A METHOD FOR THE BLIND SEPARATION OF SOURCES FOR USE AS THE FIRST STAGE OF A NEONATAL SEIZURE DETECTION SYSTEM

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ABSTRACT

A method is proposed for automatically choosing independent components (ICs) of interest from neonatal EEG data, with the aim of using them in further analysis to detect seizures. This procedure greatly reduces the amount of information which needs to be processed in the seizure detection system, and reduces the effect of noise and artefacts on its performance. The Fast ICA algorithm is used to generate the ICs, and the complexity of each IC is examined to determine those of interest. The Singular Value Fraction (SVF) measure is used to reduce the number of sources containing artefacts chosen. In the best case, the 12 channel EEG used in these tests is reduced to 2 or 3 sources of interest. In every case, at least 3 sources were removed that consisted of noise.

1. INTRODUCTION

Although systems for the detection of epileptic seizures in adults have been designed with varying degrees of success, detection of the neonatal seizure is a far more complex operation. Because of the ongoing development of the brain at this age, seizure activity in neonates displays far more complex characteristics than in adults. Much of the analysis of neonatal seizures to date has concentrated on single-channel analysis [1, 2]. However, it is clear from the methodology which EEG experts use to classify neonatal EEG that a reliable neonatal seizure detection system will have to incorporate multi-channel analysis.

As a first stage to such a system it would be useful to reduce the amount of information which needs to be examined in depth, and concentrate analysis on data where some deviation from normal activity is evident. The EEG being examined is recorded at 200Hz in 12 channels, resulting in 2400 samples per second. With the availability of so much data, the computational load associated with the real-time application of detection algorithms becomes excessive leading to hardware solutions which are larger, more complicated and hence expensive. If elements of interest could be extracted from the EEG and analysed without having to analyse background EEG activity, it would greatly decrease the computational burden and simplify the seizure detection process.

Independent Component Analysis (ICA) is a technique for separating an observed set of signals into a set of statistically independent source signals, or independent components (ICs). Using this technique background activity, artefacts and seizure activity can be separated into different ICs. However, the major disadvantage with ICA is that the resulting ICs are not ordered in any way, and hence a method is needed to extract the ICs of interest at the output.

In this paper, it is proposed to use a combination of the complexity measure (Ω) developed by Roberts et al. [3] and the Singular Value Fraction (SVF) measure proposed by Kember and Fowler [4] to determine the ICs of interest.

2. METHODS

2.1. Independent component analysis

The ICA separation process is carried out without prior knowledge of the distribution of the sources, and is hence denoted Blind Source Separation (BSS). ICA can be seen as an evolution of Principle Component Analysis (PCA). However, ICA uses higher order statistics than PCA, and can find independent sources in cases where PCA fails.

There are many implementations of ICA techniques. In this paper the FastICA algorithm [5] is used. This approach is well documented and used widely in this field of research. It is straightforward to implement, fast and efficient.

The main disadvantage to ICA is that, unlike PCA, the output ICs are not ordered in any context. Hence they must be examined further to extract the source(s) required by the application. One method used to extract particular ICs is to use a reference signal which mimics the shape and timing of the desired source. This approach is known as Constrained ICA (cICA), and is used in artefact removal algorithms [6]. However, as the first stage of a proposed seizure detection system for neonates, it is only necessary to isolate

ICs that show evidence of activity, seizure or artefact, which will then be passed on for further tests. Also, using reference signals to remove artefacts may inadvertently remove neonatal seizure activity as some of the reference signals may be highly correlated with seizure sources as well as artefact sources.

2.2. Embedding space decomposition

To examine the ICs Takens method [7] is first utilised to perform an embedding space decomposition. M data points are selected from the IC and a trajectory matrix X_{traj} of dimension $d_E \times N$ is then constructed, where d_E is the embedding dimension and $N = M - d_E + 1$.

The rows of the trajectory matrix are made up of embedding vectors constructed by

$$X_i = [x_{i-(d_E-1)\Delta}, x_{i-(d_E-2)\Delta} \dots x_i]^T (d_E \leq i \leq M) \tag{1}$$

where Δ is the lag measured in number of data points. Δ and d_E are chosen using a plot of Δ versus the Singular Value Fraction [4]. From analysis of these plots over a set of neonatal EEG it was calculated that $\Delta = 1$ and $d_E = 20$ are sufficient.

The trajectory matrix is then composed by

$$X_{traj} = [X_{d_E}, X_{d_E+1} \dots X_M]^T \tag{2}$$

2.3. Complexity analysis

Performing singular value decomposition (SVD) on the trajectory matrix X_{traj} the singular values $\sigma_1 \dots \sigma_N$ can be found. Using the methods of Roberts et al. [3] the entropy of the singular spectrum is defined by first normalising the singular values such that

$$\bar{\sigma}_j = \sigma_j / \sum_i \sigma_i \tag{3}$$

for $j = 1 \dots N$, and then defining the entropy

$$H = -\sum_{i=1}^{N} \bar{\sigma}_i \log \bar{\sigma}_i \tag{4}$$

The complexity of the data in each IC is measured by the number of states Ω and is defined as

$$\Omega = 2^H \tag{5}$$

From previous work in the area of analysis of epileptic seizures in adults [8] it was shown that at epileptic seizure onset the number of states Ω generally decreased in ICs containing seizure activity, although no automatic means of extracting the ICs containing seizure activity has been developed. Therefore in this analysis Ω will be used to search for the ICs of interest.

2.4. Singular value fraction

Although the work carried out in complexity analysis shows that Ω drops at seizure onset, it is clear that it also drops for artefacts. Although the aim at this point is not to separate all artefacts from the data, it would be an advantage to remove the more obvious artefacts in the process.

From examination of singular values from sections of neonatal EEG, it is clear that there are different trends for the values obtained from non-seizure, seizure and artefact EEG. In [4] the SVF term is defined which gives the fractional power in the first k singular values. The SVF is defined as

$$SVF(k) = 1 - \frac{1}{(d_E - k)N} \sum_{i=k+1}^{d_E} \sigma_i^2 \tag{6}$$

The choice of k is suggested as either $k = 1$ or $k = d_A/2$ (where d_A is the number of indices for which $\sigma_i > \delta$, some small noise threshold). In this study $k = 1$ was used.

The SVF shows a pronounced change in value in the presence of artefacts, more so than the change in Ω and can therefore be used to signify those ICs in which the artefacts appear.

2.5. Choosing/excluding ICs

The ICs that are of interest for use in the seizure detection process are the ICs with lower complexity, Ω, and little change in the SVF.

Each IC in turn is windowed and the median value of Ω is calculated over that window. ICs which contain noise without any other significant information have much higher Ω values and these are separated at this point by clustering the median values. The remaining ICs median Ω values are scaled from the IC with the minimum median Ω, scaled to 0, to the IC with the maximum median Ω, scaled to 1.

The variance of the SVF is then calculated on each windowed IC (except those excluded by the clustering operation). For ICs containing isolated, unwanted activity the SVF will have a large variance compared to those ICs that contain information of interest. The variance of the SVF is also scaled as described above. The scaled values for Ω and the SVF are then added together, giving a value close to 0 for ICs which contain seizure information and values close to 2 for those which contain no traces of seizure activity. If the total for an IC is less than 1 it is selected as being 'of interest'.

It is obvious at this point that this stage must be designed to select too many ICs rather than too few (high sensitivity, low selectivity). If too few ICs are chosen then seizure information could be lost and this would lead to a poor detection rate for the system as a whole.

3. RESULTS

A total of 4 hours of seizure data from 4 neonates was chosen (different from training data) for evaluation of this technique. All data was collected from newborn babies with seizures in the neonatal intensive care units of Kings College Hospital in London, UK and Cork University Maternity Hospital, Ireland. A Telefactor Beehive video-EEG system or a Taugagreining Nervus Monitor was used to record 12 channels of EEG using the 10-20 system of electrode placement modified for neonates ($F_4-C_4, C_4-P_4, P_4-O_2, F_3-C_3, C_3-P_3, P_3-O_1, T_4-C_4, C_4-C_z, C_z-C_3, C_3-T_3, T_4-O_2, T_3-O_1$). A video recording was made of each neonate for the duration of the study. A clinical neurophysiologist identified and classified all periods of seizure activity in each EEG recording.

In all cases those ICs which could be seen to hold the majority of the seizure information were picked out successfully by the selection algorithm. In many cases an IC containing a low frequency near-sinusoidal signal was also chosen by the algorithm. This signal is hypothesised, from its frequency and morphology, to be a trace of the neonates respiration. Although it could be removed, the overall performance of the algorithm is not affected. In some cases ICs secondary to the main information bearing IC that were also deemed of interest were not selected by the algorithm. However, in all of these cases ICs with similar information were selected, and no loss in performance was suffered.

In cases where only very few ICs contained information of interest, there was a corresponding reduction in the number of ICs selected. In the best of these cases the amount of data was cut from the initial 12 ICs down to 3 or 4, a reduction of $\sim 70\%$. Even in cases where the seizure activity was evident across nearly all of the ICs, there were still 3 or 4 ICs containing noise which could be excluded from further analysis, hence still reducing the amount of data in the worst cases by $\sim 30\%$. The algorithm was successful in rejecting ICs containing isolated bursts of activity without seizure information.

Fig. 1 shows an example of 20 seconds of seizure EEG from a neonate. The seizure is evident on multiple channels and there is a burst of unrelated activity at 2000 samples. Fig. 2 shows the ICs calculated, and it is clear that the seizure activity has been sourced to one primary and one secondary IC (marked by the arrows). ICs containing noise can clearly be seen in ICs 9 through 12. It is also clear that the short burst of activity mentioned above affects the 'non-seizure' ICs more than the others, as expected.

Fig. 3 shows the Ω and SVF values calculated for each IC (seizure ICs in bold). The Ω values for the primary seizure IC are considerably less than the others, and the values for the secondary IC are also low. The Ω values for the 'noisy' ICs are clearly separated from the others towards the top of the plot. The SVF values show the effect of the burst of activity that was seen in Figs. 1 & 2 as large decreases in the SVF values for the respective ICs. However, the two seizure ICs are not affected by the burst, and hence their variances are considerably lower. The 'noise' ICs lie at the bottom of the plot with much lower SVF values. Table 4 shows the results for each IC including the score received from the sum of the two scaled measures (section 2.5) and the resulting action. IC 6 had both the lowest median number of states and the lowest variance in SVF and hence scored 0. IC 2 was the only other IC to score under 1.

4. CONCLUSIONS

As a first stage to a seizure detection system for neonates, a method of data reduction is needed wherein no important information is lost. This approach utilises ICA to obtain statistically independent sources and a complexity measure Ω and the SVF to choose the ICs of interest.

Although studies have previously been carried out using ICA to examine EEG, in most cases these use reference signals to find artefacts or spikes in the EEG. In this study no a priori information was assumed, making this method a more robust alternative.

As well as simply being a data reduction process, the use of the median Ω and the variance of the SVF allows the exclusion of ICs containing artefacts and noise, which should increase the performance of the seizure detection system as a whole over a system which analyses raw EEG.

Many routines were tested for choosing the appropriate ICs. Originally a threshold approach was tested to choose the ICs, but this only gave simple positive or negative results for each IC. Also the trends in Ω and the SVF shift from one EEG sample to the next, making it difficult to choose robust thresholds. A ranking routine was also tested, but while it did order the outputs by how likely they were to contain information of interest, it gave no means by which to cut off the number of ICs being selected.

The scaling routine provides a ranking of the ICs, but also a value from which the number of ICs to be chosen can be derived. The use of a threshold along with the scaling routine means that the threshold shifts in relation to the input data, providing a consistent selection of the correct ICs. Before its implementation in a neonatal seizure detection system, further tests are being carried out in this technique using a larger data set.

5. REFERENCES

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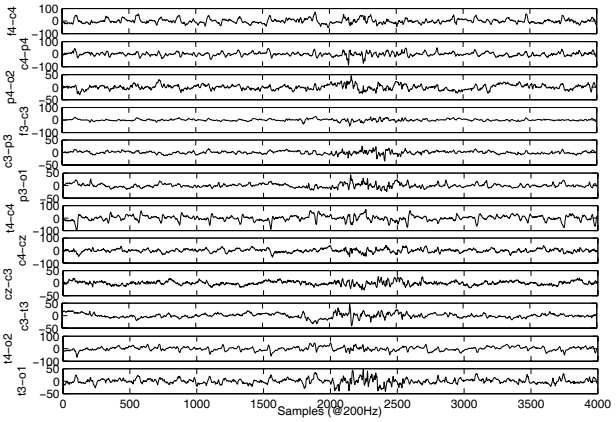

Fig. 1. Raw EEG

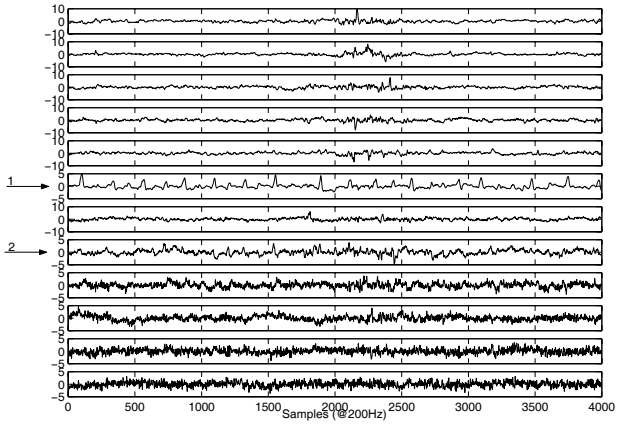

Fig. 2. Independent Components

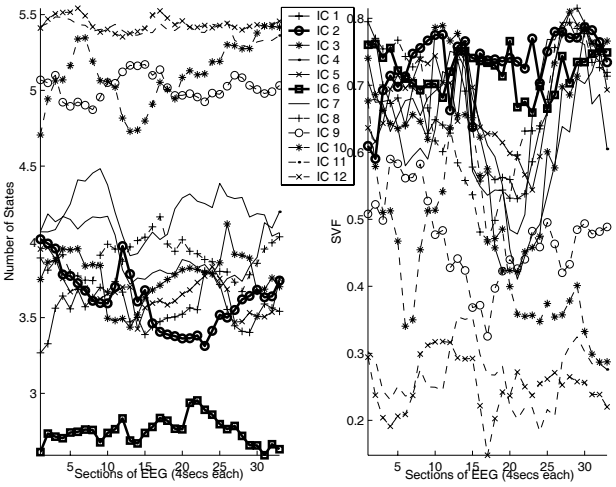

Fig. 3. Number of States (Ω) and the SVF

IC No.	Sum of Measures	Result
1	1.1724	Rejected
2	0.8083	2nd Selected
3	1.7266	Rejected
4	1.4482	Rejected
5	1.0912	Rejected
6	0.0	1st Selected
7	1.7187	Rejected
8	1.5873	Rejected
9	–	Noise
10	–	Noise
11	–	Noise
12	–	Noise

Fig. 4. Result for each IC

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