# Source Separation of Foetal Heart Sounds and Maternal Activity from Single-Channel Phonograms: A Temporal Independent Component Analysis Approach

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## Abstract

*Here we successfully extracted sources from noisy single-channel abdominal phonograms. First, an appropriate matrix of delays was constructed; then multiple independent components were calculated using TDSEP; finally, components were projected back onto the measurement space and grouped using K-means. Three single-channel phonograms from different subjects were analysed. Results showed a better-quality and more objective extraction of Foetal Heart Sounds (S1-S2), maternal activity and line-noise by using this temporal independent approach (versus a FastICA version). Future work will look for extracting more sources and a robust method to measure the quality of the extraction.*

## 1. Introduction

Long-term monitoring for foetal examination during pregnancy is an important part of foetal and maternal care [1]. Currently, monitoring of foetal well-being heavily relies on ultrasound imaging, an unsuitable method for long-term surveillance and foetal distress prediction [2]. Instead, a sensitive transducer positioned on the maternal abdomen records the abdominal phonogram, a signal that is rich in information about heart sounds (FHS), heart rate, breathing/body movements [2,3]. Together, these are considered to provide an assessment of foetal health [2]. Nevertheless, the phonogram is a low acoustic energy that is easily overlapped by environmental, maternal and “shear” sources [4], which turns the extraction of foetal information into a difficult and challenging task.

At present, different methods for foetal monitoring, based on FHS (PCG) or Foetal Breathing Movements (FBM), have been proposed [2-7]. Regrettably, there is no such foetal device yet available. The main problem, from our point of view, is that as these methods are focused on extracting pre-selected information (either FHS or FBM); they generally rely on rigid empirical criteria that: do not properly manage major changes in the SNR and irreversibly discard some extra and valuable information, i.e. maternal sources [8]. A few studies have shown some enhancement in the SNR [4-7], but the detection of FHS and FBM may still be difficult, and it looks like the solution requires a different signal processing perspective. In a previous work [8], we took advantage of the abundance of information in the phonogram, and used Single-channel Independent Component Analysis (SCICA) [9] to decompose it in two sources. This work, looking for FHS and residual noise, showed a successful extraction of S1-S2. However, three issues were evident: (1) for the FHS, the method did not always reach a complete separation (spectrum with more than one peak), (2) for the residual noise, further analysis was necessary to extract other physiological components and, (3) the components used to compose both the FHS and noise sources were manually selected.

The goal of this work was to reach a better-quality and less subjective extraction of sources from the phonogram by implementing three changes in [8]: (1) instead of FastICA to perform the decomposition [10], using Temporal Decorrelation source SEParation (TDSEP) [11], (2) instead of a two sources decomposition, looking for more sources by increasing the number of components to be extracted from two to ten and, (3) instead of a manual and highly subjective method, using K-means to find and group components corresponding to the same sources such as FHS, maternal or line-noise.

## 2. Methods

Three single-channel abdominal phonograms, between 3 and 5 minutes of length, were used. The signals were obtained from pregnant women with foetal gestation ages between 36 and 40 weeks using a PCG piezoelectric transducer connected to a general purpose amplifier. Additionally, the abdominal ECG (aECG) was recorded at 500 Hz. The signals were processed in three steps [8]. First, the single-channel signal was projected into a higher dimension using the Method of Delays (MD) [12].

Then, multiple independent components (ICs) were calculated using TDSEP [11]. Finally, to recover the sources, these components were projected back onto the measurement space and classified using K-means.

### 2.1. Preparing a multidimensional dataset

This part fulfilled one of the two primary conditions to apply ICA [10]: the number of observations available is at least as large as the number of sources we wish to extract. To overcome this condition, as we are working with a single scalar time series, *x(t)*, we used the MD [12] to map this single-channel signal into a higher dimensional space. This can be done by constructing an *m*-dimensional matrix of delays, **v**, using a series of delay vectors taken from the data *x(t)* as:

$$\mathbf{v} = \{x(t-\tau), x(t-2\tau), ..., x(t-(m-1)\tau\} \in \Re^m, \qquad (1)$$

where τ is the lag-time and *m*, given by the size of the delay vector, is the embedding dimension.

Due to Takens [13], it is known that **v** allows us to reconstruct the unknown dynamical system that generated *x(t)*. In particular, for real world data, *m* needs to be "big enough" to capture the information content necessary [8]. Then, once the optimal value for *m* is found, **v** is constructed using *N* consecutive delayed vectors. This value is determined by the length of the signal to be analysed ($N_T$) as:

$$N = N_T - (m - 1), \qquad (2)$$

If *x(t)* were sampled using an appropriate sampling frequency ($f_s$), then the practical minimum size for *m* can be chosen using the lowest frequency of the periodic components we are looking for ($f_l$) [14], and the lag-time (τ) can be set to one [8]. This is shown as:

$$m \geq f_s / f_l, \qquad (3)$$

Knowing that our signals do not contain FBM, and that the lowest frequency for FHS is 20 Hz [3], we chose $f_l$ = 10 Hz, which gave $m$= 50 [8]. Next, to select *N*, we searched for a matrix of delays that covered a quasi-stationary signal and we found that $N_T$ = 5000 samples (10s) was good enough to accomplish this requirement [8]. Finally, if τ, *m* and *N* are adequate, then **v** is rich in information about the temporal structure of the measured data, and we are ready to represent the data in **v** by a convenient spanning basis such as ICA [10,11].

### 2.2. Extraction of ICs

At present, different algorithms for performing ICA have been developed, one of them, TDSEP, is suitable for data with a rich temporal structure [11]. The basis of this computationally simple and efficient algorithm is a set of time-lagged correlation matrices of a time series *x(t)* as:

$$R_\tau^x = \mathrm{E}\{x(t)x(t+\tau)\}, \qquad (4)$$

where E means expectation and τ (= 1,2,3,…,*k*) is a certain time-lag. For independent components these matrices have to be diagonal. Therefore, to estimate the ICs and the mixing matrix (**A**), TDSEP performs a joint diagonalisation of the time-lagged correlation matrices. Here the value of *k* is important because it defines the number of time-lags and the quality of the separation. Hence, and in absence of a theoretically choice of *k*, we tested several values and found that *k*= 2 extracted ICs with a well defined single-peak spectrum.

Before ICA was applied, we made assumptions about our data as: (i) the phonogram is a linear summation of vibrations from the foetal heart, maternal and external sources; (ii) the phonogram components have disjoint spectral support [9], and (iii) the sources have non-Gaussian distributions and are statistically independent.

### 2.3. Recovering independent sources

As mentioned in [9], if we break up a scalar time series to construct **v** and we apply ICA, then we may obtain multiple components associated with a single independent source. Indeed, the nature of the mixing matrix means that many more sources will be identified over the expected number of sources underlying a measurement set. This implies that some post-processing is necessary to group ICs together, which is not a trivial task. Here, step 2.2 produced 50 ICs that were projected back onto the measurement space using:

$$\mathbf{Y}^i = \mathbf{a}_i \, \mathbf{s}_i^T, \qquad (5)$$

where $\mathbf{s}_i$ is the $i^{th}$ IC ($i$= 1,…,50), $\mathbf{a}_i$ is the corresponding column of **A** [9], and $\mathbf{Y}^i$ is a matrix of delays for that component. Next, this matrix was transformed into the $i^{th}$ projected IC using the diagonal averaging method [14]:

$$\mathrm{IC}^i = \frac{1}{50}\sum_{k=1}^{50} \mathbf{Y}^i_{k,(t+k-1)}, \qquad (6)$$

Once the whole ICs have been projected, and knowing that some of them correspond to the same subspace (i.e. FHS, maternal or line-noise), they must be grouped and used to compose the related independent sources. More specific, as ICA "learns" a zero phase filter bank (expressed in each column of **A**), it means that every IC corresponds to a filtered sequence of independent signals that can be grouped using their spectral similarity [9]. Thus, we used the Power Spectral Density (PSD) as the attribute for K-Means to identify and cluster ICs into 10 disjoint and independent subspaces ($\mathbf{IS}^j$) [9]. Then, to recover the independent sources ($is_j$), we added the ICs grouped in each $\mathbf{IS}^j$ and used both time and frequency information to manually identify them as FHS, maternal activity or line-noise sources. Finally, to compare results between this TDSEP version and the FastICA one in [8], we estimated the degree of linear dependence between all pair wise sources extracted by each method using the correlation coefficient.

## 3. Results

Figure 1 depicts a 10s segment of noisy abdominal phonogram and three of ten *is* (a, b, and c) extracted using the TDSEP method described in this work and the FastICA one described in [8]. The sources were clearly identified as: (a). FHS (S1-S2), (b). maternal activity (pulse wave peaks superimposed on a slow-respiratory component), and (c) line-noise. In the bottom, and only as a visual time reference, the abdominal ECG is shown. In addition, on the right hand side of the phonogram and these sources, we show the corresponding PSDs.

In the time domain, for the physiological sources (a) and (b), it is difficult to visually distinguish differences between sources extracted by TDSEP and FastICA options, except that the amplitude in the FHS by TDSEP is a bit larger than that in the FHS by FastICA. In (c), it is clear that the line-noise amplitude by TDSEP is larger than that by FastICA. In the frequency domain, there is a notorious difference between sources extracted by both methods, the number of peaks in the PSD. For signals extracted by TDSEP, the PSDs always showed a single and well defined peak, whilst for FastICA the PSDs usually showed more than one.

Figure 2 illustrates the dependency matrix used to calculate the degree of linear dependence between all pair wise sources extracted using methods based on: (a) FastICA [8] and (b) TDSEP. Notice that although ten sources have been extracted, only three of them, identified without any doubt, have been described in this work. In general, we observe that colors/grays are usually spread all over the matrix in (a) and only on the diagonal in (b). In particular, in (a): maternal sources $s_1$ and $s_2$ show a large lineal dependence between them as well as with $s_8$ and $s_9$. The FHS in $s_3$ shows linear dependence with $s_4$ and $s_8$, and line-noise in $s_7$ shows lineal dependence with $s_4$ and $s_5$. On the contrary, in (b), all sources a very small dependence among them.

## 4. Discussion and conclusions

Here we have used a SCICA method to successfully extract FHS, maternal activity and line-noise from noisy abdominal phonograms. This method, modified from a FastICA-subjective version in [8] to a TDSEP-unsupervised one, has shown better results. As we have seen, considering the temporal structure of the signal by using TDSEP improved the separation and extracted sources that: show PSDs with a single and well defined peak, and are less dependent among them. Besides, the inclusion of K-means gave the method the possibility not only to objectively classify components, but also to increase the number of sources to be extracted and analysed. Hence, by increasing this number from two to ten, the method managed the extraction of the main heart sounds (S1-S2), maternal respiration along with maternal pulse wave, and line-noise. This isolation of foetal and maternal activities is significant because they may overlap each other like the foetal and maternal QRSs do in the aECG. The most outstanding factor is that this separation was achieved using a single-channel temporal approach. This approach clearly extracts physiological sources from the abdominal phonogram, and we believe it will be useful for surveillance about foetal and maternal condition. Future work will look for identifying more sources and a robust method to measure their dependence.

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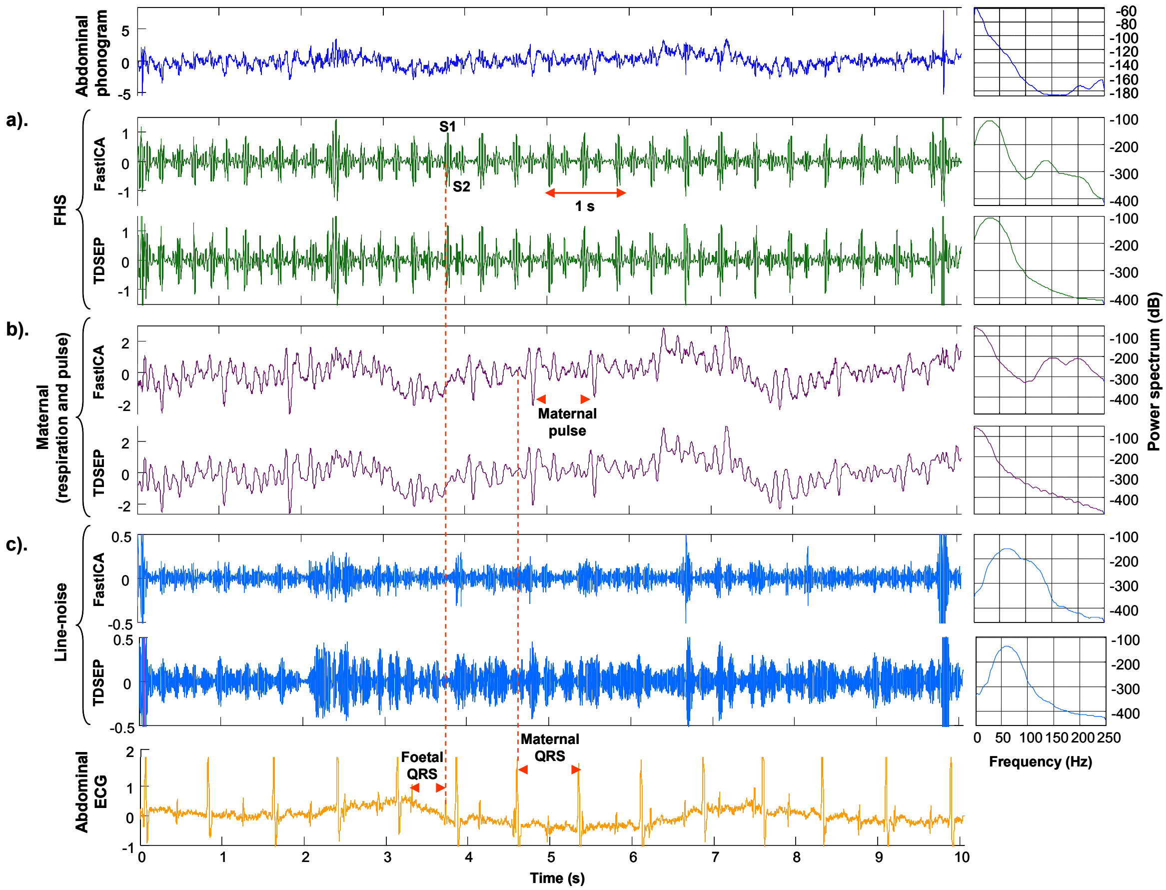


Figure 1. A segment of noisy abdominal phonogram and three independent sources extracted using methods based on FastICA and TDSEP. From top to bottom: the recorded abdominal phonogram (normalised), its sources: (a). FHS, b). maternal activity, and c). line-noise), and the abdominal ECG (used only as a visual reference). The corresponding power spectrum of the abdominal phonogram and its independent sources is shown on the right hand side.

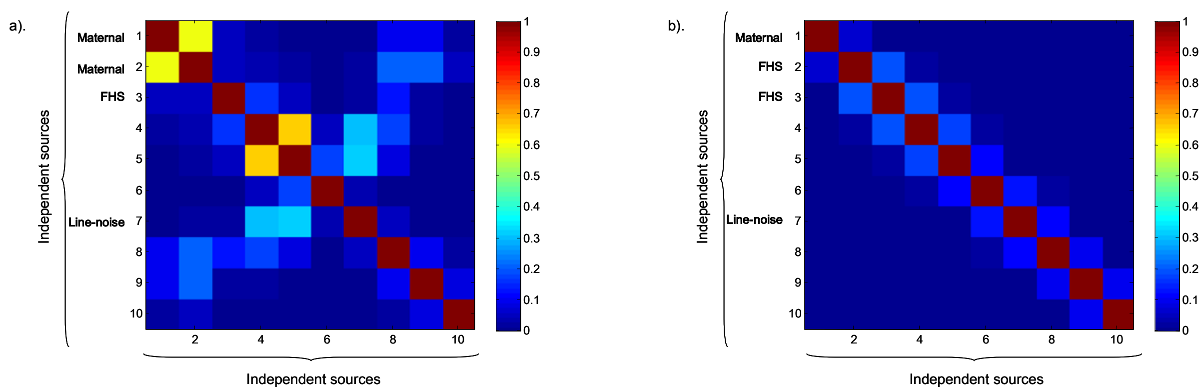


Figure 2. Dependency matrix used to express the degree of linear dependence between all pair wise sources extracted by: a). the method based on FastICA and b). the method based on TDSEP.