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Wavelet decomposition of myoelectric reflexes—Time feature extraction of the blink reflex and its use in clinical diagnosis

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Abstract

Analysis of clinical electrophysiological signals involves noise reduction, feature extraction and classification. In evoked responses, the time latencies of electrical events provide information about the underlying physiology. Time-frequency methods retain time information allowing frequency selectivity. We used the Daubechies-4 wavelet on the late blink reflex to extract time features from frequency bands where signal-to-noise ratio is the highest. This method proved to be robust in discriminating patients with multiple sclerosis from normal subjects.

Keywords: Wavelets, Daubechies-4, blink reflex, clinical diagnosis, multiple sclerosis.

1. Introduction

Time-frequency analysis can provide frequency decomposition of signals while retaining time location information. This aspect which is in contrast to Fourier analysis has been found to be particularly useful in biomedical signal analysis. In this paper, we report the use of time-frequency analysis of the late component of the blink reflex—the R2 component—which is a complex signal but produced as the random combination of a small set of myoelectric events or waveshapes. The random combination comes from the fact that the generation of these events occurs by the firing of neurons deep in the central nervous system. These neurons are normally inaccessible to functional clinical testing. The blink reflex is a contraction of the *orbicularis oculi* muscles secondary to reflex-activated motor neurons of the facial nerve. The reflex is usually elicited by supra-orbital nerve stimulation and consists of two temporally separate components, an early R1 and a late R2.[1] The R1 is a simple biphasic wave while the R2 is a complex wave. R1 is evoked only on the side of stimulation as a pontine reflex and R2 is recorded bilaterally with unilateral stimulation and is thought to be relayed through a more complex route including the pons and lateral medulla.[2] The R2 component of the blink reflex is particularly interesting due to its complex central connections. While the R1 component has been well characterised in normal individuals and in patients of some diseases, the R2 component has received less attention. The R2 component obviously contains more information about the central nervous system than the R1 component. The current methods of analysing the R2 component consist of estimating the onset latency, duration and sometimes recovery studies. However, parameters like onset latency and duration poorly discriminate normal subjects from patients with central nervous system disorders where the R2 component is likely to

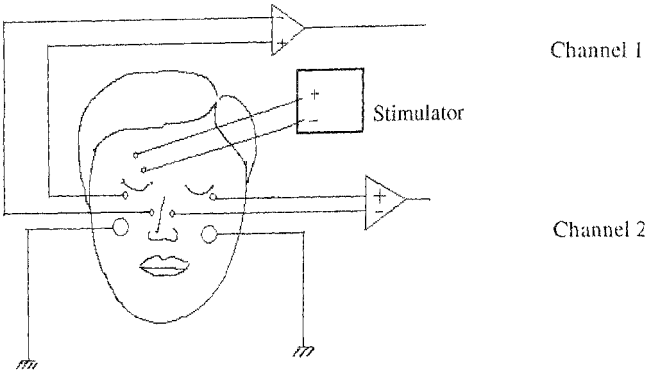

FIG 1 Schematic of recording arrangement.

be affected. Therefore, to obtain more sensitive indicators of the R2 component, we estimated statistical parameters called the *mean R2 time* and the standard deviation of the R2 time. Recordings were done on 37 normal subjects and 9 patients with multiple sclerosis. The blink reflex in multiple sclerosis patients has been studied by other investigators using classical techniques of latency and duration measurement, but its clinical diagnostic value was found to be limited.[3] The estimates of the distribution densities of these two parameters showed a marked difference between the normal group and patients with multiple sclerosis.

2. Methods

The signals from both the left and right *orbicularis oris* muscles were picked up using Ag/AgCl electrodes placed on the surface, and amplified by two differential amplifiers (Fig. 1).[4] The filters in the amplifier modules were set to have a bandwidth ranging from 32Hz to 3kHz. The signal from each channel was sampled at the rate of 8kHz and stored on disk. The recording was initiated at the time of the applied stimulus. Constant current rectangular pulses were used to stimulate the *supraorbital* nerve just above the eyebrow. The pulse width of the stimulation was 1 ms and the pulse amplitude was between 2 and 10 mA. The exact value of the stimulus pulse amplitude was different for each subject and was set such that the R2 response was reliably elicited. Very large stimulus amplitudes were avoided in order to minimise discomfort to the subject. The entire electrophysiological instrument has been developed at IIT-Bombay. It is based around a portable computer and is completely battery operated.

2.1. *Data analysis*

The main features of interest in the data are the time of occurrence of the R2 component, duration of the R2 and other time parameters. The usual time measurement done on the R2 is the

onset time and sometimes the R2 duration. There exists considerable subjectivity in the manual estimation of the onset latency and duration of the R2 signal. Noise in the signal is a major hindrance in the estimation of time parameters. The R2 component is generated by random activation of the motor units of the *orbicularis oculi* muscle, since a large number of neurons with complex interconnections are involved. On the other hand, the R1 component which is usually a simple biphasic wave is generated by a small set of neurons whose firing is less variable. In order to improve the signal-to-noise ratio (SNR) using frequency bands with high signal energy without losing time information we used time-frequency analysis by wavelet transform. The Daubechies-4 wavelet was chosen as it resembles the R1 component.

2.2. *Wavelet decomposition*

Wavelet decomposition separates the signal into a progressive set of lower-frequency components using a set of hierarchical filters in a number of stages.[5] Each stage employs a low- and a high-pass filter to separate out the low- and high-frequency components, with only the low-frequency components being passed on to the next stage. Since every stage acts on lower-frequency components the sampling rate also decreases at each stage. This downsampling allows the same digital filters to be used at every stage with effective cut-off frequencies decreasing with the sampling rate. The low-frequency components, c, and the high-frequency components, d, of the first stage are calculated from the input $x[n]$ as:

$$c_1[k_1] = \sum_{n=3}^{0} g[n]x[2k_1 - n]$$

$$d_1[k_1] = \sum_{n=-3}^{0} h[n]x[2k_1 - n]$$

Note that in the above equations, for every increment of $c[]$ and $d[]$, the independent variable $x[]$ steps up by two points; this is the downsampling. The second stage output is next calculated from the low-frequency components of the first stage (Table I).

Table I
Frequency and time parameters of wavelet levels

Level	Output array coefficient number	Wavelet cycle length (input pts)	Lower end of the frequency band	Distance between values (sample pts)	Time resolution (ms)
c_8	D[0], D[1]	512	–	–	–
d_8	D[2], D[3]	512	15.675Hz	256	32
d_7	D[4] – D[7]	256	31.25Hz	128	16
d_6	D[8] – D[15]	128	62.5Hz	64	8
d_5	D[16] – D[31]	64	125Hz	32	4
d_4	D[32] – D[63]	32	250Hz	16	2
d_3	D[64] – D[127]	16	500Hz	8	1
d_2	D[128] – D[255]	8	1KHz	4	0.5
d_1	D[256] – D[511]	4	2KHz	2	0.25

Table I
Sensitivity of calculations to baseline noise

Trial no.	Raw data sensitivity	Level 4 sensitivity	Level 3 sensitivity
1	0.127521	0.013067	0.049982
2	0.186700	0.018169	0.062762
3	0.190657	0.049045	0.073758
4	0.210900	0.057856	0.083024
5	0.117007	0.037147	0.003031
6	0.096193	0.059174	0.000329
7	0.117064	0.066060	0.003760
8	0.167374	0.083268	0.087771
9	0.082292	0.030129	0.016683
10	0.201876	0.078684	0.073843
11	0.166657	0.005813	0.090305
12	0.151392	0.069634	0.068683
13	0.153547	0.013853	0.051747
14	0.159248	0.012949	0.031723
15	0.215647	0.034242	0.065400

$$c_2[k_2] = \sum_{n_1=3}^{0} g[n_1]c_1[2k_2 - n_1]$$

$$d_2[k_2] = \sum_{n_1=-3}^{0} h[n_1]c_1[2k_2 - n_1]$$

The downsampling is repeated again at this stage, which means that for every step of the second stage $x[]$ has incremented by four sample points. Similarly, the mth stage calculates its output using low-frequency output of the $(m-1)$th stage. The wavelet transform is computed by multiplying a data array of size N points by an $N \times N$ filter matrix, which produces stage 1 output. The low-frequency components are separated and multiplied by an $N/2 \times N/2$ matrix and so on.[6] The final result is a set of N coefficients for all the $\log_2 N$ stages. Table II gives the output array index with its corresponding wavelet stage, the frequency bands and the time resolution for an input data array of 512 points and sampling rate of 8 kHz. The set of coefficients from the wavelet transform describes the signal $x[n]$ in terms of wavelets, i.e.

$$x[n] = \text{level 1 wavelets} + \text{level 2 wavelets} + \text{level 3 wavelets} + \ldots$$

$$x[n] = \sum_{k_1=0}^{N/2-1} d_1[k_1] \cdot \psi_1[n - 2 \cdot k_1] + \sum_{k_2=0}^{N/4-1} d_2[k_2] \cdot \psi_2[n - 4 \cdot k_2] + \ldots$$

where ψ_m is the shape of the wavelet in stage m. All the wavelets are, of course, time-scaled versions of the basic wavelet. This manner of synthesising the signal from wavelets is analogous to synthesising a signal using sinusoids as is done in the Fourier method. Table I lists the time and frequency values of the wavelets at different levels.

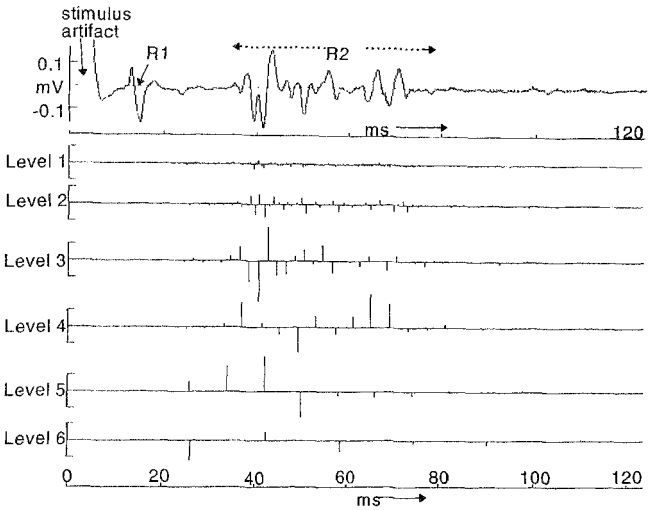

FIG. 2. A typical recording of the blink reflex (top trace) and the first six wavelet levels of the R2 component (time 0 to 25 ms was zeroed before wavelet transform).

2.3. *Time feature measurements*

The R2 component of the data was subjected to Daub-4 wavelet transform. Figure 2 shows a typical recorded signal and the wavelet transform of the signal in the time interval from 25 to 100 ms; the coefficients of the first six levels are shown. The wavelet coefficients can be compared to frequency bands in the Fourier spectrum; the frequency band 1 to 2 kHz corresponds to wavelet level 2, the band 500 Hz to 1 kHz to wavelet level 3, the band 250 to 500 Hz to wavelet level 4, the band 125 to 250 Hz to wavelet level 5, etc. We used levels 3 and 4 for time feature estimation since time resolution in these levels is better than in later levels. Figure 3 shows a blink reflex recording from a patient with multiple sclerosis. The prolonged R2 component is obvious. The difficulty of determining the ending time of the R2 component can also be seen from this figure where the gradual decrease of the R2 merges into the baseline noise.

Statistical parameters of the R2 time: The occurrence of R2 may be regarded as statistically random since even for a normal subject simple parameters like the onset latency and ending time are not constant over different trials during a single recording session. Hence, we decided to use the simplest statistical parameters of the time of occurrence of R2, namely, the mean value and standard deviation.

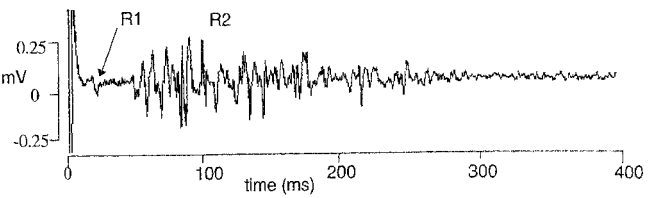

FIG. 3. Blink reflex recorded from a patient with multiple sclerosis.

Mean R2 time using raw data: The mean time using raw data was estimated as:

$$\mu_T = \frac{\sum |x[n]| \cdot n \cdot \Delta T_s}{\sum |x[n]|}$$

where ΔT_s is the sampling interval. The range of summation is over the time interval begining from 25 ms (in order to exclude all previous components like the stimulus artefact and R1).

Mean and standard deviation of the R2 interval using time-frequency analysis: The mean time of the R2 component, μ_T, was computed using wavelet coefficients from levels 3 and 4. Since both these levels yielded practically the same values as the mean, only level 3 values are reported for all the data. The mean value at level 3 is defined as:

$$\mu_T = \frac{\sum_{k_3=0}^{N/8-1} |d_3[k_3]| \cdot k_3 \cdot \Delta T_3}{\sum_{k_3=0}^{N/8-1} |d_3[k_3]|}.$$

The standard deviation of the R2 interval, σ_T, was computed (from level 3) as

$$\sigma_T = \sqrt{\frac{\sum_{k_3=0}^{N/8-1} \{k_3 \cdot \Delta T_3 - \mu_T\}^2 |d_3[k_3]|}{\sum_{k_3=0}^{N/8-1} |d_3[k_3]|}}$$

where ΔT_3 is the time resolution at level 3.

Onset time estimation: An algorithm to estimate the onset time automatically was developed. The data from 20 to 25 ms contained only the baseline noise. This portion was subjected to wavelet transform at level 3 and the highest value of the coefficient in this time interval was identified. A threshold was set to about four times the value of this coefficient and the time where the first coefficient in the R2 signal crossed the threshold was marked as the onset time. The threshold needs to be adjusted for different levels of baseline noise.

2.4. *Data sets*

Five trials from each normal subject were taken and put in a group. Three trials from each patient with multiple sclerosis were chosen and put in another group. The density distributions for the two statistical parameters in each group were estimated. The density distributions of each feature were calculated using the sliding Parzen window technique.[7] This method is better than a simple histogram plot since the Parzen window (or *bin*) is continuously slid over the data instead of using fixed non-overlapping bins. Therefore, it yields a smooth continuous curve for density distribution.

2.5. *Selection of normal subjects and patients*

The normal volunteers came from two groups; students in the age group 18–30 and female volunteers in the age group 15–55. Recordings were carried out on 37 normal volunteers. The patient group was obtained from the Multiple Sclerosis Society of India in Mumbai. The blink reflex was recorded from nine patients with a history of multiple sclerosis. In all these patients, the diagnosis of multiple sclerosis was confirmed with MRI scans; the patients presented with varying degrees of severity. Most of the patients were in the remissive phase while two patients were on medication for relief from the acute stage.

3. Results and discussion

Table II shows the sensitivity of calculations of the mean time to baseline noise when using the raw data (column 1), wavelet level 4 (column 2) and wavelet level 3 (column 3). The mean time in each case was calculated using two lengths of every trial data for 30 trials (a) 25 to 100 ms and (b) 25 to 125 ms. Every one of these trials had R2 concluding before 100 ms. Therefore, both lengths a and b contain the complete R2, but b contains more baseline. Thus, if the technique of estimating the mean R2 time is affected by baseline noise, the two calculations will give different values. Hence, sensitivity-to-baseline noise is quantified as:

$$S = \left| \frac{\mu_{Ta} - \mu_{Tb}}{\mu_{Ta}} \right|.$$

Therefore, the smaller the value of s, the more insensitive is the method to the baseline noise or other estimation error. Table II shows 15 trials in which the sensitivity of the three methods is computed. It can be seen that using the raw data for mean-time calculations is very sensitive to baseline noise, while using the wavelet coefficients (either level 3 or 4) is about five times less sensitive. Figure 4 shows the density distribution of the onset latencies in the normal

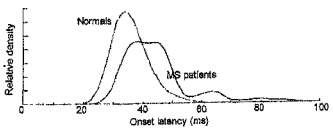

FIG. 4. Comparison of the onset time distribution in normals and multiple sclerosis (MS) patients.

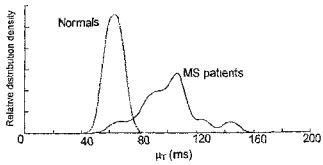

FIG. 5. Mean R2 time in normals and patients

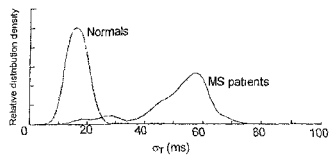

FIG. 6. Standard deviation of the R2 time in normals and patients.

group and in patients with multiple sclerosis. As is evident there is a considerable overlap between the two distributions. This means most of the patients had onset latency of R2 not distinct from normal. Thus, the onset latency poorly distinguishes normals from patients. Figure 5 compares the distribution of the mean R2 time in normals and in patients. A clear distinction between the two distributions is seen. Figure 6 shows the distribution densities of the standard deviation of the R2 interval in normals and in multiple sclerosis patients. Here again, a clear-cut demarcation between the normals and patients is evident. The above results suggest that the statistical parameters of the R2 time are superior to simple parameters like the onset time. Due to variability of the R2 signal, the best way to describe these parameters is in terms of density distributions. For this, a set of trials needs to be recorded from each subject. It is possible that the estimates of a few trials in the patients may fall into the normal range; however, the distribution densities will clearly distinguish the patient. The use of wavelet transform enables automatic robust estimation of the two statistical parameters of the R2 component, eliminating subjectivity associated with the manual method.

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