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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 representation is the band power of the signal. Secondly selected frequency-domain feature is energy. Energy is elicited by the summation of the squared FFT parameters called as coefficients. Another feature is the magnitude which means a measure of the normalized value of the FFT coefficients and facilitates the recognition of the differences between activities[3]. The final frequency-domain features are defined as the mean, max and min values of the signal. The DC feature is the mean acceleration value of the signal[4].

#### *2.2.3. Time-frequency (wavelet) domain features*

We extract nine sets of time-frequency domain features from each window for each axis x, y and z. First, Discrete Wavelet Transform is used to convert data to time-frequency domain from time domain. Similar to recent studies the most accurate three feature set is chosen. The features that are selected were proposed in Tamura et al's study[5]. This study describes these features as measurements of signal's power. The power of signal was elicited by the summation of the squared detailed coefficients where by the fourth and fifth levels of the wavelet transform[3]. This set uses Daubechies 3 as the wavelet mother and produces 6 features at the total. The second set is the squared coefficients. It is obtained by decomposing the signal into five levels using Daubechies 2 wavelet mother transformation. We then sum up the squared detailed coefficients for each five level. Thus, at the end, it returns 15 features at the total[3]. The last feature set is calculated by the summations of the absolute values of detailed coefficients for each level. It is again uses Daubechies 2 as wavelet mother and produces 15 features at the end.

### *2.3. Data filtering*

To avoid the defects that can be caused by the noises and to be able to examine the differences between filtered and non-filtered data classifications, we consider using a digital filter. According to characteristics of our data we determine the cutoff frequency as 1 Hz and at a certain sampling rate f. A high pass and a low pass filter are applied to data separately and features are calculated again in three domains that we mentioned above. The results are compared with filtered and non-filtered classification accuracies for f=52 and f=208.

### *2.4. Classification*

The task of an activity recognition algorithm is to classify the input signal pattern into one of given activity classes. To experiment the performance of different classifiers, we employ Random Forest, k-Nearest Neighbor and Support Vector Machine.

Random Forest method builds a number of multiple decision trees to train a model, where a decision tree is a flowchart-like structure in which each internal node represents a test on a feature representing the corresponding sample[10]. Each branch represents the result of the test and each leaf node represents a class label, i.e. the final decision over all feature evaluations. Each decision tree is constructed by randomly selected values from the input data. If original feature vector has *m* features, each tree uses a random selection of *n* features which are chosen from all features. The decision trees are allowed to grow until its capacity reaches to *n*. After training the forest, it enables to pass each test row through it, in order to output a prediction. A query is classified by voting over built decision trees.

k-Nearest Neighbor is one of the instance-based lazy learning algorithms. The algorithm starts with checking the class labels of k nearest neighbors in training set. The query sample is classified by votes of its neighbors. The class which gets the maximum vote is assigned as the predicted class for query sample. In our experiment we select Euclidean distance to compare feature vectors.

SVM classification methodology is a two-step process. First, the classifier's high dimensional input is non-linearly mapped into another feature space. Second, a new linear hyper plane is composed from this feature space with the maximum margin to separate the classes of the instances. SVM algorithm uses support vectors while other similar algorithms such as Neural Networks need to check all possibilities of hyper planes to build a decision surface. SVM is known as less prone to over fitting than several different algorithms.

### *2.5. Feature selection*

Feature selection is the task of creating a reduced and possibly more informative subset of all features over whole samples of given data. It is proven to be a critical need in several applications to get accurate and trustworthy classification results[11,12]. Given a variety of feature selection methods in the literature, we here exploit an ensemble approach based on the consensus of several common feature selection methods (Figure 1). To this end, we feed all 110 features extracted from time domain, frequency domain and time-frequency domain representations into five selection models[11], i.e. Chi-square selection, Correlation-based feature selection (CFS), ReliefF selection, Information-gain based selection (InfoGain) and Gain-ratio-based selection (GainRatio) separately and then retrieve their consensus list from their output. This scheme provides a more reliable selection of features while each individual selection method may yield different results.

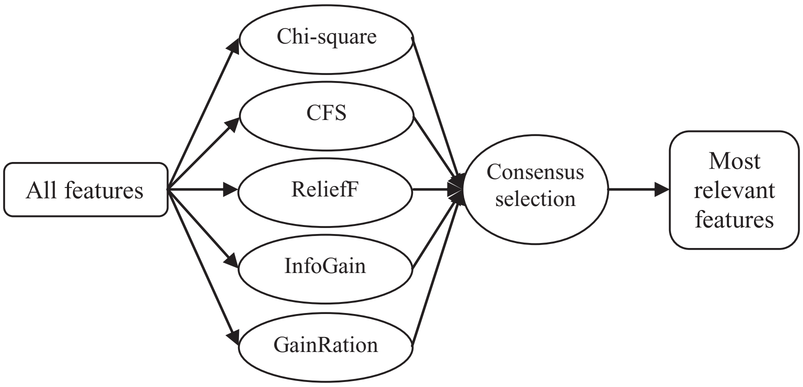


Fig. 1 Ensemble feature selection strategy.

## 3. Results

### 3.1. Data set

To perform the experiments, we used the publicly available dataset provided by Casale et al[2]. Accelerometer data were collected from a mobile phone accelerometer worn at chest. The dataset contains signals collected from 15 participants who perform 7 physical activities; (1) Working at computer, (2) Standing up, walking and going up\down stairs, (3) Standing, (4) Walking, (5) Going up\down Stairs, (6) Walking and talking with someone and (7) Talking while standing. The sampling frequency of the accelerometer is 5 Hz. Accelerometer data are uncalibrated. In the original study, it was used for biometric identification of people based on their activity patterns. Here, we used the dataset for the task of recognizing activity itself. The original data can be downloaded from https://archive.ics.uci.edu/ml/datasets.html.

### 3.2. Evaluation

We conducted classification experiments in a ten-fold cross-validation setup. In this setup, the dataset is divided into ten equal partitions such that each partition has a balanced number of samples from all categories. Each sample is then predicted using the classification models trained by other nine partitions which do not have the query sample. All samples are guaranteed to go through a prediction stage after repetition of same experiments ten times with a different training set in each. The average of the classification performances obtained in these folds is reported as the final performance of the system under consideration. Accuracy measure was used to evaluate the performance of approaches;

$$\text{Accuracy} = \frac{TN+TP}{TP+TN+FP+FN} \times 100$$

where TP, FP, TN and FN refer to number of true positives, false positives, true negatives and false negatives respectively.

Table 1. Classification results.

| **Classifier** | **Features** | | | | | | |
|---|---|---|---|---|---|---|---|
| | Time Domain | Frequency Domain | Wavelet Domain | Time+ Wavelet | Time+ Frequency | Frequency + Wavelet | Time+ Frequency+Wavelet |
| Random Forest | 87% | 84% | 52% | 85% | 86% | 82% | 85% |
| k-NN (k=5) | 62% | 80% | 45% | 61% | 62% | 77% | 62% |
| SVM (RBF) | 32% | 32% | 47% | 33% | 31% | 32% | 31% |
| SVM (Linear) | 65% | 60% | 45% | 65% | 64% | 60% | 64% |

### *3.3. Empirical results*

Table 1 shows classification accuracies achieved with different classifiers. For Random Forest classifier, maximum number of trees is set to 100 where the depth is allowed to be unlimited. In kNN, k was set to various values between 1 and 9. The best accuracy was obtained with 5 (other data were not shown). SVM was compiled with linear and RBF kernels with their suggested parameters in LibSVM library[13]. In our experiments, best accuracy was achieved with Random Forest classifier when only time domain features were fed.

Table 2. Effect of filtering on classification performance.

| **Filtering applied** | **Features** | | | | | | |
|---|---|---|---|---|---|---|---|
| | Time Domain | Frequency Domain | Wavelet Domain | Time+ Wavelet | Time+ Frequency | Frequency + Wavelet | Time+ Frequency+Wavelet |
| None | 87% | 84% | 52% | 86% | 85% | 82% | 85% |
| High-Pass (f=208) | 86% | 83% | 51% | 84% | 86% | 79% | 84% |
| Low-Pass (f=208) | 82% | 80% | 57% | 81% | 82% | 79% | 81% |
| High-Pass (f=52) | 74% | 75% | 52% | 73% | 74% | 62% | 73% |
| Low-Pass (f=52) | 84% | 81% | 54% | 84% | 81% | 78% | 82% |

Table 2 shows the classification accuracies for filtered data. Various high pass and low pass filters with different sampling rates were applied. As shown, filtering had no improvement on the prediction accuracy whilst it may reduce the overall accuracy in many cases.

Table 3. The selected features, their axis and domain

| **Name** | **Axis** | **Domain** |
|---|---|---|
| Maximum Value | *x* | Time |
| Minimum Value | *x* | Time |
| Entropy | *x* | Time |
| Interquartile Range | *x* | Time |
| Maximum Value | *y* | Time |
| Index of Minimum Value | *y* | Time |
| Mean of absolute deviation | *y* | Time |
| Median | *y* | Time |
| Skewness | *y* | Time |
| Standard deviation | *y* | Time |
| Root mean square error | *y* | Time |
| Skewness | *z* | Time |
| Normalized value of FFT coefficients | *x* | Frequency |
| Normalized value of FFT coefficients | *y* | Frequency |

| | | |
|---|---|---|
| Normalized value of FFT coefficients | $z$ | Frequency |

The application of our ensemble feature selection scheme has resulted with selection of 16 attributes. These selected attributes are specified at Table 3. The results determine that most representative features are obtained from time domain representation of accelerometer signal, where normalized values of FFT coefficients are also important. The features extracted from the signals in $x$ and $y$ axes are more relevant than those of $z$ axis in determining the activities in question. When we compiled the same classifiers with these selected feature subset, we observed that the prediction accuracy can be improved slightly compared with the case that no feature selection was applied (Table 4).

Table 4. Effect of feature selection on classification performance.

| **Classifier** | All features | Selected features |
|---|---|---|
| Random Forest | 85% | 88% |
| k-NN | 62% | 80% |
| SVM (RBF) | 31% | 67% |

## 4. Conclusion

We study the activity recognition problem through a single triaxial accelerometer worn in the chest. While the problem can be considered as a typical supervised classification task, we rather focus on which features are most relevant in associating the raw sensor signal with predefined activity labels and which preprocessing techniques should be applied before the extraction of these features. We also propose an ensemble-based feature selecting method will improve the prediction accuracy of the system. According to the experiments performed on a real dataset of accelerometer signals for daily activities, we infer three conclusions: (1) time-domain features are most effective in discriminating activities from accelerometer signals, (2) frequency-domain features can be complementary to time-domain features provided that they are jointly used over a feature selection scheme, (3) an ensemble-based feature selection strategy can improve overall prediction accuracy, (4) random forest classifiers can outperform other popular alternatives such as support vector machines in accelerometer signal classification.

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