Human Daily Activity Recognition Using Neural Networks and Ontology-Based Activity Representation

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Abstract. In real-life people live together in the same place, recognize their activities is challenging than activities of one single resident, but essential to collect information about real life activities inside home, then ease the assisted living in the real environment. This paper presents a multilayer perceptron model and a supervised learning technique called backpropagation to train a neural network in order to recognize multi-users activities inside smart home, and select useful features according to minimum redundancy maximum relevance. The results show that different feature datasets and different number of neurons of hidden layer of neural network yield different activity recognition accuracy. The selection of suitable feature datasets increases the activity recognition accuracy and reduces the time of execution. Our experimental results show that we achieve an accuracy of 99% with the winner method and 96% with the threshold method, respectively, for recognizing multi-user activities.

Keywords: Multi-users · Activity recognition · Smart home
Multilayer perceptron · Back-propagation · Features selection
Mutual information

1 Introduction

Recognize human activities inside home can reduce costs of health and elderly care that exceed $7 trillion annually and rising [1], ensure comfort, homecare [2], safety, and reduces energy consumption. For these reasons, researchers and organizations focused in development of a real smart home project. A smart home is a normal house, but equipped with sensors and others technologies, which anticipates and responds to the needs and requirements of the elderly people, working to promote their luxury, convenience, security, and entertainment [3]. A key point in development of smart home is recognition of normal and daily routine activities of its residents. Human Activity Recognition (HAR) is a challenging and well-researched problem. In fact, a large number of research focuses in recognition of Activities of Daily Living [4] (ADLs) which means activities, performed in user daily routine, such as eating, cooking, sleeping, and toileting; there are various reasons why ADLs are the most covered in literature. Citing as examples, first those activities are general, real, and common between young and old people. Second, ADLs are the most use in standard tests of user

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autonomy because disability with ADLs is the most common reason that older people live in nursing homes [5]. Finally, ADLs are the best suited for use as inputs to perform different home applications.

However in real-life, there are often multiple residents living in the same environment, and perform ADLs together or separately. Recognizing multi-user activities is more challenging than recognizing single-user activities. The main challenges are knows activities of every user at home and distinguish between two or more activities, which takes place at the same time. In this work, we use multilayer perceptron model, a type of Artificial Neural Network, the computation is performed using a set of simple units with weighted connections between them. Furthermore, Back Propagation (BP) algorithm [6, 7] to set the values of the weights. Otherwise, BP is a common method of training artificial neural networks in supervised learning method, which calculates the gradient of a loss function with respect to all the weights in the network. The gradient is fed to the optimization method, which in turn uses it to update the weights, in an attempt to minimize the loss function. Moreover, based on a ontological approach we propose a set of features adequate for multi-users, then we select the most relevant using a selection algorithm called, minimal-Redundancy-Maximal-Relevance criterion (mRMR) [8, 9] to obtain a set of subsets of features with high class-feature mutual information classification and the less feature-feature mutual information.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 explain the proposed set of features based on an ontological approaches and introduce the optimization approach method for features selection. Then, it describes the designing of multilayer perceptron network using BP algorithm applied to recognize multi-users activities. Section 4 resume the test and results. Finally, Sect. 5 concludes.

2 Literature Review

2.1 Activity Recognition Approaches

Researchers classify activity recognition approaches into two categories. The first is based on the use of visual sensing facilities, example: camera, and exploit computer vision techniques to analyse visual observations for pattern recognition [10, 11]. Such solutions are challenged because of the potential for the violation of user privacy, the difficulty of extracting robust and informative features to infer high-level activities. The second category is based on the use of emerging and wearable sensor network technologies and using data mining and machine learning techniques to analyse sensors data and determine user's behaviour [12–19]. Sensors can be wearable [12] or fixed in doors or spatial place at home. Due to low cost and low power consumption, sensors based approach became a centre of interest at the last decade, researchers have commonly tested the machine learning algorithms such as knowledge-driven approach (KDA) [13], evolutionary ensembles model (EEM) [14], support vector machine (SVM) [15], Naïve Bayes (NB) classifier [16], hidden Markov model (HMM) [17], and conditional random fields (CRF) [18].

2.2 Neural Networks and Features Selection

Neural networks algorithm, used in this paper, were first published in 1960. In the years following, many new techniques have been developed in the field of neural networks, and the discipline is growing rapidly [19]. Neural network has proven successful in different fields [20–23] among them human activity recognition in smart home environments [23]. To have high accuracy in neural network using BP algorithm, researchers have studied indirect or direct means to select useful features, several artificial intelligence approaches were used to identify and select signal features which are the input to Neural Networks (NN) [24]. Features selection referred in this case represents distinctive information as inputs into the input layer. Moreover, feature extraction addresses the problem of finding the most compact and informative set of features, to improve the efficiency or data storage and processing [25]. Usually all features are not equally informative: some of them may be noisy [26] Usually, the best feature subset contains the least number of dimensions that contribute to higher recognition accuracy, therefore, it is necessary to remove the remaining and unimportant features to reduce the time execution and noise. In [27] submitted to 4th edition of international colloquium on Information science and technology in Tangier, we use back-propagation algorithm and a set of selected features in order to recognise activities of one single user. In this paper, we use an ontological approach to list more powerful features, select them based in mRMR method and use back propagation algorithm to recognise multi-users activities inside home.

2.3 Multi-users Activities

Multi-users activities can be classified into tree big categories:

(1) Single user performs activities one by one
(2) Multiple users perform the same activity together
(3) Multiple users perform different activities independently [28].

To the best of our knowledge, there is less study on recognizing multi-user activities in a smart home environment. A series of research work has been done in the CASAS smart home project at WSU [29], in [30] a various kinds of sensors and a multiple users' preferences is done based on sensor readings. In [12] authors develop a multi-modal, wearable sensor platform to collect sensor data for multiple users. These works are still in a development phase because of the complexity of multi-users activities.

3 A Methodology for Activity Recognition

3.1 Activities of Daily Living

ADLs are defined as the routine activities that a person perform every day inside home without help. The ability of doing ADLs is crucial for health care to provide if required caring service. To validate our methodology for activity recognition, we relied on a smart home testbed located on Cairo in Egypt and is maintained as part of WSU Smart

Apartment ADL Multi-Resident Testbed [31] as presented in Fig. 2. The data was collected over three months while volunteer adult couple and a dog performed their normal work routines in the environment. In the smart home test bed activities to recognize are 13. These activities include both activities of the woman and the man at home. Below Table 1 describe tasks with the number of times the activity appears in the data.

Table 1. Present a description of tasks with the number of times the activity appears in the data.

Number	Name	Description	N° of time
Activity 1	Bed_to_toilet	One of the users move between bed and toilet at night	30
Activity 2	Breakfast	The two residents eat breakfast together	48
Activity 3	R1_sleep	Resident number 1 sleep	50
Activity 4	R1_wake	Resident number 1 wake	53
Activity 5	R1_work_in_office	Resident number 1 work in office at home	46
Activity 6	Dinner	The two residents eat dinner together	46
Activity 7	Laundry	One of the resident washes clothes	10
Activity 8	Leave_home	One of the residents leave home	69
Activity 9	Lunch	The two residents eat lunch together	37
Activity 10	Night_wandering	Residents wander around at night	67
Activity 11	R2_sleep	Resident number 2 sleep	52
Activity 12	R2_take_medicine	Resident number 2 take medicine	44
Activity 13	R2_wake	Resident number 2 wake up	52

3.2 Features Listing

To achieve a better representation of ADLs, we extract divers features for constructing the activity model. Features extraction refers to the process of extraction informations from raw data. Informations may include, time, location, duration, variance and average. An ontological approach is employed for features extraction, which is explicated in Fig. 1.

Based on this ontological approach, we have extracted 17 features, detailed below:

1.
$$S_i = \frac{1}{n_i}\sum\nolimits_{k=1}^{n_i} S_{ik} \quad (1)$$

   Si the means of Sensors ID of activity i, ni is the number of motion and door sensors noted in the dataset between the beginning and end of the activity, and Sik is the kth Sensor ID.
2. The logical value of the first Sensor ID triggered by the current activity;
3. The logical value of the second Sensor ID triggered by the current activity;
4. The logical value of the last Sensor ID triggered by the current activity;

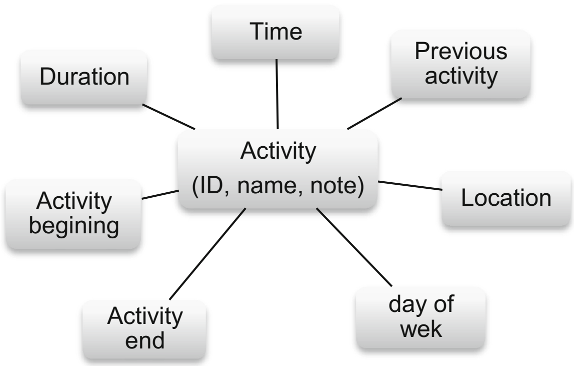

Fig. 1. Ontological representation of activity

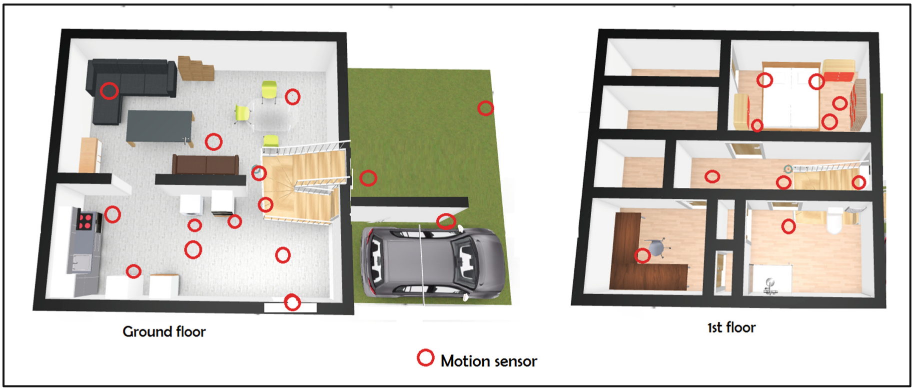

Fig. 2. Motion sensors location in the smart apartment testbed [31]

5. The logical value of before the last Sensor ID triggered by the current activity;
6. The name of the first sensor triggered by the current activity;
7. The name of the last sensor triggered by the current activity;
8. The variance of all Sensor IDs triggered by the current activity:
9. The beginning time of the current activity;
10. The ending time of the current activity;
11. The duration of the current activity;
12. Day of week, which is converted into a value in the range of 0 to 6;
13. Previous activity, which represents the activity that occurred before the current activity;
14. Activity length, which is the number of instances between the beginig and the end of current activity;
15. The name of the dominant sensor durant the current activity;
16. Location of the dominant sensor;
17. Frequance of the dominant sensor.

3.3 Features Selection Method mRMR

Features selection, or variable subset selection is used for selection of a subset of features to construct models. Two important aspects of features selection are: minimum redundancy and maximum relevance.

Features values are uniformly distributed in different classes. If a feature is strongly differentially expressed for different classes, it should have large mutual information with classes. Thus, we use mutual information as a measure of relevance of features. For discrete variables, the mutual information *I* of two variables *x* and *y* is defined based on their joint probabilistic distribution *p(x,y)* and the respective marginal probabilities *p(x)* and *p(y)*:

$$I(x,y) = \sum\nolimits_{i,j} p(x_i, y_i) log \frac{p(x_i, y_i)}{p(x_i)p(y_i)} \tag{2}$$

For categorical variables, we use mutual information to measure the level of "similarity" between features. The idea of minimum redundancy is to select the feature such that they are mutually maximally dissimilar. Let *S = {S1,S2, ...Ss}* denote the subset of features we are seeking. The minimum redundancy condition is:

$$\min[W_1, W_s], \quad W_I = \frac{1}{s^2} \sum\nolimits_{i,j \in S} I\left(f_i, f_j\right) \tag{3}$$

Where $I(f_i, f_j)$ is the mutual information between feature f_i and f_j, *s* is the number of features in S and $W_I \in [W_1, W_n]$. To measure the level of discriminant powers of features when they are differentially expressed for different target classes *T = {T1, T2, ... Tt},* we again use mutual information between targeted classes and the features. Thus the maximum relevance condition is to maximize the total relevance of all features in S:

$$\max[V_1, V_s], \quad V_I = \frac{1}{s} \sum\nolimits_{i \in S} I(f_i, T) \tag{4}$$

Where $V_I \in [V_1, V_n]$. The mRMR features set is obtained by optimizing the conditions in Eqs. (3) and (4) simultaneously. Optimization of both conditions requires combining them into a single criterion function.

$$max\{VI - WI\}_{I=1}^{s} \tag{5}$$

In this paper, in order to obtain better recognition accuracy, we have classified the features according to the mRMR score, in Table 3. Then we tested with data that contains the total features and after we eliminate one by one and we tested using back-propagation algorithm each time to compare results.

3.4 Model of Neural Network Using BP Algorithm

A Multilayer Perceptron medel is composed by three layers: The input layer, the hidden layer and the output layer, all linked by weighted connections. Back propagation algorithm attempts to associate a relationship 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 process that carried on until the errors decrease to a certain tolerance level. Initially, before adjust weights, they will be set randomly. Then the neuron learns from training subset and correct weights value, finally load to the testing mode. The Fig. 3 represent MP model which contains only one hidden layer. According to Kolmogorov's theorem, the network might be capable to have better performance using one hidden layer, just if the number of input neuron is n, and the inputs are normalized between 0 and 1, a network with only one hidden layer exactly map these inputs to the outputs.

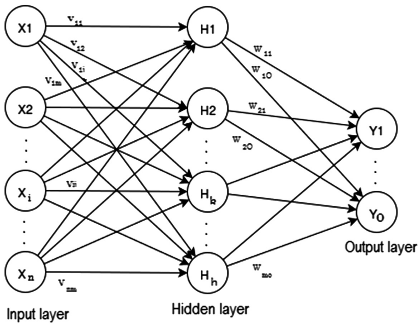

Fig. 3. Multilayer perceptron model

The active function f used in our work is a Sigmoid function:

$$f(x) = \frac{1}{1 + e^{x}} \tag{6}$$

The objective of BP approach is to minimize not only local error but also minimize the sum-squares-error function defined by:

$$\mathrm{E} = \frac{1}{2}(\mathrm{D} - \mathrm{O})^2 = \frac{1}{2}\sum\nolimits_{j=1}^{m} (\mathrm{d_j} - \mathrm{o_j})^2 \tag{7}$$

With $\mathrm{o_j}$ presnet the real vector and $\mathrm{d_j}$ present the target vector.

4 Experiments and Results

4.1 Parameters

The value of each feature is normalized as

$$X_n = \frac{X}{X_{max}} \tag{8}$$

All 13 activities were performed in neural network using BP algorithm, output contains 13 neurons and only one node produces an output close to 1 when presents with a given activity and all others close to 0. In the test, the activity recognition accuracy is performed in two methods, first referring to a threshold to choose the result, in this paper we have chosen a threshold equal to 0.7, second called the winner which choose the maximum output vector value that correspond in recognition result. Table 2 describe other parameters of neural network using BP algorithm.

Table 2. Parameters of neural network using BP algorithm

Learning rate η	Number of iteration	Error threshold
0.1	2000	0.001

4.2 Determination of Feature Subset

Table 4 presents the comparison results of the two method of activity recognition accuracy of the different feature datasets and the performance measures of multilayer perceptron neural network using BP algorithm, the subsets are described based in mRMR classification in Table 3.

Subset 1: all features without selection;
Subset 2: all features are selected except $\{f_9\}$;
Subset 3: all features are selected except $\{f_9, f_{10}\}$;
Subset 4: all features are selected except $\{f_9, f_{10}, f_{11}\}$;
Subset 5: all features are selected except $\{f_9, f_{10}, f_{11}, f_{14}\}$;
Subset 6: all features are selected except $\{f_9, f_{10}, f_{11}, f_{14}, f_{13}\}$;
Subset 7: all features are selected except $\{f_9, f_{10}, f_{11}, f_{14}, f_{13}, f_{17}\}$.

Table 4 shows the comparison results of activity recognition accuracy performance of the seven different feature subsets. It can be seen that the activity recognition accuracy is lower for subset 1 a bit more in subset 2 … etc. Subset 5 have relatively higher proportion of recognition accuracy. However, in the subset 6 and 7, the accuracy rate decreases. Obviously, if the number of features is quite low the recognition performance of neural network using BP algorithm it degrades.

Table 3. Features classification based in their mRMR score

9	f10	f11	f14	f13	f17	f6	f7	f15
3.59	3.57	3.32	2.89	2.18	2.15	1.93	1.90	1.60
f16	f4	f3	f1	f5	f2	f12	f8	
1.30	0.19	0.10	0.06	0.05	0.03	0.02	0.01	

Table 4. Comparison results of the two method of activity recognition accuracy of the different feature datasets

	Hidden neurons	Accuracy-threshold (%)	Accuracy-winner (%)
Subset1	17	88	92
	18	80	90
	19	82	90
	20	80	90
	21	82	92
	22	88	92
	23	90	90
	24	94	96
Subset 2	16	88	90
	17	96	98
	18	84	92
	19	84	92
	20	86	94
	21	80	88
	22	82	92
	23	84	90
Subset 3	15	80	96
	16	82	90
	17	90	96
	18	80	88
	19	86	94
	20	80	90
	21	74	86
	22	80	88
Subset 4	14	78	92
	15	82	92
	16	80	92
	17	94	96
	18	78	90
	19	82	92
	20	70	90
	21	76	90
Subset 5	13	74	82
	14	96	99
	15	74	86
	16	70	90
	17	94	99
	18	78	88
	19	74	94
	20	70	86

(*continued*)

Table 4. (*continued*)

	Hidden neurons	Accuracy-threshold (%)	Accuracy-winner (%)
Subset 6	12	84	94
	13	72	94
	14	72	90
	15	76	90
	16	74	88
	17	88	94
	18	74	86
	19	70	90
Subset 7	11	68	88
	12	70	86
	13	68	86
	14	78	96
	15	74	88
	16	66	86
	17	80	92

Selecting Subset 5 generates the best result and represents the relatively better recognition than others with fewer instances. Exactly, the recognition accuracy has been improved to 99% in the winner method and 96% in the threshold method for a number of neurons in the hidden layer equal to 14 with only 13 features. The variance of Sensor IDs with low mutual information score value means that redundant information degrades the recognition performance of neural network using BP algorithm. Therefore, the results indicate that the improper selection of Number of neurons increases the computational complexity and degrades the activity recognition accuracy.

In summary, considering the factors including total accuracy and training error convergence rate, the best features subset is set to Subset 5.

5 Conclusion

In this paper, we use backpropagation algorithm for training the network and mRMR technique to choose adequate features between proposed ones. We conclude that different features set and different number of neurons in hidden layer generate different multi-users activity recognition accuracy, the selection of unsuitable feature sets increases influence of noise 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 experimenting on more efficient methods for activity recognition (e.g. deep learning), as well as construct activities models in order to recognise human activities in real time.

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