# The Language of Cortical Dynamics

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**Abstract.** Cortical dynamics can be recorded in various ways. Theoretical works suggest that analyzing the dynamics of recorded activities might reveal the workings of the underlying neural system. Here we describe the extraction of an activity pattern language that characterizes the dynamics of high-resolution EEG data recorded. We show that the language can be formulated in terms of probabilistic continuation rules which predict reasonably well the dynamics of activity patterns in the data.

## 1 Introduction

Cortical dynamics has been analyzed since the availability of appropriate recording machinery and methodology (e.g., EEG, fMRI, etc.). There are several theories that explain some aspects of the observed dynamics [6][8][11].

Recent works have shown that observed cortical dynamics in awake animals in stimulus free environment resemble very much the cortical activity observed in stimulus rich environment [5][9]. It has been shown that the orientation column structure of cat V1 can be reconstructed by classification of activity patterns recorded from an animal in stimulus free environment [9]. It has also been shown that the activity patterns in the visual cortex of awake adult ferrets in stimulus free environment resemble to around 80% the activity of the visual cortex recorded in stimulus rich environment [5].

The above results suggest that the cortex performs continuous information processing, which is independent to a good extent from the actual environmental input to the nervous system. One way to test this hypothesis is to analyze high resolution cortical activity recordings and try to extract a probabilistic grammar describing the evolution of recorded activity patterns [2][3][4]. The hypothesis is confirmed if it is possible to extract a such grammar, which can predict the evolution of cortical activity sufficiently correctly. We note that similar approaches have been used before to analyse and describe multiple neural spike trains [12] and simultaneous recordings from single neurons [1][13].

Here we analyze high resolution EEG data recorded from cat cortex and we aim to extract regularities that can be used to predict the changes in the activity patterns. The results show that it is possible to extract high reliability rules that link together activity patterns. The set of such rules can be seen as an abstract probabilistic grammar of the cortical activity representing the language of cortical dynamics.

The paper is structured as follows. First we discuss the data, second we present the analysis methodology, third we show the analysis results and analyze the extracted language of cortical dynamics, and finally, we discuss the results and their implications.

## 2 The data

The high resolution surface EEG (electro-encephalogram) data was recorded from cat cortex in the lab of WJ Freeman. The data consists of 20 sequences of 64-channel recordings, each sequence having 3000 recordings (i.e. the total data consists of 20 times 3000 items of 64-dimensional vectors = 60000 64-dimensional vectors). The recording was done in awake animals using high resolution recording from relatively small patches of exposed cortical surface. Further details and earlier analyses of the data in terms of similar models have been reported in other papers [7][11].

To reduce the variation in the data we consider the difference series of the original data, i.e., the 64 dimensional difference vectors between consecutive original recordings. A set of example recordings are shown in Figure 1. The 64 data values were organized into an 8 x 8 square (i.e. first 8 values in the first row, second 8 values in the second row, and so on).

## 3 Data analysis: methods and results

Our aim is to find a set of typical activity patterns (i.e. activity patterns that occur with high frequency int he data) in the high resolution EEG data and to establish probabilistic regularities describing which activity pattern follows earlier activity patterns.

### 3.1 Searching for typical activity patterns

We segmented the data into 2 x 2, 3 x 3 and 4 x 4 data matrices (i.e. the 8 x 8 data matrices are divided in smaller components, for example dividing the 8 x 8 matrices in 4 x 4 matrices means that the 8 x 8 matrices are divided in the middle horizontally and vertically resulting four 4 x 4 data matrices - upper-left, upper-right, lower-left, lower-right). We did the segmentation with and without overlap between the segments in order to capture many possible configurations of cortical activities that may organize into typical activity patterns. (Note that the segmentation does not induce a resolution hierarchy in a strict sense.)

For each such data matrix we analyzed the joint activity of the corresponding recordings with the aim of finding typical activity patterns. We consider an activity pattern typical if it appears regularly (i.e. with high frequency), possibly with minor random modifications.

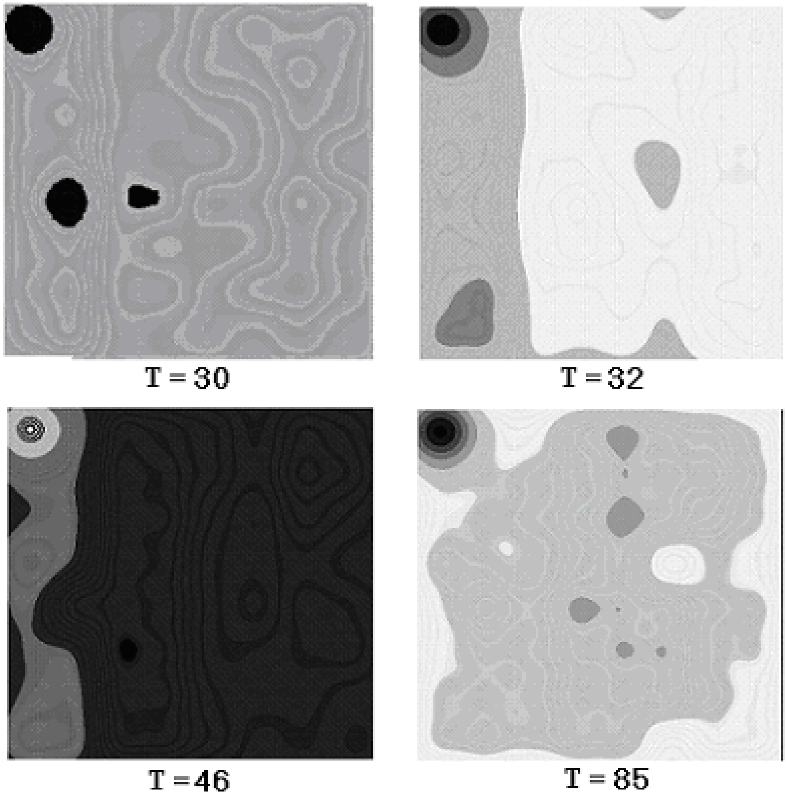


**Fig. 1.** High resolution EEG recordings from cat auditory cortex. The data is represented using pseudo-gray-scale colors. The T values indicate the sequential position of the data within the data sequence (each sequence contains 3000 data sets).

We used Kohonen networks to find the typical activity patterns [10]. For each data matrix (i.e. a data matrix is defined by its size and position, for example there are four 4 x 4 data matrices with no overlap) we built a separate Kohonen network with 25 nodes, containing a prototype vector and a position vector (note that the dimensionality of the prototype vector is equal with the dimensionality of the data vectors, i.e., the number of recordings within the data matrix; the dimensionality of the position vectors is 2, i.e., the Kohonen network nodes are arranged into a planar lattice). The Kohonen networks were trained with the corresponding data vectors (i.e., the 2 x 2, 3 x 3, 4 x 4 data matrices selected from each 64 electrode recordings, from 10 data sets considered for training of the networks). The training process is described by the following equations:

$$i = \arg\min_j ||x_t - w_j|| \tag{1}$$

$$I = \{j|\rho_t > ||v_j - v_i||\} \tag{2}$$

$$w_j = w_j + c_t \cdot (x_t - w_j), \quad j \in I \tag{3}$$

where $x_t$ is the t-th data vector presented to the network. The values $\rho_t, c_t$ are parameters that change gradually during the training process, starting from relatively large values towards zero. The training process stops when the values of these parameters reach zero (or get very close to zero).

An interpretation of the training process is the following: equation (1) selects the node of the network, with index i, which attracts the data vector $x_t$ ; equation (2) defines the neighborhood of the node with index i within the planar lattice of nodes; equation (3) updates the value of prototype vectors contained in nodes belonging to the neighborhood of the node which attracts the currently presented data vector $x_t$ The updating of prototype vectors means that they are moved slightly closer to the presented data vector.

The nodes of the Kohonen networks learn the representative data prototypes. At the same time the Kohonen networks preserve the topological structure of the original data space, which means that similar data vectors are attracted by the same prototype vector. Data vectors attracted by each Kohonen network node form a class of data vectors.

We analyzed each class of activity patterns identified by the trained Kohonen network to assess its compactness. Our underlying hypothesis is that if data vectors forming a class show little variation then they are likely to be representatives of a typical activity pattern. To measure the compactness of classes we computed the variance of the distances of data vectors belonging to the class from the prototype vector contained in the Kohonen network node, which attracts the data vectors of the class. Compact activity pattern classes identified by the Kohonen network were considered as typical activity patterns represented by their prototype activity pattern extracted by the Kohonen network.

We detected 437 typical activity patterns in the EEG data. In 77% of all data matrices we were able to detect at least one typical activity pattern. The number of typical activity patterns detected for each data matrix varied between 0 and 21. The average number of detected typical activity pattern for data matrices with at least one such pattern was 10.16, i.e., in average we detected around ten typical activity patterns for each data matrix.

The original data series were analyzed using the trained Kohonen networks. We classified the appropriately grouped data values and we generated a symbolic representation of the data sets using the detected typical activity patterns. If we found that they belong to a class corresponding to an identified typical activity pattern we included the associated symbol of the typical activity pattern in the symbolic translation of the data vector. In this way every 64 dimensional original data vector was translated into a set of symbols, each symbol corresponding to an identified typical activity pattern. An example of such translation is shown in Figure 2.

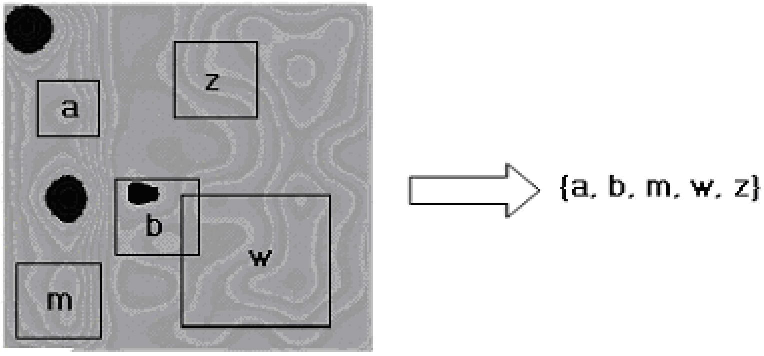


**Fig. 2.** Translation of original activity data into symbolic data. The rectangles surround the data matrices for which we are able to classify the data as belonging to a class associated with a typical activity pattern. The letters in the rectangles are the symbols associated with these typical activity patterns. On the right hand side of the arrow is the symbolic translation of the original data.

### 3.2 Searching for language rules

We analyzed the consecutiveness relationships between typical activity patterns with the aim of establishing probabilistic continuation rules (i.e. one-step ahead continuation rules). We note that in general many-steps ahead continuation rules may play important role in determining the evolution of cortical dynamics. In our approach we approximate the complete set of continuation rules (which includes many-steps ahead rules as well) by a Markovian approximation consisting of one-step ahead rules.

For each typical activity pattern represented by a symbol in the translated data series, we considered all preceding sets of symbols. For example, if 'w' is symbol representing a typical activity pattern, which occurs in the symbolic translation of data vectors $x_{t_1}, x_{t_2}, x_{t_3}$,we consider as preceding symbol sets the symbol translations corresponding to the data vectors $x_{t_1-1}, x_{t_2-1}, x_{t_3-1}$. If the symbol set translations of these latter data vectors are $\{a, m, r\}$, $\{a, m, n, k, z\}$, $\{a, m, t, y\}$, then these symbol sets will be considered as preceding sets for the symbol 'w'.

Considering all preceding sets for a selected symbol we aim to identify subsets of these preceding sets, such that these subsets predict with relatively high likelihood the occurrence of the selected symbol in the symbol set translation of the next data vector. We call these subsets predictor sets of the selected symbol. Taking into account that the number of all possible combinations of symbols present in preceding sets can be extremely large, we adopt a simplified approach. We take all pairs of symbols in preceding sets and count the frequencies of such symbol pairs. We construct a graph of symbols found in preceding sets with weighted edges representing the frequency of the corresponding symbol pair. Cliques in this graph with all edges having a weight higher than an appropriately set lower limit are considered potential predictor sets of the selected symbol (in the case of our data we set this lower limit to be 20, i.e., we consider the cliques of the graph which contains edges between nodes which appear simultaneously in preceding sets more than 20 times). For all such potential predictor sets we count their occurrences in the whole data set and also the occurrences of the selected symbol in the symbol representation of the data vector following data vectors that contain in their symbol representation the potential predictor set. We accepted as predictor sets those potential predictor sets, which predicted the occurrence of the selected symbol with likelihood $P(\textit{selected symbol} \mid \textit{predictor set}) > 0.2$ . We call continuation rules the relationships between predictor sets and predicted symbols.

We established for each typical activity pattern a set of continuation rules of the form

$$P^i_X(X|R^i(X)) \tag{4}$$

where X is an activity pattern, R(X) is the predictor set of activity patterns for the activity pattern X, is the number of the rule among the rules related to the activity pattern X, and the rule gives the probability of generating X given the earlier generation of the predictor set. We also call the predictor set of an activity patter X the reference set of this activity pattern [3]. The rules describing the probabilistic relationship between production of the pattern X after the preceding generation of patterns forming the reference set, are also called referencing rules of the pattern X [3]. Note that the same pattern may be generated by many rules, and the reference sets may overlap providing reference for many possible rules to generate new patterns. In general reference sets may contain earlier activity patterns with variable time distance between the predicted pattern and the pattern in the reference set. In the case of our analysis we restricted the reference sets to symbol sets generated immediately before the generation of the pattern X, implying that the rules that we extracted describe a Markovian language (i.e., symbols at time t+1 depend only on symbols that were present at time t).

Our analysis led to a set of rules describing which activity patterns may emerge after the presence of a set of activity patterns present at a given moment in the data. The set of these probabilistic rules constitute a probabilistic grammar describing the activity patterns emerging in the analyzed EEG data. In our view this rule set is an approximation of the true grammar governing the generation of activity patterns determining cortical dynamics. An example of such rules is presented in Figure 3.

### 3.3 Validation of language rules

To evaluate the correctness of predictions of established grammatical rules we analyzed another data set of similar EEG recordings that was not considered during the rule extraction phase.

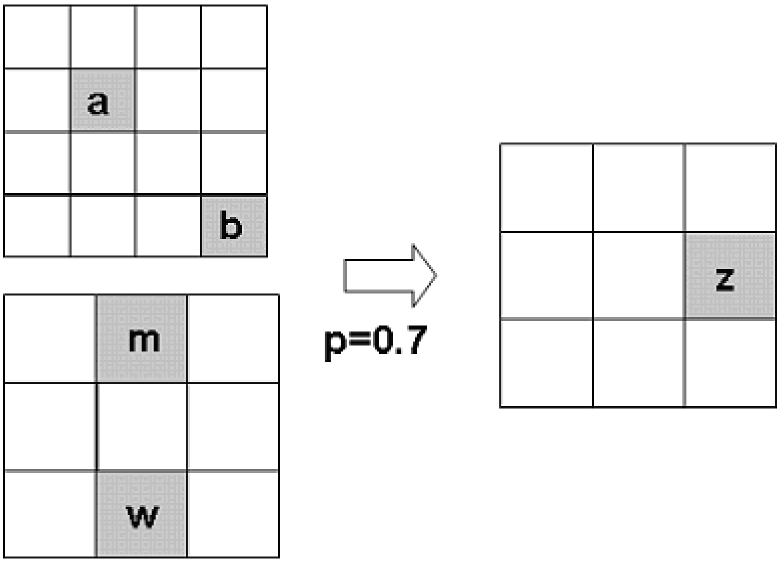


**Fig. 3.** An example of the language rules of the EEG data. The activity patterns on the left constitute a predictor set for the activity pattern on the right. The activity pattern on the right occurs with probability 0.7 after the occurrence of the predictor set. The letters represent identifiers of typical activity patterns in the corresponding data matrix.

The test data series were analyzed using the same Kohonen networks that were trained with the data used for rule extraction. The data vectors of test series were translated into series of symbol sets following the classification of the data matrices contained in the data vectors by the trained Kohonen networks. We searched for all occurrences of all established predictor sets for each of the 437 typical activity patterns. For each predictor set we calculated the probability of the predictor set being followed by the appropriate typical activity pattern. In this way we arrived to a set of probabilistic rules of the form

$$\hat{P}_X^i\,(X|R^i(X)) \tag{5}$$

a test rule being calculated for each of the established reference rules.

If the calculated reference rules are correct and they describe the dynamics of cortical activity, we expect that the probability values of rules in equations (4) and (5) do not differ significantly. Figure 4 shows the results for one 2 x 2 data matrix and for typical activity patterns associated with this data matrix. We calculated the differences between the calculated reference rule probabilities and the probabilities calculated for the same reference rule using the test data (i.e., $P_X^i(X|R^i(X)) - \hat{P}_X^i\,(X|R^i(X))$). We averaged these differences for each typical activity pattern across all referencing rules of the given typical activity pattern. For each averaged difference we calculated the measure of how significantly it differs from zero using the t-test. The average difference does not differ significantly from zero if the significance measure (t-value) in absolute value is below 1.96, which is the case in 5 out of 11 cases, and it differs very significantly from zero if the absolute value is above 2.57, which is the situation in 4 out of 11 cases, the remaining 2 cases having intermediary values of difference.

The results show that in half of the cases the rules are valid for the unseen data, and there are fewer cases in which there is a statistically very significant difference between the predictions of the extracted rules and the dynamics of the unseen data. The results are not overly impressive, in the sense that there are several rules which are detected, but not confirmed by analyzing the test data (though, these are the minority of the cases). However, these results show that it is possible to extract a relatively correct Markovian approximation of the language of cortical dynamics by performing the above described analysis of high resolution EEG data.

## 4 Discussion

The methodology described in the paper aims to extract the rule set of a probabilistic grammar from high resolution EEG data. The results show that the proposed methodology is promising and the extraction of the rules set is possible to some extent. The extracted activity pattern language can be used to predict the dynamics of activity patterns detectable in the EEG data. It is important to note that the methodology focuses on the internal processing that is represented by the data and ignores the association of input/output transformations related to this processing. This implies that any understanding of the data that might be derived from the extracted pattern activity language may not be related in any direct way to input/output processing and may not reveal explicitly how inputs are represented and processed within the system, and how outputs of the system under study are generated. Earlier theoretical analysis [2][3] suggests that such internal computations should be critical for computations performed by neural systems, and without understanding them it might not be possible to understand how action-perception cycles of the system are generated in the context of the system's experience and processing structure.

We note that the data analysis that we applied to determine the abstract language of the EEG data is equivalent to learning an abstract language from positive examples only. Such learning problems as data analysis problems are ill defined in principle, and can be solved correctly under appropriate constraints, which regularize the search space of possible language rules. The implication of this for the presented work is that the rules that we extract form the data might be side effects of the actual rules. At the same time another factor that contributes to establishment of incorrect rules is that we search for a Markovian approximation (i.e., current state depends only on the previous state) of the full

| | | | | |
|---|---|---|---|---|
| 1: X | 2: X | 3: X | 4: X | 5: X |
| 6: X | 7: X | 8: 2.0924 | 9: 3.6264 | 10: 1.5205 |
| 11: 3.0546 | 12: 2.4206 | 13: 7.1962 | 14: 3.0181 | 15: X |
| 16: 1.6241 | 17: 0.5750 | 18: X | 19: -0.4839 | 20: X |
| 21: X | 22: -0.4544 | 23: X | 24: X | 25: X |

**Fig. 4.** The significance of differences between probabilities associated with language rules and corresponding probabilities determined from the test data. Out of the 25 possible (corresponding to the 25 nodes of the Kohonen network) typical activity patterns 11 were recognized (i.e., these formed sufficiently compact classes around the prototype activity pattern). The differences between the probabilities of corresponding referencing rules were calculated, and we calculated how significantly the average of these differences differs from zero using the t-test. The significance measures (t-values) are shown in the lower parts of the boxes.

language that might contain referencing rules including in their reference sets activity patterns from the longer past.

We show here that it is possible to extract an internal language from EEG data and that this language can be seen as the language of cortical dynamics. This language of cortical dynamics includes in a generic sense the experience of the system and its own structure and other constraints that determine how the system processes information. The presented approach opens new avenues for research on cortical dynamics and suggests that we should focus on understanding of the inner language of cortical dynamics instead of focusing on input/output transformation properties of cortical neural activity. This focus on internal processing is in agreement with earlier theoretical works [4][3] and also with experimental findings [5][9], which show that internal processing resembles the general processing in presence and absence of external stimuli.

Finally we note that previous works on extracting similar probabilistic language descriptions of neural activity focused primarily on single neurons [1] or on small sets of neurons [13]. In a previous paper [4] we described the conceptual background of activity pattern computation in neural systems and we have shown that it can be applied to large scale neural systems through the analysis of emerging activity patterns and establishing of probabilistic continuation rules. In the present paper we continue this work and focus on the data analysis methodology and the derivation of the continuation rule representation of the language of cortical dynamics.

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