Research Paper

The use of an electronic stethoscope with dedicated software for cardiovascular screening of patients prepared for hip replacement

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ABSTRACT

Cardiovascular disease (CVD) is one of the major causes of perioperative complications. Screening of patients referred to major surgery is a costly and time and resources- consuming process. The study aimed to assess the usefulness of an electronic stethoscope with dedicated analytical software operated by a nurse for detecting heart disease in patients prepared for major orthopedic surgery. The study group consisted of 137 patients aged (46 – 91) with defined cardiovascular diseases qualified for hip or knee replacement surgery and 94 healthy age-matched volunteers. Heart auscultation with Littmann electronic stethoscope using *Littmann® StethAssist™ Heart and Lung Sound Visualization Software* software was conducted and analyzed by a trained nurse. The signal recorded was analyzed by the blinded researcher using dedicated custom- made algorithm. Finally, 91 signals (52 CVD (+) patients, 39 CVD (-) patients) were analyzed. Eventually a classifier with a sensitivity of 92% and a specificity of 97% was obtained in a group. The global accuracy of the classifier was 95%. Heart auscultation by nursing staff using Littmann® StethAssist™ Heart and Lung Sound Visualization Software with dedicated custom- made can be cheap and noninvasive method of identifying patients with cardiovascular disease made algorithm for arthroplasty.

Key words: Electronic stethoscope, heart auscultation, nurse, arthroplasty, cardiovascular disease.

INTRODUCTION

The European Society of Cardiology included hip replacement surgery as a major intermediate risk operation (1-5%) of a cardiac incident (Poldermans et al., 2009). The presence of cardiovascular disease significantly increases the risk of orthopedic surgery. Auscultation of the heart with a stethoscope conventional is a quick, comfortable, and traditional examination performed by a doctor and a nurse in everyday practice. Auscultation of the heart is not a simple task; however, for proper assessment of heart murmurs, you need many years of training and experience, which some experienced doctors also lack.

These random or additional sounds may be associated with CVD (Botsis et al., 2008; Niedziejko et al., 2011). Accuracy of an examination with an acoustic stethoscope, unlike examination using an electronic stethoscope

(Lejkowski et al., 2016; Lejkowski et al., 2017, a), is often low, variable and depends on the expertise of the person conducting the examination and their current predispositions (Nabhan Homsi et al., 2017).

The standard of auscultation of the heart using an electronic stethoscope together with proprietary software performed by a nurse is aimed at minimizing the risk of CVD complications in patients qualified for hip replacement. Phonocardiographic signal can also be analyzed using dedicated computer algorithms and transmitted over long distances to people with greater medical expertise. Examination of heart sounds and murmurs and diagnostics of diseases based on phonocardiographic signal analysis at an early stage may contribute to a reduction in the incidence rate of cardiovascular diseases. Patients reporting for hip
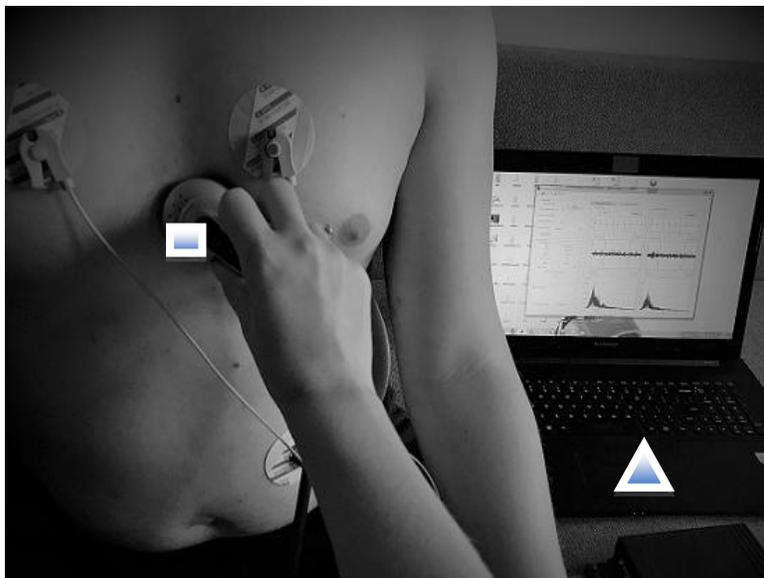
Figure 1: Patient during auscultation. Acquisition of sound using an electronic stethoscope. Square - stethoscope earpiece at the Erba point, triangle - a computer system for imaging and analysis of the full sound spectrum. 3-lead ECG electrodes visible.

replacement surgery are examined with a stethoscope, which together with the software classifies patients as healthy and sick. Healthy CVD (-) patients are qualified for surgery, and CVD (+) patients are referred for further cardiological diagnosis.

The research was undertaken in the hope that the electronic stethoscope and proprietary software could be operated and performed by a nurse.

The article aims to assess the usefulness of an electronic stethoscope with dedicated analytical software for diagnosing heart disease in orthopaedic patients.

MATERIALS AND METHODS

Study group

The study was performed at the Trauma and Orthopaedics Centre of the Military Institute of Medicine from February 1 till September 18, 2018. The study included 231 patients after arthroplasty aged 20 to 91 (112 women, 119 men). 94 of them were free from CVD, the other 137 suffered from CVD. Ninety-four healthy volunteers (HV- Healthy volunteers) after joint arthroplasty, without comorbidities who did not take permanent medications constituted a control group. 25 pts with heart failure (*HF- Heart failure*), 18 pts with coronary artery disease CAD (*Coronary artery disease*); 28 pts with myocardial infarction (*MI- Myocardial infarction*), 50 pts with hypertension (*HT- Hypertension*) and 16 pts with atrial fibrillation (*AF- Atrial fibrillation*) were included.

This study was carried out in accordance with the Helsinki Declaration. The consent for the test was approved by the Bioethics Committee of the Military Institute of Medicine in Warsaw. All participants gave written informed consent to participate in the study.

Auscultation methods and proprietary software

Each patient underwent a clinical examination (including auscultation of the heart in typical locations – Erb's point and cardiac apex). After connecting to an electrocardiogram (ECG) recording machine, an electronic stethoscope examination consisted of recording sound waves emitted by the heart in a broad spectrum (including infrasound inaudible to the human ear). Acquisition of soundwave was performed by applying the stethoscope head - for 30 s - to the chest of the examined patient in supine and sitting position (Figure 1).

The soundwaves recorded by the device have been presented in graphic form in the time domain (classic time course) and frequency domain (spectrum) in the proprietary Littmann® StethAssist ™ Heart and Lung Sound Visualization Software. A commercially available stethoscope with proprietary software and the algorithm created allows for automatic division of recorded phonocardiograms into healthy CVD (-) patients and CVD (+) cardiac patients.

Records obtained in affected patients were compared with the results obtained in the control group. All recording procedures took an average of no more than 3 min from the
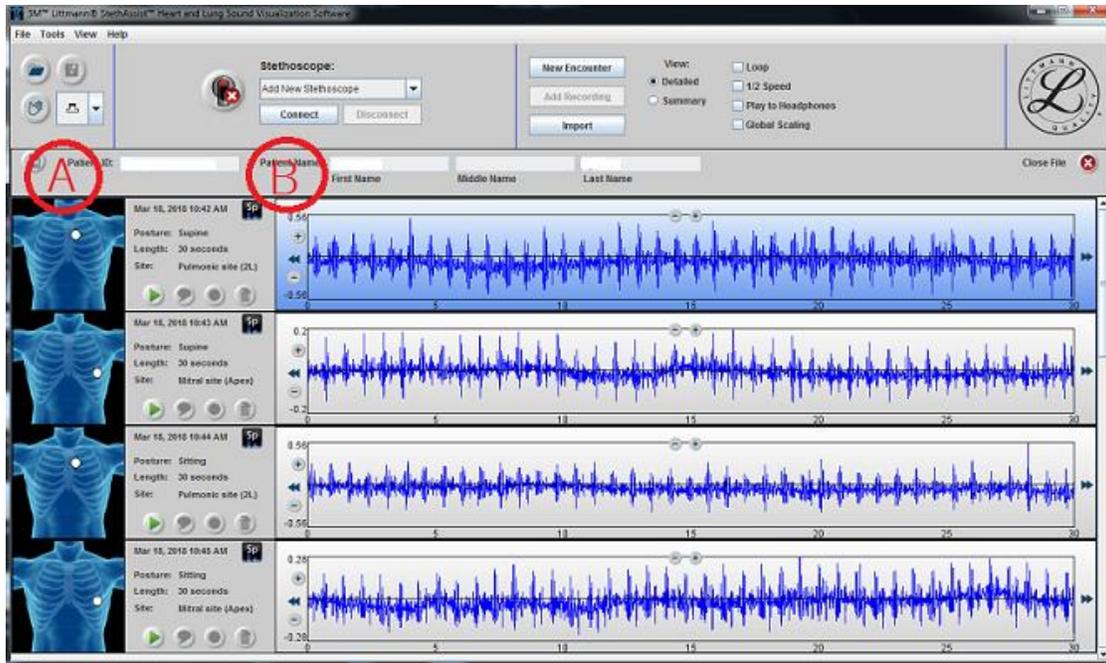
Figure 2: *Littmann® StethAssist ™ Heart and Lung Sound Visualization Software* window **A)** auscultation place **B)** phonendoscope signal for appropriately selected places.

time the application was started until the recording of phonocardiographic signals (approximately: turning on the application and synchronising the stethoscope with the application - 1 min, recording time at 1 point in a sitting position – 30 s, we normally listen to 2 points in sitting position and 2 points in lying position - 2 min).

Figure 2 showsan example of recording phonocardiographic signals. The stethoscope membrane was applied to all patients at Erb's point (anatomical landmark located on the chest surface, located at the left edge of the sternum in the 4th intercostal space) and on the cardiac apex (V intercostal space, approx. 1.5 cm to the right from the left midclavicular line). There were no reports for adverse event or difficulties in respecting the recommendations. None of the subjects reported discomfort due to auscultation of the heart in various positions. The analysis included 924 recordings of the audio signal (that is, 231 patients including 94 healthy subjects and 137 people with various cardiological diseases).

As part of heart registration, the file naming system was adopted, as shown in Table 1.

Electronic analysis

The recorded signal was analyzed by the researcher independently of medical data. Phonocardiographic signals that were heavily corrupted and disturbed by signals coming from inside the body or unwanted external sounds in the first step of digital phonocardiogram processing were subjected to the elimination of signals recorded in adverse

acoustic conditions. Examples of good and low-quality signals are shown in Figure 3.

Figure 3 representing a signal of relatively good quality clearly illustrates distinctive S1 and S2 tones. It is possible to accurately determine the rate of heartbeat and heartbeat regularity. On the other hand, a high proportion of noise can be observed in the low-quality signal, which completely disturbs visual evaluation of the signal. To automatically distinguish between good and bad quality signals, an algorithm has been designed and implemented to distinguish between signals due to the quality of the recording.

The signal recorded using an electronic stethoscope has a duration of 30 s and is sampled at a frequency of 4 kHz. In the first stage of digital processing, this signal is normalized according to the formula:

$$\hat{y}_i = \frac{y_i}{\max\left(|\vec{y}|\right)} \tag{1}$$

In the next stage, wavelet filtering is carried out using the 4th order of Daubechies wavelet (Lejkowski et al., 2017, b) The signal after wavelet filtering (the sum of details from levels 5 to 8) is devoid of constant and slow-varying component originating, among others from the patient's chest movement. Signal prepared in this way allowed to determine 8 quality parameters, the definitions of which are presented in Table 2.

The determined parameters for a group of learners of 55 reference signals were subjected to standardisation

Table 1: Naming system for audio files exported from the *Littmann® StethAssist ™* program. HV- Healthy volunteers, HF - Heart failure, CAD - Coronary artery disease; MI - Myocardial infarction; HT – Hypertension; AF - Atrial fibrillation.

Research type	Patients groups	Age	Gender		Number of patients
			F	M	
Cardiological tests	HV	20 -87	29	65	94
	HF	52 - 89	14	11	25
	CAD	66 - 90	10	8	18
	MI	46 - 91	11	17	28
	HT	49 - 88	37	13	50
	AF	62 - 88	11	5	16

(a)

(b)
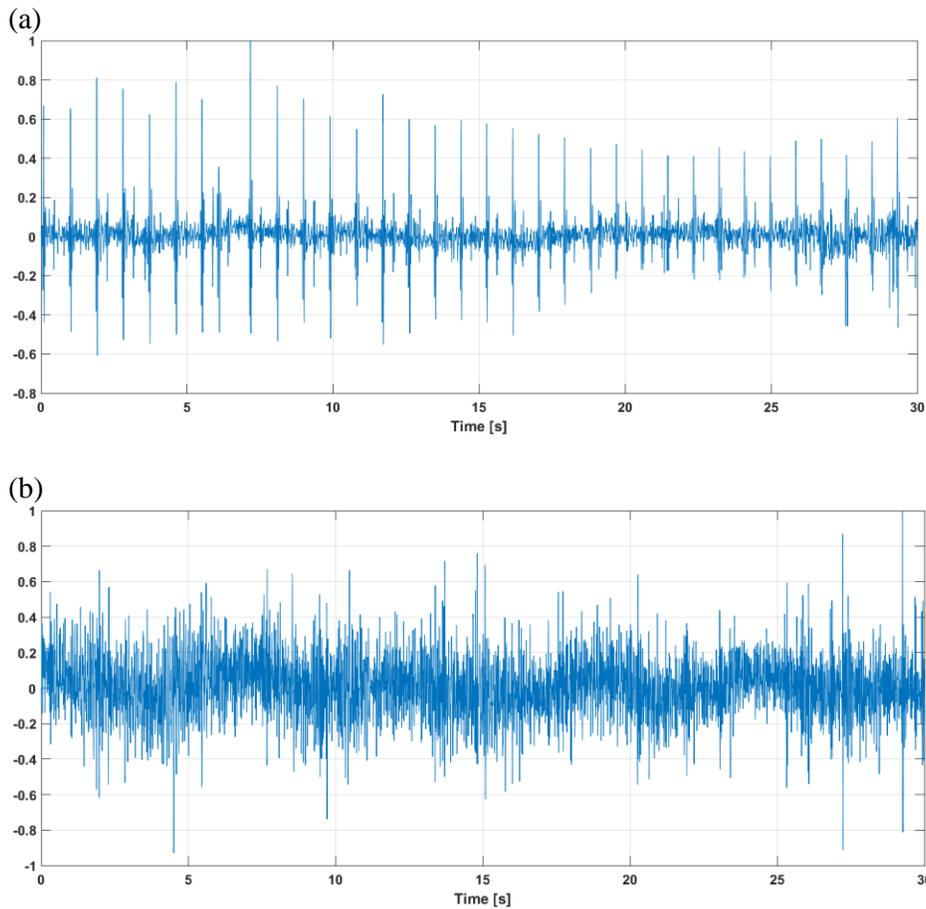
Figure 3: Sample recording of a) high and b) low quality.

according to the equation:

$$P_i = \frac{p_i - m}{\sigma}$$

(2)

where: P_i – value of p_i after standardization,

p_i – original value of the parameter of the i-th parameter,

m – mean value from the parameter population p_i,

σ – standard deviation from the parameter population p_i.

To determine the separating hyperplane, the authors decided to subject the designated features to Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and classification Support Vector Machine (SVM). Ultimately, the best classifier was chosen, which turned out to be the SVM network. The separating function is

Table 2: Definitions of quality parameters . y_{f_rms} –the rms value of the signal after wavelet filtration, y_{rms} – the effective value of the original signal, $\max{(f_{acorr})_0}$ - amplitude of the main maximum of the autocorrelation function, $\max{(f_{acorr})_1}$ - amplitude of the next maximum of the autocorrelation function, $S1_i$ – detected S1 tone, T – signal duration (30s), F_{acorr} –fundamental frequency determined from the autocorrelation function, $\overline{dS1}$ – average time interval between S1 tones, $nS1$ – number of S1 tones detected, $w(1)$ – number of time windows marked as 1, $w(0)$ – number of time windows marked as 0, $t_{y(f)>80\%}$ – total signal duration above 80% signal amplitude.

Description	Definition
The ratio of the signal energy after wavelet filtration to the energy of the original signal	$$p_1 = 10 \cdot \log_{10}\left(\frac{y_{f\_rms}^2}{y_{rms}^2}\right)$$
The ratio of the height of the highest autocorrelation peak to the height of the second highest autocorrelation peak	$$p_2 = \frac{\max{(f_{acorr})_0}}{\max{(f_{acorr})_1}}$$
Ratio of detected S1 tones to the number of tones estimated using the autocorrelation function	$$p_3 = \frac{\sum_{i=1}^{n} S1_i}{T \cdot F_{acorr}}$$
Ratio of detected S1 tones to the number of tones estimated using the average time interval between S1 tones	$$p_4 = \frac{T}{\overline{dS1} \cdot nS1}$$
The standard deviation of the determined intervals related to their average value	$$p_5 = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\overline{dS1} - dS1_i)^2}}{\overline{dS1}}$$
The square root of the mean squares of differences between two successive dS1 intervals related to their mean value	$$p_6 = \frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(dS1_{i+1} - dS1_i)^2}}{\overline{dS1}}$$
The ratio of the number of windows (2.2 s duration) containing 2 to 4 S1 tones to the total number of windows in the signal	$$p_7 = \frac{w(1)}{w(1) + w(0)}$$
The ratio of the percentage of the total signal time (after wavelet filtration) above 80% of the signal amplitude to the total signal duration.	$$p_8 = \frac{t_{y(f)>80\%}}{T}$$

presented in Figure 4. Red points indicate signals classified as poor quality, while blue points stand for qualitatively good signals. Each signal is represented by a number, that is, the result of a corresponding linear combination of selected parameters. It can be seen that all reference signals have been classified correctly.
with the value equal:

• (-1.0 ÷ -0.2) indicates a very good quality signal,
• (-0.2 ÷ 0.0) indicates a good quality signal,
• (0.0 ÷ 0.2) indicates a poor quality signal,
• (0.2 ÷ 1.0) indicates a very poor signal quality.

At a later stage, for easier interpretation, the number representing the signal (the result of the SVM procedure) was standardized to the range ± 1. Thanks to this, each registered signal is represented by a number in this range,

A total of 869 registered signals were classified, of which 576 were classified as qualitatively good, including 390 signals as very good signals, as shown in Figure 5. Statistics of recorded signals, including their quality, are presented in the Table 3 and Figure 6.
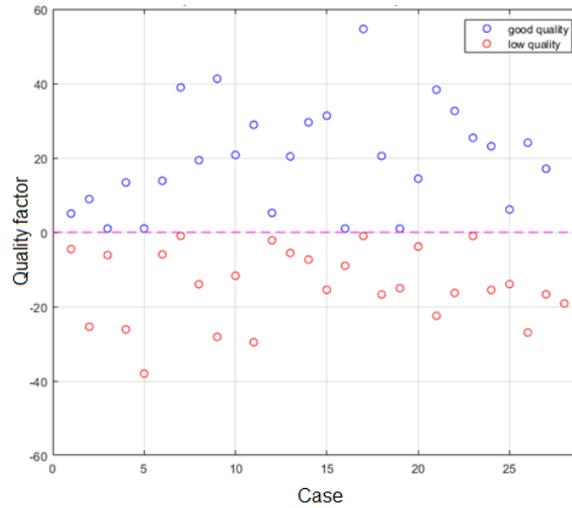
Figure 4: Hyperplane separating 55 cases of the teaching group.
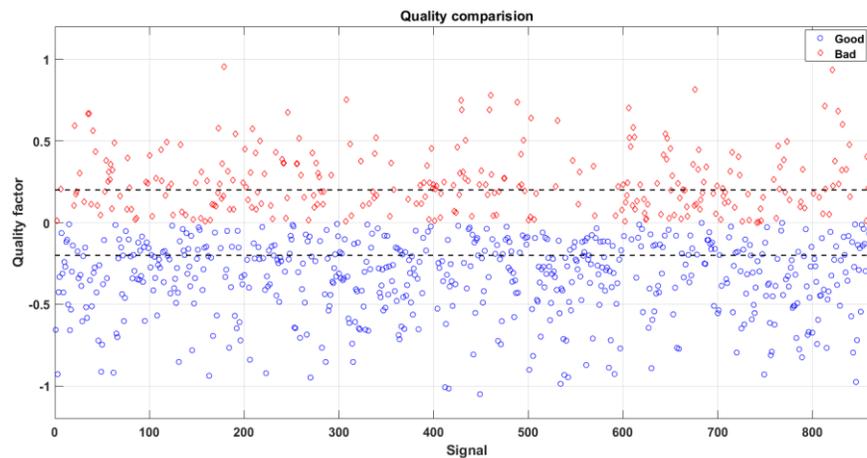

Figure 5: List of all registered cases subjected to qualitative analysis. Red indicates low and high-quality signals. The value of the quality factor is "further" from 0, the "better" signal.

Table 3: Number of recorded signals in the signal quality classification.

Signal quality classification	Number of recorded signals
Signal with very good quality	390
Good quality signal	186
Poor quality signal	138
Signal of very poor quality	155
SUM	**869**

RESULTS AND DISCUSSION

Due to the nature of phonocardiograms recorded in real conditions, in further analysis - aimed at differentiating pathological and normal cases - an innovative technique of signal averaging in the frequency domain was used, taking into account from a few to several consecutive heartbeats. In the first stage of digital signal processing, they were subjected to preliminary filtration to remove unnecessary spectral components. In the second stage, spectra of
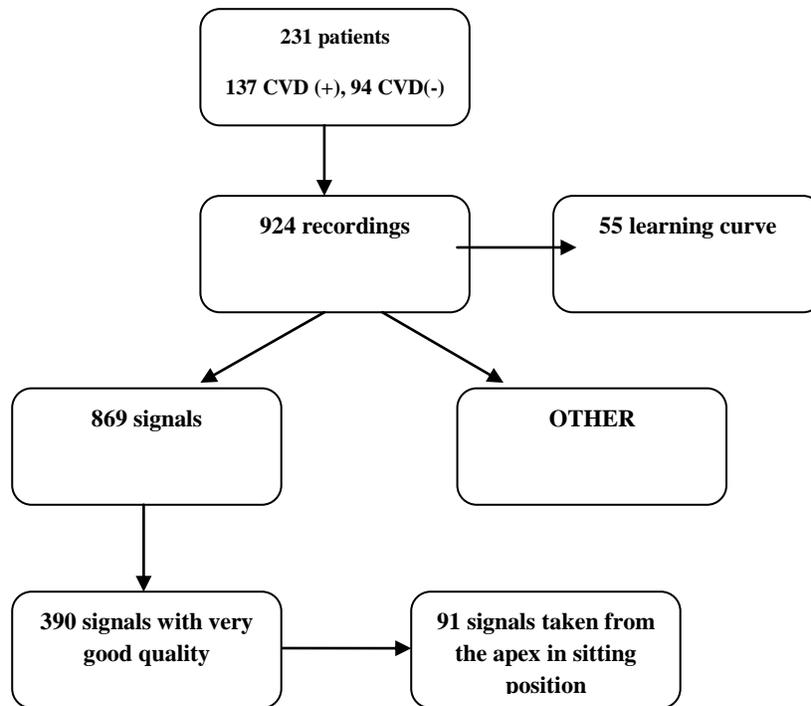
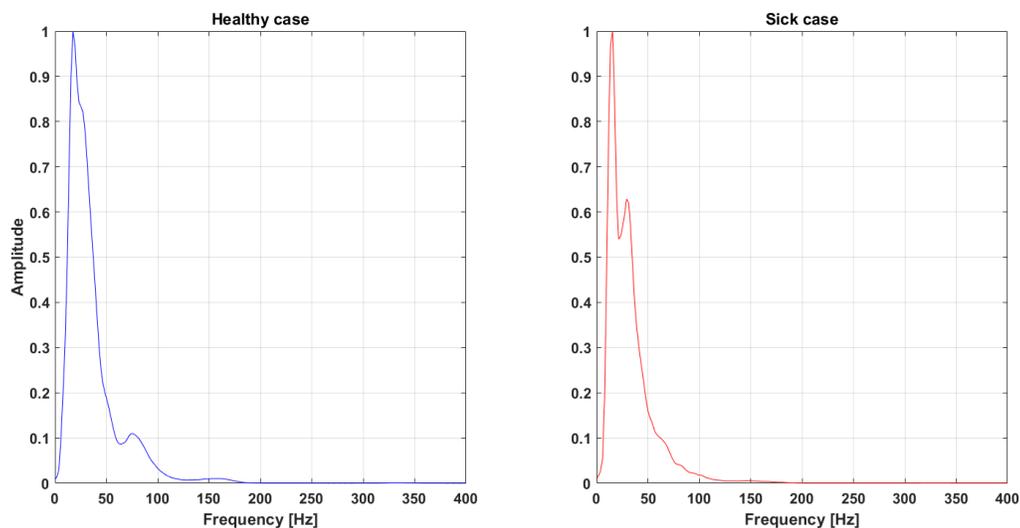**Figure 6:** For detail, see section electronic analysis.

Figure 7: Examples of S1 tone spectra for healthy (left) and sick (right) patients.

individual tones were determined using the discrete *Fourier transform algorithm*, followed by the averaging of amplitude spectra across all heartbeats. As a result, the average amplitude spectra of the S1 sound were obtained for each case studied. Sample spectra of the S1 sound of a healthy volunteer and a patient with a cardiac disorder are presented in Figure 7.

To assign the obtained mean spectra to a group of physiological or pathological cases, 46 spectral features

defined in were extracted (Lejkowski et al., 2017, b; Olszewski et al., 2019). Of all 390 signals that were classified as signals of very good quality, 91 signals were selected that were recorded at the cardiac apex and in sitting position of the patient (including 39 physiological cases and 52 pathological cases). To determine their potential discriminatory ability, Fisher significance factor was determined for each feature (Figure 8), defined as the distance between the mean values of a given feature for the
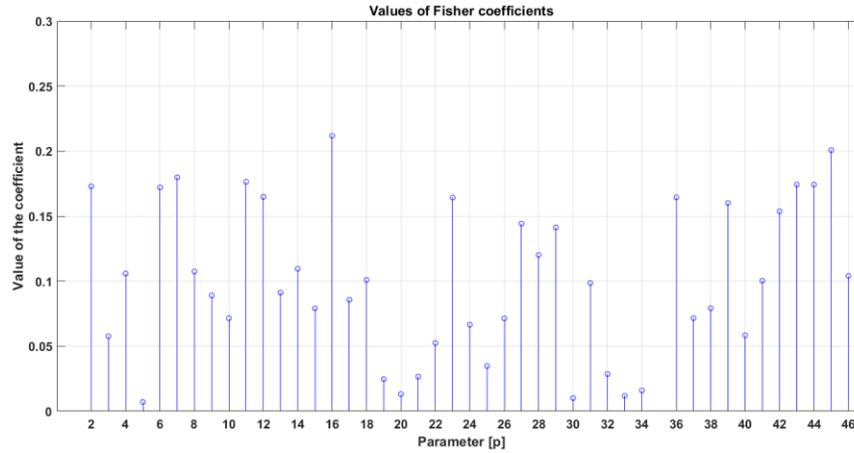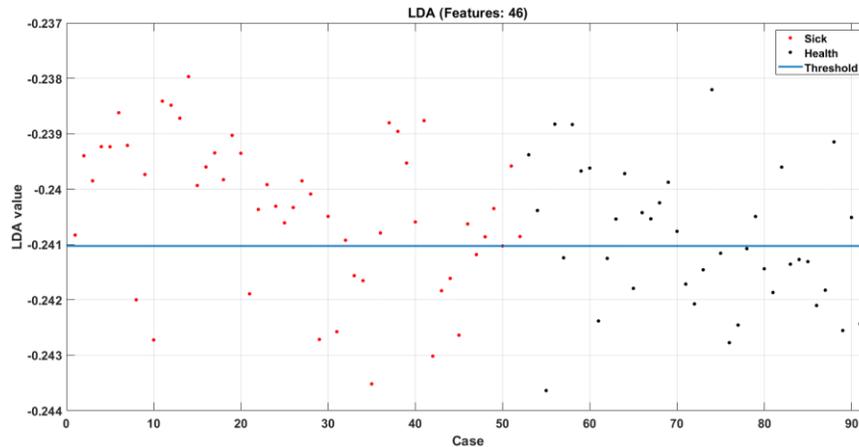
Figure 8: Fisher's coefficient values.

Figure 9: Illustration of the cases considered in the LDA imaging using all 46 features.

physiological and pathological case related to the double sum of the corresponding standard deviations, in accordance with the formula:

$$\gamma = \frac{\left|\mu_p - \mu_f\right|}{2(\sigma_p + \sigma_f)}$$

(3)

where: μ_p, μ_f – mean values of the parameter for the pathological and physiological signal; σ_p, σ_f – corresponding standard deviations.

Because individual consideration of discriminatory features does not take into account their synergy and mutual correlation, they have been visualised using PCA transformation, which allows an approximate imaging of multidimensional data, and pre-selection of the best distinctive features. Linear discriminant analysis (LDA), which is used in machine learning, was also used to find a linear combination of features that best distinguish between two or more classes of objects or events (Figure 9).

Thereafter, in order to construct an effective classifier, a genetic algorithm was used to select the features and, as a result, their number was reduced from 46 to 12 best. The result of the selection in LDA imaging is shown in Figure 10.

Further improvement of effectiveness was obtained owing to the SVM linear network (Figure 11).

Eventually, owing to SVM, a classifier with a sensitivity of 92% and a specificity of 97% was obtained in a group of 91 subjects. The global accuracy of the classifier was 95%. A trained nurse will auscultation to the patient with 42% efficiency.

The quality of the recorded phonocardiogram is not directly dependent on the examiner. It is influenced by many external and internal factors. External factors include: a room in which we auscultationed to the patient, opening or closing the door, a scream coming from an open window, and internal factors such as stomach rumbling, coughing, patient movement during auscultation.The quality of the signal may vary depending on the pressure of
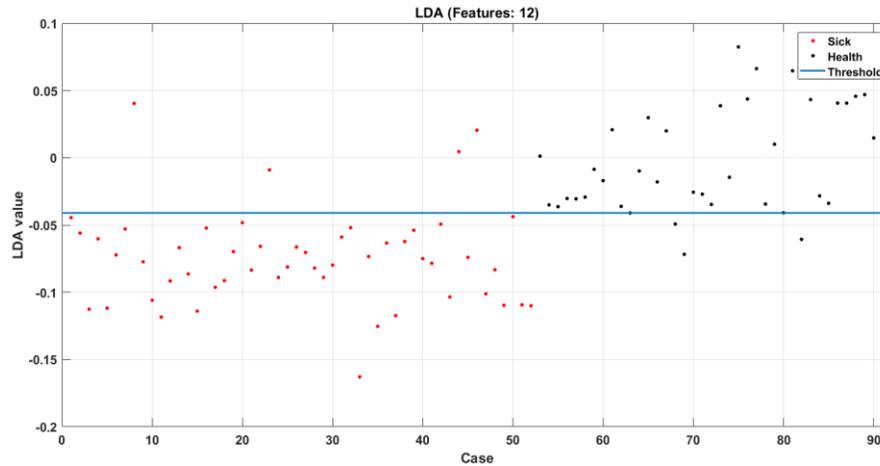
Figure 10: Illustration of cases considered in the LDA imaging using the best 12 features.
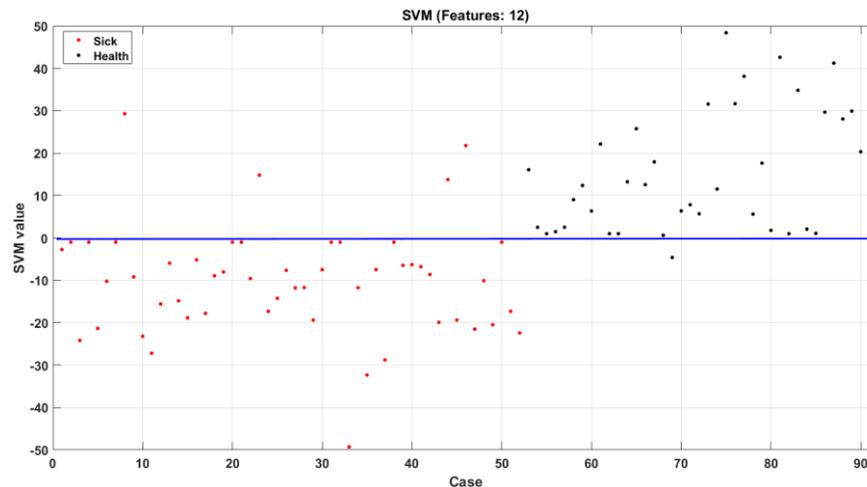

Figure 11: Illustration of considered cases in SVM imaging.

the stethoscope on the patient by the researcher.

Difficulties in auscultation are mainly associated with the conditions in which this test is performed and the so-called "Undisciplined patient". The developed algorithm needs to be checked on a large group of patients.

DISCUSSION

The main result of the study is the high efficiency of the screening test performed by a nurse using the latest electronic algorithms to detect cardiovascular diseases in patients referred for arthroplasty. An electronic stethoscope with appropriate software differentiates with 95% accuracy phonographic signals recorded in a group of people with various cardiovascular disease entities and signals received in the control group. Similar results were obtained by Chowdhury et al. (2019), who in his article described a prototype model of an intelligent digital

stethoscope system for monitoring patient's heart sounds and diagnosing any abnormalities with 97% accuracy in incorrect heart sound classification and 88% accuracy in correct heart sound classification.

The second conclusion is the fact that automatic analysis gives objective and reproducible results, not burdened with the psychophysical disposition of the auscultating researcher. It should be emphasized that electronic handset examination is completely non-invasive and does not carry any risks or side effects for the patient. The information obtained will lead to earlier detection of heart disease. The results of the study may also be important for improving health and reducing the mortality of patients at risk of cardiovascular diseases. According to Woywodt et al. (2004), electronic stethoscopes are becoming more and more popular, which is why there is a great interest in new ways of teaching simultaneous auscultation of the heart and visualization of murmurs.

Patients after joint arthroplasty, which is a commonly used surgical procedure that relieves pain and improves the quality of life in patients with degenerative joint disease, were selected for the study. These surgeries belong to planned surgical procedures, and hence appropriate preoperative management. The most frequent diseases that occur in elderly patients include cardiovascular disease (Nichols et al., 2014). These diseases are chronic, and their exacerbation in the preoperative period may postpone surgery until the patient's condition improves. Therefore, cardiological consultation of a patient qualified for orthopedic surgery is necessary. This consultation aims to determine the required pharmacological and/or invasive treatment, as well as to determine the degree of risk of cardiovascular complications. According to the classification of the European Society of Cardiology, hip replacement surgery is one of the major intermediate-risk operations (1-5%) of a cardiac incident (Poldermans et al., 2009). Appropriate assessment and preparation of the patient by the cardiologist are aimed at minimizing the risk of their occurrence. Assessment of the global risk of cardiac complications requires consideration of many factors, such as the patient's general condition, comorbidities, mode and type of planned orthopedic procedure. It should be considered whether the risks of the planned surgery outweigh its benefits (Debbal et al., 2008; Fleisher et al., 2001).

Developing a procedure and standard of cardiac auscultation by nursing staff in cardiological burdened patients or for the diagnosis of patients with a cardiovascular incident is significant for preparing the patient for the panned prosthetic arthroplasty. Digital processing of phonocardiographic signals will allow the determination of a specific, examined case to a group of patients or healthy controls with a defined, high risk (Debbal et al., 2007, 2008). In medical and nursing practice, classic stethoscopes are used, without any elements of electronics and artificial intelligence. A competitive stethoscope is the electronic version of the world-class Littmann 3200 supported by dedicated proprietary software.

Littmann stethoscope is delivered with the company software *Littmann® StethAssist™ Heart and Lung Sound Visualization Software*, which enables full communication with the stethoscope and real-time recording of phonocardiograms (Kao et al., 2011). Auscultation of the heart is a basic, common, cheap and always available method in the elderly. Based on the auscultatory examination and automatic phonocardiogram analysis, the nurse will classify the result to a group representing a cardiological disease. With the result prepared by the nurse, the patient reports to the cardiologist to recognize or confirm the final diagnosis. Studies in an Indonesian hospital using telecardiology illustrate the speed of nursing staff in the diagnosis of acute cardiac conditions (Tutik and Junaiti, 2012). The conditions for initial, accurate interpretation are the association of the effects of cardiac dysfunction by mastering a broad range of patterns in the electrocardiographic record in healthy people. As part of the uncertainty of the ECG result, it is consulted by teleconference with a physician (Atreya et al., 2010). A limitation of the study was a relatively small number of subjects, in particular in the group of patients with myocardial infarction (over 5 years), atrial fibrillation and stable coronary artery disease. The results obtained and the algorithms developed should be checked on a larger patient population.

CONCLUSION

1. An electronic stethoscope with proprietary software and custom- made algorithm in a nurse's performed screening, allows to determine the CVD (+) and CVD (-) patients qualified for orthopedic surgery.
2. LStSoV software classifies healthy and diseased cardiovascular signals with 95% efficiency. The tool for recording phonocardiographic signals presented in the article can be useful in diagnosing cardiovascular diseases.
3. Increasing the effectiveness of auscultation of the heart with an electronic stethoscope is possible owing to the elimination of external factors, and good cooperation with the patient.
4. Development of a cardiac auscultation standard by nursing staff in cardiologically ladened patients will facilitate the preparation of patients for arthroplasty.

ACKNOWLEDGMENTS

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