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Diagnosing Aortic Valve Stenosis by Parameter Extraction of Heart Sound Signals

ANDREAS VOSS,[1] ANDREA MIX,[1,2] and THOMAS HÜBNER[2]

[1]Department of Medical Engineering, University of Applied Sciences Jena, Jena, Germany and [2]Medtrans GmbH, Jena, Germany

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Abstract—The objective of this study was to develop an automatic signal analysis system for heart sound diagnosis. This should support the general practitioner in discovering aortic valve stenoses at an early stage to avoid or decrease the number of surgical interventions. The applied analysis method is based on classification of heart sound signals utilising parameter extraction. From the wavelet decomposition of a representative heart cycle as well as from the Short Time Fourier Transform (STFT) and the Wavelet Transform (WT) spectra new time series were derived. In several segments, parameters were extracted and analysed. In addition, features of the Fast Fourier Transform (FFT) of the raw signal were examined. In this study, 206 patients were enrolled, 159 with no heart valve disease or any other heart valve disease but aortic valve stenosis and 47 suffering from aortic valve stenosis in a mild, moderate or severe stage. To separate the groups, a linear discriminant function analysis was applied leading to a reduced parameter set. The introduced two classification stage (CS) system for automatic detection of aortic valve stenoses achieves a high sensitivity of 100% for moderate and severe aortic valve stenosis and a sensitivity of 75% for mild aortic valve stenosis. A specificity of 93.7% for patients without aortic valve stenosis is provided. The developed method is robust, cost effective and easy to use, and could, therefore, be a suitable method to diagnose aortic valve stenosis by general practitioners.

Keywords—Heart sound, Auscultation, Feature extraction, Wavelet Transform, Fourier Transform.

INTRODUCTION

Cardiac murmurs are often the first symptoms of a pathological change of heart valves. Therefore, the assessment of heart sounds plays an important role in the diagnosis of heart valve diseases.[7,25] For a long time auscultation was the only available method to examine the heart sound. In 1907, the phonocardiography was introduced[10] providing an instrument to record heart sound and to analyse it. Phonocardiography was a useful technique to assess the characteristics of heart murmurs, but it was not established in general clinical practice due to principal limitations such as the difficulty to obtain high-quality, artefact-free recordings.[2,6] Furthermore, auscultation and phonocardiography require high qualification and extensive practical experience by the physicians.[14,15] In 1952, a standardization of the recording hardware was developed by Maass and Weber, e.g. filters, amplifiers, etc., which provided an important improvement in phonocardiography.[20]

With the introduction of echocardiography an accurate and reliable diagnosis of heart valve diseases became possible. However, this technology is associated with relative high costs and is generally performed by cardiologists and internists only. Therefore, all patients suspected of having any heart valve disease are referred from the general practitioner to the specialist. Consequently, the general practitioner needs an easy-to-use and low-cost system to detect pathological changes in heart sounds precociously to limit the number of refers.

Several available devices and software solutions are able to record and display heart sound signals digitally, partially including the visualisation of the frequency spectra, but none of them performs a complete automatic diagnosis.[19]

For an automatic classification several approaches are recently under discussion as especially artificial neural networks.[5] This is a very powerful technique to assess complex coherences. However, the interpretation of the results regarding the correlation with pathological changes is rather difficult and the training time is often very long.

In other studies, high sensitivity and specificity for the detection of degenerated bioprosthetic valves in aortic and mitral position are already achieved, combining different frequency analysis methods with various classical classification techniques (Bayes classificator, nearest neighbour) as well as artificial neural networks.[8,9,11]

A stenosis of the aortic valve causes an overload of the heart muscle that leads to a myocardial hypertrophy and a reduced perfusion of the coronary arteries in the long term. An early detection is desirable to avoid a surgical intervention or decrease its extent.

Pavlopoulos *et al*.[24] described a method to differentiate aortic stenosis from mitral regurgitation using heart sounds

Address correspondence to Dr. A. Voss, Professor, Department of Medical Engineering, University of Applied Sciences Jena, Carl-Zeiss-Promenade 2, 07745 Jena, Germany. Electronic mail: voss@fh-jena.de

based on feature extraction and a decision tree. This method achieves high accuracy and is therefore useful for the differential diagnosis but not for a first screening by a general practitioner, because the diagnosis of a valve disease has to be known in advance.

The introduced method of classifying aortic valve stenosis is based on parameter extraction in time and frequency domain as well as on a two classification stage (CS) process, presupposing short computational times and low requirements on computer hardware. This makes the system easy to handle, low in costs and applicable for the general practitioners.

TABLE 1. Patient groups.

Group	Number of patients
REF + OVD	77 + 82
AVS_ms	27
AVS_l	20
Total	206

Note. REF + OVD: subjects without aortic valve stenosis; AVS_ms: patients with moderate or severe aortic valve stenosis; AVS_l: patients with mild aortic valve stenosis.

METHODOLOGY

Data Acquisition and Patients

Heart sound signals of 206 patients were recorded for 15 s on seven different auscultation areas (Fig. 1) using an electronic stethoscope (theStethoscope, Welch Allyn) with a linear frequency response from 20 Hz to 20 kHz. In parallel, a 1-lead ECG was recorded to provide a delimitation of separate heart cycles. Both signals were digitised by a soundcard providing a sampling frequency of 44,100 Hz as well as a 16-bit resolution and were stored in a database together with an echocardiographic report confirmed by a cardiologist.

Records were divided into single heart periods according to RR-intervals from the ECG signal. Therefore, the R peaks were detected automatically, applying a self-developed algorithm based on finding the highest periodical amplitude in the signal. All records were manually edited. Periods with any audible disturbance were excluded from further analysis.

Additionally, a method for detection of the first and second heart sound was applied. This was based on two independent procedures, the calculations of Shannon energy[16] of the wavelet filtered signal (0–172 Hz) over time and of the Total Power over time calculated by summing up all coefficients per window of the Short Time Fourier Transform (STFT) (power–time–STFT). The two highest maxima of every time series were detected within defined time frames where the heart sounds were expected (first heart sound: 0–150 ms, second heart sound: 350–600 ms). These maxima were accepted as first and second heart sound, if the difference of their position in both time series did not exceed more than 70 ms. The location of the heart sounds was finally calculated from the mean value of the maxima positions in both time series.

From all accepted periods of one record, a single representative heart period was chosen based on the highest mean correlation coefficient against all the other accepted

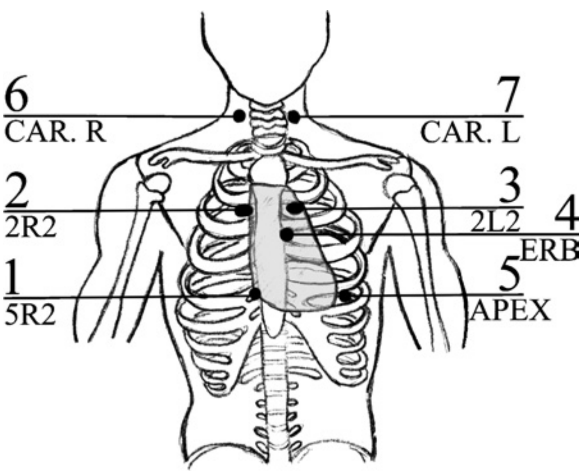

FIGURE 1. Auscultation areas 1–7.

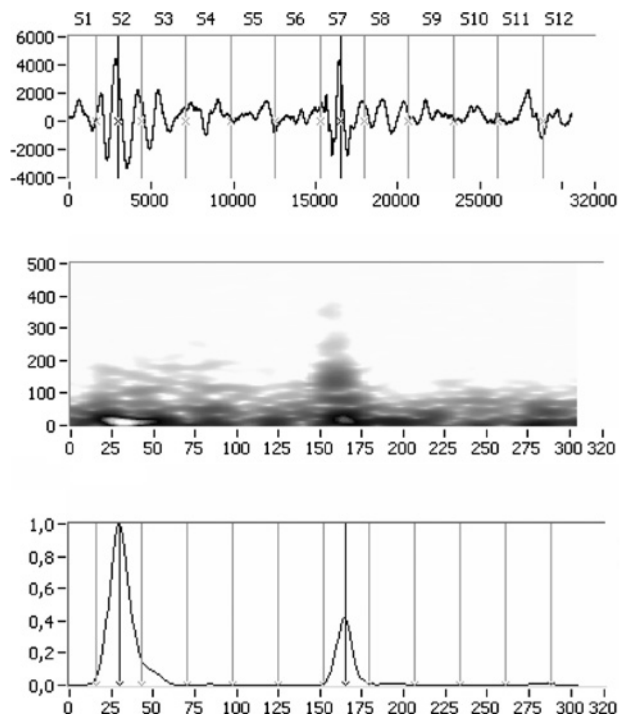

FIGURE 2. Examples of heart sound detection and segmentation, healthy subject; top—original heart sound, centre—STFT, bottom—squared sum of frequency contents.

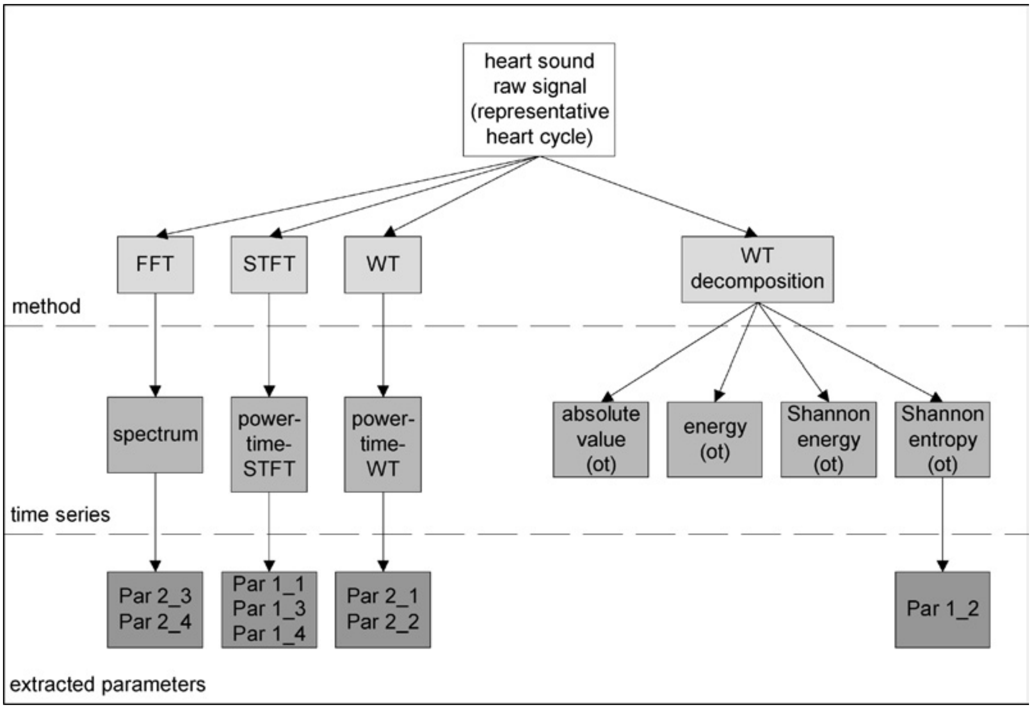

FIGURE 3. Application flow of parameter extraction, ot: over time.

periods in this record. To reduce calculating effort and time only this representative heart period was used in all further calculations.

In this study, only patients with native heart valves were enrolled. The classification procedure is divided into two steps: firstly, the detection of patients with moderate or severe aortic valve stenosis and secondly, the detection of patients with only mild aortic valve stenosis. Therefore, patients were split into three groups (Table 1):

- Patients with no heart valve disease, as healthy subjects (REF) or patients suffering from any other heart valve disease but aortic valve stenosis (OVD).

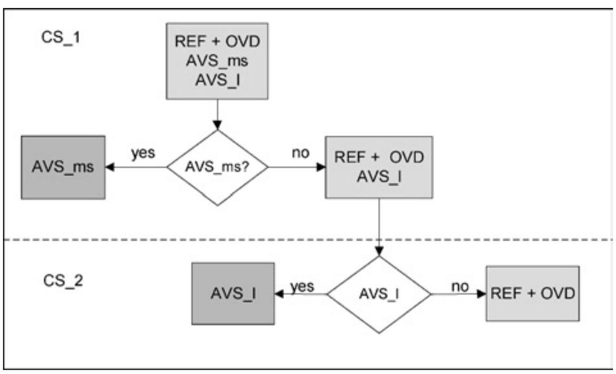

FIGURE 4. Scheme of the two classification stage (CS) process.

- Patients suffering from moderate or severe aortic valve stenosis and possibly from any other additional heart valve disease (AVS_ms).
- Patients suffering from mild aortic valve stenosis and possibly from any other additional heart valve disease (AVS_l).

Signal Processing

Multiresolution Wavelet Analysis

Comparisons of several frequency domain methods have shown that Wavelet Transform (WT) is appropriate for rejecting disturbances and noise from phonocardiograms.[23] Furthermore, heart sounds with low frequencies and heart murmurs with high frequencies can be separated sharply.[12,23]

A multiresolution wavelet decomposition (WT-decomposition) causes a bisection of the wave band with every step.[21] The part containing high frequencies remains, while the part with the low frequencies is bisected again in two wave bands. For this study, only frequency scales from 10 to 2756 Hz were analysed, recognizing that significant heart sounds and murmurs are situated within this range.

Segmentation of signals

Segmentation of the signals was based on the detection of the first and second heart sound as shown in Fig. 2. A signal is divided into 10 intervals of the same length

TABLE 2. Description of parameters selected via stepwise discriminant function analysis.

Parameter	AA	Description: Parameter extraction method	Frequency range (Hz)	Time series	Extracted parameter
PCS 1[a]					
Par 1_1	3	STFT	15–172	Power–time–STFT	Area S4
Par 1_2	2	WT decomposition	172–689	Shannon entropy (ot)	Ratio of area of S5 to total area
Par 1_3	3	STFT	15–689	Power–time–STFT	Ratio of area of S5 to total area
Par 1_4	1	STFT	172–345	Power–time–STFT	Ratio of area of S4 to total area
PCS 2[b]					
Par 2_1	1	WT	639–2205	Power–time–WT	Ratio of area of S2 to total area
Par 2_2	1	WT	79–269	Power–time–WT	Ratio of area of S4 to total area
Par 2_3	2	FFT	115–140	Spectrum	Total power
Par 2_4	2	FFT	115–165	Spectrum	Total power

Note. Significance level $\alpha \leq 0.0000001$, AA: auscultation area; ot: over time; normalized units; see also Fig. 3.
[a]REF + OVD + AVS_l vs. AVS_ms.
[b]REF + OVD vs. AVS_l.

(S2–S11), whereas the length of an interval depends on the distance between the first and second heart sound. The first heart sound is always located within segment S2, the second heart sound always within segment S7. Segment S1 consists of all samples before S2 (from the beginning of the RR interval) and segment S12 includes all samples adjacent to segment S11 (until the end of the RR interval). This dynamic partitioning guarantees that segments with same mechanical phase of the heart are being compared and analysed for different patients respectively.

Short Time Fourier Transform and Wavelet Transform

STFT and WT are appropriate frequency domain methods for the analysis of non-stationary signals and therefore suitable for analysing heart sound signals.[1]

The following parameters were chosen for STFT:

- Blackman–Harris–window function,
- window length 4096 samples (about 100 ms),
- window shifting of 100 samples (about 2.5 ms).

The Blackman–Harris–window function was chosen following the suggestions of Harris.[13] Jamous *et al*. showed that the optimal length of the time window is between 16 and 32 ms.[17] However, the window length of 4096 samples was chosen to ensure that the first and second heart sound each fits into a window completely, considering that duration of the first heart sound sometimes exceeds 50 ms. In addition, an appropriate frequency resolution was provided at the same time.

For WT, the following parameters were chosen:

- wavelet Mexican Hat,
- length of wavelet from 20 to 4410 samples (about 0.5–100 ms) increasing in 100 steps,
- wavelet shifting of 10 samples (about 0.25 ms).

Parameter Extraction

From the STFT and the WT spectrum new time series were derived calculating the total power over time (power–time–STFT, power–time–WT) for various frequency ranges. In addition, the WT decomposed signal was analysed applying calculations of the time domain measures as absolute value over time, energy over time, Shannon energy over time and Shannon entropy over time. Four groups of parameters were computed within each segment S1–S12:

(1) absolute area of one segment,
(2) ratio of area of one segment to area of all segments,

TABLE 3. Mean value and standard deviation.

Parameter	CS 1: REF + OVD + AVS_l	CS 1: AVS_ms	Parameter	CS 2: REF + OVD	CS 2: AVS_l
Par 1_1	9.831 ± 4.693	21.513 ± 4.996	Par 2_1	0.145 ± 0.104	0.141 ± 0.111
Par 1_2	0.066 ± 0.051	0.209 ± 0.093	Par 2_2	0.059 ± 0.033	0.130 ± 0.057
Par 1_3	0.064 ± 0.034	0.151 ± 0.048	Par 2_3	282.880 ± 272.147	407.861 ± 236.990
Par 1_4	0.065 ± 0.071	0.244 ± 0.112	Par 2_4	464.905 ± 437.137	702.125 ± 381.733

Note. Mean ± standard deviation of all parameters related to the different patient groups, CS: classification stage; normalized units.

TABLE 4. Results of CS 1.

CS 1	REF + OVD + AVS_l	AVS_ms
Test +	11 (fp)	26 (tp)
Test −	168 (tn)	1 (fn)

Note. Classification of patients after applying discriminant function analysis with four parameters; first group 179 patients of group REF, OVD and AVS_l, second group 27 patients of group AVS_ms. Sensitivity = 26/27 = 96.3%, Specificity = 168/179 = 93.9%, Correct classification = 194/206 = 94.2%.

(3) sum of differences between two successive samples in one segment,
(4) sum of absolute values of differences between two successive samples in one segment.

Supplementary, the total power within different wide frequency ranges of the FFT of the raw signal was examined. The complete procedure of parameter extraction is demonstrated in Fig. 3.

Statistics

Considering the problem of multiple testing, the necessary significance level of a parameter must fulfil Bonferroni's inequality to guarantee significance (new significance level $\alpha \leq 0.000003$).[3,4] The most significant parameters were used within the succeeding discriminant analysis to obtain an optimal four parameter set.[22]

Initially, patients were divided into two groups which were supposed to be separated with stepwise linear discriminant function technique.

(1) Group: REF + OVD + AVS_l.
(2) Group: AVS_ms.

While the patients suffering from mild aortic valve stenosis (AVS_l) still remained in the first group, a second discriminant function had to be applied splitting this group into the following subgroups.

TABLE 5. Results of CS 2.

CS 2	REF + OVD	AVS_l
Test +	8 (fp)	15 (tp)
Test −	151 (tn)	5 (fn)

Note. Classification of patients after applying discriminant function analysis with four parameters; first group 159 patients of group REF and OVD, second group 20 patients of group AVS_l. Sensitivity = 15/20 = 75%, Specificity = 151/159 = 95%, Correct classification = 166/179 = 92.3%.

TABLE 6. Final results after the two classification stages.

CS 1 + CS 2	REF + OVD	AVS_ms + AVS_l
Test +	3 + 7 (fp)	27 + 15 (tp)
Test −	74 + 75 (tn)	0 + 5 (fn)

Note. Classification of patients after application of two discriminant functions; patients that are tested negative in classification stage one are tested again in classification stage two. Sensitivity(AVS_ms) = 27/27 = 100%; Sensitivity(AVS_l) = 15/20 = 75%; Sensitivity(AVS_total) = 42/47 = 89.4%. Specificity = 149/159 = 93.7%. Correct classification = 191/206 = 92.7%.

(1.1) Group: REF + OVD.
(1.2) Group: AVS_l.

A two CS process (Fig. 4) including two discriminant functions each with four parameters was introduced.

The automatically selected parameter sets PCS 1 and PCS 2 are explained in Table 2.

The performance of all the developed method was evaluated by computing the percentages of sensitivity, specificity and correct classification using the following equations:

$$\text{sensitivity} = \text{tp}/(\text{tp} + \text{fn})$$

$$\text{specificity} = \text{tn}/(\text{tn} + \text{fp})$$

$$\text{correct classification} = (\text{tn} + \text{tp})/(\text{fp} + \text{tn} + \text{tp} + \text{fn})$$

where tp is the number of true positives, tn the number of true negatives, fp the number of false positives and fn the number of false negatives.

RESULTS

The aim was to separate patients with moderate or severe aortic valve stenosis from all other patients and healthy subjects respectively.

With the application of PCS 1, including Par 1_1, Par 1_2, Par 1_3 and Par 1_4 (Table 3), we achieved a sensitivity of 96.3% and a specificity of 93.9% for the correct classification of moderate or severe aortic valve stenosis (Table 4).

The aim of the second classification stage was to separate patients suffering from mild aortic valve stenosis (AVS_l) from patients with no disease on heart valves (REF) or suffering from any other heart valve disease but aortic valve stenosis (OVD). With the application of PCS 2 including Par 2_1, Par 2_2, Par 2_3 and Par 2_4 (Table 3), we achieved a sensitivity of 75% and a specificity of 94.9% for correct classification of mild aortic valve stenosis (Table 5).

Combining the results of both classification stages provides the final classification of aortic valve stenosis. All patients who are not classified as suffering from moderate or severe aortic valve stenosis in the first test stage are tested again for suffering from a mild aortic valve stenosis using the second test stage. (It has to be considered that patients from groups AVS_l and REF + OVD that are classified as AVS_ms in CS 1 are not involved in CS 2 and patients from group AVS_ms that are not detected in CS 1 are tested again in CS 2.) Finally, 100% of all patients suffering from moderate or severe aortic valve stenosis and 75% of all patients suffering from mild aortic valve stenosis are correctly diagnosed. The total sensitivity for the classification of aortic valve stenosis reaches 89.40%, the specificity for patients without aortic valve stenosis (REF + OVD) attains 93.70% (Table 6).

Figures 5–8 show examples of heart sound signals and their derived time series where the selected parameters were extracted from. Figures 5 and 6 show the differences between a subject of group REF in comparison to a subject of group AVS_ms (PCS 1). Figures 7 and 8 demonstrate the differences between a subject of group REF and a subject of group AVS_l (PCS 2).

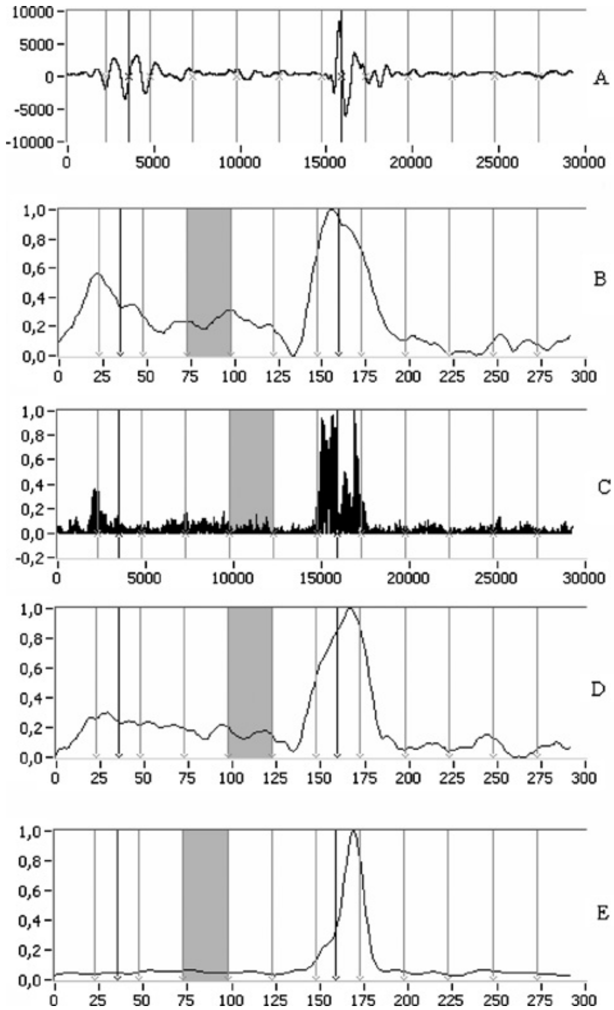

FIGURE 5. First classification stage. Heart sound of a subject of group REF. (A) Original heart sound; (B) power–time–STFT 15–172 Hz; (C) Shannon entropy over time of (A); (D) power–time–STFT 15–689 Hz; (E) power–time–STFT 172–345 Hz; significant segments in comparison to AVS_ms are highlighted.

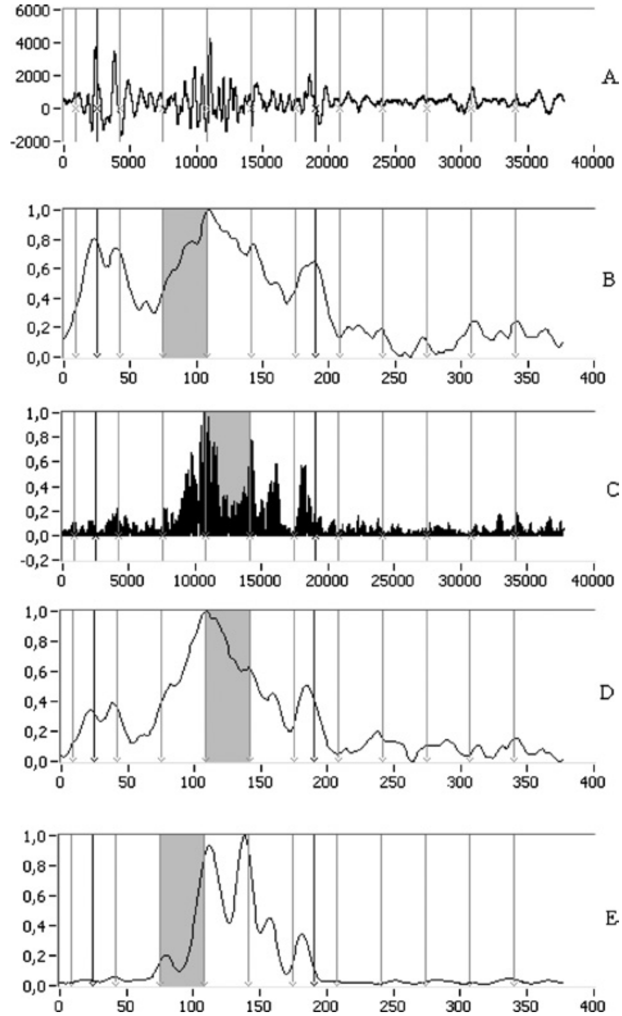

FIGURE 6. First classification stage. Heart sound of a subject of group AVS_ms. (A) Original heart sound; (B) power–time–STFT 15–172 Hz; (C) Shannon entropy over time of (A); (D) power–time–STFT 15–689 Hz; (E) power–time–STFT 172–345 Hz; significant segments in comparison to REF are highlighted.

DISCUSSION

The presented method achieved a sensitivity of 100% for the detection of moderate or severe aortic valve stenosis and a sensitivity of 75% for mild aortic valve stenosis. In only 10 cases (6.3% of all patients in REF and OVD) a misclassification as aortic valve stenosis occurred. Interestingly, 7 of these 10 patients suffer from another heart valve disease (aortic, mitral, tricuspid and/or pulmonary insufficiency in different combinations or severities) but aortic valve stenosis.

Diagnosing aortic valve diseases by auscultation is usually confirmed by a systolic murmur between the first and second heart sound.[14,15] The applied parameters Par 1_1, Par 1_2, Par 1_3, Par 1_4 and Par 2_2 correspond with this diagnosing criteria. All of these parameters are located in

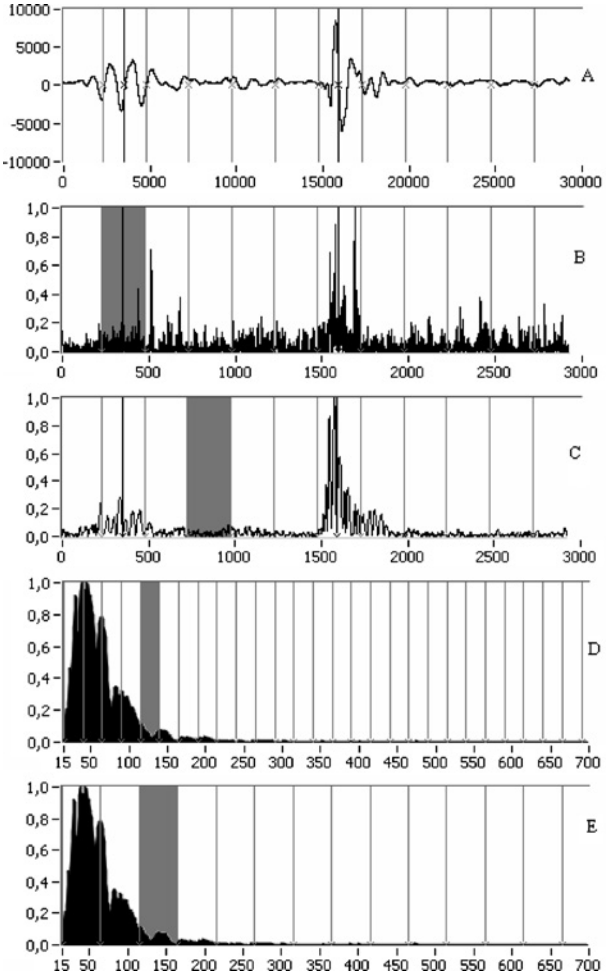

FIGURE 7. Second classification stage. Heart sound of a subject of group REF. (A) Original heart sound; (B) power–time–WT 639–2205 Hz; (C) power–time–WT 79–269 Hz; (D) FFT 15–700 Hz divided into frequency bands of 25 Hz; (E) FFT 15–700 Hz divided into frequency bands of 50 Hz; significant segments in comparison to AVS_I are highlighted.

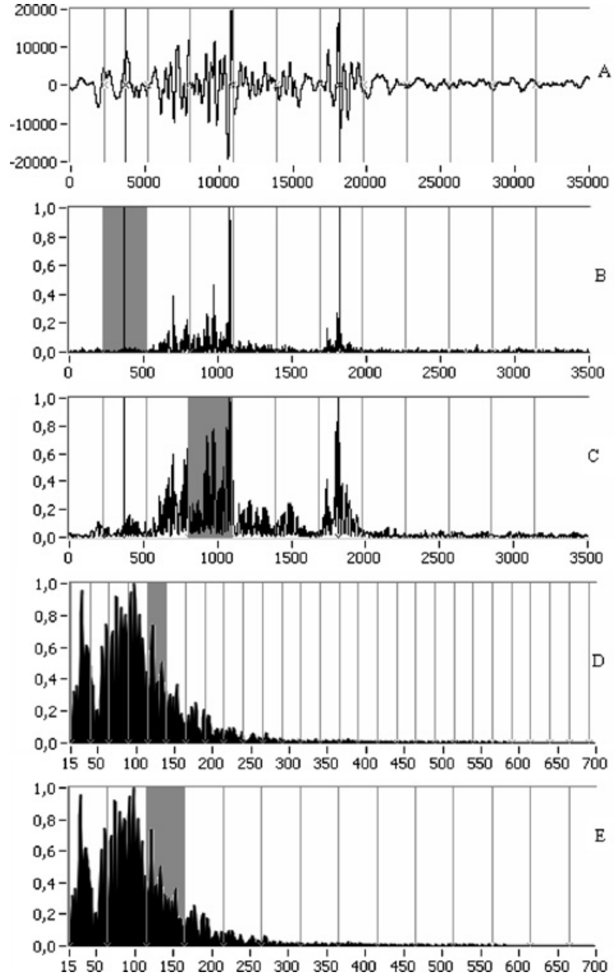

FIGURE 8. Second classification stage. Heart sound of a subject of group AVS_I. (A) Original heart sound; (B) power–time–WT 639–2205 Hz; (C) power–time–WT 79–269 Hz; (D) FFT 15–700 Hz divided into frequency bands of 25 Hz; (E) FFT 15–700 Hz divided into frequency bands of 50 Hz; significant segments in comparison to REF are highlighted.

segment 4 or 5, which are situated between first and second heart sound. Especially Figs. 5(B) and (C) and 6(B) and (C) show the differences of power and energy within the segments (located between the first and second heart sound) between a healthy subject and a subject suffering from severe AVS caused by the pathological heart murmur. Par 2_1 is located in segment S2 that indicates a change of the first heart sound. The examples in Figs. 7(B) and 8(B) lead to the assumption that the first heart sound is attenuated when suffering from a mild aortic valve stenosis. The FFT spectra in Figs. 7(D) and (E) and 8(D) and (E) show an increasing power between 100 and 200 Hz represented by parameters Par 2_3 and Par 2_4 due to the occurring heart murmur. The revealed frequency parameters Par 1_1, Par 1_3, Par 1_4 and Par 2_1–Par 2_4 represent the established frequency bands of heart murmurs caused by aortic valve stenosis. This was also proved by Kim *et al*., who showed that durations of the spectra at different frequencies were correlated to the Doppler echocardiogram-derived mean and peak pressure gradients as an indicator for an aortic valve stenosis.[18]

All selected parameters (Table 2) are extracted from recordings of auscultation area 1, 2 or 3. Parameters of auscultation area 4 or 5 did not contribute significantly to the discrimination between patients. Nevertheless, they might become relevant for diagnosing other valve diseases and, therefore, should be considered in further studies. The classification of the degree of aortic valve stenosis still remains difficult especially for lower degrees. Only one of all detected moderate or severe AVS is diagnosed as mild AVS, but six mild AVS are classified as moderate or severe AVS.

The advantages of parameter extraction are especially the low calculation and technical efforts. Parameter extraction can be performed with a common computer system, a special database is not required. Due to the low computational time, the physician receives all necessary results within consultation time. However, at least one noise free and disturbance free heart period is required from auscultation area 1–5. To preserve low noise heart sound signals, all records should be performed within a quiet environment and an adequate recording time has to be provided.

The introduced analysis will be verified in a prospective study that did already start. Furthermore, all other prevalent heart valve diseases (aortic valve insufficiency, mitral valve insufficiency) might be investigated following the same procedure. An extension on other heart diseases is also conceivable.

CONCLUSIONS

The introduced automatic heart sound classification technology offers a safe, easy-to-use and low-cost method for the general practitioner to diagnose aortic valve stenosis at an early stage. In addition, the amount of unnecessary referrals caused by false positive results can be reduced.

ACKNOWLEDGMENT

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