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Modelling of Brain Consciousness based on Collaborative Adaptive Filters

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Abstract. A novel method for the discrimination between discrete states of brain consciousness is proposed. This is achieved by examining nonlinear features within the electroencephalogram (EEG). To allow for real time mode of operation, a convex combination of a linear and nonlinear filter is used within a collaborative adaptive filtering architecture. The evolution of the mixing parameter within this structure is then used to indicate the predominantly linear or nonlinear nature of the EEG. 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 mechanism of the brain, especially consciousness states, is an active area of research. One important topic is the identification of brain death - the legal definition of brain death is 'irreversible loss of forebrain and brainstem functions' [1], however, it is very difficult to implement brain death diagnosis effectively. Specialized personnel and technology are needed to perform a series of tests which are expensive and time consuming and can put patient at a risk.

Some of the brain death tests require that medical care instruments be removed, further still, some tests require that the patient be transported out of the intensive care unit (ICU). Other, confirmatory tests, need to be performed several times with intervals of up to ten hours and can take as long as 30 minutes each. Although the diagnostic criteria are different from country to country, these tests can put the patient at potential medical risk due to the requirements of implementing tests. The tests also put stress on the already compromised organ [2]. To overcome the above difficulties, a preliminary EEG test has been proposed [3] to determine whether further brain death tests, especially those requiring patients to be disconnected from important medical devices, need to be implemented or not. From this test an initial prognosis of quasi-brain-death (QBD) is given. The term "quasi-" means that this is a preliminary decision, the final diagnosis of brain death needs further medical tests.

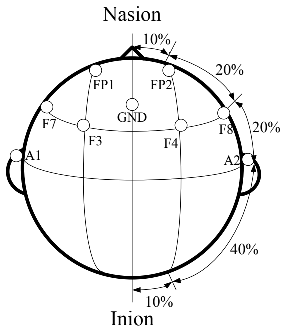

Fig. 1. The Electrode placement.

There are various methods used for studying brain states using EEG signals [4, 5]. These methods use tools like phase synchrony [6, 7], coherence [8] and nonlinear dynamical analysis [9, 10]. There is conclusive evidence [11] that tracking the dynamics of nonlinear characteristics in signals can provide a platform for analyzing EEG signals.

In [10, 11], it is argued that the assessment of the nonlinear nature in EEG signals can provide a platform for the identification of the brain consciousness states. One method for performing the assessment of EEG signals is by tracking the mixing parameter of collaborative adaptive filters. Such filters offer real time processing ability and hence reduce the risk to the patient when performing QBD tests. In addition, unlike the hypothesis testing based methods [10], which are block-based, such as the Delay Vector Variance (DVV) [12], this approach also performs testing for the degree of nonlinearity in nonstationary environments. The linear and nonlinear filter within this structure operate in parallel, producing parameterized feature maps. Thus, providing a convenient, flexible method which can, for instance, simultaneously test for several fundamental signal properties, such as the degree and type of nonlinearity (NARMA, bilinear) and sparsity [13].

In this work, we focus on the role of the degree of nonlinearity in the identification of states of brain consciousness (awake, coma, QBD). The usefulness of this approach is first evaluated on synthetic benchmark linear and nonlinear signals. It is then illustrated that such an approach can discriminate between the awake, coma and quasi-brain-death states based on real world EEG signals.

2 The EEG data

The EEG data were recorded in the ICU in HuaShan Hospital, Shanghai, China. The room was quiet, but the surrounding noise generated by other monitoring machines was high. The standardized 10-20 system was used for the EEG recording, the patients involved were all lying on bed facing up with eyes closed, and the data was obtained via nine electrodes on the forehead with channels based on the 10-20 system. That is, the electrodes were placed at positions F3, F4, F7, F8,

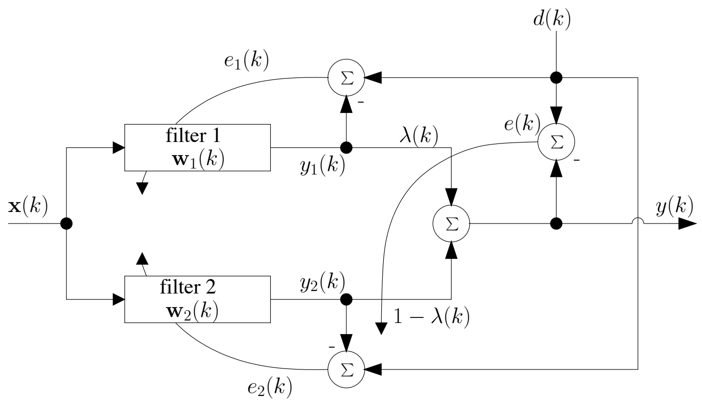

Fig. 2. Collaborative combination of two adaptive subfilters.

Fp1, Fp2 as well as GND, and also two were placed on the ears (denoted by A1 and A2 respectively). The electrodes placed on the ears act as a reference for the measurements, calculated as (A1+A2)/2. The measured voltage signal was then digitized via a portable EEG recording instrument with a sampling frequency of 1000 Hz. The position of the electrodes can be seen on Fig. 1. Experimental data were obtained from 34 patients of the ages ranging from 17 to 85 years old; 17 of the patients were in a state of coma, 17 of them were in quasi-brain-death status. A total recording of EEG signal from these 34 patients with an average signal length of five minutes were stored and analyzed.

3 The Hybrid Filtering Architecture

The convex combination of two adaptive subfilters refers to an architecture, in which both subfilters operate in parallel and feed into a mixing algorithm which produces the single output of the filter [14]. The mixing parameter $\lambda(k)$ adaptively combines the outputs of each subfilter to minimize the instantaneous square error of the overall filter, as shown in Fig. 2. Originally, the applications of hybrid filters focused mainly on the improvement in the performance over the individual constituent filters. However, recent research has shown that by appropriately selecting the subfilters, the evolution of the mixing parameter $\lambda(k)$ can give an instantaneous indication of some fundamental properties of the input signal, such as nonlinearity and sparsity [11, 13].

As our aim is to discriminate between brain states based on the nonlinearity within the EEG, the collaborative filter compromises a linear FIR adaptive subfilter trained by the least mean square (LMS) algorithm [15] and a nonlinear FIR subfilter trained by the normalized nonlinear gradient descent (NNGD) algorithm [16]. In this case, we are not interested in the overall performance of the filter but in whether the dynamics of the mixing parameter $\lambda(k)$ can give an illustration of which subfilter is responding to the modality of the input signal most effectively.

The output of subfilter 1 trained by the LMS algorithm is generated as

$$
\begin{aligned}
y_{LMS}(k) &= \mathbf{x}^T(k)\mathbf{w}_{LMS}(k) \\
e_{LMS}(k) &= d(k) - y_{LMS}(k) \\
\mathbf{w}_{LMS}(k+1) &= \mathbf{w}_{LMS}(k) + \mu e_{LMS}(k)\mathbf{x}(k)
\end{aligned} \tag{1}
$$

and $y_{NNGD}(k)$ is the corresponding output of the NNGD trained subfilter 2 and is given by

$$
\begin{aligned}
net(k) &= \mathbf{x}^T(k)\mathbf{w}_{NNGD}(k) \\
y_{NNGD}(k) &= \Phi(net(k)) \\
e_{NNGD}(k) &= d(k) - y_{NNGD}(k) \\
\mathbf{w}_{NNGD}(k+1) &= \mathbf{w}_{NNGD}(k) \\
&\quad + \eta(k)e_{NNGD}(k)\Phi^{'}(net(k))\mathbf{x}(k) \\
\eta(k) &= \frac{\mu}{[(\Phi'(net(k)))^2||\mathbf{x}(k)||_2^2] + C}
\end{aligned} \tag{2}
$$

where $d(k)$ is the desired output, $\mathbf{x}(k) = [x_1(k-1), x_2(k-2), ..., x_N(k-N)]^T$ is the tap input vector, $\Phi(\cdot)$ is the nonlinear activation function, C is the regularization parameter and μ is the step-size for both algorithms. Each subfilter is adapted based on their own errors $e_{LMS}(k)$ and $e_{NNGD}(k)$ respectively to give the individual weight updates $\mathbf{w}_{LMS}(k)$ and $\mathbf{w}_{NNGD}(k)$.

The overall filter output $y(k)$ is the convex combination of the outputs of the subfilters and is given by

$$
y(k) = \lambda(k)y_{LMS}(k) + (1 - \lambda(k))y_{NNGD}(k) \tag{3}
$$

where $\lambda(k)$ is updated based on minimization of the quadratic cost function $E(k) = \frac{1}{2}e^2(k)$, where $e(k)$ denotes the overall filter error. Using the following gradient descent adaptation

$$
\lambda(k+1) = \lambda(k) - \mu_\lambda \nabla_\lambda E(k)_{|\lambda=\lambda(k)} \tag{4}
$$

where μ_λ is the adaptation step-size, the update of $\lambda(k)$ can be obtained as [13]

$$
\begin{aligned}
\lambda(k+1) &= \lambda(k) - \frac{\mu_\lambda}{2}\frac{\partial e^2(k)}{\partial \lambda(k)} \\
&= \lambda(k) + \mu_\lambda e(k)(y_{LMS}(k) - y_{NNGD}(k))
\end{aligned} \tag{5}
$$

To illustrate the effectiveness of the hybrid filter in tracking signal nonlinearity synthetic inputs were formed by alternating nonlinear and linear signals every 1000 samples. This gives the benchmark signal of 10000 samples in length comprising the nonlinear signal [17]

$$
z(k+1) = \frac{z(k)}{1 + z^2(k)} + n^3(k) \tag{6}
$$

and stable linear AR(4) process

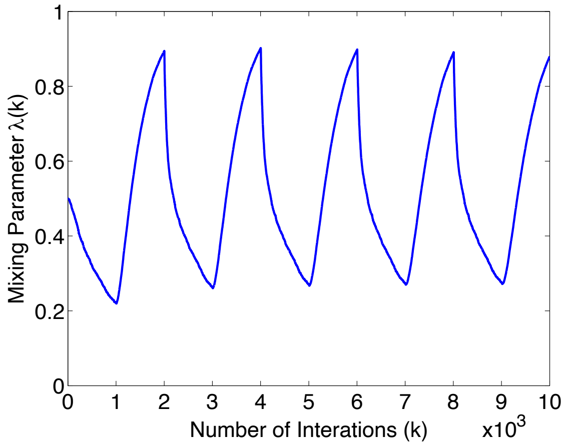

Fig. 3. The evolution of the mixing parameter $\lambda(k)$ for a signal nature alternating between nonlinear to linear.

$$\begin{aligned} r(k) = {} & 1.79r(k-1) - 1.85r(k-2) + 1.27r(k-3) \\ & - 0.41r(k-4) + n(k) \end{aligned} \tag{7}$$

where $n(k)$ is a zero mean, unit variance white Gaussian process.

In all the simulation, the filter length was $N = 10$. By design, the value of $\lambda(k)$ varies between 0 and 1, with 1 indicating strong linearity in signal nature and 0 a strong nonlinearity. The initial value of mixing parameter $\lambda(k)$ was set to 0.5, as there was no prior assumption of the signal linearity or nonlinearity.

The simulation result shown in Fig. 3 presents the evolution of the mixing parameter $\lambda(k)$ on the prediction of such a synthetic signal. As desired, the value of $\lambda(k)$ decreases towards 0.3 in the first 1000 samples, which correctly suggests the nonlinear nature of the signal described by (6). In contrast, for the linear process (sample 1000 to sample 2000), $\lambda(k)$ increased towards 0.9 indicating the linear nature of the benchmark input signal described in (7). This suggests that the hybrid filter has great potential for tracking the linearity and nonlinearity characteristics of real world signals.

4 Simulation results

We will now consider the use of hybrid filters for application on real world EEG signal for the purpose of brain consciousness identification. The step size used for the adaptation of λ was 0.01 and the initial value of $\lambda(0) = 0.5$. The learning rate of the linear FIR adaptive subfilter was 0.002. The learning rate for the nonlinear FIR subfilter trained by NNGD algorithm was 0.01. Results shown in Fig. 4, Fig. 5 and Fig. 6 present the typical EEG signals for the states of 'awake', 'coma' and 'quasi-brain-death', and the corresponding evolution of the mixing parameter $\lambda(k)$ for different brain consciousness states.

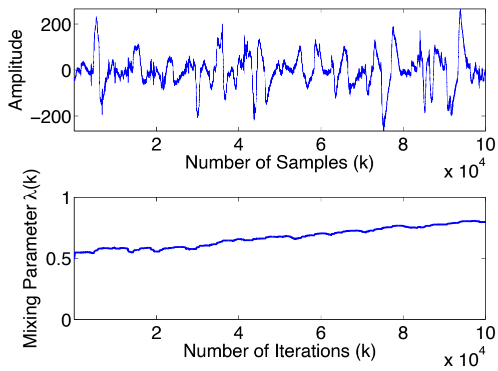

Fig. 4. Typical awake signal (top) and the dynamics of the mixing parameter $\lambda(k)$ of awake patient (bottom).

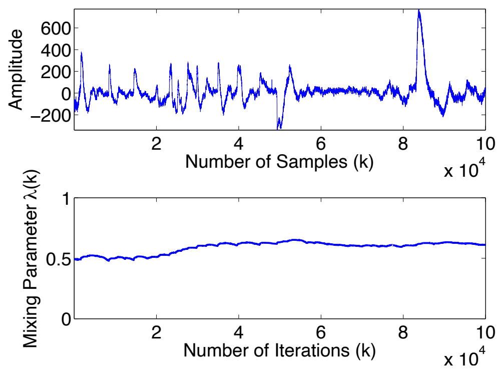

Fig. 5. Typical coma signal (top) and the dynamics of the mixing parameter $\lambda(k)$ of coma patient (bottom).

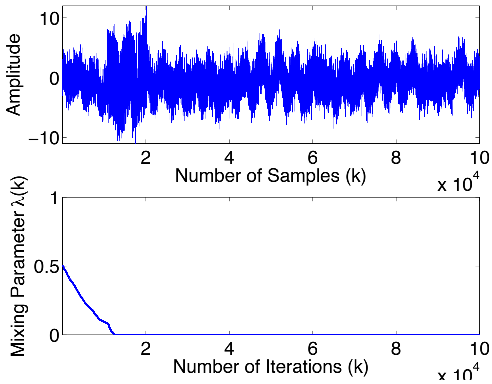

Fig. 6. Typical quasi-brain-death signal (top) and the dynamics of the mixing parameter $\lambda(k)$ of quasi-brain-death patient (bottom).

Fig. 4 shows the EEG data of a patient in an 'awake' state. The top plot presents the amplitude of the brain signal over 100 seconds. 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 the awake EEG data moves towards $\lambda = 1$ as the adaptation progresses. This suggest the linearity of the EEG signals of awake patients. Fig. 5 presents the EEG signal of a 'coma' patient; the curve of $\lambda(k)$ suggest no clear indication of signal nonlinearity. During the analysis of quasi-brain-death signals of the same time length (100 seconds), the mixing parameter $\lambda(k)$ moved towards zero, indicating the nonlinear nature of the signal.

Results in Fig. 7, Fig. 8 and Fig. 9 show the average mixing parameter $\lambda(k)$ with the standard deviation of 34, 32 and 30 patients. The results of coma patients were shown in black. The QBD analysis results were shown in grey. The errorbars were shown every 2000 iterations. It can be seen from all three figures that the average response of $\lambda(k)$ for 'quasi-brain-death' patients shows the nonlinearity characteristics of the underlying signals. However we can conclude that, on the average, for the coma patient, the results were not decisive with the value of $\lambda(k)$ around 0.5. The data were quite noisy and subject to artifacts. Thus for instance when we use all the available data, the mean curves representing the evolution of the mixing parameter λ are quite far apart, however the error bars overlap considerably, even after convergence. If we, however, include only the pair of 15 least noisy recordings, the results are excellent, as shown in Fig. 9, where perfect identification of the brain death and coma patient is achieved after convergence.

Further still, the classification method of Support Vector Machine (SVM) was applied using a Gaussian kernel to evaluate the effectiveness of the analysis. The classification accuracy and the standard deviation were envaluated on the average of 100 trials. The classification accuracy of 34, 32 and 30 patients as shown in Fig. 10 was 77.8333, 73.75 and 68.5385. Classification results can be

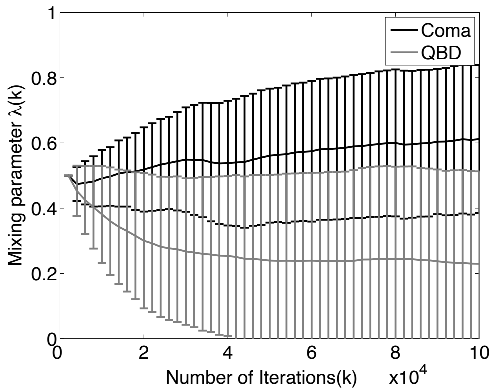

Fig. 7. The average mixing parameter $\lambda(k)$ of patients in different brain states with standard deviation - 17 coma patients, 17 QBD patients.

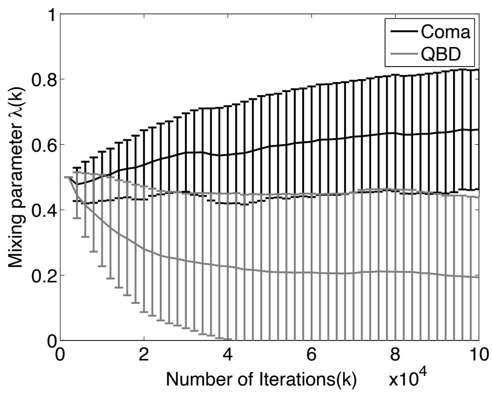

Fig. 8. The average mixing parameter $\lambda(k)$ of patients in different brain states with standard deviation - 16 coma patients, 16 QBD patients.

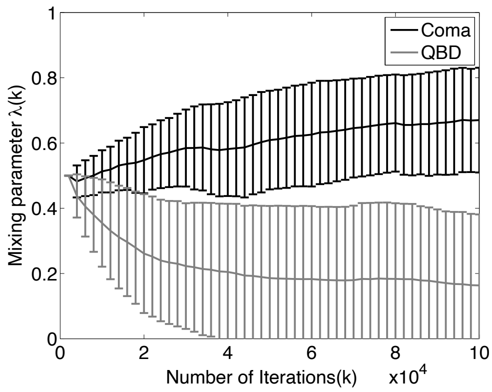

Fig. 9. The average mixing parameter $\lambda(k)$ of patients in different brain states with standard deviation - 15 coma patients, 15 QBD patients.

increased if applying SVM to the converged values of λ. However, the results shown in Fig. 10 obtained over the whole evolution of the mixing parameter λ takes the convergence into consideration. Classification results further proved that analyzing the the signal linearity using mixing parameter $\lambda(k)$ is an effective approach to identify the coma and QBD brain status.

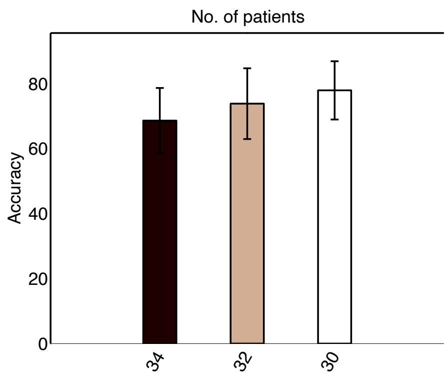

Fig. 10. The accuracy of learning using SVM.

5 Conclusion

We have proposed the nonlinearity analysis of EEG signals as a potential tool for brain states identification and illustrated how the hybrid filter can be used for this purpose. By monitoring the evolution of the mixing parameter within a hybrid filter, it has been possible to gain insight into the fundamental signal nature. Simulation results show great potential of the methodology and its application in signal nonlinearity tracking, thus providing a feature to determine brain activities.

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