35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Electrooculogram filtering using Wavelet and Wavelet Packet Transforms

Juan José Galiana-Merino, *Member, IEEE,* Daniel Ruiz-Fernández, *Member, IEEE,* and Agustín Jarones-González

Abstract— **This paper presents a proposal for filtering electrooculogram signals using the Discrete Wavelet and the Discrete Wavelet Packet Transforms. We compare our proposal with other digital filters commonly used for this type of biological signals, evaluating the results in terms of signal-to-noise ratio improvement, energy, correlation coefficient and mean absolute error reduction. For the analyzed cases, the wavelet and wavelet packet approaches improve considerably the results obtained with digital filters. Moreover, we also provide the most suitable parameters for the wavelet and the wavelet packet analysis.**

I. INTRODUCTION

The filtering of biological signals is a fundamental operation prior to its analysis. There are many factors that can alter a bio-signal measurement: external signals (e.g. noise from the power supply), other bio-signals (e.g. fetal electrocardiogram versus electrocardiogram of the mother), inherent noise of the acquisition systems. In any case, it is essential to get a clear signal in order to noise does not affect the result of the analysis of the bio-signal.

The electrooculogram (EOG) is a test which shows potential changes caused by the movement of the eyes [1] and which is obtained by surface electrodes placed around the eye area. Its strength varies between 50 and 3500 μV, while its frequency components range from 0 to 100 Hz [2]. The EOG signal is useful in many clinical activities: in the evaluation of certain mental illnesses such as schizophrenia [3], in studying sleep disorders [4] or diagnosis of eye disorders such Best's disease [5]. In recent years, it has also been used as a control element in the area of the Brain-Computer Interfaces [6]. In particular, eye blind detection and quantification is one of the useful information that can be extracted from an EOG signal for these tasks. In all these cases, it is crucial to use a high-quality signal from the beginning to avoid misleading results in the subsequent signal analysis. Thus, a filtering stage that reduces the noise without distort the signal of interest becomes an initial and important step in all EOG analyses.

There are different techniques for filtering signals, sometimes being difficult to identify which technique is best suited for a specific type of signal. For EOG data, common digital filters are usually applied: Band-pass filters or a combination of high-pass + low-pass filters (e.g. [2, 7-9]). However, for the analysis of non-stationary signals, like the EOG ones, other filtering methods can provide much better results. In this sense, the wavelet analysis has become a promising alternative in the last years, with applications in other biological signals such as electrocardiogram [10] or electromyography [11].

In this paper we have evaluated the performance of the wavelet analysis in EOG signals and we have compared the obtained results with the ones obtained using different digital filters.

II. SIGNAL ACQUISITION

Electro-oculographical signals were acquired from five individuals aged between 20 and 30 years and with no known eye problem. For the acquisition process, we used the BIOPAC MP35 system and Ag / AgCl electrodes. We used two acquisition channels, one to record information of vertical movements (vertical channel) and one for horizontal movement information (horizontal channel). Electrodes were placed on either side of the eyes (horizontal movements) and above and below them(vertical movements). The placement of the electrodes is shown in Fig. 1.

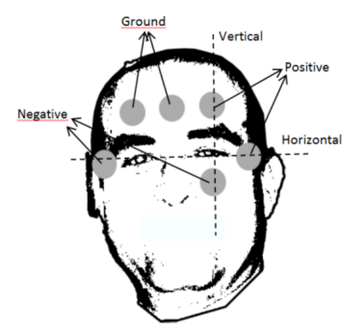

Figure 1. Placement of the electrodes.

In order to obtain signals with the highest quality, the electrodes were placed 5 minutes before the acquisition and electrolytic gel was used to improve conductivity. During the acquisition, the individuals had to follow with the eyes (without moving the head) the movements of a pencil positioned in front of the individual at a distance of about 50 cm. The pencil was moved up and down and right and left.

Before capturing the signal which is going to work, the above process was simulated (without activating the capture)

J.J. Galiana-Merino is with the Department of Physics, System Engineering and Signal Theory of the University of Alicante, P.O. 99, E-03080, Alicante, Spain (e-mail: juanjo@dfists.ua.es).

D. Ruiz-Fernández is with the Department of Computer Technology of the University of Alicante, P.O. 99, E-03080, Alicante, Spain (e-mail: druiz@dtic.ua.es).

A. Jarones-González is with the Polytechnic University College of the University of Alicante, P.O. 99, E-03080, Alicante, Spain (e-mail: agustinjgonzalez9@gmail.com).

in order the individuals were familiar with the whole process and to reduce wrong captures.

III. Wavelet and Wavelet Packet Transform

Wavelet transforms provide a time-frequency analysis which, especially in the case of non-stationary signals, is more appropriate than a separate analysis in the time or frequency domain. Some examples of these transforms are the Discrete Wavelet Transform (DWT) and the Discrete Wavelet Packet Transform (DWPT)[12, 13].

The DWT is implemented using a sub-band coding scheme, three stages of which are illustrated in Fig. 2. The operators H and G (quadrature filters) represent low-pass and high-pass filters, respectively, plus downsampling by a factor of 2 (removal of every other sample). H is known as the wavelet filter and it is derived from the corresponding mother wavelet, and G is the scaling filter.

Supposing the original signal as $s(n)=\lambda_{0,0}(n)$. At each scale, j, of the DWT, there are 2 independent signals (approximation and wavelet coefficients), which can be expressed as:

$$\begin{aligned} &\lambda_{j+1,0}(n)=H\lambda_{j,0}(n) \\ &\lambda_{j+1,1}(n)=G\lambda_{j,0}(n) \\ &j=0, \dots, L\text{-}1, \end{aligned} \tag{1}$$

where n is the sample index, j is the scale parameter and L is the maximum decomposition level. Sub-index 0 indicates coefficients from low-pass filters, while sub-index 1 indicates coefficients from high-pass filters. Thus, the wavelet coefficients $\{\lambda_{1,1}(n), \lambda_{2,1}(n),\dots, \lambda_{L,1}(n)\}$ characterize the details of the signal at different scales or resolutions, while the coefficients $\{\lambda_{1,0}(n), \lambda_{2,0}(n),\dots, \lambda_{L,0}(n)\}$represent the approximation of the signal at different scales.

Therefore, for a wavelet decomposition of L scales, the DWT returns the following set of coefficients: $\{\lambda_{L,0}(n), \lambda_{L,1}(n),\dots, \lambda_{1,1}(n)\}$. In the DWT transform, the inverse process is also guaranteed through the adjoint operators, H' and G' [12, 13].

The DWT decomposes the original signal following a fixed scheme where it is supposed that the main spectral information is contained at low frequencies. The DWPT generalizes the wavelet analysis and allows a decomposition of the time-frequency plane in such a way that it is well-suited to the signal under study.

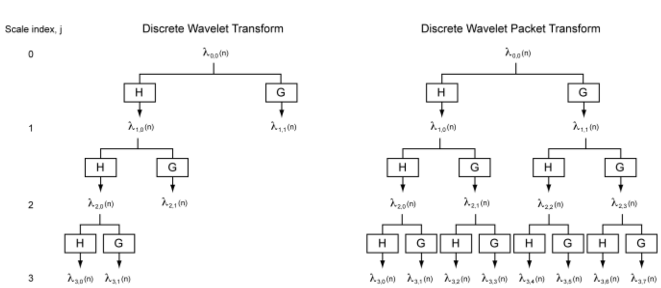

Figure 2. DWT and DWPT schemes

The DWPT follows a sub-band coding scheme as the one shown in Fig. 2 for three stages. At each scale, j, of the DWPT, there are 2^j independent signals (nodes or wavelet packet coefficients) and each of them provides two output functions:

$$\begin{aligned} &\lambda_{j+1,2r}(n)=H\lambda_{j,r}(n) \\ &\lambda_{j+1,2r+1}(n)=G\lambda_{j,r}(n) \\ &j=0, \dots, L\text{-}1, \end{aligned} \tag{2}$$

where r represents the frequency index for a given scale and varies from 0 to 2^j-1. In this way, at a given scale L we obtain a set of signals $\{\lambda_{L,0}(n), \lambda_{L,1}(n),\dots, \lambda_{L,2^L\text{-}1}(n)\}$ which is an alternative representation of $\lambda_{0,0}(n)$. These output wavelet packet coefficients become the input of the next stage in the DWPT.

In this case, there is not a fixed decomposition of the signal. There are different combinations of signals $\lambda_{j,r}(n)$ whose appropriate union can provide an equivalent representation of the original signal (e.g. $\{\lambda_{1,1}(n), \lambda_{2,1}(n), \lambda_{3,0}(n), \lambda_{3,1}(n)\}$, $\{\lambda_{2,0}(n), \lambda_{2,2}(n), \lambda_{2,3}(n), \lambda_{3,2}(n), \lambda_{3,3}(n)\}$ in Fig. 2). The only requirement is that the bandwidth of the original signal must be covered by the chosen set of signals, without overlapping, in such a way that each signal, $\lambda_{j,r}(n)$, will be associated with a frequency band.

In general, for denoising and compression processes, the selection of the wavelet packet coefficients is based on the criterion of minimum entropy. For that, some cost function or entropy is associated to every node of the wavelet packet decomposition, as for example the Shannon entropy [14], which is the one used in this work.

$$\mu[\lambda_{j,r}]= -\lambda_{j,r}(n)^2\cdot\log[\lambda_{j,r}(n)^2]. \tag{3}$$

The algorithm employed to determine the decomposition with the minimum entropy is called the "Best Basis Algorithm" [13], which provides the best selection for a given mother wavelet and cost function.

IV. Wavelet Denoising

The wavelet denoising is based on the thresholding of the wavelet or wavelet packet coefficients. In general, large values usually correspond to the eye movements, meanwhile low values correspond to the background noise. Therefore, if the values below some threshold are changed to 0, the contribution of the noise to the corresponding wavelet or wavelet packet coefficients will be reduced considerably.

There are different thresholding methods. In this work, we have tested two of them: the soft thresholding

$$\begin{aligned} &\lambda'_{j,r}(n)=\mathrm{sgn}(\lambda_{j,r}(n))\cdot(|\lambda_{j,r}(n)|\text{-}th) && |\lambda_{j,r}(n)|\geq th \\ &\lambda'_{j,r}(n)=0 && |\lambda_{j,r}(n)|<th, \end{aligned} \tag{4}$$

and the hard thresholding

$$\begin{aligned} &\lambda'_{j,r}(n)=\lambda_{j,r}(n) && |\lambda_{j,r}(n)|\geq th \\ &\lambda'_{j,r}(n)=0 && |\lambda_{j,r}(n)|<th, \end{aligned} \tag{5}$$

where the threshold is obtained as $th=[2\cdot\sigma^2\cdot\ln(N)]^{0.5}$ and σ^2 is the variance of the noise, which can be estimated as the median absolute deviation of the coefficients divided by 0.6745 for zero mean Gaussian white noise. $\lambda'_{j,r}(n)$ are the coefficients after thresholding and N is the total number of samples.

V. Results and Discussion

For the evaluation of the wavelet and wavelet packet denoising processes, very high quality EOG signals have been recorded from Biopac System and contaminated with Gaussian noise of different amplitudes. Thus, noisy signals with signal-to-noise ratio (SNR) of 10, 20 and 30dB were taken. In Fig. 3, an example of noisy signal (SNR=10dB) is shown.

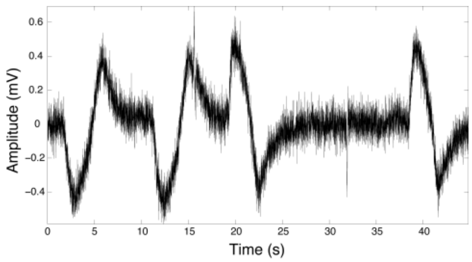

Figure 3. Noisy EOG signal (SNR=10dB)

The obtained results have been compared with the recorded signals (i.e. the signals before being contaminated with noise) and evaluated according to the following parameters: SNR increasing (ΔSNR); the percentage of energy respecting to the registered signal (without noise); the correlation coefficient; and the mean absolute error (MAE) reduction.

In order to determine the most appropriate parameters associated to the wavelet and the wavelet packet denoising methods, different mother wavelets, scales and thresholding methods have been used. From the analyzed cases, we can conclude that the best results are obtained with the mother wavelet 'sym8' and 'db5', the scale 4, and the hard thresholding, although differences between hard and soft thresholding are not very important. For scales lower that 4, the wavelet packet decomposition match the wavelet one and provide worse results. For higher scales (5 or 6), the wavelet packet analysis tends to smooth the picks (e.g. eye blinks) providing also worse results.

Finally, we have compared the wavelet and the wavelet packet denoising methods with common digital filters used in the analysis of EOG signals. Concretely we have implemented the following filters: a) High pass FIR filter with cut-off frequency at 0.5 Hz and a low pass FIR filter with cut-off frequency at 35 Hz, using a Hamming window; b) Band-pass FIR filter (0.5 – 35 Hz) with the Parks-McClellan algorithm; c) Butterworth, Type I Chebyshev and Type II Chebyshev low-pass filters with cut-off frecuency at 35 Hz.

In Table 1, we present the obtained results for the analysis of the EOG signal shown in Fig. 3. For the wavelet approaches we have chosen a mother wavelet 'db5', a scale 4, and soft thresholding.

TABLE I. Comparison Between Wavelet Denoising Methods and Digital Filters

Filtering Method	*ΔSNR (dB)*	*Energy (%)*	*Corr. Coef.*	*ΔMAE (dB)*
LP+HP Hamming	4.52	98.1	0.9841	-5.33
BP - Parks-McClellan	7.45	99.8	0.9918	-7.97
LP - Butterworth	5.66	102.1	0.9875	-5.97
LP - Chebishev I	-0.25	64.9	0.9845	-2.17
LP - Chebishev II	9.10	100.7	0.9944	-9.42
Wavelet	11.55	100	0.9533	-12.11
Wavelet Packet	11.48	100	0.9968	-12.08

In Fig. 4 and Fig. 5, we illustrate some of the obtained results, where the black and gray lines correspond to the recorded and the denoised signal, respectively.

For all the analyzed cases, the wavelet or wavelet packet denoising methods provide the best results, improving considerably the quality of the denoised signals respecting to the conventional used digital filters.

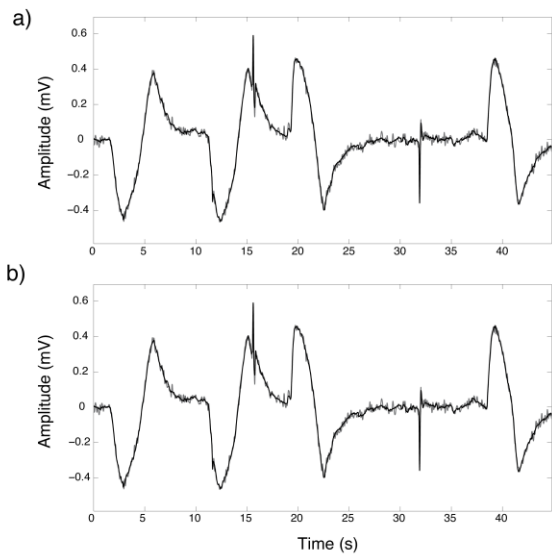

Figure 4. Denoised signals obtained with the wavelet (a) and the wavelet packet (b) denoising methods

VI. Conclusion

Observing the results, it can be concluded that the methods based on the wavelet or wavelet packet transforms provide better results in the electrooculogram filtering than the common digital filters. In these cases, the mother wavelet 'sym8' or 'db5', and the scale 4 seem to be the most suitable parameters for the wavelet and wavelet packet analysis.

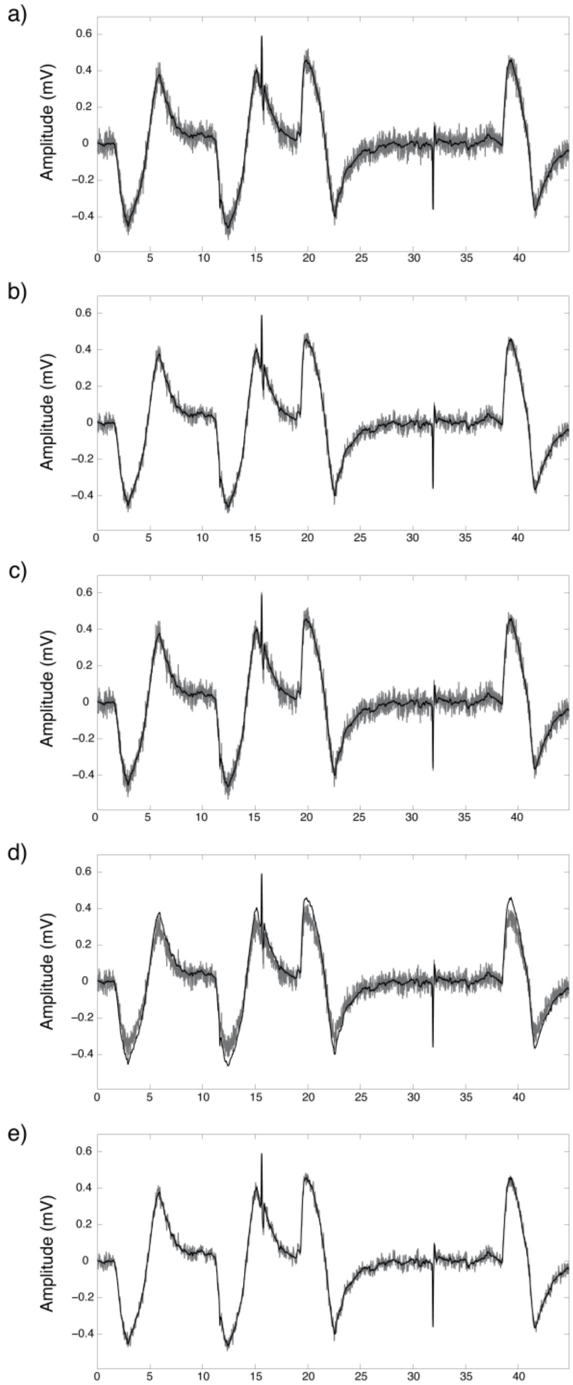

Figure 5. Denoised signals obtained with the high-pass + low-pass FIR filter (a), the band-pass FIR filter (b), the Butterworth low-pass filter (c), the Type I Chebyshev low-pass filter (d) and the Type II Chebyshev low-pass filter (e)

REFERENCES

[1] M. F. Marmor, M. G. Brigell, D. L. McCulloch, C. A. Westall, and M. Bach, "ISCEV standard for clinical electro-oculography (2010 update)," *Doc Ophthalmol,* vol. 122, pp. 1-7, Feb 2011.

[2] M. Merino, O. Rivera, Go, x, I. mez, A. Molina, and E. Dorronzoro, "A Method of EOG Signal Processing to Detect the Direction of Eye Movements," in *Sensor Device Technologies and Applications (SENSORDEVICES), 2010 First International Conference on*, 2010, pp. 100-105.

[3] H. Moriya, K. Ando, T. Kojima, Y. Shimazono, R. Ogiwara, K. Jimbo, and T. Ushikubo, "Eye Movements during Perception of Pictures in Chronic Schizophrenia," *Psychiatry and Clinical Neurosciences,* vol. 26, pp. 189-199, 1972.

[4] B. V. Vaughn and P. Giallanza, "Technical Review of Polysomnography," *CHEST Journal,* vol. 134, pp. 1310-1319, 2008.

[5] A. F. Deutman, "Electro-oculography in families with vitelliform dystrophy of the fovea: Detection of the carrier state," *Archives of Ophthalmology,* vol. 81, pp. 305-316, 1969.

[6] M. Nakanishi, Y. Mitsukura, Y. Wang, Y.-T. Wang, and T.-P. Jung, "Online Voluntary Eye Blink Detection using Electrooculogram," presented at the International Symposium on N onlinear Theory and its Applications, Majorca (Spain), 2012.

[7] Z. Lv, X.-p. Wu, M. Li, and D. Zhang, "A novel eye movement detection algorithm for EOG driven human computer interface," *Pattern Recogn. Lett.,* vol. 31, pp. 1041-1047, 2010.

[8] D. P. Belov, S. Y. Eram, S. F. Kolodyazhnyi, I. E. Kanunikov, and O. V. Getmanenko, *Electrooculogram detection of eye movements on gaze displacement* vol. 40, 2010.

[9] T. B. J. Kuo and C. C. H. Yang, "Frequency domain analysis of electrooculogram and its correlation with cardiac sympathetic function," *Experimental Neurology,* vol. 217, pp. 38-45, 2009.

[10] D. Hanlei, "Detection of Electrocardiography Based on Wavelet Transform and Extended Kalman Filter," in *Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2012 4th International Conference on*, 2012, pp. 138-140.

[11] M. S. Hussain, M. B. I. Reaz, F. Mohd-Yasin, and M. I. Ibrahimy, "Electromyography signal analysis using wavelet transform and higher order statistics to determine muscle contraction," *Expert Systems,* vol. 26, pp. 35-48, 2009.

[12] I. Daubechies, *Ten lectures on wavelets* vol. 61. Philadelphia: SIAM, 1992.

[13] M. V. Wickerhauser, *Adapted Wavelet Analysis from Theory to Software*: A. K. Peters, Ltd.,Wellesley, 1994.

[14] A. Jensen and A. la Cour-Harbo, *Ripples in Mathematics: The Discrete Wavelet Transform*. Berlin Heidelberg New York: Springer-Verlag, 2001.