Application of laser Doppler vibrometery for human heart auscultation

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Abstract— **In this study the potential of a Laser Doppler Vibrometer (LDV) was tested as a non-contact sensor for the classification of heart sounds. Of the twenty participants recorded using the LDV, five presented with Aortic Stenosis (AS), three were healthy and twelve presented with other pathologies. The recorded heart sounds were denoised and segmented using a combination of the Electrocardiogram (ECG) data and the complexity of the signal. Frequency domain features were extracted from the segmented heart sound cycles and used to train a K-nearest neighbor classifier. Due to the small number of participants, the classifier could not be trained to differentiate between normal and abnormal participants, but could successfully distinguish between participants who presented with AS and those who did not. A sensitivity of 80 % and a specificity of 100 % were achieved a test dataset.**

I. INTRODUCTION

Cardiovascular Disease (CVD) is a growing concern for developing countries, as the number of people who are diagnosed with CVD in those countries is steadily increasing. As a result, sparse health care resources are being diverted towards the detection and treatment of CVD [1]. Early detection of illnesses such as CVD is an important aspect of managing the scarce resources available in the underserved and impoverished communities. Very often there is not sufficient medical care available to provide such a service [2]. Telemedicine and automated diagnosis tools could become an important tool in providing basic medical care to those living outside urban areas.

The Laser Doppler Vibrometer (LDV) was originally developed to measure structural vibrations, but has recently been investigated for use as a non-contact biomedical sensor. The LDV has the potential to become a versatile diagnostic tool operable by an unskilled person, making it ideal for the telemedicine industry. Umberto *et al.* [3] compared the LDV output to the well-researched phonocardiogram, while De Melis *et al.* [4] studied the velocity profile to find characteristic features unique to different heart pathologies.

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Heart murmurs are high frequency noises which are audible in-between the normal heart sounds. Heart murmurs are observed when the heart valves do not function properly, either creating a narrowed flow path (stenosis) or allowing blood to flow backwards through the valve (regurgitation) [5]. The most common instrument used to detect and classify heart sounds and murmurs is the stethoscope, which requires physical contact with the patient [6]. In the interest of comparing the LDV to more well-known techniques (such as the phonocardiogram) the output of the LDV was filtered according to techniques described De Melis *et al.* [3] and Umberto *et al.* [4]. This produced a waveform visually similar to the phonocardiogram which could be analyzed with many of the same techniques. Because it is a non-contact sensor, the LDV can more easily be used in situations where contact is undesirable or impossible, such as monitoring the vital signs of burn victims or individuals inside a biohazard zone without physically being inside the contaminated are. To the authors' knowledge no attempt has been made to use the LDV as part of an automated diagnosis system at the time of this publication.

II. EXPERIMENTAL SETUP

A. *Apparatus and Measurement Approach*

The measurement setup is shown in Figure 1. The LDV (MetroLaser Inc. model 500V) is mounted with the laser beam perpendicular to the participant's chest. Laptop 1 controls the Electrocardiogram (ECG, Norav Medical model 1200HR) data acquisition and Laptop 2 controls the LDV data acquisition from the ZonicBook Medallion (ZBM). The ZBM has built-in anti-aliasing filters and the LDV signals were sampled at 5120 Hz.

The signal generator (SG) injected a 20 Hz sinusoidal signal into both the ECG data acquisition system and on a channel on the ZBM. The sinusoidal wave was used to synchronise the data recorded by the two laptops during postprocessing. The LDV data was recorded on a single position on the sternum of the participant, as suggested by De Melis *et al.* [3] and Umberto *et al.* [3]. The participant data was recorded with the participants in the supine position.

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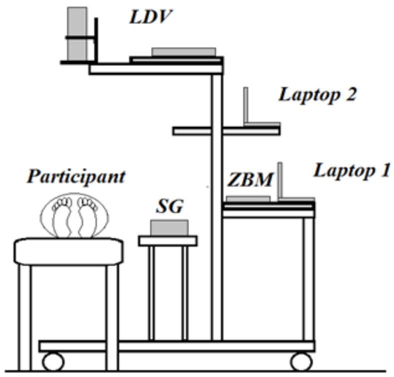

Fig 1. The test frame setup showing the positions of the data acquisition units and sensors relative to the participant.

B. Procedure

In total, 20 participants were recorded at Tygerberg Academic Hospital in Cape Town, South Africa. The study was approved by the relevant institutional review board of Stellenbosch University. All participants gave informed consent, at which point they were diagnosed by a cardiologist from the Division of Cardiology at Tygerberg Academic Hospital. Thereafter recordings were made using the LDV measurement setup.

For each recording, an accompanying ECG measurement was taken. The range of pathologies which were recorded included three participants with normal heart sounds and seventeen with abnormal heart sounds. Due to the small number of healthy participants recorded, the decision was made to attempt to differentiate between the five participants who presented with Aortic Stenosis (AS), and the fifteen participants who did not present with AS.

III. Data Analysis

A. Signal processing

The ZBM is equipped with a built-in low-pass 80 dB anti-aliasing filters for each of its channels. The signals were sampled at a frequency of 5120 Hz, which was sufficiently high to capture all the relevant heart murmur data [7]. The LDV data showed the presence of signal drop-outs, which is a common phenomenon experienced by optical sensors when an "optically rough" surface is recorded. As the surface moves, the amplitude of the Doppler-shifted signal reflected back to the LDV's signal demodulation unit falls below the minimum threshold required for the unit to be able to derive an analogue velocity waveform, and the signal "drops" away. These dropouts were removed from the recorded LDV signal using a modified global least-squares method adapted from Vanlanduit *et al.* [8]. The LDV data was then divided into two separate streams which underwent different processing. Each stream was used to extract different diagnostic data.

Stream 1 was digitally filtered with a band-pass 4th order Butterworth filter with cut-off frequencies of 15 Hz and 700 Hz. This produced a waveform similar to the phonocardiogram [3]. Stream 1 was then further denoised using wavelet analysis with a db7 mother wavelet, and Ensemble Empirical Mode Decomposition (EEMD) filtering. Stream 2 was filtered with a low-pass 4th order Butterworth filter with a cut-off frequency of 700 Hz. This yielded the velocity profile of the LDV data. Figure 2 shows the differences in the two streams.

The Stream 1 data were used to extract features for automated diagnosis while Stream 2 data were used for visual inspection of the underlying velocity characteristics of the various pathologies which were recorded. While no time-domain features were used in the automated diagnosis, future work could explore the time domain features in greater depth.

The recorded ECG data was used to segment the LDV data into the underlying heart sound cycles. The software used to record the ECG data could only record 10 seconds of ECG data, which was insufficient to record an adequate number of heart sound cycles. A second method was therefore used to segment the LDV data for which there was no ECG data.

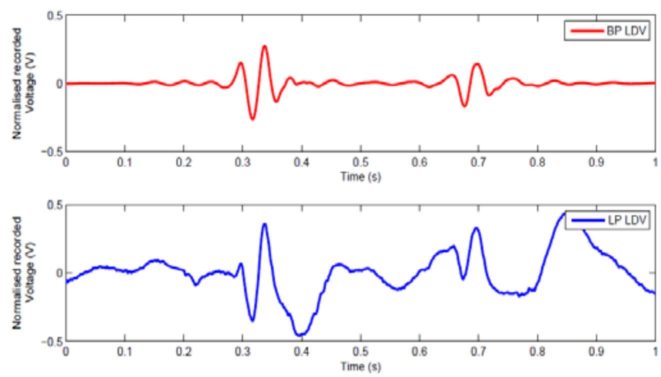

Fig. 2. The two filtered LDV data streams. Stream 1 was band-pass (BP) filtered and Stream 2 was low-pass (LP) filtered.

This method was based on a simplicity curve as proposed by Nigam and Priemer [9] to find the underlying heart sounds. The simplicity curve contrasts the much simpler waveform structure of heart sounds with the more complex noise between the heart sounds. Such a curve is shown in Figure 3. The intersection of a threshold value and the simplicity curve was used to determine the start of the heart sounds. The chosen threshold value of 0.35 was the value which consistently gave the best approximation for S1 across all the participant recordings. Figure 4 shows a comparison of the segmentation as calculated using the ECG and the simplicity curve. It can be seen from Figure 4 that the two methods produce nearly identical results.

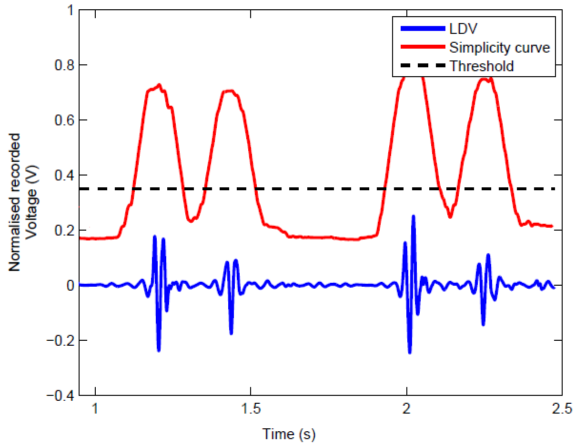

Fig 3. The simplicity curve calculated from the LDV data. The intersections of the simplicity curve and threshold line was taken as the start of the heart sounds.

B. *Feature extraction*

Stream 1 is used for feature extraction. The two-feature system proposed by Jiang *et al.* [7] was adopted for this work. The full heart sound cycle, the systolic and the diastolic segments were transformed using the Power Spectral Density (PSD). Two features were extracted from each PSD: F_{max} and F_{width} (as shown in Figure 5). The threshold value t is the normalized value where F_{width} is calculated. The optimum value, $t = 0.6$ was selected by testing various t values that resulted in the lowest classification error. A total of six features were extracted from each heart sound cycle: the F_{max} and F_{width} of the full heart sound cycle, the diastolic component and the systolic component of the same cycle.

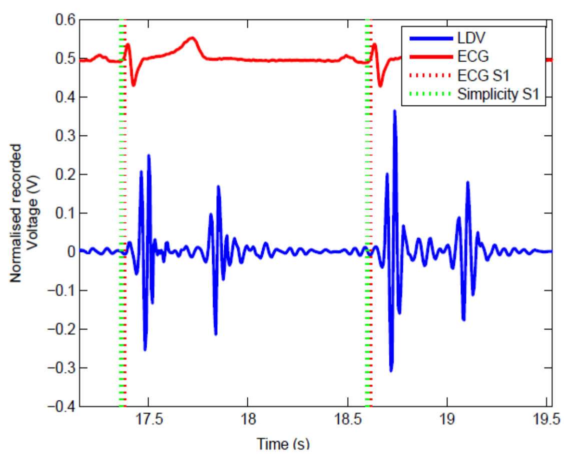

Fig. 4. A comparison of segmentation results calculated from an ECG (red dotted line) and the simplicity curve (green dotted line) for a participant with normal heart sounds. The ECG and simplicity curve methods give similar results.

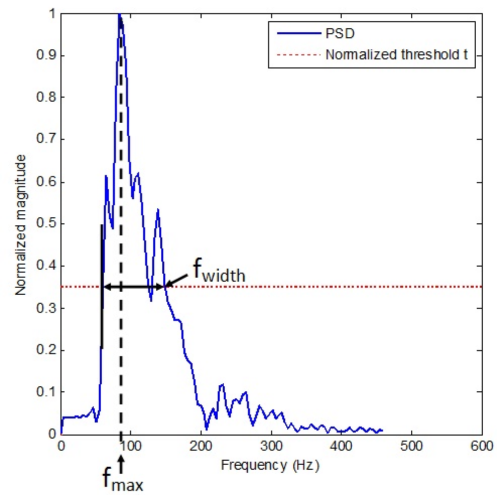

Fig 5. Extracted features F_{width} and F_{max} from a full heart sound cycle at normalized threshold value t.

C. *KNN Classification*

In order to determine whether the LDV data could be used as part of an automated diagnostic system, a proof of concept classifier was trained. K-nearest neighbors (KNN) was selected due to the ease of training [10].

KNN classifiers work on the principle that a point is classified according to the value of the K nearest points to it in the training data. These points 'vote' and the majority then define to which class the new point is assigned. To avoid distorting the classifier's performance, the data of the participant being classified was excluded from the training data. The results from all of the cycles of the participant were added together and the majority class decided which pathology the participant would be classified as.

IV. RESULTS

Due to the low number of healthy participants, the classifier was trained to distinguish between AS and those without AS. Table 1 shows the classification of each participant as a percentage of the total number of cycles classified. From the results it can be seen that the classifications generally were strongly either AS or NOT AS, with only Participant 4 and 18 showing approximately equal numbers of AS and NOT AS samples. Participant 12 was the only participant who could not be classified correctly. No combination of K and t resulted in the correct classification of Participant 12.

Table 1. Individual results for each pathology for AS or NOT AS classification as a percentage of the total number of cycles classified for K = 3 and a normalized threshold of t = 0,6. The green highlighted results indicate correctly classified participants, and the yellow indicates incorrectly classified participants. Only Participant 12 was incorrectly classified.

Participant	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
NOT AS	80	90	25	45	80	100	30	75	95	100
AS	20	10	75	55	20	0	70	25	5	0
Participant	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**

NOT AS	70	90	90	95	95	80	70	40	95	79
AS	30	10	10	5	5	20	30	60	5	21

As a measure of the classifier's performance, the sensitivity and specificity are calculated as per Equation 1 and Equation 2 respectively, where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

$$Sensitivity = \frac{\#\,TP}{\#TP + \#FN} \qquad \text{[Eq 1]}$$

$$Specificity = \frac{\#\,TN}{\#TN + \#FP} \qquad \text{[Eq 2]}$$

The classifier in the current work achieved a sensitivity of 80% and a specificity of 100%.

V. DISCUSSION

This paper investigated possibility of using the LDV as a part of an automated diagnostic system. Six frequency domain features were extracted from each of the heart sound cycles and used to train a KNN classifier with a sensitivity of 80% and a specificity of 100%. The results obtained from the proof of concept classifier indicate that it is likely possible to use the LDV data in an automated diagnosis system. The generalizability of this result is yet to be determined due to the limited number of participants recorded for the current work.

VI. CONCLUSION

Due to the small sample size used in the work, it is recommended that the study be repeated with a larger number of participants, and specifically more healthy participants. With a larger number of data points the results would be more generalizable. Different classifiers could also be investigated, such as a neural network which could potentially be extended to a classification system which can differentiate between more than two pathologies at a time.

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