35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Analysis of Adventitious Lung Sounds Originating from Pulmonary Tuberculosis

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Abstract— **Tuberculosis is a common and potentially deadly infectious disease, usually affecting the respiratory system and causing the sound properties of symptomatic infected lungs to differ from non-infected lungs. Auscultation is often ruled out as a reliable diagnostic technique for TB due to the random distribution of the infection and the varying severity of damage to the lungs. However, advancements in signal processing techniques for respiratory sounds can improve the potential of auscultation far beyond the capabilities of the conventional mechanical stethoscope. Though computer-based signal analysis of respiratory sounds has produced a significant body of research, there have not been any recent investigations into the computer-aided analysis of lung sounds associated with pulmonary Tuberculosis (TB), despite the severity of the disease in many countries. In this paper, respiratory sounds were recorded from 14 locations around the posterior and anterior chest walls of healthy volunteers and patients infected with pulmonary TB. The most significant signal features in both the time and frequency domains associated with the presence of TB, were identified by using the statistical overlap factor (SOF). These features were then employed to train a neural network to automatically classify the auscultation recordings into their respective healthy or TB-origin categories. The neural network yielded a diagnostic accuracy of 73%, but it is believed that automated filtering of the noise in the clinics, more training samples and perhaps other signal processing methods can improve the results of future studies. This work demonstrates the potential of computer-aided auscultation as an aid for the diagnosis and treatment of TB.**

I. INTRODUCTION

Tuberculosis (TB) is a common and potentially deadly infectious disease, with over one third of the world's population infected [1]. In 2005, globally 1.6 million people died of active TB [2] and the rising number of cases in developing countries has been linked to the fact that immunosuppressive drugs and the human immunodeficiency virus (HIV) compromise many citizens' immune systems [1]. In 1993 the World Health Organization (WHO) declared TB a global emergency and stated an interest in the development of rapid and inexpensive diagnostic tests to assist diagnostics at the point of care: "Rapid and cheap diagnosis will be particularly valuable in the developing world" [3].

Since pulmonary TB damages the respiratory system, the sound properties of infected lungs differ from that of healthy lungs and can therefore be expected to exhibit adventitious lung sounds, which often indicate an abnormality in the lungs, such as obstruction in the airway passages or a pulmonary disease [4]. The two main groups of adventitious sounds typically found in abnormal lungs are called wheezes and crackles. Both of these primary adventitious categories are relevant to TB, since lungs damaged by active TB result in displaced lung tissue, causing airway obstructions and hence possible wheezing sounds. A symptom of fibrosis from lung healing may also produce crackles. With these irregular waveforms and higher frequency components [5], auscultation can be assumed to be a viable, inexpensive and non-invasive diagnostic tool for TB. However, auscultation is often ruled out due to the random orientation, distribution and varying severity of damage to the lungs, resulting in a variety of adventitious sounds often mistakenly attributed to other respiratory diseases.

Publications have indicated significant successes in using signal analysis, pattern recognition, mathematical modeling, neural networks and other methods to distinguish between adventitious and normal respiratory sounds. However, to date, most studies were aimed at the autonomous identification or classification of specific adventitious sounds and did not focus on a specific disease (except for several dealing with Asthma). In particular, there has been no attempt at digital analysis of respiratory sounds associated with TB, besides a very basic study in 1983 [5]. Here the basic observation of band-pass filtered lung sound recordings on an oscilloscope indicated a difference in amplitudes between healthy and TB infected lungs [5]. This gap in the literature has left the question of whether respiratory sounds originating from lungs infected with TB possess any unique features beyond human auditory judgment that are consistent for all cases of TB, or whether the TB related lung sounds can only be used for respiratory health assessment and not diagnosis.

II. EXPERIMENTAL SETUP

A. Apparatus and Measurement Approach

Respiratory inhaling and exhaling movements were recorded using a Pneumotrace II (AD Instruments) piezoelectric belt, worn across the base chest area, containing seven electronic stethoscopes. The participants were seated in a chair in the upright position, as suggested by Rossi et al. [6]. Qualified pulmonologists from Tygerberg Academic Hospital, South Africa, determined that the seven microphones would cover the posterior and anterior chest in the most

Manuscript received January 16, 2013.
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common locations of TB infection, as indicated in Figure 1. The experimental protocol for the study was approved by the Committee for Human Research (CHR) of the Faculty of Health Sciences at Stellenbosch University (South Africa), in compliance with the principles laid down in the Declaration of Helsinki. All participants gave informed consent.

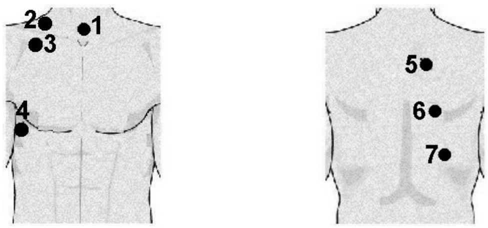

Figure 1: Stethoscope locations for right lung recording with stethoscopes numbered at (1) trachea; (2) clavicle; (3) below the clavicle on the anterior chest; (4) lateral side between the 2nd and 4th intercostal spaces; and (5,6,7) three stethoscopes down the posterior chest along the paravertebral line.

B. Procedure

The respiratory maneuvers recorded entailed: 1) five respiratory cycles at tidal breathing; and 2) three or four slow vital capacity maneuvers. This procedure was repeated three times, after which the stethoscopes were removed and placed over the adjacent lung, which resulted in a total of 14 recorded locations across the anterior and posterior chest wall. During recordings on TB patients, surgical masks and latex gloves had to be worn and all the equipment had to be disinfected after each recording session. In total, 27 healthy volunteers and 33 TB infected patients participated in the study. Three breaths per lung were selected from each participant. The patients infected with TB originated from three community clinics within the Cape Town (South Africa) metropolitan area, and were diagnosed as having pulmonary TB after obtaining three positive sputum culture tests and a positive radiography diagnosis by a qualified medical practitioner. Criteria regarding the severity of the disease were left as random as some TB patients displayed other diseases such as AIDS. Participants were of a mixed race, age and gender.

III. Data Analysis

A. Preprocessing

Analysis of the recordings required filtering to extract only the frequencies at which respiratory sounds occur. The first set of filters was analogue anti-aliasing low-pass filters built into the Zonicbook system on each recording channel. The analogue signals were sampled by the Zonicbook at 10 250 Hz, and with this sampling rate the Zonicbook system automatically adjusts the cut-off frequency for its anti-aliasing filters at 4000 Hz. All the signals were then digitally resampled in Matlab at 6 000 Hz in order to speed up the computational time for subsequent analysis. This resulted in a final analysis range of 1–3000 Hz, which is wide enough to cover the frequency extremities of all adventitious sounds [9]. As basic high-pass filtering of lung sound recordings to reduce heart sounds would remove significant components of lung sounds [10] and introduce undesirable phase shifts [11], adaptive filters were implemented in Matlab to remove low frequency heart sounds [12] and in severe cases, environmental noise as well.

B. Feature extraction

All the recordings were normalized between minimum and maximum values of -1 and 1 to reduce the effect of different ambient conditions and differences due to subject to subject variability, similar to Jain and Vepa [7]. After normalization, the mean of each recording was restored to zero. Subsequent signal analysis was completed in four categories, namely; time domain; frequency domain; wheeze parameters; and crackle parameters.

Time domain features included taking a single breath (inhalation and exhalation), calculating the root mean square (RMS) of the signal, as well as dividing the signal into ten segments (maintaining five segments over inhalation and five over exhalation) and then calculating the RMS of each segment. Furthermore, a crest factor (peak amplitude divided by RMS) was calculated for each of the ten segments and the maximum and average of the ten crest factors. A Fast Fourier Transform (FFT) was calculated for the entire inhalation and exhalation breath cycles. The frequency of the maximum amplitude was identified as a possible diagnostic feature. Further frequency domain features included the ratio between the maximum amplitude in the FFT divided by the area under the FFT graph for the entire breath cycle. Additionally, the FFT was divided into digital octave bands of 0-17 Hz, 18-45 Hz, 46-90 Hz, 91-180 Hz, 181-360 Hz, 361-720 Hz, 721-1440 Hz and 1441-3000 Hz respectively. The areas of each octave band divided by the total area of the FFT were used as additional signal features.

In the wheeze analysis the only aim was to determine if there were features in the signal matching Sovijärvi et al.'s [4] definition of a wheeze. The characteristics of a wheeze include the pitch and duration of a pseudo-sinusoidal signal present in the respiratory recording. The output of the wheeze analysis was hence merely a 0 or 1, indicating the presence or absence of wheeze characteristics in that signal. The presence of a wheeze in a respiratory signal was identified following an evaluation procedure on a spectrogram, as recommended by Kandaswamy et al. [8]. Crackle analysis involved choosing a mother wavelet and measuring the degree of similarity of scaled and shifted versions of the mother wavelet to that of the respiratory signal. Visual inspection of wavelets showed that the Daubechies 5 (db5) wavelet had the closest match to a characteristic crackle waveform. The wavelet decomposition process consisted of decomposing a signal into its low-pass approximations and high-pass details using shifted and scaled versions of the db5 wavelet. Each resulting packet is then broken down into further approximations and details, up to a decomposition level of five. A "tree" of packets is produced, containing the wavelet coefficients in packets on different levels of the tree. Peaks in the wavelet coefficient plots indicate a high degree of similarity between the mother wavelet and the respiratory signal. For each packet, statistical data such as the wavelet mode, mean, median and range of coefficients can be obtained, to be represented in a histogram.

Visual comparisons between the approximations and details from ten recordings of healthy lungs and ten recordings containing crackles (downloaded from the internet [13-15]) showed that the decomposition at wavelet packet level five using nodes (5,2), (5,3), (5,6) and (5,7) had the highest degree of variability between the healthy recordings and recordings containing crackles. Figure 2 shows examples of the wavelet decomposition at node (5,7). The low values indicate a low level of correlation between the signal and the db5 mother wavelet, and the higher values indicate a higher level of correlation between the signal and the db5 mother wavelet. Various statistical factors from these nodes were used for further consideration as signal features relating to the presence of crackles in the respiratory sound.

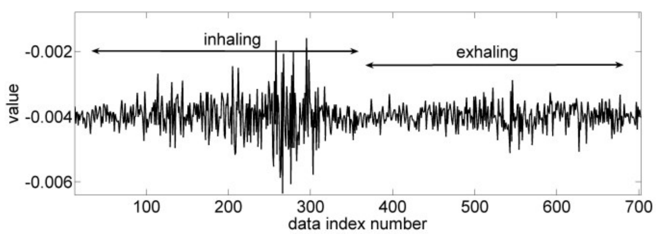

Figure 2: Wavelet decomposition of respiratory sound of TB-infected lung at node (5,7).

C. Feature reduction

Gathering all the time domain, frequency domain, crackle and wheeze features resulted in a total of 202 signal features per breathing cycle. The distribution of these 202 features across the four analysis groups were: 1-33 were time domain features, 34-45 were frequency domain features, 46 were for the presence of a wheeze characteristic (0 or 1), and 47-202 were features derived from the wavelet analysis for the detection of crackles. Being repeated for a total of 27 healthy participants and 33 patients infected with TB, and given that all participants contributed three respiratory sounds for (mostly) the left and right lung, a total of 156 respiratory sounds were obtained from healthy participants, and 189 respiratory sounds were obtained from patients infected with pulmonary TB. A method was required to determine which of the 202 signal features on which of the stethoscopes displayed the largest degree of separation between signal features from healthy and TB-infected lungs. The statistical overlap factor (SOF), often used for feature selection in such cases, is given by:

$$SOF = \left| \frac{x_h - x_{TB}}{(\sigma_h + \sigma_{TB})/2} \right| \tag{1}$$

where x_h is the mean of the particular signal feature for the healthy participants, x_{TB} is the mean of the same signal feature for patients infected with TB, σ_h is the standard deviation of the signal feature for healthy participants and σ_{TB} the standard deviation of the patients infected with TB. The SOF thus indicated the degree of separation between signal features between the two groups, while also considering the variance in the distribution of that feature. The entire feature set is also normalized for the purpose of the SOF calculation.

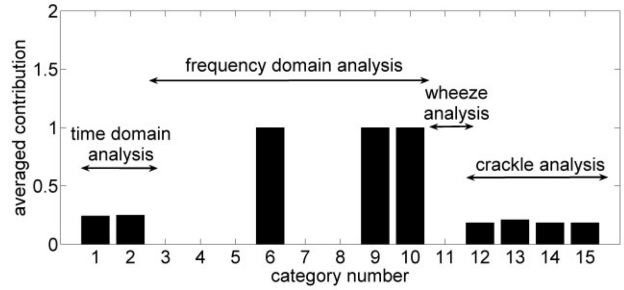

Figure 3: Weighted average contribution to the SOF. Category # 1 applies to the RMS of the signal and segments of the signal, and category # 2 to the crest factors of the signal and segments of the signal. Categories 3 – 11 are the ratios of frequency band areas ranging from 1-3000 Hz. Category # 11 describes the contribution of the wheeze analysis and category 12-15 the crackle analysis categories.

A histogram summary of the SOF results is shown in Figure 3. Since displaying 202 categories on the x-axis appears crowded the 202 results were grouped into 15 groups, namely group 1 being the RMS analysis and RMS of the signals broken into 10 segments, group 2 being the crest factors and its 10 segments, group 3 – 11 being the FFT analysis of the frequency bands ranging from 1-3000 Hz. Group 11 represents the outcome of wheeze or no wheeze present. Group 12 – 15 includes the crackle analysis. It is clear that major SOF contributions came from the following factors:

- the area under frequency certain bands in the FFT (91-180 Hz, 721-1440 Hz and 1441-3000 Hz), divided by the total area under the FTT (category 6,9 and 10);
- the RMS in of the time waveform, or segments of the time waveform (category 1 and 2);
- signal features derived from the crackle analysis (category 12 - 15).

Although there is some variation in stethoscope location and the type of signal feature, it can be theorized that a difference exists between the recordings of healthy volunteers and TB patients in the sense that the recordings from TB patients show a higher presence of crackle parameters, and this in turn contributes to the higher amplitude in higher frequency bands in the FFT. This is illustrated in the histogram summary of categories 6, 9 and 10 and 12 – 15.

D. Neural network modeling

The effectiveness of an ANN to correctly classify recordings into its respective healthy and unhealthy categories was investigated using the features with the highest SOF values as inputs to the ANN. To find the optimal ANN training algorithm, cross validation (CV) was used across four different training algorithms [7], namely: 1) adaptive learning rate back propagation (BP); 2) resilient BP; 3) scaled conjugate gradient; and 4) the Levenberg-Marquardt algorithm. For the CV approach, the ANN was trained and tested six times, each time with a new set of training and testing data rotated in such a way that the network is tested with previously unseen data. Approximately 75% of the total data was used for training and the remainder for testing.

IV. RESULTS

Analysis of the training performance across different input parameter numbers and tolerance levels indicated the Resilient BP training algorithm to have the lowest error for a tolerance of 0.4 and the number of input parameters at 14 from a possible 202. The detection performance of the algorithm is given in terms of the quantitative measures defined below, where TP, TN, FP, and FN are the number of true positive, true negative, false positive, and false negative TB detections, respectively. This can be summarized by:

$$sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$specificity = \frac{TN}{TN + FP} \tag{3}$$

$$accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{4}$$

The ANN yielded a sensitivity of 80%, specificity of 67% and consequently a total diagnostic accuracy of 73 %.

V. DISCUSSION

With the application of computer technology, a more in-depth analysis of pulmonary acoustics is possible, with results that are clinically significant. Though there is a significant body of research on digital analysis of respiratory sounds, there has been no investigation specifically into TB, despite the necessity of curbing the prevalence of this disease. This paper investigated the possibility of using electronic auscultation for the diagnosis of TB, for potential application in a rural environment or in a telemedicine setting. A large database of respiratory sounds was established and analyzed, using a wide variety of techniques, including time domain, frequency domain and both adventitious wheezes and crackle analysis. Of the 202 signal features generated, a statistical overlap factor indicated that several features displayed a degree of separation between recordings from healthy lungs and recordings from TB-infected lungs. These were entered into an ANN for automated classification of the data. ANN optimization included a CV approach across four different training algorithms, of which the final network error evaluation yielded the top 14 signal features to be used for optimal results, with a diagnostic accuracy of 73%.Though the accuracy is lower than anticipated at the onset of this study, it is believed that an improvement in the system used for data collection can enhance the diagnostic accuracy, for instance by automated filtering of ambient noise (people talking, babies crying, footsteps, etc.).

VI. CONCLUSION

It appears that high-pitched crackles are present in many of the TB patients' lungs included in this study and hence a detailed investigation, possibly involving more advanced methods, would be required in future work. It is remarkable that very little literature exist on the characteristics of respiratory sounds associated with TB, based on electronic recording and digital analysis. With the availability of more sophisticated analysis methods, it is believed that TB can be fought with a more substantial effort. Future work will include tracking TB patients and collecting more data as they are treated and recover, to determine whether the selected features are permanent or whether they normalize upon full recovery. Furthermore, the accuracy of the proposed method must be evaluated against the presence of other respiratory diseases and would be a fitting goal for future work.

ACKNOWLEDGMENT

The authors wish to acknowledge the National Research Foundation of South Africa for their financial support.

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