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Enhanced weak Doppler micro-embolic signal detection using energy fluctuations

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ABSTRACT

Ultrasound transcranial Holter offers the possibility of long-duration recordings with the micro-emboli detection process being performed offline. This offline detection allows developing much more robust micro-embolic detection procedures and applications. From a signal processing perspective, most commercial automatic detection systems, based on the short time Fourier transform, employ constant detection thresholds either on the whole band or on sub-bands. However, earlier studies highlighted many doubts about the accuracy and robustness of these systems for the detection of weak micro-embolic signatures. In this work, we present an original detection technique based on energy fluctuations as a strong tool for the detection of the weakest micro-embolic signal. Results, from a set of real signals, show a detection rate of 92% and a false alarm rate of 10%. These good performances lead us to consider the proposed technique as a good candidate to detect weak micro-embolic signals.

1. Introduction

Cerebrovascular Accident (CVA) occurs when the blood flow to a part of the brain is suddenly stopped either by a rupture of a blood vessel leading to a hemorrhage, or a blockage leading to an embolism. The relation of embolus to CVAs occurrence has been widely demonstrated [1]. CVAs, being the second cause of mortality worldwide, represent a major concern and death threat over a huge population. Therefore, CVAs are considered as a public health issue for which many research activities are performed in perspective of finding treatments or methods of early diagnosis thus avoiding its occurrence.

An effective widely used CVA diagnosis solution is the Transcranial Doppler (TCD) system [2]. This system is commonly used for the detection of micro-emboli circulating in the cerebral vascular system. Micro-embolic events are detected from the Doppler signal as high intensity transient signals (HITS), superimposed on the Doppler signal backscattered by the blood. However, TCD clinical use has been limited by several hindering points. For instance, the time needed for probe positioning can be considerably long. To reduce this time, Mackinnon et al. [3] proposed to use a servo-controlled probe. Moreover, the very short effective examination duration can be insufficient to allow the detection of several micro-embolisms. Consequently to overpass this drawback, Mackinnon et al. [3] have shown that the longer the examination duration, the better confidence in the detector.

New generations of TCD systems are being developed in a way to overcome these drawbacks. Proposed solutions involve new enhancements, such as the servo-controlled positioning of the ultrasound probe [3] and the possibility of long-term recordings with the micro-emboli detection process being performed offline through a computer [3]. A French firm, Atys Medical, implemented a Holter system based on the innovative idea of R. Aaslid [4,3]. Challenging issues fall under two main categories: artifact rejection and detection of weak micro-embolic signals. This paper focuses on weak micro-emboli detection only.

Many research works were carried out attempting to develop methods to detect weak micro-emboli robustly. Most of these works have tackled the issue by adapting the threshold to the decision information on which the detection is performed. When the decision information is time-varying, a time-varying threshold is expected and when the decision information is constant, a constant threshold is expected. Otherwise weak micro-events would never be detected.

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Concerning methods with time-varying threshold, detecting weak micro-events may consist in using a prediction modeling where the probability to find a micro-embolic event is supposed to be very weak. When the random fluctuation of the prediction error is supposed to be heteroscedastic [5] (a specific case of non-stationarity where the variance is time-varying) a GARCH Model [6,7] can be used. In addition, when the random fluctuation of the prediction error is supposed to be cyclostationary [8] (statistically stationary per cycle), a synchronous AR model can be used [9]. In such a paradigm, the decision information can be the autocorrelation of the prediction error and the problem resides in the choice of the threshold.

Concerning methods with constant threshold, as the micro-embolic event is of narrow band nature, detecting weak micro-events may consist in using band pass filters encompassing the spectral signature of the micro-embolic event [10]. This solution was first proposed in [10] and was applied directly on the Doppler signal. By using such a band pass filter on the Doppler signal amplitude, the low frequency component, related to the cardiac rhythm, is removed singly and therefore the remaining signal, composed of random fluctuations, becomes the decision information. Thus, in the decision information, the intensity of the micro-embolic event is now more magnified with respect to the background Doppler signal. Therefore, the detection capability of the detector is improved. However, in a blind detection paradigm, there is a price to pay: the frequency of the micro-embolic signal must be known before the filtering step. As it is impossible to know this frequency, other methods were introduced. These methods proposed to use a bank of juxtaposed filters in which the spectral band is divided into several narrow sub-bands and where the detection can be operated independently in each sub-band. Depending on the spectral division, several filter types can be found: bank of narrow band filters with the same width [11], discrete wavelet decomposition [12], and wavelet packet decomposition [13]. By using these different kinds of filters, the difficulty lies in the choice of the constant threshold in each sub-band and on the fusion of the detection since a micro-event can appear in several consecutive sub-bands.

To sum up, even though there exists plenty of robust methods for detecting micro-embolus, few of them are really capable of detecting very weak micro-embolic signals. As mentioned previously, the main problem lies in the choice of the threshold that must be adapted to the decision information.

In this paper, we tend to detect the lowest intensity micro-embolic signals in a robust manner using adaptive thresholding. This would allow detecting micro-emboli of very small sizes. This adaptive thresholding is applied from energy signal fluctuations. The new method will be compared to both energy-based constant threshold derived from the whole band spectrum (standard detector) and from sub-band spectrum.

Notice that this study is an extension of a previous work we proposed [14], and includes higher number of tested signals. However, in the present study, we have omitted the rise rate calculation phase we used in [14] due to its high complexity. We have also added a training phase to optimize the detection thresholds.

2. Materials and methods

2.1. The proposed offline detection unit

It is widely stated when the Rayleigh scattering is valid, that the energy of the backscattered Doppler signal is proportional to the size of the scatterer to the power of 6 [13,15,16] and the energy returned by an embolus is greater than that returned by billions of red blood cells. Hence, energy would function as a solid decision information from which the presence of micro-emboli could be detected. This justifies why our offline[1] detectors are chosen to be majorly based on energy criteria.

Commercial TCD systems (from Atys Medical, DWL®, Medilab GmbH, Natus®, Scimed™, Skidmore Medical Ltd., etc.) employ spectral estimators based on the Short Time Fourier Transform (STFT). The STFT spectral estimator with a sliding window can be formally written as:

$$S(t,f) = \left| \int x(\tau) \cdot w^*(t-\tau) \cdot \exp^{-2\pi j f \tau} \mathrm{d}\tau \right|^2, \quad (1)$$

where $x(t)$ is the analysed Doppler signal, $w(t)$ is the sliding window and * stands for complex conjugation. Note that after a preliminary stage of experimental optimization of the STFT parameters based on the study done in [17], the STFT in this study is performed using a 15 ms-Hamming window with an overlap of 65%. Moreover, calculations of the STFT and the instantaneous energy are carried out repetitively on 5 s segments extracted from the Doppler signal. This value is fixed to 5 s because it corresponds to the time duration on the spectrogram plotted on commercial devices. It allows a good visualization of different events that may occur. From STFT defined in Eq. (1), the instantaneous energy at a fixed time t can be obtained by:

$$E(t) = \int S(t,f)\mathrm{d}f. \quad (2)$$

At that stage, we assume that the instantaneous energy $E(t) = \alpha(t) + \gamma(t)$, represented in blue in Fig. 1a, can be expressed through a low frequency component $\alpha(t)$, represented in red in Fig. 1a, and a high frequency component $\gamma(t)$ represented in Fig. 1b. The low frequency component that is the cyclic cardiac component $\alpha(t)$ is removed from the instantaneous energy. This is done first by evaluating the trend $\alpha(t)$ through a smoothing step and then by subtracting it from $E(t)$. The remaining fluctuation[2]

As expected, the envelope (or the amplitude) is not constant as it fluctuates at the cardiac rhythm. The signal is heteroscedastic [5], *i.e.* its energy varies cyclically with time, due to the local time-varying amount of red blood cells in the sampling volume. On the other hand, due to the time-varying blood speed, the observed process is quasi-cyclostationary [8], since the energy fluctuation (variance) is time dependent or even quasi-periodic. Such properties already reported in previous works [9,7,18], lead to using a time-varying threshold. Histograms of the positive γ_{pos} (in blue) and negative γ_{neg} fluctuations (in green) are reported in Fig. 1c. Absolute difference signal $d(t) = |env(t) - \gamma_{pos}(t)|$ where the envelope is $env(t) = -\left|\gamma_{neg}(t) + j \cdot H\left(\gamma_{neg}(t)\right)\right|$ with $H(\cdot)$ the Hilbert transform, and a detection threshold ($6.5 \times \sigma_d$, σ_d being the standard deviation of $d(t)$) is reported in Fig. 1d (red dashed line).

In a statistic point of view, the stochastic nature of the fluctuation can be formalized by a probability density $P(\gamma)$. This probability density is assumed firstly to be the summation of the probability densities from the positive and negative parts of the energy fluctuations:

$$P(\gamma) = P(\gamma_{pos} + \gamma_{neg}) = P(\gamma_{pos}) + P(\gamma_{neg}), \quad (4)$$

[1] Note that because the system is offline, the computational cost is not a prior issue.

[2] The random fluctuation is due to the random positions of billions of red blood cells traveling into the blood flow. $\gamma(t)$ can be decomposed into a positive fluctuation $\gamma_{pos}(t)$ and a negative fluctuation $\gamma_{neg}(t)$:

$$\gamma(t) = \gamma_{pos}(t) + \gamma_{neg}(t), \quad (3)$$