S-TRANSFORM TIME-FREQUENCY FEATURE EXTRACTION OF LASER DOPPLER FLOWMETRY SIGNAL USING SVD DECOMPOSITION

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ABSTRACT

Extracting the most important features of input data is extremely important. In this paper we introduced a new approach of feature extraction based on singular value decomposition of the S-transform time-frequency matrix of the laser Doppler flowmetry signal. We used this new approach to study reactive hyperemia blood flow recordings. This kind of bio-data provides an interesting biomedical investigation for estimating microcirculation perfusion. The technique uses the singular vector associated with the time-frequency distribution to characterize the physiological activities behaviors during the hyperemia phenomena.

1. INTRODUCTION

The reactive hyperemic response is one of the most well-know tests in clinical practice for evaluating the functional aspects of the arterial blood flow [1]. By definition the reactive hyperemia is the transient increase in organ blood flow that occurs following a brief period of ischemia (e.g. arterial occlusion); the magnitude of hyperemia is related to the duration of ischemia. In general, the ability of an organ to display reactive hyperemia is similar to its ability to display auto regulation [1], [2]. During the occlusion period, blood flow is stopped. Therefore the laser Doppler signal, that reflects the perfusion value, decreases to a residual value called the biological zero [3]. When the occlusion is released, blood flow increases (hyperemia phenomenon) for a few minutes. The hyperemia occurs because during the period of occlusion tissues lack oxygen and an increase of local mediators appears. Tissue hypoxia and a build up of vasodilator metabolites (e.g. adenosine) presumably dilate arterioles and decrease vascular resistance. This provides the needs required by the cellular tissue. Several studies have been carried out on reactive hyperemia [1], [2]. Indeed, it can be used to study peripheral vascular resistance, the role of the local sensory nerves and to determine the patients suffering from peripheral arterial occlusive pathologies.

Laser Doppler flowmetry (LDF) is based on the spectral broadening of monochromatic light, that interacts with moving red blood cells in tissue [4]. The power spectral density of the backscattered light can be processed to yield an estimate of microvascular tissue perfusion. During reactive hyperemia, the LDF signal increases to a peak and then returns to a resting value.

It is known that five characteristic frequencies are present in LDF signals on humans [5]. The frequency around 1 Hz corresponds to the heart rate. The peak around 0.3 Hz is the breathing frequency. The oscillations with a frequency around 0.1 Hz are a manifestation of the myogenic activity of the smooth muscle cells displaced in the walls of resistive vessels. The peak around 0.04 Hz is attributed to the neurogenic processes. Finally, the peak around 0.015 Hz is due to the endothelial related metabolic activity. The LDF signal being a non stationary signal, the time-frequency representation (TFR) is an appropriate method to extract spectral components related to the physiological activities during reactive hyperemia. In addition, due to the high dimension of time-frequency representations, their success relies upon an appropriate form of dimensionality reduction. It is shown that the singular value decomposition (SVD) provides an effective means of concentrating that information which is important, and discarding that which is irrelevant. Its singular vectors reflect the behaviour spectral in the time of the various

physiological activities present in the laser Doppler flowmetry signal. Singular vectors (SVs) of a matrix are the span bases of the matrix, and their importance in the composition of the matrix is reflected by the related singular values [6], [7].

2. LDF SIGNAL RECORDING

Seven healthy volunteers were studied. They had no clinical sign of, or risk factor for, vascular disease. They were (mean ± SD) 30 ± 4.5 years old; height 166 ± 12 cm, weight 66 ± 11.5 kg. The volunteers were not involved in regular competition training and had not taken any drug in the week prior to this recording. The experiment was performed with the subject placed supine in a quiet room with the ambient temperature set at 23±1°C.

The laser Doppler flowmeter used was a PeriFlux 4001 Master, Perimed AB, Sweden, 780 nm, and 1mW maximal emission, with two multifibres probes. The latter were placed on the volar surface of each forearm (two sites with similar vessel networks were chosen). A cuff was placed around the left upper arm of each subject. After a period of 15 minutes acclimatization, the recordings began. The period of recording included a period of 2 minutes rest to obtain the value of the basal flow. After this period of rest, the cuff was inflated to 200 mmHg for 3 minutes. After the release of the occlusion, the recordings lasted 15 minutes. Each LDF signal was digitalized with 20 samples/s with a computerized acquisition system (Biopac, Santa Barbara, California, USA).

3. TIME-FREQUENCY FEATURE EXTRACTION

In analysing non stationary and multicomponent signals, the time-frequency techniques have been shown to outperform classical techniques based on either time or frequency domains [8]. SVs of the matrix associated with the time-frequency distribution of a signal can be used to characterise the signal. By using the SVD technique, the left and right SVs and their importance in the composition of the matrix (singular values) are computed.

3.1. The S-transform time-frequency analysis

TFRs are powerful tools for extracting features of the patterns embedded in a non stationary physiological signal [9]. The S-transform is a new approach of TFR of a signal [10]. It is an invertible time-frequency spectral localisation technique that combines elements of wavelet transforms (WT) and short-time Fourier transforms (STFT). The analysing window of the S-transform is a scaled Gaussian, whose width scales inversely, and whose height scales linearly, with the frequency. this scaling like in wavelet improves the time resolution of high frequency events, and the frequency resolution of low frequency events, in comparison of the STFT, while maintaining the absolute phase of each frequency component in contrast with the continues WT's. This transform has already been applied in geophysics [10], and medicine [11].

The expression of the *S*-transform of the signal *x(t)* given by Stockwell et al. [10] is:

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau - t)^2 f^2}{2}} e^{-i2\pi ft} dt. \quad (1)$$

In equation (1), *S* denotes the *S*-transform of *x*, which is a continuous function of time *t*; frequency is denoted by *f;* and the quantity τ is a parameter, which controls the position of the Gaussian window on the *t*-axis. The scaling property of the Gaussian window is reminiscent of the scaling property of continuous wavelets [12] because one wavelength of the Fourier frequency is always equal to one standard deviation of the window.

3.2. The singular value decomposition

The SVD method has been a valuable tool in signal processing and statistical data analysis. A SVD of an $M \times N$ matrix X, representing the TFR of the signal x, is given by:

$$X = U \Sigma V^T \quad (2)$$

where $U(M \times M)$ and $V(N \times N)$ are orthonormal matrices, and Σ is an $M \times N$ diagonal matrix of singular values (σ_{ij} = 0 if $i \neq j$ and $\sigma_{11} \geq \sigma_{22} \geq ... \geq 0$). The columns of the orthonormal matrices U and V are called the left and right SVs, respectively. An important property of U and V is that they are mutually orthogonal [6]. The singular values (σ_{ii}) represent the importance of individual SVs in the composition of the matrix. In other words, SVs corresponding to the larger singular values have more information about the structure of patterns embedded in the matrix than the other SVs.

3.3. Singular vectors to characterize signal from the TFR

In the analysis of signals in the TF domain using SVD, the type of TF distribution is important. Indeed, it is desirable that the TFR is linear and has high resolution, which is the case of the S-transform. Previous researches have mostly concentrated on features based only on the singular values of the TFD of the signals. By themselves, singular values do not carry significant information about the behaviour of components embedded in the matrix. In other words, they are not suitable features for classification purposes [6]. To find the characteristics of a signal in the TF domain using the SVD technique, we propose to use the right and left SVs corresponding to the largest singular values [7]. The reason

is that the right and left SVs contain the time and frequency domain information of the signal, respectively because both are the spectral and temporal orientations of the TF matrix. In addition, SVs related to the largest singular values have more information about the structure of the signal. Consequently, if the structure of signals is different for dissimilar classes, using SVs related to the largest singular values is more suitable for feature selection [13].

4. TF LDF FEATURE EXTRACTION

Figure 1 shows a sample of the two signals, corresponding to the 20 minutes rest recording and hyperemia.
It is shown that the hyperemia phenomena occurs at the beginning of the sixth minute after the release of occlusion. The time-frequency analysis performed by the S-transform of the two signals is shown in figure 2 and 3.

5. RESULTS AND DISCUSSION

After performing the SVD for the 14 signals (two groups: rest and hyperemia signals), figure 4 shows the first and the second left and right SVs for the 7 signals corresponding to the rest recording (in superposition). The first left SV shows the presence of an activity at frequencies around 0.8 Hz, which corresponds to the cardiac activity for six subjects and around 1.2 Hz for the seventh subject. Some other activities in the very low frequency around 0.1 Hz are better represented in the second left SV. This shows that there are high-energy activities around the frequencies in the 0-0.45 Hz band. The first and the second right SVs indicate there is no transit change over the recording duration. Figure 5 shows the first and second left and right SVs of the 7 signals corresponding to the hyperemia recordings. The first left SV shows that there is no change in the cardiac activity. However, there is an important increase in the 0-0.45 Hz band, which corresponds to the myogenic, neurogenic and metabolic activities. This increase is also shown in the second left SV. In addition, the appearance of the hyperemia phenomena is clearly shown on the first and second right SVs exactly as it is shown in the temporal signal representation. As shown above, a signal can be characterized by the SVs of its TFR. In other words, the SVs can be used as discriminating features in the hyperemia phenomena in order to show the physiological activities behavior in the very low frequency during hyperemia.

6. CONCLUSION

As shown above, a signal can be characterized by the SVs of its TFR. In other words, the SVs can be used as a tool for discriminating features in the hyperemia phenomena. However, a reduced feature set with more appropriate signatures can provide a better classification accuracy with reduced data analysis cost. In a future work, we suggest to use a feature selection technique based on the probability distribution function of the SVs Since the SVs are orthonormal, their squared elements can be treated as the different values of a power density function.

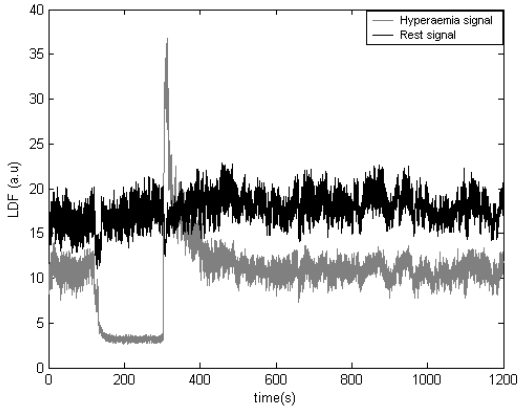

Figure 1: LDF rest and hyperemia signals.

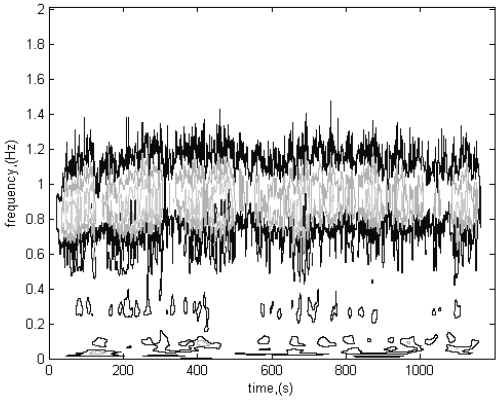

Figure 2: Time-frequency analysis of the signal corresponding to the rest recording.

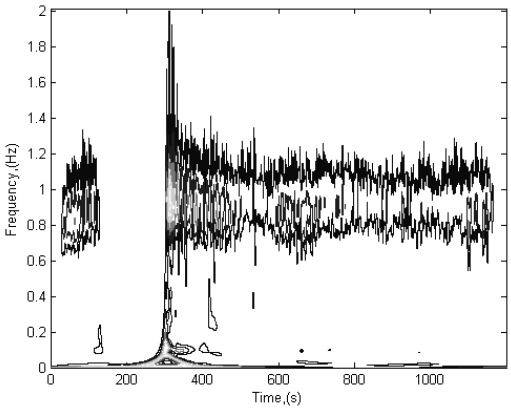

Figure 3: Time-frequency analysis of the signal corresponding to the hyperemia recording.

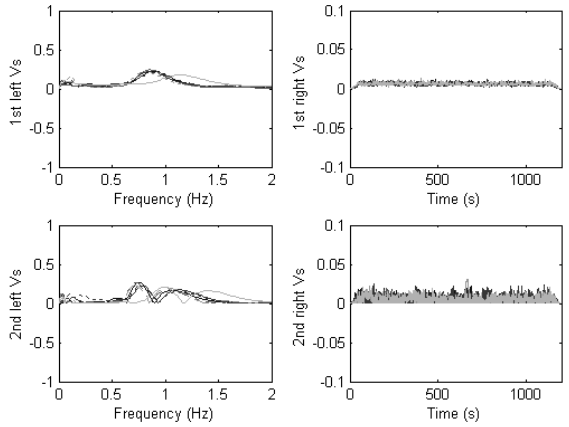

Figure 4: SVD of the seven rest signals.

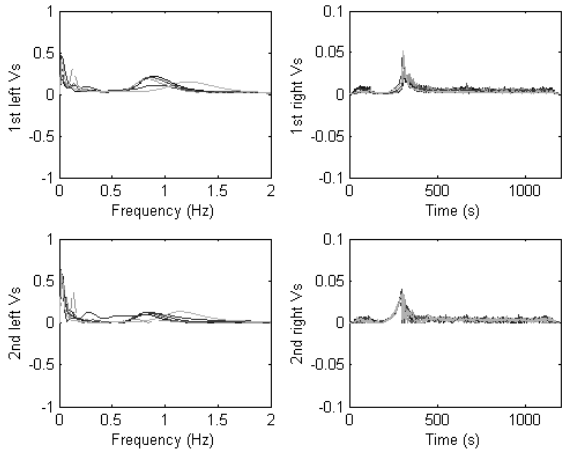

Figure 5: SVD of the seven hyperemia signals.

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