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Integrating features for accelerometer-based activity recognition

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Abstract

Activity recognition is the problem of predicting the current action of a person through the motion sensors worn on the body. The problem is usually approached as a supervised classification task where a discriminative model is learned from known samples and a new query is assigned to a known activity label using learned model. The challenging issue here is how to feed this classifier with a fixed number of features where the real input is a raw signal of varying length. In this study, we consider three possible feature sets, namely time-domain, frequency domain and wavelet-domain statistics, and their combinations to represent motion signal obtained from accelerometer reads worn in chest through a mobile phone. In addition to a systematic comparison of these feature sets, we also provide a comprehensive evaluation of some preprocessing steps such as filtering and feature selection. The results determine that feeding a random forest classifier with an ensemble selection of most relevant time-domain and frequency-domain features extracted from raw data can provide the highest accuracy in a real dataset.

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Keywords: Activity recognition; accelerometer analysis; feature selection

1. Introduction

In recent years, a weighty research effort which focuses on the monitoring and recognition of human activity patterns which collected via motion sensors has been witnessed. Various application domains contain activity recognition technologies such as health and elder care or sportive motion tracker devices. Many previous studies have proposed to use an accelerometer sensor to accomplish the recognition process. Accelerometers have been widely accepted devices for measuring personal daily activities such as walking, standing and running owing to their

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minimal size, low power requirements, cost and the ability of producing data directly from the motion. Previous researches have shown that machine learning methodologies are effective for classification of different activities from sensor data[1-9]. They often operate in two steps. First, relevant features are calculated from accelerometer signal data. Then a classifier algorithm is used to determine the activity corresponding to those features. The common features involve the statistics extracted from time-domain signal analysis, frequency-domain analysis and wavelet analysis, which is also referred as time-frequency analysis.

Ravi et al. worked on time-domain features and chosen only mean, standard deviation, energy and correlation to classify accelerometer signals using Decision Tables, Decision Trees (C4.5), K-nearest neighbors, Support Vector Machines and Naive Bayes classifiers[1]. Casale et al worked on time domain features on each time series and examined the best features for classification physical activities[2]. Their features were root mean squared and mean value of min and max sums. They used Random Forest algorithm for the classification. At Preece et al's study, the discriminative ability of time-frequency based features was compared through the physical activities[3]. They reported that using time-domain features can produce reasonably good accuracy. Wang et al. used ensemble empirical mode decomposition (EEMD)-based features to classify triaxial accelerometer signals for activity recognition[6].

In this study, our objective is (1) to compare the individual contribution of feature sets extracted from time domain, frequency domain and time-frequency domain representations of signals collected via accelerometer worn on the body, (2) to compare the performances of different machine learning classifiers in terms of prediction accuracy, (3) to evaluate the contribution of some preprocessing steps such as filtering and feature selection on activity recognition performance, and finally (4) to elicit most representative subset of features from the union set of features extracted from all domain representations. The results show that best accuracy can be achieved with a selected feature subset from time and frequency domain representations when they are fed into a Random Forest classifier without any preprocessing step.

2. Materials and methods

2.1. General overview

Activity recognition problem is considered as a supervised classification task where a subsequence of accelerometer reads is fed into a machine learning classifier. The input data is normalized as to have a mean of zero and a standard deviation of one. The features are extracted from segmented parts of normalized data where a segment refers to a number of consecutive accelerometer reads. Fixed length segments are used since no prior knowledge is available about activity boundaries. Assuming that any activity can exhibit at least one of its cycles in 4 seconds, each segment is built to have 208 samples. An overlap of 50% in length is allowed between two consecutive samples as in previous works. In classification stage, we employ several machine learning classifiers, i.e. Random Forest, k-Nearest Neighbor (kNN), and Support Vector Machine (SVM).

2.2. Feature extraction

2.2.1. Time domain features

We extract 17 time domain features from each window for each axis x, y and z. Guided by a previous work[8], the individual features for each axis involves statistical attributes such as mean, variance, standard deviation and envelope metrics, i.e. median, range maximum and minimum value, root main square metric. Furthermore, we use signal magnitude area, indexes of minimum and maximum value, power, energy, entropy, skewness, kurtosis, interquartile range, and mean absolute deviation of signal. To see the cross-relational effects of different motion axes, we also use cross correlation of binary combinations of x, y, and z.

2.2.2. Frequency domain features

We extract six frequency domain features from each window for each axis x, y and z. First, Fast Fourier Transform is used to convert data to frequency domain from time domain. The first feature in frequency domain