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Parallel Artefact Rejection for Epileptiform Activity Detection in Routine EEG

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Abstract— **The EEG signal is very often contaminated by electrical activity external to the brain. These artefacts make the accurate detection of epileptiform activity more difficult. A scheme developed to improve the detection of these artefacts (and hence epileptiform event detection) is introduced. A structure of parallel Support Vector Machine classifiers is assembled, one classifier tuned to perform the identification of epileptiform activity, the remainder trained for the detection of ocular and movement-related artefacts. This strategy enables an absolute reduction in false detection rate of 21.6% with the constraint of ensuring all epileptic events are recognized. Such a scheme is desirable given that sections of data which are heavily contaminated with artefact need not be excluded from analysis.**

I. INTRODUCTION

Electroencephalography (EEG) recordings are a well-established tool in the diagnosis and monitoring of epilepsy. During routine EEG, the diagnosis of epilepsy is dependant upon the detection of abnormal cerebral activity [1]. These abnormal waveforms, primarily consisting of spike and sharp wave activity, will typically have durations much less than one second, and while they may not in themselves constitute a seizure, their presence alone in the EEG indicates that the patient may very well be prone to epilepsy.

Signals recorded from the scalp are frequently contaminated by waveforms that are extracerebral in origin. These artefacts, by obscuring the underlying EEG activity during recording, can interfere with the interpretation of the recorded epileptiform activity. In automatic epileptiform activity detection, the presence of artefacts may lead to falsely interpreting a section of artefactual EEG as epileptiform. Furthermore, the presence of artefacts in training an epileptiform activity detection classifier, may negatively affect the performance of the classifier [2], [3].

Ocular artefacts are the most prevalent artefact found in most EEG recordings. Previous work has shown that ocular artefacts are a major contributing factor to the inaccurate classification of epileptiform activity [4]. Their amplitude can be several times larger than brain scalp potentials, thus seriously interfering with the EEG recording. As the eyeball moves, the potential difference that exists between the cornea and retina changes, producing the electrooculographic (EOG) signal. This ocular artefact signal propagates across the scalp, rapidly diminishing with distance travelled from the eyes.

Head movements can introduce a wide range of non-cerebral electrical activity into the EEG. Typically, these movements result in contamination in the form of some combination of muscle (EMG), electrode pop and movement artefacts. These component artefact signals display a wide range of characteristics. In contrast to ocular-related activity, muscle artefacts are predominantly high frequency signals, and can range from low to high amplitude [5],[6].

In many clinical EEG trials, contamination by artefacts is minimized by controlling the test situation to limit movement. In an ambulatory setting this is both unrealistic, and in cases such as diagnosing epilepsy, may even be undesirable. An ambulatory epileptiform activity detection system is thus faced with the twin problems of accurately detecting the short-duration epileptiform events while rejecting sections of EEG which are contaminated by artefacts.

Artefact detection/removal techniques can generally be split into two separate categories: rule-based techniques and classifier-based methods. The epileptic seizure detection system implemented by Hunyadi et al. [7] relies on mimicking the approach taken by the neurologist when trying to determine if an EEG segment contains seizure or not. To improve the performance of the system, a number of thresholding techniques are implemented to take into account the presence of movement and ocular artefacts. The addition of these enables the system to achieve a higher sensitivity of 84.4% while at the same time reducing the number of false detections to 0.24 FD/h.

In contrast to rule-based methods, classifier-based systems maintain continuous pseudo-probabilistic outputs. This leads to the advantage of being able to choose a threshold, tailoring the system to a specific application. For example, if the classifier is implemented in such a way that the false detection rate needs to be minimised while maintaining 100% of good detections, then the threshold may be set to achieve this. Independent component analysis is used by Krishnaveni et al. [8] to obtain each of the independent sources of the EEG signal. These components are then classified as being either artefact component or neural component using a neural network classifier. A similar method is employed in the work of Shoker et al. [9]. A Blind Source Separation algorithm is used to separate the EEG into its constituent components, before a Support Vector Machine (SVM) classifier is trained to be able to differentiate eye blink from normal EEG components.

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TABLE I

DATA CHARACTERISTICS FOR EACH RECORD

Patient	Record Length (s)	No. Abnormal Events	Total Event Duration (s)	Mean Event Duration (s)	No. Ocular Artefacts	Total Duration	Mean Duration	No. Movement Artefacts	Total Duration	Mean Duration
1	953	2	0.8	0.4	5	3.864	0.7728	0	0	0
2	1168	1	0.4	0.4	5	4.895	0.979	3	10.5	3.5
3	2736	5	3.6	0.72	0	0	0	1	14.5	14.5
4	3122	2	0.7	0.35	5	7.265	1.453	0	0	0
5	1219	13	18.2	1.4	5	5.027	1.0054	1	2	2
6	1213	4	4.8	1.2	5	7.043	1.4086	0	0	0
7	1221	14	29.8	2.129	5	6.484	1.2968	3	14.7	4.9
8	1200	1	3.9	3.9	5	4.359	0.8718	6	37.8	6.3
Mean	1604	-	-	1.312	-	-	0.9734	-	-	3.9
Total	12832	42	62.2	-	35	38.937	-	14	79.5	-

Unlike existing seizure detection methods, which generally implement any artefact removal/detection steps prior to epileptic seizure detection, this study presents a system whereby artefact identification takes place in parallel with the main detector. It is envisaged that this design can be used in conjunction with the REACT (Real-time EEG Analysis for Event Detection) technology to improve false detection rates. REACT is an ambulatory, hardware implementation that performs real-time seizure detection [10], [11] in adults.

II. METHODOLOGY

A. Data Collection

The data set used in this study consists of multichannel EEG recordings obtained from 8 patients, all suffering from idiopathic generalised epilepsy. The data set was acquired through the Department of Neurophysiology at Cork University Hospital, using the 10-20 system of electrode placement, from patients who were undergoing routine EEG tests. A NicoletOne clinical EEG machine was used for acquisition of the data. It is sampled at 250 Hz and analysed using a 16 channel bipolar montage. A total of 42 abnormal events (consisting of single focal sharp wave and spike and slow wave activity) are annotated on a per-channel basis in this data set.

Examples of ocular and movement artefact are also obtained from this same data set. The ocular artefact data consists of 35 expert-annotated events with a total duration of 38.9 seconds, recorded at the 4 frontal channels. The movement artefact data consists of 14 expert-annotated events of duration 79.5 seconds, taken from all channels. Table I provides more detailed information on this data.

B. General Detection System Structure

The template for the detection systems implemented in this study was originally designed for use in the detection of neonatal seizures [10]. It consists of four main stages, as can be observed in Fig. 1. The following paragraphs explain in more detail what is involved in each of these stages.

1) Preprocessing: A 50 Hz notch filter was initially applied to the raw EEG signal to remove contamination from electrical mains. This was followed by a process of breaking the EEG signal into overlapping epochs (of length 1s and an epoch shift of 0.1s) for analysis purposes.

2) Feature Extraction: A total of 55 features were extracted from the preprocessed EEG signal. These features encompass the time, frequency and information theory domains. The complete list of these may be found in the work of Kelleher et. al [4].

3) Classification: A two-class Gaussian kernel SVM [12] is implemented in this study. To begin with, the training data is normalised, by subtracting the mean and dividing by the standard deviation, to ensure that all features will have equal significance when training the model. The normalising template obtained is then also applied to the testing data. Five-fold cross validation on the training data is completed to find the optimum kernel parameter and generalisation parameter. Once these have been found, they are used to train the final model on all the training data.

4) Postprocessing: A sigmoid function is applied to convert the output of the SVM classifier to a posterior probability [13]. This is followed by the application of a moving average filter to each epoch of every channel, it's purpose being to filter out random noise, thus reducing the number of false alarms reported by the system.

C. Constructed Detectors

There are three separate detectors incorporated into this system as indicated in Fig. 1. All classifiers are based on the structure outlined in Section II-B.

The first classifier, henceforth referred to as the baseline detector, differentiates between epileptiform activity and normal background EEG. This normal EEG also includes noncerebral (artefact) activity. The second and third detectors are referred to as the ocular detector and the movement detector, respectively, their purpose being to identify artefact contaminated epochs which have been mistakenly identified as abnormal by the baseline detector. Two artefact detectors were created independently (as opposed to having a detector trained on both artefact types treated as one class, and normal EEG as the second class) due to the differences between the dynamics of the two artefact types, as outlined previously in Section I. With the use of a sigmoid function, for all three detectors a probability of 1 represents epileptiform activity, while 0 represents normal or artefact activity.

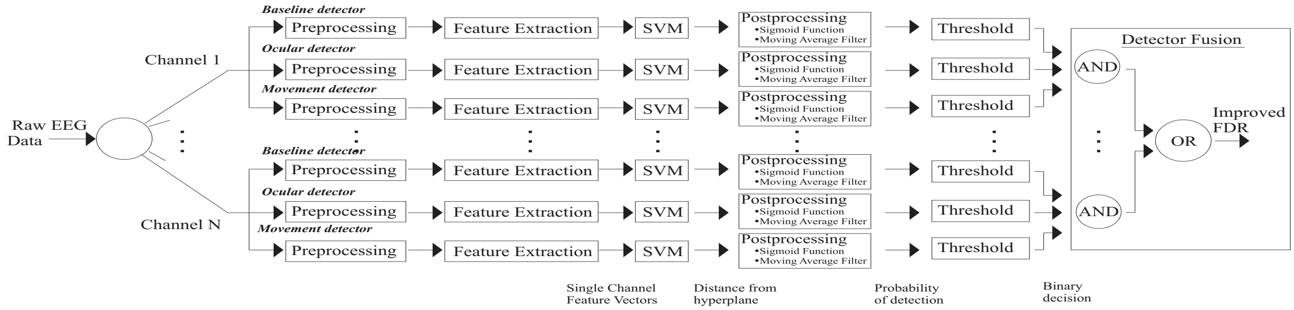

Fig. 1. The combination of decision vectors from baseline system and additional artefact detectors

D. Classifier Combination

Following the application of the sigmoid function and the moving average filter to the classifier output, a threshold is applied to this probability to obtain a binary decision vector. This threshold value is chosen to obtain a good detection rate of 100% whilst maintaining as low a false detection rate as possible. To ensure a degree of patient independence, the highest threshold found across the eight patients that gave a Good Detection Rate (GDR) of 100%, and minimised the False Detection Rate (FDR) , was then applied to all patients. This process of choosing a threshold is completed not only for the baseline classifier, but also for the two additional artefact detectors.

All epochs from the main epileptiform classifier that are flagged by the detector as epileptiform in origin are combined with their corresponding epochs from the artefact classifier that are also marked epileptiform by the detection system. This fusion is performed by means of a logical AND operation (if 1 exists in both decisions output by the epileptiform classifier and the artefact detector, then the result of the combination of the two decision vectors will also be a 1). The next stage in this process is the summation of the channels to obtain a single decision for the presence or otherwise of an epileptiform event in the current epoch (if an event is detected in one or more channels then the current epoch is labelled as having a detection). Four different configurations are implemented, as indicated in Fig. 2. It is important to note that the configurations containing the ocular detector fuse only the four frontal channels that have been annotated for ocular-related activity; all other channels from the baseline classifier are left as they are. On the other hand, the configurations involving the movement artefact detector make use of all 16 channels during the combination step. Fig. 1 provides an illustration of the classifier fusion process. The results of the combination process are presented in Section III.

E. Metrics and Performance Assessment

The GDR is an event-based metric, defined as the percentage of abnormal events correctly detected by the system. For example, if the classification system flags an event between the start and end of an expert labelled event, then a good detection is said to have taken place. The FDR is an epoch-based metric. It is a measure of the number of epochs which

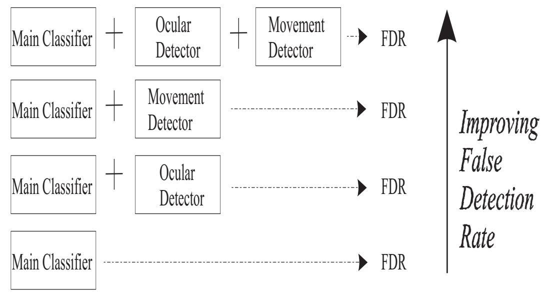

Fig. 2. Overview of all configurations compared. Best FDR achieved when both ocular and movement artefact detectors combined with the base system

are incorrectly classed as a detection by the classification system. If the strict condition is set that a perfect GDR must be maintained, then the FDR will as a consequence be high. However, if this requirement is relaxed, then the FDR will decrease. The use of the false detections per hour (FD/h) metric, which is an event-based metric, can potentially lead to a misreading of the system performance. When the additional artefact detectors are implemented in parallel with the baseline detector, the FD/h may increase. This occurs when a false detection, as identified by the baseline detector, is broken up into several independent events of shorter duration with the addition of the artefact detectors. For this reason, the FDR metric was reported instead.

An N-fold cross-validation system, where seven of the patients are used in training and the remaining patient used as the test data set, was employed to evaluate the performance of the system.

III. Results and Discussion

As has been mentioned in the introduction, in contrast to rule-based methods, the constructed detectors output a continuous pseudo-probabilistic value. This allows reporting of the curve of performance as opposed to single operating points. Fig. 3 shows that GDR increases with an increase of the FDR for each of the four implemented configurations illustrated in Fig. 2. It can be seen that the performance of the baseline system is improved with parallel artefact detectors as expected. The movement artefact detector running in parallel has a greater impact on the performance than the ocular artefact detector. This suggests that a larger proportion of false positive epochs are caused by movement artefact rather than eyeblink/eye-movement activity. It can also be explained as the ocular artefact can only block false decisions from 4 EEG channels while movement artefact operates on all 16 channels. Both artefact detectors running in parallel together with the baseline detector result in an average absolute reduction of 15.5% in FDR over all operating points with an FDR reduction of 21.6% at the operating point of GDR = 1 and a reduction of 10.9% at the operating point of GDR = 0.1.

To highlight how the implemented additional artefact detectors benefit the lowering of the FDR, analysis is performed on a per-patient basis on a single point on each of the curves of Fig. 3 (for a GDR of 1). Table II illustrates the FDR achieved for each of the 4 configurations implemented for all 8 patients. This table suggests that the inclusion of each individual artefact detector results in a decrease of the false detection rate, while the best results are obtained when both detectors are run in parallel with the baseline classifier.

It is important to note that this system of artefact rejection is designed primarily for rejection of ocular and movement-related activity; other forms of artefact signal continue to have an influence on the detection of epileptiform activity. Looking more closely at Table II, it may be observed that the use of the additional artefact detectors results in a smaller improvement of FDR for some patients over others. This is especially true for patients 4, 7 and 8. Patients 7 and 8 have the highest FDR to begin with and also see the smallest improvement when the additional artefact detectors are utilised. Patient 7 in particular, is one of the patients containing the greatest amount of epileptiform activity. When annotations were completed, an effort was made to only annotate those events that displayed distinct epileptiform activity. However, some patients contain other epileptiform activity which is less distinctly formed. Many of the false detections for these patients are caused by this activity, meaning that the artefact detector does not have as great an impact as desired on the FDR. Patient 8, to a lesser extent, also contains this type of activity. Patient 4 is a sleep-deprived record. Activity which is similar to epileptiform events is produced during this type of recording. Hence, many of the false positives may be due to this type of signal being detected as opposed to being caused by artefact.

The work presented shows that the FDR rate can be lowered with the additional artefact detectors running in parallel with the baseline epileptiform detector. A clear advantage of this system of artefact rejection is in the fact that no sections of data need to be removed prior to initial classification, as has been widely done in the past. The pseudo-probabilistic output of the classifier provides the flexibility of being able to choose the required operating point, such as a GDR of 1 resulting in no epileptiform activity being missed. This operating point allows the workload of the clinician to be reduced while preserving perfect detection of epileptiform activity. While not all types of artefact activity are covered in this work, the two types that are taken into account by this classifier enable the false detection rate to be reduced while maintaining the good detection rate of the baseline system.

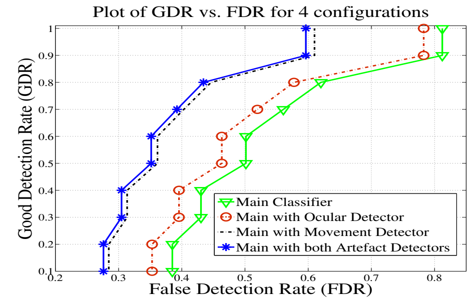

Fig. 3. A plot of the effect of changing the Good Detection Rate on the False Detection Rate of the system

TABLE II

FDR FOR EACH IMPLEMENTATION (MAINTAINING A GDR OF 100%)

Baseline		+Ocular	+Movement	+Ocular & Movement
Patient	FDR	FDR	FDR	FDR
1	0.4354	0.3707	0.2291	0.2127
2	0.8903	0.8636	0.7126	0.6956
3	0.4159	0.3905	0.0963	0.0926
4	0.9296	0.9192	0.8187	0.8034
5	0.9029	0.8514	0.5066	0.4930
6	0.9236	0.8706	0.5790	0.5490
7	0.9997	0.9980	0.9749	0.9723
8	0.9987	0.9963	0.9597	0.9480
Mean	0.8120	0.7825	0.6096	0.5958

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