On the Measurement of Physiological Similarity between Independent Components: Time-Structure versus Frequency-Based Methods

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Abstract

This work explored two methodologies for clustering independent components (ICs) into physiological groups corresponding to maternal respiratory (MR), maternal cardiac (MC), foetal cardiac (FC), or noisy (N) activities. The methods, based on frequency content (S) or time-structure (R) analyses, were tested on 750 ICs (extracted from 25 abdominal phonograms by using single-channel independent component analysis, SCICA). Results showed that the S-based methodology is more reliable at clustering similar ICs than the R-based method. On the other hand, the R-based methodology not only clusters ICs, but also identifies their physiological origin, which is a desired quality. These characteristics make both schemes interesting for automatic and fast classification of ICs extracted from the abdominal phonogram. These results were so promising that current work has already combined both methods into an enhanced version for grouping physiological ICs extracted by SCICA. Future work will analyse foetal traces for well-being information recovery.

1. Introduction

Antenatal foetal surveillance is an important part of foetal care since it makes it suitable for obstetricians to assess foetal well-being, diagnose a possible disease earlier, and increase effectiveness of treatment before delivery [1]. At present, such surveillance strongly relies on ultrasonography, which is an unsuitable method for long-term monitoring and foetal distress prediction since long exposure to ultrasound radiation may harm the foetus [2-3]. Alternatively, some works monitor foetal activity by using phonography [3-4], which consists of positioning a sensitive acoustic sensor on the maternal abdomen. This technique, which is suitable for long-term monitoring [3], produces the abdominal phonogram, a signal rich in foetal information (e.g. heart sounds, heart rate, and breathing/body movements) and therefore appropriate for assessing well-being [4-6]. Unfortunately, since the acoustic energy of the foetal components is very low, they are easily hidden by environmental, maternal, and "shear" noises [1], which turns the extraction of reliable information into a difficult and challenging task.

In previous work, single-channel Independent Component Analysis (SCICA) was used to successfully separate out the phonogram into independent components (ICs) due to foetal, maternal, and noise activities [1,7]. However, recovery of reliable information requires not only good separation, but also appropriate classification of ICs of interest. This means that, in order to retrieve meaningful traces of the sources underlying the abdominal phonogram, similar ICs must be correctly clustered in physiological groups corresponding to maternal respiration (MR), maternal cardiac (MC), foetal cardiac (FC), or noise (N) activities.

At present, some studies in the literature have visually defined similarity and manually grouped physiological components [8-11], which is not only a subjective but also a time-consuming task due to the usually large number of components to be classified. As an alternative, some studies have proposed automatic methods to group similar ICs based on time and/or frequency content [1,7,12-14], entropy [15], or mutual information [16]. The methods based on time/frequency content are easy to implement and fast to execute, but may perform poorly [1,12]. On the other hand, the methods based on entropy and mutual information perform better, but are slower to execute because of larger computational loads [15-16].

In this work, we considered that grouping can be reliable and yet efficiently performed as long as the right ICs attribute(s) are used. To do so, and based on our observations at processing the abdominal phonogram, two notorious and accessible features of its physiological ICs were studied: (a) their disjoint spectral content (given by the nice spectral decomposition achieved by SCICA in [7]) and (b) their wealthy time-structure (given by rhythmic regulatory processes underlying the abdominal

phonogram). Thus, this work explored two methodologies for grouping the physiological ICs extracted in [7], one based on frequency content analysis and another based on time-structure analysis. The next sections describe the dataset, the methodologies implemented to group similar ICs, and their performance evaluation. Then, results are presented and discussed before conclusions are given.

2. Dataset

The dataset was composed of ICs extracted from 25 single-channel abdominal phonograms by SCICA (based on Temporal Decorrelation source SEParation, TDSEP) as detailed in [7]. The signals were recorded over 3 or 5 minutes from pregnant women at gestational ages between 29 and 40 weeks. The sampling frequency was 500 Hz and, whenever possible, the abdominal ECG was simultaneously recorded as a reference.

The ICs dataset was built up by taking three segments (10 s in length) from each phonogram, one at the start, one in the middle, and one at the end. Each segment was separated out into 50 ICs by SCICA-TDSEP [7]. Next, from each decomposed segment, 10 ICs more likely to be physiological components were selected, which gave rise to a total of 750 ICs in the dataset. In addition, each IC was visually categorised as MR, MC, FC, or N, which created the reference to quantify the methodologies performance.

3. Methods

Figure 1 sketches the two stages followed by both methodologies to cluster similar ICs. Firstly, an index was calculated, either on frequency content (*S*) or on time-structure (by rhythmicity calculation, *R*). Secondly, depending on the index value, ICs were automatically classified as MR, MC, FC or N.

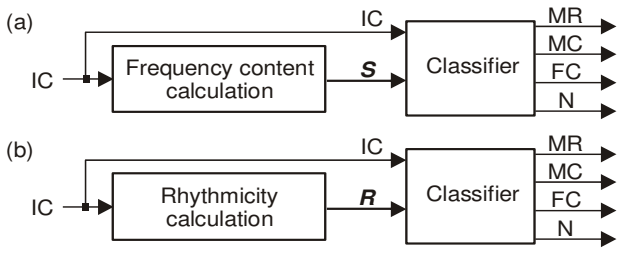

Figure 1. Stages followed to cluster ICs into groups such as maternal respiration (MR), maternal cardiac (MC), foetal cardiac (FC), or noise (N). Based on (a) frequency content analysis and (b) time-structure analysis.

3.1. Quantifying features

Each methodology calculated its index by processing every IC as follows:

A. Frequency content index (S):

Calculated from the PSD, it was estimated using the Welch's method with a Hanning window, 32 coefficients and 50% overlap. Then, from the characteristic and well defined single-peak in the resulting spectrum [7], as illustrated in figure 2, its central frequency was taken as the frequency content index (*S*) of the IC.

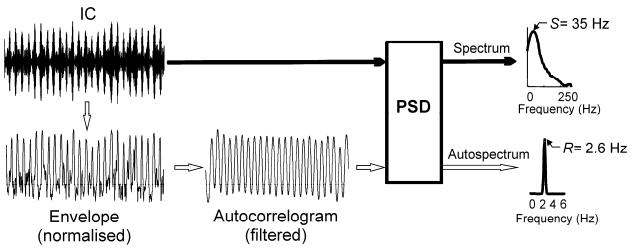

Figure 2. Steps followed by each methodology to quantify the IC features. Filled arrows: calculation of an index on frequency content (*S*), blank arrows: calculation of an index on time-structure (*R*).

B. Rhythmicity index (R):

It was calculated by autocorrelation analysis, which is a suitable tool to examine the rhythmic patterns in a time-series (i.e. time-structure). First, an IC envelope was generated by the Hilbert Transform, which has proven to be functional for signals whose envelope is slow compared to the signal variations. Next, the envelope was detrended and normalised to produce e_n. Second, the autocorrelogram of e_n was calculated as $r_{ee}(\tau) = \int_{-\infty}^{\infty} e_n(t+\tau) e_n^*(t)\, dt$, where e^*_n is the complex conjugate of e_n. Third (except for IC^{50}, which mainly encloses MR), r_{ee} was filtered between 0.7 and 3.1 Hz. This produced r_f, a signal free of harmonic effects due to MR and FC rhythms that easily lead to errors at calculating *R*. Fourth, to ease the estimation of *R*, r_f was transformed into a frequency domain representation by the Welch´s periodogram with a Hanning window and 50% overlap. Here, knowing that the filtering only left cardiac rhythms in r_f (maternal and/or foetal), we chose a window length that enclosed a suitable amount of them. Thus, a length of 2048 samples was used to include an average of four maternal and/or eight foetal heart beats. Finally, from this autospectrum, as shown in figure 2, the frequency of the dominant peak was taken as the rhythmicity index (*R*) of the IC.

3.2. Defining similarity

The values of *S* and *R* were used by the corresponding methodology to categorise the IC as MR, MC, FC or N according to the ranges in table I. Those ranges were defined based on empirical observation (for the frequency content analysis) and on physiological rates (for the time-structure analysis).

Table I. Intervals used for categorising ICs according to their (a) frequency content (*S*) or (b) time-structure (*R*).

Category	*S* (Hz)	*R* (Hz)
Foetal cardiac (FC)	(19.0 – 44.5]	(1.7 – 3.0]
Maternal cardiac (MC)	[2.0 – 19.0]	[0.8 – 1.7]
Maternal respiratory (MR)	(0.0 – 2.0)	[0.1 – 0.6]
Noise (N)	> 44.5	---

3.3. Testing performance

Once the methodologies clustered the dataset into physiological groups, their performance was evaluated by comparing their results with the reference. This was done by quantifying sensitivity (*Se*) and specificity (*Sp*) as *Se=TP/(TP+FN)* and *Sp=TN/(TN+FP)* respectively, where *TP*, *FN*, *TN*, and *FP* are respectively the number of true positives, false negatives, true negatives, and false positives. Here it is important to mention that the cardiac ICs are the most difficult components to be classified and, since their misclassification distorts considerably the foetal information retrieved, our evaluation only focused on the methods performance at distinguishing between foetal and maternal cardiac ICs.

4. Results

Figure 3 illustrates ten physiological ICs (extracted from the same segment by SCICA) along with the indexes representing their frequency content (*S*) and time-structure (*R*). As can be seen, the frequency content index of such ICs is below 50 Hz, being IC^{50} and IC^{41} the ICs with the lowest and highest values respectively, behaviour consistently observed along the dataset. Regarding the time-structure index, these particular ICs presented four rhythms: 2.0 Hz in IC^{41}, 2.3 Hz in IC^{42}-IC^{47}, 1.2 Hz in IC^{48}-IC^{49}, and 0.24 Hz in IC^{50}. Thus, according to these values, similar ICs were automatically categorised by the *S*-based methodology as: IC^{47}-IC^{49} in MC and IC^{42}-IC^{46} in FC. On the other hand, the same ICs were categorised by the *R*-based methodology as: IC^{48}-IC^{49} in MC and IC^{41}-IC^{47} in FC. Notice that *S* pointed at IC^{41} as N, and IC^{47} and IC^{50} as MC, whereas *R* pointed at IC^{41} and IC^{47} as FC, and IC^{50} as MR.

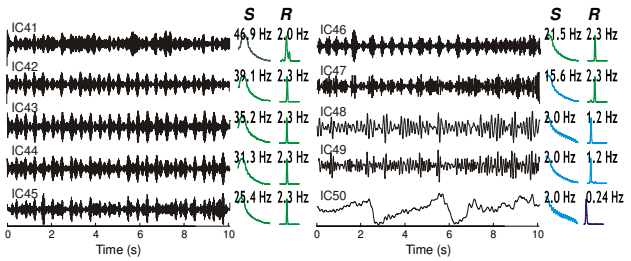

Figure 3. Ten physiological ICs along with their frequency content (*S*) and time-structure (*R*) indexes.

Figure 4 depicts the sensitivity (*Se*) and specificity (*Sp*) of both methodologies to categorise cardiac ICs as foetal or maternal. As can be seen, the optimal value (i.e. the *Se-Sp* intersection) achieved by the *S*-based methodology (0.9 at 18.8 Hz) is larger than the value achieved by the *R*-based methodology (0.7 at 1.6 Hz).

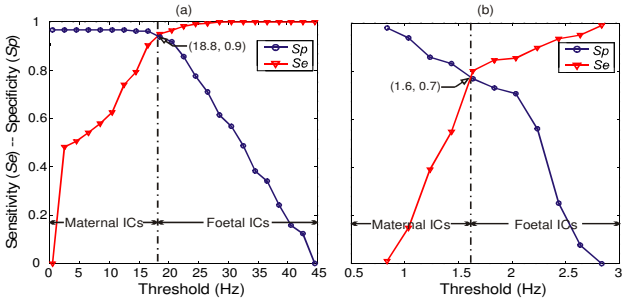

Figure 4. Performance at categorising cardiac ICs as foetal or maternal by methods based on (a) frequency content analysis and (b) time-structure analysis. The dash-dot vertical line indicates the optimal threshold.

Figure 5 depicts a segment of noisy abdominal phonogram and the estimates of the independent sources retrieved using the ten physiological ICs clustered by the *S*-based methodology in figure 3. From top to bottom, the time and frequency representations of: the abdominal phonogram, three physiological traces (FC, MC, and MR), the noise/noisy trace, and the abdominal ECG (only as a reference) are shown.

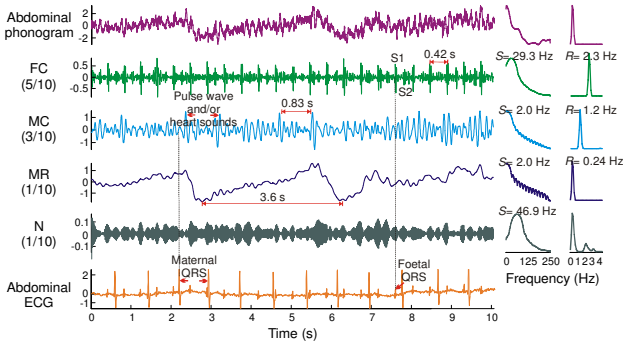

Figure 5. A noisy abdominal phonogram and the physiological sources retrieved using ten ICs clustered by the *S*-based analysis. From top to bottom: the phonogram, three physiological traces, the noise/noisy trace, and the abdominal ECG (as a visual reference).

As can be seen, the abdominal phonogram clearly shows a slow component, but the signal is so noisy that it is virtually impossible to be certain about any physiological information, especially of foetal origin. On the contrary, the retrieved traces clearly show not only narrower bandwidths, but also different physiological rhythms, which is very clear in both, time and frequency domains. Furthermore, since FC and MC are clearly

aligned with foetal and maternal QRS complexes respectively, it can be said that (a) FC represents the foetal heart sounds (FHS), whereas (b) MC represents the maternal cardiovascular activity (i.e. pulse wave and/or HS). Regarding MR, which is the trace with the narrowest frequency content and largest amplitude, it presents the slowest rhythm due to the maternal respiration. Finally, N, the trace with the largest frequency content index and composed of multiple rhythms that could distort valuable information by introducing noise or noisy components.

5. Discussion and conclusions

This work explored two methodologies for measuring physiological similarity between ICs extracted from the abdominal phonogram by SCICA. The methods, based on (a) frequency content analysis or (b) time-structure analysis, efficiently clustered ICs into physiological groups related to maternal respiratory (MR), maternal cardiac (MC), foetal cardiac (FC), or noise activities (N).

Compared with other schemes, these methods are fast and easy to implement since they are based on autocorrelation and/or spectral analysis. On a PC with a Core2 Duo processor at 2.40 GHz, they took a few seconds to process and cluster ten ICs, whilst the implementation in [15] took almost 800 s only to calculate their Sample Entropy. In particular, since the *S*-based methodology performed better than the *R*-based one, *S* seems to be more reliable than *R* to recognise similar ICs. On the other hand, *R* is more complete since rhythmicity not only finds similar ICs, but also identifies their physiological origin, which is a desired quality. Thus, both methodologies present characteristics that make them promising for automatic and efficient classification of ICs extracted from the abdominal phonogram. Actually, the combination of these two approaches already gave rise to a new scheme for classification of the physiological ICs extracted by SCICA [17]. Ongoing work is analysing the retrieved foetal time-series to recover information for well-being surveillance.

Acknowledgements

A. Jimenez-Gonzalez thanks CONACyT for sponsoring her PhD studies.

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