ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 1, Issue 6, August 2013

Intelligent Machine Learning System For Smart Room Using Sensor Network

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ABSTRACT: Advent development in the Micro and Nano electronics paves way for sophisticated living of human using sensors. In Smart environment, human interaction with the computing system is not manual commands, the need of human is predicted by the system by means of data collected through sensors, thus human can enjoy automated sophisticated living environment. The need of human is detected, analyzed and act based on the information collected by sensors. Particularly the need is predicted only by recognizing the human activity. The human activity is recognized by means of efficient machine learning system using data collected by ambient sensors, fixed in all daily usable things and wearable sensors worn by the human who is under monitoring. The aim of creating this prototype is to develop automated machine learning system that does not need any manual interpretation for decision making. Thus the proposed machine learning system is based on Adjustable Fuzzy Clustering (AFC) algorithm, for data grouping to ease the job of classification system and Fuzzy Neural Network (FNN), for supporting incremental learning. This proposed system resembles human intelligence in making accurate decision even in uncertain situation. By the implementation of this system shows higher accuracy of recognizing human activity even with large data from different sensors.

Keywords: Machine Learning, Adjustable Fuzzy Clustering, Fuzzy Neural Network, Human Intelligence, Uncertainty, Smart Environment.

I. INTRODUCTION

Rapid development in the embedded systems and electronic device manufacturing technology paves a new way towards Micro Electronic Mechanical Systems (MEMS) and Nano Electronic Mechanical Systems (NEMS). Due to this growth, the area of Pervasive Computing is also being developing. The embedded devices are very small, have high computation and speed, easy to install and very cheap because of developments in manufacturing technology. These fascinating the people to use pervasive sensors for many applications in industries, factories, public places, vehicles, agricultural field, etc for making the job easy and for monitoring [1].

Among sensor based applications creating smart environment is the most fascinating and challenging area for researchers and people who need sophisticated and luxurious living environment [2]. The characteristic of smart environment is that everything around the human are computerized, have sensors which collect data about the person especially to recognize his activities, based on his activities his needs are satisfied automatically without any manual intervention with computing and electronic devices. Thus the most important work in smart environment is Human Activity Recognition.

The activity detection using sensors in smart environment is of greater importance to the patients, physically disabled people and elderly people [5] need continuous checking and analysis by the physician, also needs someone's help for their basic things [4]. Thus arises the point of smart environment. Many steps are taken by engineers and researchers for smart environment, but the challenge is automatic decision making system, that can learn individually without manual interpretation.

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Thus the proposed Machine learning system is based on Adjustable Fuzzy Clustering (AFC) algorithm and Fuzzy Neural Network (FNN).

The example scenario for smart environment using ambient sensors based on human activity recognition is; the person sleeping in his bed, when the alarm ring and he awake from his bed and wear his slipper, heater in bathroom automatically goes on, based on the alarm data and pressure sensor in slipper for confirming his awakening. After he come out from bathroom and using dressing table, the automatic coffee maker prepare coffee and toaster prepare bread. These are automatic because of the prediction of action based on the sensors data.

II. THEORETICAL BASIS

A. ADJUSTABLE FUZZY CLUSTERING (AFC) ALGORITHM:

The AFC algorithm is clustering the input data to comfort the classification system [17]. Let Ω denote a set of training samples. First, AFC carries out FCM to group Ω into *H* clusters. Let the center vector of the *h*th ($h = 1, \ldots, H$) cluster be denoted by ***vh*** [12]. Second, for each $\boldsymbol{\omega} \in \Omega$, a "degranulation" sample $\widehat{\omega}$ is calculated by

$$\widehat{\omega} = \sum_{h=1}^{H} uh\,(\omega)^T\, vh \Big/ \sum_{h=1}^{H} uh\,(\omega)^T \tag{1}$$

The reconstruction error of the *h*th cluster is calculated by

$$Vh = \sum_{\omega\,\epsilon\,\Omega h} \|\omega - \widehat{\omega}\|^2 \tag{2}$$

Where $\Omega h = \{\boldsymbol{\omega} |\ h = \arg i \min \{\boldsymbol{\omega} - \boldsymbol{vi}\_\}, \boldsymbol{\omega} \in \Omega\}$. Third, AFC carries out dividing and combining mechanisms to the clusters to get maximum accuracy of center vector, where ε is a predefined threshold indicating the maximum reconstruction error [15].

1) ***Dividing:*** The Dividing mechanism can break a cluster into two smaller clusters to lower the reconstruction error. The calculation of two new center vectors ***v*** new *i* (*i* = 1, 2) are carried out iteratively according to

$$u_i^{new}(\omega) = u_{h0}(\omega)[\textstyle\sum_{j=1}^{2}\big(\|\omega - v_i^{new}\|/\|\omega - v_j^{new}\|\big)^{1/(\tau-1)}]^{-1} \tag{3}$$

$$v_i^{new} = \sum_{\omega\,\varepsilon\,\Omega h0} u_i^{new}(\omega)^T \omega / \sum_{\omega\,\varepsilon\,\Omega h0} u_i^{new}(\omega)^T \tag{4}$$

Detailed derivations of (3) and (4) can be found in [14]. Then, AFC recalculates the reconstruction errors of the $H + 1$ cluster. If max $\{Vh\} < \varepsilon$, the cluster dividing is terminated. Otherwise, it is repeated.

2) ***Combining****:* This can combine two clusters into a bigger cluster to reduce the number of similar clusters. The new center vector ***v*** new is calculated by

$$v^{new} = \sum_{\omega\,\varepsilon\,\Omega new} u^{new}(\omega)^T \omega / \sum_{\omega\,\varepsilon\,\Omega new} u^{new}(\omega)^T \tag{5}$$

Detailed derivation of (5) is presented in [14]. Then, AFC recalculates the reconstruction errors of the $H - 1$ clusters. If max $\{Vh\} > \varepsilon$, AFC terminates the cluster combining. Otherwise, it is repeated.

By the dividing and combining of clusters, the optimal number of clusters is obtained, and limits the reconstruction errors below the predefined threshold ε. The center vectors of these clusters are used to train a FNN instead of raw input samples [15].

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B. FUZZY NEURAL NETWORK (FNN):

FNN is the high computational and efficient learning system, more suitable for the classification of human activity which resembles human decision making ability, even in uncertainty [6].
FNN has four layers: pattern layer, max layer, min layer and competitive layer.

1) ***Pattern layer:*** The first layer is the input layer which accepts patterns into the network. Neuron is represented as INPUT-FN (Fuzzy Neuron). The algorithm of the (i, j)th INPUT-FN (as two dimension inputs) in the first layer is

$$S_{ij}[1] = Z_{ij}[1] = x_{ij}, \quad \text{for } i = 1 \text{ to } N_1, j = 1 \text{ to } N_2 \qquad (6)$$

$$Y_{ij}[1] = S_{ij}[1] / P_{umax}, \quad \text{for } i = 1 \text{ to } N_1, j = 1 \text{ to } N_2 \qquad (7)$$

Where x_{ij} is the (i, j)th vector of an input pattern ($x_{ij} \geq 0$) and P_{umax} is the maximum vector among all input patterns. The purpose of this layer is to fuzzy input patterns through a weight function w [m, k], where σ is the smoothing parameter for normalization.

$$Y_{m,k} = \exp[(x \,.\, W_{m,k} - 1)/\sigma^2] \qquad (8)$$

2) ***Max Layer:*** The minimum function is used as a aggregation function of a FN. The state of the (p, q) th MAX-FN in this layer is

$$Y_{pqm}[2] = max_{i=1}^{N1}\left(max_{j=1}^{N2}\left(w[p-i, q-j]Y_{ij}[1]\right)\right), \quad \text{for } p = 1 \text{ to } N_1, q = 1 \text{ to } N_2 \qquad (9)$$

Where $w[p-i, q-j]$ is the weight connecting the (i, j)th INPUT-FN in the first layer to the (p,q)th MAX-FN and $Y_{pqm}[2]$ is the mth output in the second layer.

3) ***Min Layer:*** We use MIN-FN in the third layer. Each MIN-FN in the third layer represents one learned pattern. Hence the number of MIN-FN's in the third layer, M could be determined only after the learning procedure is finished. The output of the mth MIN-FN in the third layer is,

$$Y_m[3] = S_m[3] = min_{p=1}^{N1}\left(min_{q=1}^{N2}\left(Y_{pqm}[2]\right)\right), \text{ for } m = 1 \text{ to } M. \qquad (13)$$

Where $S_m[3]$ represents the state of the mth MIN-FN in the third layer.

4) ***Competitive Layer:*** The fourth layer is the output layer. We use COMP-FNs in this layer, one for each of the M learned patterns, to provide non fuzzy outputs. If an input pattern is most similar to the mth learned patterns, then the output of the mth COMP-FN in the fourth layer is 1, while other outputs are 0.

The number of COMP-FN in the output layer is equal to M. The algorithm of the mth COMP-FN in the fourth layer is,

$$S_m[4] = Z_m[4] = Y_m[3], \quad \text{for } m = 1 \text{ to } M. \qquad (14)$$

$$Y_m[4] = g[S_m[4] - T] = \begin{cases} o & if\ S_m[4] < T \\ 1 & if\ S_m[4] = T \end{cases}, \quad \text{for } m = 1 \text{ to } M. \qquad (15)$$

$$T = max_{m=1}^{M}(Y_m[3]), \quad \text{for } m = 1 \text{ to } M. \qquad (16)$$

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where T is the activation threshold of all the COMP-FNs in the fourth layer.

III. SENSORS OF SMART ENVIRONMENT

Smart environment work based on the sensor data. Different sensors are taking part in single smart environment scenario. The place and position of sensor deployment is very important for human activity recognition [7]. For this scenario, three types of sensor deployment, they are on-body or wearable sensors, sensors placed on objects or things in smart room and ambient sensors [3] and [8]. In the sensor description table below as TABLE I; wearable sensor denoted as 'B', object sensors as 'O' and ambient or environmental sensors as 'E'.

TABLE I
SMART ENVIRONMENTAL SENSORS

SENSORS	OBSEVATION	DEPLOYMENT
Temperature	Heat measure in Celsius	E-O-B
Humidity	Moisture value	E
Accelerometer & Gyroscope	Distance by time and angle of rotation	O-B
Magnetometer	Orientation of body or object	O-B
Inertial sensors	Absolute orientation	O-B
Microphone	Capturing user command, observing ambient sounds, object localization	E-O-B
RFID tags and reader	For localization of user and for stock analyzing in refrigerator and shelves	E-O-B
Pressure sensor	Pressure measurement	E-O-B

A. SMART ENVIRONMENT COMMUNICATION MODEL:

Smart environment consist of sensors, data acquisition devices, centralized computing devices, electrical and electronic devices in smart room, smart phone or laptop and target communication spot [10]. In this, we categorize the computation system of smart environment into three levels.

1) ***Level 1*:** This is very basic and important level focused on data collection and acquisition by means of sensors and Data Acquisition Unit (DAU). DAU of wearable sensors is always fixed with user sensor jacket and for object and ambient sensors DAU is common, to be deployed anywhere in smart room [11].
2) ***Level 2*:** It is the computation level, have Central Computing Unit (CCU). The activity recognition is happened here based on AFC and FNN machine learning system. The decision making is done in this level for selecting appropriate action in smart environment based on user need.
3) ***Level 3*:** The last is communication level, CCU communicate to actuators and to the target communication system via mobile phone or laptop with internet facility.

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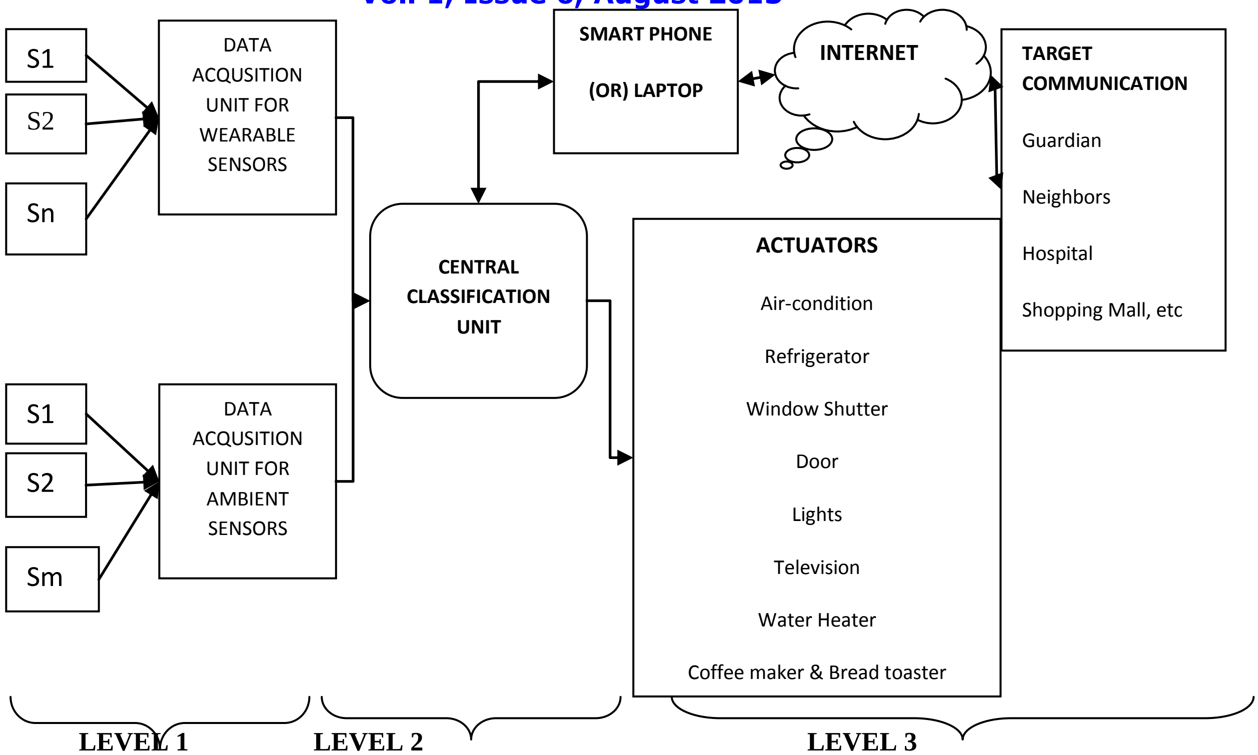
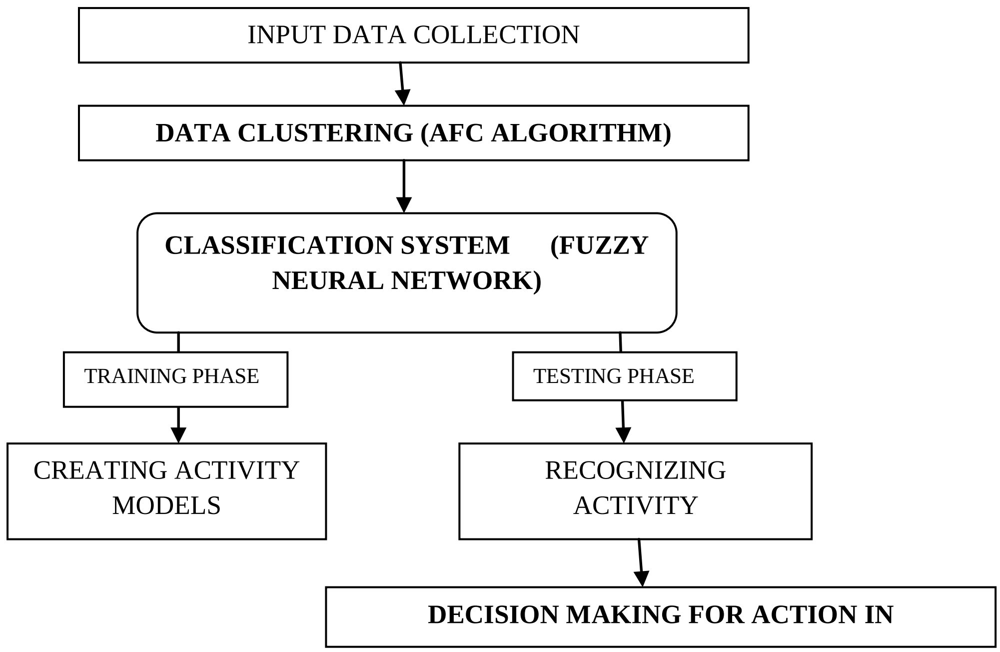


B. CENTRAL CLASSIFICATION UNIT (CCU):

The Central Classification Unit (CCU), is the Machine Learning system. This having following modules; First, Input data collection from DAU [9]. Second, data clustering based on Adjustable Fuzzy Clustering algorithm to ease the job of classification system and also reduce redundant input data to increase accuracy of recognition. Third, Classification system based on Fuzzy Neural Network, it has two phases; training phase creates activity models and activity is recognized during testing phase. Fourth, based on activity the action is selected in decision making module [13].



IV. MATLAB SIMULATION FOR FNN

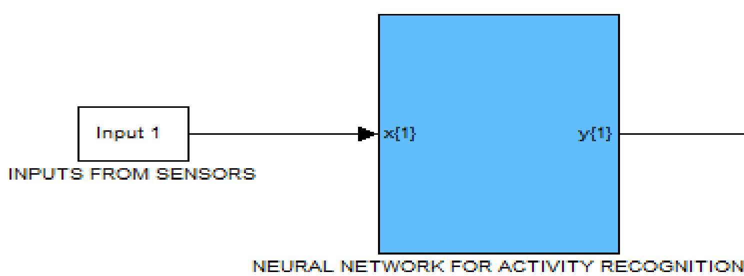


Figure 1: Simulink Model for Neural Network

V. DISCUSSION

The proposed system is tested and validated using Matlab Neural Network Toolbox. The proposed AFC and FNN are successfully evaluated using Opportunity UCI dataset for Human Activity Recognition for smart environment using sensors. The simulation results of MATLAB neural network toolbox shows very low error rate at the output layer of Fuzzy

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neural network. The simulation results are satisfactory for further development of this system.

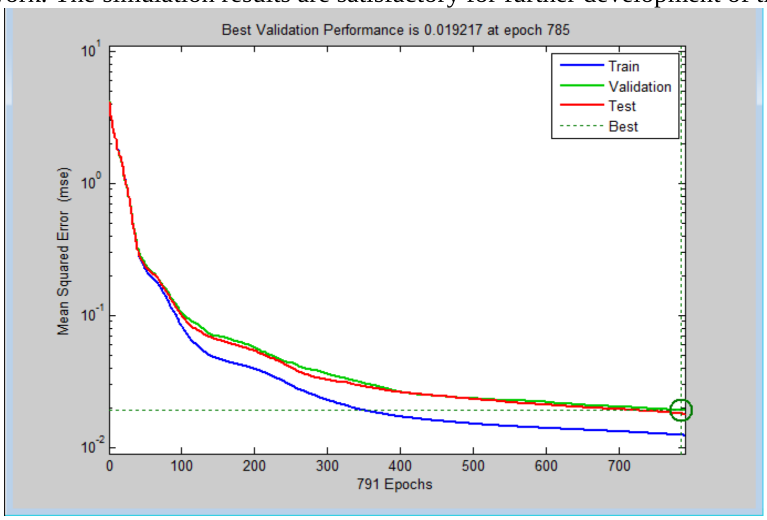

Figure 2: Recognition Error

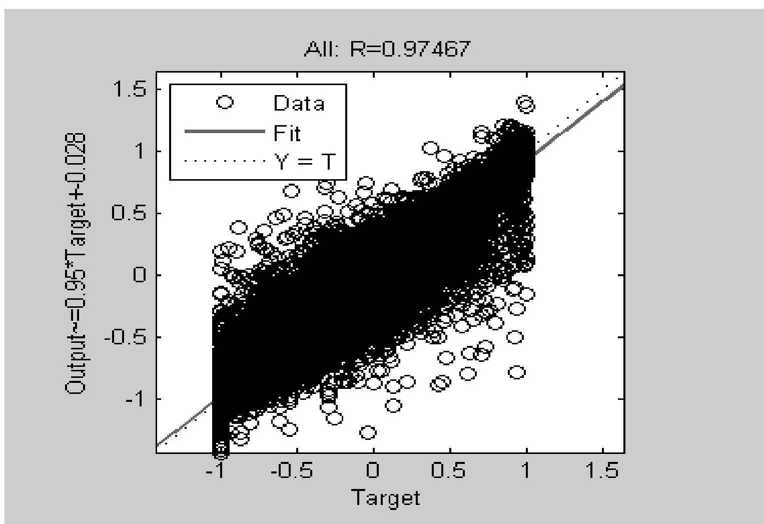

Figure 3: Data with Algorithm

VI. CONCLUSION

The attempt to create smart environment is successful and the results are satisfactory using MATLAB simulation tool. The local minima problem due to large input data and over fitting problem due to over learning are eradicated by means of Adjustable Fuzzy Clustering algorithm and Fuzzy Neural Network respectively. The real-time implementation of this proposed smart environment based on FNN machine learning system will definitely be helpful for patients with chronic diseases, elderly people and people who desire sophisticated living environment. This proposed scenario can also be more suitable for security purposes, in terms of authenticated accessing of human in confidential areas. Enhances successful smart environment, with respective of our proposed Human Intelligent Machine Learning system with higher accuracy in predicting actions based on human needs.

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