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Biologically Inspired Artificial Neural Cortex Architecture and its Formalism

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***Abstract*—**The paper attempts to elucidate the columnar structure of the cortex by answering the following questions. (1) Why the cortical neurons with similar interests tend to be vertically arrayed forming what is known as cortical columns? (2) How to describe the cortex as a whole in concise mathematical terms? (3) How to design efficient digital models of the cortex?

***Keywords*—**Cortex, pattern recognition, artificial neural cortex, computational biology, brain and neural engineering.

I. Introduction

THE cortex (neocortex) is a 2 mm thin, 0.5 m x 0.5 m sheet made of pyramidal neurons, which is wrinkled together to fit the small volume of the skull. Cortexes of monkeys, dolphins, cats, dog and other animals are less or not wrinkled because animals' cortexes are featured by a much smaller area size. The first evidence suggesting a vertical arrangement of the cortical sheet of neurons was provided by von Economo in 1929 [1]. The term column still invites some debate in the neuroscience community. Their size, function, and importance are disputed. However, the reason one can think in general terms of a columnar architecture is that the vertically aligned cortical neurons tend to respond to the same stimulus [2]. Another reason we stems from how the cortex forms. In an embryo, single precursor cells migrate from an inner brain cavity to where the cortex takes shape. Each of these cells divides to create about one hundred neurons, called a (micro) column. Hence, the term column can refer to general vertical connectivity or to specific groups of cells from the same progenitor [3]. A strong argument that supports a columnar architecture of the cortex is presented in [4]. Next part of the paper considers the following question. Why individual columns respond to different feature patterns if scientific evidence suggests that each column is interested only in a single column-specific feature? The answer to this question is related to real-world patterns that share common features. Also, it is argued that emergence of columnar architecture was stimulated by the existence of real world patterns with common features. Next, a rigorous mathematical definition of an index is offered and it is shown that indexing structures provide extremely efficient solutions to computationally complex search problems. It is argued that the existence of such an effective solution is a mathematical reason for the emergence of columnar indexing structures. An artificial neural cortex with a hierarchical indexing architecture is considered, and, finally, an example of an artificial neural cortex-based application is provided.

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II. Methods and Materials

A. Common Features of Patterns

One known instance of cortical feature columns is the visual cortex's orientation columns, whose neurons respond to lines tilted at a particular angle. The neurons in one column will respond best to boundaries tilted at 25°, those in another to 35°, etc. [5]. In the olfactory cortex, a huge family of genes encodes proteins called olfactory receptors [6]. Individual olfactory sensory neurons typically express just one of those genes. Also, each olfactory sensory neuron is hardwired via its axon to a single column in the olfactory cortex. Hence, individual olfactory columns are linked to individual features of odors. In the primary auditory cortex, its individual columns respond to particular frequencies. Individual columns of the somatosensory cortex respond to individual whiskers, etc. These examples suggest that individual cortical columns respond to their own individual features.

But, on the other hand, individual columns of cortical regions also respond to different feature patterns. For instance, a single receptor protein appears to bind (recognize) many different odors [6]. It is possible because, rather than having sensory neurons that respond selectively to odors, that is, complex feature patterns, individual cells respond (via their receptors} to sub-molecular features of the volatile chemicals coming from those objects. Therefore, any given olfactory sensory neuron will respond to many different odors as long as they ***share a common feature***. The olfactory cortex then looks at the combination of sensory neurons activated at any given time and interprets that pattern; the cortical interpretation is what is perceived as smell. In the auditory cortex, audio frequencies serve as common features of spoken words that are perceived via the auditory sense, whereas the words serve as common features of sentences. All wines share a specific functional group such as alcohol; both the sun and the character "o" are featured by the same circular shape, and so on.

It is know that almost all cortical regions show a striking structural similarity. So, it wouldn't be surprising to find out that the same working pattern holds not just for primary cortical regions, but for higher regions as well. Indeed, the authors in [7] replaced a fragment of a monkey skull with a piece of glass and a camera attached to it to see the inferotemporal region and how its spots light up when monkey is looking at an object (Fig.1). It was discovered that "…some spots activated by one object were also activated by other objects. Overlap of spots was observed when the feature was ***common*** among the objects."

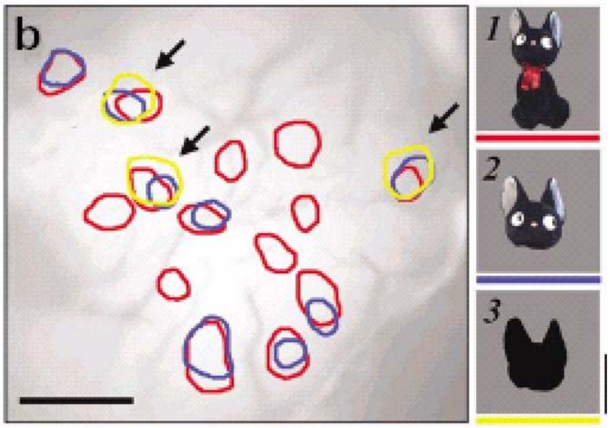

Fig. 1 Part of the Inferotemporal Cortical Region of a Monkey (reproduced from [1])

In Fig. 1, the common feature of the pictures 1-3 is the cat's head contour. Hence, the yellow circles represent the activity of the inferotemporal spots that respond to this complex feature.

B. *Cortical Pattern Recognition*

It was suggested in [8] that when the neurons fire, their synapses get strengthened. A relevant phenomenon is a long-term potentiation [9], which is a long-lasting improvement in communication between two neurons that results from stimulating them simultaneously. Since neurons communicate via chemical synapses, and because memories are believed to be stored within these synapses, long-term potentiation is widely considered one of the major cellular mechanisms that underlies learning and memory [9]. Hence, when an external input pattern activates a subset of neurons and the activation pattern persists for a sufficient time interval, one can expect that a number of new connections will emerge. Now, it seems reasonable to argue that a columnar arrangement is imposed on cortical neurons by real world patterns because they often share common features. As an individual cortical pyramidal neuron cannot develop more than 10,000 synapses ([2]), it cannot participate in more than 10,000 combinations of active neurons that represent/identify a set of 10,000 real worlds objects with common features, which is, probably, not sufficient for a life time of an individual. By lining up neurons in a 100 cell strong column (this number holds throughout the cortical surface [5]), the cortex can identify million-large groups of patterns with common features. There also exists a mathematical justification that shows a columnar arrangement to be a reasonable solution to search problems of combinatorial complexity in the domain of real-world feature patterns.

C. *Mathematics of Indexing*

Indexing techniques play a prominent role in information technologies. An excellent example is the Google search engine, which responds almost instantaneously no matter how many documents are published on the web and which is based on the Google's index [10]. Here is an index definition from Grolier Multimedia Encyclopedia. "An index is a list of the subjects contained in a book, or other compilation of recorded information. Index entries have two parts: a heading and a locator. Index headings identify the subjects, usually in a word or phrase describing them. In back-of-the-book indexes the locators are usually page numbers. The goal of an index is to provide quick, easy, and unambiguous access to the information, even though information on a specific topic may be scattered throughout the indexed material."

A rigorous mathematical definition of an index is suggested in this paper as follows. Let C be a collection of sets $\{x\}_Y$, $y \in Y$, where Y is the set of labels or names. The index is defined as an inverse collection C^{-1} of sets $\{y\}_X$. The inverse collection is composed of the sets, whose elements Y are labels y of sets $\{x\}_Y$ and whose names are elements of sets $\{x\}_Y$, such that

$$x \in \{x\}_Y \Leftrightarrow y \in \{y\}_X$$

D. *Example 1*

Let $z = \{a, c\}$, $y = \{b, c, d\}$, $u = \{a, b\}$, $x = \{a, d\}$, $v = \{d\}$ be a collection of sets. Then the inverse collection is

$$a = \{z, u, x\},\quad b = \{y, u\},\ c = \{y, z\},\ d = \{y, x, v\}$$

These collections are depicted as the two following vertical arrangements

$$\begin{array}{ccccc} & d & & & \\ c & c & b & d & \\ a & b & a & a & d \\ \hline z & y & u & x & v \end{array} \qquad\qquad \begin{array}{cccc} x & & & v \\ u & u & y & x \\ z & y & z & y \\ \hline a & b & c & d \end{array}$$

In the left-hand side arrangement, the columns in the numerator contain original sets' elements and their subscripts are the corresponding sets' labels. On the right-hand side, the columns in the numerator contain sets' labels and their subscripts are the elements of the original sets. It can be shown that for any collection of sets its inverse collection does always exists, which means that any collection of sets can be indexed.

Indexes spell extreme "computational" power. Let C be a collection of sets $\{x\}_Y$, $y \in Y$ and A be an arbitrary set. Next, the best match for A in the collection C is sought. In this case a direct approach would require comparing A to all sets from the collection C. If the average number of elements in sets from C is N then, on average, N^2 operations would be needed to compare A to a set from C. If the number of sets in a collection is N then finding a best match would require N^3 operation or $N^2|C|$ operations, where $|C|$ is the cardinality of C. It will be shown that by indexing a collection of sets the computational complexity of the search for the best match shrinks to just O(N).

E. Example 2

A book is a collection of pages $\{w\}_p$, p =1,…N, where N is the total number of pages and p is the page number. One wants to find out where, for instance, the words life and cycle appear in one context, i.e., in the same paragraph. Performing a full search, one has to keep on turning pages all through the book. But, it makes a perfect sense to index this collection of pages first, thus, creating the index $\{p\}_w$, w =1,…W, where w is the word's identity and W is the set of all words found in this book, for instance,

1 Behaviorism	15, 27
2 Cats	17, 89, 131,169, 189, 201, 286
3 Cycle	17, 21, 32, 33, 40, 46
4 Learning	66, 78, 98, 118
5 Life	34, 46, 55, 89, 101, 121
6 Memory	22, 66, 67, 68, 70, 186, 286
7 Monkey	27, 33, 111, 225, 233
………………..	

In this case, the index points directly to the columns 3 and 5. All that remains to be done now is to intersect the columns {34, 46, 55, 89, 101, 121} and {17, 21, 32, 33, 40, 46}, which would yield the paragraph number 46. The operation of intersection still requires $O(H^2)$, where H is the average length or height of the column. But, it is possible to cut down even this number by sequentially reading the numbers in the selected columns and calculating the frequencies of pages. For this example, the pages 17, 21, 32, 33, 34, 40, 55, 89, 101, 121 occur one time only, whereas the winning page number 46 occurs 2 times. This few-selected-columns ascending procedure amounts to 2*H operations only. What is more, it is possible to design the system in such a way that the amount of stored patterns will not affect the order of computational complexity, provided that a sufficient memory is available or feature patterns are ordered sets as it will be discussed later. These conditions help keep the average columnar height H at bay, which is practically feasible by controlling dynamical ranges of features.

F. Artificial Neural Cortex

Real-world patterns are represented by long sequences of features like pixels, audio frequencies, etc. Artificial neural cortex (ANC) is a memory that takes in long input patterns. However, unlike standard content-addressable memory (CAM), ANC is not a parallel memory device. This is because CAM is a power-greedy memory as all its paths (circuits) are always activate due to CAM's internal parallelism. CAM's applicability is severely limited by its power consumption.

Note: Had the cortex been a massive parallel "device", it would "shine" like a lamp all the time. But, brain imaging techniques show that only a small percentage of spots of total cortical area are simultaneously active at any given time. The only known neurological case when almost the whole brain becomes active is the epileptic seizure [12].

The other fundamental memory architecture is the random access memory (RAM), which is a fast, energy-efficient memory, where an input address points directly to the result and activates one path only. However, ANC is not a RAM-like device. This is because any RAM faces an exponential explosion of its addressable space with the growing length N of its addresses. Already at N as low as 300, the size 2^{300} of the needed address space will be greater than the number of hydrogen atoms in the Universe ([11]), which is around 10^{80} ($10^{80}<2^{300}$). A feasible solution to this problem is to cut long feature patterns into, say, N 32-bit pieces. Such approach causes an overlap of features and emergence of pattern columns, thus leading, as discussed, to a pattern index or, in other words, to a multi-addressable memory.

ANC is, basically, a multi-addressable memory, which has been used for various applications since 2001 [13]. ANC comprises a hierarchy of regions, each region being an index. All indexing modules are featured by the same columnar architecture. In 2007, US patent under the name "Neural Cortex" was granted for a design of the indexing hardware module that doesn't make use of microprocessors [14]. An example of ANC [15] hierarchy is as follows. The first level is an index of feature patterns. The inputs to the first level are low-level features such as image pixels or other features that depend on particular applications. The outputs of the first level are feature names, which, in turn, serve as inputs to the next level index. If the first level is an index of lines then its outputs are the linear clusters of pixels.

The second level can be, for instance, an index of connected shapes, whose inputs are the names of linear pixel clusters. If the third level takes shapes' names as its inputs then the outputs of the third level are the names of scenes of shapes, and so on. This hierarchical indexing structure endeavors the system with generalization capabilities. For instance, it doesn't matter whether the input is a square or a rectangle shape, whether it is skewed, scaled or rotated as long as shape's topology is preserved.

Each level of ANC is designed to solve the following search problem. Let F be a universal feature set (set of all distinct features). Given an unknown feature set {f} from F and a collection C = $\{f\}_p$, p Є P, of feature patterns, find a set $\{f\}_p$ that best matches the input {f}. A direct search will amount to $O(N^2|C|)$, where N is the average pattern length (for real-world patterns, |C|>>N). However, pattern indexing makes an intersection-based search possible

$$\bigcap_{f \in \{f\}} \{p\}_f \tag{1}$$

Here, the columns of the index contain names of patterns, whereas the subscripts of the columns are the features. Clearly, the single element in the above intersection is a name of the best match as it shares N features with the unknown input. Note that only N columns need to be accessed, where N is the number of features of the unknown input pattern. By intersecting a subset of the columns of the index that are selected by the input pattern, it is possible to drastically reduce the computational complexity of the search to just N*H, where H is the average height of columns of the index.

The above discussion implies that, if H is a constant, indexing offers an O(N)-solution to the best match search problem.

In practice, a set-theoretical intersection is a bad tool as noise would render it empty most times. But, one can evaluate (1) with the use of a name frequency function, that is, by looking for the name that occurs in the columns with subscripts {f} most frequently.

In case of partially ordered feature sets, a practical way to keep the height H at bay is by combining ordered features into pairs, triplets, etc., thus, increasing the number of columns, which, in turn, reduces the average value of H. Another trick of the trade is applicable to fully ordered feature sets $\{f\} = \{f_1, f_2, \ldots, f_N\}$. In this case, the single index $\{p\}_f$, $f \in F$, is replaced with N indexes, such that the name contents of the first index is created with the use of the feature f_1 only, name contents of the second index is created with the use of the feature f_2, etc. Clearly, this decreases the height H by the factor of N.

Note: In ANC, the columns are containers of names. It is possible to speculate that, in the biological cortex, the horizontal synaptic links to/from feature columns that jointly respond to a learnt pattern play role of patterns' names (the same name-concept was suggested in [3]).

G. Image-based Retrieval of Trademarks

In this section, an application of ANC to a problem of image-based identification of trademarks is considered. The test database contains around 1100 black and white images of trademarks. Some trademarks are shown in Fig. 2.

The following features were chosen to represent the trademarks' shapes. For each shape pixel, a circular run-length code with the radius 8 is obtained on a feature extraction stage. Fig. 3 shows two local areas with corresponding run-length features, each represented by an ordered set of integers. The size of this set depends on the neighborhood of the pixel. Internal shape pixels, where no gradient change takes place are ignored. A feature collection representing each trademark is an unordered feature set whose size changes from shape to shape. Also, identification of trademarks by their fragments may change the order of a shape's features. For example, for a set of three features:

f_1 = 24, 1, 33, 3
f_2 = 12, 2, 10, 24, 1, 33, 3
f_3 = 13, 10, 15, 20

a two-feature subset may look like

f_1 = 12, 2, 10, 24, 1, 33, 3
f_2 = 24, 1, 33, 3

Fig. 2 Trademarks

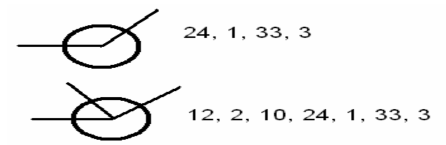

Fig. 3 Local Areas and their Features

Hence, this formal setup of the problem doesn't follow a standard pattern recognition paradigm, where objects are represented by vectors and problems are solved in an N-dimensional space. In the trademarks application, the number of shape representing features changes from 15 (simple shapes) to 7000 (complex shapes).

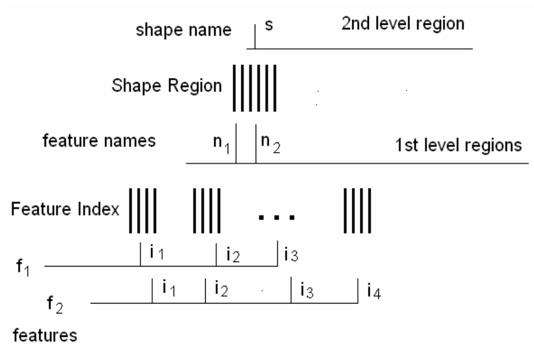

Fig. 4 Two-Level ANC

For this application, a two-level ANC was used, whose first level is a feature index and second level is a shape index (Fig.

4). The feature index comprises 16 regions: it was assumed that the number of integers in any feature is limited by 16. Each region is represented by 64 columns because the maximum positive value any integer can take is limited by 64 (circumference length). The 1st integer value in the feature is used as a subscript of the column of the 1st region, the 2nd integer value - as a subscript of the column of the 2nd region, etc. For a K integers feature, its feature name (names are generated sequentially) is to be written in K corresponding columns if and only if the maximum of the feature names' frequency response is less then K. Otherwise, the feature is identified and its name n_1 is used as the subscript to the shape index that stores trademarks identities in its columns. The shape index comprises only one region because the set of feature names representing each given shape is unordered. Shape names' frequency response is elicited by a sequence of feature names (length L) representing the input shape. (For shapes in Fig. 2, the length ranges from L=1546 to L=6636). The experiment showed that a 90% threshold of the shape names' frequency response ensures 100% identification of all 1100 trademarks (the input shape is identified if the maximum frequency response exceeds 90% of L). There is no training/testing watershed in this two-level indexing structure. New shapes and their partially new features are memorized as the system sequentially learns the shapes. Identification cycle takes 1-2 seconds on a PC, where 98% of processing time is spent on feature extraction, and shapes/features identification time (2% of processing time) only marginally increases with the database size.

III. Results

Columnar arrangement of cortical neurons is an efficient (time and energy saving) solution to search problems of combinatorial complexity in the domain of real-world feature patterns.

IV. Conclusion

The cortex is, probably, a hierarchical biological index of real-world patterns. The mathematical reason for the indexing architecture of the cortex stems from the fact that indexing offers an O(N)-divide-and-conquer solution to $O(N^3)$+ complexity of search problems in the domain of long real-world feature patterns.

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