ECG REMOVAL IN PRETERM EEG COMBINING EMPIRICAL MODE DECOMPOSITION AND ADAPTIVE FILTERING

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ABSTRACT

In neonatal electroencephalography (EEG) heart activity is a major source of artifacts which can lead to misleading results in automated analysis if they are not properly eliminated. In this work we propose a combination of empirical mode decomposition (EMD) and adaptive filtering (AF) to cancel electrocardiogram (ECG) noise in a simplified EEG montage for preterm infants. The introduction of EMD prior to AF allows to selectively remove ECG preserving at maximum the original characteristics of EEG. Cleaned signals improved up to 17% the correlation coefficient with original datasets in comparison with signals denoised solely with AF.

***Index Terms*—** EEG, ECG, Adaptive filter, RLS, EMD

1. INTRODUCTION

Prematurity (birth before 37 weeks of gestation) has become an increasing problem with important consequences for the newborns health. New effective and more specific monitoring systems are needed to prevent morbidity and reduce hospitalization costs. In practice, acquired electroencephalography is often contaminated with ECG and an appropriate artifact removal is of crucial importance for automated analysis.

Preterm EEG is remarkably nonstationary with relevant spectral content from 0.4 to 30 Hz. Since ECG noise overlaps this range of frequencies, the use of conventional FIR filters is dismissed. When interferences and the reference signal have a similar waveform, a solution can be found with adaptive filters (AF) using the recorded ECG. Celka et al. [1] used linear FIR filters and normalized least mean squares (NLMS) adaptation to cancel ECG in newborns EEG. When ECG is low correlated with pulse artifacts, or it is not available, an alternative can be found by generating an artificial reference from the contaminated EEG. However, in spite of its robustness and simplicity, adaptive filters tend to be unstable and less performing under nonstationary environments.

Another common technique is the artifact removal based in the independent component analysis (ICA). Performing ICA, the unwanted ECG artifact should be in one component [2], but the efficiency of the denoising process depends on the availability of an important number of derivations. Convolutive ICA [3] has good results separating cardiac noise from a single EEG lead and a ECG reference, but its high computational cost makes it inadequate for real-time applications.

Empirical mode decomposition (EMD) has been recently used as a tool for selective removal of artifacts in combination with other techniques as ICA [4] thanks to its efficient and natural way of decomposing data in independent oscillatory modes (IMFs). In this work EMD is employed to decompose the EEG into several IMFs, and those modes containing cardiac artifacts are denoised by an adaptive filter. This approach is related to adaptive filtering in sub-bands, where the input signal is decomposed into multiple parallel channels by a filter bank to facilitate a more effective noise cancellation with less complex sub-filters. However, while this framework employs Fourier or wavelet-based transforms to obtain the subbands, our proposal performs EMD, more advantageous with nonstationary signals [5].

2. METHODS

The proposed method is divided in four blocks (Fig. 1). First, EMD is performed to obtain M IMFs, 10 or 11 in our EEG (see example in Fig. 2). The spectral independence of IMFs allows the recomposition block to easily estimate the main frequency of each mode from its power spectral density (Burg method, order 30). Then, two components are constructed: EEG_H and EEG_L. The former is the addition of high fre-

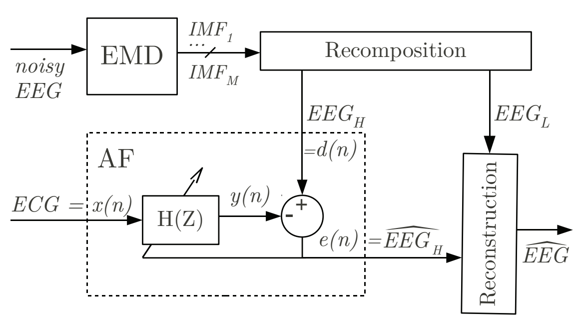

Fig. 1. Block diagram describing the proposed methodology.

quency modes carrying ECG-related content (typically $\geq$ 5 Hz), and the latter contains the remaining IMFs, carrying δ-waves (0.4 - 4 Hz) and low frequency noise (LFN). Then, the AF block removes ECG in EEG_H using the recorded ECG as a reference and yields $\widehat{EEG}_H$. Recursive least square (RLS) algorithm is used for its effective and fast adaptation to EEG complexity. Finally, the reconstruction block selects from EEG_L the noise-free IMFs to add them to the AF output and reassemble the denoised EEG. This procedure permits the AF to perform effectively because EEG_L, with nonstationary content, is set aside of the filtering process. Another implicit benefit is the omission of a high-pass filter, which may deteriorate δ-bursts in the EEG.

2.1. Empirical Mode Decomposition

Empirical mode decomposition is an adaptive method designed to unmix a non-linear and non-stationary signal $s(n)$ in a set of intrinsic modal functions (IMFs), each one containing a spectrally independent oscillatory mode [5]. They must satisfy two conditions: 1) the number of extrema and zero-crossing must be equal or differ at most by one, and 2) the mean value of the upper and lower envelopes must be zero. IMF extraction, known as sifting process, is described as follows:

1. Find local minima and maxima of $s(n)$.
2. Form upper, $e_u(n)$, and lower, $e_l(n)$, envelopes by cubic splines interpolation.
3. Find the mean, $m(n) = \frac{e_u(n)+e_l(n)}{2}$.
4. If $h(n) = s(n) - m(n)$ is not an IMF, go to step 1 using $h(n)$ instead if $s(n)$. Else, $h(n) = IMF_1(n)$.
5. If the residue, $r_1(n) = s(n) - IMF_1(n)$ has more than a zero cross, go to step 1 and find next IMF.

Once $IMF_k(n)$ are extracted, the signal can be expressed as:

$$s(n) = \sum_{k=1}^{M} IMF_k(n) + r(n) \tag{1}$$

Later, ensemble EMD (EEMD) was introduced to reduce the corruption of unmixed modes when noisy signals were analyzed. EMD is performed I times, each one decomposing $s^i(n) = s(n) + w_i(n)$, where $w_i(n)$ are different realizations ($i = 1, .., I$) of white noise, with variance ε. Then, the final oscillatory modes ($\overline{IMF}_k$) are obtained by averaging the ensemble of IMF_k^i. Recently, the complete EEMD with adaptive noise (CEEMDAN) [6] was proposed to ameliorate the spectral separation of modes and reduce computational cost. In EEMD each $s^i(n)$ is decomposed independently, so that one residue $r_k^i(n)$ for each is obtained. However, in CEEMDAN only one residue $r_k(n)$ is produced by modes, noted $\overline{IMF'_k}$. So the first residue is $r_1(n) = s(n) - \overline{IMF'_1}(n)$, where $\overline{IMF'_1}(n)$ is computed as in EEMD. Then,

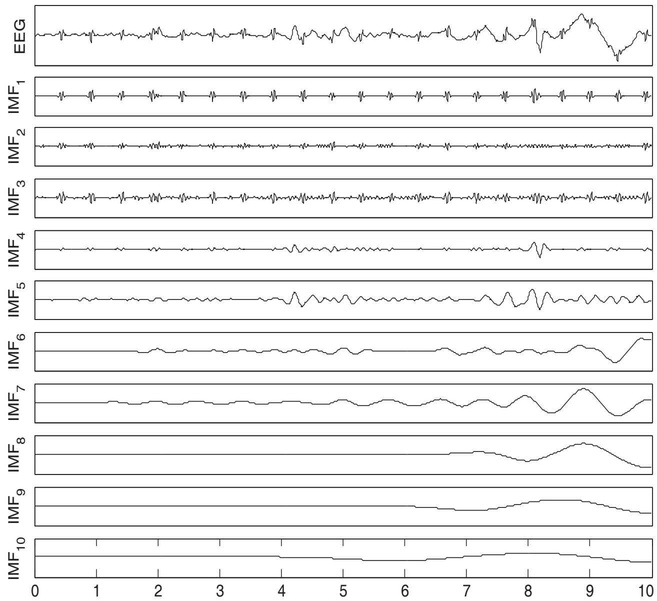

Fig. 2. Noisy EEG decomposed with EMD. The sum of IMF_1 to IMF_4 (main freq. > 5 Hz) constitutes EEG_H.

EMD is performed over a set of $r_1(n)$ plus different noise realizations, to obtain $\overline{IMF'_2}(n)$ by averaging. The next residue is $r_2(n) = r_1(n) - \overline{IMF'_2}(n)$, and so on, until the stopping criterion is achieved.

2.2. Adaptive filtering based on RLS

Adaptive filters can reduce interferences modifying iteratively their coefficients from the input $x(n)$, the recorded ECG, to generate an output $y(n)$ similar to the artifacts contained in $d(n)$, the noisy EEG (see Fig.1). The difference between $d(n)$ and $y(n)$, $e(n)$, is fed back into the linear filter H(Z), with order L and coefficients $\mathbf{w}(n)$ [7]. Adaptation minimizes the cost function, i.e. the weighted least square of $e(n)$, given by:

$$\xi(n) = \sum_{k=1}^{n} \lambda^{n-k} |e^2(k)| + \delta\lambda^n ||\mathbf{w}(n)||^2 \tag{2}$$

where λ is the forgetting factor ($0 < \lambda \leq 1$), so that the closer is its value to one, the more importance is given to recent samples. δ is the regularization factor, positive and real. Then, RLS updates the filter coefficients by means of:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + e(n)\mathbf{k}(n) \tag{3}$$

$$\mathbf{k}(n) = \frac{\mathbf{P}(n)\mathbf{u}(n)}{\lambda + \mathbf{u}^T(n)\mathbf{P}(n)\mathbf{u}(n)} \tag{4}$$

with $\mathbf{u}(n) = [e(n), e(n-1), ...e(n-L+1)]^T$. $\mathbf{P}(n)$ is the inverse correlation matrix of the input signal. Initially, $\mathbf{w}(0) = 0$ and $\mathbf{P}(0) = \delta^{-1}\mathbf{I}$, with $\mathbf{I}$ the identity matrix. Next, $\mathbf{P}(n)$ is recursively updated by performing:

$$\mathbf{P}(n) = \lambda^{-1}\mathbf{P}(n-1) - \lambda^{-1}\mathbf{k}(n)\mathbf{u}^T(n)\mathbf{P}(n-1) \tag{5}$$

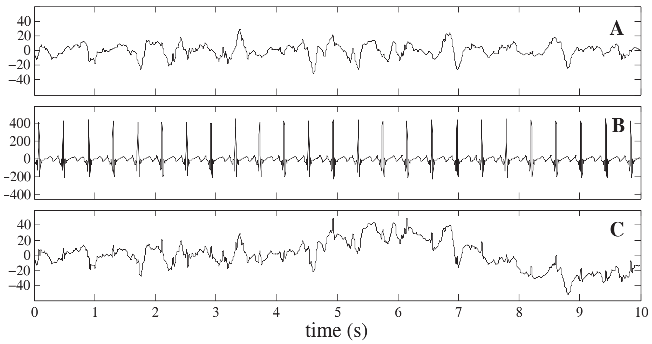

Fig. 3. Generation of artificially contaminated datasets A: EEG without artifacts. B: ECG signal. C: EEG contaminated with ECG and low frequency noise (group 3).

3. VALIDATION

To quantitatively evaluate the efficacy of the denoising method, simulation signals were created from real artifact-free EEG. Data was acquired from premature infants at the University Hospital of Rennes (CHU Rennes, France) at 512 Hz sample frequency in four scalp positions (Fp1, Fp2, T3 and T4), then subsampled to 128 Hz and low-pass filtered with a cutoff frequency of 35 Hz. Sixty representative excerpts of 10 seconds, comprising several patients and derivations, were selected after visual inspection to ensure the nonexistence of noise.

Then, we added to this selection (noted EEG) the cardiac artifacts (ECG'), creating the noisy EEG (EEG_n). ECG' was obtained by processing the recorded ECG by an order 5 filter as done in [3]. The signal-to-noise ratio was adjusted to 15 dB. To recreate different scenarios, we derived 3 groups (of 20 excerpts) from EEG_n:

1. $EEG'_1 = EEG + ECG' = EEG_n$
2. $EEG'_2 = EEG_n$ + slow δ-waves (0.4 - 1 Hz)
3. $EEG'_3 = EEG_n$ + LFN (0.1 - 0.3 Hz)

Groups 2 and 3 were created adding an entire cycle placed randomly in the excerpt, with frequencies set randomly between the limits above described. δ amplitudes were fixed according typical values [8] and LFN to 40 μV (see Fig. 3).

Once simulation signals were generated, we tested our method with 2 variations: (1) using the classical EMD algorithm, and (2) applying CEEMDAN with $I = 500$ and $\varepsilon = 0.2$. We also tested the adaptive filter without the prior EMD layer. So, EEG'_1 and EEG'_2 were cleaned directly by the AF, and EEG'_3 was previously high-pass filtered (Butterworth order 5, 0.3 Hz cut-off frequency). The order of the adaptive filter was set to 8, λ to 0.999 and δ to 0.01.

Finally, cleaned datasets ($\widehat{EEG}_i$, with $i = 1, 2, 3$ representing the three groups) were compared to the original ones by finding the normalized correlation coefficient (γ).

Signal-to-noise ratio (SNR) was also measured in $\widehat{EEG}_i$ by using equation 6:

$$SNR = 10 \log \frac{P(EEG)}{P(EEG_n - \widehat{EEG}_i)} \qquad (6)$$

where P is the power of the signal in brackets. While γ measures template matching, i.e. the preservation of the original EEG trace, SNR quantifies the residual QRS complexes in the cleaned signal, and thus, the ECG removal effectiveness.

4. RESULTS AND DISCUSSION

Regarding the results in table 1, it can be stated that the combination CEEMDAN+AF is the best method to cancel ECG retaining reliably the original EEG information. In normal EEG activity (Group 1) it has the greatest average correlation values, improving EMD+AF and AF results by 2% and 3% respectively. This combination achieves as well stable performances in different scenarios with lower standard deviations.

The presence of δ-waves in EEG (Group 2) decreases globally the performance of the denoising methods, with lower and more dispersed γ values. Here, the adaptive filter has more difficulty to track the signal, yet the introduction of EMD reduces partially this effect (see example in Fig. 4B).

Low frequency noise (Group 3) is known to perturb the AF efficacy, so prior high-pass filtering is necessary. The cardiac noise is canceled acceptably but at the cost of deteriorating the EEG (see Fig. 4C) because the cutoff frequency is very close to the delta components. Nevertheless, processing the EEG previously with EMD improves remarkably the similarity with the original signal (by 14% with classical EMD and 17% with CEEMDAN) since the low frequency noise is separated without the undesired effects of the high-pass filter.

For EMD methods, better SNR are obtained, paradoxically, when EEG contains δ and LFN. Since spectrum becomes wider, IMFs main frequencies are more spaced and

Table 1. First column: Average correlation values between the original and the unfiltered noisy EEG and its SNR before denoising. Other columns: correlations and SNRs of denoised EEG with the different techniques in the three studied scenarios (best results in bold).

	Noisy EEG	AF	EMD+FA	CEEMDAN +AF
EEG'_1				
mean±std(γ)	0.72±.08	0.94±.06	0.96±.03	**0.97±.02**
SNR(dB)	15	45.9±5.3	50.0±9.0	**50.1±7.5**
EEG'_2				
mean±std(γ)	0.78±.09	0.90±.13	0.90±.12	**0.94±.11**
SNR(dB)	15	45.9±11.5	46.1±11.1	**48.8±6.1**
EEG'_3				
mean±std(γ)	0.72±.09	0.77±.15	0.91±.10	**0.94±.07**
SNR(dB)	15	47.5±8.3	51.4±10.2	**53.5±7.5**

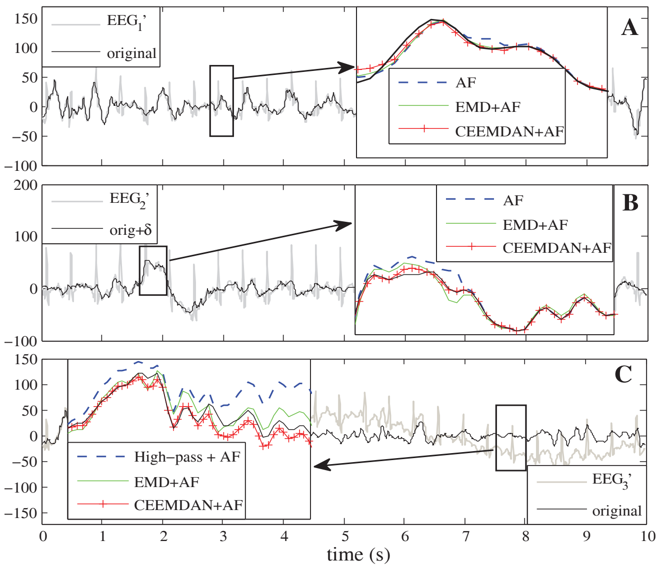

Fig. 4. Examples of denoised signals (A: $\widehat{EEG}_1$; B: $\widehat{EEG}_2$. C: $\widehat{EEG}_3$) comparing the three methods.

ECG-related modes can be isolated neatly. Superior performance of CEEMDAN is, in general, due to its better IMF spectral separation, which allows to reconstruct more reliably the original signal. However, the computational cost is high: 10^2 times EMD+AF and about 10^4 times AF.

Finally, the three methods were tested with real noisy data to verify the results. Cleaned signals (see example in Fig. 5) presented visibly better ECG cancellation, low frequency removal and better EEG preservation in combinations EMD+FA and CEEMDAN+FA.

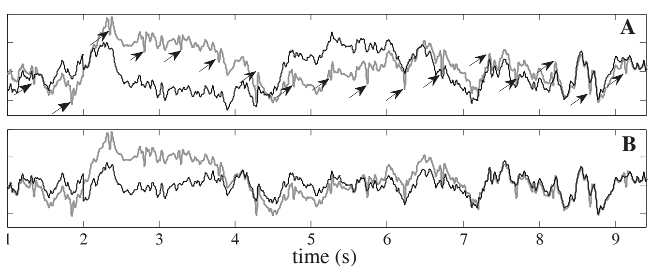

Fig. 5. A: Real EEG (grey trace) denoised by a high-pass filter + AF. Marks corresponds to ECG peaks. In black, the denoised signal. B: The same EEG denoised with EMD+AF.

5. CONCLUSION

In this work a novel methodology to cancel ECG from EEG is proposed by applying empirical mode decomposition prior to adaptive filtering. Since only one EEG lead is needed, it is suitable for neonatology recordings as they usually have a limited number of channels. Moreover, typical preterm EEG nonstationarities are set aside of the process, which allows the AF to easily cancel ECG. Denoised signal is then reconstructed, recovering δ components and rejecting low frequency noise without the need of introducing a high-pass filter. As a result, an artifact-free EEG with minimal information loss is returned. In view of the advantages of EMD and AF, this combination could be useful in neonatal polysomnography systems and clinical tools dealing with EEG quantitative analysis. In spite of CEEMDAN+AF had the best results, its time-consuming algorithm cannot be integrated in real-time applications. Classical EMD+AF arises, then, as a trade-off between speed and performance.

6. REFERENCES

[1] P. Celka, B. Boashash, and P. Colditz, "Preprocessing and time-frequency analysis of newborn EEG seizures," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 5, pp. 30–39, Oct. 2001.

[2] T. P. Jung, S. Makeig, C. Humphries, T. W. Lee, M. J. McKeown, V. Iragui, and T J Sejnowski, "Removing electroencephalographic artifacts by blind source separation," *Psychophysiology*, vol. 37, no. 2, pp. 163–178, Mar. 2000.

[3] S. Devuyst, T. Dutoit, P. Stenuit, M. Kerkhofs, and E. Stanus, "Cancelling ECG artifacts in EEG using a modified independent component analysis approach," *EURASIP Journal on Advances in Signal Processing*, vol. 2008, pp. 1–14, 2008.

[4] J.P. Lindsen and J. Bhattacharya, "Correction of blink artifacts using independent component analysis and empirical mode decomposition," *Psychophysiology*, vol. 47, no. 5, pp. 955–960, Sept. 2010.

[5] N. Huang, Z. Shen, S. Long, MC. Wu, H. Shih, Q. Zheng, N. Yen, C. Tung, and H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis," *Proceedings of the Royal Society of London.*, vol. 454, no. 1971, pp. 903 – 995, Mar. 1998.

[6] M.E. Torres, M.A. Colominas, G. Schlotthauer, and P. Flandrin, "A complete ensemble empirical mode decomposition with adaptive noise," in *ICASSP'2011*. May 2011, pp. 4144–4147, IEEE.

[7] S. Haykin, *Adaptive Filter Theory*, Pearson Education, 4 edition, 2002.

[8] M.-F. Vecchierini, M. André, and A.M. d'Allest, "Normal EEG of premature infants born between 24 and 30 weeks gestational age: Terminology, definitions and maturation aspects," *Clinical Neurophysiology*, vol. 37, no. 5, pp. 311–323, 2007.