Analysis of thoracic regional impedance changes using PCA approach

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Abstract. A multichannel impedance and one lead electrocardiographic recording system has been developed. The impedance measurement unit is built using a four-electrode technique. It consists of a sinusoidal, 40 kHz, current source and five measurement channels. Circumferential current electrodes have been located at a neck and an abdomen. Voltage measurement disk electrodes formed five two-electrode measurement ports. The impedance change waveforms (ICG) have been recorded simultaneously with ECG. The ICG waveforms have been analyzed using Principal Component Analysis (PCA). The examinations have been done for different ports configurations in relation to the heart. A dependence of obtained components on ports configurations has been found. Similar results have been obtained when examining healthy (test) persons.

1. Introduction

Impedance signals taken from the thorax are widely used for different purposes [1]. However, the most widespread application is the measurement of cardiac output [1, 5]. This application was developed under an assumption that the main source of the measured impedance changes was associated with the changing volume of aorta.

The evaluation of impedance changes associated with blood flow in the thorax requires a special measurement technique allowing measurement of very small signal in the presence of a very big one. Typically, the evaluated changes are very often not bigger than 1% of the measured signal.

PCA is a multivariate statistical procedure where the vector containing measured signal is presented as a weighted sum of orthogonal basis vectors. The central idea in PCA is to reduce the dimensionality of the data set, while retaining as much as possible of the information in the original data [4]. Thus, it allows reducing the dimentionality of data set containing a large number of interrelated variables, while preserving as much as possible of variation present in the data set. It is achieved by transforming the input data set into a new coordination system.

Generally, PCA is motivated by the two following problems: 1. given random vectors described by finite second order moments and zero mean find the linear subspace of reduced dimension that minimizes the expected distance of data from the subspace, and 2. given random vectors find the linear subspace that captures most of data variance. This problem is related to feature extraction, where the

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objective is to reduce the dimension of the data while retaining the most of its information content. Both problems have the same optimal solution, which is obtained due to knowledge of data covariance matrix.

2. Methods

2.1. A measurement system

Data for analysis have been collected using a specially developed system (figure 1). It consisted of a sinusoidal, 40 kHz, current source I(ω) and five identical measurement channels. The measurement system, known as a four-electrode one, consisted of two current electrodes, marked I_1 and I_2, and two voltage electrodes, marked V_{i1} and V_{i2}, where subscript *i* stood for current number of the measurement channel. The difference of potential measured using voltage electrodes after amplification was demodulated using a synchronous technique and the result was filtered (using Low Pass Filter, LPF) and dc component was removed (DCR). Only alternating part of the signal was amplified using a dc amplifier (Amp_{dc}) and sampled. A sampling operation was synchronous for all measurement channels. Then, the sampled signals were converted (AD) into digital ones and sent successively to the host computer (H.C.) via USB.

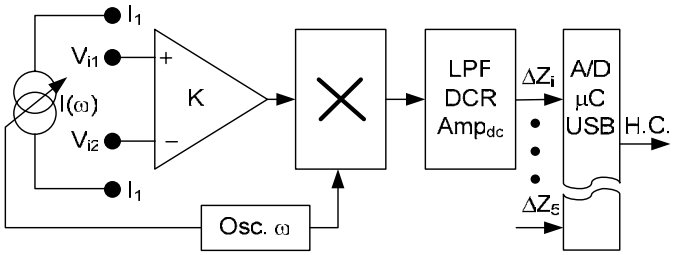

Figure1. Schematic diagram of the measurement system, a detailed description in the text.

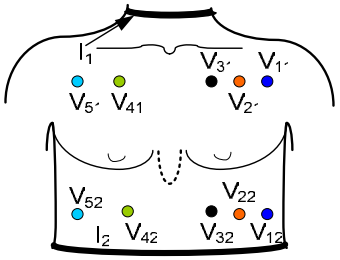

Figure 2. Localization of the electrodes on the thorax.

2.2. Collection of data

A specially developed system (figure 1) was used to collect the data by means of electrodes placed on thorax (figure 2). The current was passing between electrodes I_1 and I_2. Each pair of electrodes with identical first subscript formed a measurement lead, e.g. the electrodes V_{21} and V_{22}. According to sensitivity theorem developed by Geselowitz [2, 5] different localization of voltage measurement electrodes in spite of utilizing common, circumferential, current electrodes located on the neck and abdomen results in different distribution of spatial sensitivity. Thus, even assuming a uniform spatial distribution of current density involved by current flowing between current's electrodes the resulting sensitivity is non-uniform.

2.3. Data analysis

Data were analyzed using a Principal Component Analysis (PCA). The following algorithm adopted from [6, 8] was used:

1. Data preprocessing: The recorded signal is segmented into vectors having length M. The N similar (associated with the activity of the heart described by the same rate) are chosen. These data are formed into a single matrix **T** of dimensions N × M, so that N is the observations and M is the dimensions.
2. The mean along each dimension m = 1...M is calculated. Afterwards, all computed mean values are placed into an empirical mean row vector **u** of dimensions M.
3. The empirical mean row vector **u** is subtracted from each row of the data matrix **T**. Then a new mean-subtracted data matrix is derived.
4. The M × M empirical covariance matrix is calculated using the zero-centered data matrix **B**.

5. Calculation of the eigenvectors and eigenvalues of the covariance matrix. This step requires the use of a computer-based algorithm for computing the eigenvalue matrix **D** and the eigenvector matrix **V** of the covariance matrix. Diagonal matrix **D** having dimensions M × M and matrix **V** also of dimension M × M are obtained. The matrixes **D** and **V** contain, respectively, eigenvalues and eigenvectors of the covariance matrix **C**. The eigenvalues and eigenvectors are ordered and paired. The m^{th} eigenvalue corresponds to the m^{th} eigenvector.
6. The columns of the eigenvector matrix **V** and eigenvalue matrix **D** are sorted out in order to maintain the correct pairings between the columns in each matrix.
7. Data are converted to a new basis. The new basis is denoted as PCA-scores or the reconstruction parameter vectors (RPV). The projected vectors are the columns of the matrix **Z** (N×M). The matrix **Z** is calculated by multiplying the eigenvector matrix with the zero-mean data matrix. The rows of **Z** matrix correspond to the observations, whereas the columns refer to the components or dimensions.

3. Results

Example of waveforms recorded for a healthy person show a regular character. Moreover, they contain specific information (figure 3). A characteristic time shift between waveforms recorded at different localization of left and right sides of the thorax is easily seen. The signals recorded in the vicinity of heart (i.e. ΔZ_2 and ΔZ_3) are morphologically different from others.

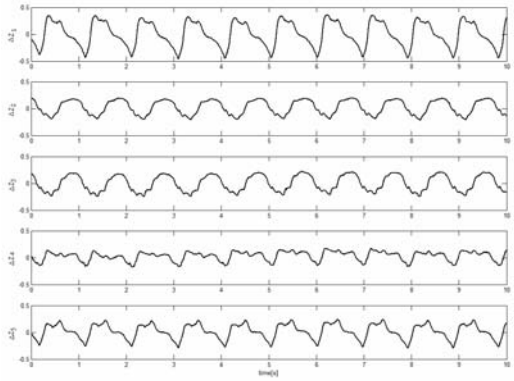

Figure 3. The measured ΔZ waveforms.

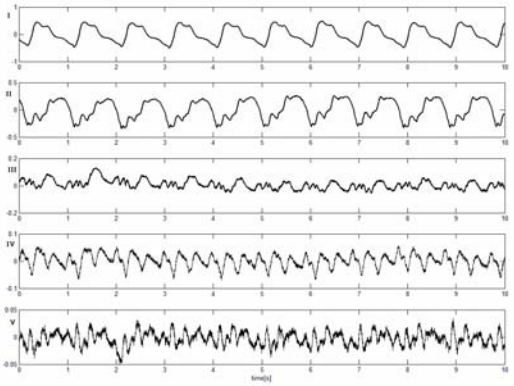

Figure 4. PCA analysis of the signals presented in the figure 3.

PCA of the set of signals presented in figure 3 shows a distinct three components exhibiting a periodic and regular character (figure 4).

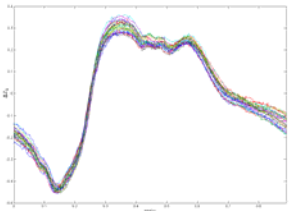

Figure 5. Selected part of the ΔZ_1 waveform recorded for channel 1 (shown in figure 3).

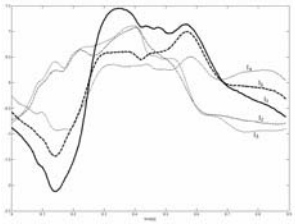

Figure 6. The first components of the signals presented in figure 3.

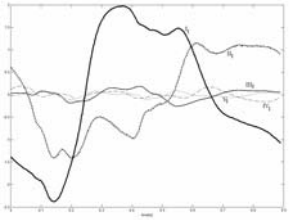

Figure 7. Result of PCA for the set of data composed by the first PC calculated for each channel.

A set of one-cycle waveforms selected from the recording has been used as data for applying PCA. Example of such data is presented in figure 5. It shows a relatively small variability. However, it

should be underlined that only samples of equal length (time duration) have been chosen and the signal has been recorded during rest.

4. Discussion and conclusions

PCA is a widely used technique in data processing. It has been shown that this approach is useful when estimating influence of respiration on ECG or ICG [7, 9], removing noise from data [8], analyzing both single-lead and multi-lead signals, compressing the data, separating signals or extracting features [8].

The recorded data show dependence of theirs morphology on localization of recording electrodes. A simple analysis of results obtained and presented in figure 4 reveals that the first and the second components present different phenomena. An initial part of the second PC resembles the corresponding part of the first one. Then, both signals changes in opposite direction. It suggests that they are dominated by different phenomena.

The PCA enables to evaluate local phenomena. In fact, according to Geselowitz [2] it is an obvious remark. The recorded data and PCA analysis allows differentiate between atrial and ventricular activity.

More exhaustive studies led on different groups including diagnosed heart diseases or disorders have to be performed.

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