Semi-automation of Doppler Spectrum Image Analysis for Grading Aortic Valve Stenosis Severity

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1. Introduction

The aging population is a major global challenge for healthcare systems. The demand to provide high quality treatment and maintain the standard of living at reasonable cost becomes a hardly achievable objective. In our work, we introduce a novel method, helping to automate diagnostic of aortic valve stenosis (AS), which is prevalent in the elderly population.

According to the recommendations of the professional cardiologists associations, a well-defined set of parameters is used to differentiate AS and its severity. Since a game-changing work of L. Hatle et al. in 1980 [1], the golden standard for AS diagnostic is to rely on echocardiography measured by Doppler ultrasound. However, a number of pitfalls the clinicians are struggling with exists – difficulty in getting good quality images, localizing the measuring area in continuous-wave or pulse-wave Doppler modes, and time consuming manual tracing of the images, which also may lead to human error.

Medical image analysis as a topic of its own has developed successfully in the last decades. There are a number of papers using signal processing techniques to structure and compare echocardiograms and electrocardiogram (ECG) signal images [2–6], where Fourier transformation, wavelet transform, and empirical mode decomposition methods have been applied. The approach and implementation for semi-automated categorization of medical images has been proposed by T. M. Lehmann, M. O. Guld, et al. [7]. Instead of using commonly applied features describing color and shape, the authors proposed to apply texture measure and resized representations of the images, like coarseness, contrast, directionality, and properties of edges within an image as global feature vectors. T. Tak et al. analyzed the intensity of the regurgitant signal obtained by continuous-wave Doppler to indicate the severity of aortic regurgitation. The methods applied by the authors included the calculation of mean pixel intensity and statistical analysis of the grouped image sets.

To our best knowledge, there is limited research on continuous-wave and pulse-wave Doppler image processing for computer-aided diagnosis. Our study contributes to the field by proposing spectrum images processing techniques for computer-aided AS diagnosis.

Keywords
Digital image processing, feature extraction, aortic valve stenosis, Doppler echocardiography

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Our main goal was to evaluate the possibility and assess the accuracy of computer-aided aortic systolic blood flow recognition from the ultrasound modalities diagnostic images. The successful computer image processing would support clinicians in routine operations of systolic flow tracing, and furthermore, provide an automated calculation of the parameters and propose third opinion in AS diagnosis and severity grading.

2. Background

2.1 Aortic Valve Stenosis

The aorta is the main artery that delivers blood from the heart to the rest of the body. The aortic valve serves as a gateway between the heart and the aorta. When the aortic valve orifice narrows due to calcification or other processes, the left ventricle has to work harder to create more pressure to pump blood out through the valve, and the blood supply might become insufficient. The described condition is called valvular AS, or AS. There are three main causes of AS: calcific AS, rheumatic AS, and congenital AS. Calcific stenosis is the most common type.

According to the latest data [8] AS is related to aging and is present in 29% of individuals older than 65 years and in 37% of individuals older than 75 years.

2.2 Diagnosing Aortic Valve Stenosis

The transthoracic two-dimensional Doppler echocardiographic permits to diagnose and estimate the severity of AS in the majority of the cases. In specific cases transesophageal echocardiography is used. The American Heart Association defines measurements by Doppler echocardiography as the gold standard for patients' diagnosis with AS, which can be performed noninvasively and with sufficient precision. The methodology for stenosis severity evaluation has been developed in the late 80s and is used since then [1, 9].

The widely accepted way to assess AS severity is to measure the peak transaortic jet velocity in the aortic valve (AV) and in the left ventricular outflow tract (LVOT), and LVOT diameter [10]. Afterwards, simplified Bernoulli equation and continuity equation [11] are used to calculate pressure gradients and aortic valve area (AVA) accordingly.

According to the guidelines of the European Association of Echocardiography, the American Society of Echocardiography and the European Society of Cardiology [10, 11], AS severity shall be classified with the parameters AV peak jet velocity, AV mean gradient, AVA, and velocity ratio as shown in Table 1. The measured parameters and formulas of the derived parameters are provided in Table 2.

Table 1  ESC/ASE/EAE guidelines to determine AS severity

<table>
<thead>
<tr>
<th>Parameter</th>
<th>No stenosis</th>
<th>Mild</th>
<th>Moderate</th>
<th>Severe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak jet velocity (m/s)</td>
<td>&lt; 2.6</td>
<td>2.6 – 3</td>
<td>3 – 4</td>
<td>&gt; 4</td>
</tr>
<tr>
<td>Mean gradient (mmHg)</td>
<td>–</td>
<td>&lt; 30</td>
<td>30 – 50</td>
<td>&gt; 50</td>
</tr>
<tr>
<td>AVA (cm²)</td>
<td>–</td>
<td>&gt; 1.5</td>
<td>1 – 1.5</td>
<td>&lt; 1</td>
</tr>
<tr>
<td>Indexed AVA (cm²/m² BSA*)</td>
<td>–</td>
<td>&gt; 0.9</td>
<td>0.6 – 0.9</td>
<td>&lt; 0.6</td>
</tr>
<tr>
<td>Velocity ratio **</td>
<td>–</td>
<td>&gt; 0.5</td>
<td>0.25 – 0.5</td>
<td>&lt; 0.25</td>
</tr>
</tbody>
</table>

* AVA divided by body surface area (BSA)
** ASE/EAE guidelines

3. Methods and Procedures

3.1 Research Data

The depersonalized and de-identified medical data have been provided by Vilnius University Santariskiu Klinikos. We retrospectively studied the clinical and Doppler echocardiographic data of 18 patients, preselected by the participating cardiologist. The selection criterion for the second-use data was the severity of AS. Of these patients, five had no clinical signs of AS, five patients had mild AS, four patients moderate AS, and four patients manifested severe AS. The clinical measurements for AS grading and diagnosis, provided by the participating cardiologists, have been used as the golden standard in the study.

The initial data set consisted of 36 aortic valve and 35 left ventricle output tract spectrogram images. The list of measured and calculated clinical, parameters is provided in Table 2.

Table 2  The list of measured and calculated echocardiographic parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Type</th>
<th>Units</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v_{\text{max}}$ (peak systolic velocity)</td>
<td>Velocity</td>
<td>m/s</td>
<td>–</td>
</tr>
<tr>
<td>$T$ (duration time)</td>
<td>Time</td>
<td>s</td>
<td>–</td>
</tr>
<tr>
<td>$v$ (mean systolic velocity)</td>
<td>Formula</td>
<td>m/s</td>
<td>$\frac{V_{\text{TI}}}{T}$</td>
</tr>
<tr>
<td>LVOT D</td>
<td>Diameter</td>
<td>cm</td>
<td>–</td>
</tr>
<tr>
<td>$\Delta P$ (mean pressure gradient)</td>
<td>Formula</td>
<td>mmHg</td>
<td>$\Delta P = \frac{\sum 4v^2}{N}$</td>
</tr>
<tr>
<td>$\Delta P_{\text{max}}$ (peak pressure gradient)</td>
<td>Formula</td>
<td>mmHg</td>
<td>$\Delta P_{\text{max}} = 4v_{\text{max}}^2$</td>
</tr>
<tr>
<td>AVA (aortic valve area)</td>
<td>Formula</td>
<td>cm²</td>
<td>$\frac{\pi \times LVOT \ D^2 \times LVOT \ VTI}{4 \times AV \ VTI}$</td>
</tr>
<tr>
<td>$V_{\text{TI}}$ (Velocity time integral)</td>
<td>Formula</td>
<td>cm</td>
<td>$V_{\text{TI}} = \int v(t) , dt$</td>
</tr>
<tr>
<td>$V_{\text{I}}$ (Velocity index)</td>
<td>Formula</td>
<td>–</td>
<td>$V_{\text{I}} = \frac{LVOT \ VTI}{AV \ VTI}$</td>
</tr>
</tbody>
</table>
3.2 Measuring Doppler Echocardiographic Data

In our experiments, blood flow velocity was measured with a 5-chamber view continuous-way Doppler for AV flow, and pulsed-way Doppler for LVOT flow. A noise filter of ultrasound device, which eliminates low and high frequency noise, with default parameters was used. The transducer’s alignment with blood stream across the valve was checked with Color Doppler. The measured blood flow had a real time graphical visualization, with waveform spectrogram image (Figure 1), which was stored in the hospital’s PACS system, and then exported in DICOM format.

A normal aortic valve spectral Doppler trace has a single rounded systolic wave below the baseline, as blood flow is away from the transducer. The systolic wave is enclosed within AV opening click and closing clicks.

In order to evaluate the time savings of systole tracing automation, we have tracked the time spent by two experienced cardiologists for manual AV and LVOT systole wave tracing. The participating clinicians have chosen three random AV and three LVOT spectrogram images. The AV wave tracing took from 9 seconds up to 13.4 seconds; LVOT wave – accordingly from 5.7 seconds up to 11.9 seconds per one measurement. The durations of the measurements are provided in Table 3.

According to the participating cardiologists, the time spent for a single measurement depends on the size of the systole, the quality of the spectrogram, especially sharpness of the edges. In addition, duration depends on the working pace of the specific doctor. Cardiologists typically make from one to four measurements per patient, dependable on the clinical indications. Generally, it is recommended to perform at least 2–3 measurements per patient, when diagnosing AS [6].

3.3 Image Data Analysis Methodology

In general, systolic peak extraction from the diagnostic image involves four steps as visualized in Figure 2.

The image data preprocessing methods were implemented in R [12], ImageJ [13, 14] library functions were used for the first step of the image preprocessing tasks.

3.3.1 Step 1 – Image Preprocessing

First, 8-bit spectrogram images have been converted to 1-bit images. Isodata [15] algorithm was used to determine the threshold level, which differentiate foreground and background of the image. The resulting image is shown in Figure 3 b.

G. Landin’s implementation [16], based on flood filling algorithm [17] was used to smooth larger edges and correct data losses (filling holes) after image conversion to 1-bit. The resulting image is shown in Figure 3c.

Then, Sobel’s edge detector [18, 19] was used to separate spectrogram image curve from the rest. Two 3 by 3 convolution kernels were used to generate vertical and horizontal derivatives, to produce the final image. Outline filter, which generates a one pixel wide outline of the objects in the image, was applied as an alternative solution. Our experiments showed that outline filter gave more precise and consistent results on AV and LVOT spectrogram images.

To reduce noise artifacts, typical for echocardiographic images, we used a depeckling filter, which replaces a pixel by the median of the 3 × 3 surrounding pixels when it deviates by certain threshold. The results of the outlining and depeckling are shown in Figure 3d.

3.3.2 Step 2 – Approximation of Spectrogram Image Curve

The resulting image from the image preprocessing step represents an outline of the systole, matching the one measured by ultrasound equipment. We have ignored excessive data by considering only the 10th decile of data. While random notches, were

<table>
<thead>
<tr>
<th>Spectrum type</th>
<th>Systole measurement time, sec</th>
</tr>
</thead>
<tbody>
<tr>
<td>AV</td>
<td>Min</td>
</tr>
<tr>
<td>1</td>
<td>13.08</td>
</tr>
<tr>
<td>2</td>
<td>10.1</td>
</tr>
<tr>
<td>3</td>
<td>9.94</td>
</tr>
<tr>
<td>4</td>
<td>8.99</td>
</tr>
<tr>
<td>5</td>
<td>11.4</td>
</tr>
<tr>
<td>6</td>
<td>13.44</td>
</tr>
<tr>
<td>LVOT</td>
<td>Min</td>
</tr>
<tr>
<td>1</td>
<td>11.9</td>
</tr>
<tr>
<td>2</td>
<td>9.89</td>
</tr>
<tr>
<td>3</td>
<td>9.89</td>
</tr>
<tr>
<td>4</td>
<td>10.1</td>
</tr>
<tr>
<td>5</td>
<td>5.66</td>
</tr>
<tr>
<td>6</td>
<td>6.78</td>
</tr>
</tbody>
</table>

Table 3

Manual systole tracing measurements net time.

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removed by smoothing the curve with a help of local polynomial regression fitting [20].

The illustration of the steps is shown in Figure 4.

### 3.3.3 Step 3 – Identification and Cropping of the Valid Systole Peak Cycles

Since a spectrogram image might contain a varying number of peak systolic waves (in our study – from one to three), a method identifying and cropping a complete systole cycle was created. Considering the range of possible peaks frequency and possible minimum and maximum peak values, we have eliminated smaller peaks – marked (s) in Figure 5. The incomplete systoles have been rejected as well – marked (i) in Figure 5.

![Figure 2](image2.png)

**Figure 2**

Semi-automated AS evaluation methodology

![Figure 3](image3.png)

**Figure 3**

The initial echocardiographic systolic flow Doppler spectrum preprocessing steps. AV flow images on the left, LVOT flow images on the right. Preprocessing steps in horizontal layers from top to bottom: a) original image, b) binarized image, c) images with filled holes, d) outlined after despeckling filter images.
The identified systole cycles are indicated in Figure 5.

By applying the introduced algorithm, a set of AV and LVOT systole cycles have been captured for each patient. From one to five systole cycles per patient have been captured by the algorithm for further processing. Typically, two cycles per patient have been captured. In a few cases, more images have been provided, which resulted in three to five cycles per patient. In a few LVOT images only one cycle was defined by the algorithm.

3.3.4 Step 4 – Calculation of the Diagnostic Parameters.

Before performing calculations, images have been scaled to the predefined Doppler ultrasound images axis values. All diagnostic spectrogram images had a fixed duration of two seconds on abscissa, and variable velocity value on ordinate. The average systole cycle of a patient has been derived by local polynomial regression fitting (Figure 6). Finally, the parameters – duration and peak systolic velocity ($v_{\text{max}}$) – were directly calculated, respectfully as the cropped parabola's length on abscissa, and its height on ordinate. For VTI calculation, the curve was fitted with 2nd degree polynomial and its definite integral was calculated. Higher order polynomials were not used to avoid overfitting and scalability problems.

Other required parameters have been calculated using formulas provided in Table 2.

4. Results

The initial data set consisted of 71 spectrogram images. By applying our method, the spectrogram images were transformed to the traced 71 AV and 68 LVOT blood flow velocity complete systole cycles.

In order to evaluate the effectiveness of our proposed method, we compared manual measurement performed by the cardiologist (M) with the measurement results of the proposed semi-automated method (A). The performance of the proposed method is reported with Pearson correlation coefficient and Bland-Altman limits of agreement. Introduced by J. M. Bland and D. G. Altman, the limits of agreement (LoA) are acceptable prediction limits for the difference between the measurements of the two methods on a randomly chosen item [21].

The Bland Altman model is formulated as a two-way analysis of variance model. For the future measurement prediction, Bland-Altman model stipulates the difference of the new values, obtained with each of the methods, from the first measured value.

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two compared methods, is within the limits of agreement with 95% probability. In the most cases, we observed a good agreement between the two methods.

The values of parameters directly derived from the processed images relate to the compared manually obtained values as follows:

1. Values of AV \( V_{\text{max}} \) and AV \( V_{\text{TI}} \) measured by the two methods were strongly and significantly correlated. For AV \( V_{\text{max}} \): \( R^2 = 0.999 \), p-value < 0.0001; AV \( V_{\text{TI}} \) \( R^2 = 0.988 \), p-value < 0.0001. However, LVOT \( V_{\text{TI}} \) measurement showed a lower degree of correlation: \( R^2 = 0.68 \), p-value < 0.0001.

2. Bland-Altman plots for the parameters AV \( V_{\text{max}} \), AV \( V_{\text{TI}} \), and LVOT \( V_{\text{TI}} \) (Figure 7), outline Limits of Agreement, and the means of the differences \( A-M \):
   - AV \( V_{\text{max}} \) \( \bar{d} = 0.02 \text{ m/s} \),
   - AV \( V_{\text{TI}} \) \( \bar{d} = 0.16 \text{ cm} \),
   - LVOT \( V_{\text{TI}} \) \( \bar{d} = 3.43 \text{ cm} \).

Of the highest importance for AS diagnosis, the remaining calculated parameters – mean pressure gradient (PGmean) and aortic valve area (AVA) – relate to the corresponding values of manual measurements as follows:

- PGmean \( R^2 = 0.994 \), p-value < 0.0001, \( d(M - A) \in [-13.37, 5.20] \), \( d = 4.09 \text{ mmHg} \).
• AVA \( R^2 = 0.894, \) p-value < 0.0001, \\
\( d(M - A) \in [-0.33, 0.70], d = 0.19 \text{ cm}^2. \)

In addition, we have compared manual measurements with the values of averaged spectrograms, calculated in the step 4 of the method (automated averages – AA). The Comparison generally showed lower values of Pearson coefficient and wider Limits of Agreement:

• AV \( v_{\text{max}} \) \( R^2 = 0.999, \) p-value < 0.0001, \\
\( d(M - AA) \in [-0.29, 0.15], d = 0.07 \text{ m/s} \)
• AV VTI \( R^2 = 0.988, \) p-value < 0.0001, \\
\( d(M - AA) \in [-32.40, 49.10], d = 8.35 \text{ cm} \)
• LVOT VTI \( R^2 = 0.68, \) p-value < 0.0001, \\
\( d(M - AA) \in [-6.83, 23.24], d = 8.20 \text{ cm} \)
• \( \Delta P \) \( R^2 = 0.9868, \) p-value < 0.0001, \\
\( d(M - AA) \in [-20.55, 6.64], d = 6.96 \text{ mmHg} \)
• AVA \( R^2 = 0.759, \) p-value < 0.0001, \\
\( d(M - AA) \in [-0.56, 1.03], d = 0.24 \text{ cm}^2 \)

Comparison of the time needed to perform measurements and calculations using method (M), and method (A) has the following results: taking an average flow of 20 patients per day, total amount of measurements will be 20 by 6 (3 AV and 3 LVOT) measurements, which would lead to 20 minutes of net measurement time (according to the average durations provided in Table 3). In addition, total time spent by doctors, will include time needed for systole selection, manual comparing of the measured and calculated parameters values, which according to our experiments adds around 20–40 per cent overhead. Summarizing, the time spent for manual tracing and processing of the measurements is 72–84 seconds per patient, which makes 24–28 minutes per cardiologist with a flow of 20 patients per day.

Running time of the spectrogram image analysis method implementation on the consumer type personal computer was in between 1–2 seconds per spectrogram image, containing from 1 to 3 systole waves. Thus, the total projected timesaving per cardiologist with a hypothetic flow of 20 patients per day is around 22–26 minutes.

5. Discussion

In this study, we have demonstrated how to implement semi-automated blood flow spectrograms tracing and calculating hemodynamic parameters, aiming to help in AS severity grading. The outcome results, presented in Section 4, showed a good agreement between the introduced method and the standard measurement method, typically provided by ultrasound equipment and used by the cardiologists.

It is notable to mention, the calculated parameters of mean gradient and the aortic valve area provided by the ultrasound machine and our method are not directly comparable, as the diagnostic equipment vendors use proprietary calculation algorithms. For the comparison purposes, we used formulas derived from simplified Bernoulli and continuity equations [11] on the measurements provided by ultrasound machines (as outlined in Table 1). Our calculated values showed strong correlation with proprietary ultrasound’s values, with \( R^2 = 0.799, \) p-value < 0.0001 and mean methods’ difference of 0.16 cm; the calculated \( \Delta P(v_{\text{max}}) \) measurements compared to ultrasound’s \( \Delta P(v_{\text{max}}) \) showed \( R^2 = 0.99 \) and p-value < 0.0001 with mean methods difference of 1.84 mmHg.

Comparison of manual measurements with the derived results of the averaged systole images showed poorer performance. This could be explained that the average systole cycle, derived by averaging all available complete systole cycles of the data set (separately for AV and LVOT spectrogram images), has not always matched the best AV or LVOT cycles, selected by the clinician for the tracing and measurements to be performed. Here we see a potentially useful application of our method, revealing untypically big differences in semi-automated and manual measurements, which would probably indicate inconsistency in either of the methods outcomes, or the non-representative systole cycle, selected by the cardiologist.

Comparison of the time needed for measurement and calculation of the diagnostic parameters by manual measurement and the automated one can only be partly completed, since the implementation of the spectrogram image analysis method for AS grading is not integrated into ultrasound equipment software and therefore requires additional image export/import steps allowing to process the images offline. However, comparing the time needed for a cardiologist to perform manual measurement with the net processing time of our method implementation shows that up to 26 minutes can be saved per cardiologist, with a hypothetical flow of 20 patients per day.

There are additional application possibilities of the proposed method, in detecting manifestations of other cardiology diseases, which also rely on the Doppler ultrasound imaging of patients’ blood flow. One of the possibilities is to use the proposed method for Mitral valve stenosis diagnostics. This will require adaptation of the method’s 4th step, adding the calculations of pressure half-time and slope, required for Mitral Stenosis severity evaluation. Another potentially rewarding application is the quantitative regurgitation assessment, which would also require further parameterization and adaptation of the presented image processing techniques.

5.1 Limitations of the Study

The proposed echocardiography spectrogram images processing methods have been implemented for offline processing and are not integrated into proprietary software of the ultrasound equipment. This limitation imposes an additional manual step for the cardiologist – exporting of Doppler spectrum images from ultrasound workstation or PACS software. Integration of our proposed digital image processing techniques into software of ultrasound equipment would allow fully automated image processing and computer-aided diagnosis support.

The study has been validated with a small dataset consisting of 71 spectrogram images, representing 18 patients with AS manifestations of different severity. Arguably, higher volume of spectrograms with different clinical conditions, and acquired using different ultrasound equipment may lead to a higher error rate. In addition, atypical cases of stenosis, as so-called paradoxical low-flow and low-gradient stenosis cases [22] may increase unpre-
dicted variability in the images. Therefore, the developed method needs further approval and possibly further optimization.

6. Conclusion

Current diagnostic practice requires clinicians to perform manual image processing activities. This is a tedious process, which requires accuracy; arguably, it might also lead to inaccurate measurements. Therefore, a semi-automated echocardiography spectrogram image data analysis tool was created to help medical practitioners avoid or minimize tedious and time-consuming image preprocessing tasks.

We have shown that the proposed automated tracing of the blood flow spectrogram and calculation of hemodynamic parameters method is reliable and could be used as a supplementary tool for the AS severity grading. The correlation between the results of automated and standard manual measurement methods is high and there is a good agreement between both approaches according to Bland-Altman limits of agreement.

It is anticipated that the semi-automated extraction of AS grading features could help clinicians to save time, up to 1.5 minutes per patient, and acquire reliable and objective measurement results. Arguably, it could also help to reduce human error. However, current implementation requires manual exporting images from native ultrasound environment to perform offline processing. Future integration with the native ultrasound equipment software would allow complete automation of the process.

The main limitation of the study was limited experimental validation of the method, due to a small data set. In future work, we plan to further test and optimize the method on a larger image dataset, before the semi-automated AS grading method can be used in a hospital setting. Moreover, we aim to improve the accuracy of left ventricle outflow tract spectrograms tracing. Finally, the clinical decisions support system to be created, supplementing the introduced semi-automated echocardiography image processing method with data mining techniques.

References