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Estimation of Human Concentration using Echo State Networks

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Abstract. We introduce a very simple and portable device for estimating the human concentration. We developed a Brain-Computer Interface system based on EEG signals which is able to produce highly accurate prediction of the human activities. There are two types of mental activities, one requires high concentration and another one requires relaxation. We show that it is possible to estimate the human concentration with few brain signals. The classification problem is solved using Neural Networks. In particular, we obtain a very accurate classifier using the fast and robust Echo State Network method.

1 Introduction

Every human being performs several tasks in daily life which requires attention or concentration. In particular situations we need to assess emotional responses for making assessments about real state of mental focus and concentration in a specific task. These situations include jobs which requires high concentration, psychological tests, medical diagnostics, and educational purposes. Brain Computer Interface (BCI) can be useful for studying emotional responses and interpreting human brain activities [2]. BCI system provides interaction between a wired brain and an external device, it fundamentally consists of three components [4]: acquisition system for brain information (for example: EEG signals, MRI, fMRI, etc.), processing information system that contains a Machine Learning tool, and an external device (for example a robotic arm, wheel chair). In a BCI system the subjects perform mental tasks, it means they do not realize the activity itself, the subjects imagine the realisation of some specific activity. Hence, it is useful for assisting and repairing human cognitive and sensory-motor functions. Recent years BCI has broad usage in several diverse areas such as: emotion recognition, clinical applications, communications devices, learning systems, human performance evaluations, entertainment [6, 8, 4].

In this article, inspired by the BCI system we present a portable system that collects brain wave information, and is able to estimate the mental concentration during human activities. Instead of collecting the brain information during mental tasks (like in a BCI system), in our system we collect the EEG during real activities, which require high mental concentration. A Neural Network (NN)

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solves the classification problem with the binary output variable: high focus on the task (concentration) *yes* or *not*. The subject's variables and emotional states are time-dependent thus we use a temporal learning method. We considered a type of NNs namely Echo State Network (ESN), which is commonly used for solving temporal learning problems [16]. This model has shown good performances in several real-world problems, and it has the following two main advantages with respect to other learning tools: the training process is fast and robust. Moreover, we can adapt easily our system to process new training data, as well as the system can be specifically trained for each subject.

The rest of the paper is organized as follows. We introduced the ESN method in the next section. We present the experimental methodology in Section 3. Section 4 shows and discuss the obtained results. We discuss future research lines and conclude in the Section 5.

2 Echo State Network

An ESN contains at least three well distinguished parts: input layer, hidden structure (named reservoir) and output layer (readout) [13]. It has the following two particularities: the hidden structure is recurrent in order of memorizing patterns, and it is randomly initialized it keeps fixed during the training procedure. Only the readout structure is trained, which is composed by the output weight parameters. In the original ESN and LSM models, the readout structure is a linear regression. Let's define the notation. We consider an ESN with N_{u} input neurons, a reservoir size of N_{x} neurons and N_{y} outputs neurons. We use the ESN for learning the relation between a given data set $\mathbf{u}$ and a desired binary output $\mathbf{y}_{\mathrm{target}}$. In our case, the given input data is composed of the EEG signals. The binary output variable is 1 when we assume that the person is doing an activity with high mental concentration, 0 otherwise. As in the canonical ESN model, we use linear regression for training the output weights. For that we minimize the mean squared error between the predictions of the model and the desired values. The model parameters are : input weights $\mathbf{W}^{\mathrm{in}}$ a matrix $N_{\mathrm{x}} \times N_{\mathrm{u}}$, reservoir weights $\mathbf{W}^{\mathrm{r}}$ a matrix $N_{\mathrm{x}} \times N_{\mathrm{x}}$, and output weights $\mathbf{W}^{\mathrm{out}}$ a matrix $N_{\mathrm{y}} \times N_{\mathrm{x}}$. We omit explicit notation for the bias term. For computing the output of the ESN, first we compute the reservoir state using $\mathbf{x}(t)$:

$$\mathbf{x}(t) = \tanh(\mathbf{W}^{\mathrm{in}}\mathbf{u}(t) + \mathbf{W}^{\mathrm{r}}\mathbf{x}(t-1)), \tag{1}$$

where $\mathbf{u}(t)$ is the data at time t, $\mathbf{x}(t-1)$ is the previous value of the reservoir state, and $\tanh(\cdot)$ is the hyperbolic tangent. We initialized the reservoir state with a null vector. The model prediction is computed using linear regression:

$$\mathbf{y}(t) = \mathbf{W}^{\mathrm{out}}\mathbf{x}(t). \tag{2}$$

An important characteristic is that $\mathbf{W}^{\mathrm{in}}$ and $\mathbf{W}^{\mathrm{r}}$ are fixed in the training algorithm. The learning only modifies the parameters $\mathbf{W}^{\mathrm{out}}$. Due to algebraic reasons, an important property of the model is named Echo State Property (ESP).

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The property guarantees that under certain algebraic conditions the reservoir dynamics are asymptotically independent of the initial state conditions. In practice, the ESP is almost ensured scaling the reservoir weights [18, 3]. The $\mathbf{W}^{\mathrm{r}}$ matrix is scaled [13] as: $\mathbf{W}^{\mathrm{r}} = \nu \frac{\mathbf{W}^{\mathrm{r}}}{\rho}$, where $0 < \nu < 1$ is a scaling factor and ρ is the largest absolute eigenvalue of $\mathbf{W}^{\mathrm{r}}$. There are other factors that impact in the performance of an ESN model, for more details see [9, 16].

There are several variations and extensions of the canonical ESN model. In [14] was introduced a reservoir with leaky neurons, where the reservoir neuron performs a more smooth state update that is controlled by a leaky rate. Reservoir neurons with noise have been evaluated in [17], and recently deep reservoirs have been developed [11, 10]. Recently, a model named ESQN combines queueing networks with ESN, the model has two reservoir matrices one represent inhibitive weights and the other one excitatory weights [5].

3 Methodology

3.1 Data Collection

The set of experiments were designed for recording EEG signals while a subject performs some specific activity[1]. The data was collected during the sessions with 4 healthy subjects aged from 23 to 38. All the subjects were right handed. The subject was sitting on a comfortable chair located one meter from a 17" monitor. The subjects performed instructions that were displayed on a screen. There were two type of actions: command A and command B. In the command A we asked to the subject for reading and handwriting the displayed text. In the another command we asked to the subject for being relaxed. We used a Lua script for displaying the images, which were pages selected randomly from the Kafka's book:"The trial" [15]. The total time of the experiment for each subject was 300 seconds. The actions A and B were alternating between them. Figure 1 shows a general view of the whole experiment. The experiment starts with 5 washout seconds (*getting ready* (GR) in the diagram 1). An important technical issue in this type of experiments is to capture EEG signals which perfectly correspond to subject's actions (without delays), and to tag the EEG time intervals that correspond to the actions A or B. This synchronization was made using Openvibe software platform [7] and Lua language. The EEG signals were recorded using NeuroSky's Mindset device [12], which provides data in forms of the delta, theta, alpha, beta, and gamma signals. Delta signal provides information about brain disorders, theta signal gives data about meditation of subject, alpha and beta signals represents mental activity or highly engaged mind and gamma signal is related to cognitive or motor functions of subject [1].

[1] The collected dataset and the source code are available at: `http://aic.fel.cvut.cz/basterrech/`.

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3.2 Data Processing

We used the first 25 seconds of the experimental test as washout interval, it was necessary time for the subject for became familiarized with the experiment. It is also cut out the last 5 seconds of the experimental test.

We identify and remove artifacts in order of improving the improve EEG-based classification. According to the 3σ rule [6], a sample $\mathbf{u}(k)$ is considered as an artifact if any coordinate of the vector $\mathbf{u}(k)$ does not belong to the interval $(\hat{u_j} - 3\sigma_j, \hat{u_j} + 3\sigma_j)$, where $\hat{u_j}$ is the mean of the coordinate input variable j, and σ_j is the standard deviation of this variable j. In addition, we verified that this rule does not exclude more 7% of the total data. Then, we normalize the data in the range of $[0, 1]$. In total there are 13 input variables from the Neurosky device, and the binary output variable that corresponds to the action.

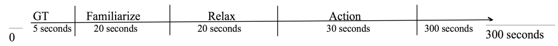

Figure 1: Diagram shows the sequence of actions in our experiment.

4 Experimental Results

As usual in the context of temporal learning we divide the learning sequences in training and testing. The training set contains 90994 samples (70% of the learning data). We sort randomly the learning set as follows. We divide the original data in time windows of 100 time steps $\mathcal{L} = [\Delta_1, \ldots, \Delta_M]$ where Δ_i contains 100 instances. The new learning dataset is given by the permutation of the time widows, for instance an example of permutation is: $\mathcal{L} = [\Delta_j, \ldots, \Delta_M, \Delta_1, \ldots \Delta_i]$. The predictions of the ESN model are real numbers, then we discretize the prediction in $\{0, 1\}$ (if $y(t) > 0.5$ then we assign $y(t) = 1$, and if $y(t) <= 0.5$ then we assign $y(t) = 0$). We evaluate the ESN model with different reservoir characteristics, we generate reservoirs with all the combinations of values (N_x, ρ), where ρ is the spectral radius of the reservoir matrix and N_x the reservoir size. In addition, we consider ESN model with a leaky rate $\delta \in [0, 1]$, that are given by a reservoir state update following the expression [14]:

$$\mathbf{x}(t) = \delta\mathbf{x}(t-1) + (1-\delta)(\tanh(\mathbf{W}^{\mathrm{in}}\mathbf{u} + \mathbf{W}^{\mathrm{r}}\mathbf{x}(t-1))).$$

Model	Subject 1	Subject 2	Subject 3	Subject 4
Standard ESN	82.18%	81.10%	77.63%	83.34%
Leaky-ESN ($\delta = 0.5$)	81.70%	79.36%	74.56%	82.35%
Leaky-ESN ($\delta = 0.9$)	78.03%	77.99%	72.52%	78.54%

Table 1: Test accuracy results for each subject. The accuracy was obtained with a standard ESN and leaky-ESN with parameters: $\rho = 0.2$, $N_\mathrm{x} = 300$.

We used the first 20% of learning dataset for evaluating the best combination of (N_x, ρ) parameters. We run 30 trials (different reservoir random initializations) for each of that combinations. Figure 2 depict the averages of the Mean

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Square Error (MSE) values among those 30 trials. The curve in the left side shows the accuracy obtained by an ESN with leaking rate $\delta = 0$ and in the right side the curve shows the accuracy obtained with an ESN with leaking rate $\delta = 0.5$. Figure 3 shows an example of ESN prediction in a specific time interval with and without discretization in $\{0, 1\}$. Table 1 presents the obtained results for each subject. We can see that the model with leaky rate does not improve the model accuracy. The final obtained accuracy is around 80%, what is *acceptable* due to the characteristics of the input information.

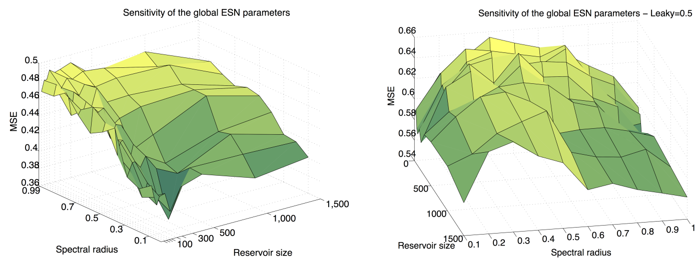

Figure 2: Sensitive analysis of the main global parameters of the ESN model.

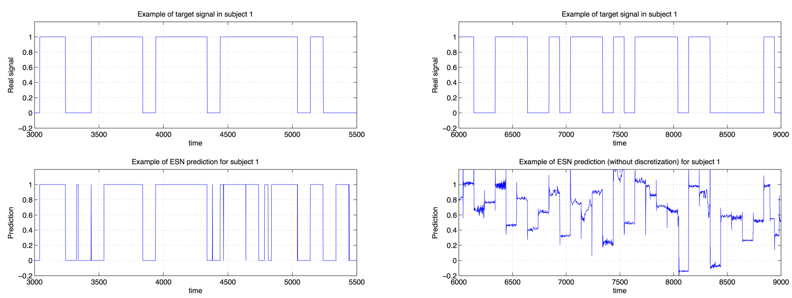

Figure 3: Example of the target signal and the ESN prediction with and without a discretization.

5 Conclusions

We present an approach for using EEG signals for computing the human concentration during specific activities. We are particularly interested in collecting the brain information using a portable and non-invasive device. Then, the brain information was collected with NeuroSky Mindset, which collects few signals and it has a low cost in the market. The obtained results are promising, independently of the person the accuracy was around 80%. Besides the good accuracy, the main advantage of ESN and RC models with respect other learning tools is that the learning process is fast and robust. Then, it is possible in few seconds to adjust the model parameters for each subject. In the near future, we plan to apply other preprocessing techniques of the EEG signals (such as ICA and some

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filters), to evaluate other RC models, and to analyze our procedure when the subject is doing other activities.

References

[1] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, and Jorge L Reyes-Ortiz. Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In *Ambient assisted living and home care*, pages 216–223. Springer, 2012.

[2] Ling Bao and Stephen S Intille. Activity recognition from user-annotated acceleration data. In *Pervasive computing*, pages 1–17. Springer, 2004.

[3] Sebastián Basterrech. Empirical Analysis of the Necessary and Sufficient Conditions of the Echo State Property. In *2017 International Joint Conference on Neural Networks, IJCNN 2017, Anchorage, AK, USA, May 14-19, 2017*, pages 888–896, 2017.

[4] Sebastián Basterrech, Pavel Bobrov, Alexander Frolov, and Dušan Husek. Nature-inspired Algorithms for Selecting EEG Sources for Motor Imagery Based BCI. In *Artificial Intelligence and Soft Computing*, volume 9120 of *Lecture Notes in Computer Science*, pages 79–90. Springer International Publishing, 2015.

[5] Sebastián Basterrech and Gerardo Rubino. Echo State Queueing Networks: A Combination of Reservoir Computing and Random Neural Networks. *Probability in the Engineering and Informational Sciences*, pages 1–20, 2017.

[6] P. Bobrov, A. A. Frolov, C. Cantor, I. Fedulova, M. Bakhnyan, and A. Zhavoronkov. Brain-computer interface based on generation of visual images. *PLOS ONE*, 6(6):1–12, 2011.

[7] Jorg Ott Dirk Kutscher. Dynamic device access for mobile users. In *Proceedings of the Eighth International Conference on Personal Wireless Communications*, September 2003.

[8] A. A. Frolov, D. Husek, P. Bobrov, A. Korshakov, L. Chernikova, R. Konovalov, and O. Mokienko. Sources of EEG activity most relevant to performance of brain-computer interface based on motor imagery. *Neural Network World*, 22(1):21–37, 2012.

[9] Claudio Gallicchio and Alessio Micheli. Architectural and Markovian factors of echo state networks. *Neural Networks*, 24(5):440 – 456, 2011.

[10] Claudio Gallicchio and Alessio Micheli. Echo state property of deep reservoir computing networks. *Cognitive Computation*, 9(3):337–350, Jun 2017.

[11] Claudio Gallicchio, Alessio Micheli, and Luca Pedrelli. Deep reservoir computing: A critical experimental analysis. *Neurocomputing*, 268(Supplement C):87 – 99, 2017. Advances in artificial neural networks, machine learning and computational intelligence.

[12] Udo Huebner, N. B. Abraham, and C. O. Weiss. The Santa Fe Time Series Competition Data. Available at: http://goo.gl/6IKBb9, date of access: 12 September 2013.

[13] Herbert Jaeger. The "echo state" approach to analysing and training recurrent neural networks. Technical Report 148, German National Research Center for Information Technology, 2001.

[14] Herbert Jaeger, Mantas Lukoševičius, Dan Popovici, and Udo Siewert. Optimization and applications of Echo State Networks with leaky-integrator neurons. *Neural Networks*, 20(3):335–352, 2007.

[15] Franz Kafka. *The trial.* Der Prozeß, 1925. Translated by David Wyllie.

[16] Mantas Lukoševičius and Hebert Jaeger. Reservoir Computing Approaches to Recurrent Neural Network Training. *Computer Science Review*, 3:127–149, 2009.

[17] Ali Rodan and Peter Tiňo. Minimum Complexity Echo State Network. *IEEE Transactions on Neural Networks*, 22:131–144, 2011.

[18] I. B. Yildiza, H. Jaeger, and S. J. Kiebela. Re-visiting the echo state property. *Neural Networks*, 35:1–9, 2012.