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Preliminary study: mobile phone as a phonocardiographic signal recorder

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***Abstract*—The aim of this paper is to analyze the possibility of using a mobile phone with a voice recorder function as a phonocardiographic signal recorder. Test measurements were carried out by placing the phone at various points on the chest. For one selected point, measurements were carried out for a group of 120 people, using different models of mobile phones. Data on weight, height and age were collected through a survey. Participants of the study were also asked about diagnosed heart defects and potential problems related to the measurement. Signal quality was assessed using quality parameters. It was checked how the selected methods of signal pre-processing (editing of recordings, filtering) affect the values of quality parameters. The obtained recordings were subjected to automatic signal classification.**

The result of this work is an extended analysis of the use of mobile phones as electronic stethoscopes and an analysis of the usefulness of signals obtained using this measurement method. The results of these studies are important for the field of medical diagnostics, especially in situations where access to traditional stethoscopes is limited. If mobile phones prove to be effective recorders of phonocardiographic signals, it will open new possibilities in the field of remote heart monitoring and telemedicine. However, it should be noted that further research, including validation and comparison of results obtained with mobile phones with those obtained with traditional stethoscopes, is needed before this technology is introduced into clinical practice.

***Keywords*—phonocardiography; signal processing; acoustics**

I. Introduction

A. PCG signal

Phonocardiography [1] (PCG) is a non-invasive diagnostic technique in the field of cardiology that enables the recording and analysis of acoustic signals generated by the heart during the cardiac cycle. It is the process of acquiring heart sounds using highly sensitive sensors such as microphones or piezoelectric sensors and processing them using signal processing techniques. During phonocardiography, heart sounds are recorded to assess the function and structure of the heart and detect possible abnormalities. During the cardiac cycle, valve movements and blood flow within the heart generate characteristic sounds such as heart sounds and additional murmurs and pathological murmurs. These sounds contain information about heart function, the presence of heart defects, valvular diseases and other cardiac diseases. Phonocardiography can be used as a stand-alone test, as a preliminary test or as a complement to other diagnostic tests such as electrocardiography (ECG) or echocardiography.

B. PCG signal analysis

Cardiac sounds are assessed for their time, frequency and strength characteristics [2,3].

1) First tone (S1):

- The loudness of the heartbeat is mainly assessed, although a loud tone is not always pathological - it happens in slim people or with a fast heart rate. It may also indicate premature ventricular contractions or mitral valve stenosis.
- A very quiet tone occurs in obese people, with a barrel chest (in the course of Chronic obstructive pulmonary disease COPD) or emphysematous changes in the lungs. It may also be a symptom of heart failure, heart attack, first degree atrioventricular block or mitral valve regurgitation.
- Variable loudness of S1 occurs in second degree atrioventricular block.
- If splitting of the first tone is audible during auscultation, it may indicate complete right bundle branch block.

2) Second tone (S2):

- The main thing that is assessed is the split.
- Normally, the aortic valve closes slightly earlier than the pulmonary valve. The correct splitting of the second tone can be heard especially during inspiration.
- Rigid splitting of the second sound is a significant splitting that does not change during breathing, is already abnormal and occurs in atrial septal defect or advanced heart failure. If the wide splitting of the second sound deepens during inspiration, it may indicate, for example, a complete block of the right bundle branch. A split second tone occurs when the pulmonary valve is heard before the aortic valve and the split occurs during expiration. The most common causes: complete left bundle branch block, aortic valve stenosis, right ventricular pacing with a pacemaker.
- A single second sound occurs in elderly people with emphysematous changes in the lungs or with significant stenosis of the aortic valve or pulmonary trunk.
- The second heart sound may be louder in people with hypertension.
- With stenosis of the aortic or pulmonary valves, the 2nd heart sound is quiet.

3) Third and fourth tones (S3 and S4):

- Tone S3 occurs physiologically in children and adolescents; is

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enhanced by physical activity and coughing. Tone S3 in adults is a serious symptom of heart disease leading to left ventricular failure. It sometimes precedes the occurrence of pulmonary edema.

- Tone S4, like the previous one, occurs in young, physically fit people. Tone S4 in adults, this is a disturbing symptom. It indicates severe hypertension, aortic valve stenosis, ischemic heart disease, hypertrophic cardiomyopathy or left ventricular hypertrophy.

4) Other sounds

The PCG signal may also include the so-called early diastolic clicks, which occur immediately after the first heart sound (S1). They occur when the aortic valve narrows or the aorta widens. Mid-systolic and late-systolic clicks may indicate mitral valve regurgitation caused by mitral valve leaflet prolapse.

The last type of sound that appears in the PCG signal are heart murmurs. They are audible when changing laminar blood flow to turbulent. Some murmurs are normal in children. However, many of them indicate pathological conditions. They may indicate, among other things, that:

- blood flow increases significantly, e.g. during fever, pregnancy, hyperthyroidism;
- the outflow tract is narrowed or blood flows into a dilated vessel;
- blood flows back due to incompetence of one of the valves;
- there are abnormal blood leaks, e.g. atrial septal defect.

This work focused on analyzing the quality of recorded heart sounds due to the quality of tones recording (mainly S1 and S2).

C. *PCG signal measurement methods*

Typically, an electronic stethoscope is used to measure the PCG signal, which is an extension of the standard stethoscope with the ability to convert an acoustic signal into an electrical signal. This is a professional solution addressed to medical staff, hence the price is often inadequate to the capabilities of the average patient. Hence, you can find proposals for cheaper stethoscope designs [4] or modifications of relatively cheap stethoscopes [5].

There have also been proposals to use a mobile phone to record the PCG signal. The phone can be used in two ways - as a signal recorder with a connected external microphone [6,7,8] or using the phone's built-in microphone [9,10]. The last method is particularly interesting due to the availability and popularity of mobile phones and the lack of need to use additional devices. Therefore, the question should be answered whether a potential patient is able to obtain correct recordings using an average phone, which could also be subjected to automatic classification algorithms.

D. *Paper arrangement*

Chapter II presents preliminary measurements carried out on one person at 5 measurement points on the chest. Chapter III presents the database of recordings obtained as part of the research. Chapter IV presents the results of quality assessment carried out using two methods taken from other studies. Chapter V describes the results of signal classification in terms of assessing whether cardiac abnormalities are detected. Finally, the conclusions are presented.

II. INITIAL TESTS

Initial tests were performed on one person (male, 31 years old, without heart defect). The phone with the voice recorder turned on was placed to the chest at 5 points as shown in the Fig. 1.

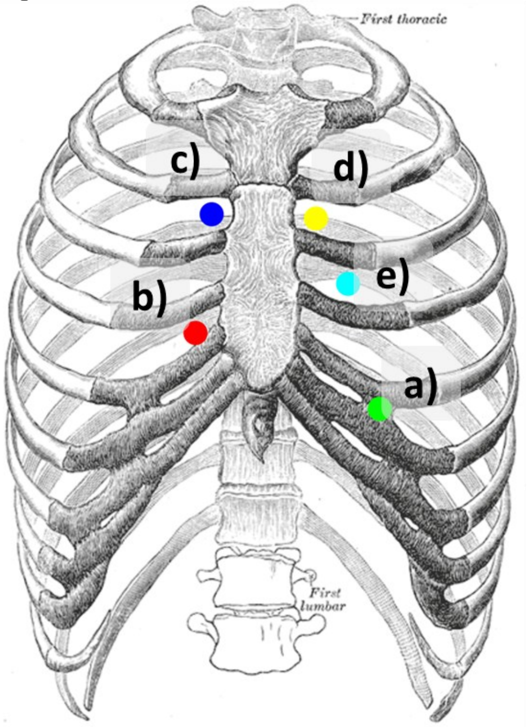

Fig. 1 PCG signal measurement points: a) green – mitral valve (bicuspid); b) red - tricuspid valve; c) blue - aortic valve; d) yellow - pulmonary valve; e) light blue - Erb's point.

Fragments of the time courses of the obtained signals are shown in Fig. 2.

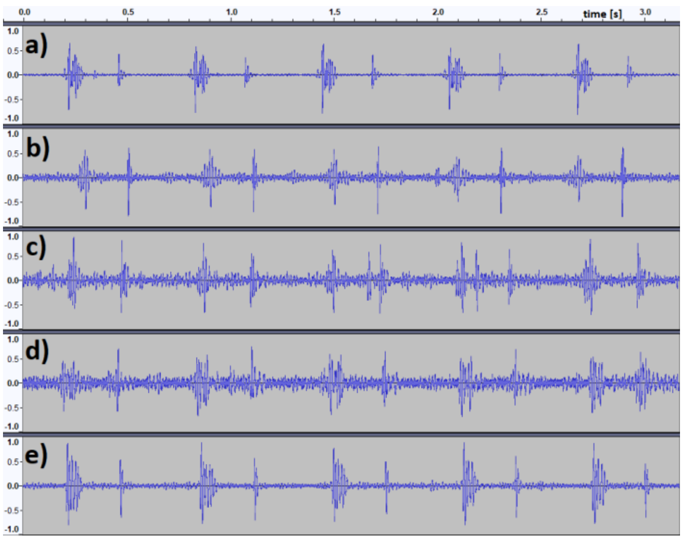

Fig. 2 Time courses of PCG signals recorded by phone at various points in the chest, a) mitral valve, b) tricuspid valve, c) aortic valve, d) pulmonary valve, e) Erb's point

The recordings presented were obtained on the first attempt without making repeated recordings. The heart sound is identifiable in the recording from every point. Based on the obtained recordings, it can be seen that the best quality signal was obtained for points a) and e), and the worst quality signal was obtained for point d). Therefore, it was decided that the remaining recordings would be made for one selected point - this point is Erb's point (recording e).

III. RECORDING DATABASE

A group of 120 people were asked to record the sound of their heart using a private phone. Before recording highest available recording quality was set and protective cases were removed. Then, the location of the microphone in the phone was indicated (usually a hole on the bottom edge) and the measurement point (Erb's point) was indicated in the diagram. It was indicated that the phone should be slightly pressed against the body. The participants of the experiment should make recordings lasting approximately 60 seconds. After recording, all participants completed a survey in which they answered the following questions:
- age,
- sex,
- height and weight,
- phone model,
- whether any heart defects have been diagnosed by a doctor,
- were there any problems with perform recordings?
- consent to participate in research.

The research group included 15 women and 105 men aged 18 to 24. The Body Mass Index (BMI) of the examined people ranges from 16.8 to 34.1 (3.5% underweight, 72.1% normal, 18.6% overweight, 5.8% obese). This is a group that represents its age group in a similar way. According to statistics in Poland in 2019 [11], 5.4% were in the 20-29 age group, 58.7% were of normal weight, 28.4% were overweight and 6.8% were obese.

Three people reported heart defects diagnosed by a doctor. These were arrhythmia, hypertension and a slight heart valve leak.

Phones of various brands were used to record heart sounds: Huawei (models P9, P10), iPhone (models 7, 8, 11, 12, 13, 14, Xs), LG models V30, Motorola model G8, One Plus model 9, Oppo (Reno 5, Reno 6 models), Poco X3, Realme (9, GT, RMX models), Samsung (models including A32, A52, M23, S10, S20, S8, S9), Sony (Xperia 10 models, Xperia L1) and Xiaomi (models including Redmi 7, Redmi 8, Redmi 9, Redmi 10, Redmi 11). The distribution of the number of phones of a given brand used in the study is presented in Fig. 3.

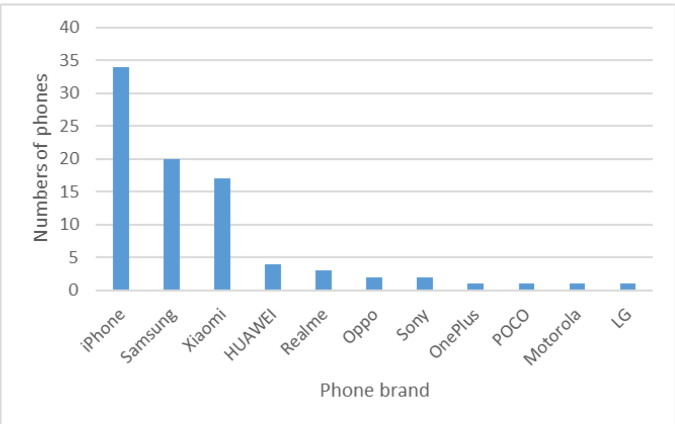

Fig. 3 Number of phones of a given brand used in the study

In general, there was no significant relationship between signal registration problems and phone brand.

Then, each recording was listened to and edited to determine the longest possible fragment without interference. Disturbances were identified auditorily and visually based on time course and spectrogram analysis. Sounds with a level higher than heart sounds and sounds with a wide frequency band were considered interference. An example of this type of interference occurring at the beginning and end of the recording is shown in Fig. 4.

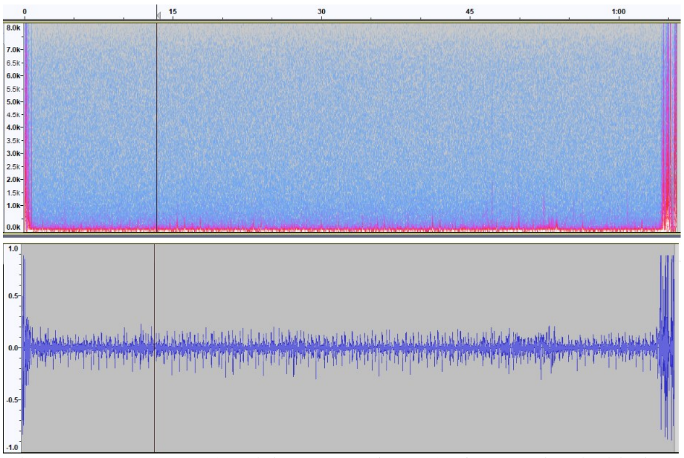

Fig. 4 Spectrogram (top) and time course (bottom) of a PCG signal with short broadband interference

Some recordings did not require major editing (often removing the beginning and end of the recording), but many recordings were characterized by a lot of noise. The average duration of the original recordings is 67.4 s and the average duration of the cleaned recordings is 36.8 s. A detailed summary of the duration of the recordings before and after cleaning is shown in Fig. 5.

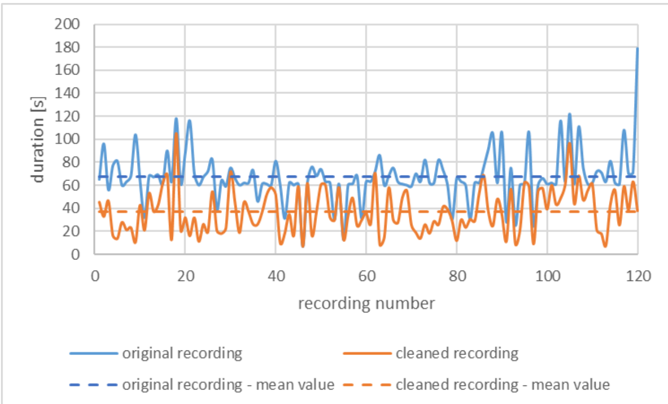

Fig. 5 Duration of individual original and edited recordings with average values marked

It could be seen that some of the recordings required a lot of editing, which means there was a lot of noise in the recording.

IV. QUALITY ASSESSMENT

The quality of the recordings was assessed using two methods. The first method was proposed by Hongxing Luo et all [9]. A good quality signal was determined by at least one heartbeat, with both the first (S1) and second heart sound

(S2) clearly visible in the raw recordings. Bad signal quality was defined by the absence of any heartbeat from S1 and S2. A signal of unsure quality was defined if the observer felt that the signal required further processing to reliably identify heartbeats. According to this evaluation method, 103 recordings of good quality (86%), 9 recordings of unsure quality (8%) and 8 recordings of bad quality (7%) were obtained. In Hongxing Luo et all experiment, recordings from 1,148 participants were analyzed. Recordings of good, unsure and bad quality were obtained in 74.6%, 6.2% and 19.2%, respectively. It can be considered that similar results were obtained. The differences may result from a different number of participants and a different approach to recording (one longer recording instead of several short ones).

The second quality assessment method was based on the quality assessment parameters proposed by Lejkowski W. [12,13]. Nine parameters (p1-p9) and the SVM (Support Vector Machines) classifier are described.

The first parameter describes the ratio of the signal energy after wavelet filtering to the energy of the original signal (1).

$$p_1 = 10\log_{10}\left(\frac{{y_{f\_rms}}^2}{{y_{rms}}^2}\right) \tag{1}$$

y_{f_rms} – RMS value of the signal after wavelet filtering
y_{rms} – RMS value of the signal before filtering

The second parameter (2) describes the ratio of the main (zero) maximum of the autocorrelation function of the signal normalized in 1.5 second windows to the value of the next maximum.

$$p_2 = \frac{max(f_{acorr})_0}{max(f_{acorr})_1} \tag{2}$$

$max(f_{acorr})_0$ – amplitude of the main maximum of the autocorrelation function
$max(f_{acorr})_1$ – amplitude of the next maximum of the autocorrelation function

The third parameter (3) determines the ratio of the number of detected S1 tones to the number of tones estimated using the autocorrelation function.

$$p_3 = \frac{\sum_{i=1}^{N} S1_i}{T \cdot F_{acorr}} \tag{3}$$

$S1_i$ – S1 tone detected
T – signal duration
F_{acorr} – fundamental frequency determined from the autocorrelation function

The fourth parameter (4) describes the percentage ratio of the number of detected S1 tones to the number of tones estimated using the average intervals between S1 tones.

$$p_4 = \frac{T}{\overline{dS1} \cdot nS1} \tag{4}$$

$\overline{dS1}$ – mean inter-tone interval time S1
$nS1$ – number of S1 tones detected

The fifth parameter (5) is calculated based on the standard deviation of the intervals between S1 tones related to the average value of these intervals.

$$p_5 = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\overline{dS1} - dS1_i)^2}}{\overline{dS1}} \tag{5}$$

The sixth parameter (6) is calculated as the square root of the mean square of differences between the next two intervals between S1 tones related to their average value RMSSD (root mean square of successive differences).

$$p_6 = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(dS1_{i+1} - dS1_i)^2}}{\overline{dS1}} \tag{6}$$

The seventh parameter (7) carries information about the correct number of S1 tones in a time window of 2.2 seconds. If the number of tones in the window is from 2 to 4, the window is marked as 1. If not, the window is marked as 0. The seventh parameter is calculated as the percentage of the number of windows containing from 2 to 4 S1 tones in relation to the total number of windows.

$$p_7 = \frac{w(1)}{w(1)+w(0)} \tag{7}$$

$w(1)$ – number of time windows marked as 1
$w(0)$ – number of time windows marked as 0

The eighth parameter (8) is defined as the percentage ratio of the total duration of the signal above 40% of the amplitude to the total duration of the signal.

$$p_8 = \frac{t_{y(f)>40\%}}{T} \tag{8}$$

$t_{y(f)>40\%}$ – total signal duration greater than 40% of the signal amplitude

The ninth parameter specifies the percentage of the total time the signal module occurs above the 0.85 quantile.

A similar classification was made using data received from the author of the cited work. Original recordings (before editing) were classified first. The classification results are as follows: good quality (65%), unsure quality 6%, bad quality 29%. Detailed classification errors for original recordings (before editing) in relation to quality assessment using the first method of quality assessment [9] are shown in Fig. 6.

		Reference Data			
		Good	**Unsure**	**Bad**	**Total**
Classified Data	**Good**	66	5	3	**74**
	Unsure	5	1	1	**7**
	Bad	26	3	4	**33**
	Total	**97**	**9**	**8**	**114**

Fig. 6 Classification error matrix for original unedited recordings (the matrix shows the quantities of classified signals)

A significant part of the recordings assessed using the first method as good quality recordings were assessed as bad quality recordings. The reason may be to classify the recordings before editing. However, the incorrect assignment of bad quality recordings as good quality recordings indicates errors in the quality assessment of one of the two tested methods.

Then, the edited recordings, which do not contain any removable distortions such as crackles and bangs, were subjected to SVM classification. The classification results are as follows: good quality (82%), unsure quality 3%, bad quality 15%. Detailed classification errors for edited recordings in relation to quality assessment using the first method of quality assessment [9] are shown in Fig. 7.

		Reference Data			
		Good	Unsure	Bad	Total
Classified Data	Good	88	7	3	**98**
	Unsure	4	0	0	**4**
	Bad	11	2	5	**18**
	Total	**103**	**9**	**8**	**120**

Fig. 7 Classification error matrix for recordings cleaned after editing (the matrix shows the quantities of classified signals)

The classification results for edited recordings are very similar to the quality assessment results of the first method. However, in the classification error matrix it can be seen that relatively many recordings were misclassified. A particular problem is bad quality recordings classified as good quality recordings. These are three recordings, in two of which only noise can be heard and in one the presence of tones can be heard very quietly.

Then, the quality of the recordings was classified after editing with additional frequency filtering. FIR low-pass filters with order 100 and cutoff frequencies of 300 Hz, 400 Hz, 500 Hz, 600 Hz, 700 Hz, 800 Hz, 900 Hz and 1000 Hz were used. Fig. 8 shows the percentage of recordings classified as good.

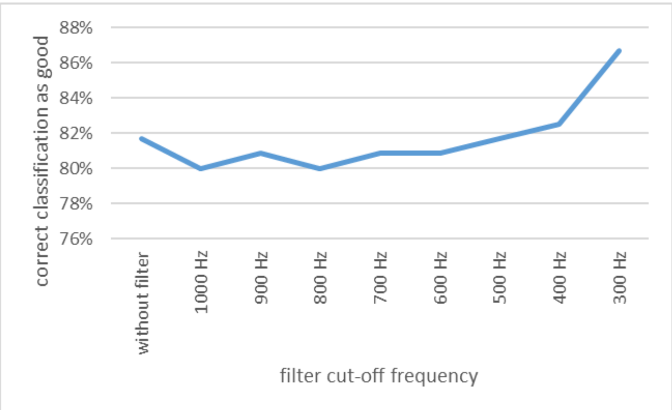

Fig. 8 Percentage of recordings classified as good quality for frequency filtered signals

Using a filter with a cut-off frequency of 300 Hz, 87% of the recordings (103 recordings) were classified as good. This is the value closest to the quality assessment using the first method. Detailed classification errors for edited recordings with additional frequency filtering in relation to quality assessment using the first method of quality assessment [9] are shown in Fig. 9.

		Reference Data			
		Good	Unsure	Bad	Total
Classified Data	Good	92	6	6	**104**
	Unsure	2	1	0	**3**
	Bad	9	2	2	**13**
	Total	**103**	**9**	**8**	**120**

Fig. 9 Classification error matrix for recordings cleaned with a filter with a cut-off frequency of 300 Hz (the matrix shows the quantities of classified signals)

As many as 92 recordings out of 104 classified as good were classified correctly.

V. NORMAL/ABNORMAL CLASSIFICATION

In the last stage, all recordings that were assessed as good quality using the first method were automatically classified into "normal" and "abnormal" recordings. For this purpose, examples provided by MathWorks [14] were used. The example uses wavelet scattering as the feature extractor used for PCG classification. In wavelet scattering, data is propagated through a series of wavelet transforms, nonlinearities, and averaging to obtain low-variance representations of the data. These are then used as input to the classifier. Data from the PhysioNet Computing in Cardiology Challenge 2016 [15,16] open database were used as training data for classification. Recordings obtained as part of this paper were entered as test data. People who reported a heart defect diagnosed by a doctor in the survey were also excluded from the test group. The test group consisted of 96 recordings. The aim was to obtain a set of recordings of people without heart defects. Therefore, ideally, within the classification framework, 100% of recordings should be classified as "normal" recordings. The classification results for recordings edited without filtration and with filtering with filters with different cut-off frequencies are shown in Fig. 10.

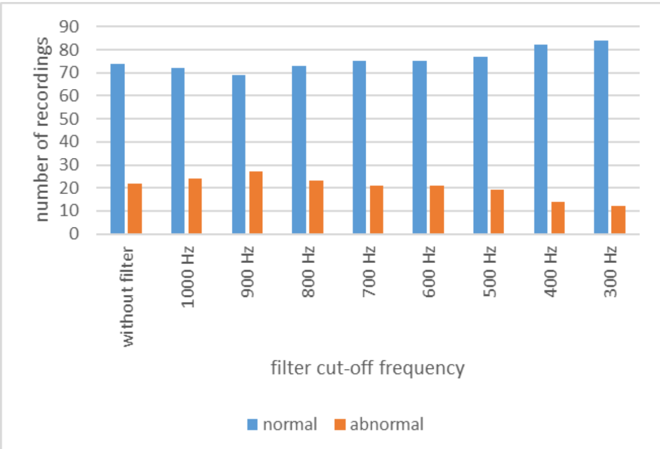

Fig. 10 Results of classification of recordings of people without heart defects using filters with different cut-off frequencies

The most correct classifications were obtained for recordings with a filter with a cut-off frequency of 300 Hz.

Conclusion

PCG recordings made with a mobile phone contain a lot of noise, such as crackles and bangs, and therefore require editing. A method should be developed to automatically clean heart sound recordings from noise because manual cleaning is a labor-intensive task. For this purpose, one can probably use the criterion presented in Chapter III, i.e. detection of short sounds with a wide frequency band.

Classification of the quality of recordings using the SVM classifier for unedited recordings showed a significantly smaller number of good quality recordings than for edited recordings. This confirms the need to edit the recordings by removing noise such as crackles and bangs. Frequency filtering with a low-pass filter also improves the results. The best results were obtained for the filter with the lowest tested cut-off frequency, i.e. 300 Hz.

However, there are differences in quality assessment between the two methods tested. This indicates the need for further work on quality assessment parameters and quality classifiers.

Similarly to the quality classification, also in the case of the classification of recordings due to heart defects, the highest classification accuracy was achieved for recordings with a filter with a cut-off frequency of 300 Hz. In the further stages of work, it is necessary to check whether frequency filtering affects the deterioration of the possibility of diagnosing heart defects and what is the lowest limit frequency that can be used to filter interference.

Acknowledgements

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