EEG Montage Analysis in Blind Source Separation

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Abstract: Blind source separation (BSS) is a relatively recent technique, more and more applied in electroencephalographic (EEG) signal processing. Still, the classical mixing model of the BSS does not take into account the real recording set-up. In fact, a major problem in electrophysiological recording systems (*e.g.* ECG, EEG, EMG) is to find a region in the human body whose bio-potential activity can be considered as neutral as possible *i.e.*, a quasi-inactive reference place. Nowadays, it is well known that it is impossible to find a "zero-potential" site on the human body. In particular, the most common way of performing EEG recordings is by using as a common reference an electrode placed somewhere on the head. Starting from this Common Reference Montage (CRM), several other montages can be constructed for interpretation or processing purposes. Regardless of the chosen montage, the reference electrode intervenes in the mixing model of the BSS. The objective of this work is to analyse the influence of the montage on the mixing matrix and the quality of the BSS solution. This communication proposes to formalize the source separation problem in a non zero-potential reference context and shows that the Average Reference Montage (ARM), augmented by a virtual "average measure", leads to better source separation results (separability index *IS*). This conclusion is supported by simulated EEGs using the most common montages *i.e.* Common Reference Montage, Average Reference Montage and Bipolar-Longitudinal Montage, as well as by real EEG examples.

Keywords: Reference electrode, EEG Montages, Blind Source Separation

1. INTRODUCTION

An important issue for the actual standard systems for bio-potentials recording (electrophysiological activity measuring systems as ECG, EEG, EMG) is to find a region in the human body whose bio-potential activity could be considered as neutral as possible. That is desirable because the electrical activity at that place affects measurements at all other active electrode sites, see Dien (1998) and Yao (2001).

In Electroencephalography (EEG), one of the most common recording systems is the 10-20 system of electrode placement. EEG recordings are performed by using electrodes placed at standardized locations on the head. These *measuring electrodes* are referenced either to cephalic or non-cephalic *reference electrodes*. This paper focuses on the former, *i.e*. the most frequently employed cephalic reference. The anatomical landmarks most frequently used as cephalic references sites are the nasion, the inion, over the occipital area, the preauricular points, … see Schachter (2006). All this reference sites contribute with some non-desirable effects on the recordings.

The previously described recoding set-up is known as Common Reference Montage (CRM, cephalic) and it is the basis montage in modern acquisition systems. Nevertheless, to ease interpretation and processing in the absence of a zero-potential reference, several multiple combinations of differential measures have been derived from the CRM by some simple manipulations (see section 3). The most common of these montages are the Average Reference Montage (ARM) and the Bipolar-Longitudinal Montage (BLM), see Fisch and Spehlmann (1999).

Regardless of the employed montage, all measured EEG signals can be seen as a result of an unknown mixture of several unknown cortical sources, extra-cortical artefacts and noise. A relatively recent signal processing technique, the Blind Source Separation (BSS), can be used to separate these mixed measured signals in "independent" sources, which can be further-on used either for artefact elimination or for brain activity evaluation, see Croft (2000), Delorme (2001), James (2003), Ting (2006), Romo (2007). A brief description of the general BSS model is presented section 2.

The classical BSS model supposes ideally measured signals, *i.e.* zero-referenced, while real electrophysiological recordings have a non-null reference. A solution proposed by Hu *et al* (2007) consists in identifying the reference signal by constraining the BSS model to particular mixing system which implies that the non-zero reference signal is independent from all other measures. In the recording set-up used by the authors (intra-cranial measures), this approach is based on the hypothesis that the reference electrode placed on the scalp is not influenced by the intracranial measures.

If for intra-cranial measures this hypothesis (although not proven) can be employed, in a cephalic referenced scalp EEG (CRM) context it cannot hold, as the reference electrode itself records a noisy mixture of cerebral and extra-cerebral sources. Therefore it is important to evaluate the quality of the obtained separation function of the input signals, *i.e.* from the employed montage. One could object that all the different montages can be obtained by linear transformation from the CRM (and therefore the source separation solution should be the same). Still, the noise affects them differently, and the solutions are not identical, as it is shown in section 3 and illustrated by simulation and by real examples in section 4.

The employed evaluation criterion is the classical Separability Index (*IS*), see Cichocki (2002). In particular, it is proven that the ARM, augmented by a "virtual measure" consisting in the actual average of the CRM signals, performs better than CRM or BLM and that it tends asymptotically towards an ideal zero-referenced montage (ZRM), and therefore should be used when source separation algorithms are applied.

2. SOURCE SEPARATION

The final objective of blind source separation is to recover all the independent sources from the observed EEG recordings. In general, these observations are modelled as a linear mixture of independent sources, both the mixing system and the sources being unknown.

Several Blind Source Separation (BSS) algorithms have been proposed and analysed during the last decades. However, it is not the objective of this paper to explore the effectiveness of these different methods. We have therefore chosen one of the most robust algorithms for temporally auto-correlated sources, namely SOBI-RO (Robust Second Order Blind Identification), introduced by A. Belouchrani *et al* (1997, 2000). This algorithm was already successfully used for EEG separation, for example by Kierkels (2006) and Romero (2008).

2.1 Classical BSS Model

The classical linear mixing model can be written, at each instant *k*, as:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \qquad (1)$$

where $\mathbf{x}$ is a vector of M observed signals (EEG electrodes), $\mathbf{A}$ is the unknown full-column rank mixing matrix ($M\times N$) and $\mathbf{s}$ is the vector of N independent unknown sources (in the classical approach $M=N$, that is, we have the same number of sensors and sources). In order to estimate the original sources it is necessary to calculate the following linear transformation:

$$\mathbf{y} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} \qquad (2)$$

where $\mathbf{y}$ is a vector of N estimated sources and $\mathbf{W}$ is the $N\times M$ linear transformation that allows separating the mixed signals in their independent components. Theoretically, such transformation $\mathbf{W}$ should be the (left-) inverse of the mixing matrix $\mathbf{A}$, when sources are perfectly recovered. However, obtaining the exact inverse of the mixing matrix $\mathbf{A}$ is impossible to achieve, see for example Cichocki (2002). Thus, source separation algorithms are focused in finding a matrix $\mathbf{W}$ such as $\mathbf{G=WA}$ be a permuted and scaled diagonal matrix (one non-null value by line and column), which implies that the sources are recovered, excepting their order and their amplitude.

A more realistic model considers noisy measures and it can be written as follows:

$$\tilde{\mathbf{x}} = \mathbf{A}\mathbf{s} + \mathbf{n} \qquad (3)$$

where $\tilde{\mathbf{x}}$ is the noisy measure vector ($M\times 1$), $\mathbf{A}$ is the unknown full-column rank mixing matrix ($M\times N$) , $\mathbf{s}$ is the sources vector ($N\times 1$) and $\mathbf{n}$ is a vector ($M\times 1$) of independent Gaussian noises. By BSS, one will find a separation matrix $\mathbf{W}$ and noisy source estimates $\tilde{\mathbf{y}}$.

2.2 Performance Evaluation

The classical performance evaluation for source separation algorithms is based on the transfer matrix $\mathbf{G}$ between original sources $\mathbf{s}$ and estimated ones $\tilde{\mathbf{y}}$ ($\mathbf{G=WA}$).

The separability index *IS* is a distance measure between $\mathbf{G}$ and a diagonal permuted matrix and is computed by performing the following manipulations: the first step is to normalize the rows $\mathbf{g}_i$ of the matrix $\mathbf{G}$ by dividing each element by the maximum absolute value of the row:

$$\mathbf{g}'_i = \frac{|\mathbf{g}_i|}{\max|\mathbf{g}_i|} \qquad (4)$$

From the normalized matrix $\mathbf{G'}$, the separability index is computed as follows:

$$IS = \frac{\sum_{j=1}^{N}\left(\sum_{i=1}^{N}\left(\mathbf{G}'(i,j)\right)-1\right)}{N(N-1)} \qquad (5)$$

From (5) we can see that for a perfect separation, the IS index is zero.

3. SOURCE SEPARATION ON REFERENCED EEG RECORDINGS

The previously proposed model considers sources $\mathbf{s}$ and sensors $\mathbf{x}$ as measured relatively to an ideal null reference. However, in clinical implementation, it is not possible to measure relatively to a "zero-potential" electrode. In practice, one should consider "the measure" as the electrode pair made by the recording electrode and the reference electrode. Therefore, it is necessary to consider the way the measures are performed, *i.e.*, the recording set-up employed (CRM, ARM or BLM). In particular, when a cephalic reference is used, the reference electrode is not exempt from the influence of the same sources as the other measuring electrodes.

We propose here to formalize the source separation problem in a non zero-potential reference context for cephalic reference. The newly derived models will allow a more precise definition of the different montages and of their influence on the performances of the BSS algorithms.

3.1 Common Reference Montage (CRM)

Nowadays, the EEG recordings are obtained from a basic CRM, which is used further-on to derive the other montages such as ARM and BLM. Consider a simple ideal model with N zero-referenced sources s_i ($i=1..N$), N zero-referenced measuring electrodes x_i and one so-called reference electrode

$R=x_{N+1}$ (zero-referenced itself). The $N+1$ noisy mixed signals are modelled, in a source separation framework, as:

$$\tilde{\mathbf{x}} = \mathbf{As} + \mathbf{n} \tag{6}$$

with $\mathbf{A}$ a ($N+1\times N$) full-column rank mixing matrix.

On the other hand, in a realistic noisy set-up, the common-referenced observations $\tilde{x}_{R,i}$ (EEG signals) can be represented as:

$$\tilde{x}_{R,i} = \tilde{x}_i - \tilde{R}\ ,\ \tilde{R} = \tilde{x}_{N+1}\ ,\ i = [1,2,...,N] \tag{7}$$

where $\tilde{x}_{R,i}$ is a vector which contains the i-th cephalic-referenced electrode, $\tilde{x}_i$ is a hypothetical zero-referenced vector containing the noisy records from the i-th recording electrode, $\tilde{R}$ is the reference vector associated to the cephalic reference electrode $\tilde{x}_{N+1}$. To separate the informative measures and the noise, equation (6) can be rewritten as:

$$\tilde{x}_{R,i} = x_i - x_{N+1} + (n_i - n_{N+1}) = x_{R,i} + n_{R,i} \tag{8}$$

In a source separation framework, the model for the real common reference montage becomes:

$$\tilde{\mathbf{x}}_R = \mathbf{A}_R \cdot \mathbf{s} + \mathbf{n}_R \tag{9}$$

with the elements of the $\mathbf{A}_R$ matrix being

$$a_{R_{i,j}} = (a_{i,j} - a_{N+1,j}) \text{ where, } i,j = [1,2,...,N] \tag{10}$$

Starting from $\tilde{x}_{R,i}$, the source separation algorithm will compute a ($N\times N$) non-singular separation matrix $\mathbf{W}_R$, which can be used to obtain the transfer matrix $\mathbf{G}_R$=$\mathbf{W}_R\mathbf{A}_R$ and to compute the *IS* for the CRM (4) and (5).

A. Estimating the Noise in CRM

As the noise affects the reference electrode as the others, it will be present in the common referenced signals $\tilde{x}_{R,i}$ in (8):

$$n_{R,i} = n_i - n_{N+1} \tag{11}$$

Considering that all noises are independent zero-mean white Gaussian of standard deviation σ, we can compute the power of $n_{R,i}$ as follows

$$\sigma_r^2 = \sigma_i^2 + \sigma_{N+1}^2 = 2\sigma^2 \tag{12}$$

that is, the noise affecting the CRM measures is twice as powerful as for the ideal zero-referenced montage. Consequently, even if all sources are found by source separation, the performance index *IS* should be worse.

3.2 Average Reference Montage (ARM)

As mentioned above, the Average Reference Montage is obtained from the previously described CRM. More precisely, the mixed signals of the ARM can be derived from the CRM as follows:

$$\tilde{x}_{Avg,i} = \tilde{x}_{R,i} - \tilde{R}_{avg}\ ,\ \tilde{R}_{avg} = \frac{1}{N}\sum_{j=1}^{N}\tilde{x}_{R,j}\ ,\ i = [1,2,...,N] \tag{13}$$

As our goal is to estimate the *IS*, we must write the newly obtained average-referenced measures as a mixture of the original sources $\mathbf{s}$. Writing (13) in terms of its hypothetical zero-referenced real potentials and noise vectors we obtain:

$$\begin{aligned} \tilde{x}_{Avg,i} &= x_i - \frac{1}{N}\sum_{j=1}^{N} x_j + n_i - \frac{1}{N}\sum_{j=1}^{N} n_j \\ \tilde{x}_{Avg,i} &= x_{Avg,i} + n_{Avg,i} \end{aligned} \tag{14}$$

Now, is possible to write new BSS model for the average reference montage as follows:

$$\tilde{\mathbf{x}}_{Avg} = \mathbf{A}_{Avg} \cdot \mathbf{s} + \mathbf{n}_{Avg} \tag{15}$$

with

$$a_{Avg_{i,j}} = (a_{i,j} - a_{N+1,j}) - \frac{1}{N}\cdot\sum_{i=1}^{N}(a_{i,j} - a_{N+1,j}) \tag{16}$$

$$i = j = [1,2,...,N]$$

However, the $\mathbf{A}_{Avg}$ matrix (16) is singular, so any BSS algorithm fails in finding all the sources. From another point of view, the singularity of the mixing matrix enlightens the fact that by removing the mean signal we lose some information. In order to avoid this lost of information one can add the average reference as an extra virtual signal in the average reference montage. Consequently, one can obtain an augmented ARM having N+1 measures. For purposes of following the same logic in the equations we define our last measure as $-\tilde{R}_{avg}$, thus we have:

$$\begin{aligned} \tilde{x}_{Avg,N+1} &= x_{N+1} - \frac{1}{N}\sum_{j=1}^{N} x_j + n_{N+1} - \frac{1}{N}\sum_{j=1}^{N} n_j \\ \tilde{x}_{Avg,N+1} &= x_{Avg,N+1} + n_{Avg,N+1} \end{aligned} \tag{17}$$

In matrix form, the augmented measures vector $\tilde{\mathbf{x}}'_{Avg}$ can be obtained as noisy mixture of the original sources as follows:

$$\tilde{\mathbf{x}}'_{Avg} = \mathbf{A}'_{Avg} \cdot \mathbf{s} + \mathbf{n}'_{Avg} \tag{18}$$

with $\mathbf{A}'_{Avg}$, a full-column matrix. The elements of rows 1…N of $\mathbf{A}'_{Avg}$ are:

$$a'_{Avg_{i,j}} = (a_{i,j} - a_{N+1,j}) - \frac{1}{N}\cdot\sum_{i=1}^{N}(a_{i,j} - a_{N+1,j}) \tag{19}$$

and those of the last row N+1:

$$a'_{Avg_{N+1,j}} = -\frac{1}{N}\cdot\sum_{i=1}^{N}(a_{i,j} - a_{N+1,j})$$

$$i = [1,2,...,N]$$

Thus, the obtained mixture is over determined and classical BSS algorithms have to be slightly modified to take into account this problem. The most currently employed solution is to evaluate the number of sources in the mixture (in our case N sources for $N+1$ measures) by using some criterion based on the eigen-values of the covariance matrix of the measured signals (Akaike Information Criterion AIC, Minimum Description Length MDL or Bayesian Information

Criterion BIC, see Cichocki 2002 for details). In this paper, the effectiveness of source number evaluation by these criteria is not tested, as again, the objective is to evaluate the different montages and not source separation methods. Therefore, we have imposed the number of sources to N (nevertheless, in our simulated set-up, MDL systematically gave the same result). Consequently, SOBI-RO returns a separation matrix $\mathbf{W}'_{Avg}$ ($N\times N+1$) and the complete transfer matrix $\mathbf{G}'_{Avg}=\mathbf{W}'_{Avg}\mathbf{A}'_{Avg}$ is square, and therefore the separability index can again be computed according to (4) and (5).

A. Estimating the Noise in ARM

In the same way we did for CRM if we want to perform a noise analysis, from (23) we have:

$$\begin{aligned} n'_{Avg,i} &= n_i - \frac{1}{N}\sum_{j=1}^{N} n_j \\ n'_{Avg,N+1} &= n_{N+1} - \frac{1}{N}\sum_{j=1}^{N} n_j \end{aligned} \tag{20}$$

From (20), considering that all noise presented in x'_{Avg} are zero-mean white Gaussian independent noises of standard deviation σ, we can compute the power of $n'_{Avg,i}$ as follows:

$$\begin{aligned} \sigma^2_{Avg,i} &= \mathbf{E}\left(\left(n'_{Avg,i}\right)^2\right) = \frac{N-1}{N}\sigma^2 \\ \sigma^2_{Avg,N} &= \mathbf{E}\left(\left(n'_{Avg,N}\right)^2\right) = \frac{N+1}{N}\sigma^2 \end{aligned} \tag{21}$$

where $\mathbf{E}(\cdot)$ is the expected value operator.

3.3 Bipolar Longitudinal Montage (BLM)

As ARM, bipolar montages can be obtained also from the CRM EEG recordings as follows:

$$\tilde{x}_{Long,i} = \tilde{x}_{R,i} - \tilde{x}_{R,j} \tag{22}$$

where $i=[1,2,...N-1]$, $j=[2,3,...N]$. Considering the N CRM measures, only N-1 BLM independent measures can be obtained, so the system will be under-determined and the BSS solution will be incomplete. To simplify the notation, we consider here the N-1 measures as being obtained from (22) with $j=i+1$. To avoid the indetermination, a N^{th} measure can be introduced in the model as $\tilde{x}_{Long,N}=\tilde{x}_{R,N}$ *i.e.* a common reference measure (another solution, without any physiological signification though, would be to close the loop by considering $\tilde{x}_{Long,N}=\tilde{x}_{R,N}-\tilde{x}_{R,1}$). Equation (22) can be written in terms of its hypothetical zero-referenced potentials and noise vectors as follows:

$$\begin{aligned} \tilde{x}_{Long,i} &= \tilde{x}_{R,i} - \tilde{x}_{R,i+1} = x_i - x_{i+1} + n_i - n_{i+1} \\ \tilde{x}_{Long,N} &= \tilde{x}_{R,N} = x_N - x_{N+1} + n_N - n_{N+1} \end{aligned} \tag{23}$$

Thus, it is possible to write a new BSS model for the BLM as follows:

$$\tilde{\mathbf{x}}_{Long} = \mathbf{A}_{Long}\cdot\mathbf{s} + \mathbf{n}_{Long} \tag{24}$$

with the elements of rows $1\ldots N$ of $\mathbf{A}_{Long}$ are:

$$a_{Long_{i,j}} = \left(a_{i,j} - a_{i+1,j}\right) \tag{25}$$

where, $i,j=[1,2,...N]$. The system being full-ranked, BSS algorithms provide a separation matrix $\mathbf{W}_{Long}$ and the separability index is calculated from the $N\times N$ transfer matrix:

$$\mathbf{G}_{Long} = \mathbf{W}_{Long}\mathbf{A}_{Long} \tag{26}$$

by equations (6) and (7).

A. Estimating the Noise in BLM

According to (23), the noise affecting longitudinal measures is:

$$n_{Long,i} = n_i - n_{i+1} \tag{27}$$

If we compare (27) with (11) we can see that they are similar, thus the noise power in longitudinal montage can be obtained by (12).

4. SIMULATION RESULTS

To validate the previous discussion, we simulated four different noisy montages: an "ideal" zero-referenced montage ZRM (3), with a mixing matrix ($N+1\times N$), the "realistic" common cephalic reference montage CRM (10) and the derived augmented average ARM (18) and bipolar BLM (24) montages.

A. Simulated Sources

A set of N=6 signals with different frequencies and shapes with a duration time of 5 s and a sampling rate of 256 Hz was created to be the original zero-referenced source signals (brain frequency range signals and eye artefacts). In order to obtain the EEG recordings in our simulation the original simulated sources were mixed up by using 1000 random ($N+1\times N$) mixing matrices. For each mixture, 5 levels of Gaussian noise were added (SNR = 0, 5, 10, 15 and 20 dB). Then, with the obtained $N+1$ mixed signals (EEG simulated potentials) we proceeded to implement the four different montages mentioned before in previous sections (ZRM, CRM, ARM, BLM see Fig. 1. and Fig. 2.).

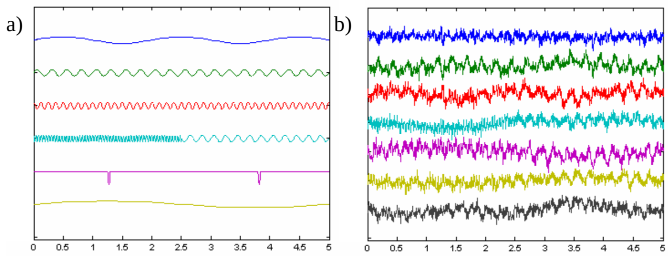

Fig. 1. a) Original Simulated Brain Sources. b) Noisy mixture using a $N+1\times N$ mixing matrix (ZRM).

B. Source Separation

As mentioned, the robust second order blind information algorithm (SOBI-RO) was applied to perform source separation on the EEG signals obtained for the 4 simulated

EEG montages. In order to evaluate the performance in the obtained separated signals we computed the evaluation criterion mentioned in previous sections (Separability Index, *IS*) Table I. presents the average over 1000 different simulations for the 5 different SNR values. According to the noise evaluation from (12) and (21), the separation results should be different.

Table I. Performance Evaluation IS.

EEG Montages	Noise Interval in Signal to Noise Ratio (SNR, dB)				
	0	**5**	**10**	**15**	**20**
ZRM	.1022	.0546	.0288	.0170	.0125
CRM	.1390	.0944	.0620	.0404	.0273
ARM	.1183	.0807	.0531	.0346	.0234
BLM	.1387	.0948	.0622	.0404	.0274

Indeed, as expected, the ideal Zero-Reference Montage presented the best performances, but this ideal condition cannot be obtained in practice and should be seen as an asymptotic best possible value.

Among the possible realistic montages, the ARM obtained the best *IS* indices, as the noise that affects it is smaller than for CRM and for BLM. Moreover, as seen in (20), when the number of sources N increases, the average montage noise tends towards the ZRM noise. The other two classical montages (CRM and BLM) are noisier and therefore the obtained results are less accurate. Even if this conclusion is not visually apparent for the simulated examples presented figure 2, real EEG implementations seem to confirm it. As seen figure 3, the source separation solutions are different (not only in order and amplitude) for the three montages.

Visually identifiable artefacts are simultaneously present on several estimated sources for CRM and BLM based

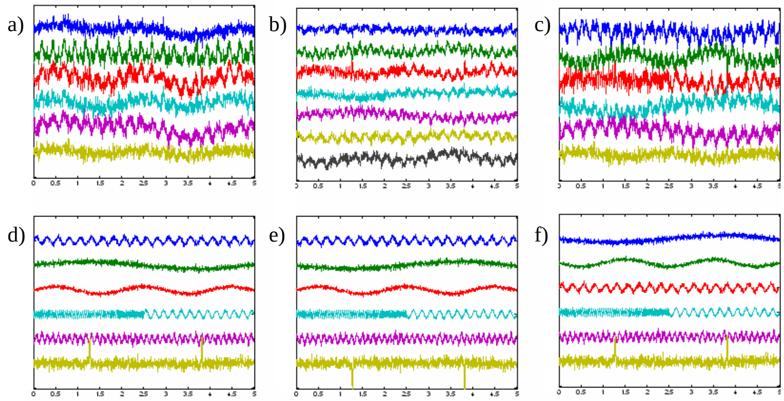

Fig. 2. a) Simulated noisy (white Gaussian) CRM. b) Simulated noisy ARM. c) Simulated noisy BLM. d) Source Separation for CRM, SNR = 10 dB. e) Source Separation for ARM, SNR = 10 dB. f) Source Separation for BLM, SNR = 10 dB.

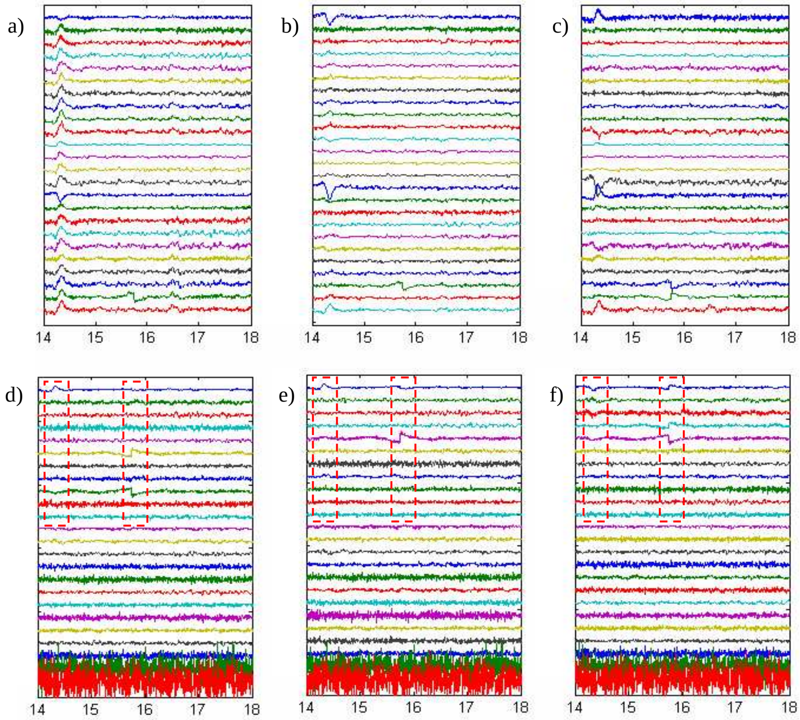

Fig. 3. a) CRM, EEG real signals. b) ARM, implemented from CRM EEG real signals. c) BLM, from CRM EEG real signals. d) Source Separation for CRM. e) Source Separation for ARM. f) Source Separation for BLM.

separation (figures 3.d and 3.f), but correctly separated for the ARM (figure 3.e). Moreover, the number of estimated sources (applying the MDL criterion) is different according to the employed montage. Although not investigated here, this observation supports the conclusion that source separation solutions are highly dependent on the montage.

Consequently, whenever source separation is needed for EEG processing, the role of the montage should be investigated. According to our first results, the ARM should be privileged, but this conclusion needs a more detailed and precise clinical evaluation on real EEG signals.

6. CONCLUSIONS AND FURTHER WORK

The main goal of this communication is to analyse the most employed EEG montages from a source separation point of view. We have shown that, in noisy conditions, the best results are obtained by using the Average Referenced Montage (ARM), who tends asymptotically to the best possible solution (Zero Referenced ZRM). This conclusion, although confirmed on real EEG examples, needs a more precise and detailed validation on real 10-20 acquired signals, as well as on high-density EEGs.

An interesting point, currently under analysis, is the non-cephalic reference acquisition system analysis. This approach will be presented and compared to the cephalic recording system in a future work.

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