

First Heart Sound Detection Methods

A Comparison of Wavelet Transform and Fourier Analysis in Different Frequency Bands

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Keywords: First Heart Sound, Respiration, Stroke Volume, Correlation, Wavelet Transform, Fourier Analysis.

Abstract: Methods of heart sound pre-processing are compared in this study. These methods are wavelet transform and Fourier analysis in different frequency bands. After pre-processing, the first heart sound was detected. Correlation of the first heart sound with respiration was chosen, as a sign of optimal detection. The results are demonstrated in a study of 30 volunteers. Optimal band selection for heart sound filtering is shown to be strongly individual, and is far more important than selecting Fourier analysis or wavelet transform as filtering method. Correlation with respiration proved to be a good sign for first heart sound detection evaluation.

1 INTRODUCTION

Evaluation of heart sound has been used for diagnosis for a long time. Despite advances in ECG it still has the potential to provide a cost-effective technology for monitoring valuable information about the heart. Normally, the heart sound is made up of two separated sounds, the first and the second heart sound. Together, they are known as the fundamental heart sound (FHS). According to valvular theory FHS emanate from a source located near the valves. However, cardiohaemic theory says that the heart and blood are an interdependent system that vibrates as a whole (Smith and Craig 1988). When we focus on valvular theory, the first heart sound (S1) is caused by closure of the atrioventricular valves at the beginning of ventricular contraction, thus identifying early systole. The second heart sound (S2) is caused by closure of the semilunar valves at the end of ventricular systole. The time between S1 and S2 is known as left ventricular ejection time (LVET) or systole. LVET is an important parameter in number of applications such as computing left ventricular stroke volume (SV) according to (Bernstein and Lemmens, 2005; Cybulski, 2011). One possible way of computing SV is represented by equation (1). In addition to LVET, the maximum of derived thorax

impedance $dZ(t)/dt_{max}$, raw thorax impedance Z_0 , and a constant based on body weight, height and thorax volume V_{ITBV}/ζ^2 are also used for SV calculation. When we realize that the changes in Z_0 value are minimal, there are just two parameters that influence SV, namely $dZ(t)/dt_{max}$ and LVET. Accurate detection of S1 and S2 is therefore crucial for correct definition of LVET and SV.

$$SV = \frac{V_{ITBV}}{\zeta^2} \sqrt{\frac{dZ(t)/dt_{max}}{Z_0}} LVET \quad (1)$$

Heart sound is a highly non-stationary and complex signal. S1 consists of two main components, the closure of the mitral valve (M1) and the closure of the tricuspid valve (T1) (Debbal and Bereksi-Reguig 2008), as shown in Figure 1. S1 has quite a stable position within the R-R interval. It is located from the R-wave + 5 % of the R-R distance to the R-wave + 20 % of the R-R distance, abbreviated to 0.05R-R to 0.2R-R (El-Segaier *et al* 2005). Information concerning the spectrum of the S1 is not clear in the literature. One source claims the spectrum is in the interval 50–150 Hz (Abdelghani and Fethi 2000), another source claims 20–150 Hz (JiZhong and Scalzo 2013).

Many studies have tried to find a successful automated heart sound classification algorithm. The

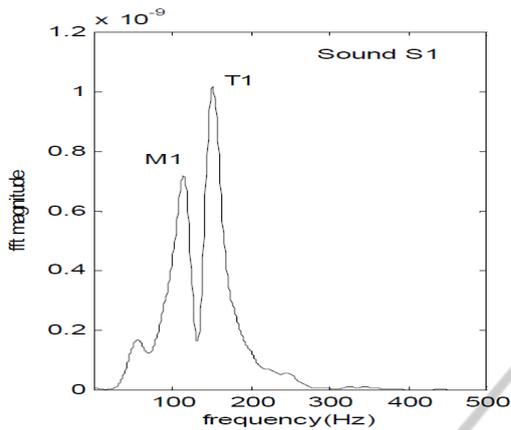


Figure 1: Spectrum of S1 (Debbal and Bereksi-Reguig 2008).

most frequent contributor to their success is robust and reliable detection of fragments making up heart sounds. These fragments include FHS, heart

murmurs and extra heart sounds – third and fourth heart sounds. Pre-processing techniques used include wavelet transform (Xinpei *et al* 2009) and the use of Fourier analysis (El-Segaier 2005).

This study focuses on filtering techniques that prepare heart sound for the detection of S1 in an optimal way. The study compares the use of Fourier analysis and wavelet transform in a number of bands and decompositions.

2 METHODS

The study presented was performed on 30 volunteers in good health. During the experiment, the volunteers were in the supine position. ECG, heart sound and thorax bioimpedance were measured continuously. Two types of breathing were measured; the first was 10-second period breathing

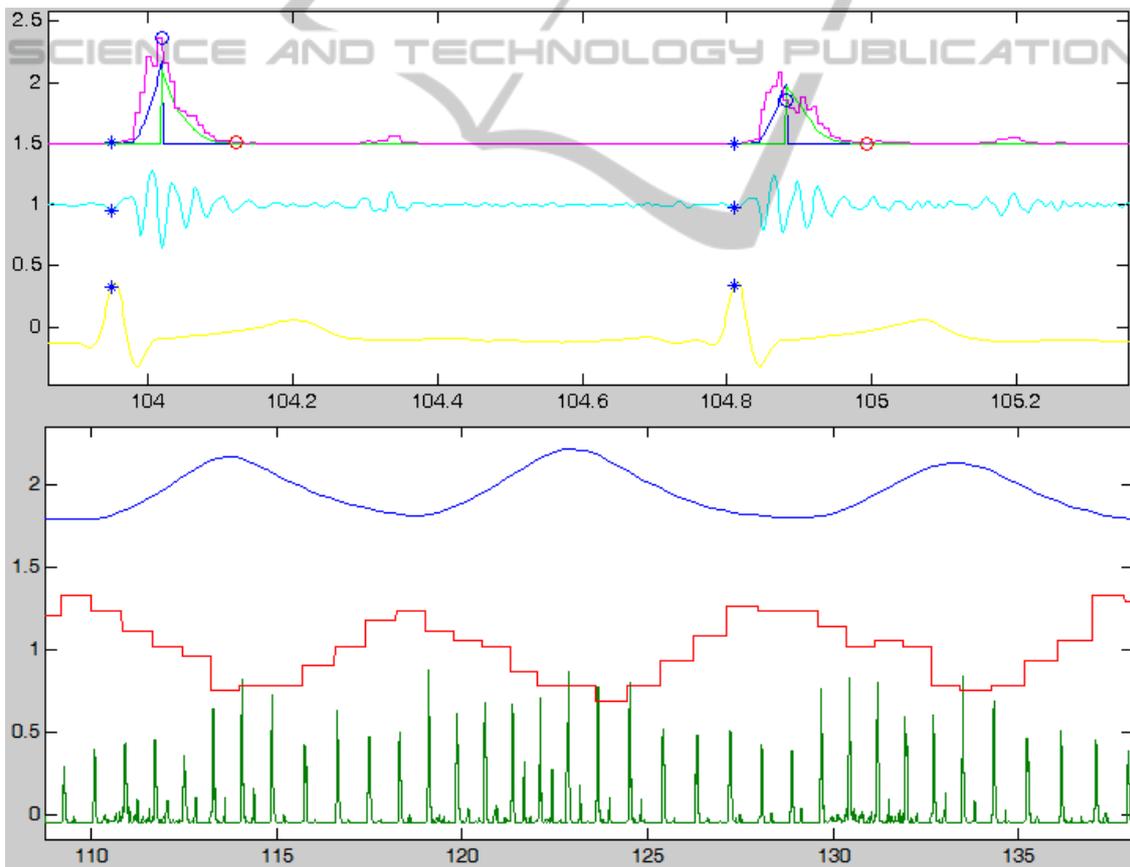


Figure 2: Upper part of the figure: 20-80 Hz envelope (magenta) of the heart sound with integrals (blue, green) representing gravity center computation, next, heart sound filtered in band 20-80 Hz (cyan) and the last ECG (yellow). Blue asterisk represent R-wave position, red circle is 20% of R-R interval, blue circle is centre of gravity or S1. The lower part of the figure represents respiration curve (blue), next R-S1 function (red) and the last one heart sound envelope (green) of volunteer number 55 during short part of deep breathing. The x-axis represents time in seconds. Time scales differ between the upper and the lower part of the figure.

and lasted 5 minutes, it was referred to as deep breathing. At the end of this exercise, the volunteers were asked to breathe normally. The second type of breathing was recorded after 2 minutes of rest. This type was referred to as spontaneous breathing and was also recorded for 5 minutes. Spontaneous breathing records the normal breathing of the volunteer. The heart sound was recorded using a microphone held in place by an elastic bandage. It was measured with a sampling frequency of 500 Hz. An example of heart sound filtered in the 20–80 Hz band can be seen as the second curve in the upper part of Figure 2 coloured cyan. The R-wave was detected from the ECG signal. It was used as a reference for S1 detection. Thorax bioimpedance was filtered with a low-pass filter with a cut-off frequency at 0.8 Hz. This produces a curve representing respiration. Impedance was used only for extracting the respiration curve. The respiration curve can be seen in the lower part of Figure 2, third from the bottom, coloured blue.

This study evaluates combinations of filtering techniques and frequency bands. Stages involved in filtering techniques evaluation are depicted in Figure 3. At the beginning, heart sound was filtered. The first type of filtering technique was Fourier analysis. For this purpose raw heart sound signal was filtered with a band-pass filter. Filtering was performed in Matlab environment (MATLAB 2009) by eliminating frequencies outside of the pass band using *filtfilt* function. Transitional parts after filtering at the beginning and at the end of the signal were excluded from the signal. As cut-off frequencies for signal filtering, all combinations of low cut-off frequencies: 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 Hz and high cut-off frequencies: 10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 80, 100, 120, 150 Hz were used. A table with all these combinations can be

seen in Figure 4. The upper two tables represent filtering using Fourier analysis, with a bottom band cut-off frequency in the leftmost column. The upper cut-off frequencies are in the first row. For example band pass filter with low cut-off frequency 20 and the high cut-off frequency 80 is located in the fifth row marked with 20 and the twelfth column marked with 80. The second type of filter used was wavelet transform in which filter banks from the Daubechies family, numbers 4 and 14 (db4, db14) were used. A filter bank from the Coiflet family, number 2 (coif2) was also used. They showed the best results during the initial phase of this study and were also evaluated by a previous study (Messer *et al* 2001). Wavelet transform decomposed the signal into a 5 level details. Again, Matlab environment (MATLAB 2009) was used for signal decomposition, namely function *swt*. The spectrum of the first level detail corresponds to approximately a band of 125–250 Hz, the second detail level to 62.5–125 Hz, the third detail level to 31.25–62.5 Hz, the fourth detail level to 15.5–31 Hz and the fifth detail level to 8–15.5 Hz. The signal is reconstructed by summing detail levels. Let $x_1^d(n)$, $x_2^d(n)$, $x_3^d(n)$, $x_4^d(n)$ and $x_5^d(n)$ be the detail levels of the original signal $x(n)$. Reconstructed signal x' is then

$$x'(n) = \sum_{i=l}^h x_i^d(n) \quad (2),$$

where $l \in \langle 1,5 \rangle$, $h \in \langle 2,5 \rangle$, $l \leq h$. The equation (2) is the sum of details ranging from the lowest detail $-l$ to the highest detail $-h$. Note, that the highest and the lowest detail can be of the same level and that the highest detail of the sum is greater than the lowest. All the combinations from the equation (2) were used for the signal filtering. These

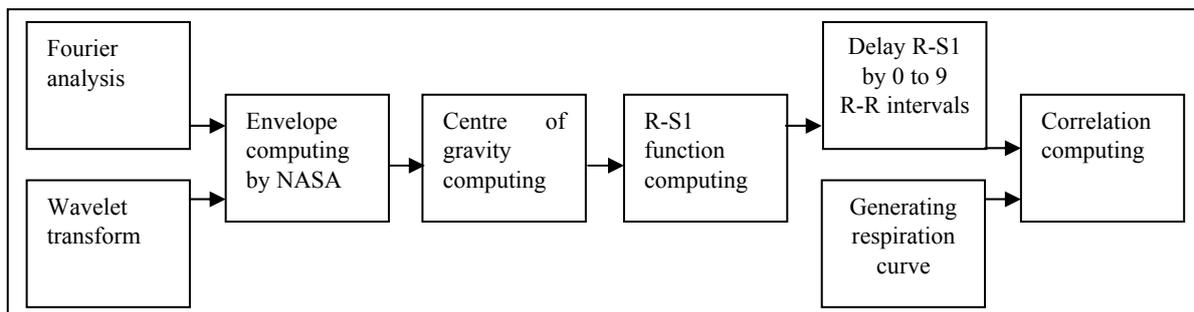


Figure 3: Block diagram with steps involved in comparing filtering techniques. First, heart sound was filtered using Fourier analysis or wavelet transform. Next, envelope was computed using NASA (normalized average Shannon energy detection algorithm - equation (3)) and then centre of gravity (S1) of interval starting from R-wave to the R-wave + 20 % of the R-R distance, abbreviated <R, 0.2R-R> was computed. S1 distance from R-wave was determined for every R-R interval, thus creating R-S1 function. R-S1 was delayed from 0 to 9 R-R intervals towards respiration and then R-S1 was correlated with respiration curve.

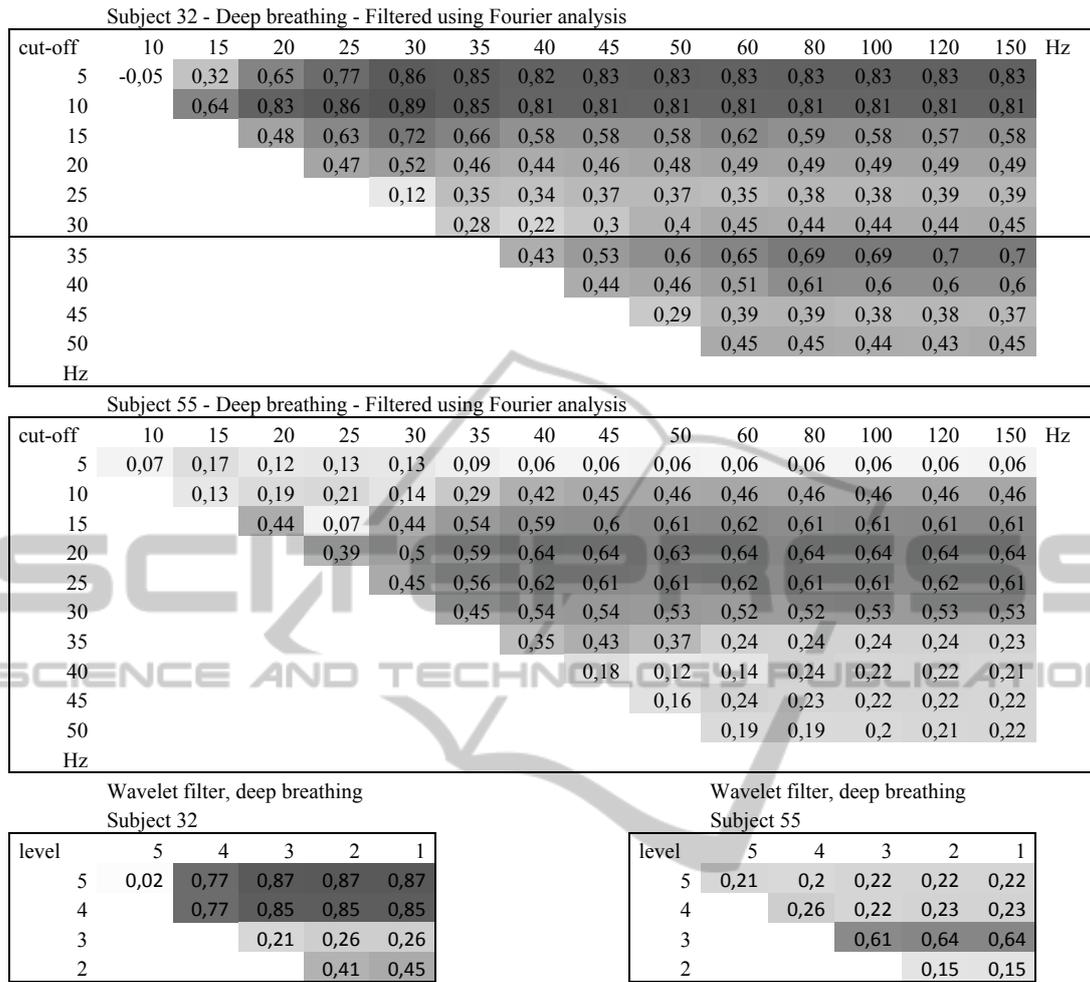


Figure 4: Numbers in the tables represent correlations between R-S1 function and respiration of volunteers number 32 and 55 after heart sound was filtered with a band-pass filter using Fourier analysis with low cut-off frequency from first column and high cut-off frequency from first row in upper two tables. Lower two tables represent the same correlations after summing wavelet detail levels ranging from the lowest detail from first column to highest detail from first row.

combinations can be seen in the lower part of Figure 4. For example, the sum of details 5, 4, 3 used for signal reconstruction are located in row marked with 5 in the table representing the highest detail, and column marked with 3, representing the lowest detail used in the sum. Another example, single detail 2 used for reconstruction, is in row 2 (highest detail) and in column 2 (the lowest detail of the sum). After the signal had been filtered, an envelope was computed using a normalized average Shannon energy detection algorithm (NASA) (3),

$$E_{hs} = \frac{1}{N} \sum_{i=1}^N |x(i)|^3 \log|x(i)|^3 \quad (3)$$

The envelope of heart sound can be seen as the first curve in the upper part of Figure 2 and the very

bottom curve in the lower part of Figure 2. The second one is significantly squeezed, which can be observed on the x-axis representing time. Next, in interval starting from R-wave to the R-wave + 20 % of the R-R distance, abbreviated $\langle R, 0.2R-R \rangle$, the centre of gravity was computed. Computation of the gravity centre is depicted in Figure 2, the first curve in the upper part of the figure. Integrals of the envelope were computed from the left and right side of the interval $\langle R, 0.2R-R \rangle$. Particular integrals are also depicted in the same place as the envelope with the blue and green colour. The point at which these integrals have the same value was found. This point was declared the centre of gravity and was also S1.

We assume that if S1 was detected correctly then it should correlate with respiration. For every R-R interval we computed the mean value of the

respiration curve and also the R-S1 distance which is the distance between the R-wave and the detected S1. The R-S1 function can be seen as the second curve from the bottom in the lower part of Figure 2. When we look at the R-S1 function and respiration in the lower part of Figure 2 it is clear that they are shifted in respect of each other. Therefore, we delayed the R-S1 curve towards the respiration curve in 10 steps, always by one R-R interval. In this way, we had 10 R-S1 curves, delayed from 0 to 9 R-R intervals. Next, we computed correlation with all 10 R-S1 functions and R-R segmented respiration curve as a sign of good or bad detection capability for the given filter. We found the highest of the 10 correlation coefficients and declared it the correlation between R-S1 and respiration for the given filter.

3 RESULTS

We assume that the higher the correlation, the better the detection of S1. Correlation for spontaneous and deep breathing was computed separately for each volunteer. Correlations were entered into the tables as shown in Figure 4. This figure shows the results for volunteer number 32 and volunteer number 55 for deep breathing after filtering using Fourier analysis in the upper part of the figure and after filtering using wavelet transform at the bottom of the figure. The values of the correlations are coloured for better orientation in the tables. Values are coloured with a grey scale ranging from 1 –darkest to 0 –white.

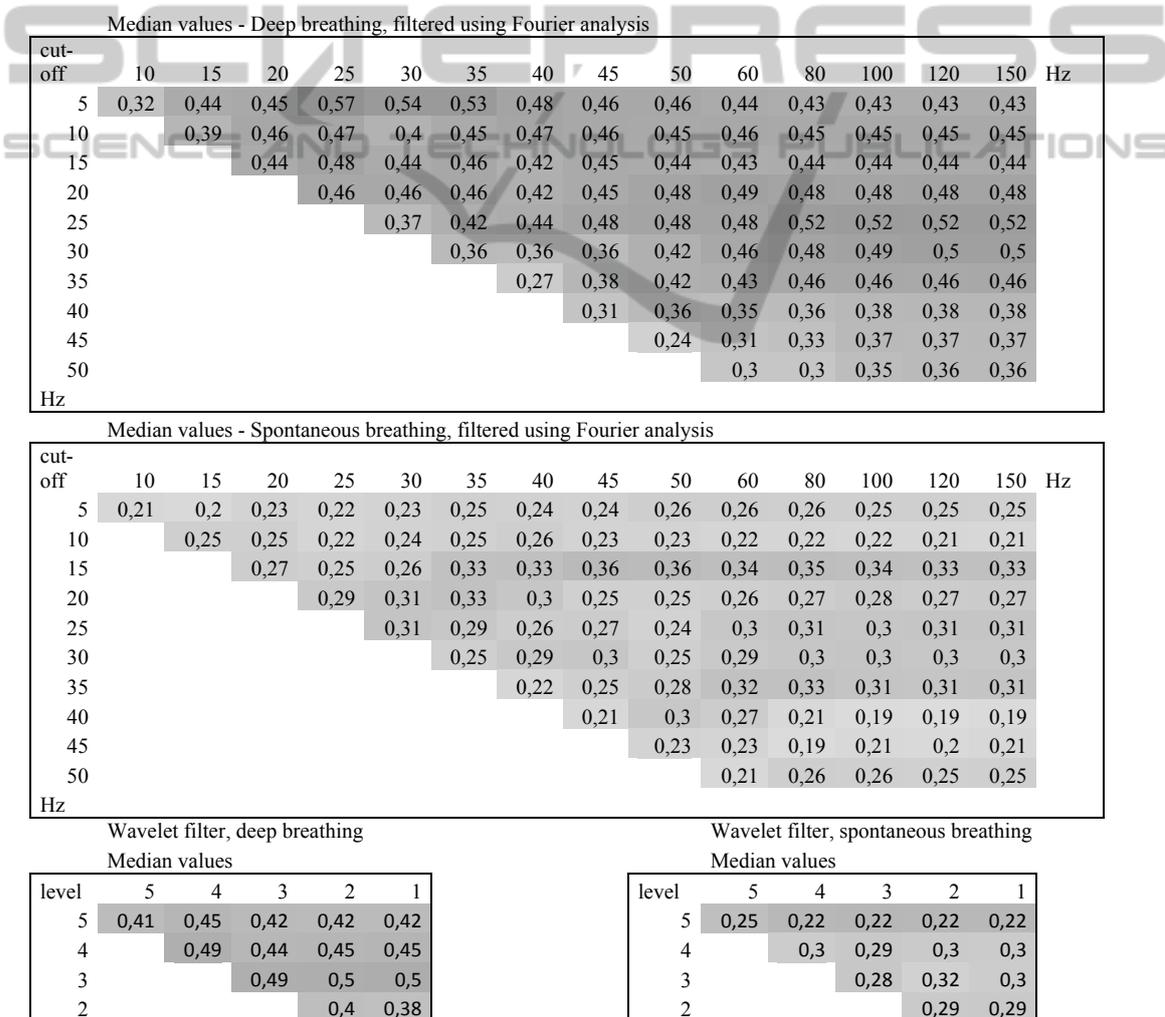


Figure 5: Numbers in the tables represent median correlations between R-S1 function and respiration of all 30 volunteers after heart sound was filtered with a band-pass filter using Fourier analysis with low cut-off frequency from first column and high cut-off frequency from first row in upper two tables. Lower two tables represent the same correlations after summing wavelet detail levels ranging from the lowest detail from first column to highest detail from first row.

4 CONCLUSIONS

As can be seen in Figure 4, individuals have different frequency bands in which they correlate with respiration. This is true for both deep and spontaneous breathing. As can be seen in Figure 5 median values of correlations do not reach significantly higher values in any particular areas as compared to the rest of the table, which strengthens the claim that the spectrum of S1 that correlates with breathing is highly individual for each volunteer. We can say that for each volunteer there is a frequency band in which heart sound correlates significantly with breathing. If we compute median of maximum correlations of all volunteers across all the bands, we get a median correlation of 0.718 for deep breathing and 0.585 for spontaneous breathing. We can now say that R-S1 correlates with respiration for some filter for each volunteer. Another piece of information gained from this study is that deep breathing produces larger values of correlation than spontaneous breathing. When we compare wavelets and Fourier analysis, wavelets are not so sensitive in selecting the optimal band, while the advantage of Fourier analysis is its capability to tune bands more precisely. Filter banks db4, db14 and coif2 did not produce very different results when compared to each other. On the basis of this study, we can say that Fourier analysis is sufficient for heart sound pre-processing. The crucial thing here is appropriate frequency band selection for each individual. Computing correlation with respiration proved to be good sign for correct S1 detection. Further study would be beneficial for S2 and also for LVET detection.

ACKNOWLEDGEMENTS

This work was partially supported by grant no. P102/12/2034 from the Grant Agency of the Czech Republic and by the European Regional Development Fund – Projects FNUSA-ICRC CZ.1.05/1.1.00/02.0123

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