Non-Invasive Fault Detection in Axial Flow Blood Pump Used As Ventricular Assistive Device

Rohit Rana
Non-Invasive Fault Detection in Axial Flow Blood Pump Used As Ventricular Assistive Device

by

Rohit Rana

SUBMITTED TO THE DEPARTMENT OF MECHANICAL ENGINEERING IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTERS OF SCIENCE IN MECHANICAL ENGINEERING AT THE ROCHESTER INSTITUTE OF TECHNOLOGY KATE GLEASON COLLEGE OF ENGINEERING JULY 2014

Approved by:

Dr. Jason Kolodziej ____________________________________________
Associate Professor, Department of Mechanical Engineering (Thesis Advisor)

Dr. Steven Day __________________________________________________
Associate Professor, Department of Mechanical Engineering

Dr. Risa Robinson _______________________________________________
Professor, Department of Mechanical Engineering

Karl Q. Schwarz, M.D. ___________________________________________
Professor-School of Medicine and Dentistry, University of Rochester
ABSTRACT

A Ventricular Assistive Device (VAD) is a mechanical pump used to assist the functioning of a weak heart. A catastrophic obstruction in the VAD system could cost the patient their life. This thesis presents a set of fault detection techniques using the commercially available Jarvik 2000 Flowmaker® VAD in a closed loop circuit that incorporates the ability to alter common causes of VAD congestion. The first goals of this research is to determine the nominal pressure-flow performance of the Jarvik pump, which is a graphical presentation of the static head and guides us about the major and minor losses in the system. Second goal is to characterize the health of the VAD system using frequency analysis of the acoustic signature. Principal Component Analysis, a data compression technique used to discover patterns in data of high dimension, is implemented on the frequency analysis and is followed by a health classification based on Bayes theorem. The classification results indicate that this technique is accurate to a high degree in detecting different levels of obstruction in the VAD system.
Acknowledgements

Foremost, I would like to express my sincere gratitude to my advisor Prof. Jason kolodziej and Dr. Karl Q. Schwarz for the continuous support of my masters study and research, for their patience, motivation, enthusiasm, and immense knowledge. Their guidance helped me in all the time of research and writing of this thesis. I could not have imagined having better advisors and mentors for my masters study.

I wish to thank Dr. Robert Jarvik for supplying the Jarvik pump, RITs Mechanical Engineering Machine shop for providing the equipment to fabricate the setup, and the staff, Rob Karynik and Jan Maneti, who helped us fabricate the various chambers and fixtures used in this research.

Last but not the least, I would like to thank my parents for giving me everything I ever wanted and my friends who supported me throughout my masters.
# Contents

Abstract.......................................................................................................................... iii
Acknowledgement........................................................................................................... iv
List of figures................................................................................................................... vi
List of tables.................................................................................................................... ix

1 Introduction................................................................................................................... 1
   1.1 Thesis outline........................................................................................................ 1
   1.2 Related work....................................................................................................... 3
       1.2.1 Spectral analysis......................................................................................... 3
       1.2.2 Measurement of Fluid mechanical variable.............................................. 8
       1.2.3 Ventricular assistive device in human body............................................. 15

2 Ventricular Assistive Device and Apparatus............................................................. 20
   2.1 Continues........................................................................................................... 21
   2.2 Pulsatile............................................................................................................ 22
   2.3 Experimental setup and apparatus.................................................................... 23

3 Head Flow Curves...................................................................................................... 28
   3.1 Clinical evaluation of VAD using H-Q curves................................................. 28
       3.1.1 Cardiac cycle............................................................................................ 29
       3.1.2 Circulation of blood through LVAD......................................................... 30
   3.2 Pressure and Flow characteristic of Jarvik 2000............................................ 31
       3.2.1 H-Q relation to controller speed and rotational velocity......................... 31
       3.2.2 H-Q relation at varying resistance and occult obstruction................. 33
   3.3 Detection of blockage using H-Q curves......................................................... 36

4 Frequency Analysis of VAD’s Acoustic Signature.................................................. 38
   4.1 Classification methodology.............................................................................. 38
   4.2 Results.............................................................................................................. 48
   4.3 Summary........................................................................................................... 72

5 Conclusion and Future work..................................................................................... 73
List of Figures

Figure-1: Spectral analysis from output blockage in the pump and normal pump [2].................................................................4
Figure-2: Graph displaying contrast of the ANN output between damaged and undamaged device. Higher mean magnitudes were obtained with the damaged device [3]. .................................................................5
Figure-3: Compared PSD of normal and failed pump [4]...............................7
Figure-4: Infusion pressure at (a) Kinking, (b) leaking [6]...........................12
Figure-5: Pump speed vs. time during simulation [7].................................14
Figure-6: Control index vs. time [7]............................................................14
Figure-7: Classification of Ventricular assistive devices............................21
Figure-8: Jarvik 2000 Flowmaker® [15, 16]..............................................22
Figure-9: The setup to test Jarvik 2000.......................................................23
Figure-10: Jarvik 2000 mounted inside a vacuum chamber......................24
Figure-11: Flow circuit of the test configuration........................................24
Figure-12: Anastomosis outflow assembly.................................................25

Figure 13: (a) Male sockets of the obstruction, (b) Schematic of different orifice.................................................................26
Figure 14: Pressure profile during pulsatile flow collected at speed-2.........27
Figure 15: Flow profile during pulsatile flow collected at speed-4...........27
Figure 16: Heart anatomy [Left] [17], Pressure of characteristic of different chambers of the heart [Right] [18].................................................................29
Figure 17: Human heart inserted with a VAD (A) Location of VAD in the cardiac chamber (B) outflow graft connecting the pump to the aorta (C) common obstruction at aortic anastomosis. [19]..........................30
Figure 18: Rotational velocity of the pump compared to tested ranges of flow. ..............................................................................30
Figure 19: Rotational velocity of the pump compared to tested ranges of pressure .......................................................................32
Figure-20: Head-flow curve (differential pressure). Graph between change in pressure across the pump and flow rate. The family of curves represents the VAD speed setting................................................32
Figure-21: Head-flow curve (aortic pressure). Graph between pressure measured at anastomosis and flow rate. The family of curves represents the respective VAD speed setting and occult obstruction................34
Figure-22: Method of utilizing H-Q curves to detect possible obstruction in the VAD circuit.......................................................36
Figure-23: Proposed classification methodology.........................................................39
Figure 24. Raw voltage signal for three obstruction levels at speed-1.............40
Figure-25. FFT of all 5 different speed setting between 120-220 Hz with 0% obstruction and collected from the hydrophone.....................................................41
Figure 26. Frequency spectrum of the acoustic signal collected at speed-5...43
FIGURE 27. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 0% obstruction and collected from the hydrophone........50
FIGURE 28. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 25% obstruction and collected from the hydrophone........50
FIGURE 29. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 50% obstruction and collected from the hydrophone........51
FIGURE 30. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 0% obstruction and collected from the ultrasound doppler machine........................................................................................................................................52
FIGURE 31. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 25% obstruction and collected from the ultrasound doppler machine........................................................................................................................................52
FIGURE 32. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 50% obstruction and collected from the ultrasound doppler machine........................................................................................................................................53
FIGURE 33. Frequency spectrum of the acoustic signal from hydrophone for Speed-5........................................................................................................................................54
FIGURE 34. Frequency spectrum of the acoustic signal from Doppler for speed-5........................................................................................................................................55
FIGURE 35. Binned Frequency spectrum at Speed-1 for each obstruction (0%, 25% & 50%) respectively from hydrophone..............................................56
FIGURE 36. Binned Frequency spectrum at Speed-1 for each obstruction (0%, 25% & 50%) respectively from doppler ultrasound machine.............56
FIGURE 37. Classification results for the hydrophone for Speed-1 [top], % contribution to the variance [bottom], 0% misclassification..................57
FIGURE 38. Classification results for the hydrophone for Speed-2 [top], % contribution to the variance [bottom], 0% misclassification..................57
FIGURE 39. Classification results for the hydrophone for Speed-3 [top], % contribution to the variance [bottom], 0% misclassification..................58
FIGURE 40. Classification results for the hydrophone for Speed-4 [top], % contribution to the variance [bottom], 0% misclassification..................58
FIGURE 41. Classification results for the hydrophone for Speed-5 [top], % contribution to the variance [bottom], 0% misclassification..................59
<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>42</td>
<td>Classification results for the Doppler ultrasound machine for Speed-1 [top], % contribution to the variance [bottom], 0% misclassification.</td>
</tr>
<tr>
<td>43</td>
<td>Classification results for the Doppler ultrasound machine for Speed-2 [top], % contribution to the variance [bottom], 0% misclassification.</td>
</tr>
<tr>
<td>44</td>
<td>Classification results for the Doppler ultrasound machine for Speed-3 [top], % contribution to the variance [bottom], 0% misclassification.</td>
</tr>
<tr>
<td>45</td>
<td>Classification results for the Doppler ultrasound machine for Speed-4 [top], % contribution to the variance [bottom], 0% misclassification.</td>
</tr>
<tr>
<td>46</td>
<td>Classification results for the Doppler ultrasound machine for Speed-5 [top], % contribution to the variance [bottom], 0% misclassification.</td>
</tr>
<tr>
<td>47</td>
<td>Classification results from the Hydrophone for Speed-4 with added vascular resistance.</td>
</tr>
<tr>
<td>48</td>
<td>Classification results from the Hydrophone for Speed-5 with added vascular resistance.</td>
</tr>
<tr>
<td>49</td>
<td>Classification results (Pulsatile low) from the Hydrophone for Speed-1 [top], % contribution to the variance [bottom]. (Misclassification linear -25%, quadratic-35%).</td>
</tr>
<tr>
<td>50</td>
<td>Classification results (Pulsatile low) from the Hydrophone for Speed-2 [top], % contribution to the variance [bottom]. (Misclassification linear -20%, quadratic-16%).</td>
</tr>
<tr>
<td>51</td>
<td>Classification results (Pulsatile low) from the Hydrophone for Speed-3 [top], % contribution to the variance [bottom]. (Misclassification linear -33.33%, quadratic-31.66%).</td>
</tr>
<tr>
<td>52</td>
<td>Classification results (Pulsatile low) from the Hydrophone for Speed-4 [top], % contribution to the variance [bottom]. (Misclassification linear -28.33%, quadratic-33.33%).</td>
</tr>
<tr>
<td>53</td>
<td>Classification results (Pulsatile low) from the Hydrophone for Speed-5 [top], % contribution to the variance [bottom]. (Misclassification linear -26.6%, quadratic-30%).</td>
</tr>
<tr>
<td>54</td>
<td>Classification results (Pulsatile low) from the Hydrophone for Speed-2 using 3 principal components. (Misclassification linear -13.3%, quadratic-13.3%).</td>
</tr>
</tbody>
</table>
List of Tables

Table 1. Jarvik 2000 expected vs. estimated speeds (Unobstructed).............49
Table 2. Classification results (Pulsatile flow) from the Hydrophone for
Speed-1, linear boundary [Left] and quadratic boundary [right].....................68
Table 3. Classification results (Pulsatile flow) from the Hydrophone for
Speed-2, linear boundary [Left] and quadratic boundary [right].....................69
Table 4. Classification results (Pulsatile flow) from the Hydrophone for
Speed-3, linear boundary [Left] and quadratic boundary [right].....................69
Table 5. Classification results (Pulsatile flow) from the Hydrophone for
Speed-4, linear boundary [Left] and quadratic boundary [right].....................69
Table 6. Classification results (Pulsatile flow) from the Hydrophone for
Speed-5, linear boundary [Left] and quadratic boundary [right].....................70
Table 7. Classification results (Pulsatile flow) from the Hydrophone for
Speed-2 (3d), linear boundary [Left] and quadratic boundary [right].............71
Chapter 1

Introduction

A Ventricular Assistive Device (VAD) is a mechanical pump, an alternative to cardiac transplantation, which is used to supplement the pumping function of the heart [1]. The VAD assessed in this research is the Jarvik 2000 Flowmaker®, which has a unique design in that the pump mechanism in addition to the inlet orifice is physically located within the left ventricular cavity. Current generation pumps have relatively rudimentary reporting capabilities on device performance as most of them provide only an estimate of power consumption and may or may not have confirmation of the rotational speed, let alone flow rate. A majority of VAD function with an open loop control, meaning the controller supplies a constant power to the pump irrespective of the blood flow rate through the pump. On the occasion of a fault, the patient becomes uncomfortable and could lead to extreme health risk and potential expensive surgery to investigate the VAD failure. These non-invasive techniques could detect the faults at a very early stage of complication and reduce the risk of fatal health condition. The results obtained in this research are taken from an experimental circuit incorporating the basic element of a VAD implanted in the human circulation. They are effective and inexpensive techniques for fault detection, which are highly capable for medical diagnosing in a clinical environment.

1.1 Thesis outline

This chapter is a foundation to the basic definition of Ventricular assistive devices and the pump used in this analysis. It signifies the
importance of the research and introduces the concept of fault detection. An investigation of the alternative fault detection routines is also offered to the reader to demonstrate the importance of the research and grasp the insight of the basic concept.

Chapter 2 signifies the importance of ventricular assistive devices and their functioning in the human body. It also discusses the mechanism of the Jarvik 2000 and other types of VAD available for medical application. An illustration of all the instruments utilized for data collection including the sensors and data acquisition system are also listed.

Chapter 3 demonstrates the pressure and flow characteristic of the Jarvik heart pump. It explains, how these curves are used by medical professionals to assess the health of the pump. In this research both continues and pulsatile flow are assessed separately.

Chapter 4 is the frequency analysis of the VAD's acoustic signature. The classification methodology of how a acoustic signal is used to classify the speed and the obstruction is explained. The theory contains the mathematical techniques and concept used for the classification. Remainder of the chapter reveals the results of the speed classification and obstruction classification at different controller speed and various obstructions.

Chapter 5 concludes the thesis with the brief summary of the results. It discusses how this method can be practically implemented in clinical environment and followed up by the future work.
1.2 Related work

Condition monitoring of a VAD requires thorough understanding of their operations and different faults that are to be tested. The following section discusses the different modes of fault detection, the methods used for condition monitoring and features that can used to classify these pumps.

1.2.1 Spectral analysis

A method for condition monitoring was proposed to analyze a blood pump by Jammu V.B [2]. A Hemadyne blood pump which is a six vane pump was evaluated. Eight different sensors were implemented to collect data: Two accelerometers, radial and axial, a dynamic pressure sensor, static inlet and outlet pressure sensors, current sensor, microphone and a flow sensor. Statistical and spectral analyses were executed. Five different VAD faults were triggered to generate data, which included inlet outlet blockages, deposition on wanes, imbalance and bearing failure.

Investigating the RMS of the AC signal with pressure and radial acceleration, the inlet outlet blockage fault was characterized. In case of a outlet blockage RMS of pressure increased while the RMS of acceleration decreased. Instance of inlet blockage caused notable pressure decrease and acceleration decrease. Spectrum analyses of dynamic pressure (Figure-1) resulted a change from 200 Hz in normal condition to low frequency (0-50Hz) in the case of outlet blockage. The inlet blockage was characterized due to a persisting signal in high frequency range. Unfortunately it was not compared to what the normal signal would have been at high frequency. Blade deposition fault was categorized using the spectra of dynamic pressure sensor, where the intensity of the signal tripled at the pump running speed (100Hz).
Irregular signals were observed when an imbalanced pump was experimented. The spectra of the axial acceleration demonstrated peaks at running speed and its harmonics. Bearing failure was analyzed with time frequency technique. Axial accelerometer data was analyzed exhibiting principal variations in the 16th minute of the experiment.

![Spectral analysis from output blockage in the pump and normal pump](image)

**Figure-1:** Spectral analysis from output blockage in the pump and normal pump [2].

Data classification based on acoustic signals was discussed in the paper presented by Kim H. C [3] to characterize the difference between a damaged and undamaged artificial heart. The experimentation utilized artificial neural network analysis (ANN); a computation used for solving data classification and pattern recognition problems. The device classified in the experiment was an electro-hydraulic total artificial heart; it has more mechanical components than a pneumatic heart or a blood pump. Elevated vibrations are achieved
with more mechanical component and a better acoustic signal. The ANN computation technique utilizes previous examples as a mode of learning and has capabilities to characterize irrelevant data. The main components of the setup are a brushless DC motor, which drives the axial flow pump and two blood pumps for the bearing test.

![Graph displaying contrast of the ANN output between damaged and undamaged device. Higher mean magnitudes were obtained with the damaged device [3].](image)

**Figure-2:** Graph displaying contrast of the ANN output between damaged and undamaged device. Higher mean magnitudes were obtained with the damaged device [3].

The various sources of defects, which could obstruct the vibrations were the diaphragm, thrombus formation, bearing, motor, heart valves and noise. The biggest emphasis was given to the imperfection in the bearings. Bearing dysfunctions could lead to pressure variations, which are imposed on the skin and could be transmitted through diaphragm of the microphone. For this
experiment the pumps were set to run at 6000 RPM corresponding to 60 beats per minute. Data collection was done at the moment when system attained steady state. To test for the in-vivo condition eight postmortem sheep were used, where EHTAH (Electro-hydraulic total artificial heart) replaced the natural heart and placed beneath the lungs to imitate natural conditions. Among the eight EHTAH, half of them were damaged and half undamaged.

For the analysis, each input was multiplied by a weighting factor and all inputs were assembled to a single value. The ANN was trained with 10 damaged and 10 undamaged data sets. Evaluation of the spectrum displayed higher magnitude with the damaged devices than the undamaged ones (figure-2). ANN was trained with different data sets for testing purposes, which included training with in-vitro data and then in-vivo data was fed as an input.

The algorithm was successful to a high degree in detecting the bearing failure with acoustic signals. Two crucial aspects for effective classification were the training data set and the validation data set. This research motivates the aspect that acoustic signals can be a significant features, which could be used for classification. As Jarvik 2000 is also a mechanical device and would create sound spectrum due to mechanical vibration, acoustic data was used to differentiate between different faults in this proposed research.

Another research was conducted by Lee [4] on Electromechanical total artificial heart (ETAH). As mentioned, an ETAH consists of many moving parts (mechanical component, prosthetic valves and blood flow), all these modules generate sound, which could be utilized to classify between different conditions of the ETAH. The paper discusses a sound spectrum evaluation technique, which categorize different malfunctions in the ETAH. This
technique can be implemented in different implantable devices as most of them have dynamically active mechanical component and create sound.

Their arrangement consisted of a brushless DC motor, which is connected through a planetary gear train to provide elevated torque. The motion of the motor is converted to a back and forth motion that pumps blood to the body. Two microphones are used, one perceives sound from the ETAH and other measures surrounding noise. The primary signal is processed through an adaptive filter that is tuned to minimize the error between primary signal and the reference signal. The location of the microphone is a prime importance to the measurement therefore it was tested at six different positions. When motor current was compared to the magnitude of squared sound signal (voltage obtained from microphone), a linear relationship was found.

![Figure-3](image-url)  
**Figure-3:** Compared PSD of normal and failed pump [4].
To obtain the transfer function of the sound transmission properties, a power spectral density (PSD) of the measured acoustic signal of the implanted device was compared to the PSD before implantation. The active noise control (ANC) algorithm was implemented to segregate the noise from the signal, which was done by adjusting the gain. The sound signal gathered from all six positions was analyzed and it was observed that only one of the positions corresponded to the same pattern as the current waveform. It was concluded that this position correlated to the location where most of the mechanical components were located. The evaluation of the sound spectrum showed 2 peaks at around 1.3 KHz and 700 KHz. The spectrum of the damaged device had higher harmonics and a spectral shift shown in fig. 3, which was due to the increased beat rate. The increase in beat rate was due to more mechanical friction in the damaged device.

The ANC algorithm can be utilized effectively to remove noise from the signal. and implementation can be done directly for real time processing using a microprocessor, as the least mean square algorithm is not complicated. For the evaluation a damaged ETAH shows higher harmonics and spectral shift would be observed from an undamaged device. For better performance and accurate results the author proposed more experimentation. Continuous monitoring of the ETAH can be achieved with this analysis and classification between a damaged and undamaged device is possible. The study demonstrates that analyzing the sound spectrum is a successful method to evaluate the performance of implanted mechanical devices.

1.2.2 Measurement of Fluid mechanical variable

Measurements from implantable rotary blood pumps (IRBP) and left ventricular assistive devices are crucial to study. Condition monitoring
requires precise data collection for the correct diagnosis. Bertram [5] discusses miscellaneous computation done by various researches on these devices and complications associated with them.

The author discusses the problem of long term operation of the pressure transducers in implantable devices. Many different designs were proposed among which the sensor was placed inside the cannula connecting the device to the heart and developing miniature axial pump, which helped in placement of the pressure transducers. It was found that Impeller pumps faced complications with the drive shaft fiction. This hindered the pressure head and flow readings derived from the motor current. For monitoring pressure, continuous wave ultrasonic Doppler has been used in form of a wristwatch together with pneumatic cuff.

The solution for these problem was to develop H-Q curve on a laboratory bench. With the help of these family of curves, pump characteristic could be measured easily and accurately. An equation between flow rate and change in pressure was developed for Terumo Capiox SP-101, which is a centrifugal pump given in (1.1)

\[ \Delta P = K_1 \omega^2 - K_2 Q \]  \hspace{1cm} (1.1)

Where \( \Delta P \) is change in pressure, \( Q \) is flow rate, \( \omega \) is the angular velocity and \( K \) constant of proportionality. They found the constant \( K \) varied on patient’s heart condition, whether he was undergoing recovery from a surgery or living a normal life.

According to the research, there are few methods to calculate the flow rate through the LVAD, as flow is not directly related to \( P_{out} \). But a relation can
be developed between motor current and flow rate, which could be used to evaluate the flow rate. The same paper discusses a research by Takami et al in which a linear relations was computed between motor current and the flow rate.

Another observation concluded that computation of $\Delta P$ could be done with estimation of $Q$ and $\omega$ angular speed. A further development in equations relating the flow and $\omega$ also incorporated heart rate. This resulted into

$$Q = K_1 W - K_2 \omega - K_3 f + K_4$$

(1.2)

where $f$ is the heart rate, $W$ is the power consumed $K_1, K_2, K_3$ and $K_4$ are constant of proportionality.

Another fault detection algorithm was formulated by Choung [6] based on fluid pressure of a ventricular assistive device. The algorithm calculates the pressure derivatives, which are equated to the predetermined threshold values of defects. A rotating impeller assistive device possess issues with thrombus formation, maintaining reliable bearing and heat generation from the mechanical friction. The system consisted of a AB-180 CSS which is a centrifugal LVAD. It is connected to a purge system which delivers purge fluid (a mixture of sterile water and heparin) and the system is monitored by a flow sensor and a pressure transducer.

The pressure waveform from the measurement is broken down into dc level and frequency content. The contrast of the mean dc pressure, which depends on vacuum in the pump, describes the condition of seal geometry in the pump. It was found that the frequency content is directly associated to the rotational speed of the purge pump. Pressure derivatives were calculated within which the zero crossings were observed over a certain time period. The
zero crossings were used to estimate the pump speed and eliminated the need for frequency analysis. The equation used to calculate the pressure derivative is given by

\[ \dot{P}(t_k) = \frac{P(t_k) - P(t_k-1)}{T} \]

(1.3)

where P is pressure and T is sampling period.

The algorithm was tested for six condition in the system: (1) Everything normal (2) Blockage in the infusion line (3) Leakage in the infusion line (Fig. 4) (4) Stopped purge pump (5) 25% higher infusion rate (6) 25% lower infusion rate. A flow sensor was applied to calculate the flow rate and tubing clamp was implemented to imitate the faults. All six conditions were tested through the entire pressure range by data collection at the highest and lowest infusion pressure. The highest mean infusion pressure is at the lowest speed of the LVAD and similarly the lowest pressure at highest speed.

The results concluded that a blockage in the infusion line increased the pressure gradually, which further saturated at 750 mmHg. Leakage in the infusion line resulted in pressure below 20 mmHg. When the pump was off, the magnitude of pressure derivative was less than one. At a higher infusion rate, zero crossings were greater than 55 counts in a 10 minutes sample whereas at lower infusion rates it went down to less than 35 counts in the same sample time. The algorithm differentiated all the faults on the basis of changes in pressure and its derivatives. It was also recommended that a digital low pass filter could be used to remove the noise from the measured pressure derivative.
Boston, J.R (2000) [7] discusses a control algorithm, which is also a fault detection tool to assess continuous flow pump. The study was conducted to develop control algorithm for two ventricular assistive device Streamliner VAD and Heartmate 2, Nimbus medical. Ventricular suction was been detected using 2 techniques, one based on measurements directly from the flow waveform, the other based on pump current and speed. Emphasis has also been given on using voltage and current as device inputs to evaluate the hemodynamic state variables. Suction can damage the heart therefore it should be sensed early. Controlling the output of these pumps is a difficult task as they are insensitive to ventricular preload and highly sensitive to ventricular after-load.

To classify between suction and no suction four indices were investigated : flow estimated from the current waveform, rate of change of flow rate with varying pump speed, minimum flow rate and current waveform analysis. Due to the pulsatile nature of the heart, the pump flow and current
waveform are also pulsatile. An equation was established for the Nimbus LVAD, to relate flow rate to current and angular velocity:

$$Q = \frac{1}{a_2 \omega^2} \left( \frac{3}{2} K_b I - j \frac{d\omega}{dt} - B\omega - a_0 \omega^3 \right)$$  \hspace{1cm} (1.4)

Where Q is the flow rate, \(\omega\) is the angular velocity, \(K_b\) is the motor constant, \(I\) is the current, \(j\) is the moment of the inertia of the motor and \(a_2, B, a_0\) are constants.

Figure-5 is the step response of the pump speed and fig. 6 is the plot of the control index (flow rate) vs. time. Using these plots the response of the pump speed was analyzed and characteristics were studied. During the simulation the left ventricular pressure and the aortic pressure was also analyzed. This was done to check for suction status. When the left ventricular pressure is greater than the the aortic pressure, suction is developed and these were recorded. At the moment when suction develops flow rate reduces tremendously and reverse flow is possible therefore a minimum flow index was calculated.

The experimentation was performed in 42 in-vivo conditions in three different calves. Pump speed was varied from 8000 to 15000 revolutions per minute (rpm) in fixed steps of 500 to 1000 rpm. The Bayesian classifier had the highest accuracy in comparison to a fuzzy method and Dempster-Shafer method. If suction is detected the pump reduces the speed immediately by 500RPM. The study concluded that the maximum cardiac output is achieved at a speed lower to the point when suction starts to happen. Measurement of current and speed can be used to classify the health of the pump as well as for control algorithms.
**Figure-5:** Pump speed vs. time during simulation [7].

**Figure-6:** Control index vs. time [7].
1.2.3 Ventricular assistive device in human body

Congestive heart failure is a prime difficulty in United States; about 400,000 cases are detected each year. Due to a shortage of donor organs, mechanical apparatus like a left ventricular assistive device are a common choice. The research paper by Goldstein [8] discusses medical application and human heart complication in accordance with left ventricular assistive device.

Patients who are recovering from a heart attack and are diagnosed with a LVAD, absolute evacuation of the ventricle is critical to maximize subendocardial perfusion (circulation of the blood to the inner most layer of the heart). In an unhealthy heart with a VAD, the aortic valve opens very rarely therefore it is supported by the pump. The pump production imitates the pumping of the cardiac output.

Much emphasis has been given on evolution of operative and completely implantable devices. Common complications associated with early generation pulsatile VAD are because of an external venting chamber, which can cause build up of unwanted fibrous tissue and accumulation of water in the venting chamber due to moisture. One of the major complication related to the VAD is ventricular ischemia (insufficient supply of blood through the device), which could lead to right sided heart failure. Uncontrolled flow of the LVAD could lead to arrhythmia, a condition where the heart beats too fast or too slow. Drugs and electricity are used to cure the condition; the process is known as cardioversion.

Irregular pressure in the left and right ventricle could leads to abnormal flow through the left ventricle. Surgical implantation should be given immense importance as it could lead to oxygen desaturation, which could further lead
to septal defects. Patients on ventricular assistive devices were found in a healthier state compared to patients on dobutamine dosage (drug used in treatment of heart failure). In a six minute walk test patient with implanted VAD covered more distance. The oxygen inhalation was also higher in these patients with the VAD. Medical centers reported a much improved cardiac function on patient assisted with the LVAD and these improvements were such that these patient could survive without the VAD.

Although these patients would require weeks of nutritional support and a healthy living style, they can attain adequate restoration of muscle mass and well being.

LVAD Manufacturers are researching continuously to make this exceptional life saving technology more elementary, convenient and reliable. Studying the issues associated with the VAD can lead us to new diagnosing techniques for the health of the heart pump and distinguishing it from other septic complication inside the heart.

Subha V. Raman [9] emulated the use of echocardiography with CCT (cardiac computed tomography). According to the research CCT with ECG (electrocardiographic) is more dominant than just echocardiography. For the experiment, center of attention was on the ascending aorta. 15-20 ml of iodinated contrast was injected to calculate the optimal moment for the data collection.

A total of thirty two CCT scans were carried out on twenty eight patients. CCT was successful in evaluating symptoms of low cardiac output and was also able to depict the cannula position. Among these thirty two scans the results of the six patients from cardiac computed tomography, one with
outflow cannula thrombus and five with inflow cannula thrombus were detected. One of the patient with inflow cannula thrombus developed acute decompensated heart failure. Echocardiography was not competent to determine the critical finding done by the CCT.

One of the patients who demonstrated hemodynamic instability CCT failed to determine cannula position. Thrombus formation was found on arterial valve of this patient when undergoing surgical operation. A echocardiogram displayed air bubbles entering the aorta in one of the test cases opposed to the CCT measurement, which displayed no air bubbles. Further it was found CCT data set was correct and no evidence of stroke was found. Acoustic shadowing was another complication observed when imaging with echocardiograph, as it failed to investigate cannula position in one test case.

The blood circulation in the VAD is either pulsatile or continues. From the left ventricle through the outflow graft to the mid-ascending aorta, cannulation is standard for any type of flow device in human heart. Blockage of the inflow cannula in the left ventricle is a result of poor implantation of the device in the human heart. If irregularities are not observed on the position of the outflow cannula, surgical philosophy suggested smaller outflow graft to counteract defects. CCT allowed 3-dimensional imaging analysis whereas echocardiography restricts a lot of available information because of acoustic window and shadowing. Angle of incidence between the Doppler and cannula flow should not exceed 20 degrees as the results for the velocity profile become unreliable. CCT is superior over echocardiography as it allows entire 3-d imaging of the device, on the other hand echocardiography is not that detailed.
For the research conducted in this work using the Jarvik 2000, echocardiograph is one of the measurement collected. Additional to imaging, this experiment would be associated with the sound measurement focused on inflow and rotor of the pump.

Sonna M. Patel [10] assessed in vitro testing and in vivo testing of various artificial blood pumps available and under testing in United States. The pumps tested have been categorized as commercially approved, clinically employed, pumps in clinic testing and pumps currently undergoing laboratory evaluation.

Among the commercially approved pumps, the Novacor LVAS was tested in 12 different circulatory loops imitating human physiological condition. The pump was assessed on basis of pressure and flow readings, which concluded a reliability of 88% over a 2-year time period. Experimentation involved submerging the pump units in saline water at 37 degree C and examining different load condition using mock loops. In vivo testing resulted in 3 years operation without failure, while during in-vitro testing wear of the energy converter in the main shaft led to failure in 3.04 years. An exponential model was proposed to describe all the random failures in the device. The Thoratec HeartMate-2 VAD was also examined using the mock loops with a duration of 6 months without malfunctions. The Jarvik 2000 was also assessed in this research. During the experimentation pump speed was sustained at 10,000RPM corresponding to flow of 5-6 L/min. problems in Jarvik 2000 were broken electrical wire, impeller imperfection, thrombus formation and infection. Although these problems were known, there was no potential detection solution to these problems. Individual component testing was also done; mock circulatory loops were used to test the pump bearings with heated
saline water and pulsatile left ventricle. The device has been further approved for bridge to transplant (BTT) use in more than 160 patients.

For appropriate testing of any blood pump the following tests are imperative: 1) in-vitro 2) in-vivo 3) clinical and 4) human and other device interaction. Apart from the experimental analysis assessment of theoretical models are very important. Faulty heart models are another asset which could provide beneficial insight into the physiologic response to heart pump. It is expected that data extraction from heart rate, blood pressures and respiratory rate may help distinguish between different modes of failure in the heart.

A lot of experimentation has been done in techniques for collection of measurements. To develop an ideal and precise condition monitoring system, a lot of experimentation has been done in techniques for collection of measurements, but essential features have to be selected, which could be accumulated with low errors and vary with health of the device. Some of the significant features that we would be working upon are pressure, flow, current withdrawn, voltage supplied and microphone measurements. These measurements could be used to develop a fault detection scheme which could detect pump malfunction or obstruction in the cannula.
Chapter 2

Ventricular Assistive Device and Apparatus

Heart disease is one of the leading sources of death in the developed world [11]. Patients suffering from congestive heart failure (CHF) due to severe left ventricular (LV) systolic dysfunction may require some form of cardiac replacement to maintain adequate circulation. Heart transplantation is a viable option, however the demand for donor organs far outweigh the available supply [12]. Originally designed as a “cardiac assist device”, currently available VADs are designed to draw blood from the left ventricular cavity and pump it into the aorta [13], with the aortic valve providing the dam separating the high pressure aorta from the low pressure LV cavity. The aortic valve in most VAD patients either does not open or opens minimally with no native ventricular ejection. These patients are functionally “VAD dependent”, meaning the mechanical pump is providing 100% of the cardiac output. This parallel pump circuit has the advantage of providing a safety reserve, should the mechanical device fail, but it also makes diagnosing VAD malfunction slightly more difficult as the ventricular contribution to cardiac output may obscure the mechanical pump failure. This technology has progressed with time. The implantation of ventricular assistive devices began in 1988, when a pump from Heart-mate was implanted the first time. This pump was a pulsatile pump meaning the blood from the left ventricle was sucked into the device and then pushed into the aorta. Since then several different style have been designed and implemented. Figure 7 is a classification for different types of ventricular assistive devices.
2.1 Continuous

The second generation of ventricular assistive devices replaced the positive displacement pumps because of their large geometry and inefficiencies. These pumps are continuous and operate in a rotary motion. Radial centrifugal pump rely on centrifugal force to move the fluid around. In the centre of this pump is a impeller, which has a series of curved planes covered inside shroud plates. The impeller is always immersed in the fluid and when it is made to rotate, it rotates the fluid surrounding it. This imparts centrifugal force to the fluid particle and the fluid moves radially out. In this process the pressure and kinetic energy of the fluid on the outside diameter rises. While on the inside the fluid is getting displaced, therefore a negative pressure is induced. This low pressure helps to suck in more blood from the heart. The impeller is placed inside the casing and fluid moves in the direction of the rotating impeller to the discharge nozzle. Some example of centrifugal pump are Heartmate 3, DeltaStream, VentrAssist etc.

Axial flow pumps are very similar to the radial centrifugal pumps. In these pump the fluid is pushed parallel to the pump's rotating shaft, instead of
radial direction. A drive shaft extends in the process flow with a propeller attached to the end. When the propeller turns, it pulls the fluid down the shaft line.

Jarvik 2000 Flowmaker® is such a pump and is the focus in this research, it is an intra-ventricular axial flow pump (fig. 8). It has a unique design in which, the pump mechanism in addition to the inlet orifice is physically located within the LV cavity. The pump system contains an external controller and battery which are portable. These are connected to the pump via cable which runs through the abdomen. The diameter of this pump is 25 mm [14] and has length of 55 mm and weighs about 85 gm. The pump is driven with a brushless DC-motor and the impeller rotates between 8000-12000 RPM.

![Jarvik 2000 Flowmaker®](image)

**Figure-8:** Jarvik 2000 Flowmaker® [15, 16]

### 2.2 Pulsatile

The first generation of pumps were pulsatile pumps. These pumps emulated the human heart by sucking the blood from the left ventricle and pushing it to the aorta. They were comparatively larger than the new
generation pumps and in some of them the pump mechanism was located outside the body, example; Thoratec pVAD, Heartmate pneumatic (IP) LVAD.

These devices are also known as positive displacement pumps as these devices had a pumping chamber and separate inflow and outflow valves. They operate in a cyclic process in which the chamber is filled and emptied with blood, creating a stroke volume.

2.3 Experimental setup and apparatus

The apparatus for the test setup is fabricated in a way that emulates the basic elements of a VAD implanted in the human circulation. The basic elements being: (1) Preload or inflow pressure/volume, (2) pump in a vacuum chamber, and (3) after-load or arterial pressure. To achieve this, a system of tubing and fabricated chamber is assembled on a laboratory bench (fig. 9).

![Figure-9: The setup to test Jarvik 2000.](image)
Figure-10: Jarvik 2000 mounted inside a vacuum chamber.

Figure-11: Flow circuit of the test configuration.
The circuit includes a Jarvik 2000 pump fitted into a water-tight test chamber that emulates the left ventricular cavity (fig. 10). The output of the Jarvik 2000 travels through a system of plastic tubing to a reservoir and then back to the VAD inlet and represents the balance of the human body. A mechanical clamp on the tubing allows for setting the baseline vascular resistance of the system and to incorporate patient to patient variability.

![Figure-12: Anastomosis outflow assembly.](image)

To gather acoustic signal form from the pump a hydrophone (Amphibico, Inc.) is used. It is an inexpensive hydro-acoustic microphone used commonly in underwater video and is connected to an ART Tube MP Studio Mic Preamp (ART ProAudio) common to the music industry. It is coupled to the test chamber using acoustic jelly (Aquasonic 100 ultrasound transmission gel, Parker Laboratories). An ultrasound probe commonly utilized in a clinical environment is in-line with the VAD flow with a 2- MHz pulse wave Doppler ultrasound targeting the inlet orifice (Vivid-i, GE Ultrasound, Horton, Norway). Differential pressure is monitored across the pump with a DP-15 (Validyne Engineering) transducer along with the flow in the system by a T206
(Transonic Systems) clamp-on ultrasonic sensor. Fig. 11 shows a schematic of the flow circuit. Differential pressure, flow, hydrophone audio and audio Doppler are sampled at 20kHz using a custom Labview-based data acquisition system (USB-6215, National Instruments).

![Image](image_url)

**Figure 13**: (a) Male sockets of the obstruction, (b) Schematic of different orifice.

The objective is to detect, difficult to diagnose clinically, an outlet obstruction (outflow anastomosis) between the discharge of the pump and the graft reconnecting with the aorta. Seeded faults are fabricated obstructions placed within a separate aortic chamber (fig. 12). The Jarvik 2000 outflow cannula is 0.5 inches in diameter and connected to a mechanical fixture to emulate outflow with three levels of obstruction. Three anastomosis levels are shown in fig. 13 and are: (i) 0.5-inch diameter orifice or 0% blockage, (ii) 0.375-inch diameter orifice or 25% blockage, and (iii) 0.25-inch diameter orifice or 50% blockage. These area stenosis values are chosen to best emulate no, mild and moderate stenosis that might be seen in a clinical environment.
An arrangement to generate pulsatile flow through the circuit is constructed using a syringe pump, which is directly connected to the Jarvik chamber through plastic tubing. The motion of the syringe pump is governed manually by pushing the fluid in and out of the syringe. Fig. 14 is the pressure profile at Speed-2 and Fig. 15 is flow profile collected at Speed-4 with no added obstruction. The images display that this method was effective in creating rhythmic changes in pressure and flow measurements, which correspond to the effect of native ventricular contraction in a human heart.

![Figure 14](image1)

**Figure 14**: Pressure profile during pulsatile flow collected at Speed-2.

![Figure 15](image2)

**Figure 15**: Flow profile during pulsatile flow collected at Speed-4.
Chapter 3

Head Flow Curve (H-Q curve)

An axial flow pump operating at a continuous pace can draw any capacity from zero to maximum depending on the differential pressure, flow rate and suction condition. Performance of the pump is measured by means of curves which represent the pump’s characteristic. The performance curves in this chapter are obtained from testing the Jarvik 2000 through standardized test condition. These plots will relate the expected flow rate to the pressure differential across the pump. This information can be used by clinicians or manufacturers to determine if the pump system is functioning to design specification as documented in in-vitro apparatus plots, which is free of the many anatomical issues that can be present when the device is implanted in the patients.

3.1 Clinical evaluation of VAD using H-Q curves.

As mentioned a VAD is a device that pressurizes the aorta by pumping blood from the left ventricular (LV) cavity into the aortic root. The system bridges the aortic valve, which maintains the pressure gradient between the LV cavity and aortic root. When the system is working properly, the pressure is the aortic root is higher than the LV pressure through most phases of the cardiac cycle, keeping the aortic valve closed. In some cases, native ventricular contraction is strong enough to just open the aortic valve, but there is typically no little to no ejection through the aortic valve if the pump is working properly. This section explains the left heart anatomy and how the path of circulation of blood through the VAD.
3.1.1 Cardiac cycle

There are two main stages of the cardiac cycle (a) heart contraction known as systole, (b) heart relaxation (diastole). While the mitral valve is open, blood flows from the left atrium (LA) to the left ventricle (LV). The image on the right in fig. 16 is the pressure profile in different sections of the heart.

![Heart anatomy and pressure profile](image16.png)

**Figure 16**: Heart anatomy [Left] [17], Pressure of characteristic of different chambers of the heart [Right] [18].

In one cycle of heart beat the LV pressure is low most of the time. The blood flowing from the LA to the LV builds up the pressure in the LV. At the point of muscle contraction (systole), the pressure in the LV begins to increase and the moment the pressure in LV is greater the LA the mitral valve closes. This leads to a rapid rise of pressure in the LV and there is a slight drop of aortic pressure as the blood is rushing away. When the aortic pressure is very slightly below the LV pressure, the aortic valves open. The blood from the LV rushes to the aorta and the pressure of the aorta follows the path of the left ventricle. When the heart muscle starts to relax (diastole), the pressure in the aorta and LV goes down. At some point the aortic pressure is still high because
of the resistance from the blood vessels, but the LV pressure becomes lower than the aortic pressure. This leads to the shut down of the aortic valves and the LV continues to relax and the pressure decreases more. The pressure in the LV goes down almost to zero and becomes lower than the LA pressure. At this moment the the mitral valve opens up and blood flows from the LA to the LV. This process repeats with every beat in the heart.

3.1.2 Circulation of blood through LVAD

A left VAD is inserted in the left ventricle and the pump sucks the blood from the left ventricle into the aorta. Current generation pumps are continuous pumps, so a person feels reduced pulse. The Jarvik 2000 can be seen implanted in the left ventricular apex (fig. 17) with the inlet of the pump pointed towards the mitral valve (A). The outflow cannula can be seen traveling up over the right ventricle (B) with an end-to-side anastomosis on the anterior wall of the proximal aortic root (C).

Figure 17: Human heart inserted with a VAD (A) Location of VAD in the cardiac chamber (B) outflow graft connecting the pump to the aorta (C) common obstruction at aortic anastomosis. [19]
3.2 Pressure and flow characteristic of Jarvik 2000

To generate the pump performance curves, the Jarvik pump was tested at all five different speeds (labeled 1 through 5 on the controller device). At each speed, six different levels of vascular resistance are altered by adjusting the mechanical clamp in the circuit. These resistance ranged between no added resistance to near occlusion of the flow tube. Pressure and flow measurements are made at every vascular resistance and for all three anastomosis obstructions. The experiment was repeated three times at each setting for accuracy. Pressure is observed at two different locations, differential pressure across the pump and static pressure at the occult obstruction. The pressure measure at the occult obstruction resembles the blood pressure of a human body.

To determine if phasic pressure within the Jarvik VAD altered the rotational velocity or non-invasive flow measurements, the system is tested with pulsatile flow and the pressure flow curve is formulated.

3.2.1 H-Q relation to controller speed and rotational velocity.

The Jarvik pump yields a pressure gradient between 26.3 and 136.0 mmHg which is the differential pressure across the pump and the flow varies between 1.29 and 6.56 liter /min. Fig. 18 and 19 shows the variance of flow and pressure across across the pump respectively vs. estimated frequency and these are the tested ranges for the Jarvik pump.
**Figure 18:** Rotational frequency of the pump compared to tested ranges of flow.

**Figure 19:** Rotational frequency of the pump compared to tested ranges of pressure.
The rotational velocity of the pump is identified by analyzing the frequency spectrum of the audio signal. The audio signal is gathered using a hydrophone which is placed on the pump chamber and a clinical ultrasound machine. The method of detection of the rotational velocity is explained in detail in Chapter 4. Using the above mentioned instruments it is found the the rotational speed of the pump is independent of the pressure loading or flow rate. This indicates that the speed of the VAD is controlled at a given controller setting regardless of the back pressure.

3.2.2 H-Q relation at varying resistance and occult obstructions.

The effect of varying resistance on flow rate and differential pressure is shown in fig. 20. The three different legends in the plot represent the level of occult obstruction in the system and the five individual linear regression lines are plotted for each respective controller speed setting.

The pressure differential measured (units of mmHg) across the pump is plotted on the x-axes and the flow rate (units of litre per minute) is plotted on the y axis. The intercept for each speed setting is found using linear regression. The goal of linear regression is to adjust the values of slope and intercept in finding the line that predicts Y to X. For this research a first order regression line is fitted between the data points and is given by :-

\[ \hat{y} = b_0 + b_1 x \]  \hspace{1cm} (3.1)

\[ b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \]  \hspace{1cm} (3.2)
\[ b_0 = \bar{y} - b_1 \bar{x} \]  

(3.3)

where \( x \) and \( \bar{y} \) are the mean of data points.

As expected the flow decreased as the pump faces an higher differential pressure. One interesting aspect of this plot is that the differential pressure and flow relation doesn’t change even if an additional obstruction is added. This indicates that the slope of this curve is independent of the added pressure drop in the system. However when the pressure at the anastomosis was plotted against flow (fig. 21), it yielded a significant change in the slope of the linear regression as a result of added obstruction. The plot shows fifteen intercepts which are plotted for five controller speed setting at three different obstructions.

**Figure-20:** Head-flow curve (differential pressure). Graph between change in pressure across the pump and flow rate. The family of curves represents the VAD speed setting.
In the plot the five red intercepts are the pressure flow relation for zero added obstruction, similarly the green intercepts are for twenty five percent obstruction and blue for fifty percent obstruction. It is proved that for an added resistance in the system which corresponds to an occult obstruction in the outflow graft will not be on the linear regression between the pump's differential pressure and flow rate. Future research would involves validation of these curves on humans with inserted VAD.

3.3 Detection of blockage using H-Q curves.

To asses a VAD which is inserted in a human heart the various measurements required are inflow and outflow pressure gradients, aortic left ventricle pressure, flow rate through the pump and rotational velocity of the pump. Textbook of clinical echocardiography [20] shows how clinicians use doppler measurements to calculate the inflow and outflow pressure gradient.

Figure-21: Head-flow curve (aortic pressure). Graph between pressure measured at anastomosis and flow rate. The family of curves represents the respective VAD speed setting and occult obstruction.
through the pump. The calculation is based on the mean velocity of blood through the heart and further Bernoulli's principle is used to mathematically calculate the pressure gradient. The aortic left ventricle pressure is the cuff pressure measured at the time of systole as the aortic valve is open. The doppler ultrasound can be used to estimate the flow (Q) using the method shown in Schwarz [21] using the measured mean velocity. Rotational velocity of the pump can be calculated using audio spectra of the pump. This method is further explained in chapter 4.

![Diagram showing head-flow curves](image)

**Figure-22:** Method of utilizing H-Q curves to detect possible obstruction in the VAD circuit.

Once these measurements are available, using the head-flow curves shown, extrapolating right from the Y-axis mark of the flow rate on to the curve of the respective speed the pressure is observed (Fig. 22). If the calculated VAD output at the calculated VAD load corresponds to the table VAD speed-specific HQ curve, then we know the VAD pump is working properly and there are no blockage in the cannula. If the calculated VAD output at the
calculated VAD load is lower than the table VAD speed-specific HQ curve, then there could be an issue with the VAD pump system.
Chapter 4

Frequency analysis of the VAD’s acoustic signature.

The main goal of this research is to develop non invasive methods to classify the health of the VAD. The most common complications in a VAD circulatory system are broadly divided into two categories: pump malfunction and cannula obstruction. Pump malfunction includes thrombus formation inside the pump through deposition of fibrous tissue on impeller vanes [22], bearing failure or mechanical breakdown. These can lead to mechanical imperfection in the pump and causes changes in the rotational speed of the pump. Cannula obstruction can occur at the pump inlet (“wall suck”), in the outlet tubing, or at the aortic anastomosis [23], this work focusses on the later of the two categories. The proposed method begins by performing speed classification, this determines the rotational speed by investigating the frequency response of the acoustic spectrum. To detect the level of obstruction in the VAD system a method is proposed which classifies the obstruction using Principal Component Analysis (PCA) of the expanded acoustic spectrum used for the speed classification. The following section contains the methodology used for the classification and the results display the successful extent of this method in classifying the health of the VAD.

4.1 Classification methodology

The approach to fault classification is shown in fig. 23. Raw acoustic data from both the Hydrophone and doppler ultrasound machine in the form of voltage is acquired in five second audio files for each condition pertaining to the occult obstruction. At each speed a total of 90 second of data divided into
90 one second files are used for the classification. Out of the 90 files, thirty are collected at each of the three obstruction fixture and among the thirty files, ten are used for training and twenty for validation. The data collection protocol is as follows: (i) an outflow obstruction fixture (0%, 25%, 50%) is attached to the flow circuit (fig.-13), (ii) The Jarvik 2000 is set to one of five possible controller speed settings, (iii) Acoustic data is collected. Steps (ii) and (iii) are repeated for each of the five speed settings. The outflow obstruction fixture is changed and the protocol repeated for each fixture. The entire protocol is repeated three times at each condition to obtain training and validation test data for the classifier. Once the acoustic data is collected the frequency spectrum is calculated by taking a FFT, which is an algorithm to calculate the Discrete Fourier Transform (DFT) of an input vector. It converts a signal consisting of equally spaced samples into a list of coefficients of complex sinusoids in order of their frequencies. The basic equation of a DFT is given by,
\[ x(k) = \sum_{n=0}^{N-1} x(n) e^{-i2\pi k \frac{n}{N}} \quad k = 0, 1, \ldots, N-1 \quad (4.1) \]

where \( x(k) \) is the DFT of sequence \( x(n) \). The frequency content of a signal, especially one from rotating machinery, is often of interest in fault detection as many faults have characteristic frequencies associated with them.

**Figure 24.** Raw voltage signal for three obstruction levels at Speed-1.

Figure-24 displays the raw acoustic signal from the hydrophone in the time domain acquired at 20-kHz. The signal in the figure is collected at Speed-1 obtained from all three obstructions. The bottom plot contains all
three signals overlaid and it is visually impossible to differentiate among the three.

![Figure-25. FFT of all 5 different speed setting between 120-220 Hz with 0% obstruction and collected from the hydrophone.](image)

Figure-25 is the frequency spectrum of the raw data from the hydrophone collected with 0% obstruction. The plot shows the frequency at which the pump is rotating between 120-220 Hz but for all 5 different speeds.

With the frequency spectra determined the first stage of the proposed approach is to empirically determine the pump speed. Under normal operating conditions the Jarvik 2000 is speed controlled based on a patient selected setting on the controller that resides external to the body. The algorithm first calculates the highest magnitude of the FFT between 120-220Hz. This corresponds to the expected operating range of the Jarvik 2000. If the peak frequency matches the corresponding manual speed setting on the controller then the first conclusion is that the motor is spinning at the
appropriate speed and there is no mechanical fault with the rotation of the device.

Once the correct speed is classified and the pump is determined to be working properly the fuller audio frequency spectrum is analyzed. For a one second audio file with a sampling rate of 20kHz (for an allowable Nyquist limited frequency range up to 10kHz) results in a total of 16,385 points with a 0.61Hz frequency resolution. Unless specific frequency bands are known a priori to be investigated (as in the pump speed estimation) this is far too many data points to be used as features for classification and thus data reduction is necessary.

Initially it is decided to truncate the frequency content to 3,000-Hz from the 10KHz spectra shown in fig. 26. This was selected in an ad-hoc manner, which significantly reduces the feature vector and still yield a successful result. Future work is planned to further analyze the frequency content. The truncation results in a reduction to 4,915 points. To reduce the feature vector further the approach is to group the FFT values into \(N_b\) number of frequency bins. The principle is to assign a single value to a range of frequencies based on the magnitude of the spectrum over that range. To compute the magnitude of a bin \(Y\) the spectrum is numerically integrated using a trapezoidal rule,

\[
Y_{1\ldots N_b} = \int_{f_1}^{f_2} X(f) df = \sum_{k=f_1}^{f_2-\delta f} \frac{X(k) + X(k + 1)}{2} \delta f \quad (4.2)
\]

where \(f_1\) and \(f_2\) are the starting and ending frequencies of the bin, \(\delta f\) is the frequency resolution, and \(X(f)\) is the FFT of the acoustic signal over the bin range. This process is repeated to cover the entire range of interest. For this
work, a bin size of 10Hz is selected resulting in 300 ($N_B$) averaged values. This bin size is selected to significantly reduce the feature vector and still yield a successful result. Future work is planned to further analyze the bin size selection.

The resulting binned feature vector forms a single data set consisting of $N_B$ elements,

$$Y = [y_1, y_2 \cdots y_{N_B}]^T$$  \hspace{1cm} (4.3)

where each of the components of $Y$ corresponds to the magnitude of the binned FFT at groupings of frequencies for a single data file. The process is also repeated for each condition (speed & obstruction) to obtain a set of training data.
In order to further reduce the dimension, a transformation is needed to map from a space with a large dimension, $N_B$, to a smaller dimension, $D$. This is accomplished using the linear transformation,

$$ z = W \ast Y \quad (4.4) $$

The linear transformation (or weight) matrix, $W$, maps the binned FFT vector $Y$ onto the reduced dimension feature vector $z$.

Principal Components Analysis (PCA) is chosen to obtain the components of the weight matrix using data from the training set. A training set consists of binned FFT computations from signal data collected from a population of known healthy conditions and those that have known obstructions. The goal of the PCA technique when applied in this manner is to obtain a transformation matrix that weighs the bins that give the most insight into the health of the VAD more heavily (i.e. those that differ between healthy and obstruction). The bins that differ in magnitude between healthy and obstruction data should produce a larger variance resulting in a larger weighting.

PCA is a technique commonly applied in data compression applications that convert a large data set to an alternative coordinate system with the possibility of far fewer points while minimizing data loss. It is a mathematical calculation of recognizing patterns in the data of high dimension. First, PCA determines the covariance matrix of the training data set obtained from the FFT binning for all known health classes. The eigenvalues and eigenvectors of the covariance matrix are calculated with the eigenvalues arranged in descending order. The larger the eigenvalue the more significantly it
represents the variance in the data. The eigenvectors are correspondingly ordered to form the weight matrix, $W$. From Eq. (4) the PCA technique maps the vector $Y$ onto the feature vector (also known as principal component vector), $z$ by

$$z_i = w_{i1} y_1 + w_{i2} y_2 + w_{i3} y_3 + \cdots w_{iN} y_{N_B} \quad (4.5)$$

where the coefficients $w$ are the weight matrix values and are equal to the eigenvector components from the PCA. Therefore, the first principal component, $z_1$ explains the most training set variance, the second component, $z_2$ explains the second most variance, and so on. The amount of information represented by a single eigenvalue is estimated from the percentage that the eigenvalue represents of the sum of all eigenvalues. The components that explain the majority of the variation in the training set are retained while the other components are discarded in order to reduce the number of features. For a complete treatment on PCA see the text by Jackson [12].

Initially there is a substantial data matrix consisting of the binned FFT’s from the training measurements. For this work 300 bins are used for each measurement for each of the health condition, 30 data sets are taken for a total training data set of $300 \times 30$. PCA then maps this into a 2D principal component vector space which could be mathematically and visually worked upon.

The combined use of frequency binning and PCA has been used successfully in previous research dealing with rotating machinery. Chirico and
Kolodziej [25] applied this technique to separate bearing faults in electro-mechanical actuators, Holzenkamp [26] successfully applied the method to various journal bearing failures on a reciprocating compressor.

The PCA procedure reduces the dimension of the entire binned frequency spectrum to \( z \) principal components which become features to the classifier. The classifier implemented for this research is a Bayesian classifier primarily because of its proven widespread acceptance in many fields and the future ease of a practical implementation in an embedded controller.

A classifier looks for certain patterns in recorded measurements and as a result the classification process assigns the measured object to a class. Following feature extraction, the objective is to assign a class label \( w \) to an object with true class, \( w_k \). The assignment is based on the feature vector, \( z \), which could be pure measurement, a modeling result, or a signal processing technique such as PCA as in this work. The possible classes is defined by the set of \( k \) classes,

\[
\Omega = \{w_1, \ldots, w_k\}
\]  

and in this application the object class relates to the health status of the VAD system specifically outlet blockage. For instance, the health status may be defined by the set class = \{“Healthy”, “25% Blocked”, “50% Blocked”\} based on the cases implemented from the seeded fault testing of common blockages. Future work is planned to expand the class set by adding other common fault types such as thrombosis on the impeller and inlet flow blockage.
As mentioned this research utilizes a statistical approach based on applying Bayes theorem to select the class of an object from a set which are assumed to be mutually exclusive. The class with the minimum amount of risk is assigned by the classifier, which amounts to solving Eq. (7),

$$w(z) = \underset{k}{\operatorname{argmin}} \left\{ \sum_{i=1}^{K} C(\hat{w}_i \mid w_k) p(z \mid w_k) P(w_k) \right\} \quad (4.7)$$

where the cost function $C(w_i \mid w_k)$ is the penalty of assigning the class $w_i$ coming from an object with true class $w_k$. The prior probability that the object belongs to class $w_k$ before any measurements are taken (unconditional) is $P(w_k)$ and since the classes are assumed to be mutually exclusive, the probability of each class must add up to one. The conditional density, $P(z \mid w_k)$ comes from the distribution of the data from known classes. The model form of the probability density function is assumed known with unknown parameters that are determined from training data. The most common conditional density, and the one used in this work, is normally distributed and is expressed by the parametric equation,

$$p(z \mid w_k) = \frac{1}{\sqrt{(2\pi)^D |S_k|}} \exp \left( -\frac{1}{2} (z - \mu_k)^T S_k^{-1} (z - \mu_k) \right) \quad (4.8)$$

where the parameters, $\mu_k$ and $S_k$ represent the expectation vector (mean) and covariance matrix, respectively, of the random feature vector $z$ coming from an object with true class $w_k$. Assuming that the mean and covariance matrix
are unknown, they may be estimated from the training set data by equations, (9) and (10),

\[
\hat{\mu}_k = \frac{1}{N_k} \sum_{n=1}^{N_k} z_n \tag{4.9}
\]

\[
\hat{S}_k = \frac{1}{N_k - 1} \sum_{n=1}^{N_k} (z_n - \hat{\mu}_k)(z_n - \hat{\mu}_k)^T \tag{4.10}
\]

where \( N_k \) represents the number of training samples coming from class \( \omega_k \) and \( z_n \) is the feature vector.

For this work the prior probability for each class is assumed equal \((P(\omega_k)=1/3)\) with a uniform cost matrix \( C(\omega_i \mid \omega_k) \). That implies no additional penalty for misclassification (e.g. false, positives). While these assumptions are used throughout this research, they are noted as significant potential future expansion of the technique.

### 4.2 Results

This section shows the experimental results of the methodology proposed in this work. Table-1 shows the expected frequency at which the pump rotates as specified by the manufacturer (RPM (nom.)) along with the estimated RPM with no added obstruction.

The rotational speed of the pump is of great importance since it is strongly related to the flow rate and excessive or inadequate flow may cause an unhealthy heart condition. Moreover, the pump speed can also indicate if there is a fault in the controller when a deviation from the expected is found.
Finally, for the proposed approach, estimating the pump speed determines which trained classifier to use.

<table>
<thead>
<tr>
<th>Speed</th>
<th>RPM (nom.)</th>
<th>Measured frequency</th>
<th>Estimated RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8000</td>
<td>135.2</td>
<td>8,112</td>
</tr>
<tr>
<td>2</td>
<td>9000</td>
<td>153.4</td>
<td>9,210</td>
</tr>
<tr>
<td>3</td>
<td>10000</td>
<td>172.2</td>
<td>10,332</td>
</tr>
<tr>
<td>4</td>
<td>11000</td>
<td>188.0</td>
<td>11,280</td>
</tr>
<tr>
<td>5</td>
<td>12000</td>
<td>203.4</td>
<td>12,204</td>
</tr>
</tbody>
</table>

**Table-1.** Jarvik 2000 expected vs. estimated speeds (Unobstructed).

Figure 27 is the frequency spectrum of the raw data from the hydrophone collected with 0% obstruction. The plot shows the frequency at which the pump is rotating between 120-220 Hz but for all five different speeds. It is visible that the highest peak in each spectrum corresponds to the expected pump speed. Similar estimation results are found for tests performed with increasing degrees of obstruction. Fig. 28 and 29 is the frequency spectrum data from the hydrophone collected with 25% and 50% obstruction respectively. Indicating that the VAD is clearly speed control regardless of the obstruction.

It is noteworthy that, apart from obstruction classification, the hydro-acoustic microphone is capable of determining the rotational speed of the pump. This finding alone is valuable in a clinical setting for VAD patients because there no longer would be a need for an expensive Doppler ultrasound system to determine some pump performance. However continued in-patient experimentation is required for further proof.
FIGURE 27. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 0% obstruction and collected from the hydrophone.

FIGURE 28. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 25% obstruction and collected from the hydrophone.
Similarly to the hydrophone the speed classification is performed using the audio spectra from the Doppler ultrasound machine. To use a comparison fig. 30, 31 and 32 are the frequency spectrum of the raw data from the doppler ultrasound machine collected with 0%, 25% and 50% obstruction respectively. Not surprisingly the Doppler ultrasound frequency spectrum is much “cleaner” than the inexpensive hydrophone. Both measurement technique will subsequently be used for the obstruction classification to provide a comparison.

**FIGURE 29.** Frequency spectrum of all 5 different speed setting between 120-220 Hz with 50% obstruction and collected from the hydrophone.
FIGURE 30. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 0% obstruction and collected from the ultrasound doppler machine.

FIGURE 31. Frequency spectrum of all 5 different speed setting between 120-220 Hz with 25% obstruction and collected from the ultrasound doppler machine.
For the obstruction classifier this section expands on the theory with graphical representations and examples on how the obstruction classification is done. The same data sets used to classify speed are used again but across a wider frequency spectrum. For example, fig. 33 is the frequency spectrum of the hydrophone audio spectra, collected at Speed-5 with no obstruction between 0-3000Hz. There are a number of decipherable frequencies in the plot apart from the pump rotational speed at 203 Hz. While none of these peaks individually are predetermined to be critical the concept is that as a collective they can be used to determine obstruction.

**FIGURE 32.** Frequency spectrum of all 5 different speed setting between 20-220 Hz with 50% obstruction and collected from the ultrasound doppler.
Figure 34 is the frequency spectrum of the Doppler ultrasound audio spectra, collected at Speed-5 with no obstruction between 0-600Hz. It is observed that above 600Hz the ultrasound didn’t depict any significant signal which could be used for classification. The only major critical peak in this signal was the rotational speed of the pump at 203 Hz.

Figure 35 shows how the FFT values collected from the hydrophone are binned to 300 bins (NB). The binning process reduced the 4,915 (0-3000Hz) point spectrum to 300 points. The data in this figure is collected at Speed-1 for all three obstructions. The top plot is for 0% obstruction (blue), the middle for 25% obstruction (red), and the bottom one for 50% obstruction (black).
**FIGURE 34.** Frequency spectrum of the acoustic signal from Doppler for Speed-5.

**FIGURE 35.** Binned Frequency spectrum at Speed-1 for each obstruction (0%, 25% & 50%) respectively from hydrophone.
A 10-Hz bin size is chosen in an ad hoc manner that sufficiently reduces the data set but did not overgeneralize. While for the binning process for the ultrasound signal, the binning process converted 985 (0-600Hz) points to 100 points, with a 6 Hz binning window (Fig. 36). A smaller binning window is chosen because of a higher resolution of FFT in a smaller domain (0-600Hz).

Once the binning process is complete the PCA portion of the approach follows. For a given speed setting seeded training data are compiled into a matrix (3*N x N_B) where N=10 is the number of training data FFTs per obstruction level and N_B is the number of bins. PCA is then applied to this total data matrix. For ease of visual representation, as well as accounting for greater than 80% of the data variance for the hydrophone and the doppler in nearly all cases tested, the first two principal components are selected as features to the classifier. The classification results are shown in fig. 37-41 and are implemented at controller Speed 1-5 respectively and is from the hydrophone acoustic spectrum.

![FIGURE 36. Binned Frequency spectrum at Speed-1 for each obstruction (0%, 25% & 50%) respectively from doppler ultrasound machine.](image-url)
FIGURE 37. Classification results for the hydrophone for Speed-1 [top], % contribution to the variance [bottom], 0% misclassification.

FIGURE 38. Classification results for the hydrophone for Speed-2 [top], % contribution to the variance [bottom], 0% misclassification.
FIGURE 39. Classification results for the hydrophone for Speed-3 [top], % contribution to the variance [bottom], 0% misclassification.

FIGURE 40. Classification results for the hydrophone for Speed-4 [top], % contribution to the variance [bottom], 0% misclassification.
The 2D feature vector for the training data sets are marked with circles and crosses mark the validation data. The training data probability density functions are assumed normally distributed for each health class and are displayed as contours. The two classification boundaries, linear (black) and quadratic (blue) are also shown in the image. The linear boundary was generated using a common covariance matrix and quadratic using the class dependent covariance matrix from the training data. A quadratic decision boundary formulates better decision criteria than a linear bound, while a linear boundary is visually distinctive and easy to implement. Even though the covariance is clearly class dependent.

The results generated from the hydrophone data show perfect classification of the validation points. Both the quadratic and the linear classification boundaries meet with 100% accuracy in classifying the three

FIGURE 41. Classification results for the hydrophone for Speed-5 [top], % contribution to the variance [bottom], 0% misclassification.
obstruction classes. The bar chart at the bottom of the figure shows the contribution of the first 20 principal components. It is evident that the first two principal components of the 300 can account for greater than 70% of the variance in the data. This is a very important motivation for reducing the data to two features for the classification from 300.

The same routine was implemented on the acoustic spectrum of the Doppler ultrasound data. Fig. 42-46 are the results of the classification from controller Speed 1-5 respectively. The same legend scheme is used, where the training data sets are marked with circles and crosses mark the validation data. The training data probability density functions are assumed normally distributed for each health class and are displayed as contours. The two classification boundaries, linear (black) and quadratic (blue) are also shown in the image.

**FIGURE 42.** Classification results for the Doppler ultrasound machine for Speed-1 [top], % contribution to the variance [bottom], 0% misclassification.
FIGURE 43. Classification results for the Doppler ultrasound machine for Speed-2 [top], % contribution to the variance [bottom], 0% misclassification.

FIGURE 44. Classification results for the Doppler ultrasound machine for Speed-3 [top], % contribution to the variance [bottom], 0% misclassification.
**FIGURE 45.** Classification results for the Doppler ultrasound machine for Speed-4 [top], % contribution to the variance [bottom], 0% misclassification.

**FIGURE 46.** Classification results for the Doppler ultrasound machine for Speed-5 [top], % contribution to the variance [bottom], 6.6% misclassification.
The results generated from the doppler ultrasound machine acknowledged the fact that this method of classification from acoustic data is a potential solution for health classification of the VAD. Although in the results from the doppler ultrasound audio spectra at Speed-5, three misclassifications are observed using the quadratic boundary condition.

Blood pressure is a variable quantity that can differ from patient to patient. For this algorithm training sets are used to train the classifier for known obstruction in the circuit. There could be a situation where the same level of obstruction exist in patients with different blood pressure. To investigate the effect of this phenomenon on the classification, the algorithm is tested by altering the vascular resistance in the circuit. At each anastomosis obstruction four different levels of vascular resistance are altered by adjusting the mechanical clamp in the circuit. These resistance are set at no added resistance, 1 turn, 1.5 turn and 2 full turns of the vice clamp. The data collection protocol is as follows: (i) an outflow obstruction fixture (0%, 25%, 50%) is attached to the flow circuit, (ii) The Jarvik 2000 is set to one of five possible controller speed settings, (iii) Mechanical clamp is adjusted to one of the four vascular resistance, (iv) Acoustic data is collected. Steps (iii) and (iv) is repeated for each of the four vascular resistance and the whole process is repeated for every obstruction fixture.

Figure 47 is the result of PCA accumulated at Speed-4 with the hydrophone acoustic data. The legend scheme which is used is in this analysis is as follow: The marker color blue, red and black are for the three obstruction fixture at 0%, 25% and 50% respectively and the circles mark the points collected at zero back pressure, the stars for one turn, the plus signs for one and a half turn and triangles for two turns.
The anticipation from this PCA analysis is whether it could classify the three different obstruction fixtures as it did without the additional back pressure. But this alteration resulted into a scattered plot where no classification was possible. The classification is also done at Speed 5 and shown in fig. 48. This result is not entirely unexpected since a given level of obstruction when added to a given clamp level would likely be similar to a larger obstruction level with a reduced clamp level. A potential solution to this problem is to add a third input to the classifier referencing the patient blood pressure to account for the patient to patient variability.
To determine if phasic pressure within the Jarvik pump altered the classification, this technique is further examined during pulsatile flow. During this analysis the three obstruction fixtures are classified (0%, 25% and 50 %) and the same data collection protocol is followed which is explained earlier in the methodology section. The pulsatile conditions were achieved using the syringe pump arrangement and fluid is pushed in and out manually. An example of pressure and flow profile during pulsatile flow can be seen in Fig. 14 and 15.

Figure 49 shows the classification results achieved at Speed-1 and followed by the plots of classification achieved at all other controller speed settings.
FIGURE 49. Classification results (Pulsatile flow) from the Hydrophone for Speed-1 [top], % contribution to the variance [bottom]. (Misclassification linear -25%, quadratic-36.67%)

FIGURE 50. Classification results (Pulsatile flow) from the Hydrophone for Speed-2 [top], % contribution to the variance [bottom]. (Misclassification linear -20%, quadratic-16%)
FIGURE 51. Classification results (Pulsatile flow) from the Hydrophone for Speed-3 [top], % contribution to the variance [bottom]. (Misclassification linear -33.33%, quadratic-31.66%)
**FIGURE 53.** Classification results (Pulsatile flow) from the Hydrophone for Speed-5 [top], % contribution to the variance [bottom]. (Misclassification linear -26.6%, quadratic-30%)

Confusion matrix, speed-1, linear

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>19/20</td>
</tr>
<tr>
<td>25%</td>
<td>0/20</td>
</tr>
<tr>
<td>50%</td>
<td>1/20</td>
</tr>
</tbody>
</table>

Confusion matrix, speed-1, quadratic

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>14/20</td>
</tr>
<tr>
<td>25%</td>
<td>0/20</td>
</tr>
<tr>
<td>50%</td>
<td>1/20</td>
</tr>
</tbody>
</table>

**Table 2.** Classification results (Pulsatile flow) from the Hydrophone for Speed-1, linear boundary [Left] and quadratic boundary [right].
### Table 3. Classification results (Pulsatile flow) from the Hydrophone for Speed-2, linear boundary [Left] and quadratic boundary [right].

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>25%</td>
<td>20:2</td>
</tr>
<tr>
<td>50%</td>
<td>0:20</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0:20</td>
</tr>
<tr>
<td>25%</td>
<td>12:2</td>
</tr>
<tr>
<td>50%</td>
<td>8:20</td>
</tr>
</tbody>
</table>

### Table 4. Classification results (Pulsatile flow) from the Hydrophone for Speed-3, linear boundary [Left] and quadratic boundary [right].

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>25%</td>
<td>0:20</td>
</tr>
<tr>
<td>50%</td>
<td>0:20</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0:20</td>
</tr>
<tr>
<td>25%</td>
<td>11:2</td>
</tr>
<tr>
<td>50%</td>
<td>9:20</td>
</tr>
</tbody>
</table>

### Table 5. Classification results (Pulsatile flow) from the Hydrophone for Speed-4, linear boundary [Left] and quadratic boundary [right].

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>19:20</td>
</tr>
<tr>
<td>25%</td>
<td>4:20</td>
</tr>
<tr>
<td>50%</td>
<td>16:2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>19:20</td>
</tr>
<tr>
<td>25%</td>
<td>5:20</td>
</tr>
<tr>
<td>50%</td>
<td>14:2</td>
</tr>
</tbody>
</table>
As shown in fig. 49-53 the classification is effected as a result of added pulsatility in the flow. To analyze the performance of the algorithm, the results of the classification are written in the confusion matrices (Table-2 to 6) and percentage misclassification is calculated. A miss classification of 16-33.33% is evident from the analysis and this is also shown in the percentage covered by the first two variance which decreases to minimum of 45% in Speed-3. These results conclude that pulsatility is a big factor which influence the audio measurement.

The classification during pulsatile flow is further investigated incorporating the third principal component. This is done because it is expected that adding the variance of the third principal component could decrease the misclassification. Fig. 54 is the classification plot for this analysis which is obtained at Speed-2. Using the confusion matrix, it is observed that the misclassification reduced to 13.33% for the linear classifier and quadratic
classifier, as compared to 20% and 16% for linear and quadratic respectively using two principal components. This is an area that should be investigated more with better equipment and human experiments.

**FIGURE 54.** Classification results (Pulsatile flow) from the Hydrophone for Speed-2 using 3 principal components. (Misclassification linear -13.3%, quadratic-13.3%)

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
<th>Confusion matrix (3d), speed-2, linear</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>25%</td>
<td>20%</td>
<td>20%</td>
</tr>
<tr>
<td>50%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classified</th>
<th>Actual</th>
<th>Confusion matrix (3d), speed-2, quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>25%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>50%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

**Table 7.** Classification results (Pulsatile flow) from the Hydrophone for Speed-2 (3d), linear boundary [Left] and quadratic boundary [right].
4.3 Summary

Comprehensively this technique of classification using audio spectra does a decent job. 100% classification is achieved at continues flow conditions, which is an excellent result to the fact that this technique is used for the first time to assess a VAD. This concludes that the hydro microphone is a feasible sensor to be utilized in monitoring the VAD’s health.

In the condition of varying back pressure, the scattered plots suggests that the classification could be directly related to the flow rate or pressure gradient across the pump, as it is assumed that the audio frequencies are from the flow dynamics of the pump. These analysis could be further utilized in future research to build a better mathematical model to classify the health of the pump. A possible solution is to add another input to the classifier that is more patient specific where the patient “back pressure” presumably would remain more consistent.

For this research it is observed that the syringe pump arrangement, which is used to create the pulsatility in the system may have hindered the acoustic data as a result of noise from the actuation. For future research, a more efficient device to create pulsatility could improve the classification. It is proposed that as the algorithm has a better performance with the continues flow, signal processing can be used to alter the audio files and remove the “pulses” from the audio spectra and then execute the classification with the left over continues data.
Chapter 5

Conclusions and Future Work

This research is based on non-invasive fault detection in Ventricular Assistive Devices. A robust health monitoring approach for the Jarvik 2000 Flowmaker is developed which could classify two kinds of faults: pump malfunction and outlet cannula obstruction. The techniques proposed in this work utilize Head-flow curves, which are pump performance curves that relate pressure and flow characteristics. The other technique utilizes a data-driven approach through frequency analysis of the acoustic signature from the blood pump by means of an inexpensive and non-invasive hydrophone.

To study the physiology of the pump, four indices were investigated. these are :- (1) pump rotational frequency against flow, (2) pump rotational frequency against pressure gradient across pump, (3) differential pressure against flow rate, (4) pressure at obstruction anastomosis against flow rate. To measure these indices five sensors are used which are :-(1) ultrasonic flow sensor (2) differential pressure sensor (3) static pressure sensor (4) hydro acoustic microphone and (5) Doppler ultrasound machine. These indices can be used by pump manufacturers for quality assurance of new pumps and to develop better devices. It also helps clinicians to study the performance of the pump by comparing the pressure flow characteristics and diagnose cannula obstruction. For future work these indices should be developed using actual blood with human testing critical.

The data driven approach incorporates a FFT of the acoustic signal and data compression using frequency binning and principal component analysis.
Finally, classification is done using a trained Bayesian classifier. The algorithm tested with a validation data set is found to be successful in computing the speed of the pump and isolating the obstruction level in the flow circuit of the Jarvik 2000. Through the use of a hydrophone measuring the acoustic signature on a laboratory bench setup and seeded fault data, the method is tested to classify three obstruction levels which resulted in excellent performance with a 100% diagnosis rate, when the VAD system is operating in a continuous flow rate.

The same routine is also tested using pulsatile flow in the system and classification is done. The results indicated miss classification between 25-47% at different speeds. The reason for the misclassification could be the decreased percentage variance of the first two principal component which could be the result of the added pulsatility if the circuit. It is suggested that adding a second input to the system like pressure, flow or current drawn from the controller would make the classification more robust.

Further, the effect of varying back pressure on classification is also investigated. The motivation of varying the back pressure is the variability in blood pressure in humans. The result obtained from this classification resulted in scattered plots and couldn't be distinguished. The reason for this is assumed that the additional back pressure added to the level of obstruction which made it similar to a larger obstruction. A solution to this problem could be an third input to the classifier which is more patient specific e.g. blood pressure.

By observing the performance of this approach the method can be implemented and tried on other ventricular assistive devices for non-invasive health monitoring like the Heartmate II and DeBakey VAD.
Future research is significant. First, human testing is the ultimate goal which involves data collection from an implanted Jarvik 2000 in a patient with a known VAD condition. Important future investigations beneficial to this approach includes, but it is not limited to, optimizing the length of frequency spectrum used for the analysis, optimizing the size of the bins, and the signal processing which involves windowing and data filtration. Bayesian classification also provides a great deal of flexibility in density function selection and in placing risk levels on the classification (false-positives, etc.) Ultimately, the proposed method may lead to a non-surgical diagnosis that is painless, inexpensive, and easy to implement.
References


[18] http://cnx.org/content/m46661/latest/2029_Cardiac_Cycle_vs_Heart_Sounds.jpg

[19] http://radiographics.rsna.org/content/30/2/429/F13.medium.gif


