EVALUATION OF NON-INVASIVE FOETAL ECG EXTRACTION ALGORITHMS USING NON-STATIONARY MIXTURES

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Abstract: The non-invasive foetal electrocardiogram obtained from abdominal electrodes is an alternative for assessing the foetal health state. This study evaluates the behavior of two well-known methods (Independent Component Analysis and Template Subtraction). These techniques are often referred to in literature for extracting the FECG from the abdominal mixture. Our analysis quantifies the extraction results in terms of accuracy of foetal peak detection using the F_1 measure. 1750 five-minute-long simulations considering the absence and presence of non-stationarity mixtures served as dataset for this study. In terms of the F_1 measure, on average ICA (97.3 ± 0.1 %) was found to outperform TS (88.1 ± 0.2 %). Moreover, we have shown that the presence of non-stationarities can degrade the performance of both methods considerably, indicating a beat-by-beat adaptive approach may be preferable.

Keywords: fetal electrocardiogram, abdominal electrocardiogram, independent component analysis, template subtraction.

Introduction

Non-invasive foetal electrocardiograms (NI-FECGs) present an alternative mean for ante and intrapartum assessment of the foetal cardiac activity. Despite being a favorable measuring technique, which provides long-term recordings along most of the second and third semester of pregnancy, the foetal signal has varying (usually low) power. The NI-FECG signal is particularly contaminated by the maternal ECG (MECG), which usually has much higher power than the foetal ECG. In order to extract the NI-FECG, advanced signal processing techniques are required. Several methods have been proposed for extracting the NI-FECG (e.g. [1– 4]). However, existing studies often use proprietary datasets, which renders comparison between different studies practically impossible.

The open source NI-FECG synthetic simulator (*fecgsyn*) described by Behar *et al* .[5,6], allows for quantitative comparisons of extraction methods, whilst modelling several realistic scenarios. The simulator uses a Gaussian model to simulate ECG beats originally introduced by Mc Sharry *et al.* [13] and further developed by Sameni *et al* .[14]. The *fecgsyn* generates synthesized NI-FECG signals with adjustable noise sources, heart rate and heart rate variability, rotation of maternal and foetal heart axes relative to respiration, foetal movement, contractions, ectopic beats and multiple pregnancies. Any desired number of observations (i.e. “electrodes”) can be placed on the mother’s abdomen. The tool is particularly helpful to generate rare events which are clinically important but difficult to be recorded, such as abrupt heart rate increase.

This work aims at evaluating the performance of two state-of-art techniques for FECG extraction in the presence and absence of physiological non-stationarities. The evaluated techniques are Independent Component Analysis (ICA) and Template Subtraction (TS), which will be described later on. The benchmark considers the baseline simulation, i.e. a simulated fetal maternal mixture without added noise or non-stationary events, and six different scenarios.

Materials and methods

Simulations – A total of 1750 simulations were generated using *fecgsyn*. Each simulation comprised 5-minutes projections over 32 abdominal and 2 maternal reference channels (“electrodes”). In order to limit the amount of available information for the extraction methods, only 8 abdominal channels were used (see Fig. 1). This restriction is particularly relevant for ICA, since it is a multichannel approach that requires a number of observations equal to or greater than the number of sources for performing source separation. The specific electrode selection was motivated by their geometrical distribution across most of the volume conductor. Table 1 lists the key parameters used throughout the modeling in this study. These parameters, derived from [5], reflect physiological conditions which influence the resulting propagated cardiac signals observed on the “electrodes”.

The simulations were divided into:
- Baseline: abdominal mixture no noise or events
- Case 0: abdominal mixture without any event
- Case 1: foetal movement
- Case 2: MHR /FHR acceleration / decelerations
- Case 3: uterine contraction
- Case 4: ectopic beats (for both foetus and mother)
- Case 5: additional NI-FECG (twin pregnancy)

The “baseline” and “Case 0” are regarded as stationary cases, while the remaining cases represent non-stationary scenarios, i.e. containing events that change signal’s statistical properties. For each baseline simulation, the parameters were randomly selected within the ranges defined in Table 1 and for further cases kept unchanged.

Preprocessing - Before extracting the NI-FECG, each channel was band-pass filtered. This step was performed using 3rd and 5th order Butterworth filters with corner frequencies of 3 and 100 Hz for the high and low-pass filters respectively. Signals were processed in forward and backward directions for zero-phase filtering. Finally, the signals were normalized by the absolute maximum of each channel. Using a higher cut-off frequency for removing the baseline was shown to increase the performance of the extraction method for FQRS detection in Behar *et al.* [2].

Extraction of Fetal ECG – Many extraction techniques have been described in literature; for detailed overviews about these methods and associated open source code, see Behar *et al.* [2,7]. These algorithms may be divided into temporal and spatial techniques. Temporal methods make use of the time-decorrelation and pseudo-periodicity of the maternal and foetal ECG, while spatial techniques separate the signals using information on the spatial distribution of the source signals. In this work, we attempted to separate the MECG using one member of each group, namely TS and ICA. Despite the vast amount of sophisticated methods available in both categories, using less complex versions of those algorithms have the advantage of permitting a clearer understanding of these methods’ behaviors and the conditions under which these techniques fail.

ICA is a well-known approach for blind source separation. It assumes the observation of several signals, which are supposed to represent linear combinations of different sources. ICA estimates such sources by maximizing the independency between channels. In this study FAST-ICA [8] was applied using all eight channels, in a similar manner to the work of Varanini *et al.* [9], i.e. using the hyperbolic tangent as contrast function. The demixing matrix was calculated on 60 second windows, in order to provide a statistically significant number of samples.

TS methods attempt to estimate the MECG signal by coherent-averaging various maternal beats, generating a template, and adapting this template back into the abdominal signal using an adaptive gain. TS was implemented as in Cerutti *et al* .[10], that is using a unique scaling factor in making the template fit each maternal beat, therefore minimizing the mean-squared error between both signals. In this work, 20 beats were used for constructing the template MECG (as suggested in [2]) and the maternal QRS complexes’ timestamps were considered to be known.

QRS Detection – A Pan and Tompkins-like detector [11] was used for detecting foetal QRS (FQRS) complexes, open-source code available in [2].

Table 1: Key parameters used to simulate foeto-maternal mixtures. $N(\mu,\sigma^2)$ represents normal distributions with mean μ and variance σ^2. |MHR|/|FHR| denotes the magnitude of the maternal/foetal heart rate changes. Maternal and foetal respiratory rates influence the rotation of the cardiac axes, therefore modulating the propagated ECG signals’ amplitudes.

Parameter	**Range**	**Unit**
Foetal-maternal SNR	N(-9,2)	dB
Maternal SNR	0,3,6,9 or 12	dB
Maternal respiration	N(0.25,0.05)	Hz
Foetal respiration	N(0.90,0.05)	Hz
|MHR|	N(80,20)	bpm
|FHR|	N(135,25)	bpm

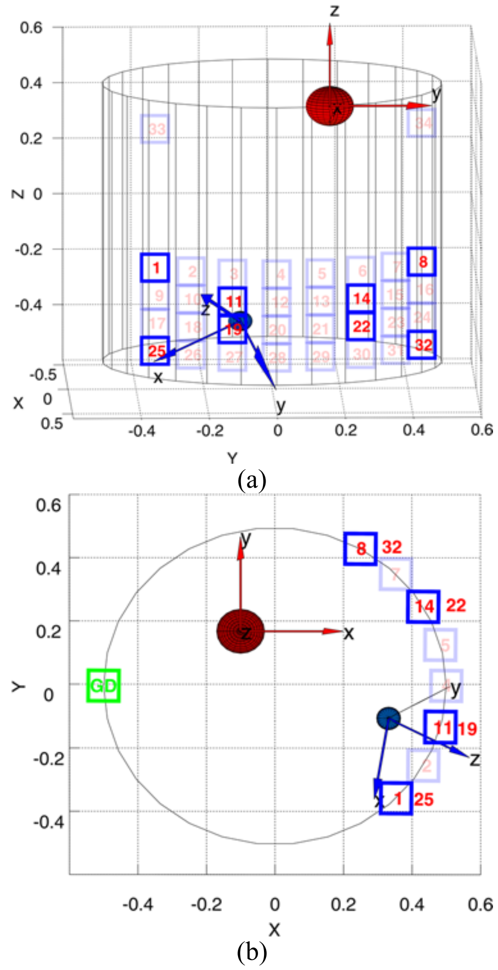

Figure 1: Side (a) and upper (b) view of volume conductor. Positions for foetal (blue) and maternal (red) hearts are shown. Electrodes 1, 8, 11, 14, 19, 22, 25 and 32 were used for further processing.

The algorithm was run on 15 seconds windows to avoid that large artefacts cause the threshold to be overestimated.

Performance Measures – The performance of the FQRS detections were evaluated using two different measures. The F_1 measure is the harmonic mean between the positive predictive value (PPV) and sensitivity (SE), thus providing a good and symmetrical summary (in terms of SE and PPV) metric for the detection accuracy. The accuracy of the detections was assessed by means of F_1 [7] as follows

$$F1 = 2.\frac{PPV \cdot SE}{PPV+SE} = \frac{2 \cdot TP}{2 \cdot TP+FN+FP} \quad , \qquad (1)$$

TP is the number of true positives (correctly detected peaks), FN the number of false negatives (missed peaks) and FP the false positives (erroneously detected peaks). An acceptance interval of ±50 ms was used as in [1,7]. The distance between each FQRS reference (RR_i) and true positive detections ($\widehat{RR_i}$) was also calculated using the root mean-squared (RMS) as follows

$$RMS = \sqrt{\frac{1}{(TP-1)} \sum_i \left(RR_i - \widehat{RR_i}\right)^2} \quad . \qquad (2)$$

For both extraction methods, only the results for the channel with highest F_1 were reported. This choice has been made to demonstrate what the best possible performance of the extraction methods, assuming it is possible to select the best residual (for TS) or choose most relevant independent component for ICA.

Results

Table 2 shows the average results using described statistics. The median RMS value for ICA was 3.88 ms and for TS was 2.13 ms. Figure 2 depicts both methods' performances, in terms of FQRS detection accuracy in each simulated scenario. Figure 3 shows exemplary extracted signals using both TS and ICA.

Discussion

In terms of F_1, both methods performed well in extracting the NI-FECG (see Table. 2 and Figure 2-3).

Table 2: Statistical results' summary using all the generated data, i.e. taking the average baseline and events together. Results are shown as (mean ± standard deviation).

Method	F_1 (%)	RMS (ms)	PPV (%)	SE (%)
ICA	*97.3 ± 0.1*	*4.11 ± 3.09*	*98.6 ± 0.1*	*96.6 ± 0.1*
TS	88.1 ± *0.2*	4.32 ± *4.82*	87.6 ± *0.2*	89.8 ± *0.1*

The results suggest that in the ideal case, ICA outperforms TS. However, these results have to be analyzed with caution. First of all, state-of-art techniques were applied, but we did not implement some key steps, which are present in real world scenarios. For instance, the independent component (output from ICA) selection is a challenging and decisive step, which is likely to cause an accuracy decrease.

Moreover, ICA strongly depends on the number of input observations (electrodes) available, usually requiring at least the same amount of sources and observations, whereas TS can be used with a single channel. In this work, 8 channels have been shown to be sufficient to guarantee a good performance from ICA.
From Figure 2 it can be seen that TS and ICA perform similarly in cases 0, 1, 2 and 4. Uterine contractions (case 3) are intermittent muscular artefacts of large magnitude. In such case, ICA generally outperforms TS, since it is able to separate the muscular from the cardiac sources. The same principle applies to case 5 (twin pregnancy), TS appears to confound between both fetuses QRS complexes, while ICA is often able to separate one from another.

Further work should evaluate how the reduction of this number of electrodes and their relative position to the foetal heart can affect the performance of ICA. Case 5 offers us a preview of the influence of reduced

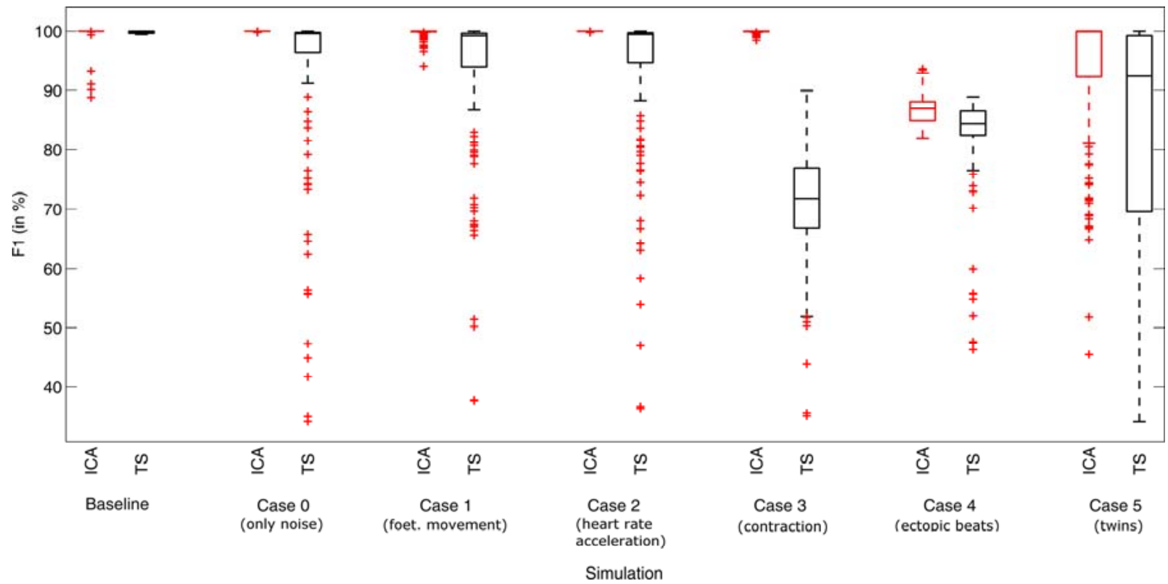

Figure 2: Boxplot showing FQRS detections for ICA and TS.

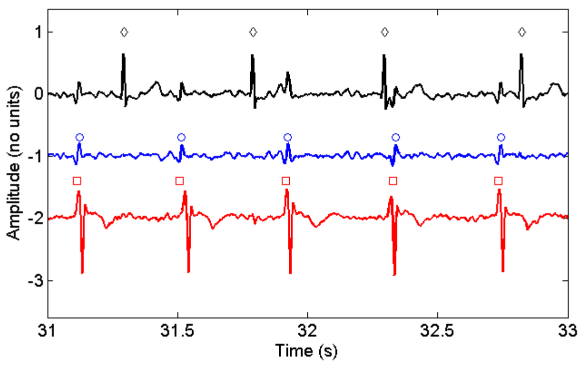

Figure 3: Segment of exemplary NI-FECG extraction using TS (blue) and ICA (red) for maternal SNR = 6dB. Diamonds represent maternal QRS locations, circle and squares represent detected FQRS complex using TS and ICA, respectively.

observations, since including an additional source (twin heart) is somehow similar to removing electrodes. In this case, it was shown that the performance tends to be worse, since ICA is not able to separate accurately both foetal sources. Despite Table 2 showing that, in terms of the RMS value, TS and ICA have similar performances, the RMS of TS (2.13 ms) was better than ICA's (3.88 ms). This is due to the fact that the morphology of the foetal signal in the source domain does not necessarily reflect the projections on the observation domain.

Lastly, no morphological analysis was performed in this work. The Physionet/Computing in Cardiology Challenge 2013 [12] mainly focused on fetal heart rate estimation; nevertheless the morphological analysis of the NI-FECG is particularly important. To push the field forward it is essential that the extraction techniques do not distort its morphology, particularly in terms of the QT interval or ST segment. Future work making use of the *fecgsyn* code should consider evaluating how morphological information is preserved when using different extraction techniques.

Conclusion

The results obtained using the *fecgsyn* show that the presence of non-stationarities in the mixture can considerably degrade the performance of both ICA and TS methods. Further studies should evaluate how the morphology of the NI-FECG signal may be altered by using different extraction techniques and how robust morphological measures are in the presence of noise and non-stationarities. The open-source code for *fecgsyn* toolbox is available at [6] under the GNU General Public License (GPL).

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