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Preliminary Processing of Biomedical Signals Using Time-Frequency Representations

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1. Introduction

Biomedical signals usually result from superimposing of several parallel sources. Mostly, the recording conditions are unfavourable, and interferences of different nature are added – from the mains, different kinds of acoustic noise (ventilators, speech, music, droughts, speaking doors, etc.). One of the main tasks of signal processing is to separate the signal coming from the process studied, from the rest of the signals, considered as interferences. Conventional frequency domain separation methods are in most cases ineffective because of spectral overlapping between the signal of interest and the inferences.

Recently signal processing was enriched by the technique of time-frequency distributions, transferred from the quantum-mechanics. Their main ides was the representation of an arbitrary signal as a superposition of basic signals – “atoms”, located in time and frequency. These atoms may be derived by means of a special operation on a single parent atom. Parent atoms and derivation operation are usually chosen such as to enable the construction of an orthonormal system. Also, special mathematical properties may be designed allowing the detection of non-regularities that often carry the most important information about the underlying process.

The logic signal is an oscillating function of a limited effective duration. This allows localizing the different elements of the signal in time, while retaining the frequency analyzing property, as a measure of repetitiveness.

As a result of the transformation, the one-dimensional signal is represented as a two-dimensional one in a tiled time-frequency plain. Increasing the dimensionality does not add new information. It just changes the structure, making the representation more comprehensive. A new type of observation and interpretation is now possible, along with time-frequency filtering and synthesis (inverse transform).

The present investigation applies the Short Time Fourier Transform, the Wavelet and the Wavelet-Packet Transform. All of these methods prove to be useful in biomedical signal processing.

2. Time-frequency Representations

2.1. Short-time Fourier transform

The continuous Time Fourier Analysis (CTFT) decomposes the signal over a basis of sines and cosines functions of infinitive time continuance and different frequencies. To obtain adequate map in a single frequency one needs all the time information. On the other hand sharp discontinuities are represented by a lot of basis functions and are spread out over the whole frequency axis.

An improvement of the CTFT is the short-time Fourier Transform (STFT). It windows the basic functions before the decompositions, thus introducing a time dependence and forming a time-frequency representation of the signal. The expression is

(1) $$F(s, w) = \int_{-\infty}^{\infty} f(t)\, h(t-s) e^{-jwt}\, dt.$$

To guarantee the inverse transform the window $h(t)$ must have unique norm:

(2) $$\int_{-\infty}^{\infty} (h(t))^2\, dt = 1.$$

Though shifting the window $h(t)$ over the time axis and changing the frequency w, tiling the time-frequency plane is achieved. The time resolution is equal to the effective length of the window. One cannot narrow it because of widening of frequency windows. Both are linked with uncertainty principle of Heisenberg (Papoulis [6]).

(3) $$\Delta s \Delta w \leq 2\pi.$$

The window $h(t)$ distorts the transformation result and leads to the so called "spectral leaks" (Duvant [3]). The proper choice of the window type reduces this drawback (Daubechies [2]). There is a big redundancy in the two-dimensional representation (1). This allows a combined time and frequency discretisation:

(4) $$s_i = \{i\Delta s,\ i \in \mathbf{Z}\}, \qquad w_k = \{k\Delta w,\ k \in \mathbf{Z}\}.$$

For good time-frequency resolution the limitation for s and w must be strict inequality (Papoulis [6])

(5) $$\Delta s \Delta w < 2\pi.$$

Some practical improvement of frequency resolution without changing the time window can be obtained by overlapping the successive windows.

2.1.1. Wavelet transform

The wavelet transform (WT) is a signal decomposition over a family of real orthogonal functions (bases) $y_{m,n}(x)$ obtained through translation and dilation of a function $y(x)$ called mother wavelet or prototype wavelet.

(6) $$\psi_{m,n}(x) = \frac{1}{\sqrt{2^m}} \psi(2^{-m} t - n).$$

The coefficients of the wavelet decomposition can be obtained through orthogonal projection of the signal onto a wavelet space, using:

(7) $$c_{m,n} = \int_{-\infty}^{\infty} f(t) \psi_{m,n}(t) dt.$$

Having these coefficients one can restore the function $f(x)$ using the synthesizing formula

(8) $$f(t) = \sum c_{m,n}\, \psi_{m,n}(t).$$

A substantial role in the wavelet theory plays the so called scaling function $\Phi(x)$ that must satisfy the equation (Daubechies [2])

(9) $$\Phi = \sqrt{2} \sum_{k} g(k)\, \Phi(2t - k).$$

This function is related to the analyzing wavelet through the following equation:

(10) $$\psi(t) = \sqrt{2} \sum_{k} g(k)\, \Phi(2t - k).$$

where

(11) $$g(n) = (-1)^{1-n}\, h(1-n).$$

The coefficients $h(k)$ must meet several additional conditions assuring the orthogonality and certain regularity of the base functions (6) (Daubechies [2]). To determine the wavelet coefficients it is not necessary to use the analytical expressions for $\psi(x)$ and $\Phi(x)$. Both discrete sequences $h(k)$ and $g(k)$ allow the creation of fast algorithms, especially for discrete signals. In the signal processing literature they are called "quadrature-mirror filters" (QMF) since they have mirror frequency response and cover low half-pass and high half-pass of the signal spectrum.

Let's assume that the discrete signal $x(k)=c_{0,k}$ represents a continuous function $f(t)$ over the basis of shifted versions of the scaling function $\Phi(t)$. For signal decomposition in J scales, we can write:

(12) $$f(t) = \sum_{k} c_{j+1,k}\, \Phi_{j+1,k}(t) + \sum_{j=0}^{J} d_{j+1,k}\, \psi_{j+1,k}(t)).$$

The coefficients $c_{j+1,n}$ and $d_{j+1,n}$ for the scale $j+1$ are linked with previous scale coefficients through:

(13) $$c_{j+1,n} = \sum_{k} c_{j+1,k}\, h(k - 2n),$$
$$d_{j+1,n} = \sum_{k} d_{j+1,k}\, g(k - 2n).$$

The equations (13) allow recursive wavelet decomposition algorithm having $h(k)$ and $g(k)$ only. The wavelet coefficients $d_{j,n}$ give account of each scale into the detail structure while $c_{j,n}$ – the coarse. The inverse transform assures perfect reconstruction:

(14) $$c_{j,k} = \sum_{j+1,n} h(k - 2n) + \sum_{n} d_{j+1,n}\, g(k - 2n).$$

Expressions (13) can be considered as passing the signal $c_{j,n}$ through QMF pair followed by output signal decimation. We receive half the number of coefficients for each next scale (so-called "pyramid" algorithm). The signal reconstruction is accomplished through interpolation: inserting a zero between every two coefficients and passing through filters having inverse impulse responses compared to $h(n)$ and $g(n)$.

While in STFT time and frequency resolutions are constant, in WT the tiles are of different size but of constant area (uncertainty principle) and one can trade time resolution for frequency resolution and vice versa. The wavelet transform is suitable for signals consisting primarily of low frequencies and short time (high frequency) transitions. This is due to the fact that it allows good time resolution for high-frequency components and good frequency resolution for low-frequency components. However, this transform may not be suitable for signals, whose characteristic frequencies are located in the middle or high frequency regions.

The concept of wavelet bases has been generalized to include so called wavelet packet (WP) dictionaries and wavelet packet libraries of bases. The aim is to tile the time-frequency plane in arbitrary frequency manner. A WP dictionary can be determined by a function w_0 as follows:

$$w_{2n} = \sqrt{2}\sum_k h(k) w_n (2t-k), \tag{15}$$

$$w_{2n+1} = \sqrt{2}\sum_k g(k) w_n (2t-k).$$

The following can be considered as analogous: $w_0(t)$ and $\Phi(t)$ as well $w_1(t)$ and $\psi(t)$. Each basic function is determined by a triplet of parameters l, k, n: a scaling parameter l, a frequency parameter k and time parameter t.

A fast algorithm for WPT can be considered, applying equations (13) not only on coarse coefficients but on detail coefficients too. In this case one an obtain a set of coefficients placed in the binary tree nodes, characterized by a coefficient indices triplet l, k, n. The difference between WT and WPT is that the latter leads to decomposition with redundancy and one can bring show that for signal with N samples, (N-dimensional vector) full decomposition contains more than 2N orthogonal bases. This redundancy ensures good possibilities for result interpretation: one can search for a most efficient signal representation minimizing a measure of information; one can search for signal features making reconstruction based on a part of the basic coefficients only (orthogonal projection onto a less dimensional vector space) or one can search for the best level (best frequency resolution) (Coifman et al. [1]).

2.2. Practical algorithms

WT and WPT have been accomplished for a library of basic functions, containing cubic spline wavelets (Battle-Lemarie (BL) wavelets) (Mallat [4]), Daubeshies wavelets (Daubeshies [2]) and C12 coiffet (Meyer [5]).

BL wavelets are symmetric. They haven't compact support, but decay exponentionally and their representative coefficients may be truncated for large indices. We have explored 16-tap sequence. Daubeshies wavelets and C12 coiffet are compactly supported.

We have obtained WP decomposition for six successive scales on signal vectors 8192 samples long.

We have implemented STFT on the same signal vectors for data segments 128 samples long, windowed by Henning window and successfully overlapping 64 samples.

3. Application

Time-frequency decompositions have been orientated on respiration sounds analysis in asthmatic patients.

3.1. Method

Respiration sounds were recorded using an electrodynamic microphone housed in a flat plastic holder of a 30 mm outer diameter. The inner opening containing the microphone is of 12 mm, thus forming an air chamber with the entire transducer assembly applied to the patient skin surface. A small hole of 1 mm diameter connects the chamber to the outer atmosphere.

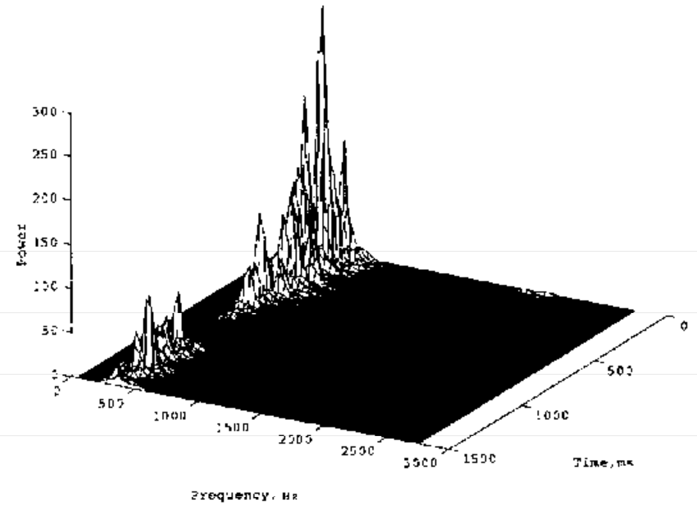

Fig. 1. Time-frequency distribution by STFT for a healthy subject

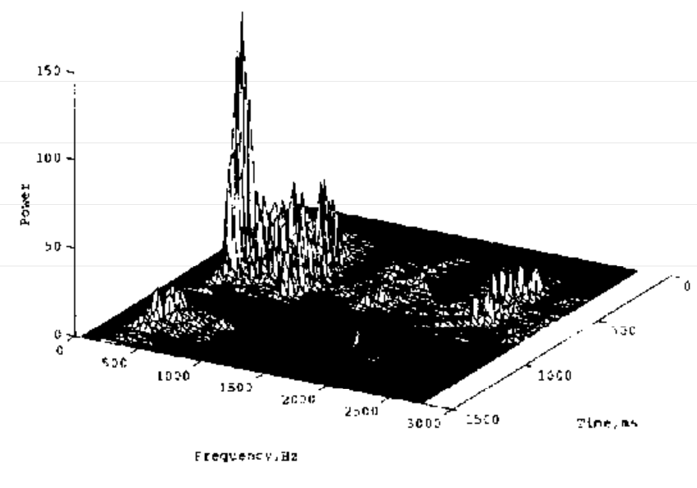

Fig. 2. Time-frequency distribution by STFT for an asthmatic subject

This transducer was applied over the trachea by a smooth elastic band or held by the operator like a stethoscope membrane. The output signal amplitude depends on the breathing intensity, i.e., on the air flow through the trachea, and was usually about 100 mV to 500 mV. An amplifier was used with a frequency band of 100 to 3000 Hz (–3 dB) to feed the 16-bit AD converter connected to an IBM compatible PC. The amplitude resolution thus obtained was of 0.02 mV per bit with a sampling rate of 5.5 kHz.

The transducer frequency response could not be properly measured, especially having in view the air chamber and the skin contact interface. The microphone free air response is within 3 dB limits in the frequency range considered. However, it will be seen from the results that the differentiation between healthy individuals and asthmatic patients practically does not depend on eventual frequency characteristic deviations of the transducer.

Tracheal sounds were obtained from 10 patients and 5 healthy volunteers, inspiration and expiration phases were marked by visual observation.

3.2. Results

The time-frequency plots revealed that in healthy subjects in both respiration phases the signal frequency band was limited to about 800 Hz. In patients practically the same time of basic signal components were obtained, but in addition wheezing sounds were detected in the 1000–2000 Hz band and whistling sounds in the upper frequencies in the range 2000–2750 Hz. Figs. 1 and 2 show time-frequency distribution obtained by STFT for healthy and asthmatic subjects respectively.

The results received through STFT permit to delineate three frequency bands: low frequency (LF) – 100 to 800 Hz; middle frequency (MF) 1000 to 2000 Hz; high frequency – 2000 to 2750 Hz. Quantitative parameters can be introduced for the entire inspiration or expiration phases, e.g., the signal power within the above defined bands in mV.Hz. These parameters can be used to form ratios, such as MF/LF. HF/LF, MF/total HF/total. Further, time parameters measures can be added in ms and thus obtaining "volume" parameter measure (e.g. MF in mV.Hz.ms) and their ratios, or computing the time intervals where MF or HF components have been detected in percentage to the entire inspiration or expiration duration. Further studies will involve forced expiration sounds analysis, as well as coughing sounds and possibly phonation of vowels.

As far as WP representations are concerned they give good possibilities for alternative interpretation. One can search for best decomposition level thus obtaining the satisfactory frequency resolution for asthma detection. The implementation of inverse transform for some coefficients may bring to quantitative results for the individual contribution of the important frequency bands.

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Предварительная обработка биомедицинских сигналов при помощи временового-частотного представления

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(Р е з ю м е)

Предложен временовой-частотный подход предварительной обработки биомедицинских сигналов. Он включает коротко-временовое Фурье- представление, волновая трансформация и пакетная волновая трансформация для декомпозиции анализируемого сигнала при наличии шума. Представлены возможности техники декомпозиции при исследовании респираторных сигналов пациентов с астматическим синдромом.