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Sound Processing using Reconfigurable Hardware and Wavelets in Wearable Device Application

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Abstract: A wearable device based on reconfigurable system using the PsoC mixed-signal controllers is proposed. Lung sound is monitored using a chest microphone from what after a filtering process we extract the information that contribute to four types of lung disease detection. We use the wavelet coefficients in order to extract the patterns that identify the lung disease. Neuro-fuzzy decision system implemented software is used in order to detect and alert the patient. A wireless communication based bluetooth™ chip is used to connect a wearable device to micro server that uses the TCP/IP protocol in order to communicate with the medic. Experimentally results are presented and future research direction is taken into account.

Key-Words: lung sound, reconfigurable hardware, wavelets, neuro-fuzzy inference system, wearable device

1 Introduction

Auscultation of the chest using stethoscopes is a widely used method followed by medic to obtain information about the subject's respiratory system [9]. The subjectivity of the auditory system and the variability from verbal description are inherent present in diagnostic of the lung sounds. The diagnosis process depends on physician's own experience, hearing, ability to make difference among patterns generated by different lung sounds [7].

The computer based recognition of respiratory sounds must take into account the variability and diversity due to age, sex, weights, and the evolution of pathology in the same subject. However, for a personalized patient, an adaptive monitoring system based on electronic stethoscope and a small number of possible lung diseases could be very useful.

Lung sound signals are normally due airflow during inspiration/expiration. Lung sounds are usually associated with pulmonary pathology and they can be divided in two main categories: normal and adventitious sounds. The adventitious sound includes crackles, whistles, and musical sounds (wheeze, stridors or squawks). Patients with diseases like asthma often suffer from other manifestation as coughing or dispneea.

The records are usually made by accelerometers that act as pressure sensors or chest electret microphones.

The lung sound measured signal is often disturbed by noise due to instrument or air-conditioning. An adaptive filtering least-mean square (LMS) is the common method used to eliminate the interferences [5].

The interest in patient's monitoring system for heath or e-health has been substantially increased in the last time. A wireless stethoscope system based on Bluetooth ™ chip and Pulse-Code Modulation (PCM) for data transmission between condition circuit and Bluetooth ™ has been proposed in [4]. The output from Bluetooth ™ receiver module can be connected via serial interface to PC or PDA [4].

Usually, a flowmeter signal is used to label the lung sounds corresponding to the two phases of respiration cycle: inspiration and expiration.

Wavelets proved to be a good tool for analyze of non-stationary signals [1]-[2]. The extracted coefficients from wavelet transform (WT) are features used to feed the decision system made by six different neuro-fuzzy ANFIS classifiers that use Gaussian bell membership function (MF) [2].

The discrete wavelet transform (DWT) was used as method of analysis of lung sounds [7]. The denoising method that has been used is wavelet shrinkage denoising (nonlinear shrinking of wavelet coefficients and obtain the inverse wavelet transform of the wavelet coefficient). An artificial neural network was used as classifier the lung sound in one of the six categories: normal, wheeze, crackle, squawk stridor and rhoncus.

2 Problem Formulation

We will take into account normal lung sounds, crackles, whistles and wheeze with no additional manifestations.

Normal lung sounds are in the range 100 Hz-1 kHz with no discrete peaks (some authors indicate the range 100 Hz-600 Hz). The adventitious sounds are usually a frequency spectrum of 100-2 kHz. Crackles (fine or coarse crackles) are discontinuous sounds, explosive and transient having a les than 20 ms duration with typically wide frequencies content. A typical crackle waveform is showed in Fig. 1. Wheezes are continuous sounds having a musical character with a dominant frequency over 100 Hz and having duration greater than 100 ms.

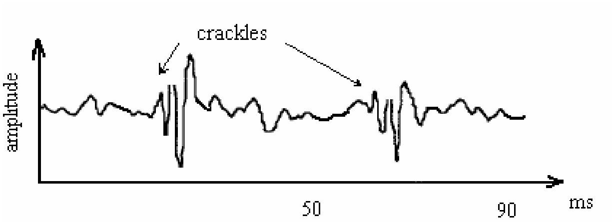

Fig. 1 A typical crackle waveform

We used an electret air coupled microphone attached to the chest, insensitive to the fluctuation of the skin-electric impedance.

3 Method and tools

We will use the wavelet coefficients in order to select pattern for decision maker. The wavelet transform is proven to be a useful instrument for non-stationary signal

However, a DWT choice is made usually by heuristic method. By the best knowledge of the authors no paper that analyzes systematically how to make a correct wavelet for the best results has been published. So, we tried a set of well known bi-orthogonal wavelet, Mallat, Daubechies, Morlet, etc.

The DFW that has been chosen must have the properties to be easy implemented using an embedded system based on microcontroller. Taking into account that the decision maker must be implemented in the same reconfigurable system, the memory allocation and the calculus of the DWT could be critical for an efficient real time response.

The PSoC has no Bluetooth module so, the PCB must include this and the serial communication with it.

3.1 Wavelet transforms and vector of features extraction

A discrete wavelet transform (DWT) is applied to sampled signal. DWT analyze a given signal at different scales and resolutions (Multiresolution analysis). We will have good time resolution at high frequencies and good frequencies resolution at low frequencies.

The DWT of one sequential signal is a recursively decomposition of a sampled signal into two components that are in octave band, respectively the approximation and the detail of the decomposition. The DWT can be expressed in terms of low-pass filters and high pass filters that satisfy the standard quadrature mirror filter condition. The filtering coefficients are calculated:

$$a_{j+1}(n) = \sum_{k=0}^{L-1} h(k) \cdot a_j(2n-k) \tag{1}$$

$$d_{j+1}(n) = \sum_{k=0}^{L-1} g(k) \cdot a_j(2n-k) \tag{2}$$

The wavelets coefficients data are too large in order to be considered directly as inputs for decision systems. A 1024 vector of floating numbers is extremely hard to be manipulated as pattern for a decision maker, e.g. the reduction of dimensionality is the preferred method in order to make feasible the solution for decision maker. The algorithms for selection of the significant coefficients that represent the input pattern are very few [11]. In order to avoid computational effort need by the clustering algorithm as in [11], other heuristic methods have been proved to be efficiently of a given case.

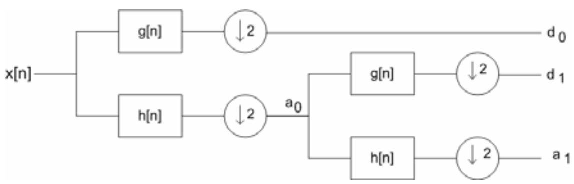

Fig. 2 Mallat's fast wavelet transform for two levels

3.3 ANFIS system architecture

We used a neuro-fuzzy model based on ANFIS architecture [6], presented in Fig. 3.

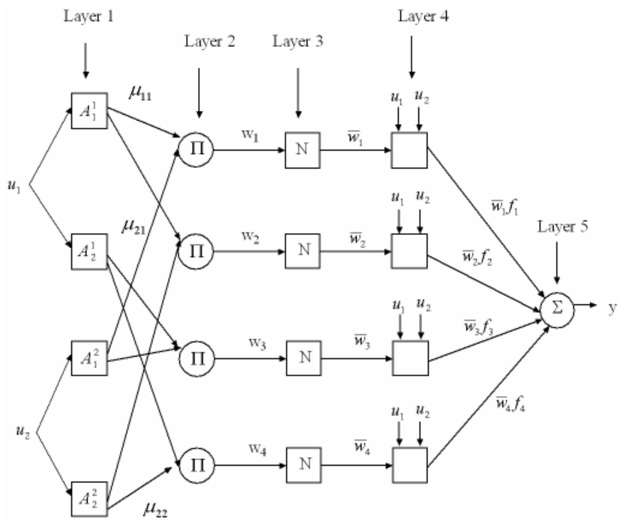

Fig. 3. The ANFIS structure

The fuzzy if-then rules based on second order Takagi-Sugeno model are considered:

Rule 1: If u_1 is A_1^1 and u_2 is A_1^2 then $f_1 = p_1u_1 + q_1u_2 + r_1$ (3)

Rule 2: If u_1 is A_1^1 and u_2 is A_2^2 then $f_2 = p_2u_1 + q_2u_2 + r_2$ (4)

Rule 3: If u_1 is A_2^1 and u_2 is A_1^2 then $f_3 = p_3u_1 + q_3u_2 + r_3$ (5)

Rule 4: If u_1 is A_2^1 and u_2 is A_2^2 then $f_4 = p_4u_1 + q_4u_2 + r_4$ (6)

$$w_j = \prod_{i_1, i_2, \ldots, i_m} \mu_{1i_1} \cdot \mu_{2i_2} \cdot \ldots \cdot \mu_{mi_m} \quad (7)$$

$$\overline{w}_i = \frac{w_i}{w_1 + w_2 + \ldots + w_m} = \frac{w_i}{\sum_{k=1}^{m} w_k} \quad (8)$$

$$y = \sum_k g_k = \sum_k \overline{w}_k \cdot f_k = \frac{\sum_k w_k \cdot f_k}{\sum_i w_i} \quad (9)$$

Gaussian or bell membership functions are usually used for μ_{ij} representation. However, if we are looking for an efficient reprezentation in VLSI implementation by memmory allocation point of view, a triangular membership function is more adequate. Usually, a curve is represented in embedded system by a tabelar function with a number of segments depending on the desired precision. A triangular membership function (Fig. 4) need only tree floating point values in order to represent a triangular membership function (Fig. 3). The membership function is given by:

$$\mu_{A_i^k}(x_k) = \mu_{ki} = \begin{cases} \dfrac{x - a_i^k}{b_i^k - a_i^k} \ if \ a_i^k \le x_k \le b_i^k, a_i^k \ne b_i^k \\ \dfrac{c_i^k - x_k}{c_i^k - b_i^k} \ if \ b_i^k < x_k \le c_i^k, b_i^k \ne c_i^k \\ 0 \ otherwise \end{cases} \quad (10)$$

If $a_i^k = b_i^k$ or $b_i^k = c_i^k$ we have:

$$\mu_{A_i^k}(x_k) = \mu_{ki} = \begin{cases} \dfrac{c_i^k - x_k}{c_i^k - b_i^k} \ if \ b_i^k \le x_k \le c_i^k, b_i^k \ne c_i^k \\ 0 \ otherwise \end{cases} \quad (11)$$

$$\mu_{A_i^k}(x_k) = \mu_{ki} = \begin{cases} \dfrac{x - a_i^k}{b_i^k - a_i^k} \ if \ a_i^k \le x_k \le b_i^k, a_i^k \ne b_i^k \\ 0 \ otherwise \end{cases} \quad (12)$$

The case $a_i^k = b_i^k = c_i^k$ that is, a singleton representation is excluded by imposing a minimum overlapping of adiacent membership function.

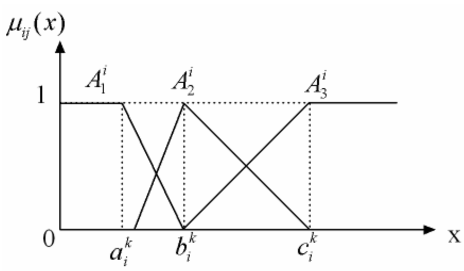

Fig. 4. Triangular membership function (k=2)

In formulas above $\overline{w}_k$ is the output of the layer 4. The parameters $\{p_i, q_i, r_i\}$ are usually named consequent parameters. The parameters $\{a_i^k, b_i^k, c_i^k\}$ are the premise parameters. In order to estimate the parameters we use a hybrid method, similar to method proposed by Jang in [6]. The premise parameters are estimated by gradient descent method meanwhile the consequent parameters are estimated by LSE (Least Square Estimator).

The number of membership function (MF) is chosen to be between 3 and 11. A greater number of MF's will conduct to abruptly increasing of number of calculus and as result an infeasible training time for neuro-fuzzy system. The same effect will be produced by a high number of inputs, so we limited the number of inputs to ten.

4 Experimental Results

The bi-orthogonal DWT coefficients for normal, fine crackles and wheeze are presented in Fig. 5-7. We can see clearly that a correct selection of the coefficient will produce a good discrimination among the signals.

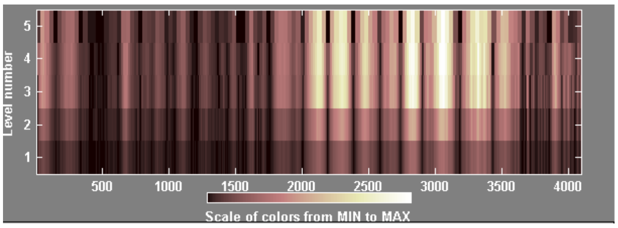

Fig. 5. Discrete wavelets coefficients for normal lung sound.

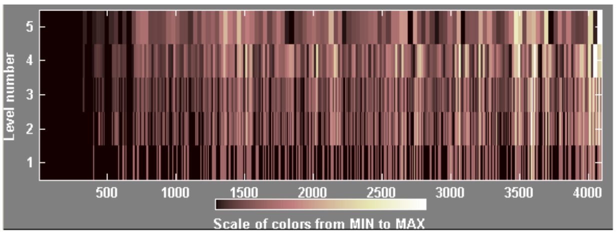

Fig. 6. Discrete wavelets coefficients for fine crackles.

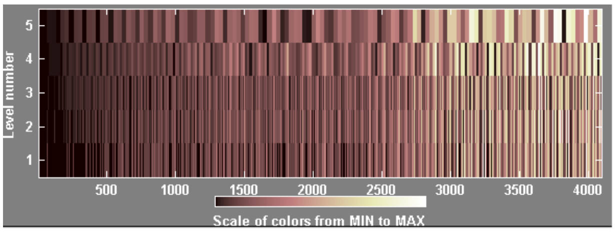

Fig. 7. Discrete wavelets coefficients for wheeze

The selection of the discrete wavelets coefficients are made usually be taking into account particular observations due to a specific application case. We propose an algorithm that selects the significant coefficients in an exhaustive manner.

In order to calculate the similarity/dissimilarity measure between vectors that belong to different classes we need a distance measure.

Many distances can be taken into account. We used a distance that take into account the variability of the variables when we determine its distance from the center. Mahalanobis distance can be defined as a dissimilarity measure between two random vectors and of the same distribution within the covariance matrix:

$$d_M(x,y) = \sqrt{(x-y)^t S^{-1}(x-y)} \qquad (13)$$

where $x = (x_1, x_2, ..., x_n)^t$ and $y = (y_1, y_2, ..., y_n)^t$

The covariance matrix S is given by:

$$S = \frac{1}{n-1}(x-y)(x-y)^t \qquad (15)$$

In our algorithm, the number of selected coefficients is prescribed, according to feasible number of inputs in neuro-fuzzy decision maker.

We calculate all the d_M distance among all the truncated vectors belonging different classes. The indexes for what the distance is maxim will be indexes of the variables from vector of coefficients that are patterns for decision maker inputs. A truncated vector is a vector that has only k coefficients, $k < n$. We will try all the combination of n variables taken by k in order to identify the most promising coefficients.

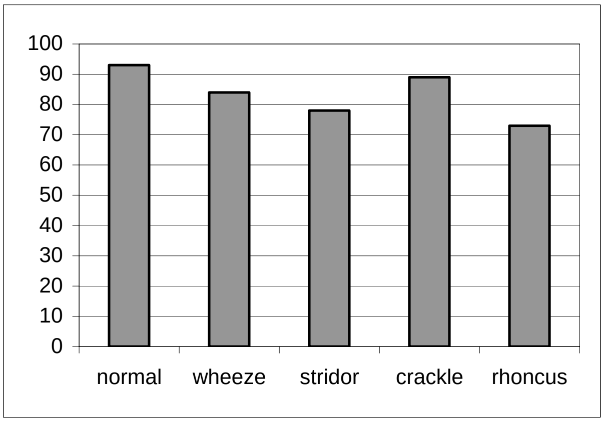

Fig. 8. The classification accuracy for test case

The total classification accuracy for test case is showed in Fig. 8. In this case we used Daubechies of order 2. The classification accuracy is lower that in literature but taking into account the restriction due to embedded system, the results seems to be satisfactory for this stage of implementation.

5 Conclusion

We propose a wearable system based on wavelet analysis in order to make a fast alert for medic about the patient's lung sound.

Our preliminary results indicated and accuracy acceptable for patient alert. More data collected and personalization of the patterns according to patient historical record is one way to improve the accuracy of the results. The medic has to possibility to ask via Internet a complete sampled signal in order to be analyzed off-line by more performing tools.

We didn't take into account the order of coefficients to construct an optimal vector pattern. The ranking weights multiplied by coefficient could be a solution for more accurate selection of the coefficients. Again, the proposed algorithm is greedy. However, taking into balance the learning time and the time consuming by coefficients selection, for 1024 coefficients we have 127,6% percent time consuming that in empirical case.

Our structure can be faster in computational terms if we use parallelization as in [10],[12]. This approach is in progress. We plan to use 8 microcontrollers with a parallel RTOS (Real Time Operating System) and open source as start point for communication.

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