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HUMAN ACTIVITIES RECOGNITION BASED ON AUTO-ENCODER PRE-TRAINING AND BACK-PROPAGATION ALGORITHM

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ABSTRACT

In this paper, Auto-Encoder algorithm (AE) has been used in unsupervised feature selection, then, Back-propagation (BP) algorithm has been used to train reconstructed subsets in supervised learning; in order to recognize human activities inside smart home. Subsequently, the performances of auto-encoder have been evaluated and compared with traditional weighting technique for features selection. The experimental results demonstrate that neural network using auto-encoder achieves an average of over 91.46 % for one user and 90.62 % for two-users, relatively better than neural network using traditional weighting technique.

Keywords: *Auto-Encoder Pre-Training, Deep Network, Activity Recognition, Back-Propagation Algorithm, Smart Home.*

1. INTRODUCTION

Smart homes have been a center of interest for nearly two decades now. They are characterized by ambient intelligence and automation devices/systems, which allow it to respond to residents' needs automatically and provide them with various facilities [1]. The standard approach to build smart homes is to computerize it. A set of sensors gather different types of data, regarding the residents' actions inside homes and its utilities consumption. Computers or devices with computing power analyze these data to identify actions of residents or events that occurred. It can respond to these actions and events by controlling certain mechanisms that are built in the home [2]. Therefore, recognize activities of humans are the first key of the smart homes. Human Activity Recognition (HAR) intends to observe human-related actions in order to obtain understanding of what type of individuals activities/routines will performed within a time interval in order to providing a useful feedback for the system [3]. Through this paper, we referred to recognition of Activities of Daily Living (ADLs). ADLs are defined as routine activities that people tend to do every day and performed to live independently [4]. ADL consist of basic activities that response to primary needs of a person, these activities are composed of only a few steps and do not require real planning, such as eating, bathing, dressing, toileting and walking … [5]. And instrumental activities, this kind of activity needs basic planning to be performed and implies objects manipulations, like the ability to use the telephone, shopping, food preparation, housekeeping, laundry, mode of transportation, responsibility for own medication and the ability to handling finances [6]. Despite advances in recognizing ADLs, this topic remains difficult. In terms of facilitate data analysis, enhance accuracy and recognize multi-users activities, etc.

A set of motion sensors, door sensors, and temperature sensors are located in different place at home to recognize human activities inside it. Those sensors generate data that is used later to recognize activities. Features representation is one of the first key steps in data analysis process, and is the largely conditioning of success of any subsequent statistics or machine-learning endeavor. In particular, it must be careful that there is no losing information at the features subset construction stage [7]. The next step is to select features in the data that are most useful or most relevant, and removes many irrelevant and redundant ones. Once good features are selected, a supervised learning algorithm can perform well. In this paper, we compare two powerful technique of features selection. The first is a feature selection method based on a weighting algorithm, in which each feature is multiplied by a weight value proportional in order to distinguish pattern classes. The second technique is auto-encoder. It is based on unsupervised pre-training, it learn automatically features from unlabeled data and reconstruct a useful representation of features. To the best of our knowledge, this is the first work that use auto-encoder combined by back-propagation algorithm to recognize ADLs inside home.

The contributions of this paper are as follows.

1. An approach to human activities recognition inside home using auto-encoder and back-propagation algorithm.
2. An experimental study that validate the accuracy of auto-encoder and back-propagation algorithm for single and multi-users at home.
3. Comparison of this approach with one other traditional technique widely used in literature.

The rest of this paper is organized as follows. Section 2 reviews the literature. The unsupervised auto-encoder and supervised back-propagation algorithm proposed to recognize human activities are described in Section 3. Section 4 presents the experimental results of activity recognition accuracy of the different feature datasets and the performance measures of the two algorithms: neural network using auto-encoder and BP algorithm. Finally, the main contributions are summarized in section 5.

2. RELATED WORKS

Activity recognition techniques have been widely researched. Several machine-learning techniques are used in literature [8-22]. Almost of those research activities were focused on one-user activities and use emerging sensors network technologies. Recognizing multi-user activities, studied in this paper, is challenging and least covered in literature. Activity recognition techniques can be grouped into probabilistic techniques [9], logic [10,11], and ontological methodologies [12, 13]. Researchers have commonly tested the machine learning algorithms. In [14] authors use a knowledge-driven approach (KDA) to real-time, continuous activity recognition. In [15] a novel Evolutionary Ensembles Model (EEM) based on a Genetic Algorithm (GA) are introduced [16]. To handle the non-deterministic nature of activities, authors in [17] used support vector machine (SVM), in [18] authors used Naïve Bayes (NB) classifier, hidden Markov model (HMM) in [19], and conditional random fields in (CRF) [20]. The most popular and powerful algorithms are: NB, SVM, and HMM. Although, neural networks using BP algorithm [21] has proven successful in human activity recognition in smart home environments. In this paper [21] Fong Compare the performance measures of BP with those of NB and HMM and prove that performance measures of BP are better than those of NB and HMM. To increase efficiency and accuracy of machine learning and neural networks, researchers use many feature selection algorithms, namely, minimal-redundancy maximal-relevance criterion (mRMR) [22] feature weighting algorithms and subset search algorithms, all are based on evaluate the goodness of features individually or through feature subsets [23].

In the literature, several unsupervised feature selection methods have been proposed where various criteria have been used to obtain new structure of the original data. Some of those works are spectral feature selection (SPEC) [24], Discriminative feature selection [25], Multi Cluster Feature Selection (MCFS) [26] feature selection using oppositional-based binary Kidney inspired algorithm [27] and feature selection using trace ratio criterion [28]. In this paper, a new unsupervised feature selection method has been evolved using auto-encoder [29] since it has the capacity to learn the input features without labeled data [30], an auto-encoder is ideal for unsupervised feature selection. The aim of an auto-encoder is to reconstruct a set of data, typically for the purpose of increasing efficiently and dimensionality reduction, it learn automatically features from unlabeled data and reconstruct a useful representation of features. In this paper, we proved that auto-encoder reconstructs data better than other features selection techniques and consequently improves the processing result.

3. PROPOSED WORK

A novel method for activities recognition based on auto-encoder as unsupervised feature selection and back-propagation algorithm is explained in the following subsections. First auto-encoder algorithm is discussed in details, and then back-propagation algorithm used in supervised training is given.

3.1 Unsupervised Auto-encoder Architecture

An auto-encoder [29-32] is an artificial deep neural network used in unsupervised learning for features selection. Architecturally, it is composed by an input layer, an output layer and one or more hidden layers connecting them. As in figure 1, unsupervised learning is consisting of two parts: encoder and decoder. The encoder takes an input vector $x \in [0, 1]^d$, and maps it to a hidden layer $y \in [0, 1]^{d'}$ through a deterministic mapping $y = f_\theta(x) = s(Wx + b)$, parameterized by $\theta = \{W, b\}$. W is a $d' \times d$ weight matrix and b is a bias vector. The resulting latent representation y is then mapped back to the decoder or a "reconstructed" vector $z \in [0,1]^d$ in

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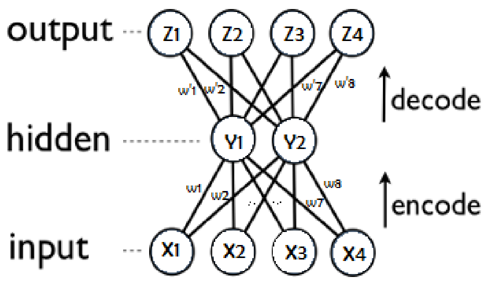

Figure 1: Unsupervised Auto-encoder Learning Architecture

input space $z = g_{\theta'}(y) = s(W'y + b')$ with $\theta' = \{W', b'\}$. The weight matrix W' of the opposite mapping may optionally be constrained by $W' = W^T$, in which case the auto-encoder is said to have tied weights.

$y = f_\theta(x) = s(Wx + b)$, parameterized by $\theta = \{W, b\}$. W is a $d' \times d$ weight matrix and b is a bias vector. The resulting latent representation y is then mapped back to the decoder or a "reconstructed" vector $z \in [0,1]^d$ in input space $z = g_{\theta'}(y) = s(W'y + b')$ with $\theta' = \{W', b'\}$. The weight matrix W' of the opposite mapping may optionally be constrained by $W' = W^T$, in which case the auto-encoder is said to have tied weights. Each training $x(i)$ is thus mapped to a corresponding $y(i)$ and a reconstruction $z(i)$. The parameters of this model are improved to reduce the average reconstruction error. Once we have a useful higher-level representation of the initial inputs, they are conducted to the second part: the supervised learning.

3.2 Back-Propagation Algorithm

In the supervised learning, we use back-propagation algorithms to train different labeled reconstructed input and choose the reconstructed subset with high performance. Back-propagation is a neural network based on multilayer perceptron model. Three layers compose this model: input layer, one hidden layer and output layer, all of these layers are linked by weighted connections. Back propagation algorithm attempts to associate a link between the input layer and the output layer, by computing the errors in the output layer and determine measures of hidden layer output errors. In way to adjust all weights connections (synaptic weights) of the network in iterative manner that carried on until the sum-squares-error decreases to a certain acceptance level (Error threshold). After training, neural network using BP algorithm is loaded with the testing samples with feature subsets going to input nodes. The classical error back-propagation algorithm can be summarized as

$$W(k+1) = W(k) + \Delta W = W(k) - \eta \frac{\partial e(W)}{\partial W}$$

Where $W = W(k)$ represents a vector of neural weights, and k = {0; 1; 2; …} represents the iteration index during training. In addition, ΔW represents new weight value at the kth iteration of the training procedure, with η denoting the learning rate which should be small enough. Furthermore, e(W) represents the sum-squares-error function that is used to monitor and control BP-training process.

4. EXPERIMENTAL RESULTS

4.1 Testbed and Data Collection

Two different data sets were used in the experiments, those datasets were made by The Center for Advanced Studies in Adaptive Systems (CASAS) in [33, 34]. CASAS project is a multi-disciplinary research project at Washington State University, which focused on the creation of an intelligent home environment. Data sets are described in the table 1, the first smart apartment test bed is located in Netherlands, an adult woman performs 10 activities, and the second is located in Egypt where two married adults perform 12 activities. The two smart apartments are equipped with motion sensors distributed in different places inside homes. Sensor data is captured using a sensor network that was designed in-house and is stored in a database. The sensor events are annotated for ADLs, which are used for training and testing the activity recognition algorithms. The two datasets are represented by the same following parameters: Date, time, and the value of sensor as well as activity target output. An extract from the Aruba dataset is presented below:

Date	Time	Sensor ID	Value	Target Output
2010-11-04	00:03:50	M003	ON	Sleeping begin
2010-11-04	00:03:57	M003	OFF	
…………				
2010-11-04	05:40:42	M007	ON	
2010-11-04	05:40:43	M003	OFF	Sleeping end

This example shows the sensor events correspond to the Sleeping activity. All activities are started by begin and finished by end.

The frequencies of activities vary from one to another. Two activities, Resperate in Aruba dataset and Laundry in Cairo dataset are filtered out, there are difficult to recognize these two activities because of too few instances. Activities are grouped into basic or instrumental activities to provide physical training data for neural network using BP algorithm. Table 2 detailed activities.

Table 1. Data Sets Description

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Data set	Country	Period	Users	instances
Aruba	Netherlands	2010-11-04 2011-06-11	1 adult	1719558
Cairo	Egypt	2009-06-10 2009-08-05	2 adult married	7 264

Table 2. ADLs Activities of Two Data Sets

Activity type	Activity name	Activity description	instances
Aruba: Basic ADL	Activity_0	Sleeping	385
	Activity_3	Work	133
	Activity_4	Relax	1095
	Activity_6	Bed_to_Toilet	155
	Activity_7	Enter_Home	431
	Activity_8	Leave_Home	431
Aruba : Instrumental ADL	Activity_1	Meal_Preparation	1034
	Activity_2	Eating	238
	Activity_5	Wash_Dishes	66
	Activity_9	Housekeeping	34
Cairo: Basic ADL	Activity_0	Bed_to_toilet	25
	Activity_2	R1_sleep	55
	Activity_3	R1_wake	58
	Activity_4	R1_work_in_office	46
	Activity_6	Leave_home	59
	Activity_9	R2_sleep	58
	Activity_11	R2_wake	64
Cairo: Instrumental ADL	Activity_1	Breakfast	49
	Activity_5	Dinner	42
	Activity_7	Lunch	37
	Activity_8	Night_wandering	47
	Activity_10	R2_take_medicine	44

4.2 Features Listing

In the experimental part, we have two different datasets with different number and names of actvities to be recognized, in this section we tried to select all significant features which characterizes most all daily life activities of the two data sets, each activity has thirteen features of the sensor events which characterize the activities:

1- $S_i = \frac{1}{n_i}\sum_{k=1}^{n_i} S_{ik}$

S_i is the mean of Sensors ID of activity i, n_i is the number of motion sensors noted in the dataset between the beginning and end of the activity, and S_{ik} is the state (on or off) of the k_{th} Sensor ID.

2- The logical value of the first Sensor ID triggered in the beginning of the current activity;
3- The logical value of the second Sensor ID triggered in the beginning of the current activity;
4- The logical value of the last Sensor ID triggered in the end of current activity;
5- The logical value of before the last Sensor ID triggered in the end of the current activity;
6- The variance of all Sensor IDs triggered by the current activity:

$$S_i^2 = \frac{1}{n_i}\sum_{k=1}^{n_i}(S_{ik} - S_i)^2$$

7- Time recorded in the beginning of the current activity;
8- Time recorded in the end of the current activity;
9- Time duration of the current activity;
10- Day of week, which is converted into a value in the range of 0 to 6;
11- Previous activity, which represents the activity that occurred before the beginning of the current activity;
12- Activity length, which is the number of instances between the beginning and the end of current activity;
13- The season of the year.

4.3 Auto-Encoder and BP Algorithm Parameters for Activity Recognition

The values of each feature of the both data sets are normalized as $\bar{X} = X/X_{max}$ where X is the actual value and X_{max} is the largest value for each feature. The weight of each neuron of auto-encoder is initialized randomly between -1 and 1. In back-propagation, only one hidden layer is adopted in this paper. In supervised learning, the number of neurons in the input layer is equal to the number of features of the selected features subset. The number of neurons in the output layer is equal to the number of activities to be recognized in the data set. In addition, the number of the hidden neurons are between the size of the input layer and the size of the output layer. It can be seen in Fig. 2 that neural network using BP algorithm tends to converge in 40,000 iterations using initial data sets of Cairo and Aruba. We adopted 40,000 iterations for all data sets but the optimal number of iterations changes a lot depending on the number of features in the data set. The 3-fold cross validation is applied on three algorithms data under the same conditions to ensure that the experimental comparison is fair.

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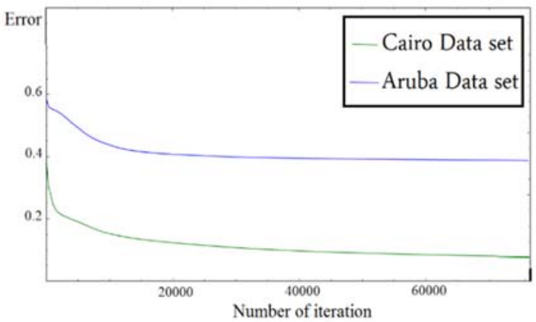
Table 3. Parameters of Neural Network Using BP Algorithm

Learning rate η	Number of iteration	Error threshold
0.01	40 000	0.01

Figure 2. Number of Iterations Depends On the Gradient Error



4.4 Results

First, we report on the first results of total activity recognition accuracy for the two initial subsets Cairo and Aruba. Thirteen features described in table 2 compose those two data sets. Table 4 show accuracy results of the two initial subsets Cairo and Aruba. Those results are presented before any data manipulation. It can be seen that the highest average of recognition accuracy performance of neural network using BP algorithm for the initial Cairo and Aruba subsets, are 85.74% and 87.38% respectively. In the majority of cases, the accuracy of basic activities is higher than instrumental ones, since basic activities are simple and require one or two sensors to be detected. Otherwise, the instrumental activity is more complex and requires a series of sensors to detect it.

Table 4. Activity Recognition Accuracy for the Two Initial Subsets: Aruba and Cairo

	Aruba				Cairo			
	Hidden neurons	Basic ADL	Instrumental ADL	Total	Hidden neurons	Basic ADL	Instrumental ADL	Total
Subset 1 13 features	10	88,58	82,78	85,68	12	82,56	84,33	83,445
	11	**89,2**	**85,57**	**87,38**	13	83,48	83,13	83,305
	12	88,58	84,05	86,315	14	81,65	80,72	81,185
	13	87,34	83,29	85,315	15	82,56	83,13	82,845
	14	86,84	83,8	85,32	16	81,65	81,92	81,785
	15	86,6	83,79	85,195	**17**	**87,15**	**84,33**	**85,74**
	16	87,09	83,79	85,44	18	85,32	84,32	84,82
	17	87,22	83,04	85,13	19	80,73	83,13	81,93
	18	87,22	82,53	84,875	20	81,65	81,93	81,79

After creating subsets with reconstructed features using auto-encoder. We presents only the results of subset 1 that consists of 12 features, subset 2 that consist of 14 features, subset 3 that consist of 16 features, subset 4 that consist of 18 features, and subset 5 that consist of 20 features. The results, in tables 5–9, reveal that the highest average accuracy of BP algorithm using auto-encoder is 91.46% for Aruba dataset and 90.62% for Cairo dataset. Tables 5–9 show the comparison results of recognition accuracy performance of neural network using BP algorithm for the five feature reconstructed subsets with different numbers of neurons of hidden layer. Activity recognition accuracy is lower for Subset 2 and Subset 3. It also can be found that for Subset 5, activity recognition accuracy is better than those previous subsets. Subset 6 presents the relatively higher proportion of recognition accuracy with 20 features; Subset 6 presents the best constructed representation of input. We clearly see a strict ordering: auto-encoder pre-training being better than no pre-training. From the results we can see, auto-encoder not only change dimensionality, but can also detect repetitive features and reconstruct new powerful ones, which can lead to good results. To avoid that the auto-encoder copy the individual elements from the input vector, number of neurons in hidden layer should be different than number of neurons in input layer. In our case, almost of features are significates, the compression is not useful. It's proved by the simulations carried out in this paper, that the reconstructed input layer using auto-encoder with a higher number of features extract a meaningful structure.

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Table 5. Accuracy of Different Hidden Neurons of Subset 2

	Aruba				Cairo			
	Hidden neurons	**Basic ADL**	**Instrumental ADL**	**Total**	**Hidden neurons**	**Basic ADL**	**Instrumental ADL**	**Total**
Subset 2 12 features	**10**	**93,42**	**76,27**	**84,845**	12	88,2	79,52	83,86
	11	90,75	76,35	83,55	13	88,2	77,81	83,005
	12	90,42	76,77	83,595	**14**	**91,04**	**78,38**	**84,71**
	13	90,5	76,19	83,345	15	89,34	79,52	84,43
	14	90,5	75,94	83,22	16	89,34	79,52	84,43

Table 6. Accuracy of Different Hidden Neurons of Subset 3

	Aruba				Cairo			
	Hidden neurons	**Basic ADL**	**Instrumental ADL**	**Total**	**Hidden neurons**	**Basic ADL**	**Instrumental ADL**	**Total**
Subset 3 14 features	10	92,09	76,27	84,18	12	89,77	84,09	86,93
	11	91,67	76,02	83,845	**13**	**90,34**	**84,09**	**87,215**
	12	91,75	76,02	83,885	14	90,34	82,95	86,645
	13	**92,5**	**75,94**	**84,22**	15	89,77	84,65	87,21
	14	91,94	75,94	83,94	16	88,06	84,09	86,075
	15	92,09	76,27	84,18	17	89,20	84,09	86,645

Table 7. Accuracy of Different Hidden Neurons of Subset 4

	Aruba				Cairo			
	Hidden neurons	**Basic ADL**	**Instrumental ADL**	**Total**	**Hidden neurons**	**Basic ADL**	**Instrumental ADL**	**Total**
Subset 4 16 features	10	92,84	81,02	86,93	**12**	**90,90**	**83,52**	**87,21**
	11	92,34	83,1	87,72	13	92,61	81,81	87,21
	12	**93,01**	**87,94**	**90,475**	14	90,34	81,81	86,075
	13	94,42	83,19	88,805	15	92,04	81,81	86,925
	14	93,09	82,19	87,64	16	90,34	81,25	85,795
	15	93,09	82,19	87,64	17	91,47	81,81	86,64
	16	92,42	81,52	86,97	18	92,04	82,38	87,21

Table 8. Accuracy of Different Hidden Neurons of Subset 5

	Aruba				Cairo			
	Hidden neurons	**Basic ADL**	**Instrumental ADL**	**Total**	**Hidden neurons**	**Basic ADL**	**Instrumental ADL**	**Total**
Subset 5 18 features	10	92,25	76,52	84,385	12	90,34	88,06	89,2
	11	92,34	75,94	84,14	13	92,04	83,52	87,78
	12	92,59	78,94	85,765	14	91,47	84,09	87,78
	13	97,17	83,69	90,43	15	92,61	82,38	87,495
	14	95,25	79,85	87,55	16	90,90	82,95	86,925
	15	92,59	76,35	84,47	17	92,04	83,52	87,78
	16	93,42	76,19	84,805	18	92,04	82,95	87,495
	17	93,25	76,19	84,72	19	90,90	82,38	86,64

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Table 9. Accuracy of Different Hidden Neurons of Subset 6

	Aruba				Cairo			
	Hidden neurons	Basic ADL	Instrumental ADL	Total	Hidden neurons	Basic ADL	Instrumental ADL	Total
Subset 6 20 features	10	91,09	78,1	84,595	12	89,20	86,36	87,78
	11	91,75	77,1	84,425	13	91,47	84,65	88,06
	12	92,51	79,61	86,06	14	92,61	88,06	90,335
	13	93,09	79,09	86,09	15	90,90	86,93	88,915
	14	93,75	81,44	87,595	**16**	92,04	85,79	88,915
	15	92,42	88,1	90,26	17	90,90	89,77	90,335
	16	**94,33**	**88,59**	**91,46**	18	90,90	84,09	87,495
	17	90,76	80,27	85,515	**19**	**92,04**	**89,20**	**90,62**
	18	90,84	78,77	84,805	20	92,61	87,5	90,05
	19	90,92	77,69	84,305	21	92,61	84,65	88,63
	20	89,84	75,77	82,805	22	90,90	84,09	87,495

4.5 Comparison Results

In this subsection, the influence of unsupervised pre-training on the recognition accuracy is evaluated by comparison with BP algorithm using traditional weighting features selection method. Table 10 presents ranking of the 13 features using weighting features selection method of Cairo and Aruba datasets. Table 11 shows, that the using of features selection reach the higher accuracy of 90.05% for Aruba dataset and 88.49% for Cairo dataset, and l

Table 10. Ranking of the 13 Features Using Weighting Features Selection Method

Ranking	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Aruba	F4	F7	F9	F10	F5	F6	F1	F12	F3	F2	F8	F13	F11
Cairo	F5	F6	F9	F10	F7	F1	F4	F3	F13	F8	F12	F2	F11

Table 11. Activity Recognition Accuracy Using BP Algorithm and Weighting Features Selection

	Aruba			Cairo		
Subset	N° of features	Hidden	Accuracy	features	Hidden	Accuracy
subset 2	12	12	89,12	12	13	84,02
subset 3	11	13	89,45	11	12	85,19
subset 4	**10**	**12**	**90,05**	10	11	85,88
subset 5	9	10	89,70	**9**	**9**	**88,49**
subset 6	8	9	88,91	8	12	80,75
subset 7	7	8	88,14	7	10	78,19
subset 8	6	7	87,24	6	9	74,45
subset 9	5	7	86,88	5	10	70,98

than BP algorithm using auto-encoder. It shows that neural network using BP algorithm performs relatively better than HMM and NB even with small number of instances. The reason is that HMM and NB algorithms evaluate human activities based on the probabilities greatly related to the finite instances. Comparison results of activity recognition accuracy rate for the four algorithms is presented in table 13. It can be concluded that the human activity recognition performances of neural network using auto-encoder pre-training and BP algorithm are better than neural network using BP algorithm and weighting features selection. The main reasons are first, that neural network using BP algorithm repeats a two-phase cycle, propagation and weight update since it uses gradient descent to tune network weights to best fit a training set of input–output pairs. Second, auto-encoder can select features that are more interesting and reconstruct new powerful and useful representations of features. Finally, different feature sets generate different human activity recognition accuracy, and the selection of suitable feature sets increases the human activity recognition accuracy.

5. CONCLUSION

This paper applies back-propagation algorithm with auto-encoder pre-training to represent and recognize human activities based on observed sensor events. From the results, it can be concluded that the human activity recognition performances of neural network using auto-encoder is better than neural network using classical method of features selection. The main reasons are that neural network using BP algorithm is immune to errors in training data since it uses gradient descent to tune network weights to best fi t a training set of input/output pairs and has strong ability in learning to interpret complex sensor events in smart home environments. Furthermore, different feature sets generate different human activity recognition accuracy, therefore, the suitable feature set must be selected in advance, and the selection of unsuitable feature sets increases the computational complexity and degrades the human activity recognition accuracy. To improve human activity recognition accuracy, an effective approach is to properly select the feature subsets.

However, there is still a lot of room for development: future works will include venturing out on more complex human activities to recognize. Furthermore, experimenting this method in real time is another subject to explore. Also, the use of smartphone platform as neural networks inputs are a few of the topics for future research.

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