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Adaptive Reduction of Heart Sounds from Lung Sounds Using a Wavelet-Based Filter

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Abstract. A new adaptive method for heart sounds reduction from lung sounds, based on wavelet transform, is presented in this paper. The use of a wavelet transform domain filtering technique as an adaptive de-noising tool, implemented in lung sounds analysis, is introduced. The multiresolution representations of the signal, produced by wavelet transform, are used for signal structure extraction. Experimental results have shown that implementation of this wavelet-based filter in lung sound analysis results in an efficient reduction of heart sounds from lung sounds, producing an almost noise-free output signal.

1. Introduction

Heart beating produces an intrusive, quasi periodic, interference that influences the clinical auscultative interpretation of lung sounds. The introduction of pseudo-periodicity, the masking of the relevant signal and the modification of the energy distribution in the spectrum of lung sounds, due to heart sounds [1], require an effective reduction of heart sounds from the contaminated lung sound signal, to yield a successful lung sounds classification. *High Pass Linear Filtering (HPF)* and *Adaptive Filtering (AF)* are the two basic approaches for heart noise reduction. Although HPF (50-150Hz) is effective in heart sound reduction [2, 3], degrades the respectively overlapped frequency region of breath sounds and fails to track the changing signal characteristics. The AF technique overcomes those limitations, since it is based on a gradual reduction of the mean square error between the *primary input signal* (contaminated lung sounds) and a recorded or artificially produced *reference signal*, highly correlated to the noise component of the input signal (heart sounds) [4, 1, 5]. In this paper, a new type of adaptive filter for de-noising the contaminated lung sounds, based on Wavelet Transform (WT) is presented. The WT sets a new perspective in lung sounds analysis, since it decomposes them into multiscale details, describing their power at each scale and position [6, 7]. Applying a threshold-based criterion at each scale, a filtering scheme can be composed, which weights WT coefficients according to signal structure. An adaptive separation of signal from "noise", *without requiring any reference signal*, can be achieved through an iterative reconstruction-decomposition process, based on the derived weighted WT coefficients, at each iteration.

2. Wavelet and Multiresolution Analysis

A time-scale description, consisted of inner products of a signal $f(t)$ with translated and dilated versions of a single function ψ, is given by the Continuous WT (CWT) [7], i.e.:

$$Wf(a,b) = |a|^{-0.5} \int_{-\infty}^{+\infty} f(t)\, \psi^*\left(\frac{t-b}{a}\right) dt\,. \tag{1}$$

where * denotes the complex conjugate. A nested sequence of subspaces ...$V_{-1} \subset V_0 \subset V_{+1}$ ... is generated such that the projection of the signal $f(t)$ into V_j is a coarse, blurred version, at a scale 2^{-j}. The decomposition of a signal into the sequence of approximation subspaces $\{V_j\}_{j\in Z}$ of $L^2(\Re)$, and into the orthogonal complement (detailed spaces) of $\{V_j\}_{j\in Z}$, $\{O_j\}_{j\in Z}$, in $\{V_{j+1}\}_{j\in Z}$, is called *multiresolution approximation* [7]. It can be realised using a pair low pass and high pass FIR filters H, G (and their *adjoints* H^*, G^*), defining a MultiResolution Decomposition-Reconstruction scheme (MRD-MRR), where $f \in V_j$ is equivalent to $f(2\cdot) \in V_{j+1}$.

3. Filtering Algorithm

The proposed algorithm is a wavelet domain filtering technique, based on the fact that explosive peaks in time domain (heart sound peaks) have large components over many wavelet scales, while "noisy" background (lung sounds) dies out swiftly with increasing scale. The definition of "noise" is not always clear. Instead, it is better to view a N-sample signal as being noisy or incoherent relative to a basis of waveforms if it does not correlate well with the waveforms of the basis [8]. From this notion, the separation of heart sounds from lung sounds becomes a matter of breath sounds coherent structure extraction. A schematic representation of the proposed algorithm, called WT STationary-NonSTationary filter (WTST-NST), is shown in Fig. 1. From Fig.1 it can be seen that an iterative MRD-MRR is employed to form different levels of noise separation. Specifically, at k iteration, the WT of $f(\lambda)$, (for $k=1$, $f(\lambda)=X(\lambda)$, $\lambda=1,\dots,N$, where $X(\lambda)$ is the normalised input signal) at m adjacent resolution scales ($m=1,\dots,M$, where $M=\log_2 N$) is first calculated, using previously-defined libraries of orthonormal bases [6]. The resulted WT coefficients at j scale are compared with a hard threshold, defined as follows:

$$THR_j^k = \sigma_j^k \cdot F_{adj} \,, \tag{2}$$

where σ_j^k is the standard deviation of WT at k iteration and j scale, and F_{adj} is an adjusting multiplicative factor, used to sustain the threshold at high value, at different scales. We have used a factor of around *3.0*. From this comparison, the WT coefficients are divided into *big* ($\geq THR_j^k$) and *small* ($<THR_j^k$) ones, $WT^{kC}(\lambda)$ and $WT^{kR}(\lambda)$, respectively. If the signal $f(\lambda)$ is coherent, then applying MRR(m scales) to $WT^{kC}(\lambda)$ and $WT^{kR}(\lambda)$ coefficients, $f(\lambda)$ can be decomposed into $C_k(\lambda)$ and $R_k(\lambda)$, respectively. The iterative procedure stops after a fixed number of decompositions (usually *8* are enough) or after the following *STopping Criterion-STC* is satisfied, i.e.:

$$STC = \left| E\{R_{k-1}^2(\lambda)\} - E\{R_k^2(\lambda)\} \right| < \varepsilon, \qquad 1 >> \varepsilon > 0. \tag{3}$$

We have used $\varepsilon=0.00001$ and $R_0(\lambda)=0$. After the last iteration (L) the coherent part of the signal (Heart Sounds Noise-HSN) is composed superposing the coherent parts derived at each iteration k, i.e.:

$$HSN(\lambda) = \sum_{k=1}^{L} C_k(\lambda), \tag{4}$$

while the remains (De-Noised Breath Sounds-DNBS), i.e.:

$$DNBS(\lambda) = R_L(\lambda), \tag{5}$$

qualify as "noise", since it cannot be well-represented by any sequence of waveforms of the basis. In fact, $R_L(\lambda)$ is the desired output, since the WTST-NST filter separates heart sounds from lung sounds, only at locations of their presence, keeping unchanged the rest of the input signal. Consequently, WTST-NST filter results in an adaptive de-noising tool of lung sounds, separating the stationary part (lung sounds) from the non-stationary one (heart sounds).

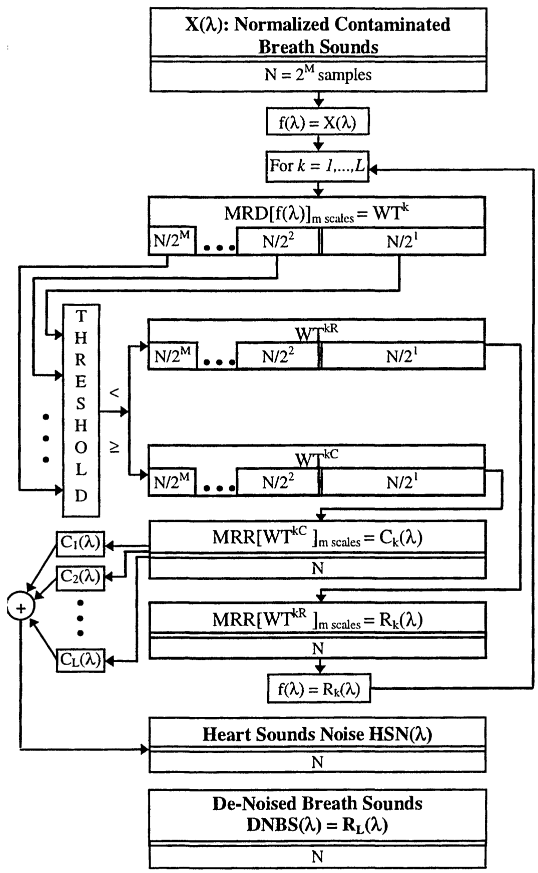

Fig. 1. A schematic representation of the Wavelet Transform STationary-NonSTationary filter (WTST-NST algorithm).

From the abovementioned description it is evident that *the proposed wavelet-based WTST-NST filter peels the recorded lung sounds in layers, reveals their coherent structure, and serves as a true adaptive de-noising tool, in separating the heart sound noise from lung sounds.*

4. Implementation

The study was conducted on *4* healthy volunteers, aged *23-50* yrs, with no known pulmonary or cardiac disorder. Several recordings took place on each subject from appropriate locations where heart sounds could be heard with the highest intensity [9], using a modified Littmann stethoscope. The whole analysis was implemented on an IBM-PC(586/120MHz) using the programming language ASYST 4.1 (Keithley). After antialiasing filtering, records of *30sec* of the signals were digitised by a 12-Bit A/D converter, at a sampling rate of *2500Hz*. Sections of *2048* samples of the recorded signal were used as an input to the algorithm. The calculation of WT was based on orthonormal bases introduced by Daubechies [6], using, her Quadrature Mirror Filters (QMFs) of *8* coefficients.

5. Results and Discussion

Due to nonavailability of pure lung sounds, a qualitative rather than a quantitative procedure must be employed to evaluate the performance of WTST-NST algorithm. A rough estimation of noise reduction can be achieved, if it is assumed that non-breathing noises do not change significantly when breathing normally or when holding one's breath [5]. With this assumption, close enough to reality, it can be possible to estimate efficiently the location and the shape of heart sound noise, especially when the signal is analysed in breath holding case. Consequently, the evaluation of the WTST-NST algorithm's performance, for both cases, except from inspecting and listening to the processed and unprocessed signals, can be achieved through the calculation of *Local Heart Noise Reduction Percentage* (L-HNRP), by means of mean energy reduction, only at locations pointed out by the WTST-NST heart sound nonzero output, since the rest of the signal remains unchanged, i.e.:

$$L-HNRP(\%)=\left\{\frac{E\{I^2\}-E\{O^2\}}{E\{I^2\}}\right\}\cdot 100, \tag{6}$$

where I is a windowed input signal, consisting of sections of each epoch at the true locations of heart sound presence, and O is the corresponding WTST-NST de-noised output.

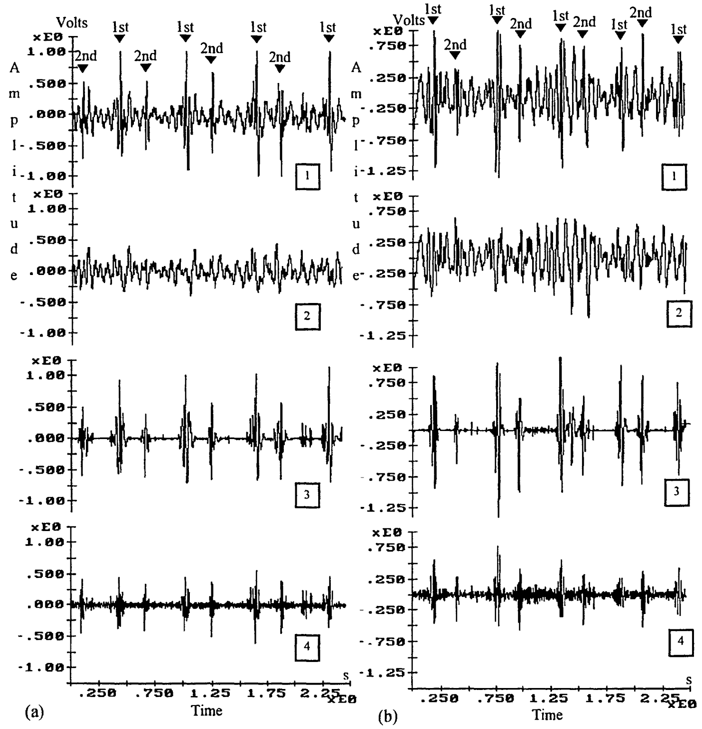

Fig. 2. A time section of 2.457s of lung sounds from a subject. (a) Breath holding case, (b) Breathing normally case. (*-1) input, (*-2) WTST-NST DNBS output, (*-3) WTST-NST HSN output, (*-4) HPF-75Hz output.

An example of the performance of the WTST-NST filter is shown in Fig. 2. The data (sections of *6144* samples) were recorded from the same subject, in case of breath holding (a) and breathing normally (b), respectively, and (*-1) [*=a or b] shows the input signal, (*-2) the de-noised breath sounds, (*-3) the estimated heart sounds by WTST-NST filter, and (*-4) the output of a High Pass Filter (HPF-75Hz), for the same input. Comparing Figs 2(*-1) and (*-3) it can be seen that the heart peak locations in input and in heart sound WTST-NST output are synchronised, without employing any reference signal. Furthermore, comparing Figs 2(*-1), (*-2) & (*-4) it can be seen that, the signal included between the heart sounds remains unchanged in (*-2) but not in (*-4). In addition, from Figs 2(*-1) & (*-4) it is obvious the loss of low frequencies of breath sounds, simultaneously with heart sounds reduction. Consequently, *the WTST-NST process has a localised effect on input signal, at the true locations of heart sound presence, without requiring any reference signal, while linear HP filtering deteriorates the whole signal, due to elimination of low frequencies.*

According to the structure of the input signals of Fig. 2(*-1), the L-HNRPs have been calculated for *8* and *9* peaks, respectively (marked with arrowheads). The mean L-HNRPs were found equal to *84.11%* and *67.76%*, for breath holding and breathing normally, respectively. Similar values of L-HNRPs were also found for the other three subjects, indicating an efficient reduction of heart sound noise from lung sounds by WTST-NST filter. To elaborate on the followed procedure, the smoothed spectrum of one epoch of 2(b-1) input (*2048* samples), of WTST-NST de-noised and HP filtering outputs were calculated. The results are illustrated in Fig. 3, corresponding to C1, C2 and C3, respectively. From Fig. 3, it is evident that *WTST-NST filtering (C2) retains frequencies higher than 120Hz and does not remove most of energy of the input signal (C1) in the frequency band below 75Hz, as does the HP filtering (C3).*

The use of soft thresholding in the WTST-NST filter instead of hard thresholding, was also examined, but it was found that hard thresholding still performed better than the soft one, revealing in an more detailed manner the HSN structure. Furthermore, according to our experi-

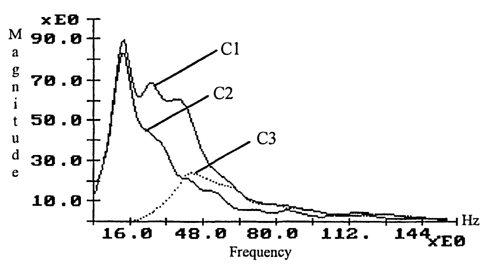

Fig. 3. A frequency domain analysis by means of smoothed FFT of *2048* samples from: C1-input Fig. 2(b-1), C2-WTST-NST DNBS output Fig. 2(b-2), C3-WTST-NST HPF-75Hz output Fig. 2(b-4).

ments, the use of Daubechies QMFs of different length, did not influence significantly the quality of the overall performance. The average execution time of the whole filtering procedure it was found roughly *8*sec/vector, with vectors of dimension *2048*, while the computation of the iterative scheme MRD-MRR, which requires *O(NlogN)* operations for a N-sample signal, accounted for *95%* of the overall computational effort. Comparing the adaptive schemes proposed by Iyer *et al.* [1] and Kompis *et al.* [5] with WTST-NST filter, we note that: i) Both Iyer's and Kompis' schemes, unlike WTST-NST filter, require a reference signal. ii) They assume similarity between 1st and 2nd heart sound in order to estimate the location and the shape of 1st and 2nd heart sound. The WTST-NST filter does not need this assumption in order to locate the true positions and time duration of the two heart sounds. iii) Iyer's method needs an extra recording in order to achieve high noise reduction percentages. Although Kompis' method avoids the extra recording, results in moderate noise reduction percentages. With the WTST-NST filter, high noise reduction percentages are achieved, without requiring any extra recording. iv) The implementation of the WTST-NST filter is simpler, easier and faster than Iyer's and Kompis'.

6. Conclusions

Summarising, a new adaptive noise reduction scheme (WTST-NST filter), that combines the efficiency of multiresolution analysis with hard thresholding, implemented in heart sound noise reduction of lung sounds, was presented. Experiments have shown that the WTST-NST filter has resulted, in all cases, in a generally high de-noised signal quality, without requiring any reference signal, with low computational cost, and with fast and easy implementation.

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