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ONLINE CLASSIFICATION OF LUNG SOUNDS USING DSP

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Abstract-**In this paper a real-time diagnosis system, based on Motorola's 56311 Digital Signal Processor (DSP) , is used for the classification of lung sounds into two classes: healthy and pathological. The instrument has two inputs the first of which is from a microphone placed on the chest of the patient while the other is from a flowmeter that is used to label the lung sounds as belonging to the inspiration or expiration cycle. The sampled lung sound of a full respiration cycle is divided into 6 phases with the help of the flowmeter signal, and each phase is divided further into 10 overlapping segments. Each segment is modeled by an Auto Regressive (AR) model of order 6 by means of the Levinson-Durbin algorithm. The classification process is done using two classifiers: k-Nearest Neighbor (k-NN) classifier with Itakura and Euclidean distance measures, and Minimum distance classifier with the Mahalanobis distance measure. The software was written entirely in assembly language and the result of the classification process is displayed on a character display (LCD) .**
***Keywords* - DSP, autocorrelation, LPC, lung sounds, k-nearest neighbor, Itakura metric, Mahalanobis metric, classification**

I. INTRODUCTION

Pulmonary diseases result in changes in the lung structure, this in turn affects the amplitude and timing of the sounds heard over the chest wall. Stethoscopes are the most common tool used nowadays to hear and diagnose these sounds, but diagnosis based on auscultation is very subjective and depends greatly on the individual's own hearing and experience. For this reason, there is a concentrated effort to standardize the computerized analysis of lung sounds [1].

DSP is a programmable semiconductor chip designed to take a stream of digital data and perform complex processing algorithms on it. The architecture of a DSP exploits the repetitive nature of signal processing and employs specialized arithmetic hardware and memory-access schemes to speed up common signal-processing routines. For example, Motorola 56311 DSP executes at a speed of 150 million instructions per second (MIPS) with a 150 MHZ clock. One reason for this speed comes from the pipelining of the instruction set so that more than one instruction can be started at the same time in parallel. 56311 also has a large on-chip RAM memory of 128K words which is sufficient for most of the signal processing algorithms without the need for memory expansion.

II. METHODOLOGY

The lung sound is recorded using an electret air-coupled microphone attached to the chest of the patient and then is amplified with a low noise amplifier so that the maximum produced voltage is limited to 2V peak-to-peak due to CODEC input level limitation. A digital band-pass FIR filter with a bandwidth of 90-2kHz was applied during the acquisition of the lung sound. The flow signal obtained using Fleisch type flowmeter was passed through a digital FIR low-pass filter with a cut-off frequency of 50 Hz. The FIR filtering process was done by the Enhanced Filter Coprocessor (EFCOP) module found on the 56311 DSP [2]. EFCOP is a programmable filter used to perform multichannel FIR filtering allowing it to process several filters concurrently by sequentially entering a different sample to each filter. The coefficients of the FIR filter with magnitudes greater than 1 were scaled down by a proper amount so as to make them compatible with the fractional number representation used on 56311 DSPs. The 56311 Evaluation Module (EVM) is hardwired for a minimum sampling frequency of 8 kHz by a 16-bit delta-sigma CODEC integrated with 56311EVM. So, both input channels were sampled at this rate but the sampling rate of flow signal was reduced to 125 Hz by omitting 63 samples out of every 64.

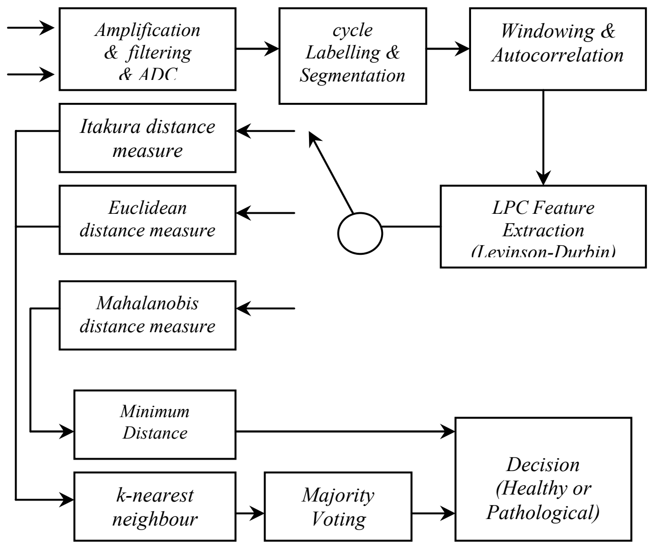

Figure 1 Functional block diagram of the system

The sign of the flow signal was used to label the lung sound as belonging to inspiration or expiration cycle. A single respiration cycle was used for each subject and only the data corresponding to flow rates above a threshold of 10% of the maximum flow signal value was stored for processing. Furthermore, to prevent the storage of false cycles resulting from noise or even from the nature of the flow signal itself, inspiration or expiration phases lasting shorter than 0.5 second were eliminated (<4000 samples).

The respiration cycle is further divided into 6 distinctive sub phases according to the information they bear and the different mechanisms that generate them: early, mid, late inspiration, and early, mid, late expiration phases. Each respiratory phase is further divided into ten 25% overlapping segments and weighted with a Hamming window of length 512. In this interval (64 ms) it is assumed that the lung sound is quasi-stationary. Since the respiration cycle varies from subject to subject, if the segment length was found to be less than 512 points then zero padding was applied to it. The starting and end addresses of these phases were determined according to the airflow volume calculated by integrating the stored inspiration and expiration flow samples separately. Here, the early, mid and late inspiration/expiration phases correspond to intervals contributing to the first 30 %, next 40 % and the last 30 % of the total inspiration/expiration air flow volume.

The respiratory system can be modeled by an all pole filter, in which the respiratory sounds are regarded as the response of this filter when excited by a Gaussian white noise [3]. In the time domain, this filter can be represented by the following difference equation:

$$S(n) = -\sum_{i=1}^{P} a_i.s(n-i)+G.e(n) \tag{1}$$

where $s(n)$ is the lung sound sample, a_i is the *ith* filter coefficient, G is the filter gain, $e(n)$ is the excitation input and P is the number of the filter coefficients (LPC order). According to this equation a lung sound sample can be estimated as a linear combination of previous lung sound samples.

For finding the LPC coefficients, the efficient Levinson-Durbin recursion was employed [4]. This algorithm needs the autocorrelation sequence of the segment under test. So, the autocorrelation function of each segment consisting of real data was calculated according to the following equation:

$$r(i) = r(-i) = -\sum_{n=0}^{N-i-1} s(n).s(n+i) \tag{2}$$

where N is the number of samples in a frame. In this study, N was chosen as 512 and LPC order of 6 was used. The autocorrelation coefficients of each frame were computed and were normalized by $r(0)$ so that they all have values in the range ±1 which is compatible with fractional number format of the DSP. Then Levinson-Durbin algorithm was applied to the normalized coefficients of each frame. The calculated autocorrelation and LPC coefficients were stored sequentially in memory. This process was repeated for all of the frames of the six phases (a total of *6x10* frames).

The k-nearest-neighbor (k-nn) classifier and the minimum distance classifier were used for the classification process [5]. K-nn is a non-parametric supervised classification algorithm in which the nearest *k* vectors in the training data space are found. Since the categories of each of the *k* nearest neighbors are known, a simple majority voting algorithm was used to determine the class of that segment. A k value of 5 was chosen. 5-nn was applied to each segment in the six respiration phases. The votes of both classes were added and the class with the maximum number of votes was chosen as the classification result of the whole respiration cycle.

The pushbutton connected to the *IRQD* interrupt line of the DSP is used for calling an interrupt service routine that chooses the desired classification algorithm. The following choices are displayed on LCD so that the user can choose one of them before starting the classification:

a) K-nearest neighbor classifier with the Euclidean or the Itakura metric [5]. Itakura distance measure is a popular metric used in the case of LPC modeling and is defined as [6]:

$$d_{m,l} = \log \frac{b^T_{i,l}.R.b_{i,l}}{a^T_m.R.a_m} \tag{3}$$

where a_m is the LPC vector identified from the mth test segment, $b_{i,l}$ is the *lth* reference LPC vector of the *ith* class and R is the autocorrelation matrix formed from the autocorrelation sequence of the segment under test. The LPC training vectors of the subjects representing the two classes were calculated using MATLAB and then were stored sequentially in the memory of the DSP.

b) Minimum distance classifier with Mahalanobis metric which is defined as:

$$d_{m,i} = (\beta_m^{(x)} - \beta_i)^T W^{-1}_i (\beta_m^{(x)} - \beta_i) \tag{4}$$

where $\beta_m^{(x)}$ is the feature vector of the segment to be classified, β_i is the estimated mean feature vector and W_i is the *ith* class covariance matrix. The modeling error of each segment was added to the LPC coefficients to be used as the feature vector in the Mahalanobis distance measure. The reference library consisting of the mean feature vectors and the inverse covariance matrices of the healthy and pathological lung sounds corresponding to the six respiratory phases were also computed separately using MATLAB, and proper scaling was applied on these values before storing them in the DSP memory. Thus, each class required the storage of 6 inverse covariance matrices and six mean feature vectors, each one corresponding to one of the respiratory phases. Finally, a liquid crystal display (LCD) was used to display the classification result.

III. CONCLUSION

High speed DSPs are making it possible to apply complex signal processing algorithms on respiratory sounds in real time. In this study, a real time DSP based system was designed for the classification of lung sounds as belonging to only two classes and very encouraging results were obtained. In a further study, the classification of three classes will be investigated. These are: restrictive, obstructive and healthy lung sounds.

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