RECOGNIZING HUMAN MOTION WITH MULTIPLE ACCELERATION SENSORS

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Abstract

In this paper experiments with acceleration sensors are described for human activity recognition of a wearable device user. The use of principal component analysis and independent component analysis with wavelet transform is tested for feature generation. Recognition of the human activity is examined with multilayer perceptron classifier. Best classification results for recognition of different human motions were 83-90%, and they were achieved by utilizing independent component analysis and principal component analysis. Difference between these methods turned out to be negligible.

Keywords

Accelerometer, movement recognition, wearable computing, principal component analysis, independent component analysis.

1 Introduction

The accelerometer based human activity monitoring enables development of various applications in the field of biomedical engineering and wearable computing.

Estimation of walking speed and incline as well as identification the type of walking are very useful information in determining energy expenditure during human activity [1],[2],[17]. Combining human activity information with other sensor information such as ambient air pressure information, angular velocity and location information, enables recognizing human moving patterns and estimating the walking distance [14], [15]. Sekine et al. and Najafi et al. have studied the use of the wavelet transform and wavelet decomposition in walking analysis [13], [17]. In these studies wavelet decomposition was used for enhancing the recognition of the changes of activity. In the work of Sekine et al. wavelet coefficients were used in walking pattern classification [17].

The indoor navigation system by Golding et al. utilizes low cost sensors and machine learning methods in modeling the indoor environment for navigation system [4]. In the work of Laerhoven et al. adaptive human activity recognition system for wearable computers was explained [18].

In this work, movements of the hip during the walking are assumed to be extracted better by using two sets of sensors instead of one. Also, the use of principal component analysis (PCA) and independent component analysis (ICA) is studied. The motivation for this is based on the idea that both methods are used for finding features, "interesting directions" in terms of statistical criteria [5, 8]. The hypothesis is that the use of the principal components (PC) or independent components (IC) as a part of the feature extraction process might help the classifier perform better. One can see this as an attempt to computationally find such new directions and scales for the sensors that the signals would be more discriminative.

Initial experiments with one set of three axis acceleration sensors were also performed. Classification results for different activities were quite poor, 39-78% when PCA was used in feature vector generation, 38-78% when ICA was used, and 48-79% when normalized original data were used. This was the motive for experiments, which are presented in this paper.

Two sets of general purpose sensor boxes [12] were attached to the front of a testee at the left and right sides of the hip providing six channel acceleration information from user activity. Walking tasks for classification experiments included walking in a corridor, walking down the stairs, walking up the stairs and opening doors. PCs and ICs were calculated from original data. PCs, ICs and original signals were wavelet transformed (WT), and the powers of certain wavelet coefficients were composed to feature vectors used for classification with multilayer perceptron (MLP) neural network.

2 Methods

PCA and ICA are well-established statistical tools, in the signal processing and data-analysis communities [5], [11]. The possibility to use both methods for sensor fusion has been studied in [16]. In this work, both methods are used here for feature extraction. It was expected that they would reveal essential information in acceleration signals that describe human activity.

2.1 Principal Component Analysis and Whitening

Let $\mathbf{x} = [x_1\ x_2\ \ldots\ x_n]^T$ be an n-dimensional random vector having zero mean. The task is to find an orthonormal matrix $\mathbf{V}$ of size $n{\times}k$, $k{\leq}n$ so that the reduced k-dimensional projection $\mathbf{x}'=\mathbf{Vx}$ retains as much of the variance of $\mathbf{x}$ as possible. The matrix $\mathbf{V}$ defines the principal directions of the projection. In practice, the principal directions and components can be calculated using the eigendecomposition $\mathbf{C}=\mathbf{E\Lambda E}^T$ of the *sample covariance matrix* $\mathbf{C}=\mathrm{E}(\mathbf{xx}^T)$. The eigenvalues $\Lambda=\mathrm{diag}(\lambda_1,\lambda_2,\ldots,\lambda_n)$ determine the variance that each PC captures. The n PCs $\mathbf{x}'=[x'_1\ x'_2\ \ldots\ x'_n]^T$ are computed by projecting the original data to the principal directions $\mathbf{x}'=\mathbf{E}^T\mathbf{x}$.

In this paper, PCA is used for whitening (decorrelation) of the signals. Whitening is a procedure where the PCs are scaled to have unit variance $\mathbf{x}^*=\mathbf{\Lambda}^{-1/2}\mathbf{E}^T\mathbf{x}$. The data is now decorrelated since $\mathrm{E}(\mathbf{x}^*\mathbf{x}^{*T})=\mathbf{I}$.

2.2 Independent Component Analysis

In the basic version of ICA the assumption is that there are n observed signals, which are different linear mixtures of n statistically independent, non-gaussian source signals [9]. The sources are elements of an n-dimensional random vector $\mathbf{s}$. The elements of the observed random vector $\mathbf{x}$ are different mixtures of the sources $\mathbf{x}=\mathbf{As}$, where $\mathbf{A}$ is an $n{\times}n$ mixing matrix. The problem is to solve the mixing matrix knowing the observed signals, that is a sample of the random variable $\mathbf{x}$. There exists a variety of methods for estimating the mixing matrix and the independent components under different assumptions on the data [8], [11].

In this study, the FastICA algorithm has been used [6], [7]. The algorithm has very fast convergence and is available as a well-documented implementation[1]. ICA has recently gained lots of interest, and there are successful applications [19].

While the PCs are naturally ordered according to the eigenvalues of the covariance matrix, the independent components lack similar kind of intrinsic order. This causes problems if such an order is required for ICs. In this work, we face the problem when comparing two sets of ICs computed from different data. Even if data sets are exactly similar, the extracted ICs appear in random order when the FastICA is applied. The problem is solved heuristically by ordering the ICs according to their kurtosis. The kurtosis is the contrast function of the basic FastICA algorithm and an approximative measure for non-gaussianity [8]. The working hypothesis is that the kurtosis can characterize the extracted ICs so that the most similar ones will be compared.

2.3 Wavelet Transform

The wavelet transform (WT) divides the original signal into wavelet coefficients c corresponding to different frequency content. Thus, enabling the signal to be analyzed with a resolution matched to the scale of the coefficient [3]. In this study, a wavelet transform utilizing a Daubechies mother wavelet order of 8 was used, which were selected for computational reasons.

2.4 Feature Vector Generation

The diagram of feature vector generation process is presented in Fig. 1. Six dimensional raw acceleration data sampled at 256 Hz was decimated by a factor of 2. The decimation process included anti-aliasing filtering. Decimated data was processed with PCA and FastICA algorithms. Three distinct data sets were composed; one by using PCA, the other by using ICA, and third by using decimated original data. Hence, three classification experiments were made. After this, data sets were normalized. The variance of each component was normalized to 1, and mean to 0. Sliding window of length 256 points and shift of 64 points was applied for normalized data sets. For each window, signals were wavelet transformed and coefficients of levels 5 to 8 were composed. Power of each

[1] http://www.cis.hut.fi/research/software.shtml

channel was calculated which resulted in a 6x4=24 dimensional feature vector for each window.

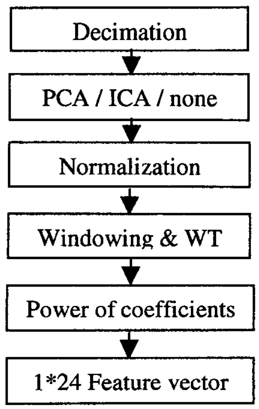

Fig.1: Diagram of feature vector generation process.

2.5 Classification

For classification purposes three multilayer perception (MLP) neural networks using back propagation learning were trained. MLPs were three layer networks of type consisting of 24 input neurons, 43 hidden neurons and 4 output neurons. All neurons used logistic scaling functions. Initial parameters were learning rate 0.1, momentum 0.1, and learning rate 0.1. A momentum based weight update was used in training.

Stratified ten-fold cross-validation was used for classifier assessment [10]. The data was randomly divided into 10 groups with the same number of samples and with approximately the same frequency of the classes. The classifier was built ten times. Each time one group in turn was excluded from the training and used solely as a test set. The cross-validated classification error is the average of the ten test set errors. All the classification results that are presented hereafter are cross-validated, and no training set errors will be presented.

3 Experiments and Results

Two sets of three axial accelerometers were attached with a belt to the front of a testee at the left and right sides of the hip (Fig. 2). Data was logged with sampling frequency of 256 Hz by using a portable laptop a user was carrying. Six testees walked a predefined scenario in office environment. The scenario consisted of walking in a corridor (level walking), walking up and down the stairs, and opening doors.

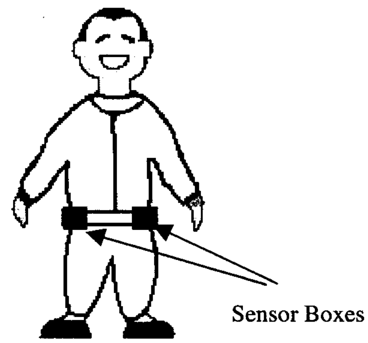

Fig. 2: Location of the sensor boxes.

The analog signal from accelerometers ADXL202 is A/D-converted and sampled with National Instruments DaqCard 1200 measurement board which is connected to a PC-CARD slot in a laptop PC. Data is stored on a file by using measurement program made in LabView® graphical programming environment. The acceleration signal vectors are analyzed offline by using the MATLAB® software of The MathWorks Inc. The objective of this study is to recognize the walking tasks of upstairs/downstairs/level and the events of stopping/starting walking that occurred in the scenario.

A typical example of original acceleration signals from each channel is presented in Fig. 3. For clarity, only short sequences of signals are shown. Activities *level walking* and *walking down the stairs* are denoted with lines above the figure. Channels 1 – 3 are from the sensor box located at the left side of the hip, and channels 4 – 6 are from the sensor box attached at the right side, respectively. Similarity of the signals on certain channels indicates which accelerometers are sensitive to same direction. Channels 1 and 4 represent accelerations in vertical direction, channels 2 and 5, represent accelerations in anterior-posterior direction while channels 3 and 6 represents accelerations in side to side direction.

In Fig. 4. a typical example of independent components calculated from six dimensional acceleration signals is presented with labels. ICs are ordered according to their kurtosis, which are presented beside the IC. ICA reveals interesting directions, which contain essential information about human movements. For example, in Fig 4. spikes marked with arrows correspond to first step when starting walk to down the stairs. One can see that these spikes are not visible in the original data (Fig. 3).

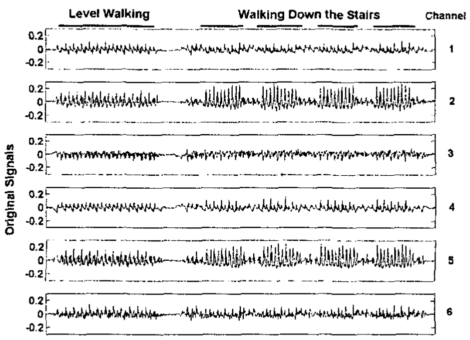

Fig. 3: A typical example of original six dimensional acceleration data. Channel numbers are on the right. Activities are denoted above the signals

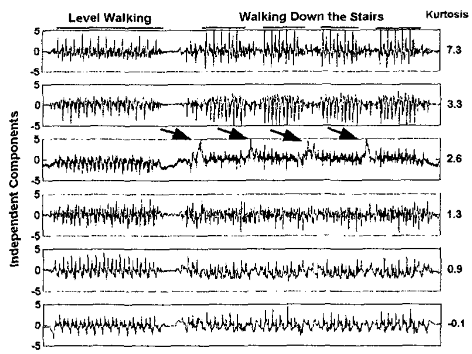

Fig. 4: A typical example of independent components. Value of the kurtosis is presented beside the IC. Activities are denoted above the ICs.

Data from measurements using 6 testee were processed to three 24 dimensional feature data sets length of 1561. The perceptual amount of feature vectors of each activity in a feature data set was: level walking 39.1%, down stairs walking 23.4%, up stairs walking 24.5%, start/stop points 13%.

The classification errors of human activities for distinct feature generation methods are presented in Fig. 5 as bar chart. The results indicate that the use of PCA and ICA in feature generation process improves classification performance considerably. Utilizing PCA and ICA produces nearly equal classification results; results for ICA are only marginally better. It seems to be that though the ICs differ from the whitened signals (normalized PCs) by an additional rotation of the signal space [8], this transformation does not help the classifier any further when wavelet coefficients are used as features.

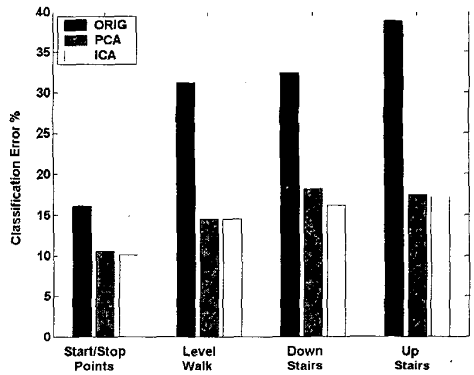

Fig. 5: Classification errors of human activities for distinct feature generation methods, none, PCA, ICA.

In order to examine the performance of classifiers more carefully, confusion matrices are presented for each feature generation method. (Tab.1, Tab.2, Tab.3). Confusion matrices are generated from averaging classification results obtained by using stratified cross-validation.

Table 1. A confusion matrix of classification results for original data. Perceptual amount of data classified to each class.

	Start/ Stop Points	Level Walk	Down Stairs	Up Stairs
Start/ Stop Points	84%	13%	1%	2%
Level Walk	6%	69%	5%	20%
Down Stairs	1%	23%	68%	8%
Up Stairs	2%	36%	1%	61%

Table 2. A confusion matrix of classification results for PCA. Perceptual amount of data classified to each class.

	Start/ Stop Points	Level Walk	Down Stairs	Up Stairs
Start/ Stop Points	89%	9%	0%	2%
Level Walk	1%	85%	5%	9%
Down Stairs	1%	16%	82%	1%
Up Stairs	2%	15%	0%	83%

Table 3. A confusion matrix of classification results for ICA. Perceptual amount of data classified to each class.

	Start/ Stop Points	Level Walk	Down Stairs	Up Stairs
Start/ Stop Points	90%	7%	0%	3%
Level Walk	1%	85%	4%	10%
Down Stairs	0%	16%	84%	0%
Up Stairs	3%	14%	0%	83%

It can be seen from Tables 1-3 that certain classes mix systematically. Classification results for class *Start/Stop Points* are quite good for all feature generation methods, although small amount of data mixes with a class *Level Walk.* Using PCA and ICA decreases misclassification (Tab. 3.). In all cases class *Level Walk* mixes with class *Up Stairs* with quite small perceptual value. The use of PCA and ICA improves this classification compared to original data set. Class *Level Walk* confuses with classes *Down Stairs* and *Up Stairs* in every confusion matrice. This suggests that the variability of walking speeds and waveforms of walking on the level are slightly similar to activities *Down Stairs* and *Up Stairs*. However, misclassification of *Down Stairs* and *Up Stairs* is negligible, which is due the difference in waveforms and frequency content on PCs and ICs. The development of two-stage classifier for separating *Down Stairs* and *Up Stairs* activities from level walking is one of the topics of the future work.

Inconsistent ordering of the ICs may eventually degrade the classification results. The use of the kurtosis in ordering the ICs must be examined more carefully in the future.

4 Summary

Experiments with two sets of three axial acceleration sensors are described for recognizing different activities of a wearable device user. The use of PCA and ICA in feature generation process with wavelet transform was tested. Recognition of the human activity is examined with multilayer perceptron classifier with ten-folded stratified cross-validation. Best classification results for recognition of different human motions were 83-90%, and they were achieved by utilizing independent component analysis to the signals before the wavelet coefficients were computed. Difference between the ICA and PCA turned out to be negligible. Results are considerably better than those obtained by using just one set of sensors.

Human activity information obtained from wearable device can be exploited for many applications in biomedical engineering and context aware wearable computing.

5 Acknowledgements

The authors would like to acknowledge the funding provided by the NOKIA Foundation.

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