Long Short-Term Memory based Human Behavior Recognition by Using RFID

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Abstract

In decades, the exponential growth of intelligent mobile devices makes daily behaviors more convenient. Sensitive sensors (aka, Wi-Fi, RFID) are embedded into these devices and it is easy to collect real-time data from the environment. Although the video-based behavior recognition has high accuracy by using Deep Learning methods, it is unavoidable for invasion of person's privacy. In this thesis, we propose the RFID-based behavior recognition that is device-free. The experiment is performed using RFID and the classification is performed by using Long Short-Term Memory (LSTM) algorithm.

1 Introduction

Human daily behavior and gestures can be recognized, which provides convenient services that is difficult to be realized by conventional computers. The technology of human behavior recognition is expected to be used in various situations. Health management, support for the elderly and daily life are examples. With regard to health management, it is possible to analyze human health and to discover potential diseases by monitoring people's lives over a long time period. For elderly, it is possible to watch the condition of elderly parents living apart by monitoring the lives of the elderly. In daily life, people can look for things forget putting somewhere by storing human actions in the computer [1]. As described above, there are various ways of using the technology of human behavior recognition.

RFID (Radio Frequency Identification) is a system that identifies and manages people and things without contact by using radio waves. Specifically, RFID tags are attached to products and people, and information of RFID tags is read and written by using reader/writer. Electronic money such as Suica is an example that uses RFID around us. Things such as books, clothes and wristbands that companies use also use RFID to manage the flow of people and physical distribution.

The technology of human behavior recognition using RFID has more advantages than using other technologies. There are many technologies (e.g., Wi-Fi, Video, Wearable sensor and RFID) applied to automatically recognize human behavior. However, the video-based approach has the potential for privacy violations and cannot be used in the dark. It might makes users feel uncomfortable, due to wearable sensor should be attached on human body or clothes. The approach using Wi-Fi has a problem that radio waves may not be connected. RFID approaches can be used in the dark and protect privacy without being attached to the human body or clothes.

In this research, we first collect 4 behavior datasets using many RFID tags and some antennas. Then, the Long Short-Term Memory technology which has superiority on sequential information is applied to classify behavior.

The rest of this paper is organized as follows. Some important related work is reviewed in Section 2. In Section 3, we mainly introduce the mechanism of LSTM. Thereafter, real-world experiment are conducted to collect raw data as the input of our proposed methods in Section 4. Finally, Section 5 concludes the paper.

2 Related Work

This section mainly introduces some related work on human behavior recognition systems by using RFID technologies.

Andoh *et al* [2] investigate to detect four states by reading tags with four antennas in a 2.5m $\times$ 2.5m environment by using passive RFID tags. In this research, the posture of a person is classified based on the combination of read RFID tags instead of directly recognizing abnormal conditions. Since the radio wave intensity changes with temperature and humidity, the radio wave intensity is binarized here and machine learning is performed with 1 or 0. The tag is pasted from the top of a person's clothes, and the four postures have been successfully classified with an average accuracy of 89.6% if the action was taken in the environment.

Furthermore, Yakushiji *et al* [3] use a passive RFID tag and research to detect multiple states by reading the tag with an antenna installed according to the environment. In this research, instead of directly recognizing the abnormal state, it recognizes the action and position and detects the abnormal state by a combination of them. An RFID tag is attached to an appropriate position on the clothes and read by a reader / writer. When the person who attached the tag takes some action within the reading range of the reader / writer, the posture is classified according to the reading situation of the tag. The acquired data is acquired by RSSI value indicating the radio field intensity, and the acquired data is classified using a learning model. As a result, when the learning model and the person to be recognized are different, we succeeded in recognizing the behavior of sitting and sleeping at 60% and position at 57% as the behavior classification accuracy. In addition, Yakushiji *et al* [3] perform cross-validation on a set of data from multiple persons because the RSSI values obtained differ depending on the location of the antenna and tag in the experiment, the physique of the subject, and the measurement date and time. It seems that the accuracy has decreased due to the lack of data for learning data. Therefore, we thought that it was necessary to create and experiment with learning data that further limited the measurement environment.

3 Method

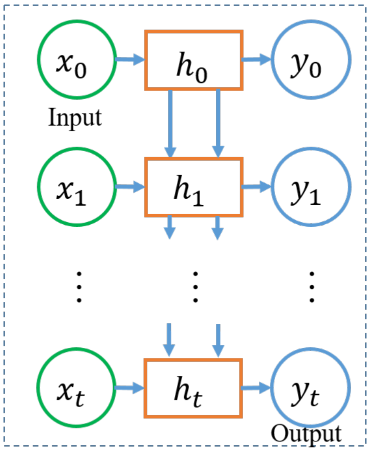
Long Short-Term Memory are explicitly proposed to avoid the long-term dependency problem. It is their practical default behavior to remember information for long periods of time.

All recurrent neural networks have the form of a chain of repeating modules of neural network. In standard RNNs, this repeating module will have a very simple structure, such as a single *tanh* layer. LSTMs also have this chain like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.

The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. It's very easy for information to just flow along it unchanged. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates.

Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation. The sigmoid layer outputs numbers between zero and one, describing how much of each component should be let through. A value of zero means "let nothing through," while a value of one means "let everything through!" LSTM based on recurrent neural network has advantage on sequential information. Given that the RFID signal is sequential and human activity is regular. Hence, we investigate to employ is to address our issue.

Furthermore, we will introduce the details in LSTM cell in which the input gate and forget gate can be expressed as:



LSTM

Figure 1: The illustration of Long Short-Term Memory technology

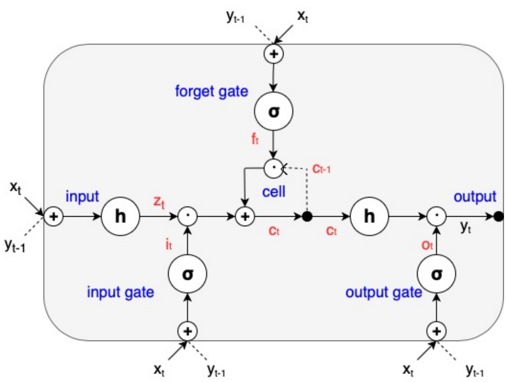


Figure 2: The internal details of Long Short-Term Memory Cell [4]

$$i_t = \sigma(W_i * x_t + R_i * y_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_f * x_t + R_f * y_{t-1} + b_f) \tag{2}$$

where, W_i, R_i, W_f and R_f are the matrices of weights for the input gate and forget gate; σ is the nonlinear function that output numbers between 0 and 1, which means how much information should let through; b_i and b_f are biases for these gates in vectors form; x_t is the raw sequential data as the input of LSTM cell.

The input information z_t is expressed as:

$$z_t = h(W_z * x_t + R_z * y_{t-1} + b_z) \tag{3}$$

where h presents the hyperbolic tangent function; W_z and R_z denotes the weights and b_z denotes the biases. Thanks to the amount of z_t to be added into the cell is determined by the input gate, the cell state can be calculated by:

$$c_t = i_t \odot z_t + f_t \odot c_{t-1} \tag{4}$$

Finally, we get the output y_t expressed as:

$$y_t = o_t \odot h(c_t) \tag{5}$$

where, o_t presents the output gate which expressed by (6) and $h()$ denotes the function which is employed to extract the information from cell state.

$$o_t = \sigma(W_o * x_t + R_o * y_{t-1} + b_o) \tag{6}$$

where, W_o and R_o denote the weights for output gate in matrices form; b_o is the vector of biases.

4 Experiment and Analysis

4.1 Experiment Design

In this section, we mainly introduce the experiment environment to validate our proposal scheme.

1. *Experiment Device*
   Firstly, we deploy the experiment environment as shown in Fig.3 and Fig.4. 49 passive RFID tags are distributed on the floor and desk to construct the environment. 3 RFID antennas are fixed on the white board near to the desk which are used to connected with RFID reader. The collected data are stored on the PC connected to the RFID reader.

Figure 3: The environment for this experiment

2. *Experiment Deployment*
   The second part includes experiment designing. One person does 4 daily life activities(like eating, watching TV, drinking and none) in the environment. The collecting time for each activity is about 9s and each activity has 120 datasets. And 100 datasets of collected datasets for each activity is used for training data, and the rest datasets is used for testing data.

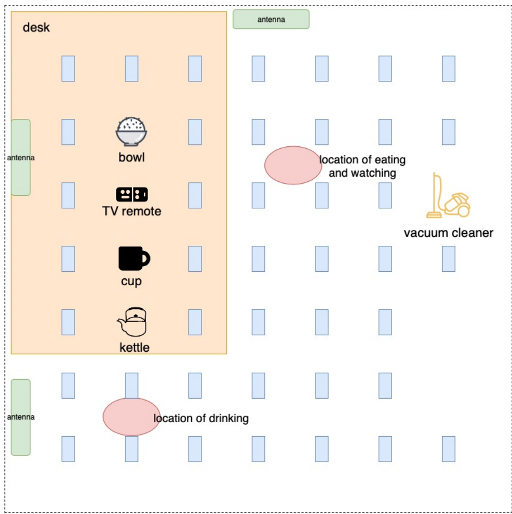


Figure 4: The illustration of the environment via 2-D grid

After collecting the experiment datasets, we try to construct LSTM model for recognizing activity by taking the collected data as input. Given to the LSTM model, we make some prediction by taking some of the collected data as input and the output is the most probability of activities.

4.2 Analysis

The result is shown in Figure 5. We can find that the average accuracy of activities recognition exceed 89%, while the accuracy of watching TV activity is lower than others.

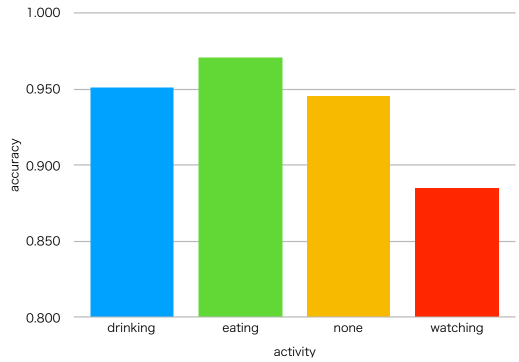


Figure 5: The accuracy of each activity

5 Conclusion

In this paper, we mainly study the application of RFID in human activity recognition. And Deep Learning Based algorithm named LSTM is applied to address the recognition problem. Thereafter, we evaluate our proposed in real-world experiment. The result show that LSTM has high accuracy for human activity recognition by using RFID.

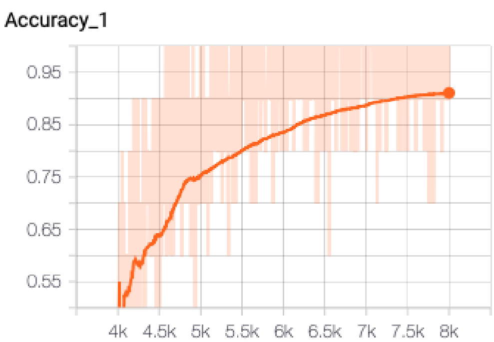


Figure 6: The accuracy in training process

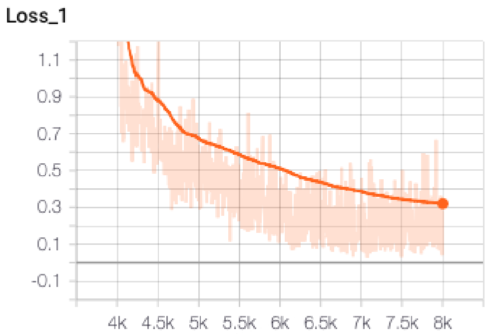


Figure 7: The illustration of training process of loss

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