Towards Online Monitoring of the Changes in Signal Modality: The Degree of Sparsity

By Beth Jelfs & Danilo Mandic

Imperial College London, UK

Abstract

A novel method for online analysis of the changes in signal modality is proposed. This is achieved by tracking the dynamics of the mixing parameter within a hybrid filter rather than the actual filter performance. Implementations of the proposed hybrid filter using a combination of sparse and nonsparse algorithms are analysed highlighting the potential of such a scheme for tracking signal sparsity. Simulations in a prediction setting support the analysis and biological applications of the approach have been illustrated on EEG data of epileptic patients.

1. Introduction

Signal modality characterisation is becoming an increasingly important area of multi-disciplinary research and large effort has been put into devising efficient algorithms for this purpose. The principle is that the changes in the signal nature between sparse and nonsparse, linear and nonlinear, and deterministic and stochastic can reveal information (knowledge) which is critical in certain applications (e.g. health conditions). The existing algorithms in this area are based on hypothesis testing and describe the changes in signal modality in a statistical manner, Schreiber & Schmitz (1997), Gautama *et al.* (2004), Gautama *et al.*(2003). However, there are very few online algorithms which are suitable for this purpose. The purpose of the new approach described is to show the possibility of an online algorithm which can be used not only to identify the nature of the signal, but also to track changes in the modality of the signal. Our focus is on the detection of changes in the sparseness within the signal.

This proposed approach develops on the tracking capabilities of adaptive filters by using their convex combinations to produce a single hybrid filter. Hybrid filters consist of multiple individual adaptive subfilters operating in parallel and all feeding into a mixing algorithm which produces the single output of the filter. This mixing algorithm is also adaptive and combines the outputs of the subfilters based on their current performance on the input signal. Previous applications of hybrid filters have focused mainly on the improved performance they can offer over the individual constituent filters. However one effect of this mixing algorithm is that it can give an indication of which filter is currently responding to the input signal most effectively. Therefore by selecting algorithms which are suitable for either sparse, Martin *et al.* (2002), Duttweiler (2000) or nonsparse signals, it is possible to cause this mixing algorithm to adapt according to fundamental properties of the input signal.

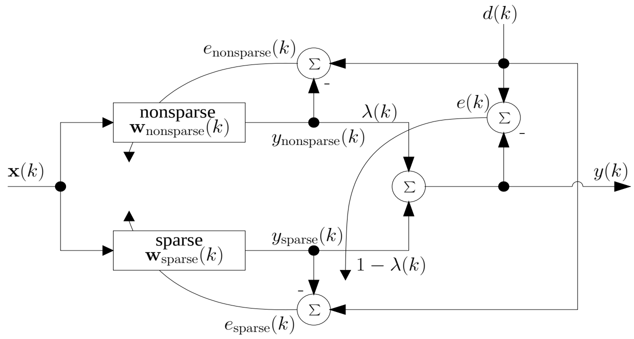

FIGURE 1. Convex combination of adaptive filters

2. Hybrid Filter

A simple form of mixing algorithm for two adaptive filters is a convex combination. Convexity can be described as, Cichocki & Unbehauen (1993)

$$\lambda x + (1 - \lambda) y \text{ where } \lambda \in [0, 1]$$

and x and y are two points on a line, the resultant of this will lie on the same line between x and y. By observing the mixing parameter λ and which of the subfilters is dominating, conclusions can then be drawn about the nature of the input signal.

The output of the hybrid filter from Fig. 1 $y(k)$ is an adaptive convex combination of the output of the sparse subfilter y_{sparse} and the output of the nonsparse subfilter $y_{nonsparse}$ and is given by

$$y(k) = \lambda(k) y_{nonsparse}(k) + (1 - \lambda(k))\, y_{sparse}(k)$$

To preserve the inherent characteristics of the subfilters, which are the basis of our approach, the constituent subfilters are each updated by their own errors $e_{nonsparse}(k)$ and $e_{sparse}(k)$, whereas the parameter λ is updated based on the overall error $e(k)$. The convex mixing parameter $\lambda(k)$ is updated using the following gradient adaptation

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

where μ_λ is the adaptation step-size. The λ update can be shown to be

$$\lambda(k+1) = \lambda(k) - \frac{\mu_\lambda}{2} \frac{\partial e^2(k)}{\partial \lambda(k)} = \lambda(k) + \mu_\lambda e(k)(y_{nonsparse}(k) - y_{sparse}(k))$$

3. Simulations

Initial simulations were performed in a prediction setting on a signal composed of alternating blocks coming from a sparse and nonsparse distribution, these were used to compare the performance of a number of different combinations of algorithms. For the nonsparse filter the normalised least-mean-square (NLMS) algorithm was found to be a better choice than the LMS due to its faster convergence speeds allowing it to adapt quickly to changes in the input signal. For the sparse filter the proportionate NLMS (PNLMS) Duttweiler (2000) and the signed sparse LMS (SSLMS) Martin *et al.* (2002) were compared.

Whilst it was found that it was fairly straightforward to detect the changes in modality, it was not always possible to detect the direction of the changes, whether from sparse to nonsparse or vice versa, or the degree of the change. Figure 2 shows the hybrid filter

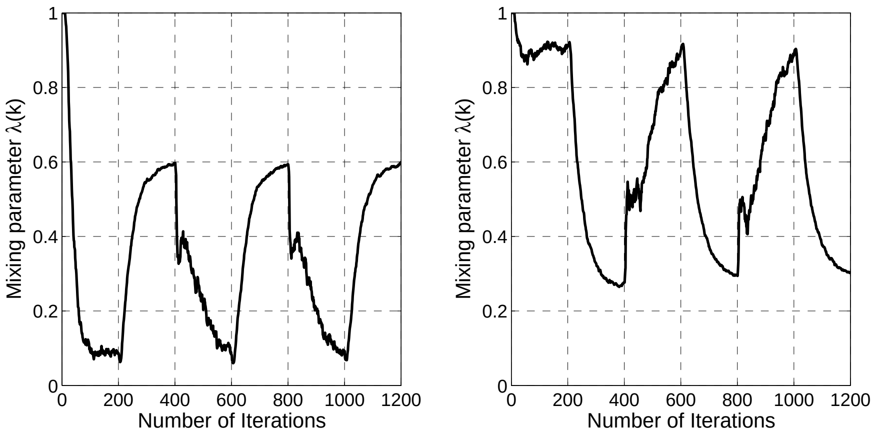

FIGURE 2. Mixing parameter λ for input nature alternating from sparse to nonsparse for different parameter settings of the PNLMS & NLMS algorithms

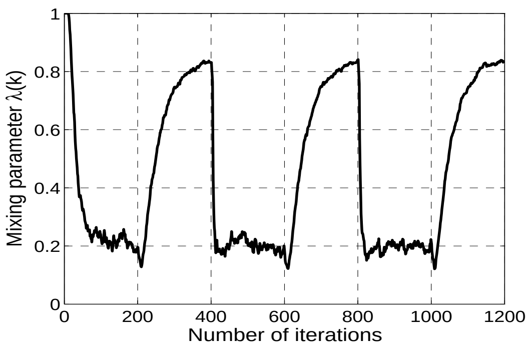

FIGURE 3. Mixing parameter λ for hybrid filter using NLMS & SSLMS with input signal altering every 200 samples

consisting of the NLMS and PNLMS for the same input signal, it can clearly be seen that whilst both plots accurately show the occurrence of the changes in the input signal, the direction of the change is inconclusive as it depends on the settings of the constituent subfilters. This is also attributed to the nature of the PNLMS and its similarities with the NLMS leading to its ability to deal equally well with the nonsparse signal.

In an attempt to overcome these limitations, the simulations were repeated replacing the PNLMS with the SSLMS. The SSLMS proved in this case to be better suited to the task and no matter what the initial parameter settings of the subfilters, the outcome always showed the changes in the signal nature to be in the same direction. Figure 3 shows the output of the hybrid filter consisting of the NLMS and the SSLMS for the alternating signal.

Finally, to examine the usefulness of the proposed approach for the processing of real world signals a set of EEG signals has been analysed. Following the standard practice, the EEG sensor signals were averaged across all the channels and any trends in the data were removed. Figure 4 shows the response of λ when applied to two different sets of EEG data from epileptic patients, both showing the onset of a seizure. These results show that the proposed approach can effectively detect changes in the nature of the EEG signals which can be very difficult to achieve otherwise.

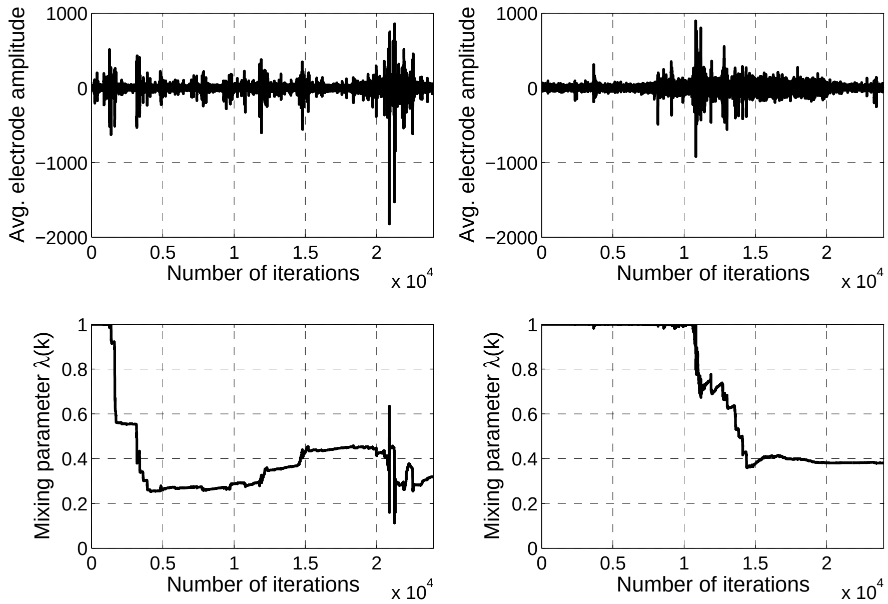

FIGURE 4. EEG signals for two patients showing epileptic seizures and corresponding λ

4. Conclusions

We have proposed a novel approach to identify changes in the modality of a signal, which is achieved by a convex combination of two adaptive filters. By training the two filters with different algorithms it is possible to exploit the different performance capabilities of each and the evolution of the adaptive convex mixing parameter λ, helps determine which filter is more suited to the current input signal dynamics, and thereby gain information about the nature of the signal. Comparison of different sparse and nonsparse filters has been carried out, indicating that the normalised least-mean-square (NLMS) and the signed sparse LMS (SSLMS) algorithms are particularly well suited to perform this task. The analysis and simulations illustrate that there is significant potential for the use of this method for online tracking of some fundamental properties of the input signal.

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