International Journal of Signal Processing
http://iaras.org/iaras/journals/ijsp

Artificial Neural Network Codifies Sensory and Cognitive Events Identifying Chaotic Attractors in EEG Signals

RITA PIZZI and MARIALESSIA MUSUMECI
Department of Computer Science - Crema Campus
Università degli Studi di Milano
Via Bramante, 65, 26013 Crema CR
ITALY
rita.pizzi@unimi.it http://www.di.unimi.it/pizzi

Abstract: - In past researches our group experimented a method to analyze multiple neural signals by means of a novel self-organizing Artificial Neural Network, highlighting the attractors in which the corresponding dynamic system is evolving. If the attractors show to be chaotic, this means that the neural signals are individually self-organized and, analyzing more signals together, that there is a form of coherence between signals. The ANN can also identify different attractors with a unique code. The ANN allows to attribute the same codes to similar but not identical brain events, reaching the necessary range of flexibility.
In the present work the method has been tested on signals from a 14 electrodes EEG system connected to immersive glasses that allow a realistic audiovisual experience. A software procedure synchronizes the acquired signals with various sensory experiences presented in a video. Aim of the research is to characterize sensory and emotional stimuli. The analysis lead to positive results, showing that the binary codes corresponding to similar cognitive and perceptive stimuli are similar, and well differentiated for the codes corresponding to different stimuli.

Key-Words: - Artificial Neural Networks, EEG signals, Cognition, Chaotic Attractors, Qualia

1 Introduction

The search for neural correlates of consciousness (NCCs) is one of the most difficult challenges of modern neuroscience. Despite of many new theories, analysis methods and tools, the subjective experience hides from a precise neurophysiological identification [1],[2],[3].

Our approach stems from a wide literature following the path laid out by Walter Freeman in his entire scientific work (see a review in [4]). These studies show how the dynamic analysis of neural signals may highlight the existence of chaotic attractors, differentiated depending on the cognitive states, by means of a novel self-organizing ANN, called ITSOM, that outlines the attractors in which the corresponding dynamic system is evolving [5],[6]. If the attractors show to be chaotic, this means that the neural signals are individually self-organized and, analyzing more signals together, that there is a form of coherence between signals. The ANN can also highlight the time course of this form of coherence.

In particular, it can identify different attractors with a unique code. The ANN allows to attribute the same codes to similar but not identical brain events, reaching the necessary range of flexibility.

2 Methods

The Self-Organizing Map (SOM) [7],[8] features are well known. The SOM is essentially a classifier that performs a vector quantization, that is a mapping from a space with many dimensions to a space with a smaller number of dimensions, preserving the initial topology.

It is constituted by an input layer (in this case the signal that flows in time in the layer, one sample for each neuron) and a competitive layer, where the neuron closest to the input "wins" and is modified in such a way that the new adjusted weight for the node is equal to the old weight, plus a fraction of the difference between the old weight and the input vector:

$$w_{inew} = w_{iold} + \alpha(x - w_{iold})z_i$$

where $0 < \alpha < 1$ slowly decreases over time with the law

$$\alpha(t) = \alpha[1 - t/\delta]$$

where δ is a suitable constant, being $z_i \neq 0$ only for the winning neuron.

Then the network cycles adapting itself up to a stable state.

As above mentioned, the ANN model adopted in this research, named ITSOM (Inductive Tracing Self-Organizing Map), is especially suited for identifying structures in temporal series.

The ITSOM architecture stems from the SOM architecture but is based on the observation that the time sequence of the SOM winning weights tends to repeat itself, constituting chaotic attractors that are isomorphic to the attractors of the signal time series, and characterize univocally the input signal that produces them.

The ITSOM network memorizes the time series of the winning nodes, and this sequence makes it possible to classify the corresponding input value much more finely than with a SOM.

A detailed description of the ITSOM's architecture is reported in [9].

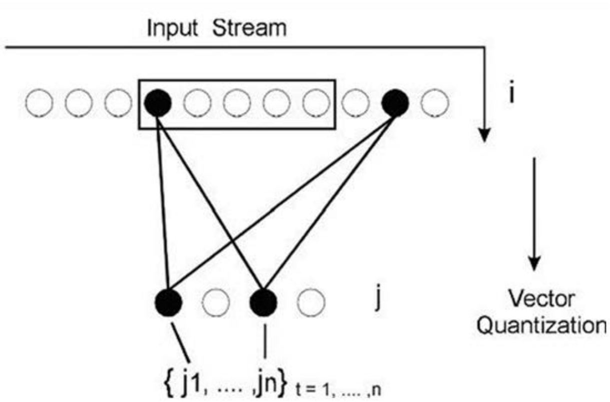


Fig. 1. the ITSOM structure: The sequence of the ANN winning nodes tends to repeat itself creating a cahotic time series that carachterizes the input signal.

A crucial feature of the ITSOM is that the cyclic configurations stabilize within a small number of epochs, that makes this model very effective for real-time applications.

The cumulative scores for each input are normalized according to the distribution of the standardized variable z given by

$$z = \frac{(x - \mu)}{\sigma}$$

where μ is the average of the scores on the neurons of the competitive layer and σ is the standard deviation.

Once set a threshold $0 < \tau \leq 1$, which therefore constitutes one of the parameters of this type of network, we put

$$z = 1 \quad for\ z > \tau$$
$$z = 0 \quad for\ z \leq \tau$$

In this way, each configuration of winning neurons is represented by a binary number formed by as many ones and zeros as many the output layer neurons.

Due to the existence of the threshold, the z-scores coincide when the series of winning sequences are approximately similar. Then the task of comparing *z*-scores becomes straightforward and allows us to identify similar or identical input patterns.

Analyzing the signals by means of the ITSOM network, it can be shown that attractors are labeled with a binary code that identifies them univocally, but the flexibility of the ANN allows to attribute the same codes to similar dynamic events: this is an important issue, as of course neural signals are never identical even when the stimulus that influences them is the same [10].

In this way we obtain a fine classification of the signal on the basis of its dynamical self-organization in time.

3 The Experimental Phase

In this study we processed signals from a 14 electrodes of the EMOTIV+ wireless EEG system [11], connected to immersive glasses that allow a realistic audiovisual experience.

The performances of the EMOTIV+ headset was evaluated in literature as equal to or better than a research EEG headsets [12].

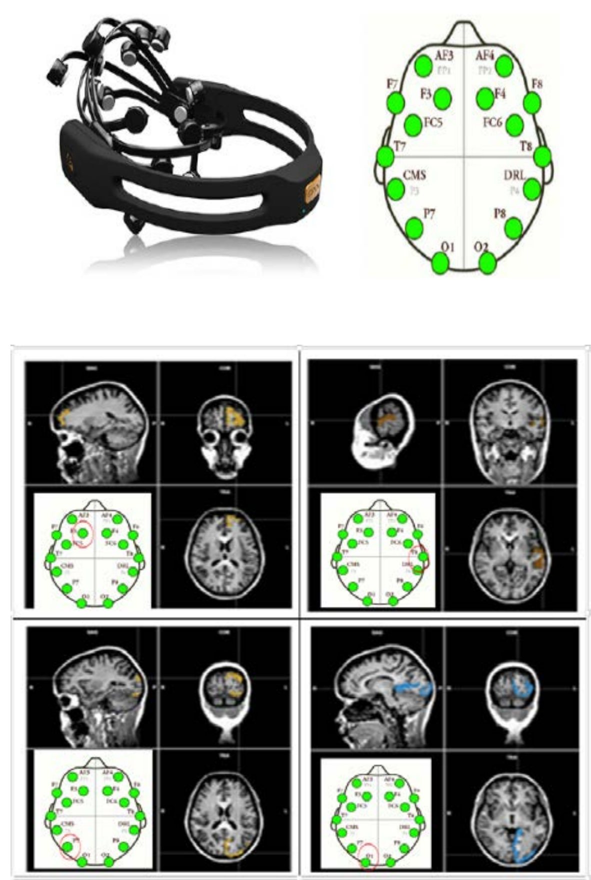


Fig. 2 . The Emotiv+ system, the 14 electrodes and the 4 channels chosen for the analysis: T8, P7, O1, F7

The subject wears both glasses and EEG headset. A video administers sensory and cognitive stimuli, each one lasting 10 s, followed by a 5 s black stimulus, as a function of control and reset (Fig. 3). We chose different colors, colored images and written words repeating the colored stimuli.

A procedure developed in MATLAB (MATLAB and Statistics Toolbox Release 2012a, The MathWorks, Inc., Natick, MA) synchronizes the acquired signals with the various sensory and cognitive experiences presented in the video.

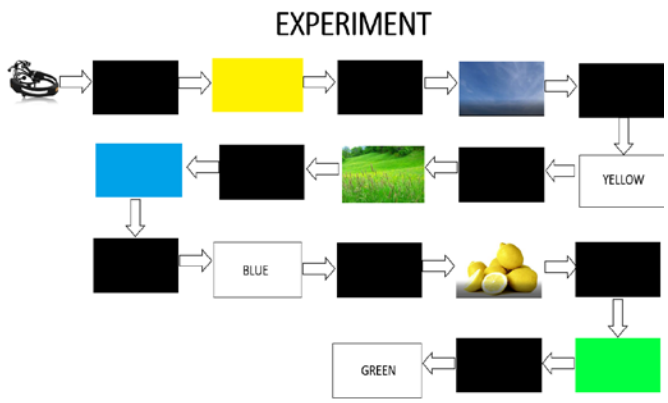


Fig. 3. The video administered to the subjects. The sensory and cognitive stimuli last 10 s and are followed by a black stimulus lasting 5 s.

At the end of the experiment, signals are recorded and the analysis procedure is applied.

We chose in particular to process four electrodes (T8, P7, O1, F7) as the most interesting to analyze the signals identifying the stimulations. In fact F7 is involved in cognitive control, T8 in episodic memory, P7 in visuospatial processing and the O1 main functional area is the primary visual cortex. The frequency analyzed were Beta (between 12.5 and 30 Hz) and Gamma (>30 Hz).

Aim of the analysis is to test if similar stimuli give rise to chaotic attractors identified with identical or similar codes.

ITSOM can process both individual signals and many signals simultaneously, highlighting the attractors in which the corresponding dynamic system is evolving. If the attractors are chaotic, this means that the signals are individually self-organized or, if you examine more signals together, that there is a form of coherence between signals. The ANN can also highlight the time course of this form of coherence. Once the time series of the attractors is available, it is also possible to quantify these complex dynamical events with many parameters useful to compare dynamics corresponding to different kinds of stimulations.

4 Results and Conclusions

Signals were acquired from six subjects: results are not comparable, as by definition each subjective experience is different from subject to subject. But the analysis of the binary codes resulted from the ITSOM processing shows the constant evidence that in any subject's signals most binary codes are identical or similar for similar patterns, and different for different patterns.

The figures show the analysis of the signals from one of the subjects. In particular, the shown analysis concerns the Gamma band of the T8 electrode. In the first columns the sensory and cognitive stimuli are shown, in the second one the binary code resulted from the ANN processing, in the third columns the attractors generated by the the dynamics of the sequence of ITSOM winning neurons: the figure represents a snapshot of movies that show a typical chaotic path (Fig. 4a, 4b, 4c).

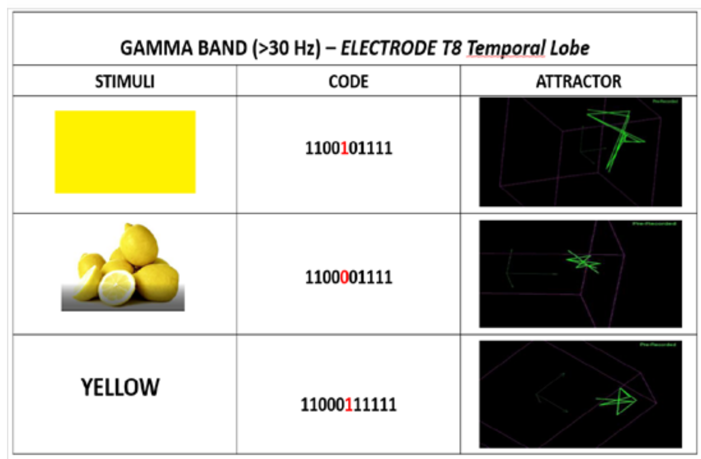


Fig. 4a. Binary codes and attractors of yellow or similar stimuli

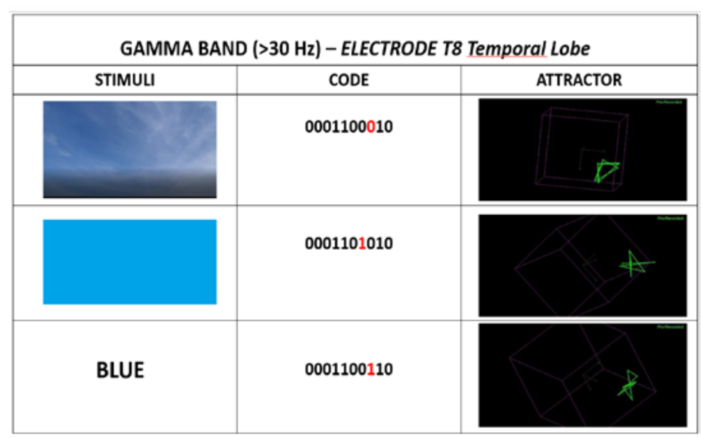


Fig. 4b. Binary codes and attractors of blue or similar stimuli

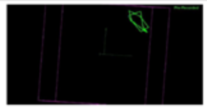
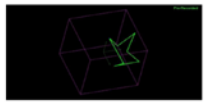
GAMMA BAND (>30 Hz) – *ELECTRODE T8 Temporal Lobe*		
STIMULI	CODE	ATTRACTOR
	0000011100	
	1000011100	
GREEN	1000001100	

Fig. 4c. Binary codes and attractors of green or similar stimuli

In summary, comparing the stimuli the results in Fig. 5 are obtained, clearly highlighting how similar stimuli give rise to similar codes, that result to be quite different from the codes obtained by different stimuli.

YELLOW -> 1100101111	BLUE -> 0001101010	GREEN-> 1000011100
LEMONS-> 1100001111	SKY -> 0001100010	MEADOW-> 0000011100
WRITTEN YELLOW -> 1100001111	WRITTEN BLUE -> 0001100110	WRITTEN GREEN -> 1000001100

Fig. 5. Summary of the results. Codes of similar stimuli are similar, codes of different stimuli are quite different.

We would be tempted to state that these codes can be a way to identify qualia, as there is an extremely high number of possible binary codes (namely, in this case, $2^{10} = 1024$ codes) but we can distinguish a set of dynamical states with unique codes that we may call qualia codes. We believe that this approach is close to that proposed by G. Tononi et al. in [13],[14],[15],[16], where the articles refer to a possible metastable states dynamics in terms of binary strings. But these papers don't fully specify the underlying dynamics and the way to identify it in signals, due to the lack of a robust quantification and representation method. We hope that our contribution may be useful to go one step further towards the connection between brain dynamics and identification of mental states.

Future developments of this research aim to identify more numerous and complex sensory and cognitive stimuli. At the moment we are experimenting a new set of visual, auditory and cognitive stimuli, overlapping and comparing them with emotional stimuli.

References:

[1] T. Metzinger, "Neural Correlates Consciousness: Empirical and Conceptual Questions", *MIT Press*, 2000.

[2] G. Tononi, C. Koch, "The neural correlates of consciousness: an update", *New York Academy of Sciences* , vol. 1124, 2008, pp. 239–261.

[3] C. Koch, M. Massimini, M. Boly, G. Tononi, "Neural correlates of consciousness: progress and problems.", *Nature Reviews Neuroscience*, vol. 17, 2016, pp. 307–321.

[4] W.J. Freeman, *Neurodynamics: An Exploration in Mesoscopic Brain Dynamics*, Springer, 2000.

[5] R. Pizzi, G. Cino, F. Gelain, D. Rossetti, A. Vescovi, "Learning in human neural networks on microelectrode arrays", *Biosystems*, vol. 88, 2007, pp. 1-15.

[6] R. Pizzi, D. Rossetti, G. Cino, D. Marino, A.L. Vescovi, W. Baer,"A cultured human neural network operates a robotic actuator.", *Biosystems*, vol. 95, 2009 , pp.137-144.

[7] T. Kohonen, *Self-Organisation and Association Memory*, Springer Verlag, 1983.

[8] T. Kohonen, "Physiological Interpretation of the Self-Organizing Map Algorithm", *Neural Networks*, vol. 6, 1993, pp. 895-905.

[9] R. Pizzi, M. Musumeci, *Artificial Neural Networks, Dynamical Systems and Self-Organization*, CreateSpace NC, 2017.

[10] R. Pizzi, M. De Curtis, C. Dickson, "Evidence of chaotic attractors in cortical fast oscillations tested by an Artificial Neural Network", *Advances in Soft Computing*, Springer, Physica-Verlag Heidelberg, 2003, p. 11-22.

[11] Emotiv, Inc, San Francisco, [Online]. Available: https://www.emotiv.com

[12] N.A. Badcock, K.A. Preece, B. De Wit, K. Glenn, N. Fieder, J.Thie, G. McArthur, "Validation of the Emotiv EPOC EEG system for research quality auditory event-related potentials in children", *PeerJ*, vol 3, 2015, e907.

[13] D. Balduzzi, G. Tononi, "Integrated information in discrete dynamical systems: motivation and theoretical framework.", *PLoS Comput, Biol*,. vol 4, 2008, 1000091.

[14] G. Tononi, "Consciousness as Integrated Information: a Provisional Manifesto", *Biol. Bull.*, vol. 215, 2008, pp. 216–242.

[15] D. Balduzzi, G. Tononi, "Integrated Information in Discrete Dynamical Systems: Motivation and Theoretical Framework." , *PLoS Computational Biology*, vol 4, n. 6, 2008, e1000091.

[16] G. Tononi, "Integrated information theory of consciousness: an updated account", *Archives Italiennes de Biologie*, vol. 150, n. 4, 2012, pp. 293-329.

R. Pizzi is Senior Researcher at the Dept. of Computer Science, Università degli Studi di Milano, via Bramante 65 , 26013 Crema CR, Italy (corresponding author: tel. +390250330072; e-mail: rita.pizzi@unimi.it).

M. Musumeci is PhD student at the Department of Computer Science, Università degli Studi di Milano (e-mail: marialessia.musumeci@unimi.it).