Reducing Motion Artifacts for Robust QRS Detection in Capacitive Sensor Arrays

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ABSTRACT

Non-contact capacitive ECG measurements (cECG) have applications in various unobtrusive and ubiquitous systems. However, cECG signals are frequently corrupted by interference and motion artifacts. In this work array processing methods, such as blind source separation, were used to reduce the impact of motion artifacts on QRS detection. The capacitive sensor array was integrated in a bed mattress and covered with two insulating sheets. The array processing methods were compared in terms of their QRS detection error rates (De). Results of our study with five healthy subjects in different recording conditions showed that, when using array processing methods, QRS detection performance during body motion can be substantially improved (De reduced from 0.46 on raw sensor data to 0.06 for a channel difference method). We concluded that array processing is a promising approach to achieve motion-resistant QRS detection and thus suggest wider use of capacitive sensor arrays.

Categories and Subject Descriptors

I.m [**Computing Methodologies**]: Miscellaneous

General Terms

Measurements, Algorithms

1. INTRODUCTION

The great advantage of capacitive electrodes is that they provide an electrocardiogram (ECG) without the need of direct skin contact. Since their introduction in the 1960s, they have been integrated in many different ubiquitous systems, ranging from bed mattresses [12] to car seats [17]. Capacitive electrodes have been used to capture heart rate up to 40 cm from the body [2] and to faithfully represent ECG pattern for clinical use on dressed patients [6].

Although a large variety of ECG systems based on capacitive electrodes have been reported in the literature, they are not yet used in clinical routine. The main reason is that the signal of interest is often corrupted by power-line interference and motion-induced artifacts [5]. Motion-induced artifacts are distortions of the signal, created by variations in capacitive coupling during the recording process. They have different origins, including triboelectricity at the electrode-body interface [18] and variation in the electrode-to-skin distance [8]. The chaotic nature of the motion artifacts makes them particularly hard to extract or filter out. Only a few signal-processing approaches for motion artifacts reduction in cECG have been presented so far. A wavelet-based filter was used in [11] to isolate the unwanted component and correct the cECG signal, whereas in [8], the cECG signal was reconstructed using models of the electrode behavior. This later attempt required precise knowledge of the coupling capacitance. Recently, a technique to enhance the cECG signal quality based on the stationary wavelet transform and principal component analysis (PCA) was proposed and tested on one subject [14].

In this work, we investigate how array processing methods, such as blind source separation (BSS), can reduce motion artifacts in cECG. BSS techniques do not focus on a particular type of artifact and do not require *a priori* knowledge on the system. The considered techniques rely on redundant information provided by a capacitive sensor array to separate noise from cECG components. After this decomposition stage, a selection of the component of interest could be performed. Although the use of capacitive sensor arrays for ECG monitoring had already been investigated in recent papers, e.g. in [12, 17], to our knowledge, no array processing on capacitive arrays has been reported so far.

The main purpose of this work is therefore to assess the benefit of using array processing methods in cECG signals that are disturbed by motion-induced artifacts. We studied the benefits of different methods in enhancing heartbeat (QRS complex) detection performance. Different recording situations (prone, supine, with and without body movement) and different analysis conditions (automated or manual channel selection, varying window sizes) were considered to select the best performing solutions.

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2. ARRAY PROCESSING METHODS

2.1 Motivation and assumptions

Array signal processing exploits the fact that every sensor in an array records partially redundant information. Fusing sensor-array data should therefore improve the extraction of the signal of interest compared to a single-channel data analysis. In our recordings (4-channel cECG), the source signal of interest (QRS complexes of the ECG) appears to be mixed with other source signals such as electromyograms, power-line interferences and motion artifacts. The goal is thus to find a suitable technique to undo the mixing. Since the source signals and the mixing process are unknown, unmixing can be considered as a BSS problem. We assumed that cECG subspace and motion artifact subspace were independent and linearly instantaneously mixed and that we recorded as many mixtures as source signals. Consequently, standard BSS techniques could be used to derive a new representation of the data, in which the source signals are unmixed. From these estimated sources, the source of interest must be selected subsequently. The assumption of a linear instantaneous mixture is relevant since the electrical propagation in biological tissues is very fast. Note that our limited number of recorded mixtures, that is four, limits the unmixing process.

BSS techniques have been successfully applied on conventional ECG recordings to identify the noise subspace and reconstruct the corrected ECG, e.g. in [7, 13]. Therefore, if *capacitive* motion artifacts could be similarly separated from the cECG components, BSS techniques would provide effective source separation.

2.2 BSS principle

With BSS techniques, the source signals are unmixed based on statistical measures, such as variance in PCA and a measure of non-Gaussianity (e.g. Kurtosis) in independent component analysis (ICA). PCA utilizes the variance to separate independent Gaussian sources along orthogonal axes, whereas ICA uses higher-order statistics to separate non-Gaussian independent sources. If $X = AS$ represents the recorded linear mixtures (with A being the mixing matrix), the aim of BSS is to discover a matrix B, which undoes the mixing. If B is the inverse of A (up to permutation and scaling), then the source signals S can be fully recovered via $S = BX$. In practice, BSS provides source estimates (*components*) $\hat{S} = BX$.

2.3 Investigated algorithms

2.3.1 BSS

Three well-known and widely-used approaches are evaluated and compared in this study to solve the BSS problem: PCA, JADE and FastICA. PCA is often used as an intermediate step in problems related to ECG noise reduction [4] but it may also be used stand-alone to isolate the highest-energy, uncorrelated noise component from some orthogonal ECG-related components. The PCA approach is not expected to provide source separation, but it is considered here for its computational simplicity and capability of signal decomposition. FastICA is an efficient fixed-point algorithm that performs ICA by minimizing the mutual independence of signals [9]. JADE ICA, developed by Cardoso et al. [3], maximizes the independence of signal components by involving the cumulants of order 2 and 4.

2.3.2 Channel differences procedure

In parallel to the BSS methods, a simple channel difference processing (Diff) was considered in our comparative evaluation. In our Diff approach, differences between all channel combinations were derived. We assume that the differentiation might reduce effects of motion artifacts that were spatially correlated between channels. While taking the difference of unipolar ECG channels will transform them into bipolar channels, it will not cancel the ECG information. In the case of four input channels, six linear combinations were created by the Diff procedure, which were further treated in the same way as the BSS components.

2.4 Component selection

Subsequent to the above-mentioned array processing methods, a discrimination between noise and cECG components must be performed to extract the source of interest.

Two component selection methods were considered in this work. Firstly, manual selection was used to identify the component yielding highest QRS detection performance (given reference QRS annotations). This approach provided us with the best possible performance of each array processing method. Secondly, an automated channel selection method was deployed following the approach of [10]. The method considers the variance of RR-intervals (determined from QRS detection) as discriminating feature. It is assumed that the component with the least false QRS detections will have the lowest RR-interval variance in synchronously recorded array channels of one subject.

Some alternative selection methods have been proposed for ECG recordings. In [1], a preceding template determination was required for matching. In [13], the area under the autocorrelation curve was used to discriminate the ECG signal from noise. This method does not seem to be efficient when more than two components were considered. Finally, in [7], kurtosis and variance of sub-segment variances were used to identify the noise components. However, this method requires the setting of thresholds and is not supposed to select between similar ECG signal components. The method based on the variance of the RR intervals suggested in [10], was chosen for its simplicity and expected efficiency compared to other methods.

3. EVALUATION METHODOLOGY

3.1 Analysis procedure

The considered algorithms were directly applied on sensor array recordings with the assumed number of mixed sources set to maximum corresponding to the number of array sensors. The analysis was performed in MATLAB on non-overlapping windows of 5, 10, 15, 20 and 30 seconds. Smaller window sizes are interesting for online implementation and allow the automated component selection algorithm to choose the best component more frequently. In contrast, larger window sizes provide more data to the BSS algorithms, thus providing more robust statistics.

After the array processing, QRS-complexes were detected in each derived component using a state-of-the-art algorithm based on the continuous wavelet transform (CWT) [15]. Then the best performing component was selected as described in Section 2.4. Fig. 1 provides an overview on the array processing and evaluation scheme used in this work.

3.2 Data collection

The cECG was acquired using an array of four capacitive electrodes ($\o = 16\,\mathrm{mm}$) provided by Philips Healthcare. The electrodes were arranged in a 105x180 mm rectangle on top of a mattress (foam density $= 35\,\mathrm{kg/m^3}$). The measurement setup is depicted in Fig. 2.

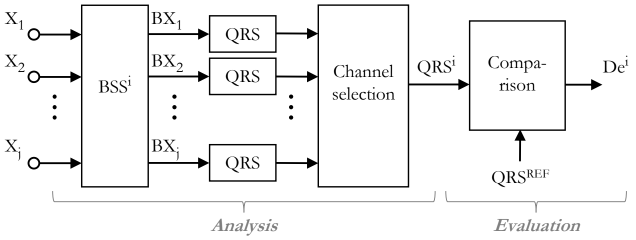

Figure 1: Overview of the array processing and evaluation scheme used in this work. The detection error ($\mathbf{De^i}$) represents the QRS detection performance that can be achieved using a particular $\mathbf{i}^{th}$ array processing technique (BSS or Diff) and channel selection method (manual or automated).

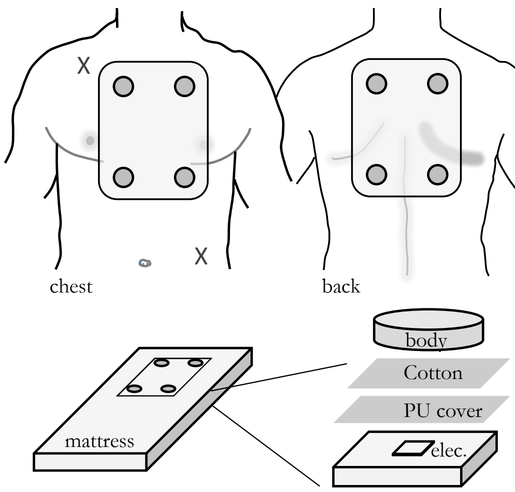

Figure 2: Measurement setup used in this work. Top pictures represent the approximate position of the sensor array relative to the body. Bottom scheme illustrates the superposition of capacitive electrodes and insulating layers on the mattress.

We observed that some variations in the position of the electrodes may occur without consequences for the signal analysis, as long as the electrode array remains covered by the trunk. Two body positions were studied: lying prone (on the chest) and supine (on the back) on the mattress-mounted electrodes array. Two insulating layers separated the electrodes' surfaces from the subject's skin: a water-resistant polyurethane-coated fabric and a cotton t-shirt. To reduce power-line interference and prevent the accumulation of static charges, a conventional adhesive Ag/AgCl electrode was attached to subject's left wrist for grounding. We considered the use of this gel ground electrode as a temporary safety precaution during the development of a fully insulated system. A standard reference ECG was recorded through two additional Ag/AgCl electrodes placed on the patient chest (indicated with X in Fig. 2). Both reference and cECG signals were recorded in parallel and sampled at a frequency of 1024 Hz using a PC data acquisition module. Frequency components below 1.5 Hz and above 100 Hz were cut off by the front-end electronics of each capacitive sensor.

The measurement protocol consists of two recording phases of 1.5 minutes per subject. During the first phase, subjects were lying at rest on the mattress. They remained quiet and breathed normally. Occasionally, some deep breaths occurred. During the second phase, they were asked to move limbs (swinging arms and legs) to create random body motions. The experiment was repeated for each of the considered body positions (prone and supine).

3.3 Performance evaluation

The performance of each array processing method in reducing the impact of motion artifacts on heart beat detection has been assessed by comparing the QRS positions detected on the selected component (QRS^i) with the reference QRS positions ($\mathrm{QRS}^{\mathrm{REF}}$), as shown in Fig. 1.

The reference QRS positions were determined by manually annotating QRS complexes in the reference ECG signal. A shift of 100 ms between algorithm QRS detection and reference annotation was allowed to score a correct detection, which is an established performance evaluation approach [15]. From this comparison, the numbers of false detections (FP), missed detections (FN) and correct detections (TP) were determined, allowing us to compute several measures of performance, including sensitivity (Se), positive predictive value (PPV) and detection error rate (De):

$$Se = \frac{TP}{TP+FN}, PPV = \frac{TP}{TP+FP}, De = \frac{FN+FP}{TP+FN}.$$

By virtue of its definition, De can be considered individually for performance comparisons.

4. RESULTS

Five healthy male subjects (1.80 m±0.05, 80 kg±5, 30 years±5) were enrolled for the evaluation. The De obtained for each array processing method across all subjects are represented in the logarithmic graphs of Fig. 3. For this analysis a manual component selection was used to determine the best possible performance of each array processing method. The first bar ("Raw signal") represents the QRS detection performance obtained without array processing.

4.1 Algorithms performance

The results in Fig. 3 show that a lower De was obtained for prone than for supine body positions, suggesting that recordings from prone position were less affected by artifacts. The least corrupted cECG signals were recorded in prone position at rest. Here, sufficient detection performances was obtained without array processing (Raw signal $De < 0.013$). A performance improvement was noticeable for ICA using large windows sizes (15 to 30 s). More errors were observed for the Diff approach using small windows (5-10 s).

In recordings under motion conditions, all considered array processing methods showed an improvement of the QRS detection performance when compared to that of the Raw signal. ICA (JADE and FastICA) generally performed better than PCA. This result could be expected since the assumptions of ICA better fit the heart model, regarding source signal distribution and non-orthogonal projection of the signal with respect to noise [16]. However, on very small windows (5 s), the performance of ICA seemed limited. Interestingly, the Diff method obtained similar or better performance compared to other methods in presence of motion artifacts.

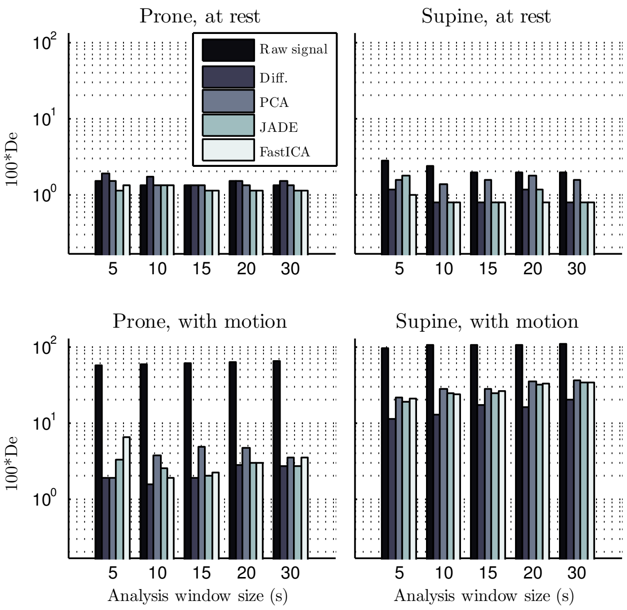

Figure 3: Logarithmic-scaled detection error rate for different recording conditions and processing window sizes. "Raw signal" represents the best-performing array sensor. For each array processing method, components were manually selected (optimal performance).

From these results, we concluded that Diff and JADE were the two best performing methods using the considered data set. In the waveform example shown in Fig. 4, 8 FP and 6 FN were introduced in *Raw* ($De = 1.75$), but no false or missed detections were observed in the corresponding Diff and JADE components ($De = 0$).

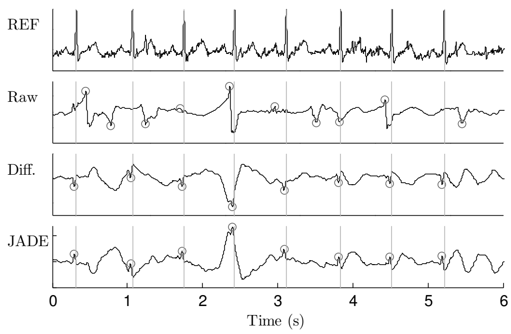

Figure 4: Example waveforms of supine recordings under body motion for reference ECG (*REF*), best cECG array sensor (*Raw*), and best Diff and JADE components. Moreover, results of the heart beat detection (circles) are shown.

4.2 Component selection performance

Fig. 5 shows the De obtained when the components of each of the two best array processing methods (Diff and JADE) were automatically selected as detailed in Sec. 2.4. In this analysis, all recording conditions were jointly considered in the performance evaluation. In Fig. 5, performance was bounded by the manual best component selection as described in Sec. 2.4 (optimal performance) and a manual selection of the component that showed the largest detection error (worst case).

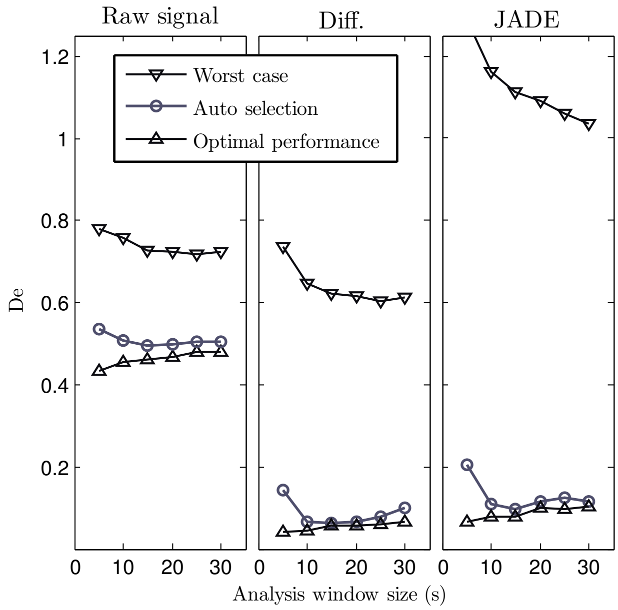

Figure 5: Detection error rates for each of the two best-performing methods (Diff and JADE) using automated component selection. The upper and lower performance bounds, referred as "Optimal performance" and "Worst case" respectively, are shown.

As the results show, our automated selection performs close to optimal for window sizes above 15 s. The automated selection is not optimal for discriminating small window sizes (5-10 s), since not enough RR intervals were available to robustly compute their variance. Nonetheless, the detection error rates remain below the ones obtained on the raw sensor signal. This result confirms the potential of array processing, with automated component selection, to improve QRS detection in artifact-rich cECG.

As a quantitative summary, sensitivity, positive predictive value and detection error rates for the full data set (229300 QRS-complexes) using manual and automated component selection are shown in Table 1 for a 15 s window size.

Table 1: Comparison of QRS detection performances on the full data set (window size: 15 s)

	Manual component sel.			Automated component sel.		
Method	Se(%)	PPV(%)	De	Se(%)	PPV(%)	De
Raw	75.40	77.78	0.461	73.62	75.97	0.496
Diff.	**96.42**	**97.88**	**0.056**	**96.29**	**97.44**	**0.062**
PCA	94.81	95.43	0.097	94.59	94.80	0.106
JADE	95.33	96.85	0.077	94.90	95.44	0.096
F-ICA	95.29	96.51	0.082	95.29	96.09	0.086

5. DISCUSSION

The clinical relevance of cECG is limited given the distortions induced in current recording systems and given that the electrodes position relative to the body is not exactly known. Consequently, the focus of this work has been to investigate the potential of capacitive sensor arrays and array processing to obtain a more accurate extraction of QRS complexes.

A clear improvement in QRS detection performance was achieved in this work by reducing the detection error rate from 0.46 to 0.06 using the Diff method. This suggests that the considered techniques (especially JADE or Diff) combined with an automatic component selection could derive the iHR accurately on segments where a CWT-based QRS detector on raw capacitive sensor data failed. The remaining detection errors when using the presented approaches confirm the severity of artifacts in the considered data set.

An interesting result of our methods comparison is that the simple channel differences approach (Diff) provides similar, if not better, QRS detection performance compared to FastICA and JADE. ICA is computationally more complex, but allows, when needed, to recover the original unipolar recordings after noise cancelation [7].

To verify the stability of our results, the analysis was repeated five times with a leave-one-subject-out approach. Each of the reduced data sets allowed us to draw the same conclusions as presented on the full data set. However, to further assess the considered array processing methods for implementing them in ubiquitous systems, data should be acquired over longer periods of time with subjects performing normal daily activities, such as sleeping or driving a car.

6. FUTURE WORK

The advantage of cECG over other measurements that provide iHR without skin contact (e.g. the ballistocardiogram) is that cECG can return information about the electrical heart activity, not restricted to beating frequency. Therefore, future work should focus on extracting further ECG-related features such as P- and T-waves from capacitive recordings. Provided that the iHR is known, HR-based source extraction techniques and HR-based signal enhancement methods could be investigated as a preprocessing step for ECG delineation algorithms.

7. ACKNOWLEDGMENTS

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