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Human activity recognition based on feature selection in smart home using back-propagation algorithm

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ABSTRACT

In this paper, Back-propagation(BP) algorithm has been used to train the feed forward neural network for human activity recognition in smart home environments, and inter-class distance method for feature selection of observed motion sensor events is discussed and tested. And then, the human activity recognition performances of neural network using BP algorithm have been evaluated and compared with other probabilistic algorithms: Naïve Bayes(NB) classifier and Hidden Markov Model(HMM). The results show that different feature datasets yield different activity recognition accuracy. The selection of unsuitable feature datasets increases the computational complexity and degrades the activity recognition accuracy. Furthermore, neural network using BP algorithm has relatively better human activity recognition performances than NB classifier and HMM.

1. Introduction

With the advent of smart home [1–16] technologies, people with cognitive impairments can lead independent lives in their homes for longer time. Smart homes can assist their residents by acting as a cognitive prosthesis, by handling various appliances/objects and also by facilitating emergency communication. Furthermore, cognitive health assessments performed in clinical settings do not always provide an adequate representation of a patient's behavior. Real life assessments of Activities of Daily Living (ADLs) [13–23] can provide a better understanding of the subject than assessments performed in a clinical setting [24].

Computer vision sensing often works in the laboratory but fails in real home settings due to clutter, variable lighting, and highly varied activities. Video feeds have been used for activity recognition. Sensors such as microphones and cameras are commonly used as recording devices. However, cameras and microphones face another challenge because they are perceived as invasive by most people [25,26]. Alternatively, motion sensor data can be used to recognize real-life activities performed in a smart home.

Smart homes provide continuous monitoring capability that conventional methodologies lack. Being able to automate the activity recognition from human motion patterns using unobtrusive sensors or other devices can be useful in monitoring older adults in their homes and keeping track of their ADLs and behavioral changes. This could lead to a better understanding of numerous medical conditions and treatments.

The Center for Advanced Studies in Adaptive Systems (CASAS) smart home project [8–10] is a multi-disciplinary research project at Washington State University, which focused on the creation of an intelligent home environment. The approach is to view a smart home as an intelligent agent that perceives its environment through the use of sensors, and can act upon the environment through the use of actuators. The research goals of the CASAS smart home project are to enhance and improve the quality of life, prolong stay at home with technology-enabled assistance, minimize the cost of maintaining the home and maximize the comfort of its inhabitants. In order to achieve these goals, smart home must be able to reason about and adapt to provide information.

To implement the goals of the CASAS smart home project, a primary challenge is to design an algorithm that labels the activity performed by an inhabitant in a smart environment from the sensor data collected by the environment during the activity. Medical professionals also believe that one of the best ways to detect emerging medical conditions before they become serious is to look for changes in the ADLs. Recently, human activity discovery and recognition has gained a lot of interest due to its enormous potential in context aware computing systems, including smart home environments. To recognize residents' activities and their daily routines can greatly help in providing automation, security,

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and more importance in remote health monitoring of elder or people with disabilities. The main object of activity recognition in smart home environments is to find interesting patterns of behavior from sensor data and to recognize such patterns. Researchers have commonly tested the machine learning algorithms such as knowledge-driven approach(KDA), evolutionary ensembles model (EEM), support vector machine (SVM), Dempster–Shafer theory of evidence(D–S), Naïve Bayes(NB) classifier, Markov model (MM), hidden Markov model (HMM) and conditional random fields (CRF) [13–23], [27–34], etc., for human activity (pattern) recognition in smart home environments. NB classifier uses the relative frequencies of feature values as well as the frequency of activity labels found in the sample training data to learn a mapping from activity features to an activity label. HMM is a statistical approach in which the underlying model is a stochastic Markovian process that is not directly observable (i.e., hidden). It can only be observed through other processes that produce the sequence of the observed features. The hidden nodes represent activities and the observable nodes represent combinations of the selected features. The probabilistic relationships between hidden nodes and observable nodes and the probabilistic transition among the hidden nodes are estimated through the relative frequency with which these relationships occur in the sample data. Given an input sequence of sensor events, the Viterbi algorithm finds the most likely sequence of hidden states, or activities, which could have generated the observed event sequence. Like HMM, CRF model makes use of the transition likelihoods between states and the emission likelihoods between the activity states and the observable states to output a label for the current data point. CRF learns a label sequence which corresponds to the observed sequence of features. Unlike HMM, weights are applied to each of the transition and emission features. These weights are learned through an expectation maximization process based on the training data. However, these methods usually have some defects to some extent. For examples, NB classifier is a simple probabilistic classifier based on the application of the Bayes' theorem, but the independence assumptions of variables are not always accurate. Another key problem is that these approaches require the knowledge about the probabilities, therefore, they yield lower accuracy rate with fewer observed samples, especially. Therefore, an approach which is not sensitive to the amount of available data is especially reasonable for activity recognition in smart home. Besides, the datasets include a large number of sensor events generated by various activities and any activity annotated in dataset has various features [35,36]. However, these feature values are usually selected in one method in all tests, and the influences of these feature values on the activity recognition performance are seldom addressed. Furthermore, the activity recognition accuracy rate generated by different algorithms should be evaluated and compared.

Since neural network using BP algorithm [37,38] has proven successful in many practical problems such as learning to recognize handwritten characters, spoken words as well as human faces, therefore, neural network using BP algorithm is applied for human activity recognition in smart home environments in this paper. Besides, inter-class distance [39] method for feature selections of observed motion sensor events is discussed and tested. And then, the activity recognition performance of neural network using BP algorithm is evaluated and compared with other probabilistic algorithms: NB classifier and HMM.

The rest of the paper is organized as follows. Section 2 describes the designing of neural network using BP algorithm applied to represent and recognize human activities, the smart apartment testbed and data collection as well as the application of inter-class distance method for feature selections of observed sensor events. Section 3 presents the comparison results of activity recognition accuracy of the different feature datasets and the performance measures of the three algorithms: neural network using BP algorithm, NB classifier as well as HMM. Section 4 summarizes the main contributions.

2. Neural network using BP algorithm applied for human activity recognition and feature selections

2.1. Model of neural network using BP algorithm

Neural network using BP algorithm is a typical forward network that consists of input layer, hidden layer and output layer, which can be used to model complex relationship between inputs and outputs or to find patterns in data. In the supervised model, the error back propagation algorithm is applied to train Multi-Layer-Perception (MLP) which is the simplest multilayer feed-forward network of neural network. According to Kolmogorov's theorem, neural network using BP algorithm with one hidden layer can uniformly approximate any continuous function on a compact input domain to arbitrary accuracy if the network has a sufficiently large number of hidden units.

A training set comprises a set of input vector $X=(X_1,X_2,\cdots,X_i,\cdots,X_n)^T$($n$ input units), correspondingly, there is a set of target vector $D=(D_1,D_2,\cdots,D_k,\cdots,D_l)^T$($l$ output units). $Y=(Y_1,Y_2,\cdots,Y_j,\cdots,Y_m)^T$ is the hidden vector (m hidden nodes). Usually, x_0 and y_0 are set to be -1 for the bias value. The output vector is $O=(O_1,O_2,\cdots,O_k,\cdots,O_l)^T$. The connection weight vector between neurons in input layer and hidden layer is $V=(V_1,V_2,\cdots,V_j,\cdots,V_m)$. $W=(W_1,W_2,\cdots W_k,\cdots,W_l)$ is the connection weight vector between neurons in hidden layer and output layer.

In the output layer, o_k, the value of the kth neuron, and the activation net_k, the kth value of the sum of the weighted values of hidden nodes, are given as

$$o_k=f(net_k) \qquad k=1,2,\cdots,l \tag{1}$$

$$net_k=\sum_{j=0}^{m} w_{jk}y_j, \qquad k=1,2,\cdots,l \tag{2}$$

where w_{jk} is the weight between the kth neuron in output layer and the jth neuron in hidden layer, y_j is the output value of the jth neuron in hidden layer.

In the hidden layer,

$$y_j=f(net_j) \qquad j=1,2,\cdots,m \tag{3}$$

$$net_j=\sum_{i=0}^{n} v_{ij}x_i \qquad j=1,2,\cdots,m \tag{4}$$

where v_{ij} is the weight between the ith neuron in input layer and the jth neuron in hidden layer, x_i is the input value of the ith neuron in input layer, net_j is the jth value of the sum of the weighted values of input nodes.

The active function $f(x)$ in (1) and (3) is Sigmoid function

$$f(x)=\frac{1}{1+e^{-x}} \tag{5}$$

A simple approach to determine the network parameters is to minimize the sum-squares-error function

$$E=\frac{1}{2}(D-O)^2=\frac{1}{2}\sum_{k=1}^{l}(d_k-o_k)^2 \tag{6}$$

Neural network using BP algorithm with a momentum factor is to avoid local minimum values. The essence is to transfer the influence of the last weight variation through a momentum factor, which modifies each weight variation by adding an extra value that is proportional to the former one to produce a new weight variation. In the $(t+1)$th iteration, the value of modification of the

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