Resident Activity Recognition in Smart Homes by Using Artificial Neural Networks

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Abstract—**Recognition and detection of human activity is one of the challenges in smart home technologies. In this paper, three algorithms of artificial neural networks, namely Quick Propagation (QP), Levenberg Marquardt (LM) and Batch Back Propagation (BBP), have been used for human activity recognition and compared according to performance on Massachusetts Institute of Technology (MIT) smart home dataset. The achieved results demonstrated that Levenberg Marquardt algorithm has better human activity recognition performance (by 92.81% accuracy) than Quick Propagation and Batch Back Propagation algorithms.**

Index Terms-- **smart home, artificial neural network, human activity recognition**

I. Introduction

The idea of home automation is almost a century old. The main aims in home automation are to control and manage household appliances and systems [1]. After 1990s, the development cost of microprocessors has dramatically decreased and computers and computerized system used at home have become available. With the improvement in computer sciences and sensors technologies, i.e., remote and intelligent control technologies and informatics, it is possible to gather data from environment, to analyze the gathered data and execute necessary commands according to the settings that are predefined by the user [2]. Moreover, sensors which are replaced in homes are used to record frequent events and interactions between residents and objects to make a decision when the events happen again [3]. Furthermore, a home management system utilizes machine learning and makes experienced system and adopts necessary services after learning to provide appropriate services according to user's habits [4].

When a system has the ability to learn and take necessary actions or makes decisions for us, it is called a smart system. Therefore, an automated home environment with learning and decision making capability may be called as a smart home. Heating, ventilation, air conditioning, entertainment, lighting, shading, home security systems, health care applications, and the control of other household appliances are the main interests of smart homes [5]. Smart homes may also be considered as part of smart grid as energy management strategies in home automation are also related to data from smart grids combined with home automation systems to use available resources.

The aim of smart homes as sensor-based systems besides reducing waste power is to create smart, secure and comfortable environment for the elderly and disabled people [6]. Thus, sensors are needed to monitor and collect required data. Routinely, motion sensors are used to recognize real activities of people in smart homes [7]. In this regard, MIT and TIAX, prepared a laboratory to study human living activities and behaviors continually to recognize human activities in throughout a whole day [8]. Recognizing human activities are included in two categories: using sensors on human body to recognize frequent motions like running and hiking, and using sensors on objects in environments to recognize moving objects and complex activities of human [9]. A smart home system can prepare suitable place and services to its residents by recognizing human activities in smart home [10].

A smart system may learn the habits or make inferences about the preferences of the residents and then take automated decisions and actions for user. For example by learning cooking time, the system can prepare the oven, and by learning bath time, it can prepare the facilities of the bathroom for the residents. The learning process or mechanism may be quite complicated and the accuracy is very important since it is directly related to decision making and action. There are different approaches available for this purpose. Artificial Neural Network (ANN) offers opportunities for both activity recognition and the learning process in smart homes. However, there is not a unique solution for the activity recognition. Other solutions may include selection method and optimization.

In this paper, we have investigated the accuracy of three available training algorithms, namely Quick Propagation, Levenberg Marquardt and Batch Back Propagation in detecting and recognizing resident activities such as bathing, grooming, going to work, *etc.*, we have used the real data set

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of MIT and TIAX, obtained from the experimental study of "Activity Recognition in the Home Setting Using Simple and Ubiquitous Sensors". In section II, a review of methodology, in section III, activity recognition and in section IV simulation test results for three algorithms are presented and compared with each other.

II. Review of Methodology

ANNs are algorithms that can emulate a nervous system, with three layers as input, hidden and output. Each layer consists of nodes that are interconnected to each other. Input layer is related to activation pattern and connected to one or more hidden layer, named computation layer where real process of system including weighted connection is done (Figure 1). Response of network is in output layer. Training process is necessary to perform tasks and the actual learning is the adjustment of weights in layers.

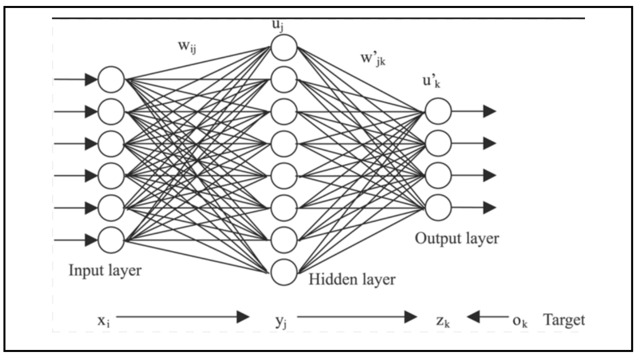

Figure 1. Neural network architecture

ANN learning process is classified as supervised, unsupervised and hybrid learning. ANN is also classified according to its architecture connection type (Feed-Forward Networks, Recurrent Neural Networks etc.), learning rule (Hebbian Rule, Perceptron Learning, Back-Propagation, etc.), and activation functions (sigmoidal, hyperbolic tangent, etc.). There are various types of ANN, such as Multi-Layer Perceptron (MLP), Echo State Networks (ESN), Radial Basis Function networks (RBFN), Boltzmann Machine, etc. ANNs are used to apply case-based reasoning applications for intelligent homes. Some applications are eldercare, healthcare and emergency solutions. In addition to personalizing habits, ANNs are used to predict energy-efficiency, too [11]. Teich *et. al.*, have studied saving energy in smart homes using some learning algorithms like ANNs for personalizing the smart home, by manual step and modeling automatic process to provide test and training database [11]. Badlani and Bhanot have studied ANNs in smart homes. They have designed a single layer perceptron model to train and predict human behavior. Furthermore, they have authenticated a user to obtain safety in a smart home [6]. J. Choi *et. al*, have studied a context-aware middleware that provides one of intelligent home services, called user's precedence. They have used six data values to predict and learn user's priority and then have created context by back propagation neural network. This adopted model could evaluate and predict pattern of personal priorities [12].

Table I. A review of usage of ANN in smart home

Purpose of use	Inputs / Parameters	Algorithm of ANN	Evaluation Metrics	Result	References
Energy saving	sunlight, wind, room temperature	Not mentioned	Not mentioned	acceptable	[11]
	temperatures, time and weather conditions	Simple Recurrent Neural Network	Not mentioned	acceptable	[13]
	Not mentioned	TB ANN	Comparison with SE and RD algorithms	TB ANN is better than two others	[15]
	hour of the day, day of the week and dates of holiday	Not mentioned	Accuracy	total savings energy 87.2%, personalized saving of 88.5%	[16]
	hour, day, temperature	Feedback ANN and the Hybrid Algorithm	Accuracy	mean absolute percentage Error 1.945	[17]
	Not mentioned	Single Layer Perceptron	Accuracy	specificity 65.52%	[6]
Security	Not mentioned	Single Layer Perceptron	Accuracy	sensitivity 96.97%	[6]
	Not mentioned	Multi-Layer Perceptron	Accuracy	80.0%	[2]
	User Id and Password	Not mentioned	Accuracy	mean square error performance 0.000979	[18]
Health care	person's motion	Not mentioned	Comparison with SVM /accuracy	true positive rate of 92%, false positive rate of 5%	[14]
	light ,TV, doors data	Not mentioned	Accuracy	behavior prediction 80%, fire alarm prediction 95%	[19]
	listening music, sleeping, leaving location	One-Pass NN	Accuracy	92%	[20]
Home care	resident location, time, home and body temperature, face expression, pulse	Back Propagation Neural Network	Accuracy	100% in training for predict priorities	[11]

Roessler *et. al.,* have used ANN to control the heating system of smart homes by different user's preferences in the same condition. Manual results for constructing ANNs represented their ability to build stable solutions. For corresponding to data of actual situation, ANNs could obtain sensible output values [13]. Teoh and Tan, have studied preparing intelligent security systems and minimizing inaccurate surrounding alarms. ANNs including training, cross validation and testing were used and they have reported that the cross validation had low performance than the others [2]. Belshaw *et. al.,* have studied recognizing elderly people fall detection by classifying fall types. They have compared the performance of Logistic Regression (LR), Support Vector Machine (SVM) and ANN methods. Their results showed that ANN had better performance than LR and SVM [14]. Paulauskaite *et. al*., have used ANN to control lighting of smart homes by person's manner and proposed algorithm Based on Threshold (TB) for similarity of data in ANNs. The results showed the ability of TB algorithm even in person's changeable behavior [15]. Hernandez *et. al.,* have studied saving electricity in smart homes and implemented a lighting control schedule program based on ANNs. For training, hour of the day, day of the week and dates of holiday were used as input vectors. The objective of vectors were to compare total and personalized energy savings [16]. Gonza´lez and Zamarren˜o have studied using feedback ANN to predict electric loading in buildings and a hybrid algorithm used in the training phase. Some of its outputs were fed back and its inputs were current load, day and hour. By evaluating the system's results and actual data, they have obtained very promising results [17]. A. Joseph *et. al.,* 2009, have chosen back propagation algorithm to train ANN by storing passwords rather than use verification table to solve user authentication problems in smart homes. By using 200 datasets of User ID and Passwords, tansig-activation function in hidden layer and purelin-activation function in output layer, they have obtained quite good performance of authentication method [18]. Hussein *et. al*., have simulated a control system based on adaptive ANNs for disabled people. They have taken into account different disabilities to facilitate their interaction with environment in smart homes [19]. Li *et. al*., have proposed One-Pass learning method of neural network to identify the person's abnormal actions in healthcare of smart homes and showed its simplicity and effectiveness [20] The comparison and results of previously discussed works have been presented in Table I.

III. ACTIVITY RECOGNITION

A. *Study and Data Collection*

We have used in the current study the data set of MIT Laboratory and TIAX, obtained from the experimental study of "Activity Recognition in the Home Setting Using Simple and Ubiquitous Sensors". To create the dataset, the data obtained from 77 installed state-change sensors were used in an apartment that a single woman lives. The sensors recorded the woman's activities for one month. The sensors were installed on objects in smart home such as kitchen cabinets, doors, windows, toilet, etc. This dataset included, activity name, date, start time and end time. Distribution of activities is shown in Table II. Table III, shows an example of data format and Figure 2, shows the positions of installed sensors in smart home.

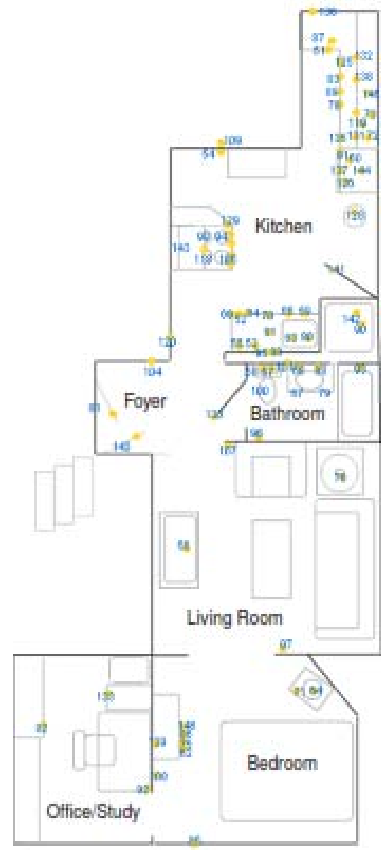

Figure 2. Sensors in smart home to recognize human motions [21]

Table II. Distribution of each activity in activity class

Activity Class	Number of Activity In Class
Bathing	18
Cleaning	9
Doing laundry	19
Dressing	20
Going out to work	12
Grooming	37
Preparing a beverage	15
Preparing a snack	15
Preparing breakfast	14
Preparing dinner	8
Preparing lunch	17
Toileting	83
Washing dishes	8

Table III. Example of data format

Activity	Date	Start Time	End Time
Bathing	4/1/2003	20:41:35	21:32:50
Grooming	4/6/2003	0:52:28	1:04:55
Toileting	4/10/2003	20:57:20	20:59:33

IV. TEST RESULTS

A. *Determining the Input and Output Layers for Different Algorithms*

After preprocessing of inputs and outputs, three features of date of the activity, start time and end time for input layers were defined. It is notable that three inputs have been converted to six inputs after preprocessing (Table IV). All algorithms have same number of inputs and outputs but different number of neurons on each hidden layer. Quick Propagation, Levenberg Marquardt and Batch Back Propagation algorithms have 9, 10 and 7 neurons in their hidden layers, respectively.

Table IV. Architecture of network

Algorithm	Architecture
Quick Propagation	6-9-13
Levenberg Marquardt	6-10-13
Batch Back Propagation	6-7-13

B. *Training and Testing:*

Resident activity recognitions have been varied out for 13 defined activities in dataset. In this study, we have tried to find the best training parameters for each algorithm to obtain better results or higher accuracy. For this purpose, a total of 278 data, 190 data for training set (68%), 44 data for validation set (16%) and 44 data for test set (16%) were used. Table V presents the obtained accuracy of each applied ANN algorithms.

Table V. Accuracies of Quick Propagation, Levenberg Marquardt, Batch Back Propagation Algorithms

Algorithm	Accuracy
Quick Propagation	89.23
Levenberg Marquardt	92.81
Batch back propagation	87.61

The LM algorithm showed better accuracy results compared to QP and BBP in overall. The difference between LM and QP and BBP is almost doubled for the recognition of washing the dishes. However, all three algorithms have very similar accuracy results for toileting. For all three algorithms, it may be interpreted from Table VI that higher repeated activities like toileting, repeated 83 times, and got higher accuracy rates than preparing dinner and washing dishes were repeated 8 times (Table II).

Table VI. Activity recognition accuracy rates of the QP, LM and BBP algorithms for each activity.

Activity	QP	LM	BBP
Bathing	8.12	8.54	7.92
Cleaning	2.90	3.04	2.87
Doing laundry	8.80	9.01	8.80
Dressing	10	10.01	9.96
Going out to work	4.20	4.40	4.18
Grooming	14	14.21	13.88
Preparing a beverage	4.42	4.88	3.84
Preparing a snack	4.42	4.88	3.84
Preparing breakfast	3.99	4.01	3.99
Preparing dinner	1.88	2.01	1.86
Preparing lunch	5.5	5.6	5.5
Toileting	19.98	20.2	19.96
Washing the dishes	1.02	2.02	1.01
Total accuracy percent (%)	89.23	92.81	87.61

V. CONCLUSIONS

Quick propagation, Levenberg Marquardt and Batch Back Propagation, three algorithms of ANNs have been used for human activity recognition and compared according to performance on MIT smart home dataset. The achieved results demonstrated that Levenberg Marquardt algorithm has better human activity recognition performance by 92.81% accuracy than Quick Propagation and Batch Back Propagation algorithms. It is noticeable that the accuracy of human activity recognition increases with the higher number of repeated activities. Furthermore, with different algorithms on distinct datasets of human activities may result in different accuracy rates. It should be noted that given results are obtained only for a single resident home. In case for a couple sharing the same environment, requires more complicated learning approaches with feature selection and the use of more sophisticated sensors to create the dataset.

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