Chapter 37
Recurrent Neural Network for Human Activity Recognition in Smart Home

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Abstract One of the most important functions of smart home is to monitor and assist individuals who are old or disabled. Recognizing the human activities is critical for the smart home application. In this paper, recurrent neural network (RNN) is applied to recognize the human activities. To evaluate the accuracy of the recognition algorithms, the results using real data collected from participants performing activities were assessed. With proper feature selections, the results of recurrent neural network show the significant ability to recognize human activities in smart home.

Keywords Smart home · Recurrent neural network · Human activity recognition · Feature selections

37.1 Introduction

The number of people who live with cognitive or physical impairments is rising because of the world's population ages. Many of old adults living in rural areas have no way to get health care [1]. Today, these old people without familiar surroundings who need special health care usually leave home to meet medical needs. Providing this health care at home will become an uncommon thing because

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of mounts of old adults can not afford to accept health care because of the high cost. Therefore, the need for smart home technologies is underscored by the aging of population, high cost of normal health care, etc. Individuals should be able to complete the Activities of Daily Living (ADLs) [2] who are independent in their own homes of the field of smart home. A range of intelligent systems built for providing health care [3] and wellness enable people to living in home with an improved overall quality of life.

The CASAS smart home project is a research project at Washington State University focused on the creation of an intelligent home environment. The CASAS smart home project consists of various sensor data collected by the smart environment such as motion sensors, light sensors, etc. Much of the theory and most of the algorithms are designed to handle one individual [4] in the space at a time. Passive tracking, activity recognition, event prediction, and behavior automation become significantly difficult. To achieve of the goal of monitoring and assistance, one of the most important step is to recognize the activity that an individual is performing in a smart environment. Over the past few years, there have been many approaches to model and recognize activities such as hidden Markov model (HMM) [5, 6], naïve Bayes classifier (NBC) [7, 8], support vector machine (SVM) [9, 10], etc.

Applying recurrent neural network to the field of human activity recognition in smart home is the main focus of this paper, which is compared with the others (HMM and NBC). In addition, the feature selections for human activity recognition is introduced simply. Finally, the experimental results are presented.

37.2 Data Collection

To validate the algorithms, we tested them in a smart apartment test bed located on the Washington State University which is maintained as part of the ongoing CASAS smart home project [11, 12]. For this studies, we used the lab space on the campus and many different kinds of activities took place throughout the room. The smart apartment is designed to equip with motion and temperature sensors as well as analog sensors. As shown in Fig. 37.1, there are three bedrooms, one bathroom, a kitchen, and a living/dining room. The motion sensors are located on the ceiling distributed approximately throughout the space. In addition sensors are equipped to provide ambient temperature readings and custom-built analog sensors to provide reading for hot water, cold water and stove burner use. Voice over IP captures phone usage using Asterisk software and contact switch sensors are used to monitor usage of a cooking pot, the phone book, and the medicine container. Sensor data [13] for activity recognition is captured using a customized sensor network and then stored in a SQL database. To maintain privacy, participant names and identifying information are removed and encrypt collected data before it is transmitted over the network.

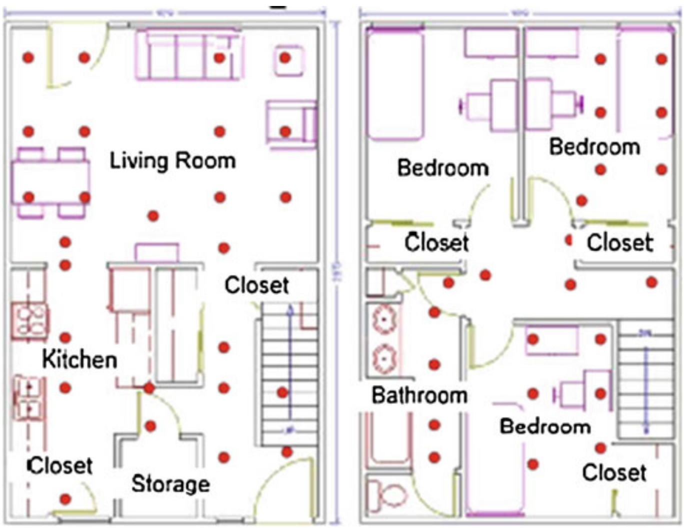

Fig. 37.1 The smart apartment testbed

37.2.1 Data Representation

To provide physical training data for this algorithms, we recruited many volunteer participants to perform a series of activities in the smart apartment. The collected sensor events were manually labeled with the activity ID. Total of 10 activities is in the smart apartment. Those activities are as follows:

- Bed to toilet (activity 0): Transition between bed and toilet in the night;
- Breakfast (activity 1): The participants have breakfast;
- Bed (activity 2): The activity is sleeping in bed marked with defined end and begin;
- Computer work (activity 3): The activity is the participant who is working in the office space of the smart home;
- Dinner (activity 4): The participants have dinner;
- Laundry (activity 5): The participants clean clothes using laundry machine in the smart home;
- Leave home (activity 6): The activity of the participant who is leaving the smart home;
- Lunch (activity 7): The participants have lunch;
- Night wondering (activity 8): The activity of the participant who is wondering in the midnight;
- Take medicine (activity 9):The activity is the participant who is taking medicine marked with defined begin and end.

37.2.2 Feature Generation

Training data were gathered during several weeks in the test space. Relevant features are generated from the annotated data that is helpful in recognizing the activities. The data gathered by CASAS smart home project is presented by the following features:

- Sensors ID
  This is an integer value from 0 to 9. Instead of using the original number of physical sensors, they are mapped to the labels in order to corresponding to the room in which the sensors installed.
- Time of the day
  This is the input time of the sensor event in seconds. The feature is an integer value from 0 to 23.
- The day of week
  The feature represent the day of the activity that occurred.
- Previous of the activity
  This is the activity that occurred before the current activity. The feature is an integer value from 0 to 9.
- Activity length
  The feature represents the length of the current activity. The feature is an integer value from 0 to 14.
- Duration of activity
  The feature represents the duration of the activity. The feature is an integer value from 0 to 9.

The CASAS smart home project middleware generates the first four fields automatically. The annotated class field is the target feature for this learning problem and represents an aim for the activity for the activity to which the other fields can be mapped. Sample data collected in the smart work place is shown in Table 37.1. There are five fields represented as follows include Date, Time, Sensor ID, Message and Label.

Table 37.1 Data used for learning

Data	Time	Sensor ID	Sensor value	Label
09-06-10	03:20:59.08	M006	ON	Night wandering begin
09-06-10	03:25:19.05	M012	ON	
09-06-10	03:25:19.08	M011	ON	
09-06-10	03:25:24.05	M011	OFF	
09-06-10	03:20:59.08	M012	OFF	Night wandering end

37.3 Recurrent Neural Network for Human Activity Recognition

The proposed recurrent neural network [14, 15] consists of three layers as shown in Fig. 37.2. The employed recurrent neural network has typical dynamic networks and the dynamic mapping characteristics by storing states and better nonlinear mapping ability [16].

In the recurrent neural network, each hidden unit is connected with itself and fully connected with all input units and other output units. Therefore, the output value of the ith output unit at cycle k is obtained as follows:

$$O_i(k) = \sum_j w_{ji}^o X_j(k) \tag{37.1}$$

$$X_i(k) = f(S_j(k)) \tag{37.2}$$

$$S_j(k) = w_j^D X_j(k-1) + \sum_m (w_{mj}^I I_m(k)) \tag{37.3}$$

where $X_j(k)$ is the output value of the jth hidden unit at the cycle k, w_{ji}^o is the weight between the jth hidden unit and the ith output unit, $X_j(k-1)$ is the output value of the jth hidden unit at cycle $k-1$, w_j^D is the weight between the output value of the jth hidden unit and the input value of the jth hidden unit, $I_m(k)$ is the output value of the mth input unit at the cycle k, $w_{mj}^I$is the weight between the mth input unit and the jth hidden unit, $S_j(k)$ is the input value of the jth hidden unit at the cycle k, $O_i(k)$ is the output value of the ith output unit at the cycle k.

The weight correction of the recurrent neural network is in training phase. The weight of the proposed recurrent neural network in training phase is as follows:

$$w_j^D(k) = w_j^D(k-1) + \eta_D \Delta w_j^D(k) + \alpha(w_j^D(k-1) - w_j^D(k-2)) \tag{37.4}$$

where η_D is the learning rate of the recurrent neural network, α is the momentum coefficient of the proposed recurrent neural network, $\Delta w_j^D(k)$ is the weight

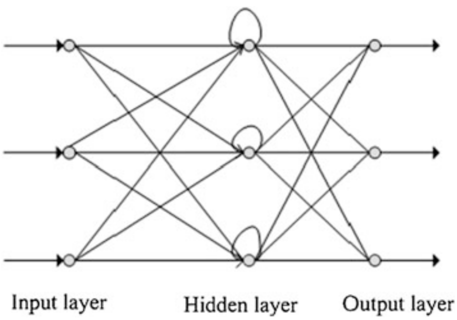

Fig. 37.2 Three layers of recurrent neural network

correction of the proposed recurrent neural network. The correction of the other weights is as same as Eq. (37.4).

The essence of recurrent neural network algorithm is to obtain the minimum issue of the error function. This algorithm uses rapid decline method in nonlinear programming and modifies weight coefficient by the negative gradient direction of the error function.

$$E_p = \frac{1}{2}\sum_i (y_i(k) - O_i(k))^2 \tag{37.5}$$

where $y_i(k)$ is the target of the output value of the ith output unit, E_p is the performance error indicator of the error function.

Learning algorithm of the recurrent neural network is to modify the each layer weights of the output value of the output layer close to the process of target.

37.4 Test Result

In the recurrent neural network, the number of neurons of the input layer is 6, the number of neurons of the output layer is 10 and the number of neurons of the hidden layer is 10. In order to simplify the calculation, all of the layers of the learning rate and the momentum coefficient were set as same size. Therefore, α is 0.9 and η is 0.005. The samples have been collected in the CASAS smart apartment testbed for 55 days, resulting in total 600 instances of these ten activities and 647,485 collected motion sensor events.

In this paper, the 3-fold cross validation is applied. The results are shown in Table 37.2, which shows that recurrent neural network performs better on the 80 % of the activities than HMM and NBC. Recurrent neural network performs better on activity 0, activity 2, activity 3, activity 5, activity 6 and activity 9. While, recurrent neural network have a lower recognition accuracy on activity 8 than the other activities. It can be found that recurrent neural network can effectively identify these activities compared with HMM and NBC.

Table 37.2 Activity recognition rate

Activity	0	1	2	3	4
HMM	0.500	0.896	0.870	0.261	0.929
NBC	0.300	0.917	0.860	0.500	1.000
RNN	0.667	0.854	0.908	0.826	1.000
Activity	5	6	7	8	9
HMM	0.400	0.884	0.892	0.582	0.795
NBC	0.300	0.928	0.973	0.940	0.705
RNN	0.800	0.942	0.838	0.537	0.909

37.5 Conclusion

In this paper, recurrent neural network were applied to solving the activity recognition problem in smart home. In order to get a better observation about the recognition performance of recurrent neural network, it was compared with hidden Markov model and naïve Bayes classifier. By the experimental results, it is obvious that recurrent neural network is better than those two algorithms in the field of human activity recognition.

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