ANALYSIS OF READING RELATED POTENTIALS BY COMBINING *WAVELET DECOMPOSITION* AND *DYNAMIC TIME WARPING*

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ABSTRACT: The problem of obtaining a reference signal for reading related potentials (RRPs) during reading tasks is here addressed. The classical procedure based on the calculation of grand-averages on a group of subjects, is strongly affected by the high inter-subject variability, that becomes especially relevant when dealing with long-latency waves related to the cognitive functions. A Dynamic Time Warping procedure is applied to pairs of RRPs after a time-scale decomposition through wavelet transform. The multi-scale decomposition of the signal permits to optimise the time warping procedure to the different temporal dynamics of the analysed components and then the reconstruction of a more reliable template

METHOD

The *Dynamic Time Warping (DTW)* [1] algorithm extends or dilates the time axes of two different sequences to minimize the distance between two corresponding samples. The alignment procedure is based on the construction of the Warping function (WF), shown in fig.1 : to build the WF the parameters *r* and *p*, defined as follow, are needed:

$$|i(k)-j(k)|\le r \qquad p=\frac{n}{m}$$

where *r* represents the maximum distance between two samples to be aligned and *p* is the ratio between the number n of diagonal steps and the number m of vertical or horizontal steps. The distance measure depends on the morphology, the first and second derivatives of the signal:

$$d(i,j)=\|x_i-y_j\|+\|\dot{x}_i-\dot{y}_j\|+\|\ddot{x}_i-\ddot{y}_j\|$$

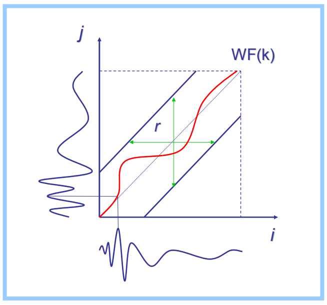


Fig.1: Warping function obtained from the two signals represented. "r" represents the allowed alignment window.

Wavelet Decomposition [2] : each RRP is characterized by long latency waves at the low frequencies and short latency waves at the high frequencies. The *Pyramidal Algorithm* separates long and short latency waves, as shown in fig.2, by the signal decomposition in approximations and details through some filters and the procedure can be iterated until the last meaningful signal.

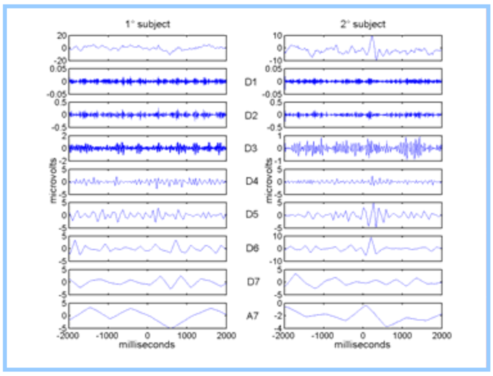
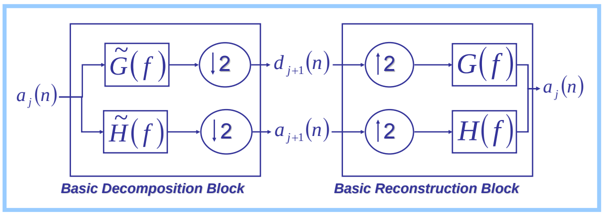


Fig.2: Wavelet decomposition of two different subjects in seven levels of details and one approximation by means of Pyramidal algorithm. The wavelet Coiflet has been used in this work.

The RRP related to each subject is decomposed in seven details and one approximation as shown in fig.2. Filtering the signal with the functions $\tilde{G}(f)$ and $\tilde{H}(f)$, we obtain respectively the detail and the approximation at level j+1; filtering the detail and the approximation at level j+1 with the functions G(f) and H(f) we obtain the reconstructed signal at level j (fig.3).

These filters are *high-pass* and *low-pass* filters: therefore the legitimacy of the sub-sampling operation is guaranteed by the Nyquist's rule (the frequency sampling f_s must be higher than the double maximum frequency f_{max} of the signal). Therefore the number of samples decreases at the coarser scale (considering long-latency waves, i.e. low frequencies) whereas it increases at the finer scale (considering short-latency waves, i.e. high frequencies).

Fig.3: High-pass and low-pass filters that constitute the Basic Decomposition and Reconstruction Block. "d" and "a" are the detail and the approximation and "j" is the scale considered.



As shown in fig.2, the three first details are composed principally by noise and eliminated whereas the meaningful peaks are located in a limited window, which dimension increases at the coarser scales. Therefore each signal has been windowed before the alignment, obtaining 18 samples, 9 pre-stimulus and 9 post-stimulus. The details and the last approximation are then aligned, obtaining the approximation and the details of the template, reconstructed using the Reconstruction Block in fig.3.

The DTW is applied to the last approximation and the last four details coming from each subject, following a binary tree: the template is then obtained by a double mean procedure [3], as shown in fig.4.

In this way, r changes with the scale considered: with the coarser scale, i.e. low-frequency waves where the number of samples decreases and the time interval between two samples increases, r (in msec) increases, while at the finer scale, i.e. high-frequency waves, r decreases. In fig.4 an example of the alignment procedure at the fourth level is shown: the green lines connect the aligned samples of the original signals whereas the black line represents the obtained template. This method is described in fig.5.

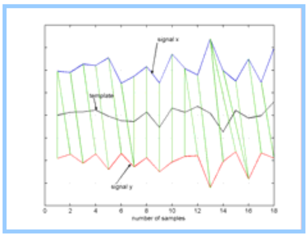
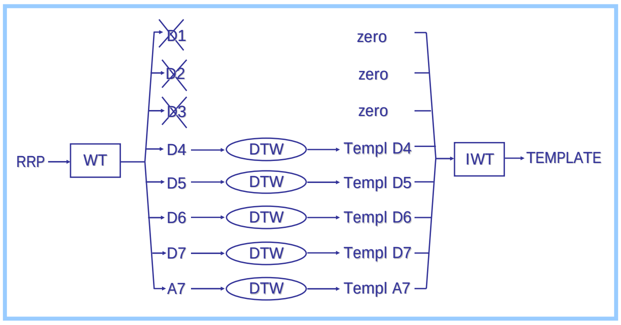


Fig.4: Alignment of the coefficients al level D4 for the subjects shown in fig.2, during symbol presentation task at Fz.

Fig.5: Diagram of the method described in this work: each RRP is decomposed through the WT, then the details of interest are aligned and the final template is reconstructed.



RESULTS

The RRPs used for this analysis were recorded from 16 normal children of mean age 9.6 ± 0.08 yrs. The subjects underwent three different tasks: symbol presentation, letter presentation and letter recognition. Five characteristic peaks were identified on the templates: $\mathbf{N_1}$, around 150 ms, related to *attention*; $\mathbf{P_2}$, around 300 ms, traditionally linked to *cognitive processes*; $\mathbf{N_3}$ and $\mathbf{N_4}$, between 400 and 500 ms, likely related to *association graphema-phonema* during reading and $\mathbf{P_{600}}$ probably related to *feed-back processes* [4]. The multi-scale decomposition of the signal permits to optimize the time warping procedure to the different temporal dynamics of the analyzed components and then to reconstruct a more reliable template, pointing out especially the long-latency waves ,as shown in fig.6.

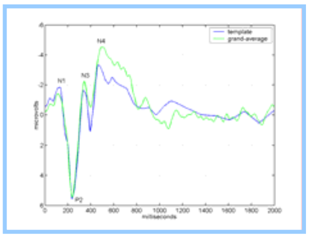


Fig.6: Template superimposed to the traditional grand-average during symbol presentation task at Fz.

Such waves do not appear consistently in the grand-average because occasionally present in single subjects and with a large inter-subject variability, producing jitter and a misalignment of the RRPs (fig.7).

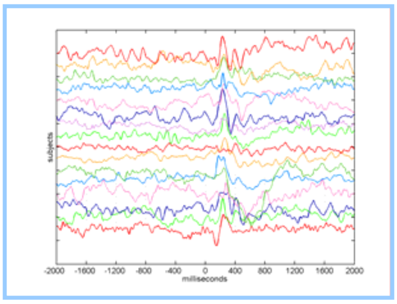


Fig.7: Superimposition of the averages of the whole set of subjects considered during symbol presentation task at Fz.

Fig.8a shows the superimposition of the grand-averages and fig. 8b the templates during three different tasks. The templates highlight long-latency waves and make easier peaks detection.

Moreover the superimposition of the three different tasks points out the morphological variability of long-latency waves, due to the increase of complexity requested by the task.

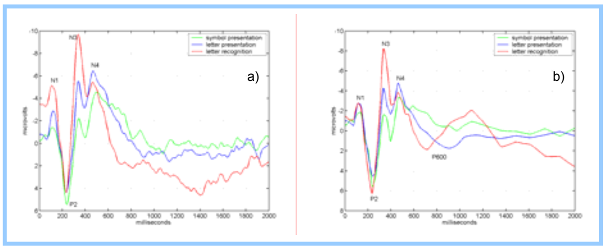


Fig.8: a) superimposition of the grand-averages for three different tasks at FZ; b) superimposition of the templates of the same tasks at Fz.

CONCLUSIONS

The presented method is proposed to calculate reliable templates of RRPs and constitutes a good alternative to the classically used grand-average. The application of the Dynamic Time Warping procedure allows to overcome some pitfalls of the grand-average, and in particular the jitter always present when different subjects are considered and mainly affecting long-latency waves with high inter-subject variability. The DTW procedure has been also optimized introducing the wavelet decomposition: in fact the algorithm parameters can be optimally tuned for the different signal details.

The method has been applied in the study of reading related potentials and allowed to highlight some mechanisms involved in the reading process. The better comprehension of the underlying mechanisms, will allow a better diagnosis and classification of dyslexia in children, the planning of an individual therapy and the follow-up of the rehabilitation.

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