Sparse Coding of Cardiac Signals for Automated Component Selection after Blind Source Separation

D Wedekind[1], D Kleyko[2], E Osipov[2], H Malberg[1], S Zaunseder[1], U Wiklund[3]

[1] Institute of Biomedical Engineering, TU Dresden, Dresden, Germany
[2] Department of Computer Science, Electrical and Space Engineering, Luleå University of
Technology, Luleå, Sweden
[3] Department of Biomedical Engineering & Informatics, Umeå University, Umeå, Sweden

Abstract

Wearable sensor technology like textile electrodes provides novel ambulatory health monitoring solutions but most often goes along with low signal quality. Blind Source Separation (BSS) is capable of extracting the Electrocardiogram (ECG) out of heavily distorted multichannel recordings. However, permutation indeterminacy has to be solved, i.e. the automated selection of the desired BSS output. To that end we propose to exploit the sparsity of the ECG modeled as a spike train of successive heartbeats. A binary code derived from a two-item dictionary {peak, no peak} and physiological a-priori information temporally represents every BSS output component. The (best) ECG component is automatically selected based on a modified Hamming distance comparing the components' code with the expected code behavior.

Non-standard ECG recordings from ten healthy subjects performing common motions while wearing a sensor garment were subsequently processed in 10 s segments with spatio-temporal BSS. Our sparsity-based selection RCODE achieved 98.1% heart beat detection accuracy (ACC) by selecting a single component each after BSS. Traditional component selection based on higher-order statistics (e.g. skewness) achieved only 67.6% ACC.

1. Introduction

Ambulatory vital sign recording supplements the standard clinical data acquisition by long-term measurements for early diagnosis of diseases or health and stress monitoring of people performing potentially dangerous tasks. Using measurement techniques like textile electrodes for wearable sensing, the recorded electrocardiogram (ECG) is of non-standard nature compared to its clinical counterpart. Moreover, the minimal-conductive measurement principle which allows for a flexible health monitoring is also strongly affected by movement artifacts [1].

Blind Source Separation (BSS) is a signal processing technique capable of separating signal mixtures (e.g. mixtures of ECG and distortions) into its constituting components [2]. Spatio-temporal Independent Component Analysis (ICA) based on the FastICA algorithm [2] is one realization of BSS which has shown a superior performance on wearable data compared to the standard ICA [1]. Despite its ability to separate ECG from distortions, ICA is typically only solved up to a permutation (i.e. separated components are available but the output is mostly unordered). Accordingly, a desired output component (e.g. the one best representing the ECG) has to be automatically selected. This selection gains special interest while processing a large number of channels. This is typical for ambulatory multi-channel health recordings and particularly spatio-temporal ICA which adds extra channels during the processing [3].

Two principles for handling permutation indeterminacy have been proposed in the context of ECG processing. The first principle identifies and discards the undesired components (i.e. artifacts) thus indirectly obtaining the ECG component. A combination of second-order and higher-order statistics was used for that purpose in [4] whereas auto-correlative periodicity manifestation was exploited in [5]. Feature decision trees were used to classify artifacts in [6]. The second approach aims at directly identifying the desired component (i.e. the ECG). Again, higher-order statistics have been utilized in [1, 7]. Moreover, template matching was applied in [8]. The morphological nature and periodicity of QRS waveforms of the ECG were exploited for instance in [9, 10]. A combination of both approaches, primarily sorting out undesired BSS components and further selecting the (best) ECG component among the residual channels, each utilizing frequency characteristics, was proposed by our group earlier in [3]. Besides these existing diversified approaches to component selection, an evaluation of their actual selection performance (like in [3, 11]) is rare. This study proposes a new approach to
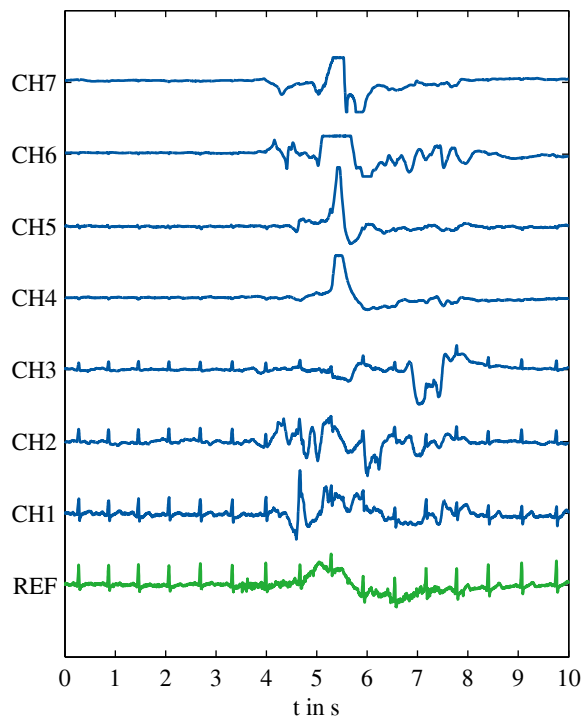
Figure 1. Input data example with heavy distortions and a large motion artifact. REF indicates the conductive reference ECG and CH1-7 the ECG leads derived from the textile electrodes.
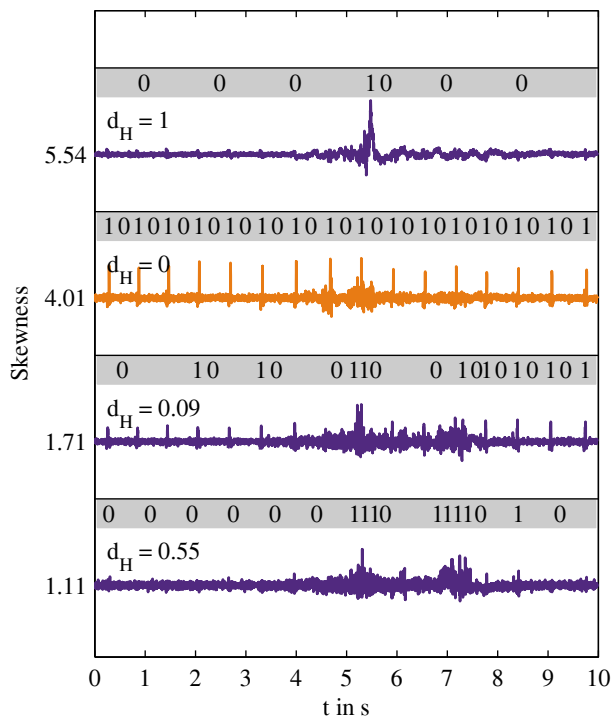

Figure 2. Spatio-temporal BSS output components (excerpt) of the input signals from Fig. 1. Components are vertically ordered according to skewness. Modified Hamming distance d_H as well as the sparse code sequence of each output component are shown in grey bars. The RCODE selection is marked orange.

solve the permutation indeterminacy problem including its performance assessment on real data.

Our novel approach aims at directly identifying ECG components in BSS outputs based on a sparse representation of each component. The sparse code itself thereby features QRS waveforms and their temporal behavior, expressed in "spike trains" typical for spatio-temporal BSS on ECG [1]. A comparison is also made with other frequently applied methods which are based on higher-order statistics.

2. Material and Methods

2.1. Wearable Dataset and Processing

We analyzed recordings from ten healthy subjects wearing a garment with integrated textile electrodes [1] while performing a protocol of motions (standing up, sitting down, walking, flexing chest muscles). Seven ECG leads obtained from the garment (sampling rate 500 Hz) were processed in subsequent 10 s segments (1 s segment shift). A total of (mean $\pm$ standard deviation) 213 ± 8 segments per subject were considered. A reference ECG recorded simultaneously using conductive electrodes

served as ground truth. See Figure 1 for a data example including a large motion artifact. Spatio-temporal BSS using FastICA algorithm with skewness maximization and ten added time lags (k $\in$ [0, 10]) [3] was applied to the seven textile ECG leads which resulted in a total of 77 output components per segment. See Figure 2 for an output component excerpt according to the input data shown in Figure 1.

2.2. Output Component Selection

Our component selection RCODE consists of three major processing steps: 1) detection of peaks in the output components; 2) coding of the temporal behavior of the peaks of each component; and 3) assessing the components' code for selection of one single component.

The key target for the peak detection is to allow for a sensitive subsequent coding, thus achieving a balance between sensitivity to distortions while maintaining the ability to detect peaks in the presence of distortions. The basic processing steps are indicated in Figure 3. An envelope (ENV) is calculated for each component (BSS) us-
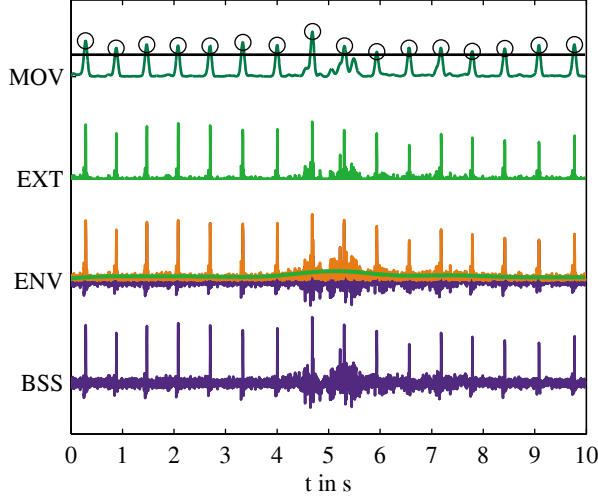
Figure 3. Data processing steps prior to the coding. Spatio-temporal BSS output channel (BSS) including its envelope (orange) and the lowpass-filtered (green) envelope (ENV), the extracted signal (EXT) and its integrated version (MOV) including the threshold (black line) and peak detections (black ∘).

ing Hilbert transformation. A new signal (EXT) is formed by extracting the signal content above the lowpass-filtered (0.5 Hz 5th-order Butterworth) envelope. This intends to match peak heights between areas with and without distortion. Peaks are further consolidated by moving window integration (MOV) using a 100 ms Hamming window (considered as QRS length [12]). Finally, peaks are detected by applying thresholding using an inversely exponentially weighted average (see black line) on MOV.

The sparse representation of each component's peak detections at times t_i ($i \in [1, I]$, I is the number of peak detections) is obtained by coding according to the dictionary {peak - 1, no peak - 0} together with temporal a-priori information. The cardiac refractory period Δt_R is considered as 0.3 s [10], whereas the maximum peak-to-peak distance Δt_{max} is considered as 1.5 s (i.e. a minimum heart rate of 45 bpm [13]). Accordingly, a sequence $(x) \in \{0, 1\}$ is obtained by:

1. $(x_i) = 1$ with $i \in [1, I]$
2. add $\lceil (t_{i+1} - t_i)/\Delta t_{max} \rceil$ zeros between x_i and x_{i+1} if $t_{i+1} - t_i > \Delta t_R$
3. add $\lfloor (t_1)/\Delta t_{max} \rfloor$ zeros to (x) at $t < t_1$
4. add $\lfloor (10 - t_I)/\Delta t_{max} \rfloor$ zeros to (x) at $t > t_I$

The sequence (x) of final length L is further assessed by a modified Hamming distance measure d_H.

d_H is designed to indicate the distance from the expected code behavior assuming a perfect ECG component

with code $(x) = 1, 0, 1, 0, \ldots$ or $(x) = 0, 1, 0, 1 \ldots$, respectively. It is constituted by two factors:

$$d_H = w_d \cdot d_{10} \tag{1}$$

where d_{10} is a distance to the expected behavior assessing only pairs of two subsequent code elements (x_i, x_{i+1}) each. It is defined by the ratio between the amount of non-desired code pairs (0,0) or (1,1) and the total amount of code pairs

$$d_{10} = \frac{|\{(x_i, x_{i+1})|(x_i, x_{i+1}) = (0, 0) \cup (1, 1)\}|}{L - 1} \tag{2}$$

with $i \in [1, L - 1]$.

w_d weights this distance regarding the length of the longest continuous sequence $(x_i, x_{i+1}, \ldots) \subseteq (x)$ of expected ECG code behavior where all pairs of subsequent code elements $(x_i, x_{i+1}) = (1, 0) \cup (0, 1)$. Accordingly,

$$w_d = 1 - \frac{l_{10}}{L - 1} \tag{3}$$

where l_{10} is the length of that longest continuous sequence of the respective (x). If $I = 1$, d_H is set to 1. Examples of code sequences (x) and derived distance measures d_H can be seen in Figure 2.

The component with the minimal d_H is selected as RCODE output. In the case of obtaining multiple components with equal minimum d_H, maximum kurtosis of components' derivative is used to select among them.

In order to compare the traditional component selection based on higher-order statistics [1,4,7], we also used skewness for an automated component selection. Since higher-order statistics are prone to outliers, an outlier-removal using Walsh's non-parametric outlier test [14] was performed on each component prior to selecting the component with the highest skewness (SKEW).

3.   Results

The performance was evaluated by the heart beat detection accuracy (ACC) [3] obtained by comparing the manual QRS annotations from the reference ECG with the QRS detections using a modified maximum search detector [15]. Figure 4 shows the according boxplots of subject-wise averaged ACC results. The input data quality was described by averaging the ACC for all seven input channels which gave 69.3 ± 14.2 % (IN). The upper performance limit of a channel selection after BSS was given by manually selecting always the component with the highest ACC which served 99.5 ± 0.8 % (BEST OUT). The newly proposed automated single channel selection RCODE achieved 98.1 ± 1.7 % whereas the usage of higher-order statistics in terms of the outlier-adjusted
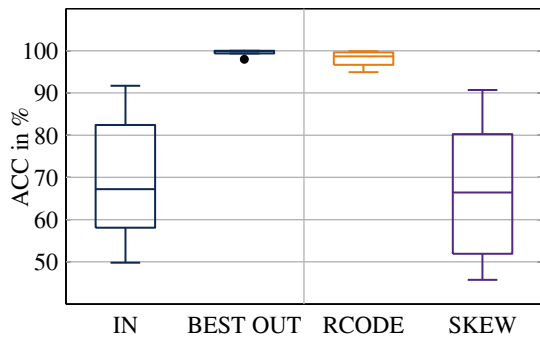
Figure 4. Boxplots showing subject-wise (N = 10) averaged heart beat detection accuracy ACC in %. Shown are the average input ACC (IN) of seven wearable ECG leads, the manually selected best possible output ACC (BEST OUT) after BSS as well the automated selections RCODE and SKEW. Outliers (•) defined as values exceeding the maximum whisker length (1.5 · interquartile range).

skewness (SKEW) only reached 67.6 ± 16.4 %. As shown by the skewness ordering in Figure 2, the outlier-adjusted skewness failed to serve as a robust selector (by selecting the component with the maximum skewness SKEW) in the presence of components with distortions. Accordingly, selecting the spatio-temporal BSS output component based on the sparse representation outperformed the traditional method based on higher-order statistics. Moreover, RCODE performed close to the upper selection limit in this particular dataset which will be verified on extended measurements in our future work.

Acknowledgements

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Address for correspondence:

Daniel Wedekind
TU Dresden
Institute of Biomedical Engineering
01062 Dresden, Germany
daniel.wedekind@tu-dresden.de