Pattern Recognition Letters 29 (2008) 2213–2220

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers

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ARTICLE INFO

Article history:
Received 8 October 2007
Received in revised form 12 April 2008
Available online 14 August 2008

Communicated by Y. Ma

Keywords:
Acceleration data
Activity recognition
Feature subset selection
Feature extraction
Neural network
Triaxial accelerometer

ABSTRACT

This paper presents a systematic design approach for constructing neural classifiers that are capable of classifying human activities using a triaxial accelerometer. The philosophy of our design approach is to apply a divide-and-conquer strategy that separates dynamic activities from static activities preliminarily and recognizes these two different types of activities separately. Since multilayer neural networks can generate complex discriminating surfaces for recognition problems, we adopt neural networks as the classifiers for activity recognition. An effective feature subset selection approach has been developed to determine significant feature subsets and compact classifier structures with satisfactory accuracy. Experimental results have successfully validated the effectiveness of the proposed recognition scheme.

1. Introduction

Human–computer interaction (HCI) is a notable discipline that bridges the gap between users and computer systems, and is increasingly being recognized as an indispensable component of daily life. One of the key techniques in HCI is pattern recognition. Users' intentions can be recognized using recognition techniques without using the traditional input devices of computer systems. Among various pattern recognition issues, activity recognition is a new technique which can recognize human activities or gestures via computer systems, and the signal for recognition can be obtained from different kinds of detectors such as electromyography (EMG), audio sensors, image sensors, and accelerometers. Due to the rapid development of technology and the omnipresence of reasonable low-cost high-performance personal computers, research on human activity recognition has grown up and activity recognition is being applied in many applications including biomedical engineering, medical nursing, and interactive entertainment (Choi et al., 2005; Delsey et al., 2005; Najafi et al., 2003; Song and Wang, 2005). Among the aforementioned sensors for activity recognition, accelerometers can return a real-time measurement of acceleration along the *x*-, *y*- or *z*-axis to be used as a human motion detector. Due to advanced miniaturization techniques, the accelerometer can be embedded within a wearable device and can send data wirelessly to a mobile computing device. This greatly reduces the users' awareness and possible discomfort during the process of data collection and recognition.

Decision tree classification methods have been successfully used for recognition problems as well as the activity recognition from acceleration data (Bao and Intille, 2004; Mathie et al., 2004; Karantonis et al., 2006; Solà i Carós et al., 2005). To name a few, Bao and Intille (2004) used five biaxial accelerometers placed on 20 subjects (in five positions: arm, wrist, hip, angle, and thigh) to recognize 20 daily human activities. They designed a data collection process annotated by the subjects themselves under semi-naturalistic conditions and compared the performances of four recognition methods: the decision table, instance-based learning (IBL), C4.5 decision tree, and Naïve Bayes classifiers. C4.5 decision trees obtained the best performance with an overall recognition accuracy rate of 84%. The decision tree method usually separates static activities from dynamic activities first, and a more detailed subclassification is made at the following hierarchical structures (Karantonis et al., 2006; Mathie et al., 2004; Solà i Carós et al., 2005). The advantages of decision trees are that they are simple, apparent, and fast in reasoning. However, traditional decision trees need to hold considerable data in each of their non-terminal roots, which increases the required memory space and computation time.

Recently, neural network techniques have provided an alternative approach to pattern recognition due to its learning capability of separating non-linearly separable classes. Neural networks can

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0167-8655/$ - see front matter
doi:10.1016/j.patrec.2008.08.002

autonomously learn the complex mappings and extract a non-linear combination of features. The weights of the networks create the decision boundaries in the feature space, and the resulting discriminating surfaces can be very complex (Safavian and Landgrebe, 1991). In general, placing more accelerometers on different body positions can recognize human movements more accurately (Bao and Intille, 2004). But this will cost more, be less comfortable, and require a higher dimension and more complex feature set. So far, only a few researchers have devoted their efforts to the investigation of recognizing uncomplicated activities via one accelerometer (Karantonis et al., 2006; Mathie et al., 2004; Solà i Carós et al., 2005).

In this paper, we adopted multilayer feedforward neural networks (FNNs) as activity classifiers and proposed an effective activity recognition method using acceleration data. The proposed approach can recognize more complicated daily activities via the use of one triaxial accelerometer on a wearable board mounted on the dominant wrist of a subject to acquire the acceleration data of his/her activity. We collected acceleration data for a set of eight common domestic activities in a controlled laboratory environment: standing, sitting, walking, running, vacuuming, scrubbing, brushing teeth, and working at a computer. The philosophy of our recognition approach is to apply a divide-and-conquer strategy that separates dynamic activities (e.g. walking, running, etc.) from static activities (e.g. standing and sitting) preliminarily and recognizes these two different types of activities separately. First, we used a neural classifier as a pre-classifier and adopted the constant threshold criterion (Karantonis et al., 2006) to distinguish static activities from dynamic activities. The development of an effective feature subset selection (FSS) approach based on the common principle component analysis (CPCA) proposed in (Krzanowski, 1979) has been conducted to reduce the dimension of the feature sets for static and dynamic activities, respectively. This approach can determine the significant feature subsets and retain the characteristics of the data distribution in feature spaces. The selected features were then used to construct neural classifiers for dynamic and static activities. Our experiments on recognizing of eight daily activities from seven subjects have successfully validated the effectiveness of the proposed recognition scheme in constructing efficient classifiers with satisfactory accuracy.

The remaining sections of this paper are organized as follows. Section 2 introduces the structure of the neural classifier. The detailed information about the proposed recognition method, including data pre-processing, feature extraction, and feature subset selection, is presented in Section 3. Section 4 provides the experimental design to validate the effectiveness of the proposed classifiers and discussions on the recognition results. Conclusions are given in the last section.

2. Structure of neural classifier

In this paper, three neural classifiers, including a pre-classifier, a static classifier, and a dynamic classifier, are constructed to recognize daily activities from acceleration data. The structure of the neural classifier, shown in Fig. 1, consists of an input layer, a hidden layer, and an output layer. $\boldsymbol{u} = [u_1, u_2, \ldots, u_r]^T$ and $\boldsymbol{y} = [y_1, y_2, \ldots, y_h]^T$ are the input and output vectors, respectively, where r represents the number of elements in the input feature set and h is the number of classes. Log sigmoid functions are selected as the activation functions f in the hidden and output neurons. In general, the backpropagation learning algorithm (a gradient descent optimization method) is used to train the FNN. However, it is known that the gradient descent learning method is subject to slow convergence and local minima. Some remedies have been provided by Hannan and Bishop (1997) and Pearlmutter (1995) for accelerating the convergence and for achieving optimal solutions.

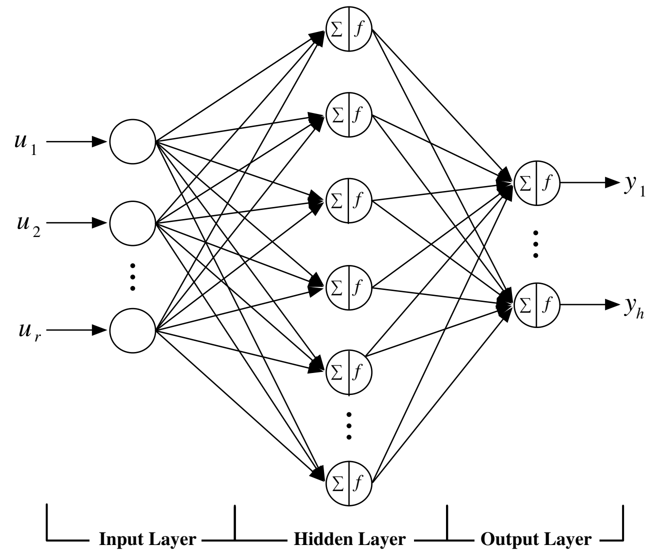

Fig. 1. The topology of the neural classifier.

The resilient backpropagation (RPROP) learning algorithm (Riedmiller and Braun, 1993) is one of the best solutions for neural network training. Research studies have shown that RPROP can remedy the drawbacks of the gradient descent (Igel and Hasken, 2003). The basic principle of RPROP is to ignore the magnitude of the gradient and only take the sign of the derivative into consideration for indicating the direction of the weight update. To accelerate the construction of classifiers, the RPROP algorithm has been adopted to train our neural classifiers. The detailed information about the RPROP can be found in (Riedmiller and Braun, 1993).

3. Activity recognition strategy

To perform activity recognition robustly, reliably, and accurately, we have developed a neural classifier construction scheme. The proposed scheme consists of two phases: pre-classifier construction phase and static/dynamic classifier construction phase, and their corresponding block diagrams are shown in Figs. 2 and 3, respectively. The objective of the pre-classifier construction phase is to identify static activities and dynamic activities. First, we filter the acceleration data to obtain human body acceleration (BA). Then the features extracted from the BA are used to train the pre-classifier. Upon completion of the pre-classifier construction, we are able to distinguish dynamic activities from static activities. In the static/dynamic classifier construction phase, we extract various features from the original acceleration data into a feature set. In order to reduce the dimension of the feature set, we utilize a feature subset selection (FSS) approach to select significant features for static and dynamic activity, respectively. The corresponding selected feature sets are fed into and used to train the static/dynamic classifiers.

3.1. Pre-classifier construction

3.1.1. Data pre-processing

In general, the acceleration data acquired from the triaxial accelerometer on the human body can be decomposed into two components consisting of gravitational acceleration (GA) and body acceleration (BA). The BA component caused by body movement is able to distinguish static activities from dynamic activities