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An Artificial Neural Network Compares Neurophysiological Events Triggered by Mutually Associated Sensory and Cognitive Stimuli

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ABSTRACT
Previous research results of our group showed the possibility to encode EEG signals related to sensory and cognitive stimuli, so as similar codes refer to similar stimuli and different codes to different stimuli.
This paper further explores this issue by testing the possibility of recognizing mutually associated sensory and cognitive stimuli. To test this possibility of identifying and comparing signals coming from conceptually overlapping stimuli we conducted an experiment using an EMOTIV EPOCH+ EEG headset analyzing 4 electrodes (T8, P7, O1, F7) on two frequency bands (Beta and Gamma).
The analysis was carried out with the same ANN used in the previous experiment. The paper analyses the results by band and electrode, finding many corrispondences between codes and overlapping patterns. The best matches are provided by the P7 and O1 electrode signals in the beta band. Other findings lead to the conclusion that the matches are probably mediated by cognitive elaborations. These preliminary results should be investigated with a higher numerosity of the samples.
Keywords - Artificial Neural Networks, chaotic attractors, neuroscience, cognition, associative reasoning

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I. INTRODUCTION

In a previous paper [1] we showed that it is possible to identify and code mental states from EEG signals, analyzing them by means of an Artificial Neural Network. We developed an Artificial Neural Network (ITSOM, Inductive Tracing Self-Organizing Map) that detects in signals and codifies the dynamic attractors related to the sensory and cognitive stimuli.

The analysis shows that the binary codes corresponding to similar cognitive and sensory stimuli are similar, and well differentiated from the codes corresponding to different stimuli.

A detailed description of the ITSOM's architecture is reported and applied in [2,3,4] . In short, the ITSOM architecture stems from the Kohonen's SOM model [5,6], 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 time series of the winning nodes is processed, and each configuration of winning neurons is represented by a binary number formed by as many ones and zeros as many the output layer neurons. The network allows a fine classification of the signal on the basis of its dynamical self-organization in time.
Another interesting feature of this ANN is that its flexibility allows to attribute the same codes to similar sensory or cognitive events, or identical events in different times.

II. METHODS

In the previous work we compared the dynamic attractors and the codes generated by the ANN using sensory and cognitive stimulations that were similar or different from each other, reaching the possibility of identifying EEG signal features, translated into binary codes, that distinguished different stimuli and recognized physical stimuli.
However, in reality many sensory and cognitive stimulations have some elements in common.
In this new experiment we have therefore used patterns with sensory or cognitive analogies, which we may call conceptual overlapping.
We start from the hypothesis that the intersection of stimuli or memories is important for the elaboration of conscious thought through mechanisms of analogy and discrimination [7,8] .
Our hypothesis is that this overlapping is fundamental in the formation of memories and conceptual elaboration, because the association of

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ideas necessary for reasoning is conveyed through the transition between different but similar concepts, while memory is recalled from items or groups of items presented to the subject through perceptions and other memories that contain them.
For this purpose, we carried out an experiment with the method used previously, applying it to patterns with multiple analogies, then evaluating and comparing the characteristics of the signals coming from stimulations related to the different patterns.
We can describe the overlapping between different patterns with the schema sketched in Fig. 1.

Fig. 1 - The patterns presented to the selected subjects and their conceptual intersection

III. EXPERIMENTATION

In this study we processed signals from a 14 electrodes of the EMOTIV EPOCH+ wireless EEG system [9,10] (Fig.2), connected to immersive glasses that allow a realistic audiovisual experience. A MATLAB [11] procedure synchronizes the acquired signals with the sensory experiences presented in a video. The video administers randomly the sensory and cognitive stimuli, each one lasting 10s, followed by a 5s black stimulus, as a function of control and reset (Fig. 3). We chose different colors, colored images and written words repeating the colored stimuli.

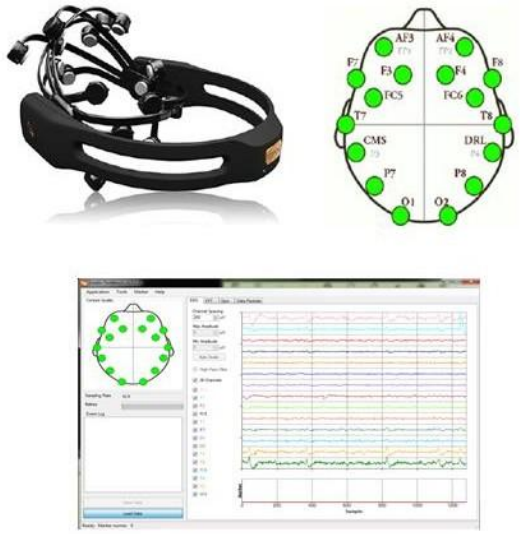
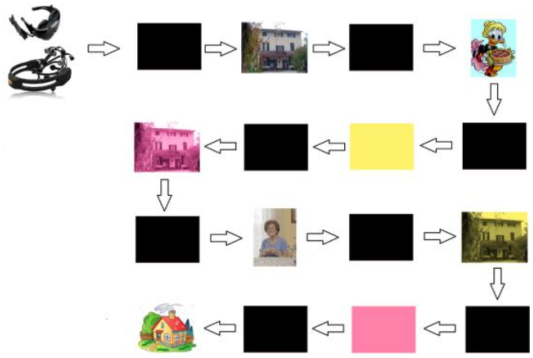


Fig. 2 - The EMOTIV EPOCH+ EEG system

Fig. 3 - Sequence of pattern presentation (shortened



sequence: the real sequence includes other identical occurrences of houses and grandmothers).

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

We chose in particular to process four electrodes (T8, P7, O1, F7) (Fig. 4) as the most interesting in relationship with the chosen 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 [12].

The frequency band analyzed were Beta (between 12.5 and 30 Hz) and Gamma (>30 Hz). As reported in any neuroscience textbook, Gamma waves mainly refer to higher mental activity, including problem solving and consciousness, whereas Beta waves refer mainly to active thinking, active concentration, arousal, and cognition [13,14].

Signals were acquired from seven subjects of both genders, between 28 and 67 years, although results are not comparable, as by definition each subjective experience is different from subject to subject. But as described in detail in the following, 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 patterns generated can be described as follows:

- grandmother (first occurrence)
- Grandma Duck (first occurrence)
- old house (first occurrence)
- Grandma Duck's house (first occurrence)
- old house with pink filter
- old house with yellow filter
- pink colour
- yellow colour
- grandmother (second occurrence)
- Grandma Duck (second occurrence)
- old house (second occurrence)
- Grandma Duck's house (second occurrence)
- black color (blank pattern interleaving the stimulation patterns)

The results consist of the binary codes generated by the individual patterns. A special software compares them and evaluates the similarity between codes.

The most interesting results were obtained with the following network configuration:

Input neurons: 500
Output neurons: 10
Learning rate: 0.002
2000 eras
Tolerance threshold: 0.2

The electrodes related to signals with the best matching codes in most subjects were P7 and T8, Beta frequency. As an example, we report the best results obtained by the same subject (Tables 1 and 2). The 00 and 11 values (that substitute respectively the values 0 and 1) are obtained through the ANN tolerance threshold, applied passing from the real numbers to the binary code. The 0 and 1 values indicate exact or nearly exact values.

PATTERN	CODES									
Grandma Duck's house 1	11	0	1	0	00	0	0	00	00	11
yellow old house	1	00	11	00	00	00	1	00	00	11
yellow	1	00	1	0	0	0	1	0	0	1
old house 1	1	00	00	11	11	11	00	11	00	11
Grandma Duck 2	1	0	0	11	1	1	0	11	0	11
Grandma Duck's house 2	11	00	1	11	11	1	11	11	11	11
old house 2	11	00	11	11	1	11	11	1	11	11
Grandma Duck 1	11	00	1	11	11	1	11	11	11	11

Table 1 - O1 Beta Coincident Codes

PATTERN	CODES									
yellow old house	00	00	00	11	00	00	00	1	00	00
yellow	00	00	00	1	00	00	00	11	00	00
pink old house	1	00	00	11	11	11	00	11	00	11
pink	1	0	0	11	1	1	0	11	0	11
old house 2	00	0	0	00	0	11	1	0	0	1
Grandma Duck's house 2	00	0	0	00	0	1	1	0	0	1
Grandma Duck 1	11	00	11	00	00	00	00	00	1	1
grandmother 1	1	00	1	0	0	0	0	00	1	1

Table 2 - P7 Beta Coincident Codes

IV. CONCLUSION

It has long been known that the ability to associate perceptions and concepts is a basic characteristic for memory and learning and ultimately for the advanced brain functions that we may call intelligence [15,16]. More recently, the possibility of evaluating associative function from the point of view of neuroscience has emerged [17,18,19].

This study therefore has a twofold objective: on the one hand, we aim to deepen with a new experimentation the ability of computational intelligence to analyse and codify mental events. The new experimentation considers patterns associable according to sensory or cognitive content.

On the other hand, the research is intended to verify that the codes generated from the EEG signals reflect the underlying mental association.

Thus we conducted an experiment in which stimuli with features that can be associated from a perceptive or cognitive point of view were administered, then the analysis and coding of the signals was carried out by means of the previously described ANN.

The analysis on the obtained signals has led to state that the codes generated by the set of patterns considered confirm the previous results, i.e. they discriminate different sensory/cognitive events and create similar codes for similar events, where similar means having no more than 1 different binary symbol. Moreover, it has been verified that in many cases similar codes also correspond to patterns that can be associated with each other.

Even second level correspondences are present, namely intersections of intersections (e.g. old house is overlapping with grandmother (first level), and grandmother is overlapping with Grandma Duck (first level), but Grandma Duck is overlapping with Grandma Duck's house (first level), so a second level correspondence is between grandmother and Grandma Duck's house).

It can be seen that in general similarities between codes coming from overlapping stimuli, are present both at first and second level, for any electrode and frequency band. In this work we concentrated on coincident codes, and we reported examples in the previous paragraph.

In fact it is worth noting that with the chosen ANN configuration (10 neurons of the competitive layer, therefore binary codes of length 10) the number of possible codes is 2^10=1024, so given a certain code there is one probability out of 1024 that an identical one can be created. In our case, however, not all the identical codes would be admissible, but only some, chosen among the 12 patterns, i.e. only those that can be associated: on average we can say half (some patterns can be associated with several patterns, others with a limited number of patterns).

As a result, the probability of code coincidence is further reduced: if we state that each binary code could have approximately 6 variants, the calculus leads to 2^10*6=6144 choices.

In particular, it has been observed that the correspondences are different depending on the electrode, both in nature and in number.

The highest number of matches occurred from the signals filtered on the Beta band and in particular from the P7 and O1 electrodes.

It is interesting to outline that these are not the same electrodes ande the same frequency band that gave the best response in the previous experiment (T8 Gamma). In this case, however, the active processing component is more intense than for the previous patterns (with greater involvement of the Beta band) and visuospatial processing and primary visual cortex (P7 and O1) are intensively involved.

As far as colours are concerned, for all electrodes and with both frequency bands very rarely false matches are detected (i.e. between colours and houses filtered with different colours) and never matches between different colours. In general, (incorrect) matches with pure colours are almost completely missing except for some cases of (correct) matches for images with colour filter.

Among the correspondences that include houses, the house filtered with pink colour is much more present than the one with yellow.

The overall results therefore seem to indicate both that the matches found are not random and that the matches include cognitive factors before and after sensory factors.

The issues involved in this study, regarding high-level mental states, are still under study in neuroscience and psychology and far from a definitive knowledge, thus this research is to be considered absolutely preliminary.

However, the good results lead us to think that, using computational intelligence methods, it is possible to conceive more complex experiments, recruiting a higher number of subjects and studying a choice of patterns from which it is possible to draw new information on the possibility of identifying complex cognitive events from neurophysiological signals.

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