

Enhanced Rheoencephalography

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INTRODUCTION

A close monitoring of the cerebrovascular parameters is essential in some neurological diseases to prevent secondary brain insults. Persistent rises in intracranial pressure caused by oedema, tumours, or haematomas may decrease the cerebral blood flow (CBF) to values below the minimum required for neuronal survival (Lang & Chesnut, 1994).

As a method to evaluate CBF, Polzer and Schuhfried proposed in 1950 to apply the well-known impedance plethysmography techniques to the head, which was specifically referred to as Rheoencephalography (REG) (Polzer & Schuhfried, 1950). For this purpose, bipolar and tetrapolar electrode arrangements, named as REG I and REG II respectively, were used to measure the impedance changes of the head synchronized to the heartbeat. In REG I, a low-amplitude current is injected through two electrodes attached to the scalp, and the related electric potential difference is measured between these electrodes, whereas in REG II, a second pair of electrodes is used to measure the electric potential difference (Geddes & Baker, 1989). The latter technique reduces eventual artifacts caused by mechanical alterations in the electrode-skin interface of the current injection electrodes.

The REG signal was assumed to be induced by the time-varying nature of the mixture ratio of two biological conductors with different electrical conductivity: namely, blood and brain. According to this, REG would reflect the changes in cerebral blood volume (CBV) associated with the cardiac cycle (Lifshitz, 1970).

However, despite the great efforts made by the scientific community on REG research during three decades,

the use of REG was not extended to the clinical practice after all, because REG ability to reflect the CBF was strongly questioned (Basano, Ottonello, Nobili, Vitali, Pallavicini, Ricca, Prastaro, Robert, & Rodríguez, 2001; Perez-Borja & Meyer, 1964). Detractors argued that a significant part of the injected current does not cross the skull, since the electrical conductivity of the skull is approximately 80 times lower than that of the scalp and brain. This means that most of the REG signal reflects the pulsatile changes in the scalp blood volume (SBV), rather than in the CBV (Laitinen, 1968). This disagreement, together with the development of the transcranial Doppler ultrasound technology, led to the abandonment of research on REG.

BACKGROUND

A sound review of the literature reveals that research on REG was very intensive during the fifties and sixties, due to the lack of reliable diagnosis tools for the assessment of cerebral blood flow (Hadjiev, 1972). However, modern neuroimaging techniques provide a great amount of information about the brain metabolism for diagnosis purposes. Yet, the idea of a noninvasive, portable, available-at-bedside, and low-cost device for real-time monitoring of the cerebrovascular system still seems attractive and necessary.

Recently, the physical principles of REG have been analyzed from a theoretical perspective for a better understanding of the mechanisms, by which the extra and intracranial blood flows contribute to the REG signal (Perez, Guijarro, & Barcia, 1999; Perez, Guijarro, & Barcia, 2000; Perez, Guijarro, & Barcia,

2004). The main findings of these theoretical studies explain the initial controversy on the origin of the REG signals, and can be summarized as follows: (i) most of the REG I signal is caused by the pulsatility of the extracranial blood flow; (ii) in some subjects, a set of tetrapolar electrode arrangements may exist to record a REG II free of extracranial information; and (iii) such electrode positions, and even their existence, are strongly dependent on the subject's physical constitution, particularly on his/her scalp thickness. In summary, previous theoretical results suggest that there is no universal electrode arrangement suitable for all individuals to register a REG II free of extracranial contamination.

Therefore, a REG II recorded from an arbitrary tetrapolar electrode arrangement contains information from both intra and extracranial blood flows, mixed in unknown proportions that, furthermore, depend on the used electrode arrangement. Attempts have been made in the past to cancel out the extracranial component from the REG signal. For instance, Seipel (1967) proposed a method to identify the contribution to REG by each one of the intra and extracranial arteries that supply the brain and scalp. It consisted in occluding some of the arteries, and then deducing their contribution by means of simple equations. However, this method was experimentally tested by Masucci, Seipel, and Kurtzke (1970), who did find no value for detecting, lateralizing, or diagnosing cerebral injury.

One unexplored way of extracting intracranial information from a REG signal could be to address the problem using the Blind Source Separation (BSS) approach. In BSS, a set of unknown signal sources is guessed from the analysis of a set of observations, each one of which is a mixture in unknown proportions of the sources. The extraction of the sources from the observations is achieved by taking advantage of some assumed property of the sources (Cardoso, 1998).

A practical example of BSS is the so-called cocktail party problem, in which the statistical independence of the sources is assumed, and its solution is reached by using the well-established Independent Component Analysis (ICA). Let us imagine a room where, for instance, three people are talking simultaneously. Three microphones placed in the same room at different sites will record a mixture of the speakers' voices, whose weights will depend on the speakers' distance to the microphones. This information mixture can be expressed as:

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + a_{13}s_3(t) \quad (1)$$

$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) + a_{23}s_3(t) \quad (2)$$

$$x_3(t) = a_{31}s_1(t) + a_{32}s_2(t) + a_{33}s_3(t) \quad (3)$$

where $s_i(t)$ are the speakers' voice signals, $x_i(t)$ the observations, and a_{ij} the mixture coefficients ($i, j = 1, \dots, 3$). Observe that both the mixture coefficients and the sources are unknown in these equations. In this example, it is reasonable to assume the statistical independence of the sources, so ICA can be applied to guess the sources and coefficients. An excellent illustration of the cocktail party problem, and ICA, can be found in Hyvärinen, Karhunen, and Oja (2001).

This mathematical tool could be of great interest in REG since, as commented above, a REG II signal can be regarded as the weighted sum of intra and extracranial information. However, statistical independence cannot be used here to separate the components, since scalp and brain perfusions are caused by the same event: the heart contraction. Therefore, to apply the BSS approach to REG, it is necessary to find a differential property between both components that could be mathematically formulated.

EXTRACTION OF THE INTRACRANIAL COMPONENT FROM THE REG: ENHANCED RHEOENCEPHALOGRAPHY

Mathematical Formulation

Let $R_1(t)$ and $R_2(t)$ be a pair of REG signals recorded simultaneously from a given subject at different electrode arrangements. Assuming the morphological invariability and negligible phase shift of both REG components (Perez, Guijarro, & Sancho, 2005), we can write:

$$R_1(t) = a_{11}C_{En}(t) + a_{12}C_{In}(t) \quad (4)$$

$$R_2(t) = a_{21}C_{En}(t) + a_{22}C_{In}(t) \quad (5)$$

where $C_{En}(t)$ and $C_{In}(t)$ are, respectively, the extra and intracranial components of the recorded REG signals normalized to unit variance (sources), and a_{ij} are the mixture coefficients that depend on the electrode ar-

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