Ignatov A., Strijov V. Human activity recognition using quasiperiodic time series collected from a single triaxial accelerometer // Multimedia Tools and Applications, 2015, 17.05.2015 : 1-14.



# Human activity recognition using quasiperiodic time series collected from a single tri-axial accelerometer

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Abstract. The current generation of portable mobile devices incorporates various types of sensors, that open up new areas for the analysis of human behavior. In this paper, we propose a method for human physical activity recognition using time series, collected from a single tri-axial accelerometer of smartphone. Primarily the method solves a problem of time series segmentation, assuming that each meaningful segment corresponds to one fundamental period of motion. To extract the fundamental period we construct the phase trajectory matrix, applying a technique of the principal component analysis. The obtained segments refer to various types of human physical activity. To recognize these activities we use $k$-nearest neighbor algorithm and neural network as alternative. We verify accuracy of proposed algorithms by testing them on the set of labeled accelerometer data from thirteen users. The results show that our method achieves high precision, ensuring nearly 96% recognition accuracy when using the bunch of segmentation and $k$-nearest neighbor algorithms.

**Keywords**: *machine learning, k-nearest neighbor method, neural network, segmentation, physical activity recognition, singular value decomposition.*

## 1 Introduction

The current generation of portable mobile devices, such as cellular phones or music players, is becoming increasingly complex. Most of these devices incorporate various types of sensors, including accelerometers, light sensors, cameras, microphones and GPS sensors, that can be applied for analysis of everyday human behavior. One its important part is human physical activity, that reflects various aspects of health and thus is exceedingly attractive for many applications in the field of healthcare monitoring. In this paper, our purpose is to perform human physical activity recognition using data, collected from the built-in tri-axial accelerometer of a mobile phone. This data represents quasiperiodic time series corresponding to one of performed activities: walking, jogging, stair climbing, sitting or standing. For each time series we have to detect the correspondent activity type. Related problems of time series classification arise in human activity recognition on the silhouette [1], face recognition [2], gestures recognition [3] and detection of activity periods [4].

In the research of human activity recognition we generally face two related challenges. The first challenge is to partition long-duration time series into meaningful segments. The basic approach for this problem is to split each time series into equal segments [5]. However, in activity recognition the quality of segmentation directly influences the recognition results, and this elemental solution is actually not enough for accurate activity estimation. Thus, there should be used more sophisticated methods, based on deep analysis of the time series' structure. One natural way is to search for fundamental period of motion in these series and to consider it as a basis of partition. To extract this period we propose a technique, based on principal component analysis.

The second challenge is to construct an efficient classification method, that assign each obtained segment to one of pre-determined classes. There exists a variety of different approaches, such as neural network [6, 7], logistic regression [5], SVM [8, 9], decision trees [7] and differen heuristic algorithms [4, 10] based on spectrum analysis.

The main contributions of this paper are twofold. First, we propose an algorithm of time series segmentation, that is based on extraction of the fundamental period. To detect this period we apply a technique of the principal component analysis. Second, we propose the classification algorithm, based on the $k$-nearest neighbor method, and evaluate optimal parameters for this algorithm. We also consider neural network as an alternative solution and compare the results, obtained by these two algorithms.

The paper is arranged as follows. Section 2 introduces some related work on human activity recognition. Section 3 introduces an overview of the whole process of human activity recognition. Section 4 presents the detailed description of the algorithms of time series segmentation, noise reduction and time series classification. Section 5 describes the experiments and provides the classification results, section 6 summarizes our conclusions.

## 2 Related work

The task of human activity recognition using accelerometer has been well addressed in literature. However, the problem of time series segmentation in context of this task was not covered adequately in earlier papers. Primarily, this problem was considered as independent and was solved without verifying its results in real applications. Another lack of proposed solutions in terms of activity recognition consists in leaving out of account some particular aspects of the data, such as quasiperiodicity and homogeneity.

The solutions for the segmentation problem can be divided into two groups. First group is based on dynamic programming [11, 12]. While these algorithms show reasonable segmentation accuracy, they are not enough fast and thus are insufficient for processing of long series. The second group represents various greedy algorithms [13, 11]. These algorithms require far less time for series segmentation and in most cases provide solutions that are very close to the optimal ones. However, neither of proposed methods use a technique based on analysis of the phase trajectory matrix, that can be applied due to the quasiperiodic nature of considered time series.

Time series classification, the second step in the human activity recognition process, has a variety of possible approaches. The commonly encountered solutions for this problem are based on the SVM [8, 9, 14], neural networks [6, 7, 15] and decision trees [7, 16, 17], while relatively little research effort has been given to the $k$-nearest neighbor method.

Among relevant researches are [16, 18] that describe the use of $k$-nearest neighbor method to recognize human daily activities. Authors propose it as an alternative solution for the classification problem, and study [18] show promising results for this method. However, these papers, like many other earliest works, are focused on the use of multiple accelerometers. Thus, works [7, 16, 17, 18, 19, 20] deal with activity recognition using data from five accelerometers. Though proposed systems are capable of identifying a wide range of activities, they are not practical while demand wearing a variety of sensors from the user.

In this paper, we propose a method for time series segmentation, based on the analysis of the phase trajectory matrix, and verify its results in the classification problem. The $k$-nearest neighbor method is adopted to classify obtained segments. The experiment is carried out on the dataset collected from a single tri-axial accelerometer of mobile phone.

## 3 Problem statement

Before developing the algorithmic approach, we introduce in this section some useful notations and provide additional information about the architecture of the proposed model.

In order to collect data for the considered supervise learning problem one has to carry a smartphone while performing a specific set of activities. Let $S = \{\mathbf{x}_t\}_{t=1}^M$, $\mathbf{x}_t \in \mathbb{R}^3$ be the time series, obtained from the accelerometer of the phone. These data represent measurements of acceleration in three directions, and for each element $\mathbf{x}_t$, $t \in \{1, 2, \dots, M\}$ there given type of physical activity $y_t \in Y$. Define a segmentation of time series $S$ as a sequence $\{S_i\}_{i=1}^n$ of $n$ segments such that $S_1 S_2 \dots S_n = S$ and each $S_i$ is non-empty.

The procedure of the human activity recognition consists of the three following steps:

1) segmentation of the initial time series $S$,
2) removal noise from each obtained segment $S_i$,
3) implementation of the $k$-nearest neighbor algorithm $f_{\text{knn}}$ to the treated segments $\{\tilde{S}_i\}_{i=1}^n$.

The scheme of the whole process is presented in Fig. 1.

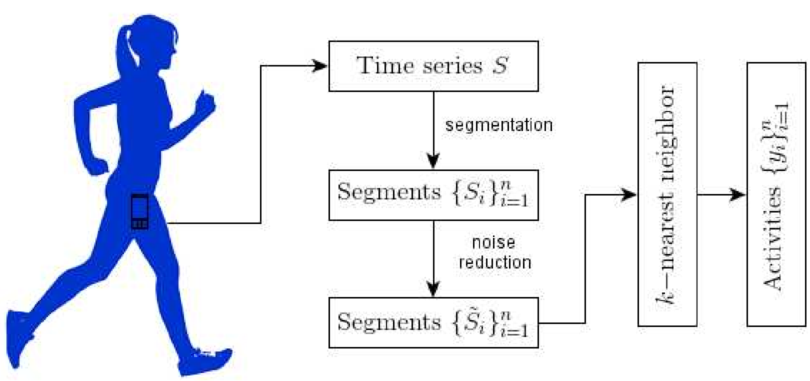


**Fig. 1.** Architecture of the proposed approach

To evaluate the overall performance of the proposed model we use the error function $G$, which is ratio between the number of incorrect estimations and the total number of observations. Denote $f_{\text{knn}}$ be our classification algorithm. Then, the accuracy of classification is:

$$G(\mathrm{X}, \mathrm{Y}, f_{\text{knn}}) = \frac{1}{N} \sum_{i=1}^{N} [y_i \neq f_{\text{knn}}(X_i)], \tag{1}$$

where $\mathrm{X} = \{X_i\}_{i=1}^N$ is the set of test samples, $\mathrm{Y} = \{y_i\}_{i=1}^N$ is the set of answers, that corresponds to X. Here, the following notation for the indicator function is used:

$$[y \neq y'] = \begin{cases} 1, & if \;\; y \neq y', \\ 0, & if \;\; y = y'. \end{cases}$$

Let $\mathcal{W}$ be the set of parameters for the considered model. Thus, we treat the classification problem as the error function minimization problem:

$$\hat{\alpha} = \arg\min_{w \in \mathcal{W}} G(\mathrm{X}, \mathrm{Y}, f_{\text{knn}}). \tag{2}$$

## 4 Algorithms

The human activity recognition procedure consists of two steps. The first step is data processing, that involves time series segmentation and noise reduction. The second step is classification of obtained segments. In this section, we provide algorithms for both of these steps, taking into account the specifics of the considered data.

**4.1 Segmentation of the quasiperiodic time series.** Hence, we propose an algorithm for the time series segmentation under the assumption of their quasiperiodicity. With this assumption the time series can be represented with high accuracy as a superposition of harmonic components with different periods. We define the harmonic with the longest period and this period as the fundamental ones.

Consider the one-dimensional time series $S = \{x_t\}_{t=1}^{M}$, and let $S' = \{x_t\}_{t=p}^{p+m}$ be its section, $p + 2m \leqslant M$. Our purpose is to extract the fundamental period from this section, assuming that its length $m$ is much grater than the length of the period. First, we construct the Hankel matrix $\mathbf{A}$, that is a square matrix with constant skew-diagonals, which first line is $S'$:

$$\mathbf{A} = \begin{pmatrix} x_p & x_{p+1} & x_{p+2} & \cdots & x_{p+m} \\ x_{p+1} & x_{p+2} & x_{p+3} & \cdots & x_{p+m+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{p+m} & x_{p+m+1} & x_{p+m+2} & \cdots & x_{p+2m-1} \end{pmatrix}.$$

Then we apply the singular value decomposition to the Hankel matrix: $\mathbf{A} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{V}^{\mathsf{T}}$, where $\boldsymbol{\Lambda}$ is a diagonal matrix, $\mathbf{U}$ and $\mathbf{V}$ are orthogonal matrixes. Let $\{\lambda_i\}_{i=1}^{N}$ be the diagonal elements of matrix $\boldsymbol{\Lambda}$, and let $\mathbf{v}_k^{\mathsf{T}}$ be the $k$-th row of matrix $\mathbf{V}^{\mathsf{T}}$. Consider $m$ principal components $\mathbf{y}_k = \mathbf{A}\mathbf{v}_k$ that account for 95% of the variance.

The obtained components $\{\mathbf{y}_k\}_{k=1}^{m}$ are mapped into the $m$-dimensional phase space $\Phi_m$, that consists of all possible values of these components. Thereby we get the phase trajectory $\mathcal{Y}$, every point of which is of the form $\mathcal{Y}(t) = (\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_m)(t)$. To extract segments we should split this trajectory by the hyperplane $\mathcal{Y}_1 = \mathcal{Y}_2 = \ldots = \mathcal{Y}_m$. Assume that the hyperplane cuts the line section which connects the points $\mathcal{Y}(t)$ and $\mathcal{Y}(t+1)$. Then the time series $S'$ should be split between $x_{p+t}$ and $x_{p+t+1}$. This performs the segmentation $\{S_i'\}_{i=1}^{n}$ of $S'$.

The obtained segments have different lengths. Since the basic classification algorithms, including $k$-nearest neighbor method, cannot be applied directly to this segments, they should be primarily reduced to an equal length. Assume that the segments should be rescaled to the predefined size $L$. For this reason, each segment $S_i'$ is approximated by the polyline $\tilde{S}_i'$ of length $l_i = |S_i'|$, so that the $k$-th vertex of this polyline is the $k$-th term of the time series $S_i'$. Then we construct the time series $X_i$ of length $L$, defined as

$$X_i(j) = \tilde{S}_i'\left(\tfrac{j \times l_i}{L}\right),$$

that corresponds to the time series $S_i'$.

**4.2 Noise reduction.** We assume that the time series $S$ contains normally distributed Gaussian noise with parameter $\mathcal{N}(0, \sigma^2)$. It introduces an additional error in the time series classification process, and in order to improve the classification accuracy we apply noise reduction. To remove noise we apply an algorithm, based on the singular value decomposition technique.

Here we use the notation introduced in the paragraph above. Let $S'$ be the section of the time series $S$, and let $\mathbf{A}$ be the Hankel matrix corresponding to this section. Consider the singular value decomposition of matrix $\mathbf{A}$. To reduce the noise level we compute $m$ principal components $\mathbf{y}_k = \mathbf{A}\mathbf{v}_k$ that account for 95% of the variance. Then we construct matrix $\mathbf{Y}$, where $k$-th row is the $k$-th principal component $\mathbf{y}_k$. Define series $\tilde{S}'$, which $i$-th element is a skew-diagonal sum of matrix $\mathbf{Y}$. The obtained series $\tilde{S}'$ has less noise variance $\sigma'^2 < \sigma^2$ than the source series $S'$.

**4.3 $K$-nearest neighbor method.** To solve the time series classification problem in this paper we use the $k$-nearest neighbor method. The brief description of the method is provided below. Let $\mathrm{X} = \{X_i\}_{i=1}^N$ be the learning sample and let $\mathrm{Y} = \{y_i\}_{i=1}^N$ be the set of answers, that corresponds to X. Suppose we need to classify the object $X' \notin \mathrm{X}$. First, we arrange objects from the learning sample X in the distance ascending order to $X'$:

$$\rho(X', X_{i_1}) \leqslant \rho(X', X_{i_2}) \leqslant \dots \leqslant \rho(X', X_{i_k}). \tag{3}$$

Here, $X_{i_n}$ is the $n$-th nearest neighbor for $X'$ and $\rho$ is the standard Minkowsky metric. Denote by $y_{i_n}$ the class of the $n$-th neighbor. Then the class $y'$ of $X'$ is defined as:

$$y' = \arg\max_{y \in \mathrm{Y}} \sum_{n=1}^{k} [y_{i_n} = y] w(n, X_{i_n}), \tag{4}$$

where $w$ is a weight function, that evaluates the significance of $n$-th neighbor for the classification of object $X'$. In this paper we consider four different weight functions, presented in the table 1.

**Table 1.** Weight functions $w$

| Function | Value |
|---|---|
| $w_1(n, X_{i_n})$ | $1$ |
| $w_2(n, X_{i_n})$ | $1 - \frac{n}{k+1}$ |
| $w_3(n, X_{i_n})$ | $\frac{1}{\rho(X', X_{i_n})}$ |
| $w_4(n, X_{i_n})$ | $\frac{1}{\rho(X', X_{i_n})^2}$ |

## 5 Experiments and evaluation

To estimate optimal parameters and to evaluate the performance of the proposed model we carried out a set of experiments, described in this section. The experimental data [21] were collected from 13 different people and represent time series from the accelerometer of a cell phone. These subjects carried the phone while performing a specific set of six activities: walking, jogging, ascending stairs, descending stairs, sitting and standing. The collected time series form the data set that was subsequently used for training and testing.

To analyze the segmentation accuracy we performed two sets of experiments. In the first set we used basic segmentation technique and split the time series into segments of equal predefined length $N$. The second set was conducted using the segmentation algorithm based on the fundamental period extraction. In both experiments we used $k$-nearest neighbor method to classify the obtained segments.

The classification technique plays the crucial role in the activity recognition problem. To compare the results obtained by the proposed model, we determined parameters and applied to the same dataset a classification method based on the neural network.

The classification accuracy for all methods was verified using ten-fold cross validation. The experiments we conducted on the set of 9069 training samples and 560 testing samples.

**5.1 Basic segmentation technique.** To determine the optimal parameters for this model the following procedures were done. First, we varied the length of segments $N$ over the range 20 to 120 and implemented the nearest neighbor algorithm. Fig. 2 shows that the best performance was for segments of length near 32. This value was used in the further experiments.

For the $k$-nearest neighbor algorithm we considered four different weight functions $w$, presented in the table 1. For each weight function the algorithm was implemented for values $k$ in range 1 to 100. The best classification results were archived with $k = 1$ for the linear weight function $w_2$.

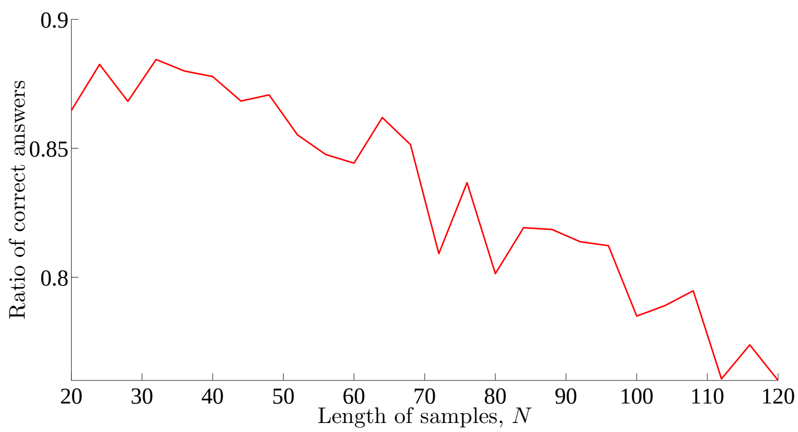


**Fig. 2.** Dependence between the ratio of correct answers and the length of segments $N$

Table 2 resumes the classification results obtained using the determined optimal parameters. The overall number of correct answers was 527 or 94.29%. Walking, sitting and standing were recognized almost perfectly, while there were some difficulties with jogging and climbing the stairs.

**Table 2.** Classification results for the basic segmentation technique

| Activity type, Y | Size of the test sample | Correct answers | Correct answers, % |
|---|---|---|---|
| Jogging | 160 | 145 | 90.6 |
| Walking | 160 | 158 | 98.8 |
| Upstairs | 80 | 73 | 91,3 |
| Downstairs | 80 | 72 | 90,0 |
| Sitting | 40 | 40 | 100 |
| Standing | 40 | 40 | 100 |

**5.2 Segmentation based on the fundamental period extraction.** In this section we describe experiment that was conducted to determine parameters and to estimate accuracy of the segmentation algorithm, proposed in this paper.

Considered algorithm had two parameters. First we had to select the threshold $M$, that cuts off segments of length less then $M$. The second parameter was length $L$, to which all the remained segments must be rescaled. In this experiment both $M$ and $L$ were over the range 14 to 50 with a two-step and the segmentation algorithm was implemented for all possible combinations of these parameters. Obtained segments were classified using the $k$-nearest neighbor lgorithm with the linear weight function $w_2$ and the value of $k = 1$. Fig. 3 shows the classification results of the experiment.

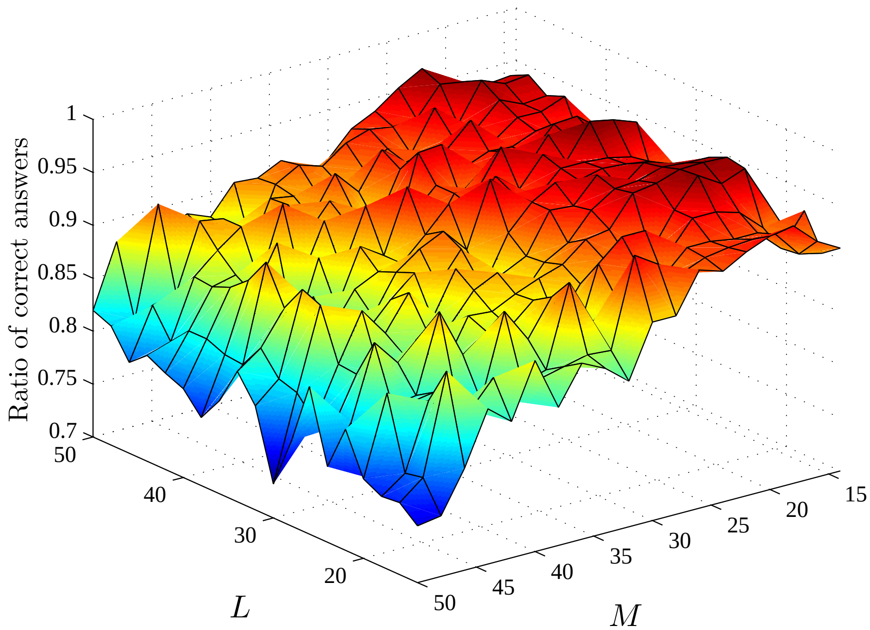


**Fig. 3.** Dependence between the ration of correct answers and parameters $M$, $L$

The figure illustrates that the best classification results correspond to the values $M$ that are between 20 and 25. There is also a slight increase of classification accuracy for coincident values of parameters $M$ and $L$. Using parameters $M = 22$, $N = 22$ we obtained final classification results, presented in the table 3. In comparison to the basic segmentation algorithm the overall accuracy was improved by more than 2% to 96.61%. In terms of individual class accuracy, the results for descending stairs remained the same, while the accuracy of recognition jogging and ascending stairs outperforms the previous results by almost 5%.

**Table 3.** Classification results for algorithm, based on the fundamental periods extraction

| Activity type, Y | Size of the test sample | Correct answers | Correct answers, % |
|---|---|---|---|
| Jogging | 160 | 155 | 96.9 |
| Walking | 160 | 159 | 99.4 |
| Upstairs | 80 | 76 | 95.0 |
| Downstairs | 80 | 72 | 90.0 |
| Sitting | 40 | 40 | 100 |
| Standing | 40 | 39 | 97.5 |

**5.3 Neural network-based approach.** This paragraph is devoted to the approach based on the neural network. Here we consider two-layer perceptron with sigmoidal activation function, trained with the backpropagation method.

Our first experiments showed that the performance of this method on the set of raw segments is rather low. Thus, we extracted a feature vector for each segment and used it in the further classification process. We calculated 15 features for each 3-dimensional segment, 5 for each direction: the mean value, the mean absolute value, the difference between maximum and minimum value, the total value of absolute differences and the mean value of the contained fundamental period.

The main parameter of the neural network was the number of neurons $H$ in the hidden unit. To estimate optimal value of this parameter we implemented neural network for $H$ over the range 8 to 32 and computed the classification accuracy and the root-mean-square error. The best results were for value of $H$ near 24, and table **??** presents classification results for this parameter. The overall number of correct answers was 517 or 92.32%. For four common activities, jogging, walking, sitting and standing, we archived perfect accuracy, while the most complicated task for the classifier was to distinguish ascending and descending stairs.

## 6 Conclusion

In this paper, we proposed a method for human activity recognition using time series, collected from an accelerometer of a cell phone. We first introduced an algorithm for the time series segmentation and then proposed the $k$-nearest neighbor algorithm for the classification of the obtained segments. The accuracy of the algorithms was verified in the computational experiment by testing them on the set of actual accelerometer data. To compare the results we applied to the same dataset a classification method based on the neural network. The results shown in this paper suggest the usefulness of combining advanced segmentation algorithms and the $k$-nearest neighbor classifier. In the classification procedure, this method outperformed the rest in terms of overall and individual class accuracy, providing over the 96% of correct answers.

**Acknowledgments.** This work is supported by the Russian Foundation for Basic Research (RFBR) under grant number 14-07-31326.

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