Non-Invasive FECG Extraction from a Set of Abdominal Sensors

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Abstract

Introduction: Despite significant advances in adult clinical electrocardiography (ECG) signal processing techniques and the power of digital processors, the analysis of non-invasive foetal ECG (NI-FECG) is still in its infancy. The PhysioNet/Computing in Cardiology Challenge 2013 addresses some of these limitations by making publicly available a set of FECG data to the scientific community for evaluation of signal processing techniques.

Methods: ECGs were first preprocessed by cascading a low pass and a high pass filter in order to remove higher frequency and baseline wander. A Notch filter to remove power interferences at 50Hz or 60Hz was applied if required. The signals were then normalised before applying various source separation techniques to cancel the maternal ECG. These techniques included: template subtraction, principal/independent component analysis, extended Kalman filter and a combination of a subset of these methods (FUSE method). FQRS detection was performed on all residuals using a Pan and Tompkins QRS detector and the channel with the smoothest FHR time series was selected.

Results: The FUSE algorithm performed better than all the individual methods on the training set data. On the validation set, best Challenge scores obtained were E4=29.6. E5=4.67 for events 4-5 respectively using the FUSE method.

1. Introduction

Despite significant advances in adult clinical electrocardiography (ECG), signal processing techniques and the potency of digital processors, few significant advances have been made in the analysis of non-invasive foetal ECG (NI-FECG). This is partly due to the relatively low signal-to-noise ratio (SNR) of the foetal ECG (FECG) compared to the maternal ECG (MECG), caused by the various media between the foetal heart and the measuring electrodes, and the fact that the foetal heart is simply smaller. Moreover, there is a less complete clinical knowledge concerning foetal cardiac function and development than for adult cardiology. Another significant barrier to the analysis of NI-FECG is the paucity of (public) gold standard databases with expert annotations and objective signals, such as independent measures of the ECG, (through direct scalp electrodes), heart rate, ischemia, rhythm etc.

Many approaches to NI-FECG extraction from abdominal (ABD) ECG have been suggested in the literature. These include: adaptive filtering [1], template subtraction (TS) [2–4] Kalman filtering (KF) [5, 6], Echo State Neural Network [7], principal component analysis (PCA) [8], independent component analysis (ICA) [9], or periodic component analysis, which makes use of the ECG's periodicity [10]. See Sameni and Clifford [11] for a good overview of these various approaches. The blind source separation (BSS) based approaches, aim to separate the underlying statistically independent sources into three groups: MECG, FECG and noise, by assuming a linear stationary mixing matrix. Despite many interesting theoretical frameworks the robustness of most of these methods has not been sufficiently quantitatively evaluated. This is due to two main factors : 1) the lack of gold standard databases with expert annotations and 2) the methodology for assessing the algorithms. The Physionet/Computing in Cardiology Challenge 2013 (PCinCC2013) attempts to address these limitations by making publicly available a set of FECG data to the scientific community for evaluation of signal processing techniques.

2. Methods

2.1. General

The PCinCC2013 consisted of three datasets; set-a (75, 1min records, training set), set-b (100, 1min records, validation set) and set-c (200, 1min records, test set). All records had four ABD channels available at a sampling frequency of fs=1kHz and 16-bit resolution. Reference FQRS were available for the training set (set-a). Five PCinCC2013 events were evaluated: E1 and E4 for foetal heart rate (FHR) measurement on set-c and set-b respectively, E2 and E5 for foetal RR interval measurement on set-c and set-b respectively and E3 for foetal QT measurement. Events E1, E2 and E3 were only available for the open source entries (assessed on the hidden set-c)[1]. The lower the score the higher the performance. The PCinCC2013 was divided in three phases corresponding to three time periods where participants were to submit a certain number of entries (phase 1: 25-04-2013 to 01-06-2013, 3 entries/ phase 2: 01-06-2013 to 25-08-2013, five entries/ phase 3: 25-08-2013 to 05-09-2013, 1 entry).

Fig.1 shows the framework of the approach undertaken in this work for FQRS detection; (1) the four ABD channels were preprocessed by removing the baseline wander and higher frequency components as well as Notch filtered if required, (2) MQRS detection was performed on each of the prefiltered channels, (3) a source separation algorithm was applied to the ABD signals in order to extract the FECG, (4) FQRS detection was performed on the post-filtering residual signals containing the FECG, (5) one of the FQRS time series detected on the residual channels was selected, and (6) the RR time series was smoothed to reduce the effect of missing and extra detected beats. Finally the RR time series and corresponding FHR were independently scored by the Physionet Challenge hosts.

A Pan and Tompkins-like QRS detector [12] with refractory periods of 250 and 150ms was used for detecting the MQRS and FQRS respectively.

Selection of the FQRS time series extracted from the individual residual channels was based on a smoothing indicator (SMI) defined as the number of occurrence where the absolute value of the instantaneous heart rate variability was superior to 30bpm. The channel with the lowest SMI was selected.

Different approaches for step (3) were evaluated using an F_1 measure defined in the context of binary classification as:

$$F_1 = 2 * \frac{PPVSe}{PPV + Se} = \frac{2TP}{2TP + FN + FP}. \quad (1)$$

where FN is the number of false negative (missed FQRS) and FP the number of false positive (extra falsely detected FQRS). FN and FP play a symmetric role in penalising the accuracy measure F_1. To compute the F_1 measure, the first two and last 2sec of each 1min segment were discarded as well as records $a54$, $a33$, $a38$, $a47$, $a52$, $a54$, $a71$, $a74$ because of inaccurate reference annotations (identified by visual inspection).

2.2. Source separation

There are many ways of classifying the methods for separating the FECG from the ABD mixture. In this work the methods are classified in four categories (Fig.-1); (i) TS is performed in the time domain (e.g. TS [2–4] , TS_{PCA} [8], TS_{EKF} [6]), (ii) applying a BSS technique directly on the ABD channels (e.g. ICA [9]), (iii) performing TS and

[1] our scores for E1-3 were not available before the conference deadline submission and are consequently not included here.

Parameter	Definition	Value
nbCycles	number of cycles for building the template ECG in TS	20
nbPC	number of principal components for TS-PCA	2
G_{EKF}	gain of the EKF for the TS-EKF	10
f_{bas}	baseline wander cut-off frequency	10Hz
f_{high}	high frequency cut-off	99Hz
BSS	blind source separation method and implementation	JADE [13]
QRSdet	method for QRS detection	P&T [12]

Table 1. Key global parameters of the NI-FECG extraction algorithms.

applying BSS on the residuals (denoted TS-ICA, TS_{PCA}-ICA, TS_{EKF}-ICA) and (iv) moving to the source domain using BSS and performing TS in that domain with an eventual final BSS step (as in [5], denoted ICA-TS-ICA).

The methods were implemented and evaluated in term of the F_1 measure without post-processing (i.e. no RR smoothing). Based on these evaluation the FUSE method was introduced. FUSE was defined as the combination of a subset of the evaluated methods (ICA-TS, ICA-TS-ICA, TS-ICA, ICA, TS) with only one FQRS time series (as detected on one of the residual channels by one of the source separation method) being selected. The assumption under the FUSE approach was that the different source separation techniques all have their strength and weaknesses and that combining them could lead to higher performances (given a good measure for picking up the 'best' FQRS time-series). FUSE-SMOOTH corresponds to the FUSE method when adding the time series smoothing block (Fig. 1) and FUSE-CHALL corresponds to the results of the FUSE method with a biased output toward the PCinCC2013 scoring system (that is, in the case of QRS detection failure the algorithm outputted a constant time series at 143bpm or at the dominant FHR mode). Detection failure was defined as the SMI being higher than 29 (this cut-off value was empirically determined on the training set).

2.3. QT extraction

The framework shown in Fig. 1 was used for QT extraction but repeated with high pass cut-off f_{bas}=2Hz (to avoid gross distortion of the foetal T-wave morphology) and using the TS_{PCA} for the 'source sep' step (Fig.1) in order to perform the analysis in the time domain. A template FECG was built on the residual signal and the QT measurement method based on fitting Gaussians, as introduced in [14], was used. Fig. 2 shows an example of FECG template build upon the extracted FECG signal and two Gaussians fitting the T-wave to allow the evaluation of the T-end point.

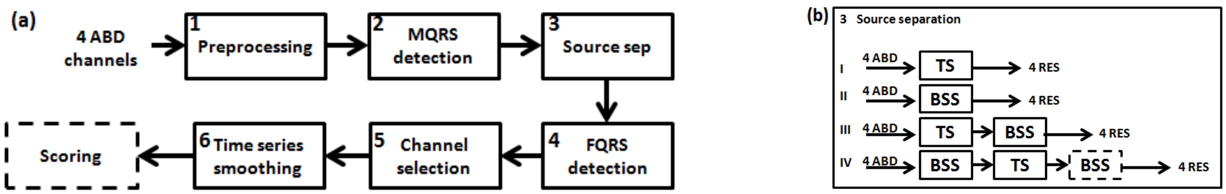

Figure 1. (a) FECG extraction block diagram. (1) The four ABD ECG channels are preprocessed, (2) MQRS detection, (3) source separation to extract the FECG from the ABD mixture, (4) FQRS detection, (5) one of the FQRS time series is selected, and (6) the resulting time series is smoothed. (b) Detail of the source separation block. ABD: abdominal, BSS: blind source separation, RES: residual, dashed line: optional step.

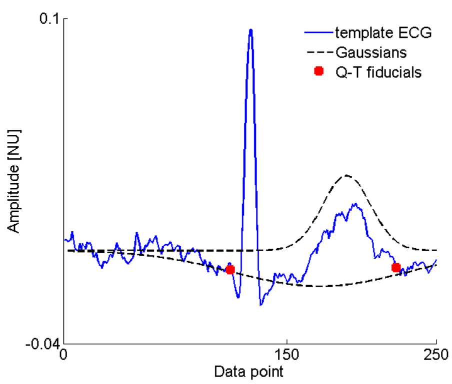

Figure 2. QT measurement on record a07. The two Gaussians marking the end of the T-wave are displayed in dotted lines as well as the corresponding T-end. For clarity the other Gaussians modelling the cycle are not displayed.

CL	Method	HRE	RRE	F_1-10Hz	F_1-2Hz
		NU	NU	%	%
I	TS	656	27.9	81.6	81.1
I	TS_{PCA}	594	21.6	86.0	83.7
I	TS_{EKF}	841	26.2	82.0	79.9
II	ICA	2852	39.3	63.8	61.7
II	PCA	3891	45.3	51.6	52.6
III	TS-ICA	272	17.1	92.0	91.4
III	TS_{PCA}-ICA	156	16.9	93.0	92.4
III	TS_{EKF}-ICA	565	27.3	81.1	80.7
IV	ICA-TS	430	19.2	90.6	89.3
IV	ICA-TS-ICA	369	18.7	91.7	91.1
	CONST-HR (143 bpm)	172	8.9	22	–
	FUSE	136	12.5	95.0	94.6
	FUSE-SMOOTH	16	6.3	96	–
	FUSE-CHALL	4.8	2.3	74.5	–

Table 2. Performance of the different algorithms on set-a. TS: template subtraction, HRE: score for the heart rate challenge event, RRE: score for the RR challenge event, CL: class of the method, NU: no unit. F_1-10Hz and F_1-3Hz represent the F_1 measure with f_{bas}=10Hz and f_{bas}=2Hz respectively. HRE and RRE are given for f_{bas}=10Hz.

3. Results

There are many parameters that have an influence on the algorithms performance. Tab. 1 lists some of the important ones with the values taken in this work.

The best result in term of F_1 measure was F_1=96% on set-a and obtained for the FUSE-SMOOTH approach. Smoothing the FQRS time series (post-processing) improved the performance by 1%. Best Challenge score obtained were E4=29.6, E5=4.67 for events 4-5 respectively.

4. Discussion and conclusion

The choice of using an F_1 measure for evaluating the algorithms and for parameters optimisation was motivated by a key problem with the PCinCC2013 scoring system; scores in the FHR based events (E1 and E4) were computed from the differences between matched reference and test FHR measurements at 12 instances (i.e. one approximately every 5sec). However in clinical practice physicians are interested in rapid variations in HR which is not reflected by the scoring system. Moreover, presenting a constant FHR time series to the scoring function at a representative range of FHR (i.e. between 120bpm and 160bpm [15]) results in a better Challenge score than a time series where a non negligible proportion of the FQRS fiducial were incorrectly estimated (see CONST-HR in Tab. 2 and how the Challenge scores compared with respect to the other methods). This is because the Challenge scores were based on a root mean square measure and as such very sensitive to outliers (in other words better to be slightly off the FHR all the time than having few bad outliers). Scores in the RR events (E2 and E5) were computed from the differences between matched reference and test RR intervals. However the function used to make this comparison was the Physionet mxm function and measurement error was calculated for each test measurement by comparing it with the reference measurement that was nearest in time (so it did not take into account the actual distance from a reference fiducial to the closest participant R peak). As such, inputting a constant time series at say 140bpm or at the dominant HR mode, will often give better results than a partially faulty FQRS detection segment. Due to these limitations of the Challenge scoring system, optimisation of the various parameters used in the FUSE approach was performed using the F_1 accuracy metric on set-a.

It is notable that using a high cut-off frequency for baseline wander removal led to improved results (compare F_1-10Hz and F_1-2Hz in Tab. 2). This was because the high cut-off results in a large reduction in the amplitude of the P- and T-waves, leaving only the MQRS and FQRS (and noise) in the ABD mixture. However such a high cut-off cannot be used for FECG morphological analysis, because the clinically interesting features (such as the T-wave) are highly distorted or completely removed.

The different extraction methods described in this work and in the literature vary highly in their adaptability to the changing ECG morphology; high adaptability results in better MECG removal but a lower FECG residual amplitude which might be non preferable, particularly in the case of overlapping MQRS and FQRS.

The PCinCC2013 was the first significant publicly available database for NI-FECG algorithms evaluation with annotations and gold standard scalp data, and in particular an independent test set which is not available (and hence over-tuning to the public data is avoided). However the Challenge still possessed a number of limitations: (i) the limited number of simultaneously acquired signals (adaptive source separation approaches, which are very promising, require more than four abdominal ECG leads [11]), (ii) the absence of chest ECG which could have strengthened the MQRS detection step and allowed evaluation of additional methods such as [1], [7], (iii) the presence of errors in some of the reference annotations, and (iv) the lack of pathological examples. Indeed, although the simulated data addressed these latter two points somewhat, no arrythmias, ST deviations, QT prolongation, late or early decelerations or contractions were present in the data.

In conclusion this work: (i) evaluated a variety of standard and state-of-the-art methods used for FECG extraction on a low dimensional public dataset, (ii) benchmarked these algorithms on the same database and with the same experimental set-up, (iii) showed that improvement can be obtained by combining different methodologies, and (iv) described and evaluated a method for foetal QT extraction. The scores obtained in the PCinCC2013 and associated high F1 values reflect the success of the FUSE algorithm in accurately extracting the FHR and foetal RR intervals.

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