IEEE Second International Conference on Data Stream Mining & Processing
August 21-25, 2018, Lviv, Ukraine

Segmentation and Parametrization of the Phonocardiogram for the Heart Conditions Classification in Newborns

Ihor Shelevytsky
Faculty of Information Technologies,
Kryvyi Rih Institute of Economics
Kriviy Rih, Ukraine
sheleviv@gmail.com

Victorya Shelevytska
Faculty of Postgraduate Education,
Dnipropetrovsk Medical Academy of Health
Kriviy Rih, Ukraine
shelevika@gmail.com

Vlad Golovko
Faculty of Information Technologies,
Kryvyi Rih Institute of Economics
Kriviy Rih, Ukraine
golovkovlad@gmail.com

Bogdan Semenov
Institute of Information Diagnostic Systems,
National Aviation University
Kyiv, Ukraine
SemenovBS@gmail.com

Abstract — **Phonocardiographs are analyzed for diagnostics of heart conditions in newborns. The algorithms of allocation of heart tones and selection of stationary periods on phonocardiograms are proposed. Dedicated heartbeats can be parameterized in different ways. The first set of parameters characterizes the shape and the time-amplitude features. The second set of parameters is the coefficients of the frequency-time decomposition of cardiac cycles with spline bases. This approach allows detecting of the Patent ductus arteriosus (PDA) by machine learning methods. Software for phonograms analysis has been developed.**

Index Terms — **Machine Learning; detection of the Patent ductus arteriosus; algorithms for segmentation of phonocardiograms; parametrization of phonocardiograms; classification of phonocardiograms**

I. Introduction

Echocardiographic ultrasonography is the classical approach to the heart defects diagnosis. However, this is a costly and long-term analysis that cannot cover all newborns. An alternative method is the electronic auscultation with the computer analysis of phonocardiogram (PCG). Studies [1] show that the accuracy of the diagnosis of congenital heart disease (CHD) by this method is more than 95%.

Children are born with the Patent Ductus Arteriosus (PDA), which should be closed by the third day. However Ductus Arteriosus remains open after the third day for the small part of newborns [2]. This case requires detailed echocardiography and observation as it may indicate a heart disease. Auscultation in newborns can be difficult due to the presence of movement sounds, breathing and crying of the baby. So the pre-selection of audio recordings is required to highlight high quality fragments. The basic algorithms for PCG analysis are the allocation of heart tones and heart cycles and the following parametrization for classification using methods of machine learning. In [3] different signal norms are used to allocate tones. However, in practice, the recordings are low quality. Therefore, for acceptable tone allocation, more sophisticated algorithms are required. It is important to take into account a priori information. For analysis and classification of PCG various methods of frequency-time analysis and parametrization are used [4]. There are two main approaches. The phonocardiogram is analyzed as a normal sound signal. Or phonocardiogram is analyzed be parameters specific for the nature and features of such signals. Determining the parameters with a clear interpretation associated with heart is more interesting for doctors and scientists. This makes it possible to understand the dependence of the sound phenomena on the work of the heart. In the paper both approaches are applied. The set of parameters of tones and intervals between them is determined and the frequency-time decomposition of heart cycles in spline bases is performed. Based on both methods, the classification of phonocardiograms according to patterns is performed to detect Patent Ductus Arteriosus.

II. Input data

The recording of the phonocardiography is performed sequentially at five standard auscultation points, 5-10 seconds at each. An electronic stethoscope Thinklabs Model ds32a + in sound amplification mode and narrowed listening sector was used for recording. The recording was performed with a Sony-ICD-UX71 digital voice recorder at a frequency of 44.1 kHz in high quality and stored in MP3 format. A typical image of the medium quality phonocardiogram is shown in Fig. 1. The records at the auscultation points are rather heterogeneous and contain sounds of breathing, newborn movements and manipulations with the stethoscope. PCG consists of heart cycles that include the first tone, the interval between the first and second tones, the second tone, the interval between the second and the first tone. First of all for the analysis of PCG it is necessary to allocate tones of the heart. Automatic segmentation of signals at points allows to select fragments of records by intervals between them. However, this is not enough for qualitative analysis. It is difficult to achieve high-quality allocation of tones without intervals and to detect the false ones.

Therefore, the selection of fragments for the analysis of tones depends on the doctor or the operator who performed the recording. The criterion in this case is the visual homogeneity of the recording and the absence of foreign sounds. The sequence should include more than six cardiac cycles. This is a quite simple operation that requires minimal training and practice.

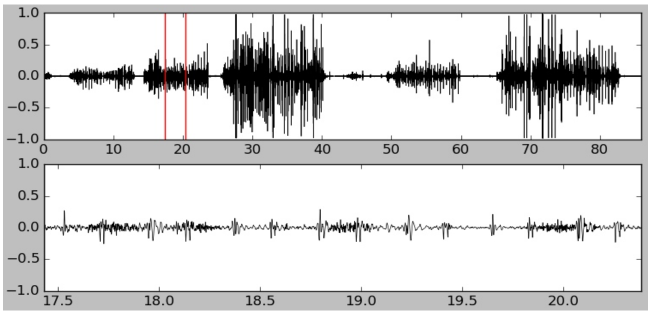

Fig. 1. The typical medium quality neonatal phonocardiogram. Top graph is the recordings at five points. Bottom graph is the selected fragment of the record at the second point.

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III. Tone allocation algorithm

The task of tones allocation requires a compromise between smoothing and sensitivity to the tone boundaries. The task was to achieve subjectively correct allocation of tones for various signal quality. Empirically, the following algorithm for tones allocation was developed.

Algorithm 1: tone seek (x)

1. Decimation of the signal module $|x|$ *in 125 times to the sampling frequency of 352.8 Hz.*

2. Low-pass filtration of the signal to the frequency of 35.28 Hz.

3. Calculation of the energy of x^2 *and normalization with respect to the maximum energy* $s = x^2/max(x^2)$

4. Determination the ranked mean and variance:

to sort $z = sort(s)$; *m=mean(z(0.1n:0.9n)); σ=std(z(0.1n:0.9n))*

5. Finding local maxima exceeding the detection threshold: 3m

6. Finding the boundaries of waves to the right and to the left of the maxima at points crossing the threshold of the lateral boundaries: m+6σ

7. Analysis of energy waves, for each wave:

if the maxima are within the boundaries of the wave then leave the highest maximum

if the distance between the waves is less than 14 ms then combine them into one wave

if the distance between waves is greater than 60 ms then it is the next wave

8. Wave selection by width:

if the wave is shorter than 17 ms then remove it

otherwise leave it as a heart tone

9. Finding the most stable fragment in 5 heart cycles:

for all 5 heart tones windows determine the sum of dispersion of the width of the tones and the intervals between them

define the window with the smallest variance for analysis

10. Determination of the number of the starting tone:

to calculate the average width of even and odd tones

if the average width of even tones is greater than the average width of the odd ones, to shift the original tone to the even one

11. List the tone indexes into the indexes of the initial data (multiply by 125 and take into account the delay of the filtration).

Figure 2 shows an example of the tones allocation with the help of the algorithm, and Fig.3 shows the result of the tones allocation.

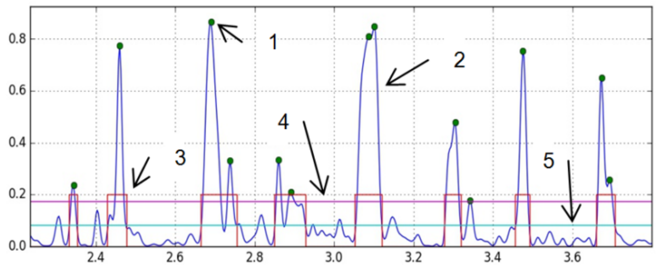

Fig. 2. PCG energy waves and tone allocation scheme. 1 - points of maxima, 2 signal energy, 3 highlighted tones, 4 thresholding, 5 threshold level of side borders of tones.

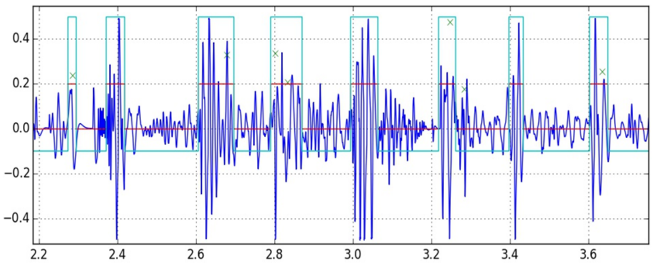

Fig. 3. PCG selected tones along with the signal.

The proposed algorithm confidently highlights the tones in the records of different quality.

IV. Parametrization of tones and intervals

The first and the second heart tones have the similar structure, so let us apply the same parameters and recognition algorithms for both of them. Indicators that characterize the shape and features of tones in the time domain are selected as the tone parameters. After the low-frequency filtration by the non-recursive digital filter with a cutoff frequency of 4410 Hz, the search for the special tone points follows. That are maxima, minima, fractures (discontinuity of the first derivative), and zero values. Figure 4 shows the result of the identifying special points.

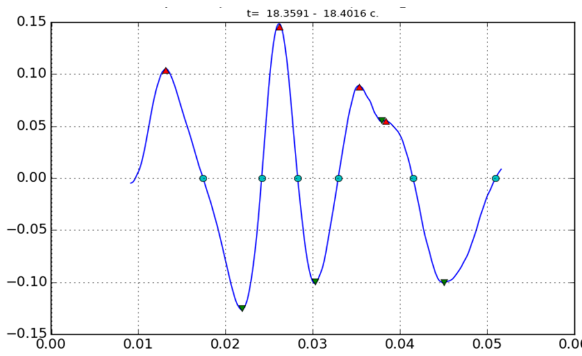

Fig. 4. Heart tones analysis: minima, maxima and zeros

The following tone parameters are calculated based on the selection of the tone and its points.

General parameters: energy – energy of the tone (sum of squares of the signal); width - width of the tone; max_t - position of the maximum of the signal module; max_a - value of the maximum of the signal module; skewnes - the asymmetry of the module maximum (max_t/width)-0.5; n_broken - the number of points in the fracture.

Parameters of the maxima: n_max - number of maxima; t_max - maximum position; a_max - maximum value; mean_t_max - average time position of maxima; std_t_max - standard deviation of the time position of the maxima; mean_dt_max - the average value of the intervals between maxima; std_dt_max - the standard deviation of the distance between the maxima.

Parameters of minima: n_min - number of minima; t_min – minimum position; a_min - minimum value; mean_t_min - average time position of the minima; std_t_min - standard deviation of the time position of the minima; mean_dt_min - the average value of the intervals between the minima; std_dt_min - standard deviation of the distance between the minima.

Parameters of zeros: n_zero - number of zeros; mean_t_zero - mean value of time coordinates of zeros; std_t_zero - standard deviation of time coordinates of zeros.

Signals at intervals between tones are not clear. They have the character of random noise, sometimes with periodic components. Therefore, the parameters for the intervals analyze the shape and intensity of this noise. Therefore the interval is divided into four fragments and the parameters are defined on the interval as a whole and on each of the fragments. Also, the module of the signal values on the interval is approximated by the method of least squares to obtain the coefficients of the polynomial characterizing the shape of the envelope.

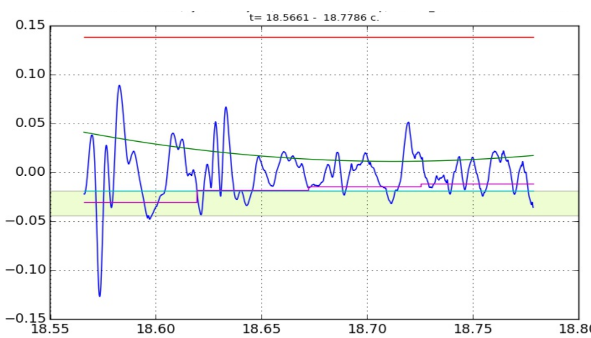

Fig. 5. Analysis of the intervals between the tones.

Parameters of the interval: width - width of the interval; n_zero - number of zeros of the interval; frq_zero – frequency of zeros; energy(m) - signal energy at the interval; energy1, energy2, energy3, energy4 - energy at fragments of the interval; mean - average amplitude; mean_1/4, mean_2/4, mean_3/4, mean_4/4 - average amplitudes at fragments of the interval; std - standard deviation; std_1/4, std_2/4, std_3/4, std_4/4 - standard deviation of the fragments; a2, a1, a0 are the coefficients of the approximation parabola of the amplitude on the interval a2 * x ^ 2 + a1* x + a0.

V. TIME-FREQUENCY ANALYSIS OF HEART CYCLES

Another approach to the analysis of heart cycles is the time-frequency decomposition of the allocated intervals. To perform the decomposition the sampling frequency has been reduced by 25 times to 1764 Hz. Usually for such decomposition the wavelet transform is used. In this paper, application of decomposition in the bases of Hermite splines with the estimation of the coefficients of approximation by the least squares method is proposed. Let's look at the process of the time-frequency decomposition in the operator form. The basic spline consisting of four fragments is $B_{\tau,\vartheta}(t)$, with τ as the offset of basis relative to the initial spline, ϑ as the scale coefficient of the basis relative to the widest one.

The basis can be written as:

$$B_{\tau,\vartheta}(t) = B_0\left(\frac{t-\tau n}{\vartheta}\right), \vartheta \in R^+, \tau = 0, \pm 1, \pm 2, \dots .$$

Let's denote obtained least square estimates of the signal $x(t)$ in the system of basis functions B_ϑ as LS. The vector of estimates (decomposition coefficients) in the ϑ scale is:

$$A_\vartheta = LS[x(t), B_\vartheta], \quad X_\vartheta = IN[A_\vartheta, B_\vartheta].$$

Approximation residuals can be denoted as RS, and the process of obtaining the residues of least square approximation as $E_\vartheta = RS[x(t), B_\vartheta]$.

In operator form, the decomposition can be written as follows:

$$A_{\vartheta_0} = LS[x(t), B_{\vartheta_0}], \qquad E_{\vartheta_0} = RS[x(t), B_{\vartheta_0}],$$

$$A_{\vartheta_k} = LS[E_{\vartheta_{k-1}}, B_{\vartheta_k}], \qquad E_{\vartheta_k} = RS[E_{\vartheta_{k-1}}, B_{\vartheta_k}],$$

$$k = \overline{1, K}.$$

As the result of the decomposition we have the vector of least squares estimates and the vector of approximation residuals at the last stage of the decomposition:

$$\Omega = \{A_{\vartheta_0}, A_{\vartheta_1}, \dots, A_{\vartheta_K}, E\}, \text{ де } E = E_{\vartheta_K}.$$

Together with the coefficients of the decomposition we also have the value of the mean square deviations of the coefficients. However, it is difficult to apply the decomposition coefficients directly for the classification task, due to the different duration of cardiac cycles and their components in newborns. This requires the ways to scale up the obtained spectrograms.

VI. RESULTS OF THE ANALYSIS

PDA diagnostic method by the PCG has been developed. In the framework of the HeartTone project, records of phonocardiograms in newborns with further ultrasound heart examination have been performed. For the processing and analysis of phonocardiograms, two versions of the

HeartTone-D program have been developed. The desktop version for detailed research is a tool for researchers. Another, WEB version of the "HeartTone-W" program is designed for the operative work of doctors.

The investigated group consists of 195 healthy newborns. No structural abnormalities in the heart and large vessels were prenatally detected. Newborns were examined from the first to the 5th day of life. The group of interest was newborn babies with an open arterial duct without structural anomalies of the heart. No abnormalities were detected for these children with a traditional (on hearing) auscultation. For the preliminary computer analysis, 27 audiograms of newborn babies with functioning arterial duct and 28 audiograms of newborns with not functioning arterial duct has been selected. In order to diagnose the CHD by the heart phonocardiograms, the binary classification using the support vector machines (SVM) with the Gaussian radial basis function has been used. The methods of machine learning of the scikit-learn package has been used to set up the support vector method. To choose the parameters for classification we rely on the maximum of the t-criteria for the parameters of cycles of phonocardiograms with PDA and without PDA. It turned out that the most statistically significant are the heart tones parameters at the second point of hearing. These are the parameters of the I and II tone - max_a (maximum amplitude of the I tone), a_min (the minimum amplitude of the II tone), the parameters of the intervals between the tones: m1_mean (average amplitude module of the first interval), mean_4/4 (the average amplitude module of the last fragment of the second interval), width (the width of the second interval). The parameters were normalized by bringing the deviations to the range -1, +1 from the mean values. The best values of the parameters gamma = 8, C = 7 have been found by the grid method. The learning of the algorithm took place on the sample, which included 128 periods of the heart tones at the second point without the PDA and 138 periods with the PDA. To evaluate the accuracy of the method, a nine-fold cross-check test with random sampling of 20 clusters has been used. In summary, the SVC classifier has been obtained with the following statistical characteristics: accuracy (ACC) 87.9% $\sigma = 1.1\%$, sensitivity or true positive rate (TPR) 83.3% $\sigma = 1.6\%$, specificity or true negative rate (TNR): 91.0% $\sigma = 1.3\%$.

The obtained classification results are preliminary, performed for a rough estimation of the possibilities of the proposed method, and require the further refinement on large samples and comparison with the classification method according to the data of the time-frequency decomposition.

VII. CONCLUSIONS

An algorithm for the allocation of heart tones on low-quality phonocardiograms and a significant variety has been developed. It allows allocating tones for 55 real audiograms in newborns in the automatic mode.

Indicators characterizing the shape of the tones and the intervals between them for interpretation and classification of phonocardiagrams have been proposed. Indicators are determined on 5 cardiac cycles at 5 heart tone points.

The time-frequency analysis of heart cycles in spline bases with the estimation of the decomposition coefficients by the method of least squares has been shown. The decomposition coefficients allow visualizing of the spectrogram and reducing the classification problem to the image recognition. However, practical implementation requires experiments with scaling of the decomposition.

The software that implements the described algorithms in Python language for the desktop and WEB has been developed.

The method of detecting the PDA in newborns by parametrization and classification by the method of support reference vectors has been proposed. It shows the accuracy of 87.9% on the given samples.

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