

# Methodologies for Foetal Phonography Signals Processing - A Survey

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**ABSTRACT:** Foetal phonocardiography is a continuous non-invasive, low-cost and accurate monitoring technique for analysing the heartbeat rate and takes care of foetal well-being. It involves picking up, through a highly sensitive microphone, sonic vibrations from the heart which are then converted into electrical energy and fed into a galvanometer and is recorded for further analysis. In this paper, we review state of the art in foetal cardiac signal de-noised extraction and analysis. Due to the long-aged history of the problem and the rich literature contribution of the various authors in the field; it is not possible to cover all the existing methods in their details. Also, due to the complexity of the problem, many of the existing methods have used a combination of approaches, some of which have been borrowed from other contexts. Therefore, In this paper, we review a selection of the available literature with special focus on the most significant ones, which have been specifically developed for the problem of interest.

**KEYWORDS:** Phonocardiograph, Foetal Heart Rate, Phonography, Phonocardiograph.

## I. INTRODUCTION

Electronic foetal monitoring (EFM) is a method for examining the condition of an unborn in the uterus by noting any unusual changes in its heart rate [1]. The EFM is either performed late in pregnancy or continuously during labour to ensure the normal delivery of a healthy baby. This method was originally introduced in the 1960s and 1970s, with the hope that it would help physicians diagnose foetal hypoxia, or lack of oxygen and abnormal heart rate in the unborn baby.

Current methods for EFM rely heavily on Ultrasound Techniques. This has two important disadvantages; firstly, there are significant chances that long-term exposure to ultrasound may harm the unborn, and secondly, the ultrasound machines and its trained operators prove to be an expensive proposition hence could not be utilized for a longer period of time [2]. Because of these reasons, the existing instruments are not suitable for carrying out the frequent and long-term recording of a foetal heart sound, which is highly recommended in high-risk pregnancies [3].

Foetal phonocardiography is a continuous non-invasive, low- cost and accurate monitoring technique for analysing the heartbeat rate and takes care of foetal well-being [4]. It involves picking up, through a highly sensitive microphone, sonic vibrations from the heart which are then converted into electrical energy and fed into a galvanometer, where they are recorded on paper. The procedure is most useful when there is evidence of heart murmurs or unusual heart sounds, such as gallops that are difficult to discern by the human ear. Most recordings are made through an externally applied microphone but intra-cardiac recordings, made through a phono catheter, are also possible.

Using this method, long term measurement of the FHR and collection of heart sound artefacts becomes possible. The widely-accepted ultrasound Doppler process is not suitable for taking measurements over extended periods of time [5]. The main advantages of the fPCG technique are its passivity (non-invasiveness) and simplicity [6].

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Despite all these advantages of fPCG, this technique is not popular with the obstetricians because of its poor signal-to-noise ratio (SNR) at the time of recording [7]. The fPCG signals recorded from the maternal abdominal surface are contaminated by various unwanted signals which can prohibit their automated analysis. These factors can be categorized as [8]:

- respiration sounds (lung mechanics),
- patient movements,
- small movements of the stethoscope ("shear noises"),
- acoustic damping through the bones and tissues, and
- external noises from the environment.

There are some other typical disturbances in the case of foetal phonocardiography:

- acoustic damping of forewaters and maternal tissues,
- acoustic noises produced by the foetal movements,
- noises of the maternal digestive system, and
- sounds of the maternal heart.

## II. REVIEW OF DIFFERENT TECHNIQUES

Foetal phonocardiograph is contaminated with various unwanted signals due to the reasons listed in the previous chapter. Hence this technique requires robust signal-processing to extract the foetal heart sound signals [9]. There have been significant efforts to develop long-term monitoring methods based on fPCG technique. These methods have projected different types of sensors and filtering schemes, as well as different numbers of channels, for this purpose.

Most of the existing phonocardiograph processing methods concern only with the diagnostic analysis of heart sounds without an adequate emphasize on the denoising of the records. Existing methods usually apply digital band-pass filters (most commonly IIR-filters of FFT-based filtering) as a simple denoising method. The cut-off frequencies of the filters are determined by empirical observations, and commonly the pass band lies between 30 and 200 Hz [10-14].

The main difficulty in dealing with the fPCG signals is their extreme variability and necessity to operate on a case-to-case basis [15]. Another important aspect of these signals is that the information of interest is often a combination of features that are well localized temporally or spatially. This requires the use of analytical methods sufficiently versatile to handle events that can be at opposite extremes in terms of their time-frequency localization.

A significant number of studies found in the literature report the implementation of the wavelet transforms for the extraction of the foetal heart rate. In particular, in the work of [16,17], a wavelet transform is applied in order to extract the wavelet-based features of the foetal cardiac signal so that the normal cases can be easily distinguished from the abnormal ones. So far, the wavelet analysis has proved to be one of the most successful techniques for the analysis of signals at multiple scales and has rendered many successful applications in the area of biomedical signal processing [18].

Another method to monitor foetal heart rate patterns is by studying the foetal heart rate variability. It has been shown that heart rate variability is an important marker for the foetal well-being [19]. Various methods have been therefore used to analyse the foetal heart rate variability, in particular concerning variables from both the time and the frequency domain [20].

Blind source separation is used in [16, 21-25]. It was reported that the results by BSS were more satisfactory than those by classical methods [24, 26]. Separating all of the source signals from a large number of observed signals takes, however, a long time and is often not necessary [25]. A more convenient choice of the method could be the source extraction method [21, 25, 27-29], that is closely related to the BSS. The source extraction methods use the basic

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principles of the BSS methods but make additional use of prior information about the autocorrelation property of the FECG from the noisy free measurements [30].

To cover up this brief review on the foetal cardiogram extraction methods, see also [30, 31], listed below are the methods used in the literature, such as:

- singular value decomposition (SVD) [32]
- matched filtering [33]
- adaptive neuro-fuzzy inference systems [34]
- dynamic neural networks [35]
- temporal structure [36]
- fuzzy logic [37]
- frequency tracking [38]
- polynomial networks [39]
- multi-reference adaptive noise cancellation [24]
- real-time signal processing [40]
- time-frequency analysis [41]

All the above techniques have been successfully applied to the extraction of the foetal cardiac component, but a maximum of them are used in the perspective of processing ECG and not PCG signals. The following sections cover the review of processing of fPCG using signal processing and pattern recognition techniques.

### III. SIGNAL PROCESSING AND COMPUTATIONAL LEARNING TECHNIQUES

Early techniques for extracting the frequency content of the phonocardiogram signal included zero-crossing analysis [42] and bandpass filter banks. McKusick et al. studied the applicability of the sound spectrograph for analysis of heart sounds and murmurs [43]. The spectrograph, originally developed for speech analysis, used a bank of bandpass filters to determine the power of the signal at each frequency band of interest. Fast Fourier Transform (FFT) has been implemented and applied to analyse the frequency spectrum of S1 and S2 [44, 45]. Time-domain processing methods included synchronized envelope averaging [46,47], computing of average power in contiguous segments [48], envelopogram estimation by Hilbert transform [49] or normalized average Shannon energy [50] and complexity-based segmentation [51]. Modern signal analysis techniques can be generally partitioned into parametric and non-parametric methods. With parametric methods, the investigated signal is first modelled by an equivalent system, and the parameters of the model are then estimated from measurements of the signal made over a limited period of time. Parametric modelling of heart sounds was studied using autoregressive modelling [52], iterative pole zero modelling [53], and adaptive spectrum analysis with matching pursuit method [54-55]. Durand et al. [56] evaluated the performance of parametric methods (all-pole and pole-zero modelling) and of FFT-based methods. They concluded that the basic periodogram (FFT) appears to be the best compromise for estimating both the spectral distribution and dominant frequency peaks of the closing sounds of artificial heart valves. Akay et al. [57] compared the ability of FFT and parametric methods to identify coronary artery disease from diastolic heart sounds and pointed out the eigenvector methods that provided the best diagnostic performance. A different type of signal modelling is probabilistic hidden Markov models (HMM), applied to heart sounds for identification of S1 and S2 [58]. Non-parametric decomposition of heart sounds was used to explore the inner structure of the signals. Homomorphic filtering was used to deconvolve heart sounds into a sum of slowly varying and fast varying components, providing a smooth and robust envelopogram [59]. The joint time-frequency analysis is a favourable method for decomposition and representation of heart sounds, due to the multi-component and nonstationary nature of these signals [60]. Wood et al. used time-frequency representations (TFR) to characterize the first heart sound in dogs [61]. They compared short-time Fourier transform (STFT), Wigner-Ville distribution (WVD), and reduced interference distributions (RID), including Choi-Williams distribution (CWD) and binomial transforms. Binomial transform was highlighted as an efficient algorithm with good cross-term suppression properties [62]. Other studies pointed out additional techniques, including cone-kernel distribution [63] continuous wavelet transform [64,65] as suitable choices for representation and analysis of S1 and S2.

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Signal processing methods enable to uncover the structure of the signal and to extract features which compactly represent the properties of the raw data. Feature extraction is usually a preceding step of a classification or regression task, which is used to infer application-specific information from the input signals. Feature selection can utilize domain-specific knowledge for choosing features with physical meaning (e.g. frequency, time interval, energy), or alternatively, may be automatic, relying on general properties of the signals. Domain-specific features used for heart sound analysis include, for example, dominant frequencies of the signal's spectrum [66], the bandwidth of the dominant frequencies, mean and total spectral energy, and the intensity ratio of S1 and S2 [67]. In the model-based signal analysis, the parameters of the model are a natural set of features. For example, Guo et al. used the coefficients of 12-order all-pole system as features [68]. Bentley et al. used a search scheme to select an optimal subset of features from a larger set, extracted using discrete wavelet transform [69]. They showed that this feature set provides better performance than morphological features extracted from CWD in classifying the condition of native and artificial heart valves. The application of identifying degenerated artificial valves from features of their closure sounds was addressed using different types of classifiers, including K-nearest neighbour (KNN), Gaussian-Bayes and neural networks. Reported results, which seem to be optimistic, indicate the high accuracy of 89%-98% in detecting degeneration of different types of artificial heart valves.

Unsupervised learning using morphological cluster analysis has been applied before to biomedical imaging modalities such as magnetic resonance imaging [70], as well as to electrocardiogram signals [71]. To the best of the knowledge of this thesis, there are no previous studies that have applied cluster analysis on the morphology of heart sounds.

The following section describes the different methods of data acquisition and methods proposed for the processing of phonocardiograph for denoised extraction of the foetal heart sound signals in the literature.

## IV. PHONOCARDIOGRAPHY WAVELETS ANALYSIS

The wavelet transform is a frequently used tool for the denoising of audio signals [8]. The choice of wavelet family, mother wavelet and de-noising algorithm greatly affects the accuracy of the wavelet analysis of the signal [72].

## V. DE NOISING ALGORITHMS

Three steps are required for de-noising of signals: Decomposition, thresholding and reconstruction. The first and last steps are performed with the selection of suitable wavelet family and mother wavelet. The thresholding step is the selection of threshold level for de-noising of the signals. The thresholding algorithms commonly employed for de-noising of the fPCG signals are —

- Universal threshold
- Minimax threshold
- Rigorous SURE threshold

These de-noising algorithms can be divided into linear and nonlinear methods. The linear method is independent of the size of empirical wavelet coefficients, and therefore the size of the coefficient by itself is not taken into account. It assumes that signal noise can be found mainly in fine scale coefficients and not in coarse scales. The nonlinear method is based on the idea that the signal noise can be found in every coefficient and is distributed over all scales. It can be applied in two ways: Hard thresholding rule and soft thresholding rule. In hard thresholding, if the value of the coefficient is less than the defined value of the threshold, then the coefficient is scaled to zero; otherwise, the value of the coefficient is maintained as it is. In soft thresholding, if the value of the coefficient is less than the defined value of the threshold, then the coefficient value is scaled to zero; otherwise, the value of the coefficient is reduced by the amount of defined value of threshold [72].

**VI. OVERVIEW OF NOISE CANCELLATION**

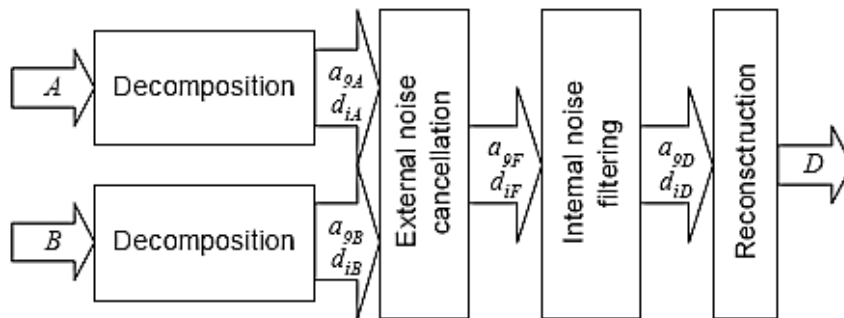


Fig.1. Block diagram of the wavelet-based denoising system.

Figure 2.1 illustrates the structure of the proposed wavelet based denoising method in [8]. It consisting of four major steps:

1. wavelet-based decomposition of both recorded signal channels A and B,
2. cancelling of external noises using the adaptive cross channel thresholding of the signal coefficients,
3. adaptive thresholding of the coefficients resulted in Step 2 in order to eliminate the internal noises, and
4. reconstruction of the D denoised signal from the threshold coefficients of Step 3.

**VII. WAVELET-BASED DECOMPOSITION AND RECONSTRUCTION**

In the following section, the various wavelet thresholding techniques and their comparison are discussed. Peer review of the wavelet based algorithm for noise cancellation is also discussed.

**VIII. 2.4.3.1 UNIVERSAL THRESHOLD**

The universal threshold de-noising algorithm is also known as VisuShrink. It uses a fixed threshold form given by

$$\lambda = \sigma \sqrt{2 \log(n)} \tag{1}$$

where ‘n’ denotes the length of the signal and  $\sigma$  is the standard deviation. This threshold was determined in an optimal context for soft thresholding with random Gaussian noise. This scheme is very easy to implement but typically provides a threshold level larger than other thresholding algorithms, therefore resulting in smoother reconstructed data. Also, such estimation does not take into account the content of the data but only depends on the data size.

**IX. 2.4.3.2 MINIMAX THRESHOLD**

The minimax threshold de-noising algorithm consists of an optimal threshold that is derived from minimizing the constant term in an upper bound of the risk involved in the estimation of the signal. This threshold level depends on the noise and signal relationships in the input data, and it is given by

$$\lambda = \sigma \lambda_{nr} \tag{2}$$

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where  $\lambda_n$  is determined by a minimax rule such that the maximum risk of estimation error across all locations of the data is minimized.

### X. 2.4.3.3 RIGOROUS SURE THRESHOLD

The de-noising algorithms described previously use global thresholds, that is, the computed threshold is applied to all wavelet coefficients. The rigorous SURE threshold algorithm describes a scheme that uses a threshold value  $\lambda_j$  at each resolution level 'j' of the wavelet coefficients. This algorithm is also known as SureShrink, and it uses the Stein's unbiased risk estimate (SURE) criterion to get an unbiased estimate.

### XI. 2.4.3.4 CROSS CHANNEL THRESHOLD

The cancellation of the external noises in [8] is a two-channel problem. A novel method was developed which utilizes the adaptive cross-channel thresholding of the wavelet transformed signal coefficients. The dyadic wavelet transformed of a signal  $f(t)$  on the  $i$ -th dyadic scale can be written as:

$$W\{f(u, 2^i)\} = \frac{1}{\sqrt{2^i}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t-u}{2^i}\right) dt = f * \tilde{\psi}_{2^i}(u) \quad (3)$$

Where  $\psi$  is the orthogonal mother wavelet, and:

$$\tilde{\psi}_{2^i}(t) = \psi_{2^i}(-t) = \frac{1}{\sqrt{2^i}} \psi\left(-\frac{t}{2^i}\right) \quad (4)$$

The discrete version of the dyadic wavelet transform can be based on digital filter banks [14]. Let us define:

$$d_i[n] = W\{f(n, 2^i)\} = \langle f(t), \psi_{2^i}(t - n) \rangle \quad (5)$$

$$a_i[n] = \langle f(t), \tilde{\psi}_{2^i}(t - n) \rangle \quad (6)$$

where  $i \geq 0$ . For a given filter  $x[n]$ ,  $x_i[n]$  denotes the filter obtained by inserting  $2^i - 1$  zeros between every filter coefficient ("holes algorithm").  $a_0[n]$  is the original signal, and its wavelet-based decomposition at the  $i+1$ th scale is:

$$a_{i+1}[n] = a_i * h_i[-n], \quad \text{and} \quad d_{i+1}[n] = d_i * g_i[-n]$$

where  $a$  defines the approximated signal and  $d$  the signal details at the given scale;  $h$  and  $g$  are biorthogonal filters, corresponding to the selected mother wavelet. The reconstruction of the signal is done by the inverse wavelet transform, which is at the  $i$ -th scale:

$$a_i[n] = \frac{1}{2} (a_{i+1} * \hat{h}_i[-n] + d_{i+1} * \hat{g}_i[-n]) \quad (7)$$

where  $\hat{h}$  and  $\hat{g}$  are the dual filters of  $h$  and  $g$ , respectively. In the case of biorthogonal filters:  $\hat{g}=h$  and  $\hat{h}=g$ .

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Table I: Base Coefficients of the Equivalent Filter Bank

$h_0$	$g_0$
-0.0007, -0.0018, 0.0056,	-0.0164, -0.0415, 0.0674
0.0237, -0.0594, -0.0765	0.3861, -0.8127, 0.4170
0.4170, 0.8127, 0.3861	0.0765, -0.0594, -0.0237
-0.0675, -0.0415, 0.0164	0.0056, 0.0018, -0.0007

It uses the Coiflet-wavelet with 4 moments equal to zero (Coiflet-2) as the mother wavelet. The two channels were wavelet decomposed up to the 9<sup>th</sup> order ( $i = 0, 1 \dots 8$ ), resulting in two sets of coefficients:  $a_{9A}, d_{9A}, d_{8A}, \dots, d_{1A}$ , and similarly:  $a_{9B}, d_{9B}, \dots, d_{1B}$ , where the A and B letters in the indices correspond to the recorded channels.

## XII. 2.4.3.5 ADAPTIVE CROSS-CHANNEL CANCELLATION OF EXTERNAL NOISES

The task of the external noise cancellation is to construct a new set of coefficients:  $a_{9F}, d_{9F}, \dots, d_{1F}$ , which can be reconstructed (inverse wavelet transformed) as the heart sound signal free of external noises. The following algorithm is proposed in [11] to obtain these coefficients:

- $a_{9F} = a_{9A}$ ,
- if  $|d_{iA}[n]| > \max(\mu, \lambda)$  then  $d_{iF}[n] = d_{iA}[n] - d_{iB}[n]$ ,  
else  $d_{iF}[n] = 0$   
where  $i = 1, 2, \dots, 9$ ;  $n = 1, 2, \dots, \dim(d_{iA})$ , and  $\lambda = 0.5 \max(|d_{iA}|)$ ,  $\mu = 2 \max(|d_{iB}|)$ .

Here, the detail coefficients  $d_{iA}$  of the abdominal channel are adaptively thresholded ( $\mu$  and  $\lambda$ ), whereby the details  $d_{iB}$  of the external channel is adaptively subtracted from  $d_{iA}$ .

## XIII. 2.4.3.6 INTERNAL NOISE CANCELLATION

Another algorithm was designed which works in the frequency band  $35 \text{ Hz} < f < 200 \text{ Hz}$  and adaptively threshold previously resulted set of coefficients  $a_{9D}, d_{9D}, \dots, d_{1D}$ :

- $a_{9D} = 0, d_{9D} = 0$
- if  $|d_{iF}[n]| > \lambda$  then  $d_{iD}[n] = d_{iF}[n]$ ,  
else  $d_{iD}[n] = 0$   
where  $i = 1, 2, \dots, 8$ ;  $n = 1, 2, \dots, \dim(d_{iF})$ , and  $\lambda = 0.5 \mu$ , where  $\mu$  is the average of the  $a_{9F}$ .

The resulted coefficient set  $a_{9D}, d_{9D}, \dots, d_{1D}$  is used at the reconstruction of the phonocardiographic signal free of noises.

It should be noted that this second thresholding cannot remove all internal noises. Disturbances still remain in the reconstructed signal; however, the overall noise cancellation performance is far better than in the case of simple band-pass filtering.

## XIV. 2.4.4 A COMPARATIVE ANALYSIS OF DE-NOISING ALGORITHMS

Vijay S. Chaurasia and A. K. Mitra [72] obtained the recordings from pregnant women with gestation age between 36 and 40 weeks. The fPCG signals were recorded from the maternal abdominal surface using a highly sensitive and

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inexpensive data-recording module (DRM) [73]. The signals were recorded with a sampling frequency of 8000 Hz, 16-bit resolution, and saved in a personal computer for further processing. Fig.2 shows the waveform of one of these fPCG signals.

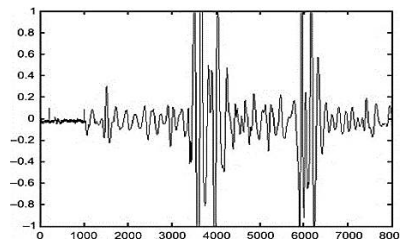


Fig.2 Waveform of the fPCG Signal

All the three de-noising algorithms are simulated in Matlab® for de-noising of the fPCG signals. The mean squared error (MSE) is used to evaluate the performance of the presented approach for the selection of appropriate de-noising algorithm. It can be obtained using the following expression:

$$MSE = \frac{\sum_{i=1}^n (s - se)^2}{n} \quad (8)$$

where ‘n’ denotes the length of the signal, ‘s’ represents the original signal and se is the estimated signal obtained from the de-noised wavelet coefficients. Figure 2.3 is a test signal generated by adding simulated random noise in the original fPCG signal, which is shown in Figure 2.2. This simulated random noise is analogous to the noise produced because of maternal organ sounds, foetal movement effects and ambient noise.

The wavelet analysis of this signal is performed with five levels of decomposition using fourth-order Coilets wavelet. This selection of mother wavelet is random and based on the fact that it possesses all the properties needed for analysis of the fPCG signals. All the three algorithms with soft or hard thresholding rule are applied for de-noising of the fPCG signal. The authors of [72] show the comparisons of the fPCG signal obtained using these optimal wavelet functions.

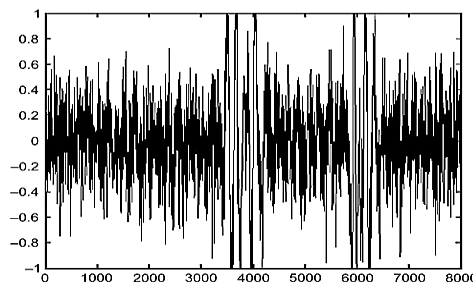


Figure 2.3 fPCG Signal with additive noise

Finally, in [72] the efficacy of the method is evaluated using fPCG signals (S1-S5) recorded from five different subjects. All the de-noising algorithms are applied for de-noising of these fPCG signals using selected mother wavelets, and the respective results generated are depicted in the tabular form [Table II] below.



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Table II: Comparison of De-Noising Algorithms

Denoising Algorithms	S1	S2	S3	S4	S5
Universal threshold algorithm with soft thresholding rule	0.5826	0.5744	1.1137	0.2615	0.2817
Universal threshold algorithm with hard thresholding rule	0.5906	0.5666	1.1137	0.2615	0.2817
Minimaxs threshold algorithm with soft thresholding rule	0.5371	0.5716	1.1137	0.2712	0.2817
Minimaxs threshold algorithm with hard thresholding rule	0.8199	0.7972	1.1137	0.8162	0.8092
Rigorous SURE threshold algorithm with soft thresholding rule	0.4661	0.5531	1.081	0.2539	0.2669
Rigorous SURE threshold algorithm with hard thresholding rule	1.0091	0.8633	1.254	1.0062	0.8851

Table II shows a comparison among three de-noising algorithms with soft or hard thresholding rule. The rigorous SURE threshold algorithm with soft thresholding rule yields the best estimation with considerably smaller MSE as compared to other algorithms for de-noising of fPCG signals.

## XV. 2.4.5 BLIND SOURCE SEPARATION AND PHONOCARDIOGRAPHY

Recently, blind source separation by Independent Component Analysis (ICA) has received attention because of its potential applications in signal processing such as in speech recognition systems, telecommunications and medical signal processing. The goal of ICA is to recover independent sources given only sensor observations that are unknown linear mixtures of the unobserved independent source signals. In contrast to correlation-based transformations such as Principal Component Analysis (PCA), ICA not only decorrelates the signals (2nd-order statistics) but also reduces higher-order statistical dependencies, attempting to make the signals as independent as possible.

There have been two different fields of research considering the analysis of independent components. On the one hand, the study of separating mixed sources observed in an array of sensors has been a classical and difficult signal processing problem. The seminal work on blind source separation is by Jutten, Herault and Guerin (1988) where they proposed an adaptive algorithm in a simple feedback architecture. The learning rule was based on a neuromimetic approach and was able to separate simultaneously unknown independent sources. This approach has been explained and further developed by Jutten and Herault (1991), Comon (1991), Karhunen and Joutsensalo (1993), Cichocki and Moczczynski (1992) and others. Furthermore, Comon (1994) introduced the concept of independent component analysis and proposed cost functions related to the minimization of mutual information between the sensors.

On the other hand, and in parallel to blind source separation studies unsupervised learning rules based on information-theory have been proposed by Linsker (1992), Becker and Hinton (1992) and others. The idea was to maximize the mutual information between the inputs and outputs of a neural network. This approach is related to redundancy reduction which was suggested by Barlow (1961) as a coding strategy in neurons. Each neuron should encode features that are statistically independent of other neurons. This leads to the notion of factorial code that has been explored for the visual processing strategy by Attik (1992). Nadal and Parga (1994) showed that in the low-noise case, the maximum of the mutual information between the input and output of a neural processor implied that the output distribution was factorial. Roth and Baram (1996) and Bell and Sejnowski (1995) independently derived stochastic gradient learning rules for this maximization and applied them, respectively to forecasting and time series

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analysis, and the blind separation of sources. Bell and Sejnowski (1995) were the first explaining the blind source separation problem from an information-theoretic viewpoint and applying them to separation and deconvolution of sources. Their adaptive methods are more plausible from a neural processing perspective than the cumulant-based cost functions proposed by Comon. A similar adaptive but 'non-neural' method for source separation has been proposed by Cardoso and Laheld (1996).

Other algorithms have been proposed from different approaches: The maximum likelihood estimation approach was first proposed by Gaeta and Lacoume (1990), negentropy maximization approach by Girolami and Fyfe (1996), nonlinear PCA algorithm developed by Karhunen and Joutsensalo (1994) and Oja (1995). Lee, Girolami and Sejnowski (1997) give a unifying framework to the source separation problem by explaining the relation of the different algorithms to each other. The derived learning rule is optimized when the natural gradient (Amari, 1997) or relative gradient (Cardoso and Laheld, 1996) is used.

The originally proposed algorithm by Bell and Sejnowski (1995) was suited to separate super-Gaussian sources. To overcome this limitation other techniques have been developed that were able to simultaneously separate sub- and super-Gaussian sources. Pearlmutter and Parra (1996) derive a generalized ICA learning rule from the maximum likelihood estimation where they explicitly model the underlying source distribution which was assumed to be fixed in the original algorithm. Although the density estimation was burdensome and required a sufficient amount of data, the algorithm was able to separate a fairly large number of the source with a wide range of distributions. A simpler and highly effective algorithm has been proposed by Girolami and Fyfe (1996) from the negentropy maximization approach. They used an extended exploratory projection pursuit network with inhibitory lateral connections that could separate sub- and super-Gaussian sources. Lee, Girolami and Sejnowski (1997) derive the same learning rule from the infomax approach preserving the simple architecture and showing superior convergence speed.

Extensive simulations have been performed to demonstrate the power of the learning algorithm. However, instantaneous mixing and unmixing simulations are toy problems, and the challenge lies in dealing with real world data. Makeig et al. (1996) applied the original infomax algorithm to EEG and ERP data showing that the algorithm can extract EEG activations and isolate artifacts. Jung et al. (1997) show that the extended infomax algorithm is able to linearly decompose EEG artifacts such as line noise, eye blinks, and cardiac noise into independent components with sub- and super-Gaussian distributions. McKeown (1997) has used the extended ICA algorithm to investigate task-related human brain activity in fMRI data. By determining the brain regions that contained significant amounts of specific temporally independent components, they were able to specify the spatial distribution of transiently task-related brain activations. Other potential applications may result from exploring independent features in natural images. Bell and Sejnowski (1997) suggest that independent components of natural scenes are edge filters. The filters are localized, mostly oriented and similar to Gabor like filters. The outputs of the ICA filters are sparsely distributed. Bartlett and Sejnowski (1997) and Gray, Movellan and Sejnowski (1997) demonstrate the successful use of the ICA filters as features in face recognition tasks and lipreading tasks respectively.

For these applications, the instantaneous mixing model may be appropriate because the propagation delays are negligible. However, in real environments, substantial time-delays may occur, and an architecture and algorithm are needed to account for the mixing of time-delayed sources and convolved sources. The multichannel blind source separation problem has been addressed by Yellin and Weinstein (1994) and Ngyuen and Jutten (1995) and others based on 4th-order cumulants criteria. An extension to time-delays and convolved sources from the infomax viewpoint using feedback architecture has been developed by Torkkola (1996). Lee, Bell and Lambert (1997) have extended the blind source separation problem to a full feedback system and a full feedforward system. The feedforward architecture allows the inversion of non-minimum phase systems. In addition, the rules are extended using polynomial filter matrix algebra in the frequency domain (Lambert, 1996). The proposed method can successfully separate voices and music recorded in a real environment. Lee, Bell and Orglmeister (1997) show that the recognition rate of an automatic speech recognition system is increased after separating the speech signals.

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Since ICA is restricted and relies on several assumptions researchers, have started to tackle a few limitations of ICA. One obvious but non-trivial extension is the nonlinear mixing model. In (Hermann and Yang, 1996; Lin and Cowan, 1997; Pajunen, 1997) nonlinear components are extracted using self-organizing-feature-maps (SOFM). Other researchers (Burel, 1992; Lee, Koehler and Orglmeister, 1997; Taleb and Jutten, 1997; Yang, Amari and Cichocki, 1997) have used a more direct extension to the previously presented ICA models. They include certain flexible nonlinearities in the mixing model, and the goal is to invert the linear mixing matrix as well as the nonlinear mixing. Other limitations such as the under-determined problem in ICA, i.e. having fewer sensors than sources and noise models in the ICA formulation are subject to current research efforts.

ICA is a fairly new and a generally applicable method to several challenges in signal processing. It reveals a diversity of theoretical questions and opens a variety of potential applications. Successful results in EEG, fMRI, speech recognition and face recognition systems indicate the power and optimistic hope in the new paradigm. Literature review reveals that there is very little work done on processing phonocardiography; especially foetal phonocardiograph processing using BSS and still have a wide scope, in the perspective of foetal heart rate monitoring and foetal wellbeing.

In the preceding paragraph, the research work, using blind source separation as a signal processing tool for processing the foetal heart signals are discussed.

Vivek Nigam [74] provides an algorithm to non-invasively estimate the phonocardiogram of an individual foetus in a multiple fetus pregnancies. A mixture of foetal phonocardiograms is modelled by a generalized pure delayed mixing model. Mutual independence of foetal phonocardiograms is assumed to apply blind source separation based techniques to extract the foetal phonocardiograms from their mixtures. The performance of the algorithm is verified through simulation results and on experimental data obtained from a phantom that is used to simulate a twin pregnancy. Bruno AZZERBONI [75] presented a new approach where they have used a recently developed Wavelet-ICA method, based on the joint use of Wavelet Analysis and ICA, to fECG extraction, in order to improve the extraction performance. V. Vigneron in [76], apply BSS to fECG extraction and showed that (i) exploiting the ECG non-stationarity could improve source separation, (ii) wavelets seems a well-suited and promising method for extracting the foetal PQRST complexes. Further investigations will include (i) a quantitative comparison of the performance of BSS algorithms and focus in particular on wavelet denoising for improving PQRST complex extraction, (ii) a qualitative evaluation (by physicians) of the foetal PQRST extracted by this method, especially in pathological cases. By projecting single-channel signal into a higher dimension, the multi-channel technique can be employed. In [77] a blind-source separation method using an SVD of the spectrogram, followed by an iterative application of ICA on both the spectral and temporal representations of the ECG signals is presented. To define the decomposition problem, they make both an assumption of statistical independence of the heart-beat occurrences, and a similar assumption on the basis vectors they used to represent the spectral slices of the individual signals. This is a reasonable assumption in this domain because each signal is a repeating fPCG complex. The method they developed is likely to be applicable to other problem domains defined by the need to separate nearly periodic sources from noisy mixtures into a higher dimension; the multi-channel technique can be employed.

## XVI. CONCLUSION

We have implemented an automatic text detection technique from an image for Inpainting. Our algorithm successfully detects the text region from the image which consists of mixed text-picture-graphic regions. We have applied our algorithm on many images and found that it successfully detect the text region.

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