Human activity recognition based on extreme learning machine in smart home

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Abstract. This paper applies extreme learning machine (ELM) to human activity recognition in smart home, evaluates the human activity recognition model established by ELM. Experimental results show that the accuracy of activity recognition of ELM model is related to the number of hidden layer units. Too many/few hidden layer units can affect the performance of the ELM mode, apparently.

1. Introduction
With the aging of society, more and more old people need to be taken care of. In the early 21st century, China's aging problem has become prominent. In 2000, the proportion of the elderly over 65 years old accounted for nearly 7% of the total population in China [1]. The United Nations predicts that by 2049, 31% of Chinese will be over 60 years old, second only to Europe [2]. Therefore, the research of smart home is of great significance. Smart home can not only provide more services for the elderly, but also create a comfortable, intelligent and energy-saving environment [3].

The premise of providing services for human beings in smart home is that it can recognize human activities, so activity recognition algorithm is important in smart home. There are many classification algorithms, such as Naive Bayes [4], Hidden Markov Model [5] and Support Vector Machine [6] have been reported.

The CASAS smart home project is an intelligent space research project supported by Washington State University. The method of CASAS is to install sensors in smart home, and then use the sensors to sense environment, and then recognize human activities through certain algorithms, and finally make corresponding actions to the environment by executing devices [7].

2. Data collection
The data are all from the smart home experiment bed of Washington State University. The smart environment consists of three bedrooms, a bathroom, a kitchen and a dining room. Figure 1 shows the distribution map of sensors in smart home. Sensors are placed in every corner to detect behaviors. There are many kinds of sensors, including motion sensor, lamp sensor, temperature sensor and item sensor. The motion sensor is placed on the ceiling. The temperature sensor and the analog sensor are used to detect the ambient temperature, the temperature of hot water, cold water and gas stove. The use of the pot, telephone and medicine box is detected by the contact switch sensor.
Fig. 1. Sensors layout in smart home

All data should be marked accordingly after being collected. The marked data is screened, processed and accessed in a certain form. The format is: `<date time sensor ID sensor status marker>`

Table 1 shows an example of night wandering.

| date    | time       | sensor ID | sensor status | marker          |
|---------|------------|-----------|---------------|-----------------|
| 2009-06-10 | 03:20:59.08 | M006      | ON            | Wandering_begin |
| 2009-06-10 | 03:25:19.05 | M012      | ON            |                 |
| 2009-06-10 | 03:25:19.08 | M011      | ON            |                 |
| 2009-06-10 | 03:25:24.05 | M011      | OFF           |                 |
| 2009-06-10 | 03:25:24.07 | M012      | OFF           | Wandering_end   |

Begin indicates the beginning of the activity, the date of which is 2009-06-10 and the time of which is 3:20:59.8. The first sensor triggered by the activity is numbered M006 and the state of the sensor is ON. M012 and M011 are also triggered during the activity, and the end indicates the end of the activity, the date of which is 2009-06-10 and the time of which is 03:25:24.07 and the state of the sensor is OFF.

The activities in this experiment are 10 human daily activities. These 10 activities will be repeated by two volunteers in the experimental environment. The 10 activities are as follows:

- Toilet (activity number 0): 30 samples.
- Breakfast (activity Number 1): 48 samples.
- Sleep (activity number 2): 207 samples.
- Work (activity No. 3): 46 samples.
- Dinner (activity No. 4): 42 samples.
- Laundry (activity No. 5): 10 samples.
- Going out (activity number 6): 69 samples.
Lunch (activity number 7): 37 samples.
Night wandering (activity number 8): 67 samples.
Drug taking (activity number 9): 44 samples.

3. Feature selection
An important part of activity recognition is feature selection [7]. Selecting appropriate features is the key to the success of the algorithm. According to the sensor data collected in CASAS, the following features can be obtained:

(1) Average sensor ID of each activity.
(2) First sensor ID triggered by the activity.
(3) Last sensor ID triggered by the activity.
(4) Length of the current activity.
(5) Start time of the current activities.
(6) End time of the current activity.
(7) Duration of the current activities.

4. Extreme learning machine
Artificial neural network (ANN) [8] is short for neural network, which is an algorithmic mathematical model for distributed parallel information processing by imitating the structure of brain synaptic connections.

In 2004, professor Guang-Bin Huang of Nanyang Technological University and his colleagues proposed the extreme learning machine [9]. The purpose of ELM is to improve the back propagation algorithm, raise the learning efficiency and reduce the learning parameters. The biggest characteristic of ELM is that for the traditional neural network, especially the feedforward neural network [10] of single hidden layer, it not only guarantees extremely high accuracy rate, but also greatly reduces workload of the algorithm, and the solution obtained is the exact solution.

ELM is a fast learning algorithm. The biggest difference between ELM and BP neural network is that ELM can randomly initialize input weights and biases and get output weights. Suppose that there are N samples \((X_i, t_i)\), where \(X\) is the feature vector and \(t\) is the label vector. For a neural network with a hidden layer node, it can be expressed as

\[
\sum_{i=1}^{N} \beta_i g(W_i \cdot X_j + b_i) = o_j, \; j = 1, \ldots, N
\]  

(1)

\(g(x)\) represents the activation function. Sigmoid function is selected as the activation function of ELM in this paper. \(W_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T\) is the input weight, \(\beta_i\) is the output weight, and \(b_i\) is the bias of the ith hidden layer. \(W_i \cdot X_j\) is the inner product between \(W_i\) and \(X_j\). The goal of the network is to minimize the error between the expected output and the actual output, which can be expressed as

\[
\sum_{j=1}^{N} \| o_j - t_j \| \tag{2}
\]

There's \(W_i\), \(X_j\), and \(\beta_i\) that make

\[
\sum_{i=1}^{L} \beta_i g(W_i \cdot X_j + b_i) = t_j, \; j = 1, \ldots, N \tag{3}
\]

The matrix form is \(H\beta = T\), where \(H\) is the output of the hidden layer, \(\beta\) is the weight of the output, and \(T\) is the target output. We want a set of \(\tilde{W}_i\), \(\tilde{b}_i\), and \(\tilde{\beta}_i\) to minimize the error, which is expressed by
Where $i = 1, 2, \ldots, L$, which is equivalent to minimizing the loss function

$$E = \sum_{j=1}^{N} \left( \sum_{i=1}^{L} \beta_i g(W_i \cdot X_j + b_i) - t_j \right)^2$$

For solving the minimum value of the loss function, the traditional gradient descent method \cite{11} can be used, but the method needs to adjust all parameters through continuous iteration. In ELM, once the input weight $W_i$ and the bias $b_i$ of the hidden layer are determined randomly, the output matrix $H$ of the hidden layer is determined accordingly. Thus, training the neural network of single hidden layer can be indirectly converted to solving a linear system $H\beta = T$. The output weight $\beta$ can be solved by formula

$$\beta = H^+ T$$

Where $H^+$ is the Moore-Penrose matrix of $H$.

The number of input nodes of ELM is 7, which corresponds to the 7 features which are normalized. The number of output nodes is 10, corresponding to 10 human activities. Since the only adjustable parameter of ELM is the number of hidden layer nodes, this paper takes the number of hidden layer units as a variable, changes its value to observe the overall recognition rate of the algorithm. The experiments adopt 3 fold cross-validation \cite{12}.

5. Experimental result

Table 2 gives recognition rates for different hidden layer units. It shows the recognition rate increases with the increasing of the number of hidden layer units, firstly, and decreases until the number of units reaches a peak value. When the number of hidden layer units is too small, the effect of network training model is very poor, which is the performance of under-fitting \cite{13}. If the number of hidden layer units is too large, the effect of network training model is also not reasonable. It shows that too many units will lead to over-fitting \cite{14}. Therefore, a higher recognition rate can be obtained by choosing the appropriate number of hidden layer units. From Table 1, it can be seen that when the number of hidden layer units is about 110, the recognition rate is the highest.

| Unit | 10  | 30  | 50  | 70  | 90  | 110 | 130 | 150 | 170 | 190 | 210 |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Accuracy     | 0.765| 0.875| 0.905| 0.908| 0.906| 0.896| 0.901| 0.886| 0.875| 0.828|     |

6. Conclusion

This paper applies extreme learning machine to recognize human activities. The experimental results show that the human activity recognition performance of ELM is good. Furthermore, different number of hidden layer units leads to different recognition accuracy, therefore, the optimal number of hidden layer units must be determined through experiment.

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