generate a FIS model and the network was trained to generate the rules. Fig 5 illustrates the recognition of each activity using labeled inputs. From Fig 5a and Fig 5b, it can be observed that although the difference between the inputs for sit and stand activities is not very significant, the proposed model was still able to classify correctly these two activities. Fig 4 shows the confusion matrix of the testing set with an overall accuracy of 98.88%.

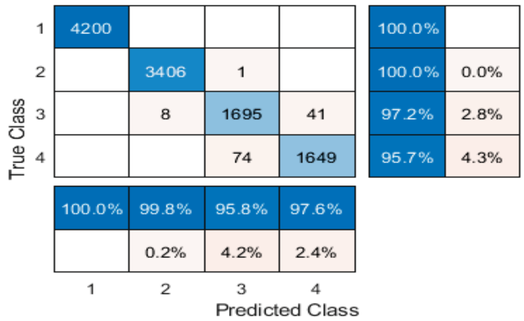


Fig. 4: Confusion Matrix

B. Performance Based on Membership Functions

The performance of eight different membership functions were also evaluated in terms of their training error and RMSE. Here ANFIS based on Generalized bell(gbellmf), Triangle(trimf), Trapezoids (trapmf), Difference between two sigmoidal(dsigmf), Product of two sigmoidal(psigmf), Pi-shaped (pimf),Gaussian (guassmf) and Gaussian combination (Gauss2mf) membership function are generated and training is performed using each of these FIS structures to investigate their training error and RMSE. Figure 6 shows the training error with each of the generated FIS over 50 training epochs. The training error of the dsigmf and psigmf were observed to be exactly the same. Figure 7 presents each membership function and their corresponding training RMSE over 50 epochs. It can be observed that although the margin between the RMSE values are not very large, the gbellmf performs better than all other ones while the trapmf is the least performed in terms of its RMSE values.

V. Conclusions

Human Activity (sit, stand, walk, and run) recognizing model was developed in this study based on Multiple-input single-output ANFIS technique. The proposed method has an advantage of simplicity and several design related parameters for such models was also investigated to determine optimal design parameters for ANFIS based HAR. Therefore, the proposed ANFIS model is rapid, readable and easily extendable, which makes it suitable and valuable for real-time human activity classification.

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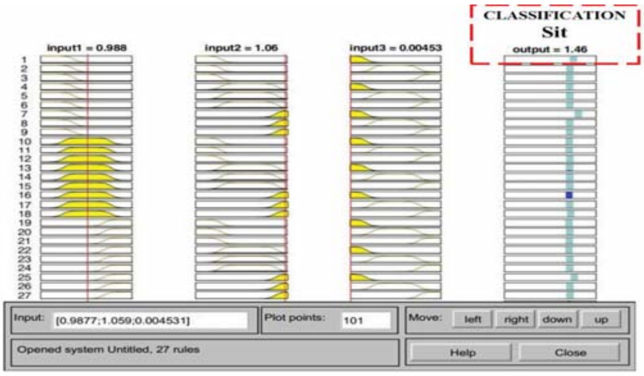
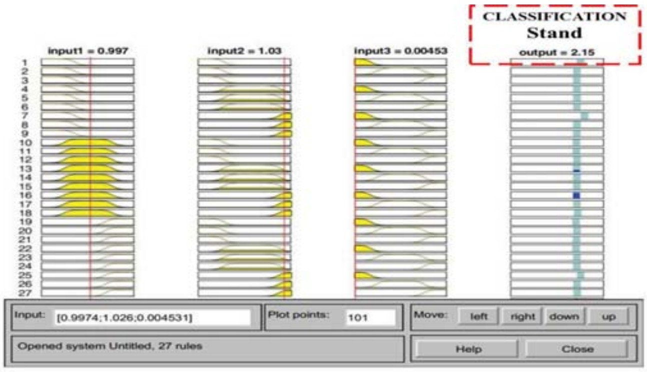
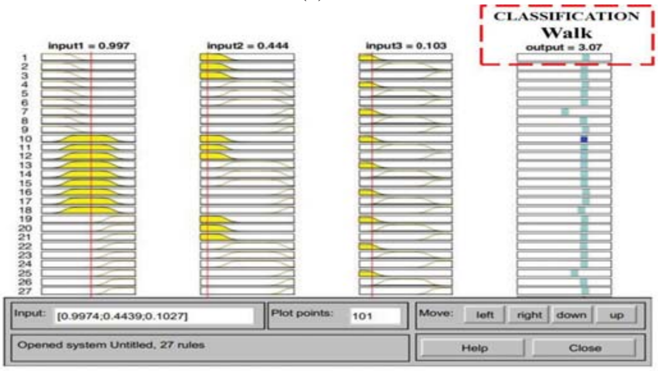


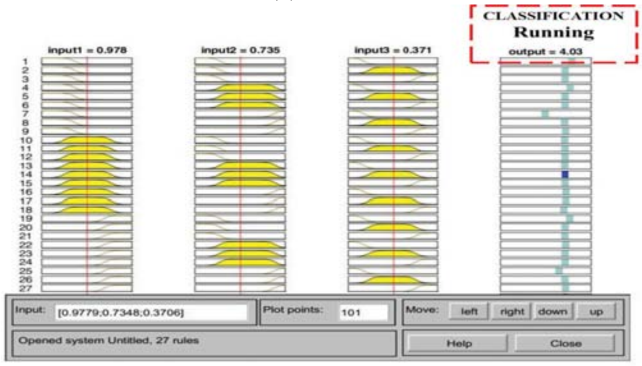
(a) Sit



(b) Stand



(c) Walk



(d) Run

Fig. 5: Illustration of Sit Stand Walk And Run Activity Classification

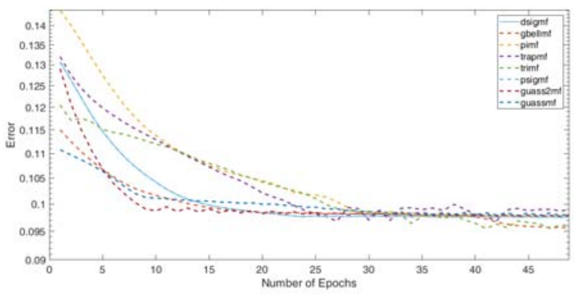


Fig. 6: Error over 50 epochs

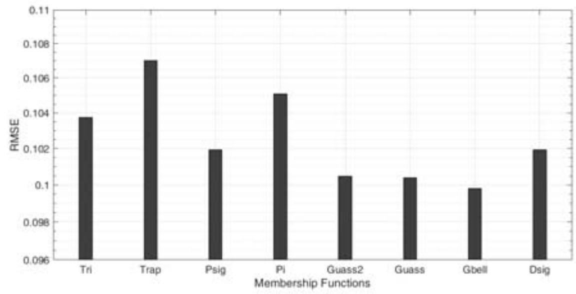


Fig. 7: Root Mean Square Error of Different Membership Functions over 50 Epochs

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