Proceedings of the World Congress on Electrical Engineering and Computer Systems and Science (EECSS 2015)
Barcelona, Spain – July 13 - 14, 2015
Paper No. 333

Application of Wavelet Scalogram and Coscalogram for Analysis of Biomedical Signals

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Abstract - In this paper, using wavelet scalograms and coscalogram of concurrent biomedical signals we were able to detect their short-lived temporal interactions. The complete analysis should include investigation of signal coherence in amplitude and phase. This is achieved with a continuous complex wavelet transform. Thus, in the algorithms developed, we use the Morlet wavelet transform and some measures based on scalograms and coscalograms. The algorithms have been developed that assist in quick and simple data analysis. Our analysis gives an indication of the cross-correlation of signals in time and frequency domain. The simultaneously recorded biomedical time series signals used, come from MIMIC database. The determined time shift between these signals, that we used to obtain adequate correlation results, may also be useful to determine various delays or information transmission times in human system.

***Keywords*:** Processing of biomedical signals, Morlet wavelet transform, Scalogram, Coscalogram, Correlation

1. Introduction

Wavelet Transform, in particular Morlet Wavelet Transform (MWT), allows multiresolution analysis in time-frequency domain of a non-stationary, transient signal, meaning that fine details of a signal can be detected and localized which is not possible with Fourier Transform or windowed Short Time Fourier Transform. Wavelet scalogram measures the local time-frequency energy density of a signal and provides valuable information about the behavior of the system over time. For example, Addison et al. (2002) used Morlet Wavelet Scalogram (MWS) to detect a previously unknown coordinated contractility behavior of the atrium during ventricular fibrillation, a phenomenon which is not captured in a normal electrocardiogram. Likewise, coscalogram measures the cross-energy density between two different signals at different frequency bands and provides a meaningful information about the effect of the two processes on the status of a system under interrogation, e.g., Kelley et al. (2001, 2005) used Morlet Wavelet Scalogram and Coscalogram to examine the initial stiffness degradation of the wind turbine blades that was found to be primarily due to early presence of high frequency energy that causes excitation of higher structural modes, leading to response coupling and energy exchange between modes. Similar applications of the MWT can also be found in González et al. (2008) and Bialasiewicz et al. (2013). The aforementioned application of wavelet scalogram and coscalogram analysis motivated this paper which is focused more on the analysis of the biomedical signals with an objective of finding meaningful information about the physiologic and disease process by examining the scalograms and coscalogram and therefore relationship between two different biomedical signals.

In particular, we present some software tools whose algorithms are programmed in MATLAB and represented as MATLAB's GUI that assists in quick and simple data analysis for obtaining meaningful information on interaction dynamics of concurrent processes. These tools are capable of detecting the short-lived temporal interactions. The investigated processes may be represented by concurrent recordings obtained at distant points of a complex dynamic system such as

- human brain in which, using EEG recordings, you would like to investigate the interaction dynamics between two anatomically distinct neuronal populations;
- human body in which you would like to examine the relation between respiratory rate and the electric impulses generated by a group of muscles and recorded as electromyography (EMG);
- Human body in which you would like to examine the relation between electrocardiographs (ECG) and blood pressure (BP) measurements over the same time period.

Using the data that represent investigated processes, our software calculates MWT scalogram and coscalogram and generates graphical presentation of the results. These results enable the qualitative evaluation of interaction dynamics of investigated processes. In addition, the implemented algorithms provide quantitative evaluations of interaction dynamics. These are the following measures:

- Wavelet Local Correlation Coefficient (WLCC)
- Cross Wavelet Coherence Function (CWCF)
- Wavelet Coherence (WC)
- Wavelet-Based Bicoherence (WBC)

And applications of these measures can also be found in Grinsted et al. (2004), Mohamed (2006), Lachaux et al. (2002), Wolfgang et al. (1999), Sanchez et al. (1995), and Li et al. (2007). Graphical User Interface (GUI) enables the user to load two processes under investigation, make choice of the required processing parameters and then perform the analysis. All obtained results are represented in a graphical window (Gross, Bialasiewicz, 2015). However, the time delay between the investigated processes was not considered. This has been the topic of research whose results are reported in (Sukiennik, Bialasiewicz, 2015). In this paper, calculation of the coscalogram, based on the time-delay-corrected convolution of continuous wavelet transforms, was introduced. It provides detailed information about the interaction of signals in the time-frequency domain.

2. Background on Scalogram and Coscalogram

2. 1. Morlet Wavelet Transform

Wavelet Transform is superior to the Fourier Transform and the Short Time Fourier Transform (STFT) because of its ability to measure the time-frequency variations in a signal at different time-frequency resolutions. Fourier Transform contains globally averaged spectral information. Thus, the transient spectral information is lost. The Heisenberg boxes in time-frequency domain illustrate the multiscale zooming property of the Wavelet Transform wherein boxes or rectangles of detail coefficients at higher frequency components of the signal span have shorter time duration whereas those at lower frequency components have wider time span.

In our applications, the wavelet scalogram and coscalogram is based on the continuous Morlet Wavelet Transform (MWT). The time series of investigated processes are analyzed on the time-scale or time-frequency plane using the MWT. Morlet wavelet that is a Gaussian-windowed complex sinusoid gives (due to the Gaussian's second order exponential decay) good time localization. The MWT is defined as follows:

$$W_x(s,\tau) = \frac{1}{\sqrt{s}} \int x(t) \psi^* \left(\frac{t-\tau}{s} \right) dt \qquad (1)$$

Where $\psi(t) = \pi^{-1/4} e^{j\omega_0 t} e^{-1/2t^2}$, *x* is the analyzed signal, and *s* is the scale.

The wavelet transform of a continuous time-dependent signal, *x*(*t*), correlates the function under interrogation with a wavelet function, ψ, at the scale '*s*' and position 'τ'. The Wavelet coefficient, $W_x(s,\tau)$, represents *x*(*t*), and its Fourier transform in the time-frequency region where the energy of the wavelet atom, $\psi_{\tau,s}(t)$, and its Fourier transform $\hat{\psi}_{\tau,s}(\omega)$ are concentrated. As such, analysis of phase and amplitude information of signals, over time, requires use of a complex analytic wavelet which has properties of analytic signal, i.e., the Fourier transform of the given wavelet function is zero for $\omega < 0$. This indicates that energy of $\hat{\psi}(\omega)$ is concentrated over a positive frequency interval centered at B_0 and the energy of $\hat{\psi}_{\tau,s}(\omega)$ is concentrated over a positive frequency interval centered at the center frequency B_0 / s. In the time-frequency plane, the wavelet atom, $\psi_{\tau,s}(t)$, is represented by a rectangular box centered at $(\tau, B_0 / s)$ whose area represents the energy spread of the wavelet atom with the standard deviation σ_t defined by the following equation:

$$\sigma_t^2 = \int_{-\infty}^{\infty} t^2 |\psi(t)| dt \tag{2}$$

As such, time varies with '*s*' whereas frequency varies with '1/*s*', i.e., the Heisenberg box in the time-frequency plane has a dimension of $s\sigma_t$ along the time-axis and σ_ω / s along the frequency axis. As the scale, *s*, varies, the height of the rectangle, representing the frequency components, changes and so does the width that represents the time component while the area of the rectangle remains constant, i.e., the energy is conserved.

2. 2. Scalograms and Coscalograms

A local time-frequency energy density, which measures the energy of *x* in the Heisenberg box of each wavelet $\psi_{\tau,s}$ is known as wavelet scalogram

$$P_W x(\tau, s) = |W_x(s,\tau)|^2 \tag{3}$$

A local time-frequency energy density, which measures the cross-energy of two processes (that identifies their local correlation), known as wavelet coscalogram, is defined as follows:

$$P_W xy(s,\tau) = W_x(s,\tau) W^*{}_y(s,\tau) \tag{4}$$

3. Using Scalograms and Coscalogram for Biomedical Signals Analysis

3. 1. Direct Applications of Scalograms and Coscalograms

Figure 1 that gives graphical illustration of scalogram and coscalogram was created using the time series of the electrocardiogram (ECG) and Arterial Blood Pressure (BP) signals obtained from Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) Database (Goldberger, et al., 2000), made freely available on PhysioNet website (http://physionet.org/). MIT's PhysioNet is part of the project whose goal is to provide easy to use tools to access physiological data. MIMIC database contains high-resolution recordings of multi-parameter data coming from monitoring critically ill patients in intensive care units. Database has been made publically available to support research community for researchers that do not have access to the medical environment**.**

In the plot presented in Fig.1, one can see ECG and BP signals, along with their scalograms and coscalogram. It is visible that two (framed) events, visible in the scalogram of ECG, have corresponding reaction in BP scalogram, but with some visible time delay. Therefore, in order to accurately represent the relationship between the analyzed signals, this delay has to be determined. The coscalogram presented, does not take into account this time delay. Also, if you exam the spikes in time-domain representation of both signals superimposed, you can see the mismatch. It is also reflected in the green box on the coscallogram (corresponding to high frequency range). This problem was investigated and genetic algorithm was employed to determine the delay (Sukiennik, Bialasiewicz, 2015).

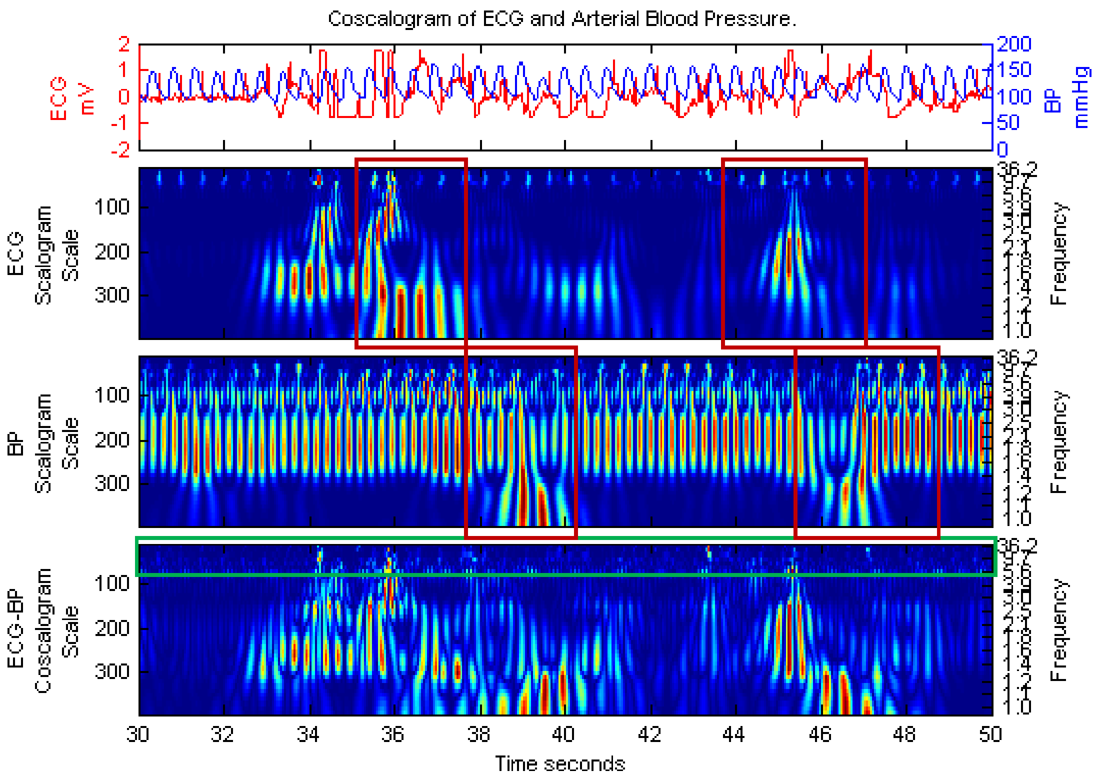

Fig. 1. ECG and BP signals, scalograms and coscalogram.

For the particular example, illustrated in Fig. 2, the delay of 2.386 seconds was determined. So, the BP signal was delayed by 2.386 seconds to obtain alignment of the associated events in the ECG and BP signals.

The results shown in Fig. 2 clearly present correlation of events due to the alignment of the analyzed signals. Specifically, the corresponding parts of scalograms in the red time-frequency boxes show more consistent correlation. There is also visible series of events in high frequencies (10 – 36 Hz) of coscalogram (marked with a green box) that are not visible on the corresponding not optimized coscalogram in Fig. 2.

Besides the fact that using the genetic algorithm it was possible to determine the delay and align the corresponding events, this method may be of interest to determine different time delays in the human system in order to investigate differences between ill and healthy people and actually to diagnose a particular disease.

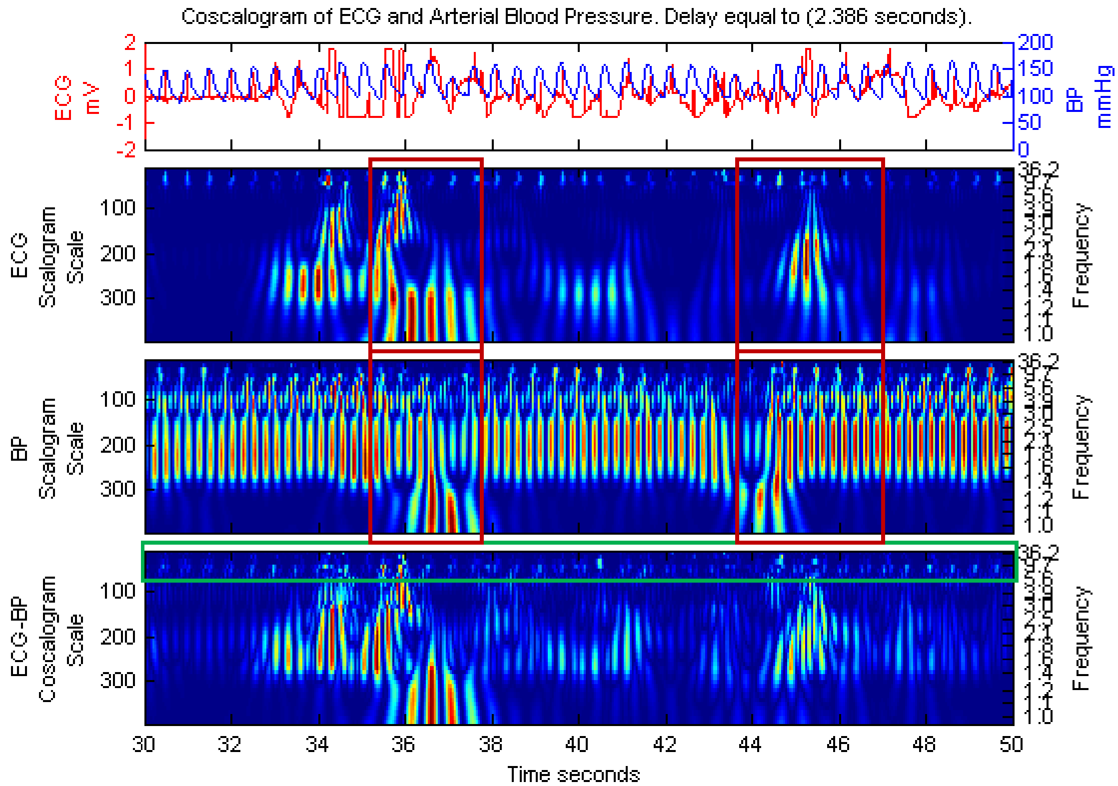

Fig. 2. Time delay optimized (BP signal delayed by 2.386 seconds)

3. 2. Indirect Applications of Scalograms and Coscalograms

In Section 3.1, we described procedures that use directly scalograms and coscalogram to establish existence of some relations between investigated processes that may find numerous applications in the analysis of biosignals. In this section, we shall present some quantitative measures of time-varying correlation measures of biomedical signals along with their graphical presentation that can be obtained using Matlab's GUI, presented in (Gross, Bialasiewicz, 2015) along with their mathematical descriptions, implemented in the algorithms. These measures have already been briefly introduced in Section 1. These are: WLCC, CWCF, WC, and WBC.

In Fig. 3, we illustrate two techniques to measure the correlation between two signals by using Wavelet Local Correlation Coefficient (WLCC) and Cross Wavelet Coherence Function (CWCF). Figure 3a shows the WLCC, which is the phase correlation. Notice the long stripes in the lower frequency bands ($1.3 < f < 3.0$ Hz), which are within the same frequency region as that seen in the coscalogram of Fig. 1. These stripes indicate that the signals have a phase correlation throughout the entire time series within these lower frequencies. Figure 3b gives the CWCF, where the color intensity represents the amplitude coherence. Again, the most intense portions are within the lower frequency band, and the intense regions match the events that can be noticed in Fig. 1.

In Fig. 4, we see the representation of the wavelet bicoherence over the total time, during consecutive events that can be noticed in Fig. 1. For all events, the bicoherence is relatively low (< 0.2), which shows that there is not a strong phase coupling or non-linear interaction.

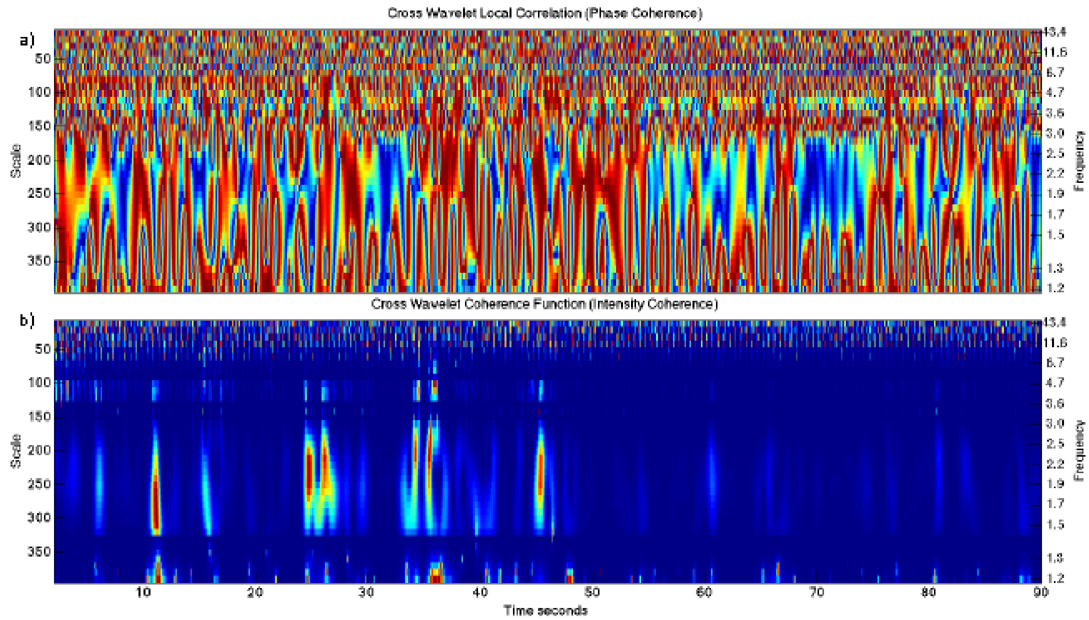

Fig. 3. a) WLCC image, where the color represents the phase coherence between the ECG and BP signals, b) CWCF image, where the color represents the amplitude strength of the coherence between the ECG and BP signals.

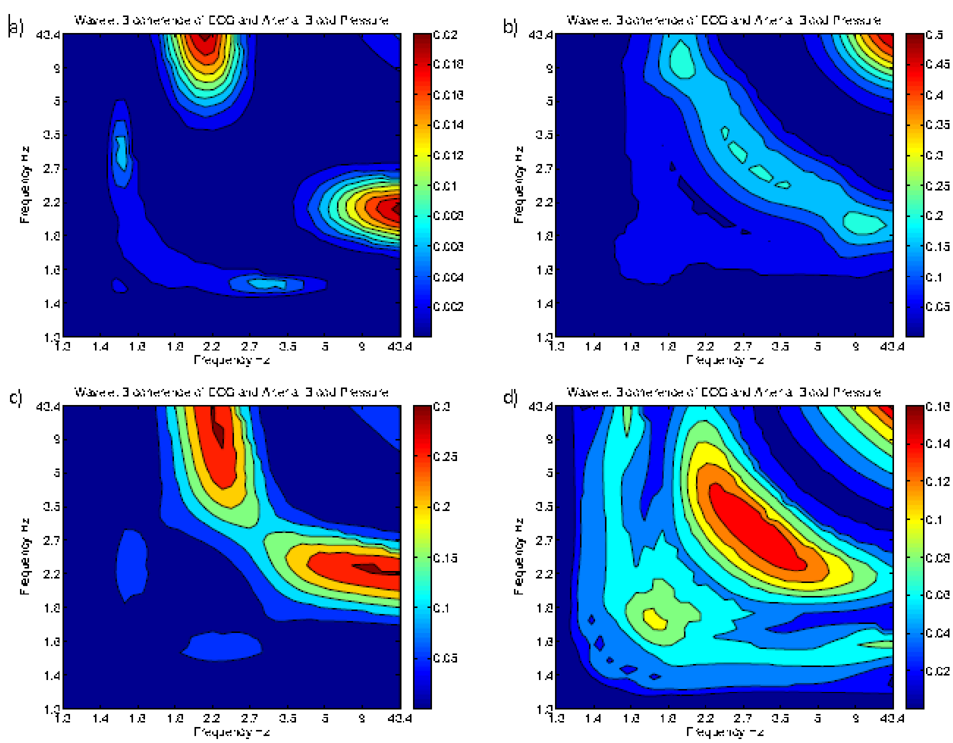

Fig. 4. Images a) through d) show the wavelet bicoherence over: the total time, during Event 2, during Event 3, and during Event 4, respectively. The bottom axes represent the ECG signal frequencies and the left axes represents the BP signal frequencies

3. 3. Indirect Applications of Scalograms and Coscalograms

Matlab GUI is very useful when analyzing two time series signals several times with different parameter settings. Figure 5, upper part, shows the screenshot of the GUI running while plotting, the time series data, the scalograms, and the coscalogram. Adjusting the time or any other parameter is very simple, in that users can change any parameter they choose, then press the button for the plot they would like created. Figure 5, lower part, presents another example that is the GUI running when plotting the wavelet coherence. Also, the WC and WB plots are created to use Matlab's parallelization function, but the GUI does not initiate the pool itself. Rather, the pool must be initiated by the user at the command line, along with closing the pool when finished.

4. Conclusions

This paper has used an ECG data set and a BP data set to show multiple continuous wavelet analysis techniques that can be used at Matlab's command line or using Matlab's GUI. When signals are dynamic over time, it is advantageous to use wavelet analysis instead of Fourier analysis. Wavelet analysis is able to maintain temporal characteristics whereas Fourier analysis removes the temporal characteristics.

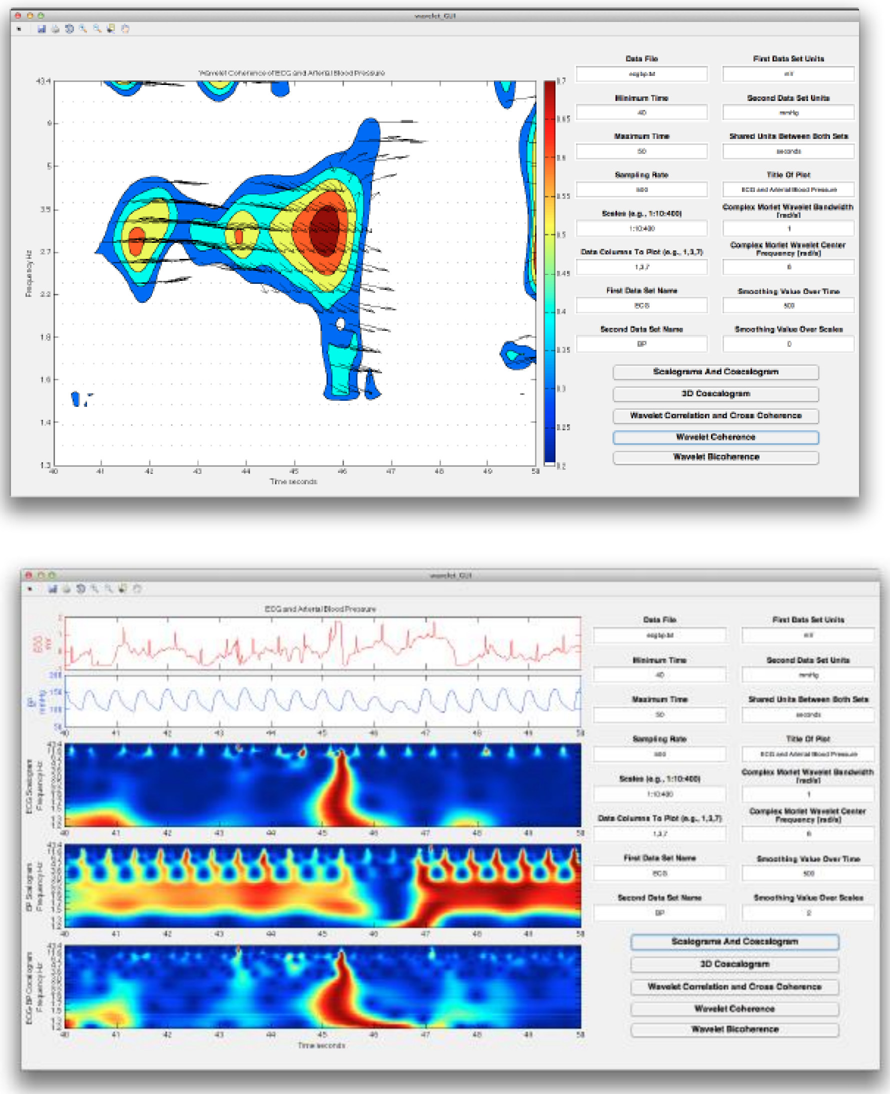

Fig. 5. Screenshots of GUI plots: time series data, scalograms, coscalograms (upper), wavelet coherence (lower)

It has been pointed out that these multiple techniques reveal interaction dynamics of time-varying signals (e.g., ECG and BP time series signals) and how they can be correlated both in amplitude and phase along with phase coupling and non-linear interactions. Analysis results presented in Figures 1 and 2 show strong coherence between the ECG and BP signals, both in amplitude and phase, and document the necessity to determine the time shift or delay between the investigated signals in order to show more consistent correlation of visible events.

Besides the fact that using the genetic algorithm it was possible to determine the delay and align the corresponding events, the obtained results may be of interest to determine different time delays in the human system in order to investigate differences between ill an healthy people and actually to diagnose a particular disease.

Acknowledgements

This research was supported by the grant awarded by the Polish-Japanese Academy of Information Technology, Warsaw, Poland.

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