Evolving Connectionist Modeling of Auditory, Visual and Combined Stimuli Perception Based on EEG Data

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Abstract
The paper introduces a method for adaptive, dynamic modeling of perceptual states of the human brain based on EEG. The method allows for the development of individual models of person's perception and for the incremental model adaptation on new data. The method is illustrated on a case study of classification of cognitive states of a person based on EEG signals, when auditory, visual and mixed stimuli are presented. For the modeling task, evolving connectionist systems (ECOS) are used. The experiments show that ECOS are appropriate techniques for the creation of evolving models of the human perception.
Keywords: adaptive systems, EEG, auditory system, visual system, multimodal processing, neural networks

1. Introduction
Being able to recognize perception states of the human brain from measured EEG signals, can be used to create general and individual perceptual models that can be adapted with the presentation of new stimuli. This can help to develop new means for an improved human-computer interaction and learning.

Main research questions in this paper are:

- Can an adaptive model of a person's perception be build, so that it can recognize the state of this person on the same stimuli but in a different session or in a different environment?
- Can one person's model be used for another person state recognition?

The following research questions will be also attempted along with the main ones:

- What are the dynamics of the perception of auditory, visual and combined stimuli (denoted as A/V/AV) for an individual?
- What are the common patterns of activity across humans for A, V and AV stimuli?
- What are the differences between individuals under same A/V/AV stimuli?
- Can an evolving connectionist system (ECOS) be used to create individual and general perception model?

2. An EEG experiment design, data collection and pre-processing

In the experiment here, four classes of brain states are used with 37 single trials each of them including the following stimuli [2]: Class1 - Auditory Stimulus; Class2 - Visual Stimulus; Class3 - Mixed Auditory and visual stimuli; Class 4 - No stimulus.

The EEG data was collected in an experiment that used four stimulus conditions [2]. In the auditory stimulus case, a 1Khz tone of 50 mSec in duration was presented to the subject in one-second intervals. The visual stimulus had the same duration and interval of the auditory stimulus and consisted of a white circle on a black background. The mixed auditory and visual stimulus combined the two stimuli already described, with the auditory stimulus presented first and then the visual stimulus presented to 100 mSec later. The fourth case is when no stimulus was presented. The EEG data were acquired using a standard 64 electrode EEG system (fig.1). Data was filtered using a 0.05Hz to 500 Hz band- pass filter and sampled at 2Khz.

For each of the two 2 subjects, stimuli were presented and raw EEG data were recorded. There were 1676 samples recorded for person A and 1556 for person B. An ECOS model was trained on-line on current data and tested on new data. Analysis of single trial EEG is an extremely difficult problem. These applications will require on-line, real-time analysis of EEG data. These data are likely to be very non-stationary and the analytical techniques used will have to be capable of adapting to the changing nature of the data. Because of their ability to adapt to new data, ECOS [1] will be explored here on this task.

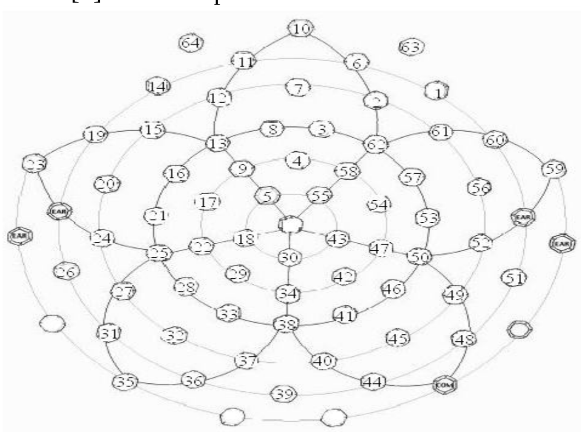

Fig.1. The location of the 64 EEG electrodes

3. ECOS for dynamic modeling and classification

Here we use one of the ECOS models called Evolving Classifier Function (ECF) [1]. The ECF algorithm, outlined below, classifies a data set into a number of classes and finds their class centres in the n-dimensional input space by "placing" a rule node. Each rule node is associated with class and with an influence (receptive) field representing a part of the n-dimensional space around the rule node. Usually, such an influence field in the n-dimensional space is a hyper-sphere.

There are two distinct phases of the ECF operation. During the learning phase, data vectors are fed into the system one by one with their known classes. The learning sequence of each iteration is described as the following steps:

1) If all vectors have been inputted, finish the current iteration; otherwise, input a vector from the data set and calculate the distances between the vector and all rule nodes already created;

2) If all distances are greater than a max-radius parameter, a new rule node is created. The position of the new rule node is the same as the current vector in the input data space and its radius is set to the min-radius parameter, and then go to step 1; otherwise:

3) If there is a rule node with a distance to the current input vector less then or equal to its radius and its class is the same as the class of the new vector, nothing will be changed and go to step 1; otherwise:

4) If there is a rule node with a distance to the input vector less then or equal to its radius and its class is different from those of the input vector, its influence field should be reduced. The radius of the new field is set to the larger value from the distance minus the min-radius, and the min-radius.

5) If there is a rule node with a distance to the input vector less then or equal to the max-radius, and its class is the same to the vector's, enlarge the influence field by taking the distance as the new radius if only such enlarged field does not cover any other rule node which has the different class; otherwise, create a new rule node the same way as in step 2, and go to step 1.

The recall (classification phase of new input vectors) is performed in the following way:

1) if the new input vector lies within the field of one or more rule nodes associated with one class, the vector belongs to this class;

2) if the input vector lies within the fields of two or more rule nodes associated with different classes, the vector will belong to the class corresponding the closest rule node.

3) if the input vector does not lie within any field, then there are two cases: (a) one-of-n mode: the vector will belong to the class corresponding the closest rule node; (b) m-of-n mode: take m highest activated by the new vector rule nodes, and calculate the average distances from the vector to the nodes with the same class; the vector will belong to the class corresponding the smallest average distance.

4. ECOS modeling of auditory, visual and combined stimuli perception

To answer the question whether one person's model can be used on another person's data, an ECF model was evolved on person A's data and tested on person B's data and vice versa. Table 1a,b presents the confusion tables for the two cases and the overall accuracy. The results suggest that it is not appropriate to use one person's model on another person's data.

Table 1a. The correctly recognized data samples by in an ECF model trained on all person's A data and tested on person's B data – 65 variables used (64 EEG channels and time)

Stimulus	A	V	AV	No	Accuracy
A	22	98	57	203	5.8%
V	24	30	108	208	8.1%
AV	26	46	59	257	15.2%

Table 1b. The correctly recognized data samples by in an ECF model trained on all person's B data and tested on all person's A data – 65 variables

Stimulus	A	V	AV	No	Accuracy
A	185	57	96	80	44.2%
V	165	76	81	118	17.2%
AV	128	84	75	113	18.5%

In the following experiment an ECF model was developed for person A (the first 10 data records) and tested on the same person's data to answer the question if it is possible to evolve an individual person perception model. First, the whole data was shuffled and then 80% of the data (1341 samples) were chosen randomly to create the training dataset. The rest 20% of the whole data (335 samples) made the test dataset. Since the training dataset was chosen randomly, the same experiment was repeated 10 times. Table 2 shows the average test results of those 10 experiments.

Table 2. The correctly recognized data samples by an ECF model trained on 80% and tested on 20% of a single person's data (person A) – 65 variables

Stimulus	A	V	AV	No	Accuracy
A	81.2	1.3	0.1	0.2	98%
V	1.1	82.4	2.9	1.8	93.4%
AV	0.6	3.3	75	1.4	93.4%
No	0.4	1.5	1.3	80.5	96.2%

The one person model seems to be generalizing well on this person's new data. For a more precise testing of the single person model, the leave-one-out cross validation method was used, when one sample was taken out from the data set and an ECF model was evolved on the rest of the data samples. This model was then tested on the left-out example, which procedure was repeated for every sample from the data set. The results, shown in Table 3 confirmed that a single person model can be successfully evolved with the use of the ECOS ECF method.

Table 3. The correctly recognized data samples by an ECF model trained and tested in a leave-one-out cross validation mode on a single person's data (person A)

Stimulus	A	V	AV	No	Accuracy
A	409	7	0	2	97.8%
V	7	421	9	3	95.7%
AV	1	9	386	4	96.5%
No	0	7	5	406	97.2%

5. Feature reduction through evolutionary optimization and adaptive learning in ECF models

In the experiments above there were 65 variables used (64 EEG channels and time). In order to find out which channels are important, genetic algorithm (GA) [3] was applied to the EEG data in the way described in [4]. The GA used a population of 10 ECF networks evolved for 10 generations using roulette wheel selection. Mutation was employed such that it occurred, on average, once per each new solution and crossover was applied twice per each sexual reproduction. As a result, only 37 EEG channels were selected and no time variable. The numbers of the selected by the GA optimal channels were: 1,4,5,6,8,9,12,13,14,15,16,18, 19,21,22,24,25,26,27,29,31,32,35,36,40,42,43,45,50,51, 52, 53,54,56,59,63,64.

The experiment from Table 1 was repeated, this time with only 37 variables and the results are shown in Table 4 and fig.2.

Table 4. The correctly recognized data samples by an ECF model trained on 80% and tested on 20% of a single person's data (person A) – a reduced set of 37 variables is used

Stimulus	A	V	AV	No	Accuracy
A	81.6	0.5	0.1	0.6	98.6%
V	0.8	84.2	2.3	0.9	95.5%
AV	0.3	2.4	76.4	1.2	95.1%
No	0.2	0.8	0.8	81.9	97.8%

The table above shows that the accuracy slightly improved when 37 variables were used in the ECF model when compared with 65 variables.

Further reduction of the features were achieved through correlation analysis between each channel and each class as shown in fig.3. For a correlation threshold of 0.1 only 34 out of 37 features were selected as follows: Class1: 1,4,5,8,13,14,18,19,25,27,35, 40,43,53, 54,63;Class2:1,5,9,12,18,19,21,24,26,27,32,36,40,45,50 ,53,54,56;Class3:1,4,5,6,8,13,18,19,21,24,25,29,35,42,5 1,52,53,56,59,63;Class4:1,4,5,6,9,12,13,14,16,18,19,21, 24,25,26,27,29,31,32,35,36,40,42,43,45,50,51,53,54,59, 63.

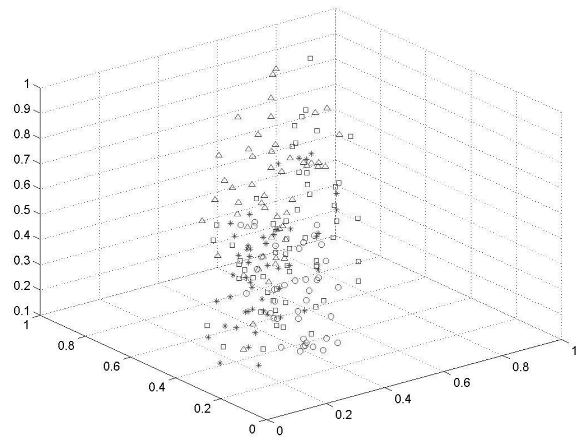

Fig. 2. The rule nodes of an evolved ECF from data of one person, 37 channels only, are plotted in the 3D PCA space. The circles represent rule nodes allocated for class 1, asterisks –class 2, squares - class 3 and triangles – class 4. It can be seen that rule nodes allocated to one stimulus are close in the space, which means that their input vectors are similar.

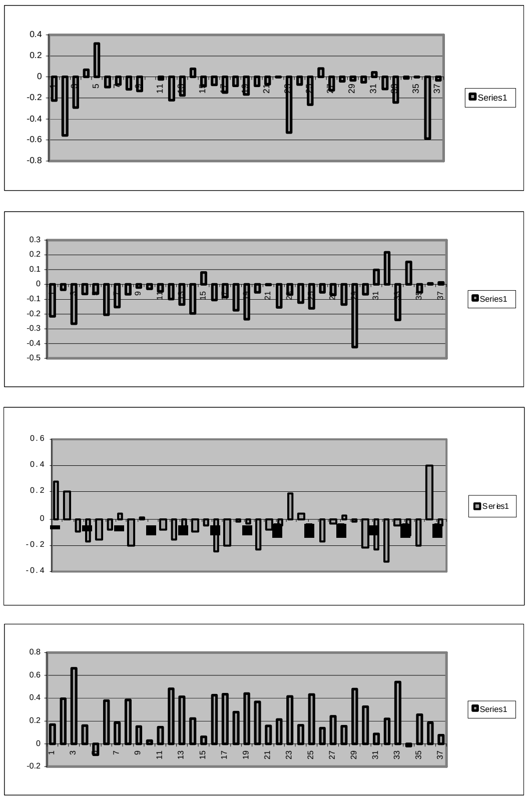

Fig.3. Correlation between the 37 channels and the classes from 1 to 4 (from top to bottom respectively

The allocation of the above selected channels for each stimulus is shown in fig. 4 (see also fig.1).

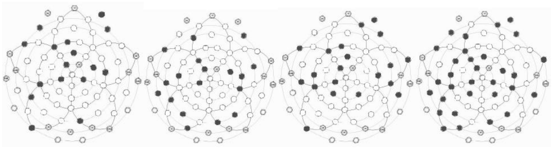

Fig.4. The location of the selected electrodes for each of the stimuli of classes from 1 to 4 (from left to right respectively)

Using the 34 channels, the same experiment as for channels 65 and 37 was repeated and results presented in table 5.

Table 5. The correctly recognized data samples by an ECF model trained on 80% and tested on 20% of a single person's data (person A) – a reduced set of 34 variables is used

	A	V	AV	No	Accuracy
A	81.4	0.6	0.1	0.7	98.3%
V	0.9	84	2.5	0.8	95.2%
AV	0.4	2.4	76.2	1.3	94.9%
No	0.3	1.1	0.6	81.7	97.6%

The results are slightly worse than the results when 37 variables were used. That suggests that the correlation analysis may not be a very appropriate technique for feature reduction and is inferior to the GA feature optimization technique.

ECOS allow for a model to be further trained (evolved) on new data, so that the model is incrementally trained and adjusted to new data for the same person. An ECF model was initially trained on samples taken from 10 time intervals and tested on new samples taken from 5 time intervals (Table 6a). Then the ECF was further trained on samples taken at 5 additional time intervals (fig.5) and tested on the same samples of new 5 time intervals as above (Table 6b). The results show improvement due to the on-line adaptation of the ECF model on new data.

Table 6a. The correctly recognized data samples by an ECF model trained on the first 10 time intervals data and tested on future 5 time intervals data of a single person (person A) – 37 variables used

	A	V	AV	No	Accuracy
A	110	41	9	52	51.89%
V	29	107	46	27	51.2%
AV	8	65	98	28	49.2%
No	12	49	41	104	50.5%

Table 6b. The correctly recognized data samples by an ECF model trained on the first 10 time intervals data, then trained additionally on another 5 time intervals data and then tested on future 5 time intervals data (as above) of a single person

	A	V	AV	No	Accuracy
A	139	31	8	34	65.6%
V	20	137	34	18	65.6%
AV	6	48	123	22	61.8%
No	9	33	36	128	62.1%

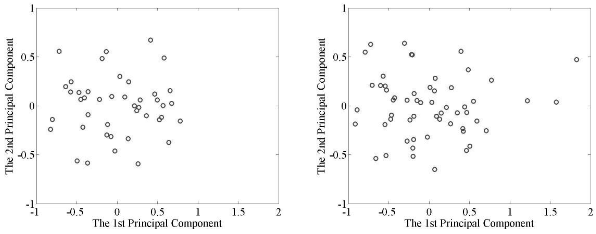

Fig.5. The evolved rule nodes in an ECF model, before (left) and after (right) adaptation for class 1, plotted in the 2D PCA space of the 37 channels.

Through ECF ECOS modeling, changes over time can be traced in the perception model .

7. Summary and Conclusions

This research demonstrates that it is possible to incrementally build a perceptual model of an individual. Evolving connectionist systems (ECOS) allow for on-line learning and model modification based on a continuous stream of input data. This feature can be utilized for an on-line creation and on-line modification of models of brain functions based on continuous EEG streams of data. Models that allow for a fusion of different sources of information (e.g. EEG, fMRI, gene data) will be explored in the future.

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