SEPARATION OF HEART MURMUR, "AORTIC REGURGITATION SOUND" FROM SOUND MIXTURE USING COMPONENT SEPARATION METHOD

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ABSTRACT

The cardiac arrest may be due to many physiological disorders. The exact tracking of the cardiac disorder is really difficult. Here we propose a method so as to listen to aortic regurgitation heart murmur in presence of human sound. The person who is affected by an aortic regurgitation may produce an audible sound due to his agony or pain and this sound is a sound which needs to be separated so as to have a clear listening of aortic insufficiency. Here we separated the mixture sound first by producing an artificial mixture and then separated it by blind source component separation technique. The artificial delayed mixed signal input which we used was clearly separated into two independent signals. The technique which involves frequency based separation is based on W disjoint orthogonality principle.

Keywords: Aortic Regurgitation, Bind Source Component Separation, Heart Murmurs.

1. INTRODUCTION

Abnormal murmurs are audible in different parts of the cardiac cycle. Aortic insufficiency or aortic regurgitation, which allows backflow of blood when the incompetent valve closes with only partial effectiveness.

The aorta is the largest artery in the body, originating from the left ventricle of the heart and extending down to the abdomen, where it bifurcates into two smaller arteries. The aorta distributes oxygenated blood to all parts of the body. Aortic regurgitation is reflux of blood from the aorta (the big vessel carrying blood out of the heart). The problem occurs when some of the blood pumped out falls back into the heart, because of an incompetent working of the aortic valve. Aortic
regurgitation (AR), is the leaking of the aortic valve of the heart that causes blood to flow in the reverse direction during ventricular diastole, from the aorta into the left ventricle.

Gradation of murmurs is shown in Table 1. Phonograms from normal and abnormal heart sounds are shown in figure 1.

### Table 1: Gradations of Murmurs

<table>
<thead>
<tr>
<th>Grade</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>Grade 1</td>
<td>Very faint, heard only after listener has &quot;tuned in&quot;; may not be heard in all positions.</td>
</tr>
<tr>
<td>Grade 2</td>
<td>Quiet, but heard immediately after placing the stethoscope on the chest.</td>
</tr>
<tr>
<td>Grade 3</td>
<td>Moderately loud.</td>
</tr>
<tr>
<td>Grade 4</td>
<td>Loud, with palpable thrill (i.e., a tremor or vibration felt on palpation)</td>
</tr>
<tr>
<td>Grade 5</td>
<td>Very loud, with thrill. May be heard when stethoscope is partly off the chest.</td>
</tr>
<tr>
<td>Grade 6</td>
<td>Very loud, with thrill. May be heard with stethoscope entirely off the chest.</td>
</tr>
</tbody>
</table>

![Figure 1: Phonograms from normal & abnormal heart sound](image)

### 2. RELEVANCE OF TECHNOLOGY

Auscultating the heart sounds is inadvertently the preliminary diagnosis conducted by any physician. The outcome of the auscultation solely governs a doctor’s diagnosis and further proceedings. As such, any error that could creep in could prove fatal. It is mandatory that the doctor receives the actual heart sounds with no noise intrusion from the environment and the patient. For ensuring this, the Heart sound has to be separated from all the noises generated in and around the patient. On implementation, this also enables the patient to talk freely during diagnosis. It is very common in many human beings to get affected by the diagnosis procedure. Being still in front of the doctor during diagnosis varies the patient’s normal body functioning and yield erroneous readings.
For instance, the blood pressure of the patient might shoot up or heart rate increase during diagnosis period due to the mentality of the patient. Hence, it is of the utmost importance that the patient must be as comfortable as possible. This technology enables doctors to diagnose patient in the comfort zone of the patient giving an accurate reading. Also, diagnosis can be carried out in any environment and at any time.

3. DEGENERATE UN MIXING ESTIMATION TECHNIQUE

Blind Source Separation (BSS) deals with the problem of separating unknown mixed signals without prior knowledge of the signals. The methods for achieving BSS are not tied to any specific type of signals, but in this paper, mixed audio signals and heart sounds are used in the derivation and experiments. The goal is to let a person speak and his heart sound is captured by two microphones placed some distance apart from each other. An adaptive algorithm would then separate the speakers, despite the fact that their frequencies should not be in the same range and that no explicit desired signal is available to control the adaption. Here one speech signal is used. An algorithm that would perform the signal separation in real-time is introduced and implement in Matlab. Early on in the project the Degenerate Unmixing Estimation Technique (DUET) was found while investigating new approaches to the problem [1]. DUET was decided to be more interesting because it performs source separation by frequency domain processing and is independent of the number of mixed sources. All efforts are put into implementing DUET in Matlab.

To introduce the DUET algorithm a model for describing the mixing of sources is established. The specific example of two microphone channels is taken. The sources, which in our case is represented by a sound produced by a person and his heartbeat. Both these signals are captured as shown in figure 2.

The DUET algorithm operates in the frequency domain. No inverse matrix is calculated and it is one of the reasons it shows very good performance. Another bonus compared to Bayesian Independent Component Analysis is that the number of sources can be greater than the number of mixtures; in fact it can be used for an arbitrary number of sources. The DUET algorithm [2], which has been developed especially with a real-time implementation in mind is modified in order to incorporate variable time frequency resolution.

![Figure 2: Two-channel microphone arrangement with multiple sources. Here four sources are shown. Two microphone arrangements are used in DUET Technique for sound separation](image)

4. DUET TECHNIQUE

A version of the DUET algorithm was chosen to be implemented because of the good results presented in [2]. There are many fields where Blind Source Separation could be useful, e.g. separation of radio signals in telecommunication, separation of brain waves from medical sensors or
in audio applications as in hearing aids or for demixing stereo recordings [3]. It is fast and the implementation is about 5 times faster than real time. It separates an arbitrary number of sources from a set number of mixtures. For a two-channel microphone arrangement with K sources, the incoming mixed signals x1 and x2 can be described as

\[ x_1(n) = \sum_{j=1}^{k} S_j(n) \]  
\[ x_2(n) = \sum_{j=1}^{k} a_j S_j(n - \delta_j) \]

The mixtures x1 and x2 are sampled and split into blocks of length N with overlap. These sample blocks are multiplied with a windowing function W and then Discrete Fourier Transformed to

\[ x_{1,2}(n) = W(n) x_{1,2}(n) \]  
\[ X_{1,2}(k) = \sum_{n=0}^{N-1} x_{1,2}(n) e^{-j2\pi nk/N} \]

In each of the sample blocks in the frequency domain, the frequencies are determined and the minimum difference, \( \Delta f \) between these frequencies are determined. The width of the window size is determined by this difference \( \Delta f \). The window width allotted will be greater for blocks having lesser \( \Delta f \) and narrower for blocks having greater \( \Delta f \). Thus the time-frequency resolution is adaptively changed according to the frequencies present in each sample blocks.

Transforming the mixtures gives us a spectrogram with a two-dimensional time-frequency grid. Since x1(n) and x2(n) consists of a mixture of the original sources s_j(n), transforming the mixtures means that the sources now also have undergone a Short-Time Fast Fourier Transform (ST-FFT). Let the Fourier transform of the sources be S_j(\omega). For a given source j we can describe the ST-FFT of (1) and (2) as

\[
\begin{bmatrix}
X_1(\omega) \\
X_2(\omega)
\end{bmatrix} = \begin{bmatrix}
1 \\
a_j e^{-j\omega \delta}
\end{bmatrix} S_j(\omega)
\]

The DUET algorithm is based on the basic assumption that all of the sources have a different frequency spectrum for any given time. This implies that each time-frequency point in the spectrogram shown in Fig. 4 is associated with only one source. This property, which is essential for the DUET algorithm, is called the W-disjoint orthogonality property and is described as in the equation given below.

\[ S_i(\omega) S_j(\omega) = 0 \quad \forall \quad i \neq j \]

To find the parameters in the online DUET algorithm, Maximum Likelihood (ML) gradient search is used. Let us define

\[ \rho_j(\omega) = \frac{1}{1 + a_j} \left| X_1(\omega) a_j e^{j\omega \delta} - X_2(\omega) \right|^2 \]
We can see that for any given source \( j \) there is a function \( \alpha_j(\omega) = 0 \) which is zero for all frequencies that belong to \( j \). That is
\[
\rho_j(\omega) = 0
\]  
(8)

As shown in [2] the smooth ML objective function is given by
\[
J = \min_{\mathbf{a}} \sum_{\omega} \frac{1}{I} \ln(e^{j\omega} + e^{j\omega} + \ldots + e^{j\omega})
\]
(9)
where \( \lambda \) is the amplification factor.

and the partial derivative of \( J \) with respect to \( \delta_j \) is
\[
\frac{\partial J}{\partial \delta_j} = \sum_{\omega} \frac{e^{-j\omega}}{\sum_{r=1}^k e^{-j\omega}} \frac{2}{1 + a_j} \omega a_j \cdot \left(\text{Im}\{X_1 e^{j\omega \delta}\} \text{Re}\{X_2\} - \text{Re}\{X_1 e^{j\omega \delta}\} \text{Im}\{X_2\}\right)
\]
(10)

and the partial derivative of \( J \) with respect to \( a_j \) is
\[
\frac{\partial J}{\partial a_j} = \sum_{\omega} \frac{e^{-j\omega}}{\sum_{r=1}^k e^{-j\omega}} \frac{2}{1 + a_j} \omega a_j \cdot \left(\text{Re}\{X_1 e^{j\omega \delta}\} \text{Re}\{X_3\} - \text{Im}\{X_1 e^{j\omega \delta}\} \text{Im}\{X_3\}\right)
\]
(11)

These partials were recalculated, since the algorithm given in [2] failed to function.

The number of sources in the mixtures is assumed to be known and an amplitude \( a_j \) and a delay \( \delta_j \) estimate for each source are initialized. The parameters \( a_j \) and \( \delta_j \) are updated based on the previous estimate and the current gradient as
\[
a_j[k] = a_j[k-1] - \beta \alpha_j[k] \frac{\partial J}{\partial a_j}
\]
(12)
\[
\delta_j[k] = \delta_j[k-1] - \beta \alpha_j[k] \frac{\partial J}{\partial \delta_j}
\]
(13)
where \( \beta \) is the learning factor and \( \alpha_j[k] \) is a time and mixing parameter dependent learning rate for time index \( k \) and estimate \( j \). The mixing energy can be described as
\[
q_{j[k]} = \sum_{\omega} \frac{e^{-j\omega}}{\sum_{r=1}^k e^{-j\omega}} |X_1||X_2|
\]
(14)

and define
\[
q[k] = \gamma q[k-1] + q[k]
\]
(15)
where \( \gamma \) is the forgetting factor. This allows us to write the parameter dependent update rate \( \alpha_j[k] \) as
\[
\alpha_j[k] = \frac{q[k]}{q[k]}
\]
(16)
We know that $\rho_j$ is minimum for any given time-frequency point that belongs to $s_j$. If this is not the case, the time-frequency point belongs to another source. We can therefore construct a time-frequency mask based on the ML parameter estimator.

$$\Omega_j(\omega) = \begin{cases} 1 & \forall \rho_j(\omega) \leq \rho_m(\omega), \ m \neq j \\ 0 & \text{otherwise} \end{cases}$$

(17)

Now extract the discrete time Fourier transform estimate of the $j$th source from mixture $X_j(\omega)$

$$\tilde{S}_j(\omega) = \Omega_j(\omega) X_j(\omega)$$

(18)

$$\tilde{S}_j^{\theta}(\omega) = \frac{1}{N} \sum_{n=0}^{N-1} \tilde{S}_j^{(k)} e^{\frac{j2\pi n}{N}}$$

(19)

Figure 3: Experimental set up for two sources

5.1 Experiments

Since the algorithm required input from two microphones simultaneously, these were connected to the line-in input of the soundcard via a microphone amplifier, so that one microphone connected to the left channel and the other one to the right channel. Matlab was used to capture the audio signals from the line-in input, separate the sources. The mixture was mixed by artificial delayed mixing. The output was separated by utilising $W$ disjoint orthogonality. Data to the soundcard, was obtained according to the block diagram in Fig. 3.

5.2 Matlab implementation of DUET algorithm

The algorithm is written in Matlab 6.5 and was run on a PC. It works by taking a two-channel wav-file, with one mixture per channel, and reading it, or part of it, into an array. The program could easily be modified to take samples directly from the soundcard. It then takes 1024 samples at a time from this array and the Fast Fourier Transform (FFT) for this set of samples is calculated. Once this is done we can estimate the parameter changes and update the parameters using equations given. After updating the parameters, we can separate the signals from this block using a binomial mask as in the equation given in the next session. The separated two-channel array is then either saved to a wav-file or played by the soundcard. We then wait, if needed, until the buffer has enough elements and start over with the next 1024 samples. This process is repeated until the whole file has been demixed.
To facilitate sound recording, analysis of results and saving of separated data, developed a Graphical User Interface (GUI) for the Blind Source Separation application. This was done by using the user interface editor guide in Matlab.

In the Input source box, the user can choose whether to use audio data from a sound file or to perform a live recording from the soundcard. It is possible to adjust the beta, gamma and lambda parameters to optimise the performance of the algorithm. The user can also change other settings concerned with recording and playback of audio data. After pressing the Start separation button, the input data is acquired either from a file or the soundcard. Thereafter the algorithm separated the sources in real-time. After the separation is done, the amplitude difference and time delay between the sources are plotted in the window.

5.3 Parameters
The following parameters were used during experiments: \( \gamma = 2, \beta = 0.1 \) and \( \alpha = 0.2 \) where \( \gamma \) is the amplification factor, \( \beta \) is the forgetting factor and \( \alpha \) is the learning factor. As a windowing function a rectangular window was used. It was found that different window-functions did not produce noticeably different results, but that the FFT size was important.

5.4 Demixing of Artificial Mixtures
To get source mixtures of audio files, the Matlab function wavread was used, to read the contents of a file into an array. By mixing two arrays it was able to get a mixture, which could be tried to separate block-wise in real-time. The resulting demixed signals were saved into new arrays which could be stored to file using wavwrite.

Endocarditis is an inflammation of the inner layer of the heart, the endocardium. It usually involves the heart valves. In acute AI, as may be seen with acute perforation of the aortic valve due to endocarditis, there will be a sudden increase in the volume of blood in the left ventricle. The ventricle is unable to deal with the sudden change in volume. In terms of the Frank-Starling curve, the end-diastolic volume will be very high, such that further increases in volume result in less and less efficient contraction. The filling pressure of the left ventricle will increase. This causes pressure in the left atrium to rise, and the individual will develop pulmonary edema. Pulmonary edema is fluid accumulation in the air spaces and parenchyma of the lungs. It leads to impaired gas exchange and may cause respiratory failure. Figure 4 shows the blood flowing in the case of a normal healthy valve and of an abnormal heart valve which has aortic regurgitation.

![Figure 4: Heart pumping blood in the case of heart valve with aortic regurgitation and a normal healthy valve](image-url)
6. RESULTS

6.1. Demixing of Mixtures

The algorithm was able to demix all mixed audio files. The algorithm was implemented for two sound mixtures. The files were read separately and mixed within Matlab. The algorithm converges very fast and the best separation contains almost no trace of the other source. In this, as mixtures, the mixed signals used were, aortic regurgitation sound and a human speech. The amplitude difference and time delay plots of real mixtures are shown in Figure 5. Separated mixtures are shown in Figure 6 and Figure 7.

7. CONCLUSION & FUTURE SCOPE

Severe acute aortic insufficiency is considered as a medical emergency. There is a high mortality rate if the individual does not undergo immediate surgery for aortic valve replacement. Because of the importance of severe aortic insufficiency, we tried to contribute our part of the work to the world, by improving the sound quality of aortic regurgitation sound. Speaker’s voice and heart sound is separated and this indeed adds legibility and quality of sounds, to a doctor. Indeed we hope that with God’s grace it will be remarkable turnings in the present world were the patient was supposed to keep silence as the doctor examines him. Here we mixed aortic regurgitation sound and speech signals. Our results show that the patient can be allowed to talk freely while the doctor examines him.

The results which we have obtained can be properly utilized and can be emulated in future to serve the present day world. Cardiac deaths are really high in this era. So proper health care can be given if a machine is detecting a disease. Our result can be a remarkable finding to an instrument, which utilises our result as input for the prediction of a disease after learning the disease characteristics.

Figure 5: The amplitude difference and time delay plots of mixtures
8. REFERENCES


[8] “Heart Sounds & Murmurs”, Dr R S MacWalter, Consultant Physician, Tayside University Hospitals Hospitals NHS Trust, Honorary Senior Lecutrer, University of Dundee, Ninewells Hospital & Medical School, Dundee, Scotland, Duncan MacWalter and Gordon MacWalter.