Romanian Reports in Physics **72**, 607 (2020)

REMOVAL OF REPETITIVE MAGNETIC INTERFERENCES UPON UNSHIELDED FETAL MAGNETOCARDIOGRAMS

B. ARVINTI[1], A. ISAR[2], R. STOLZ[3], M. COSTACHE[1]

[1] "Politehnica" University Timisoara, Foundamentals of Physics for Engineers, Romania
[2] "Politehnica" University Timisoara, Electronics and Telecommunicatons Department, Romania
[3] Research Group Magnetometry, Leibniz-Institute for Photonic Technology, Jena, Germany
Corresponding author: *marius.costache@upt.ro*

Received March 24, 2020

Abstract. Fetal magnetocardiograms are highly sensitive to interferences in unshielded environments, the measurements being realized indirectly. We aimed at removing repetitive deterministic interferences, applying the Wiener filter in the wavelet domain. An effective compression of data is performed using the Walsh-Hadamard Transform. Real fetal data has been analyzed, with promising results for the development of an automated diagnosis system.

Key words: wavelets, Wiener filter, Walsh-Hadamard transform.

1. INTRODUCTION

Time-frequency analysis upon non-stationary processes, such as the recording of biomedical signals is an up-to-date research area, cardiovascular diseases being a major health risk for nowadays society. Romania reports one of the highest fetal mortality rates in the European Union [1]. Electrocardiography (ECG) and magnetocardiography (MCG) are passive clinical methods for investigating the electrical functionality of the human heart. Fetal signal offer an additional challenge during the acquisition process, due to their low magnitude (some picoTesla). MCG signals recorded in clinical environment, in stress conditions, will not allow us to estimate the exact value of the noise distribution. Extraction of the clinically relevant MCG data is therefore a challenging task. Working environments are strongly affected nowadays by the surrounding magnetic radiance [2]. Low frequency magnetic field is generated by power equipments, raising the question of biological effects and health risk from exposure to electromagnetic fields [3, 4]. The interferences are visible and overlapping the characteristic waveforms during the recording of the magnetic field of the human heart (Fig. 1). A noise source for unshielded magnetocardiograms is given through stray magnetic fields that accompany the propagation of electric current through power lines [5, 6] and will be removed from the MCG recordings using an IIR 50 Hz notch filter. Analyzing the frequency spectrum of the fetal MCG, displayed in Fig. 1, we notice that the MCG is a quasi-periodical signal with fetal heart rate between 120–200 beats/second, resulting a fundamental period between

2 Hz and 4 Hz. Thus the range of the MCG spectrum is covering some 10th multiples of Hz (as can be seen in Fig. 1), the rest of the spectrum corresponding to interferences. The interferences are deterministic signals with a fixed frequency, as those given by the current network and will introduce constant (repetitive) noise artifacts upon the MCG shape.

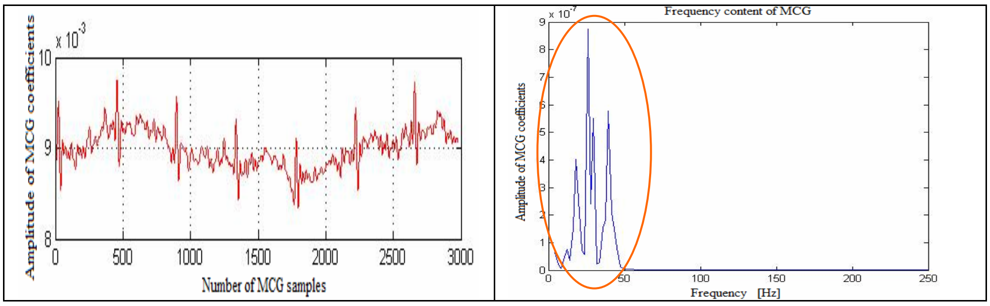

Fig. 1 – Original noisy MCG recorded in unshielded environment (left) and MCG frequency spectrum.

Wavelet analysis has known an increasing development in the recent decades [7, 8]. Engineers have discovered a useful analysis tool for tracking the temporal evolution of a signal. It overcomes the shortcomings of classical Fourier Transform, which provide no accurate information whether a frequency is briefly affecting a signal or is present during its entire evolution [7]. Wavelets for instance show the ability of providing information about local temporal variations of non-stationary biological signals [8]. A wavelet ψ(t) is generated through the translation (in time) and dilation (in frequency) of a basis scaling function called mother wavelet MW. Basis functions can be thus scaled to provide multiple resolutions of the original function [8], using different scaling/filter coefficients a_k, k ∈ Z.

$$\psi(x) = \sum_{\infty} (-1)^k \cdot a_{1-k} \cdot \phi(2x - k). \qquad (1)$$

The filter coefficients a_k are computed at each scaling (decomposition) level by imposing conditions upon the scaling function [9]:

1) the scaling function should be uniquely defined, thus the area under the scaling function is normalized to unity => $\sum_{\infty} a_k = 2$;

2) the scaling function should be orthogonal to any of its integer translates ⇒ $\sum_{\infty} a_k a_{k+2n} = 2\delta_{0,n}, \quad \delta_{0,n} = \begin{cases} 1, & n = 0 \\ 0, & \text{otherwise} \end{cases}, \ n \in Z;$

3) the scaling function should be able to represent polynomials up to order of $p \Rightarrow \sum_{\infty} (-1)^k a_k k^p = 0, \quad p = 0,\ 1,\ 2, \ldots\ l-1.$

The scaling function necessary for wavelet analysis will be recursively constructed from its filter coefficients. A major challenge while processing unshielded MCGs is that we do not know the exact signature of the surrounding magnetic interferences. This means that we can but approximate the distribution of the noisy wavelet coefficients. According to the Central Limit Theorem (CLT), if the sample size of random variables gets larger (for databases larger than 30 samples), the sampling distribution of their means tends toward a normal Gaussian distribution, no matter of the shape of the population distribution [10]. Therefore, when analyzing the signal using wavelets, we will consider the noise coefficients as having a Gaussian distribution, with zero mean (due to its wave nature) and variance σ^2_{noise}, where K is the $n \times n$ length matrix (2):

$$x(t) = \frac{1}{\sqrt{2\pi^n \det K}} \cdot e^{-\frac{(x-mean(x))^T \cdot K^{-1}(x-mean(x))}{2}}. \tag{2}$$

Several denoising techniques for extracting the sole fetal signal are available in literature [11, 12], each showing advantages but also shortcomings. In a previous study [13], we also focused on the effects of an adaptive filtering procedure based on Stein's Unbiased Risk Estimate. Still, the procedure is suited for reducing high interference peaks noticed at specific frequencies, although we also aimed at reducing low-peaked repetitive magnetic artifacts given by the surrounding electronic devices. In the present paper, we focused on taking a different insight into the nature of unshielded MCGs, developing a general method for removing unwanted repetitive magnetic artifacts and compressing the signal for further processing. We focused on developing a filter to shield external magnetic influences. We aim thus to develop an automatic MCG diagnosis system, avoiding through software algorithms the necessity of an expensive, shielded magnetic room for data acquisition.

2. WIENER FILTER APPLIED IN THE WAVELET DOMAIN

Magnetocardiography captures the biomagnetic signals given through cardiac contractions that vary over time. Wavelets transform a function of one independent time variable into a function with two independent variables [7], defining both time and frequency of the processed signal. A translation coefficient i, defines the temporal window when the signal is analyzed, while a scale coefficient j gives us the dilation factor of the analysis window. At each decomposition level the initial frequency is halved. The procedure is less redundant in practice, if the translation and the dilation factors are set equal to factors of 2 (eq. 3)

$$\psi_{j,i}(t) = \sqrt{2^j}\,\psi(2^j t - i), \tag{3}$$

where *i* is a translation factor and *j* a scale factor. Thus, the wavelet transform of a function $y(t) \in L^p(R)$, ($1 \leq p \leq \infty$) is given by the projection of the analyzed signal $y(t)$ on the daughter wavelet $\psi_{j,i}(t)$. This wavelet has been obtained through dilation and translation of one mother wavelet $\psi(t)$. This projection is dependent on the characteristics of the analyzed signal:

$$P_{\psi}x(j,i) = \left\langle x(t), \psi_{j,i}(t) \right\rangle \qquad \Leftrightarrow$$

$$P_{\psi}y(j,i) = \int_{-\infty}^{\infty} y(t) \cdot \frac{1}{\sqrt{j}} \psi^{*}\left(\frac{t-i}{j}\right) \mathrm{d}t, \quad i > 0, \quad j \in R. \tag{4}$$

The present study aimed at developing a general threshold level for MCG, to enable the design of a fast computing and accurate MCG filtering algorithm. To avoid the loss of important data for cardiac diagnosis, we will use a translation invariant transform, the Undecimated Wavelet Transform (UWT). After applying the proposed algorithm upon several decomposition levels, the MCG is reconstructed using the inverse transform. The Wiener filter is a linear estimation method (eq. 5), which considers noise as a random process additively superposed to the uncorrupted data $x(t)$ [14]. The filtering procedure aims at minimizing the Mean Square Error MSE between the real uncorrupted signal and an estimation of this noise-free signal [15]. We improved the denoising performances, enhancing the Wiener filter (Fig. 2) through its application on a multiscale wavelet analysis of the MCG signal. According to the CLT, a large number of random variables will exhibit a normal dispersion. Therefore, we have modeled the noisy signal as showing a Gaussian distribution, in order to obtain a realistic estimation of the properties of the noisy signal.

$$y(t) = x(t) * h(t). \tag{5}$$

As the clinical diagnosis is given upon visual inspection, the preservation of relevant data can be outlined. A visual evaluation of the results has been included in our study. The visually calibrated adaptive smoothing algorithm [16] is used in the wavelet domain in order to estimate the noise coefficients.

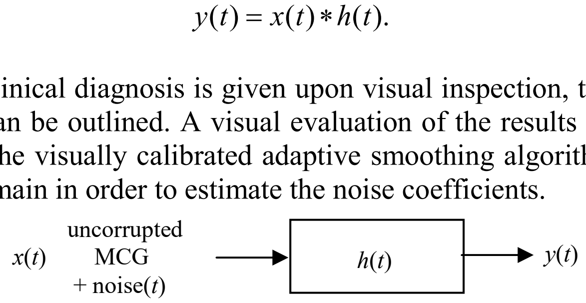

Fig. 2 – Linear structure of the Wiener filter.

As the wavelet approximation coefficients describe the general tendency of the signals, the noise is contained by the detail wavelet coefficients. As shown in

[17], Donoho's universal threshold is not accurate enough, therefore the algorithm will be applied on each decomposition level. A soft-thresholding procedure applies the visually spatially adaptive threshold (eq. 6) to obtain a preliminary denoising upon the detail wavelet coefficients of the processed fetal MCG

$$MCG_{VisuThreshold} = \sqrt{2 * \log(n_{MCG\_samples})}. \tag{6}$$

The Wiener filter is applied to improve the denoising effect and targets a Gaussian dispersion of the noise. The filtered signal is obtained after computing the inverse wavelet transform (Fig. 3). We also included an objective estimator of the performances, given by the Signal-to-noise ratios SNR of the input and output fetal MCG. The SNR is more relevant in terms of SNR improvement, given through the difference between the wavelet coefficients of the input and output MCG. The SNR is related to the values of the wavelet coefficients (and thus to the MW used). As we have no *a-priori* data about the exact dispersion of the artifact coefficients, we will estimate the noise in terms of the difference between the input noisy MCG and filtered processed MCG. Still, an advantage of processing biological signals is that a cardiac diagnosis is put by a physician upon visual inspection of the waveform and we can effectively see the filtering performance graphically displayed and thus interpret the results.

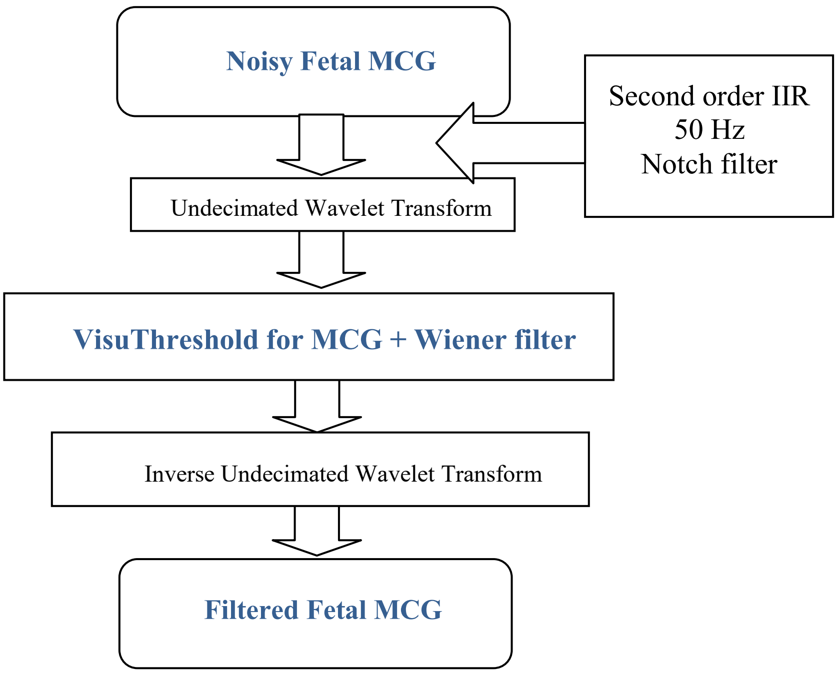

Fig. 3 – Scheme of the proposed MCG processing algorithm.

3. FILTERING PERFORMANCES FOR FETAL MAGNETOCARDIOGRAMS

The study has been performed on real fetal signals, the acquisition system for MCGs being developed at Leibniz-Institute for Photonic Technology [5]. A six channel gradiometric system is recording the fetal magnetic signals in unshielded environment. A sample rate of 103 Hz (a high sampling rate for biological signals) has been used. The signals are processed using *MATLAB*. Analyzing the noisy input MCG (Fig. 1), we notice a high baseline drift, artifacts and flicker effects on the MCG which overlap the single heartbeats, making a cardiac diagnosis difficult. A baseline drift reduction procedure should be applied [17], if we aim at a future development of an automatic processing system. The baseline drift filter is a low-pass filter with a small cut-off frequency so as to match the fundamental frequency of the MCG and to filter out other interferences. The two procedures will be interwoven, using the same wavelet transform and MW. Applying the UWT on 4 decomposition levels, we have checked the influence of several parameters, testing whether the filtering performances are dependent with the chosen parameters. We have kept the number of iteration levels constant, and studied the influence of MWs with different characteristics upon the same signal, to outline the best performances. The results are graphically displayed in Fig. 4 and Fig. 5, for the main orthogonal families of MW. Analyzing the results, we notice that the algorithm is stable, as there are no significant differences with the change of most MW families. There are less interferences displayed, especially the artifacts at 50 Hz have been filtered out. Thus, once the parameters chosen, the algorithm can be implemented into an automatic MCG processing and diagnosis system. The dependence of the estimated SNR with the number of vanishing moments and class of MW is given in Table 1. Through filtering and baseline drift correction the SNR is doubled.

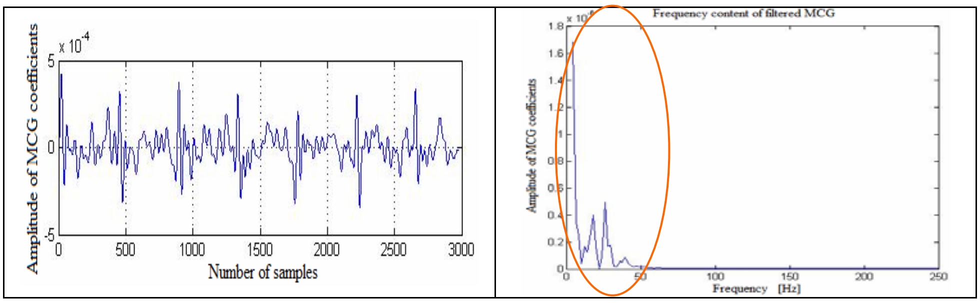

Fig. 4 – Filtered MCG, using db20 MW (left) and MCG frequency spectrum (right).

The denoising process will be realized cautiously (dealing with medical signals) aiming at preserving clinically relevant data. Before the final choice of the analysis wavelet, MWs with reduced number of vanishing moments should be avoided. Although they show a mean SNR improvement of aprox.11 dB, there can be noticed a too strong cut-off of the amplitude of the signals (Fig. 5, right side). The SNR being related to the wavelet coefficients, a high SNR improvement will result in a stronger filtering of the coefficients. As the medical interpretation of MCGs is not done solely on objective performance criteria, we can check the performance of the algorithm inspecting visually the MCG. With a medium SNR improvement of 6 dB, the single MCG components are more outlined, enabling thus a more precise cardiac diagnosis. Still, a strong filtering (SNR improvement > 9 dB), as realized with bior.2.6 MW, enhances a better detection of the QRS-complexes, allowing a fast determination of the fetal heart rate. To gain more insight into the nature of the magnetic disturbances affecting the acquisition of fetal MCGs in unshielded environments, the filtered noise has been represented in Fig. 6. The periodic oscillatory waves indicate a constant source of magnetic disturbances (possible interferences due to the power line or surrounding medical devices), captured by the sensitive SQUIDs. The developed algorithm can be used for removing constant magnetic interferences, reducing thus the necessity of an expensive magnetically shielded chamber. Lossy compression algorithms are a different way of filtering out repetitive artifacts, but such algorithms are not noise selective. Therefore we have first applied a Wiener filter in the wavelet domain. Still, a timely monitoring is necessary to perceive the cardiac health state of the fetus. The measurements generate a considerable quantity of data, which needs to be stored for future investigations and interpretations. An effective compression algorithm uses the fast Walsh-Hadamard Transform (WHT). It can be applied to biomedical signals [18], and we want to study its effectiveness on MCG signals. The processed MCG is decomposed into a set of orthogonal basis functions, which are fast computing as they require only real values. The Walsh functions are different combinations of square waves with the values +1 and –1. Contrary to wavelets, the analysis is not performed on multiple levels, the energy of the signal is stored into a set of WHT coefficients. Therefore, the low valued Walsh coefficients will be put to zero and only the high valued ones will be stored. For the analyzed fetal MCG, with an acquisition length of 35 s (resulting in 35000 sample values) we will store only the first 6000 (Fig. 7). The MCG will be reconstructed applying the inverse transform fWHT. We notice that the reconstruction has a good accuracy, with no visible distortions to be perceived (Fig. 8). A compression ratio of approximately 6:1 has been achieved.

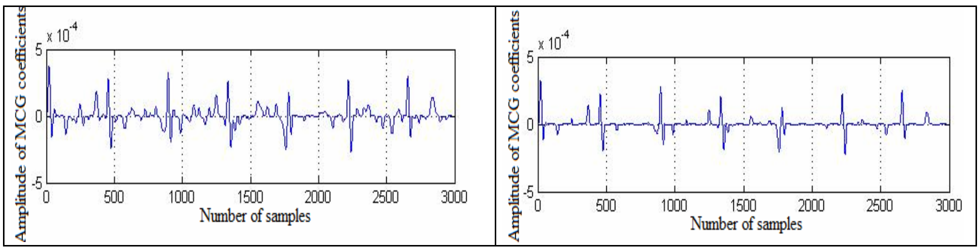

Fig. 5 – Filtered MCG, using sym3 MW (left) and filtered MCG, using bior2.6 MW (right).

Table 1

Values of the SNR for Fetal MCGs before and after denoising

Mother Wavelet	SNR input Fetal MCG	SNR filtered Fetal MCG	SNR improvement
Daubechies4	8.94	15.86	6.92
Daubechies6	9.16	15.43	6.27
Daubechies10	9.03	15.30	6.27
Daubechies20	8.85	15.19	6.34
Daubechies40	8.71	15.13	6.42
Coiflet2	8.94	15.81	6.87
Coiflet3	9.12	15.41	6.29
Coiflet4	9.06	15.33	6.27
Symlet3	**7.90**	**16.99**	**9.09**
Symlet4	8.92	15.86	6.93
Symlet6	9.16	15.43	6.27
Symlet10	9.04	15.30	6.25
Biorthogonal2.6	***5.89***	***18.93***	***13.04***
Biorthogonal3.3	8.82	16.07	7.25
Biorthogonal4.4	9.04	15.75	6.71
Biorthogonal5.5	9.20	15.48	6.28
Biorthogonal6.8	9.12	15.39	6.27
Reverse Biorthogonal1.3	**7.80**	**17.11**	**9.31**
Reverse Biorthogonal2.4	8.67	16.18	7.51
Reverse Biorthogonal3.5	8.97	15.78	6.81
Reverse Biorthogonal4.4	8.75	16.02	7.27
Reverse Biorthogonal5.5	8.79	15.89	7.10
Reverse Biorthogonal6.8	9.12	15.38	6.25

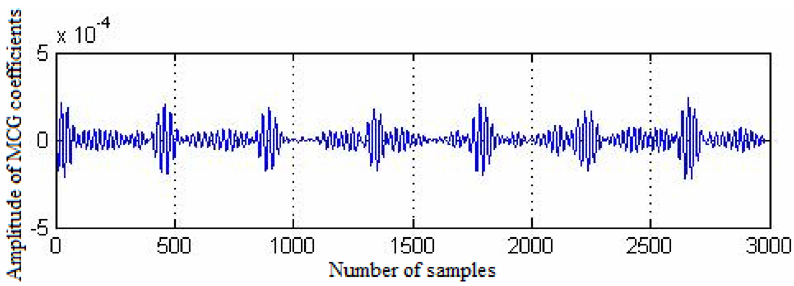

Fig. 6 – Noise filtered from the MCG, using the proposed algorithm, db20 MW.

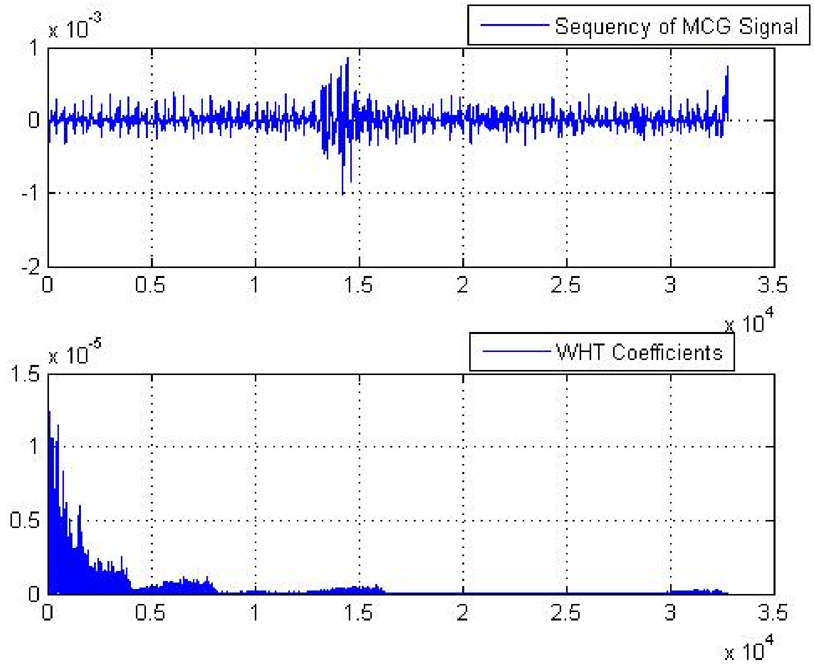

Fig. 7 – Original MCG sequency (top) and the computed Walsh-Hadamard coefficients (bottom).

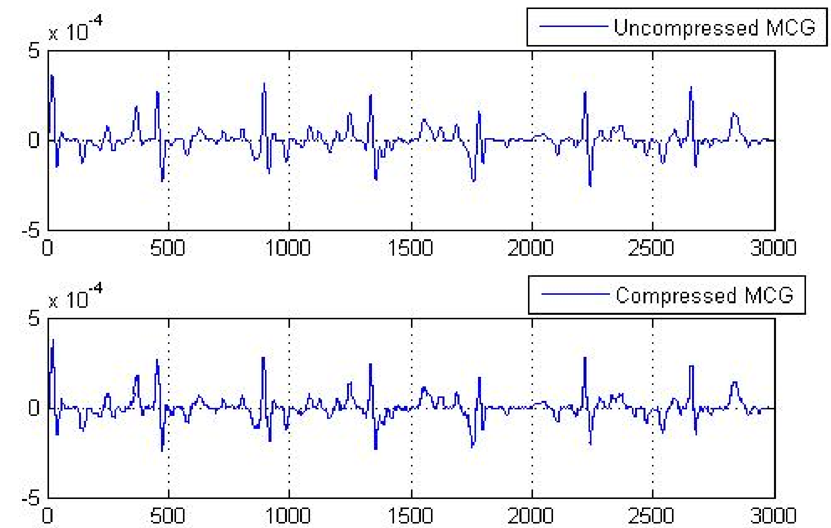

Fig. 8 – MCG sequency before the performed compression (top) and the reconstructed MCG sequency.

4. CONCLUSION

Research of fetal electrocardiograms is still in development stage, due to the challenges disclosed when investigating such fable signals, as provided by fetuses. Direct measurements are not implemented as a standard procedure up to day, being risky and dangerous for the unborn child. Therefore, the measurements are realized only indirectly through the mother's abdomen. Still, such signals collected from the body surface are strongly affected by noise. We developed a filtering algorithm for removing the magnetic interferences upon the fetal MCG. We took into account the most probable distribution of noisy artifacts: a large number of variables will sum up to a normal dispersion. A visually calibrated smoothing algorithm has been combined with a Wiener filter applied in the wavelet domain. Analyzing the performances (Figs. 4–5), we notice a reduction of repetitive noise affecting the initial fetal MCG. For a more objective evaluation of the performance, we also computed the SNR of the input and filtered signal. There is a SNR gain of 6–7 dB to be noticed at most MWs, proving the stability of the algorithm. Some MWs denote a higher SNR and better filtering performances (sym3, rbio1.3). Still, very high SNR improvements should be avoided as the cut-off of the MCGs amplitude is too strong, distorting the signal. We aimed at finding optimal performance parameters and recommend the Daubechies MWs. A competitive denoising system can be envisaged in the future, especially as the UWT uses an efficient filter-bank decomposition system, which is fast computing and robust. Large quantities of recorded data can be compressed and stored for a future use applying the Walsh-Hadamard Transform. The reconstructed fetal MCG shows a good accuracy, with no visible distortions for a compression factor of 6:1. Future research directions should aim at improving the results, outlining each useful waveform and allowing the development of a robust fetal morphology extraction system.

REFERENCES

1. World Health Organisation (2019), *World health statistics 2019: monitoring health for the SDGs*, https://apps.who.int/iris/bitstream/handle/10665/324835/9789241565707-eng.pdf (2019).
2. M. Morega, I. M. Băran, A. M. Morega, Alnamir Kazem Leaibi Hussain, *On The Assessment of Human Exposure To Low Frequency Magnetic Field At The Workplace*, Rev. Roum. Sci. Techn.– Électrotechn. et Énerg. **63**, 162–171 (2018).
3. IEEE*, Standard for Safety Levels with Respect to Human Exposure to Electromagnetic Fields, 0–3 kHz*, IEEE Standard C95.6-2002.
4. D. Stoica, C. Miron, Al. Jipa, *The Study of the Periodical Phenomena*, Romanian Reports in Physics **66** (4), 1285–1300 (2014).
5. R. Stolz, V. Zakosarenko, N. Bondarenko, M. Schulz, L. Fritzsch, N. Oukhanski, H.-G. Meyer, *Integrated SQUID-Gradiometer System for Magneto-Cardiography Without Magnetic Shielding*, IEEE Transactions on Applied Superconductivity **13**, 356–359 (2003).
6. G. Rosu, M. C. Rau, O. Baltag, *Comparison of Signal Processing Methods Applied on a Magnetocardiographic Signal,* 10th International Symposium on Advanced Topics In Electrical Engineering, Bucharest, Romania, DOI: 10.1109/ATEE.2017.7905161 (2017).

7. Paul C. Liu, *A Fifteen Minutes Introduction of Wavelet Transform and Applications*, researchgate.net (2013).
8. D. Popescu, S. Miclos, I. Paşol, V.I.R. Niculescu, *Wavelet and Short Time Fourier Transformations – Two Complementary Methods for Spectral Analysis of Muscle Electrical Activity,* Romanian Reports in Physics **68** (3), 486–496 (2016).
9. John Williams, Kevin Amaratunga, *Introduction to wavelets in engineering*, International Journal for Numerical Methods in Engineering, **37**, 2365–2388 (1994).
10. Alka S. Barhatte, Rajesh Ghongade, Sachin V. Tekale, *Noise Analysis of ECG Signal Using Fast ICA*, 2016 IEEE Conference on Advances in Signal Processing (CASP), Cummins College of Engineering for Women, Pune, 118–122 (2016).
11. M. Niknazar, B. Rivet, C. Jutten, *Fetal ECG Extraction by Extended State Kalman Filtering Based On Single-Channel Recordings*, IEEE Transactions on Biomedical Engineering **60** (5), 1345–1352 (2013).
12. D. Geue, H. Zavala-Fernandez, S. Lange, M. Burghoff, R. Orglmeister, D. Grönemeyer, P. van Leeuwen, *Processing the magnetocardiographic signal in the identification of fetal and maternal heart beats in a triplet pregnancy*, Proceedings Biomedizinische Technik, 2007 .
13. B. Arvinti, A. Isar, R. Stolz, M. Costache, *Effects of Combining Stein's Unbiased Risk Estimate and Wavelets for Denoising Magnetocardiograms*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg. **63** (3), 344–349 (2018).
14. Lukáš Smital, M. Vítek, Jiří Kozumplík, Ivo Provazník, *Adaptive Wavelet Wiener Filtering of ECG Signals*, IEEE Transactions on Biomedical Engineering **60** (2), 437–445 (2013).
15. Jin Wang, Jiaji Wu, Zhensen Wu, Jechang Jeong, Gwanggil Jeon, *Wiener filter-based wavelet domain denoising*, Displays **46** (2017), 37–41 (2017).
16. Kusum Tharani, Chandra Mani and Ishaan Arora, *A Comparative Study of Image Denoising Methods Using Wavelet Thresholding Techniques,* Int. Journal of Engineering Research and Application **6** (12), 73–77 (2016).
17. B. Arvinti, M. Costache, R. Stolz, *Testing Biorthogonal Wavelets on Magnetocardiogram Processing Algorithms*, Advances in Intelligent Systems and Computing, Springer **357** (2014).
18. M. Trikha, D. Kumar, *Use of Walsh-Hadamard Transform in Processing of ECG Signal*, MIT International Journal of Electrical and Instrumentation Engineering **5** (1), 2015.