Modelling and Classification of Respiratory Volume Waveforms

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***Abstract*-A technique is proposed for classifying respiratory volume waveforms(RVW) into normal and abnormal categories of respiratory pathways. The proposed method transforms the temporal sequence into frequency domain by using an orthogonal transform, namely discrete cosine transform (DCT) and the transformed signal is pole-zero modelled. A Bayes classifier using model pole angles as the feature vector performed satisfactorily when a limited number of RVWs recorded under deep and rapid (DR) manoeuvre are classified.**

I. Introduction

Frequency domain analysis of respiratory flow or volume waveforms has been used to distinguish between normal subjects and those with abnormalities of respiratory pathways such as airway restriction (AWR) or airway obstruction (AWO) [1,2]. Analysis of breathing patterns in acutely ill patients reveals distinct differences from those observed in normal subjects.

In this paper, we transform the RVW signals into frequency domain using discrete cosine transform (DCT) and pole-zero model the transformed signal to establish a relation between the significant points of the temporal sequence and the model parameters. To this end, we use the result that the DCT of a bell shaped monophasic wave can be pole-zero modelled with a system function of order (2,2) using the Steiglitz-McBride (SM) iteration method. Conversely, the inverse discrete cosine transform (IDCT) of the model impulse response gives back the time signal with all its features intact. A scheme is proposed for the classification of RVW signals into normal (n) and abnormal (ab) categories using the model pole angles as feature vector.

II. Method

A. Modelling

For a discrete time signal, a parametric model in z-domain may be written as,

$$X(z) = \frac{B(z)}{A(z)} = \frac{b_0+b_1z^{-1}+\ldots\ldots+b_qz^{-q}}{1+a_1z^{-1}+\ldots\ldots+a_pz^{-p}} \qquad (1)$$

In the proposed method, the modelling procedure involves modelling X(k), the DCT of RVW signal x(n) to get X(z) and obtain $\hat{x}(n)$, the reconstructed output by computing the IDCT of X(k), the impulse response of the model. If $x_i(n) = x(n)\delta(n-i)$, an impulse of amplitude x_i occurring at a time n= i, then its DCT is an undamped cosine wave whose amplitude and frequency are functions of the pulse location. Let there be M monophasic component waves in a signal x(n) of length N samples with their peak sample numbers at m_k, k = 1,2,...,M. The peak sample number of the kth monophasic wave can be approximated by the relation

$$m_k \approx (\theta_k/180)N \text{ deg.} \qquad (2)$$

The number of samples, N, being a constant, m_k and θ_k are directly related. The RVW signal may be considered as a juxtaposition of two overlapping monophasic waves. As the RVWs are generally not sharp waveforms, they are modelled with systems of order (4,4) for good reproduction. The end of inspiration and the beginning of expiration are indicated by the two pole angles in the z-plane. For a typical RVW signal shown in Fig. 1(a), the pole-zero (PZ) plot is shown in Fig. 1(b).

The criteria used for the evaluation of the algorithms are (i) the percentage Normalized Root Mean Square Error (NRMS-E) (ii) the error between the location of the peak sample number determined visually in a time domain component wave and the one estimated from the model using (2).

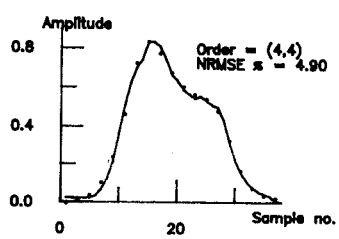
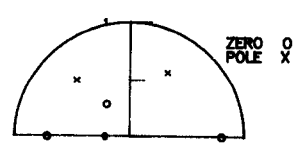


Fig. 1a RVW signal and model output (dotted line)



(b) Corresponding PZ plot

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TABLE I

Comparison of computed sample numbers with those of temporal sequence

	First peak sample #		Second peak sample #	
	Actual	Calculated	Actual	Calculated
Mean	16.9	16.6	33.5	33.79
Variance	17.69	22.0	52.45	48.88

B. Bayes Classifier for respiratory waveforms

For the purpose of uniformity, signals of different amplitudes and lengths have been normalized before modelling. This allows comparison of various types of signals without altering the shape or features present in them. All the normalized signals (both n's and ab's) are modelled with a function of order (4,4) and a heuristic feature vector X= = $[\theta_1,\theta_2]$ is formed using the complex conjugate pole angles θ_1,θ_2 obtained from the model. A part of the database is used as the training set and the remaining as the test set. Assuming the probability density functions (PDFs) are Gaussian. It means m_n and m_{ab} and covariances k_n and k_{ab} for the n's and ab's respectively, the test set in the database is classified using a Bayes classifier with the following discriminant function,

$$g(x) = (x-m_{ab})^T k_{ab}^{-1}(x-m_{ab}) - (x-m_n)^T k_n^{-1} (x-m_n) + \ln \frac{|k_{ab}|}{|k_n|} - 2 \ln \frac{PC_{ab}(C_{ab})}{PC_n(C_n)} \quad (3)$$

where C_{ab} and C_n denote abnormal and normal classes respectively.

III. Results

For the respiratory signals, the separation of inspiratory and expiratory phases is carried out using the above analysis. For the signal considered in Fig. 1(a), the end of inspiration computed from the pile angle θ_1 = 65.21, is 23.18 samples which is close to the actual sample number 25. The mean and variance of the peak sample numbers from the temporal sequence of the entire database are compared with those of the computed sample numbers in Table I. The variation between the computed sample numbers and the actual values was not more than two for the entire database considered.

In the database we had 26 normals (n) and 13 abnormals (ab) patterns with AWO and AWR as classified by a specialist clinician. Out of this, 13 n's and 8 ab's are used as the training set while the remaining 13 n's and 5 ab's are used in the test set. All the signals,i.e both n's and ab's are modelled with order (4,4) after amplitude and length normalization. For the training set, we obtained,

$$k_n = \begin{bmatrix} 55.22 & 65.3 \\ 65.34 & 172.6 \end{bmatrix}, \quad k_{ab} = \begin{bmatrix} 17.14 & 11.39 \\ 11.39 & 24.05 \end{bmatrix}$$

The decision boundary obtained using g(X) for this training set is a second order curve in the feature space as shown in Fig. 2. The test set is also shown in the same figure with normals marked as crosses and ab's in circles. The classifier detected one false negative (marked as 3) and two false positives (marked as 1 and 2) in Fig. 3. However to establish the effectiveness of the method, a large patient population need be studied.

VI. Conclusion

The discrete cosine transformed RVW signals are pole-zero modelled. Salient features in the respiratory waveforms extracted from model poles and zeros are found to match very well with the actual values in the input signals. Using pole angles of the system function in the z-plane as a feature vector, respiratory waveforms are classified into normal and abnormal categories with good accuracy.

References

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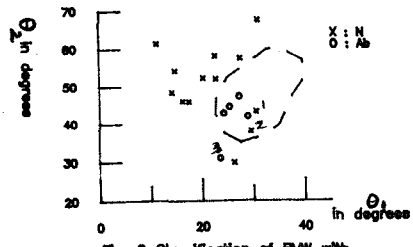

Fig. 2 Classification of RVW with with decision boundary