A COLLABORATIVE ADAPTIVE FILTERING APPROACH FOR QUASI-BRAIN-DEATH EEG ANALYSIS

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ABSTRACT

Evaluating the significance differences between the group of comatose patients and the group of brain death is important in the detection of brain death. This paper presents a novel method for the discrimination between discrete states of brain consciousness. Based on a collaborative adaptive filtering architecture using a convex combination of two heterogeneous adaptive filters, the evolution of the mixing parameter can be used as an indicator of the fundamental signal nature of different EEG recordings. Simulations illustrate the suitability of this approach to differentiate between the coma and quasi-brain-death states.

1. INTRODUCTION

The investigation of the information processing mechanisms of the brain, including consciousness states, is an active area of research. When considering consciousness status the identification of brain death is an important topic within such research as there can be severe implications of declaring a patient brain dead - the legal definition of brain death is "irreversible loss of forebrain and brainstem functions" [1]. However, different medical criteria for determining brain death have been established in the different countries [2]. One such diagnostic example is the Takeuchi criterion [3] which involves the subsequent series of tests: coma test, pupil test, brainstem reflexes test, apnea test, and EEG confirmatory test [4]. As can be imagined, with such thorough testing hierachy, it can be difficult to implement brain death diagnosis effectively and timely. Specialized personnel and technology are needed to perform a series of tests which are expensive, time consuming and can put patient at a risk, for example, in apnea tests, medical case instruments should be removed, confirmatory tests can take as long as 30 minutes each and need to be performed several times over intervals of up to ten hours, these tests put stress on already compromised organs [5]. To overcome the above difficulties, preliminary EEG tests have been proposed in [6, 7], to be used to determine whether further brain death tests, especially those requiring patients to be disconnected from important medical devices, need to be implemented, in this way an initial prognosis of quasi-brain-death (QBD) is given. The term "quasi-" means that this is a preliminary decision, because this brain death diagnosis was made at an early stage, judged independently by medical doctors or physicians, whereas the final diagnosis of brain death needs further medical tests (apnea test, EEG confirmatory test).

Recent advance in collaborative adaptive filtering [8] enlightens the possibility for performing online assessment of the fundamental characteristics of a signal. By implementing the collaborative structure with two heterogenous adaptive filters, tracking the adaptive mixing parameter within such a structure is possible to gain an indication of which subfilter within the structure currently has the better performance in term of its estimation error, and hence an hint on signal nature can be obtained by the type of the dominant subfilter, i.e. linearity/nonlinearity, sparsity/nonsparsity [9]. Thus, this technique provides a convenient and flexible method which can test for fundamental signal properties as compared with hypothesis and block-based methods [10, 11]. From the medical viewpoint, such collaborative structure offers real time processing ability and hence reduces the risk to the patient when performing preliminary EEG tests.

In this paper, we propose to use a collaborative adaptive filter in the complex domain to perform preliminary EEG test by discriminating two kinds of brain consciousness states, called coma and QBD respectively. By design, spatially symmetric pairs of EEG electrodes are used to construct complex-valued signals, and such scheme facilitates the use of cross information and simultaneous modelling of the amplitude-phase relationships [12]. To identify the underlying amplitude-phase relationship within different types of EEG signals, we here employ standard CLMS algorithm

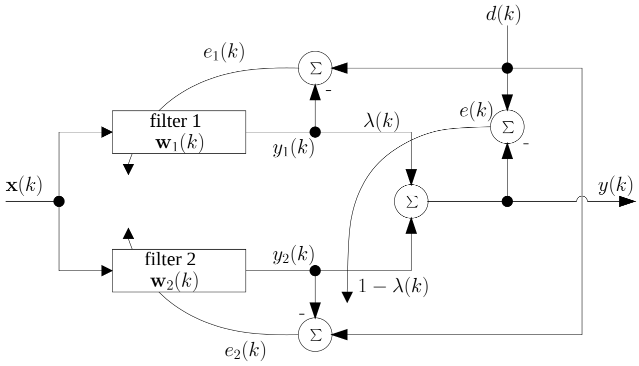

Fig. 1. The structure of convex combination of two subfilters. Each subfilter is adapted using its own cost function, with the mixing parameter $\lambda(k)$ adapted to minimise the overall cost function.

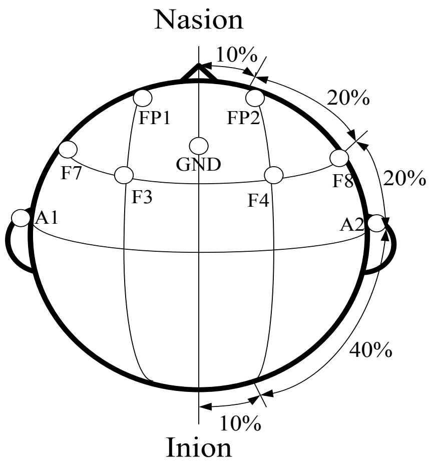

Fig. 2. The Electrode placement.

[13] and recently proposed Least Mean Phase (LMP) algorithm [14] to train the subfilters. Unlike the mean squared error criterion based CLMS algorithm, the LMP algorithm is derived based on least mean square phase error, and hence outperforms CLMS algorithm in the situations where the performance depends primarily on the phase information within the signals [15] or the signal amplitude undergoes very faster variations than that in phase [14]. Via a collaborative adaptive combination of these two subfilters, we will find that the evolution of the mixing parameter illustrate the suitability of this approach to differentiate between the pair-wise coma and QBD states based on their underlying amplitude-phase relationships.

2. COLLABORATIVE FILTERING STRUCTURE

As shown in Fig. 1, the adaptive convex combination scheme obtains the output of the overall filter, given by

$$y(k) = \lambda(k)y_1(k) + \big(1-\lambda(k)\big)y_2(k) \tag{1}$$

where $y_1(k)$ and $y_2(k)$ are the outputs of CLMS and LMP trained adaptive filters respectively, and $\lambda(k)$ is the mixing parameter at time instant k, being kept between 0 and 1. The CLMS algorithm can be described as [13]

$$\begin{aligned} y_1(k) &= \mathbf{x}^T(k)\mathbf{w}_1(k) \\ e_1(k) &= d(k) - y(k) \\ \mathbf{w}_1(k+1) &= \mathbf{w}_1(k) - \mu\nabla_{\mathbf{w}_1}E_1(k) \\ &= \mathbf{w}_1(k) + \mu e(k)\mathbf{x}^*(k) \end{aligned} \tag{2}$$

where $\mathbf{w}_1(k)$ is the $N \times 1$ weight vector of filter coefficients, $\mathbf{x}(k)$ denotes the input vector $[x(k),\ldots,x(k-N+1)]^T$ with the same length, $E_1(k) = \frac{1}{2}|e_1(k)|^2$ is cost function, and μ_1 is the step-size.

The LMP algorithm is derived based on the mean phase error cost function $E_2(k) = \frac{1}{2}e_2^2(k)$, and can be described as[14]

$$\begin{aligned} y_2(k) &= \mathbf{x}^T(k)\mathbf{w}_2(k) \\ e_2(k) &= \angle d(k) - \angle y(k) \\ \mathbf{w}_2(k+1) &= \mathbf{w}_2(k) - \mu_2\nabla_{\mathbf{w}_2}E_2(k) \\ &= \mathbf{w}_2(k) + \frac{\jmath\mu_2 e_2(k)\mathbf{x}^*(k)}{\big(\mathbf{x}^T(k)\mathbf{w}_2(k)\big)^*} \end{aligned} \tag{3}$$

where $\angle(\cdot)$ is the phase operation. A geometric analysis of this algorithm has illustrated that this phase error based cost function can correct the error in phase of the estimated signal by rotating the estimated signal toward the desired signal [14], and hence outperforms CLMS algorithm in the situations where the performance depends primarily on the phase information within the signals.

The mixing parameter $\lambda(k)$ is made adaptive, and is updated by minimising the overall cost function

$$E(k) = \frac{1}{2}|e(k)|^2 = \frac{1}{2}|d(k)-y(k)|^2 \tag{4}$$

The update can be obtained by using the following gradient decent adaptation

$$\lambda(k+1) = \lambda(k) - \mu_\lambda\nabla_\lambda E(k) \tag{5}$$

where μ_λ is a small positive constant. The gradient of the overall cost function with respect to $\lambda(k)$ is given by

$$\nabla_\lambda E(k) = \frac{1}{2}\big(e(k)\frac{\partial e^*(k)}{\partial\lambda(k)} + e^*(k)\frac{\partial e(k)}{\partial\lambda(k)}\big) \tag{6}$$

The two gradient terms from 6 can be evaluated as

$$\begin{aligned} \frac{\partial e(k)}{\partial\lambda(k)} &= \frac{\partial e_r(k)}{\partial\lambda(k)} + \jmath\frac{\partial e_i(k)}{\partial\lambda(k)} \\ \frac{\partial e^*(k)}{\partial\lambda(k)} &= \frac{\partial e_r(k)}{\partial\lambda(k)} - \jmath\frac{\partial e_i(k)}{\partial\lambda(k)} \end{aligned} \tag{7}$$

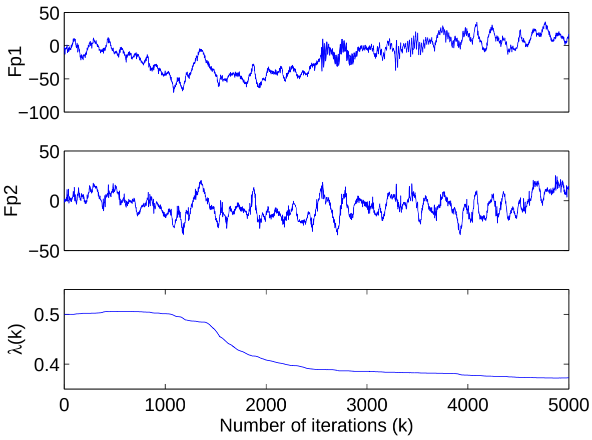

Fig. 3. Two channel recordings of a coma patient and the evolution of the corresponding mixing parameter $\lambda(k)$.

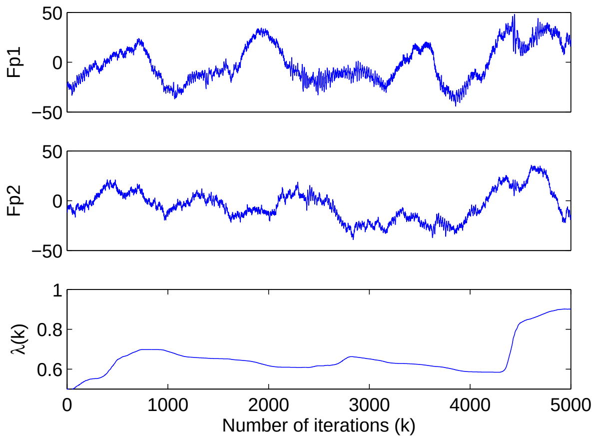

Fig. 4. Two channel recordings of a QBD patient and the evolution of the corresponding mixing parameter $\lambda(k)$.

where $(\cdot)_r$ and $(\cdot)_i$ denote respectively the real and imaginary part of a complex-valued number. Rewriting (1) in terms of its real and imaginary parts and substituting into (4) yields

$$\frac{\partial e(k)}{\partial \lambda(k)} = y_1(k) - y_2(k) \text{ and } \frac{\partial e^*(k)}{\partial \lambda(k)} = (y_1(k) - y_2(k))^* \tag{8}$$

Finally, the gradient becomes

$$\nabla_\lambda E(k) = \Re\big(e(k)(y_1(k) - y_2(k))^*\big) \tag{9}$$

where $\Re(\cdot)$ denotes the real part of a complex number. This yields the mixing parameter update as

$$\lambda(k+1) = \lambda(k) + \mu_\lambda \Re\big(e(k)(y_1(k) - y_2(k))^*\big) \tag{10}$$

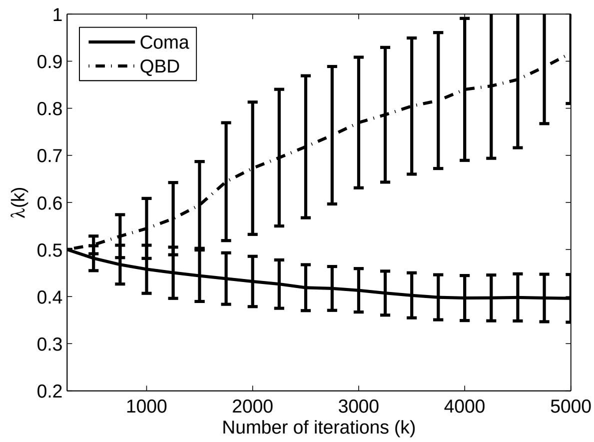

Fig. 5. The average evolution of the mixing parameter $\lambda(k)$ with corresponding standard deviation error bars for 17 coma patient and 17 QBD patients.

3. THE EEG DATA

The patient's brain activity was directly recorded at the bedside with a portable EEG system (NEUROSCAN ESI) in the intensive care unit (ICU) in Shanghai Huashan Hospital affiliated to Fudan University China. In the experiment, nine electrodes were chosen to apply to patients. Among these electrodes, six exploring electrodes (F3, F4, F7, F8, Fp1, Fp2) as well as GND were placed on the forehead, whereas two electrodes (A1, A2) as the reference were placed on the earlobes, as shown in Fig. 2. The measured voltage signal was digitized with a sampling rate 1 kHz and the resistances of the electrodes were set to be less than 8 kΩ. Experimental data was obtained from 34 patients of ages ranging from 17 to 85 years old; half of the patients were in a state of coma, and the other half had already been assessed to be in quasi-brain-death status by clinical doctors. Due to the fact that the strongest voltage signals are normally obtained from forehead area, we focus our research on signals extracted from pairing spatially symmetric electrodes Fp1 and Fp2, furthermore, a complex-valued EEG signal representation is constructed as Fp1+$\jmath$Fp2 to facilitate the use of cross information and simultaneous modelling of the amplitude-phase relationships [12].

4. SIMULATIONS

To illustrate the robustness of the proposed collaborative filtering structure for brain consciousness state discrimination, simulations were conducted on the pre-defined coma and QBD EEG signals in one step-ahead prediction setting. The filter length N of both subfilters was 10 with the step-size $\mu_\lambda = 0.001$, and the initial value of $\lambda(0) = 0.5$ for a fair initialisation of both subfilters.

Fig. 3 shows the amplitudes of the pair-wise EEG signals recorded from Fp1 and Fp2 for a typical coma patient with a time window lasting for 5 seconds, and the evolution of the corresponding mixing parameter $\lambda(k)$ is shown in the bottom graph. It can be seen that the value of $\lambda(k)$ for this coma patient decreased below 0.5 and converged at 0.37 in the end, indicating that the subfilter 2, trained based on mean squared phase error, achieved more accurate estimation performance than that of its counterpart based on standard mean squared amplitude error, and hence more weight was adaptively given to the subfilter 2. As contrast, the amplitudes of the EEG signals recorded from Fp1 and Fp2 for a QBD patient were illustrated in the top and middle graphes in Fig. 4, although the amplitudes of this QBD EEG signals were in a very similar range as that of coma EEG signals shown in Fig. 4, the recordings contained more obvious small amplitude but fast oscillations, resulting in a noise-like phase information and consequently a worse performance of LMP based subfilter 2 than that of CLMS based subfilter 1, and the evolution of the corresponding mixing parameter $\lambda(k)$ increased gradually as the adaptation progressed. This phenomenon happened in all QBD patients we investigated. In order to have a general knowledge of the all available EEG data, the average values of mixing parameter $\lambda(k)$ for coma and QBD patients respectively, together with standard deviations calculated per 250 samples (0.25 second), were shown in Fig. 5. It can been seen that the average response of $\lambda(k)$ for QBD signals illustrated a predominant weight of amplitude based CLMS algorithm contributed to the overall collaborative adaptive filter, whereas in case of coma EEG signals, LMP, the phase error based estimation algorithm, contribute more to the overall performance, consequently, a clear discrimination between coma and QBD signals cna be obtained by the opposite trends in the evolution of $\lambda(k)$ in both cases.

5. CONCLUSION

In this paper, an online method for the EEG-based preliminary examination in the process of clinical diagnosis for brain death has been proposed. This is achieved by using the collaborative adaptive filter, which composes of both magnitude-based and phase-based adaptive filters and by a convenient representation in the complex domain of pair-wise EEG signals recorded from spatially symmetric electrodes. According to different underlying amplitude-phase relationships within coma and QBD states, the evolution of the mixing parameter can be used as an indicate to discriminate them.

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