A Neural Network Model of Cerebral Cortex that Combines Bayesian Network, SOM, ICA and Reinforcement Learning

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Abstract—**The author is trying to achieve a breakthrough in the elucidation of information processing of the cerebral cortex, in order to realize highly intelligent robots like human beings. The author designed a computational model of the cerebral cortex, called BESOM model. The neural network that executes the derived algorithm of the model is very similar to six-layer and column structures that represent the anatomical characteristics of a cerebral cortex.**

I. Introduction

In light of recent findings related to neuroscience and machine learning, the author is engaged in elucidating the brain's information processing principles, with a view to realizing robots as highly intelligent as human beings.

The author designed a neural network model of the cerebral cortex, called the *BESOM* (BidirEctional SOM) model[5][6]. The BESOM model is a combination of four machine learning technologies, the self-organizing map (SOM)[1], Bayesian network[2], independent component analysis (ICA)[3], and reinforcement learning[4], and has appropriate computational characteristics as a model for reproducing brain functions. Surprisingly, the neural network that executes the algorithm derived theoretically accords extremely well with main anatomical characteristics of the cerebral cortex [5]. Therefore, it is almost certain that this is an appropriate model for explaining the information processing principles of the cerebral cortex. Using this model, concrete methods will be developed for reproducing the main functions of the cerebral cortex, such as concept acquisition, pattern recognition, action acquisition, thought and language comprehension.

Although the neural network model is not yet complete and is not able to perform computer simulations, the author believes that it is an extremely promising model.

The outline of the BESOM model is explained in the following section. Furthermore, brain's various functions, such as pattern recognition, inference, action acquisition, sequence learning, action planning, and language comprehension, are discussed with respect to the BESOM model.

II. Elements of the BESOM Model

From the overall macro-scale structure of the brain to the micro-scale structures of individual neuron functions, the BESOM model is widely related to the brain.

At present, the BESOM model comprises two mechanisms, the *BESOM net* and the reinforcement learning mechanism. The BESOM net is structured as shown in Fig. 1.

The BESOM net has hierarchical structure of *bases*.

A basis is composed of *nodes* that represent random variables. The variables represented by the nodes within one basis become mutually independent as a result of independent component analysis.

Nodes contained in bases at the different levels of hierarchy are connected by edges. Thus, the nodes form a directed acyclic graph. This network of nodes acts as a Bayesian network.

The nodes are composed of multiple *units*. The nodes are random variables, while the units correspond to possible random-variable values. At the same time, each node acts as a competitive layer of a SOM, which compresses the input from its child nodes. Meanings of the values of each random variable are acquired by the SOM.

The algorithm to operate the BESOM net is currently expressed using about 10 types of variables (Chapter IV). The repetitive algorithm can be realized by a neural network (Chapter V).

The hierarchical structure of the bases, the number of nodes within the bases, and the number of units within the nodes are not changed by learning, while only the *weights of connections* between units change.

Table I shows the correspondence between the elements that comprise the cerebral cortex and the structural elements of the BESOM model.

III. Basic Behavior of BESOM net

BESOM uses SOM and ICA to self-organize a model of the external world, and expresses it using a Bayesian network. Using this Bayesian network, BESOM carries out a variety of information processing, which includes recognition, motor control, logical inference and probabilistic inference about the external world.

A node of a BESOM net behaves as follows. During learning steps, each node acts as a SOM competitive layer, as shown in the left of Fig. 2: the input from its child nodes are compressed and learned. The learning result becomes a conditional probability table of a Bayesian network. A variety

Elements of the Brain	Size in Human	Number in Human	Elements of the BESOM Model
Cerebral Cortex	Approx. 200,000mm^2	1	BESOM Net
Area Hierarchy	-	Approx. 10	Basis Hierarchy
Area	Approx. 40,000mm^2	Approx. 50	Basis
Hypercolumn	Approx. 1mm^2	Approx. 200,000	Node
Column	Approx. 0.01mm^2	Approx. 2 x 10^7	Unit
Neuron	-	Approx. 1.4 x 10^{10}	Variables of the algorithm
Synapse	-	Approx. 10^{13}	Weight of Connection

TABLE I
CORRESPONDENCE BETWEEN ELEMENTS COMPRISING THE CEREBRAL CORTEX AND THE BESOM MODEL.

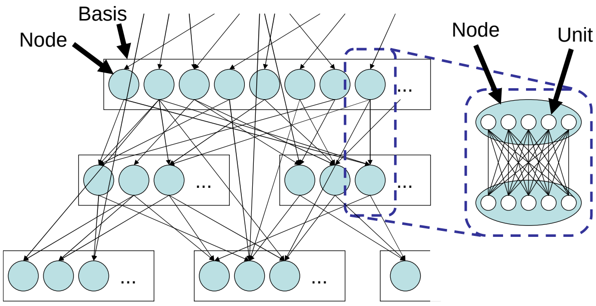

Fig. 1. Elements comprising the BESOM net. The rectangles denote bases, the circles inside the bases denote nodes, and the white circles inside the nodes denote units.

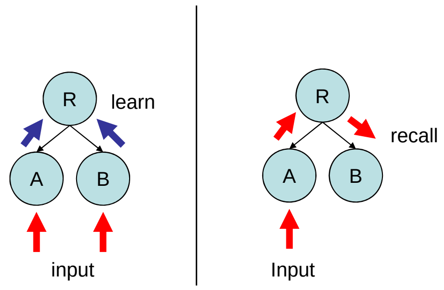

Fig. 2. Learning and recall according to BESOM. Each node compresses and learns inputs from its child nodes (left). When the values of a subset of child nodes are given as observed values, it is possible to recall the associated values of the other child nodes (right).

of information processing is possible using this table. For example, recall of memories is carried out in the following manner. As is shown in the left of Fig. 2, assume that node R has finished learning about the relationship between the outputs of the two child nodes A and B. At this point, if the bottom-up input to B is blocked, as shown in the right of Fig. 2, the unit output of R is determined only by the top-down signal from A, and the unit output of B is determined only by the top-down signal from R. In other words, the memories that have been evoked from the pattern expressed by node A are recalled in node B.

According to the BESOM model, each area of the cerebral cortex is an enormous table that has been ingeniously compressed using the hierarchical SOM and the hierarchical ICA. The table is the simplest and the most general purpose data structure; it would be appropriate if the brain has selected the data structure. A table can express a variety of information depending on its uses. For instance, there are conditional probability tables for the Bayesian networks, relational database tables for remembering and searching knowledge, state-action pair tables for reinforcement learning, function tables for approximating non-linear functions, state transition tables for handling sequential information, etc.

$$
\begin{aligned}
\boldsymbol{l}_{XY}^{t+1} &= \boldsymbol{z}_Y^t + \boldsymbol{W}_{XY}\boldsymbol{o}_Y^t \\
\boldsymbol{o}_X^{t+1} &= \prod_{Y\in children(X)}^{\otimes} \boldsymbol{l}_{XY}^{t+1} \\
\boldsymbol{k}_{UX}^{t+1} &= \boldsymbol{W}_{UX}^T \boldsymbol{b}_U^t \\
\boldsymbol{p}_X^{t+1} &= \sum_{U\in parents(X)} \boldsymbol{k}_{UX}^{t+1} \\
\boldsymbol{r}_X^{t+1} &= \boldsymbol{o}_X^{t+1} \otimes \boldsymbol{p}_X^{t+1} \\
Z_X^{t+1} &= \sum_i (r_X^{t+1})_i \ \ (= \|\boldsymbol{r}_X^{t+1}\|_1 = \boldsymbol{o}_X^{t+1} \bullet \boldsymbol{p}_X^{t+1}) \\
\boldsymbol{z}_X^{t+1} &= (Z_X^{t+1}, Z_X^{t+1}, \cdots, Z_X^{t+1})^T \\
\boldsymbol{b}_X^{t+1} &= (1/Z_X^{t+1})\boldsymbol{r}_X^{t+1}
\end{aligned}
$$

where

$$
\boldsymbol{x} \otimes \boldsymbol{y} = (x_1y_1, x_2y_2, \cdots, x_ny_n)^T
$$

Fig. 3. The approximate Belief Propagation Algorithm[5].

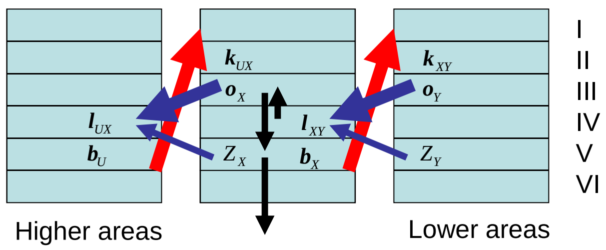

Fig. 4. The approximate belief propagation algorithm corresponds well with the connection rules between the six-layered structures of two areas in the cerebral cortex.

IV. Approximate Belief Propagation Algorithm

The BESOM model uses an algorithm, approximate belief propagation algorithm [5] (Fig. 3) that is approximated with some assumptions. T indicates a transposed matrix, and t and $t+1$ indicate time. Using the other variable values in t, the values in $t+1$ are calculated. A subscript X denotes a node name. For example, the variable $\boldsymbol{b}_X$ exists in each node. Furthermore, the subscripts XY and UX are used to indicate the edge between two nodes. For example, the variable $\boldsymbol{l}_{XY}$ and the matrix W_{XY} exist along each edge.

Assume that the number of units is s for all nodes. W_{XY} is a matrix of size $s \times s$ indicating connection weights between units of node X and its child node Y. Z_X is a scalar value, while the other variables $\boldsymbol{l}_{XY}$, $\boldsymbol{o}_X$, $\boldsymbol{k}_{UX}$, $\boldsymbol{p}_X$, $\boldsymbol{r}_X$, $\boldsymbol{z}_X$ and $\boldsymbol{b}_X$ are column vectors of length s.

The i-th elements of variables $\boldsymbol{l}_{XY}$, $\boldsymbol{o}_X$, $\boldsymbol{k}_{UX}$, $\boldsymbol{p}_X$, $\boldsymbol{r}_X$ and $\boldsymbol{b}_X$ concern with a unit x_i of a node X. An element w_{ij} of W_{XY} is a conditional probability $P(Y = y_j|X = x_i)$.

The initial value of each variable is arbitrary. The value of each variable is repeatedly updated until the value reaches a certain degree of convergence. The value of W_{XY} does not change during execution of the approximate belief propagation algorithm.

The variable $\boldsymbol{o}_X$ means observation that mainly use bottom-up information, while $\boldsymbol{p}_X$ means predictions using top-down information; $\boldsymbol{r}_X$ is the product of these two values, and the normalized value $\boldsymbol{b}_X$ (abbreviation of 'belief') means the posterior probabilities of the values of the node X.

V. Correspondence with Neuroscience Findings

A. Anatomical Features of the Cerebral Cortex

The cerebral cortex has a six-layer structure. There is a bi-directional connection between the areas of the cerebral cortex, and it is known that there is regularity in the make-up of this connection [7]. Bottom-up connections, which proceed from lower areas near the sensory input to higher areas near the frontal lobe and the hippocampus, connect mainly from layer 3 to layer 4. There are also instances in which connections connect from layer 5 to layer 4. Top-down connections, which proceed from the higher areas to the lower areas, connect mainly from layers 5 and 6 to layer 1. (There are also a few connections from layer 3 to layer 1.)

Furthermore, from the distribution of the dendrites and axons of the dominant neurons within the cerebral cortex, it can be said that information input at layer 4 within a column passes through layers 2 and 3 before being outputted to other areas from layer 5 [8]. Information of Layer 5 is then inputted into layer 4 after passing through layer 6.

When we consider these two findings together, we see that layer 3 information, which is the intermediate result of intra-column information processing, is sent to the upper areas, while the layer 5 information, which is the final result, is returned to the lower areas, making an exceedingly strange structure. The functional meaning of this structure is unknown.

B. Correspondence between the Six-layer Structure and the Approximate Algorithms

Out of the seven variables that appear in the approximate belief propagation algorithm, we apply the five variables that pertain to inter-nodal signals to the inter-area connection rules. The results are as shown in Fig. 4. $\boldsymbol{k}_{UX}$, which computes the inner product, is considered as being at layer 2, and not layer 1, which contains almost no neurons. And while Z_X may also appear in layer 3, it is taken as being at layers 5 and 6, due to the depth of its correlation with $\boldsymbol{b}_X$.

As shown in the figure, the approximate algorithm exhibits a straightforward correspondence with the inter-area connection rules, which cannot be considered to be coincidental.

In addition, based upon the various neuroscientific findings related to the six-layer structure, Fig. 5 shows a representation of the approximate belief propagation algorithm in a neural network. The previously-discussed progression of information in the order of layer 4, layers 2 and 3, layer 5 corresponds to the progression of information in the order of variables $\boldsymbol{l}_{XY}$,$\boldsymbol{o}_X$,$\boldsymbol{r}_X$,$\boldsymbol{b}_X$ (Please refer to Section VI-D concerning the flow of information from layer 5 to layer 6 to layer 4.)

In the neural network shown in Fig. 5, the following consistencies with anatomical findings can be seen. (1) Within the columns, almost all information processing is carried out only in the vertical direction. (2) Many horizontal fibers are visible in layers 1, 4, and 5. (3) There are many small neurons in layers 2 and 4.

VI. Realization of Cerebral Cortex Functions using BESOM model

In this section, we discuss the outline by which the BESOM network obtains the structure discussed in the previous section, which may prove useful in realizing the cerebral cortex functions.

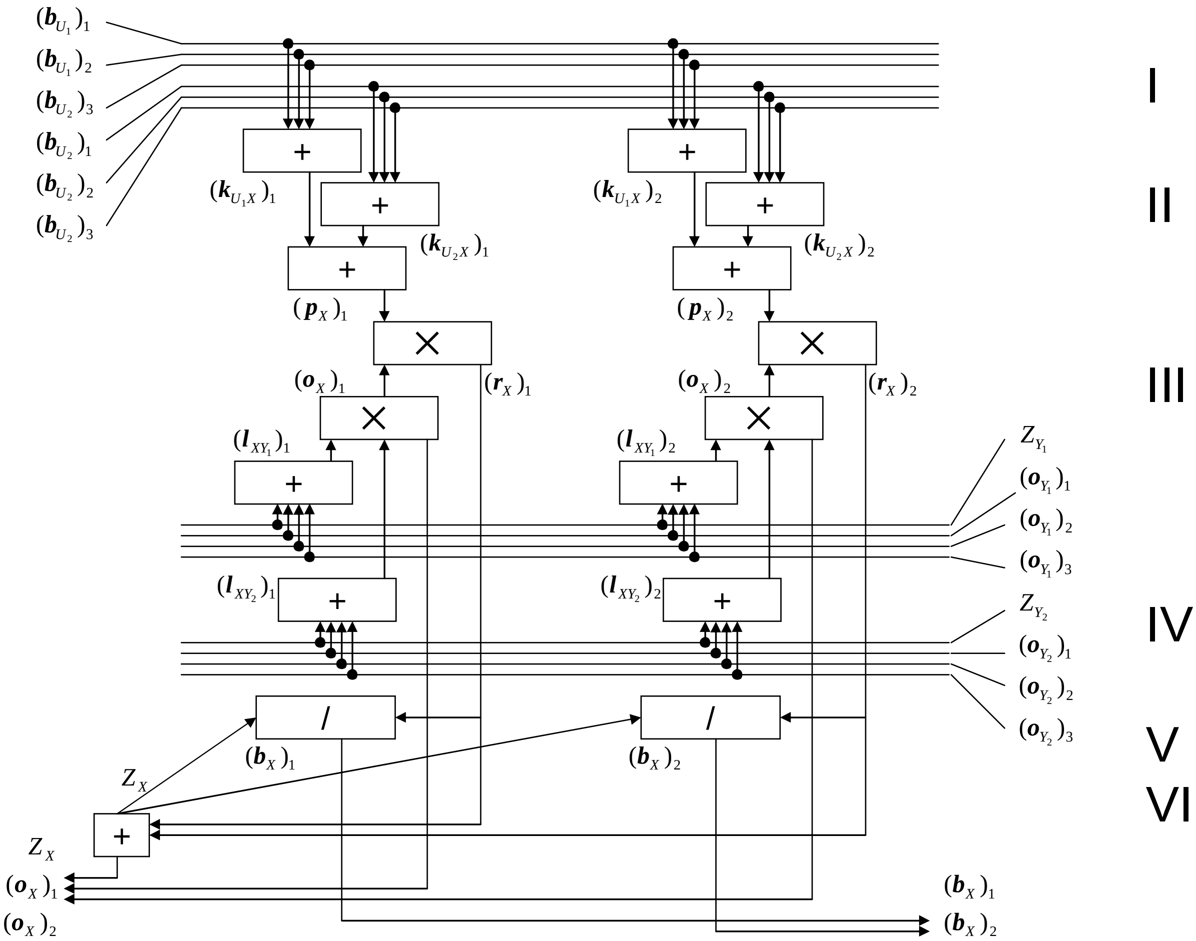

Fig. 5. Neural network that executes the approximate belief propagation algorithm. The variable positions and interconnections accord at several points with anatomical findings related to the six-layered structure, providing extremely strong evidence in support of the BESOM model being the appropriate model of the cerebral cortex.

A. Pattern Recognition

Pattern recognition may be possible using the BESOM model.

When sensory stimuli are provided by the lowest terminal nodes, information is hierarchically compressed by the hierarchical SOM function, and information having a degree of abstraction as high as that found in the higher area is expressed. When perceiving something, the posterior probability of a letter or an object before your eyes is calculated by Bayes' theorem and the Bayesian network function based upon the sensory stimuli provided by the lowest terminal nodes. The perception result is the letter or the object having the highest posterior probability.

It is known that when human beings perceive an object, the perception result changes depending upon the context. Because in the Bayesian network contextual information is conveyed from parent node to child node, it becomes possible to explain this property of the brain.

While pattern recognition according to BESOM qualitatively follows the Neocognitron, which is a neural network model related to the visual areas, and the expanded SAM [9] structure, which adds top-down signals to the Neocognitron, it differs from them in its possession of Bayes' theorem as a theoretical background.

B. Inference

SOM resembles a relational database that possesses an assembly of multiple attribute values, and using this, it is possible to make a variety of inferences. For example, as is shown in Fig. 6, let us say that there is node R, which learns an assembly of four animal attributes, such as name, color, shape, and size. When we speculate, "What color is a rabbit?", first of all the phoneme "rabbit" is recalled to the name node, simultaneously with which we have only to block the bottom-up input to the color, shape, and size nodes by means of the selective attention function. According to the Bayesian network function, an image of the color of a rabbit is recalled to the color node through the information remembered in node R.

If we wish to speculate, "What is the name of an animal that is the same color as a rabbit?", we maintain our image of

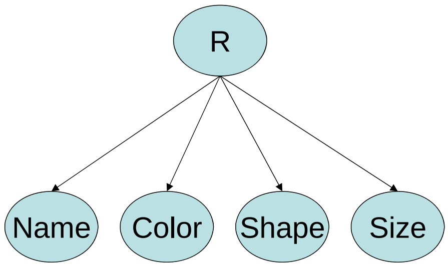

Fig. 6. Example of a BESOM relational database.

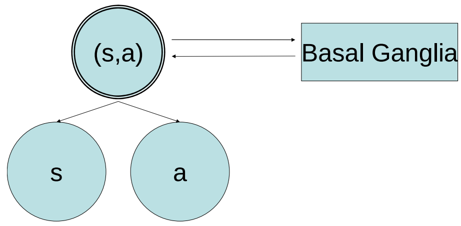

Fig. 7. Reinforcement learning using the BESOM net. The motor area learns the state-action pairs. At the same time, the values of the state-action pairs are also learned at the basal ganglia. Selection of an action which has the highest value in a given situation, take place at a closed loop between the cerebral cortex and the basal ganglia.

the color as it is, and then may use any method to control the flow of information such that it is recalled in the name node via R.

In this way, by appropriately controlling the two-way flow of information between two layers, it is possible to realize a human-like inference which combines the characteristics of both symbol processing and pattern processing. This has already been shown in the PATON [10] neural network model. It is believed that if we add an appropriate information-flow control function according to selective attention, then it will be possible for BESOM to exhibit the same abilities as PATON.

C. Action Acquisition at the Motor Area

It is possible to combine BESOM with reinforcement learning (Fig. 7).

The nodes at the motor area may learn state-action pairs during reinforcement learning. In other words, the motor area SOM compresses and learns the current state and the action currently being performed. At the same time, another learning takes place for the values of state-action pairs using the basal ganglia. When selecting an action, the state-action pair with the highest value is chosen based upon the perception results of the current situation, after which it is necessary only to 'recall' the corresponding action.

This is an expansion of the Doya's model [11] (which is related to reinforcement learning in the closed loop between the cerebral cortex and the ganglia), wherein a cerebral cortex role has been added to the Doya's model, which is neuroscientifically plausible.

In actuality, the motor area periphery possesses an even more complex and distinctive structure than is indicated in Fig. 7, but it is still possible to understand it qualitatively using the BESOM model[6].

D. Sequence Learning

If special child nodes, which possess each node's past recognition results as values, are added to the BESOM network, sequence learning will become possible, similar to the Elman network[12].

Anatomically, as was discussed in Section V-A, the structure is known in which the information on information processing results output from layer 5 passes through layer 6 and then recursively returns to the input-receiving layer 4; the author conjectures that this structure may perhaps be for the purpose of sequence learning.

E. Action Planning at the Prefrontal Cortex

When a certain action a is performed while the external world is in a certain state s, the world around will then change to a new state s', which human beings are able to predict based upon past experiences. SOM is able to learn this three values, (s, s', a). It is possible to realize this state-change prediction mechanism by carrying out a slight expansion of BESOM[6].

Using this mechanism, a variety of action sequences may be simulated within the mind, and that 'action planning' becomes possible, whereby appropriate actions are singled out for execution. Action planning is one of the important function of the prefrontal cortex.

Furthermore, this mechanism may also be useful in making estimations of invisible states in the partially-observable Markov decision process.

F. Language Comprehension

The cerebral cortex may compress and learn words (phoneme sequences) and information expressed in other areas. It may explain how word's meanings are learned. If learning progresses, it becomes possible to recall from the word the firing patterns in the several areas of the cerebral cortex. This is recall of the word's meanings. For example, if a little child hears the words, "If you touch the heater it's very hot," then within the child's mind are recalled the action of touching a heater, and the unpleasant sensation of heat. It is likely that this recall is almost exactly the same as the firing pattern that would occur in the cerebral cortex if the child were actually to touch the heater and feel heat. If the word-induced firing pattern recall is successful, it is furthermore possible for another SOM to learn the relationship between the action of touching the heater, and the sensation of heat. This can be for no other reason than that the knowledge that "the heater is hot" has been communicated by using words. The child will probably henceforth avoid the heater.

VII. Conclusion

Using the BESOM model, we have started clarifying the information processing in the brain.

Because it may be possible to efficiently realize this neural network model using a computer, this neural network model is also promising in the area of engineering applications. The author is currently involved in detailing the model for use in computer simulations. Using this model, it will be possible to progressively realize robots that possess the same intelligence as human beings do.

We hope that, by many researchers coming to an understanding of this paper, and by then applying their efforts towards resolving the problems that remain to be solved. The implementation of the brain's information processing principles might be realized in the not too distant future.

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