EEG-Based Event Detection Using Optimized Echo State Networks with Leaky Integrator Neurons

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Abstract—**This study investigates the classification ability of linear and nonlinear classifiers on biological signals using the electroencephalogram (EEG) and examines the impact of architectural changes within the classifier in order to enhance the classification. Consequently, artificial events were used to validate a prototype EEG-based microsleep detection system based around an echo state network (ESN) and a linear discriminant analysis (LDA) classifier. The artificial events comprised infrequent 2-s long bursts of 15 Hz sinusoids superimposed on prerecorded 16-channel EEG data which provided a means of determining and optimizing the accuracy of overall classifier on 'gold standard' events. The performance of this system was tested on different signal-to-noise amplitude ratios (SNRs) ranging from 16 down to 0.03. Results from several feature selection/reduction and pattern classification modules indicated that training the classifier using a leaky-integrator neuron ESN structure yielded highest classification accuracy. For datasets with a low SNR of 0.3, training the leaky-neuron ESN using only those features which directly correspond to the underlying event, resulted in a phi correlation of 0.92 compared to 0.37 that employed principal component analysis (PCA). On the same datasets, other classifiers such as LDA and simple ESNs using PCA performed weakly with a correlation of 0.05 and 0 respectively. These results suggest that ESNs with leaky neuron architectures have superior pattern recognition properties. This, in turn, may reflect their superior ability to exploit differences in state dynamics and, hence, provide superior temporal characteristics in learning.**

I. INTRODUCTION

Long-haul truck drivers, train drivers and commercial airline pilots routinely experience monotonous and extended driving periods in a sedentary position, which has been associated with drowsiness, microsleeps, and, consequently, serious accidents. Microsleeps are brief involuntary events of lapses in attention or responsiveness, associated with events such as prolonged eye closure which usually last from 0.5-15 s [1].

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Consequently, the detection and preferable prediction of the microsleeps in subjects, especially those working in these high-risk occupations, is very important to workplace safety. Ultimately, a real-time lapse warning devices is required, where an individual's state of responsiveness is monitored continuously and could be used to trigger an alert to rouse a user from a predicted microsleep or an attention lapse, potentially avoiding a catastrophe.

EEG is widely used in sleep research with several studies having associating lapses with changes in EEG spectra [1 - 3]. An EEG-based lapse detector was developed based on spectral power features from EEG, aimed at detecting lapses with second-scale resolution [1]. Another study used long short-term memory (LSTM) recurrent neural network (RNN) implementation to detect lapses [4]. The current study aims at developing a microsleep detector using the novel recurrent neural network architecture of an echo state network (ESN) and represents progression of our research from previous methods [1, 4].

Echo state networks are a novel engineering approach to the implementation, training, and analysis of a RNN [5]. They are the counterpart of another novel structure, liquid state machines, which are designed to model biological networks [6]. The ESN approach is based on the observation that if a random RNN possesses certain algebraic properties, training only a linear readout is often sufficient to achieve superior performance in many practical applications [5, 7, 8]. The initially untrained component of an ESN is called a dynamical reservoir and the resulting states are termed echoes of its input history [8]. Therefore, ESNs are similar to more traditional RNNs in that have short-term memory in addition to their dynamical property [9].

ESNs are extensively used in several machine learning applications [7 - 10]. Nevertheless, their main disadvantage is that it is difficult to slow down their internal network dynamics as the time constant within their standard sigmoid neurons cannot be constrained. As a result, these networks are more suitable for modelling discrete time systems with high frequency changes (e.g., mixed sinusoidal oscillators and noise modelling) making their behaviour quite vulnerable in some occasions where the system needs to perform on slow dynamics [9, 10].

To overcome this disadvantage, a much superior ESN architecture, using leaky integrator neurons as the internal units instead of the standard sigmoidal neurons, was utilized for the proposed prototype microsleep detection model. Leaky neuron model incorporates a time constant with multiple individual state dynamics that can be exploited in

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various ways to adapt the network to the temporal characteristics of a learning task [11].

The proposed microsleep detection system (Fig. 1) involves pre-processing/conditioning, feature extraction, feature selection/reduction, and pattern classification stages. Pre-processing comprises EEG signal acquisition, mean removal, and rescaling. The feature extraction stage converts the processed EEG data into a set of EEG features for the classifier. Given the high dimensionality of EEG and EEG-feature datasets, feature reduction is required so as to pass only significant features to, and not overload, the pattern classification stage. The feature reduction stage generates meta-features from the original features, by, for example, PCA, so as to minimize and optimize the number of features passed to the classifier and without loss of significant information from the feature sets. Feature selection, on the other hand, reduces the existing data by selecting, but not altering, an optimal subset of features. Finally, the pattern classification stage assigns class labels to a given input value based on the training algorithm.

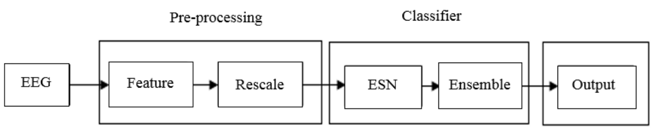

Fig. 1: Proposed prototype microsleep detection system

Different configurations and combinations of pre-processing, feature extraction, feature reduction/selection, and pattern recognition were tested and performance evaluated on detection of 'gold standard' artificial events superimposed on multichannel EEG.

II. DATA GENERATION

A. Artificial datasets

EEG datasets consisted of two 1-hour 16-channel EEG recordings from 8 healthy non-sleep-deprived male volunteers aged 18–36 years [1]. The EEG was recorded from scalp electrodes placed according to the International 10-20 system, bandpass filtered to 0.1–100 Hz, and digitized at 256 Hz.

To loosely approximate microsleep-type transient events, simulated artificial events were superimposed on subsets of the EEG data. Our objectives were to (i) determine the sensitivity of various classifier configurations to SNR and (ii) determine the detection performance of various detection systems/configurations on a gold-standard dataset for which the events were precisely known.

An 'event' in this artificial data was a 15-Hz sinusoidal burst, lasting 2.0 s. EEG of 300 s (5 min) duration were taken from each of the 8 subjects. A total of 34 spectral features were extracted at 1.0-s intervals from each channel, resulting in 544 features. The sine wave was scaled relative to the EEG signal to generate data with amplitude SNRs of "very easy" (SNR=16), "easy" (SNR=3), "average" (SNR=1), "hard" (SNR =0.3), and "very hard" (SNR =0.03), to allow exploration of effect of reducing SNR on classification performance

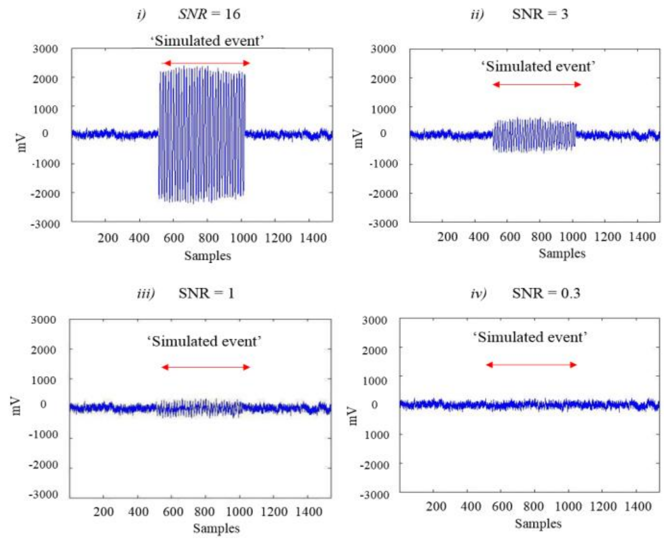

Fig. 2: An artificial event (15 Hz sinusoidal burst) superimposed on the ambient EEG.

Six of the 2-s segments had the 15 Hz sinusoidal bursts, equating to 2% of the time being events and 98% non-events. This highly unbalanced dataset parallels that of the relatively rare, albeit surprisingly high, occurrence of microsleeps [12]. Additionally, five balanced datasets, each with 150 events and 150 non-events, were created with SNRs identical to those of the unbalanced datasets

B. Performance Evaluation

Multiple tests were performed on each module and the same methods used for the performance analysis in prior research [1, 4] were reproduced. Classification performance was determined by leave-one-out cross-validation of the artificial datasets corresponding to the 8 subjects. Performance metrics used were mean accuracy, sensitivity, specificity, selectivity, and phi correlation.

III. METHODS

A. Feature selection/ reduction

Feature reduction/selection was by either PCA or average distance between events and non-events (ADEN). With ADEN, all observations of each class are averaged together for each of the features and the resultant vectors are then subtracted from each other and the largest distances between events and non-events found. The features corresponding to the largest average distances are retained, and the rest discarded, ADEN-1 (corresponds to one particular vector in which the distance between the resultant features is maximum). With event-based feature selection (EFS), only features that increase directly with the 15 Hz sinusoidal event are referred to as 'optimal lapse features', are passed on to the classifier. A new gold-standard is created by multiplying the 'optimal lapse feature set' (where all the optimal lapse features are considered as events (1's) and the rest are non-events (0's)) to the existing temporal gold-standard. This new gold-standard is used to train the classifier.

B. Pattern Recognition

ESNs represent a fundamentally new approach in the design and training of recurrent neural networks [7]. The fundamental principle of the echo state, which distinguishes it from other RNNs, can be summarized as follows [7, 9]

- ESNs use a large and random sparse matrix as an excitable medium –- called a reservoir. When driven by input signals, each unit in the RNN creates its own nonlinear transform of the input;
- Output signals in an ESN model are read out from the excited RNN by some readout mechanism, typically a simple linear combination of the reservoir signals;
- Outputs from an ESN model can be trained using supervised learning, that maps high- dimensionality space to a state vector.

The typical configuration of an ESN is shown in Figure 3.

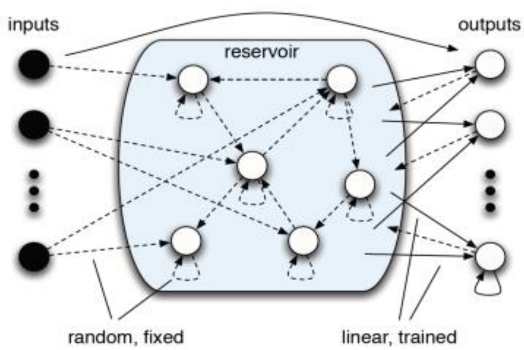

Fig. 3: The basic schema of an ESN with fixed and random connections (adopted from [7]).

The network consists of an input node, the dynamical reservoir (DR) that is made up of a large number of sigmoidal units sparsely connected to each other, linear trainable output weights, and an output node. The DR has the ability to map the inputs into a high-dimensional space and reserve the useful prior information.

C. Echo state property

The definition of the echo state property is (adopted from [8]): A network E: $\mathbf{X} \times \mathbf{U} \rightarrow \mathbf{X}$, where $\mathbf{U}$ is the input range and $\mathbf{X}$ is the state space, has the echo state property with respect to $\mathbf{U}$: if for any left infinite input sequence $\mathbf{u}^{-\infty} \in \mathbf{U}^{-\infty}$ and any two state vector sequences ($\mathbf{x}^{-\infty}$, $\mathbf{y}^{-\infty} \in \mathbf{X}^{-\infty}$) compatible with $\mathbf{u}^{-\infty}$, it holds that $x_0 = y_0$.

Internal states $\mathbf{x}(n)$ can be calculated based on neural structure of internal units and the final output is calculated by

$$\mathbf{y}(n+1) = f_{out}(\mathbf{W}_{out}(\mathbf{u}(n+1), \mathbf{x}(n+1), \mathbf{y}(n))) \qquad (1)$$

The conditions of this echo state property, described in detail in [8], conclude that, for an ESN with standard sigmoid units, the echo state property can be achieved by scaling the spectral radius (the largest absolute eigenvalue) of internal weight matrix to $|\lambda_{max}| < 1$.

D. Leaky integrator neuron

The conditions for a continuous-time leaky integrator neuron are described by the differential equation

$$\dot{\mathbf{x}} = C\,(-a\mathbf{x} + f(\mathbf{W}_{in}\,\mathbf{u} + \mathbf{W}\mathbf{x} + \mathbf{W}_{back}\,\mathbf{y})), \qquad (2)$$

where C is a time constant, a is the leakage rate, $\mathbf{W}_{in}$ is the input weights matrix and $\mathbf{W}_{back}$ is the feedback weight matrix [10]. By incorporating a retainment potential (leaking decay rate) of the neuron, $-a\mathbf{x}$ describes the previous state of the neuron. The higher the value of C, the faster are the resultant system dynamics. Similarly, the higher the decay rate, the faster the attenuation of the previous states and the higher the effect of input from other neurons. In our implementation, the values of C and a were set at 1.0 and 0.20 respectively.

E. Modelling using ESN

ESNs transform input to an excited state where they can be linearly mapped to outputs using a training set. State vectors represent intermediary functions that facilitate such mapping. Results from the simple ESN approach provided insight that warranted further investigation and led to a more complex architecture that utilized leaky integrator neurons.

As stated in the Section I, the leaky neuron models are highly effective when modelling continuously slow transforming systems. This classifier structure was used to model the proposed prototype microsleep detector system. The major advantage with this structure is that even smaller networks (e.g., 5 leaky integrator neurons) are capable of achieving superior performance. However, one of the drawbacks of this approach is possible overfitting within the network, especially if the global parameters of the network and the reservoir size are not chosen carefully. Therefore, several system parameters from the simple Euler approximations were adjusted to 'tune' the network for optimum performance.

Moreover, as the weight matrices are randomly generated and fixed for the entire training cycle, this model exhibited small variations in terms of the results obtained. Therefore, our proposed solution required interconnections of several individual networks to form a combined classifier (ensemble learning method).

Class hypotheses from each of these classifiers were then combined and the mean of the individual votes calculated for each of the classifiers. Calculating the mean of the vote combination is used because this averages out vote fluctuations due to any single classifier's biases. Accordingly, 500 5-leaky neuron ESNs were trained on the simulated data to form a combined classifier model as depicted in Fig. 4.

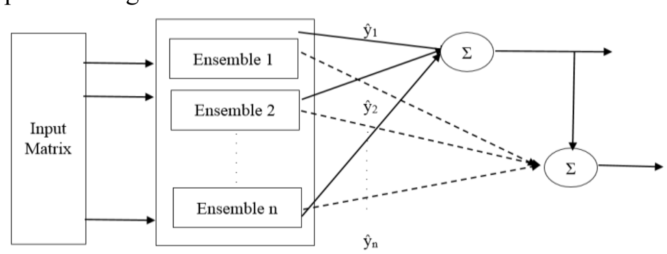

Fig. 4: Ensemble classification with Leaky- ESN.

IV. RESULTS

LDA was used to form classification models as baselines for performance. Multiple tests were performed on all the configurations (feature selection/ reduction and pattern classification) and phi correlation was used as the primary performance metric because of its independence from class distributions and being the best integrated measure of the other performance metrics. Both the balanced and unbalanced datasets used in this study were cross-validated for several modular configurations, and performance of all these configurations recorded.

Classification performance through cross validation on the unbalanced datasets for the SNRs 0.3 (hard) and 0.03 (very hard) is represented in Table 1.

TABLE 1: CLASSIFIER PERFORMANCE

a) Pattern classification on 'hard' (SNR = 0.3) dataset

Module	LDA (ADEN)	ESN (ADEN)	ESN (EFS)
Sensitivity	0.85	0.88	0.94
Specificity	1.00	1.00	1.00
Selectivity	0.84	0.87	0.96
Phi	0.85	0.88	0.92

b) Pattern classification on 'very hard' (SNR = 0.03) dataset

Module	LDA (ADEN)	ESN (ADEN)	ESN (EFS)
Sensitivity	0	0.13	0.33
Specificity	0.98	0.90	0.82
Selectivity	0	0.06	0.58
Phi	-0.01	0.04	0.18

c) Feature reduction/selection on 'hard' (SNR = 0.3) dataset. Classifier – Leaky integrator ESN

Module	PCA	ADEN1	ADEN 10	EFS
Sensitivity	0.58	0.88	0.88	0.94
Specificity	0.85	1.00	1.00	1.00
Selectivity	0.72	0.87	0.88	0.96
Phi	0.37	0.88	0.86	0.92

Results from Table 1 indicate that the application of leaky integrator neuron scheme to the ESNs lead to consistent and higher performance scores (for SNRs less than 0.3) than any other type of classifier used in this study.

V. DISCUSSION

To summarise, Leaky Integrator ESNs with EFS method were found to marginally dominate all the other modules, in terms of performance, by achieving the highest phi correlation of 0.92 on the hard dataset (SNR = 0.3) compared to any other classifier.

ADEN was another feature selection method which performed consistently with the exception of the 'very hard' datasets (SNR = 0.03). While PCA did not perform well on the same data, EFS yielded better performance even with all 544 features which contained redundant information. However, ADEN 1 selects only a single feature eliminating most of the redundant information. This indicates that the generation of meta-features, as opposed to selecting a subset of existing features, loses important information required for optimal event detection. ESNs (leaky or standard sigmoidal) indicated better results compared to LDA. On the datasets with SNR of 0.3, LDA using PCA, had no appreciable performance in contrast to leaky integrator ESN using PCA for which phi was 0.37.

As expected, with the decrease in the amplitude of the simulated event, harder it got for the classifier to differentiate from the background EEG. For the 'very hard' dataset, EFS with leaky integrator ESN was the only module that resulted in a marginal phi correlation value at 0.18.

VI. CONCLUSION

ESNs with leaky integrator neurons provided consistent and encouraging results. Even with the superior performance on the 'hard' datasets (SNR=0.3), none of the classifier structures (not even leaky integrator ESNs) were successful at classification within the 'very hard' datasets (SNR=0.03), it appeared as if the amplitude of the simulated event has dropped off to an extent which was not distinguishable from the background EEG. A possible reason may be that the EEG data used in this 'simulated' study was contaminated with other noise sources such as the ocular and motion artifacts. However, Actual microsleep detection is likely to be more difficult than the artificial 'hard' datasets (SNR = 0.3). Therefore, future research will be directed at examining and implementing the optimal configurations of modules, such as leaky integrator ESNs, to better classify the actual microsleeps from the EEG data.

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