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A hybrid neural network model for consciousness*

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Abstract: A new framework for consciousness is introduced based upon traditional artificial neural network models. This framework reflects explicit connections between two parts of the brain: one global working memory and distributed modular cerebral networks relating to specific brain functions. Accordingly this framework is composed of three layers, physical mnemonic layer and abstract thinking layer, which cooperate together through a recognition layer to accomplish information storage and cognition using algorithms of how these interactions contribute to consciousness: (1) the reception process whereby cerebral subsystems group distributed signals into coherent object patterns; (2) the partial recognition process whereby patterns from particular subsystems are compared or stored as knowledge; and (3) the resonant learning process whereby global workspace stably adjusts its structure to adapt to patterns' changes. Using this framework, various sorts of human actions can be explained, leading to a general approach for analyzing brain functions.

Key words: Neural network, Global workspace, Consciousness
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INTRODUCTION

The goal of understanding the brain and making artificial minds has propelled many scientific fields greatly. In a sense it may be the final goal of the whole science. It is impossible that one unified theory will be sufficient for explaining the brain's functionality because of its unimaginable complexity. Multi-discipline combinations have brought about so many achievements towards this goal. Taylor (1994) introduced the "relational mind" approach in terms of various control structures and processing strategies, and their possible neurobiological identifications in brain sites. He also believed that the inner content of consciousness arises from the resulting relational features between inputs from the outside and stored memories. Rakovic brought about a hierarchically organized and interconnected paradigm for information processing inside the brain (Rakovic, 1997). He believed that the brain control was achieved locally and the response depended only on the experiences and stimulus. The significant role of brainwaves was also discussed in his paper. Other scientists also contributed to the problem of consciousness from their own perspective: Vitiello brought about a quantum model of brain memory recording (Vitiello, 2003), Rennie *et al.*(2002) introduced a model for evoked potentials (the brain's transient electrical responses to discrete stimuli). All these models and paradigms showed that understanding human consciousness leads to modeling neural processes at different levels. To understand cognition one should identify different levels of description, find the models appropriate to a given level and show how, at least in principle, higher levels may be reduced to lower levels

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(Wlodzislaw, 1996). Thus, higher levels of complex brain functions require a number of neural modules to cooperate together. This paper proposed a framework for consciousness at those higher levels, which postulates that:

1. At any given time, many modular cerebral networks are running in parallel and process data from outside in an unconscious manner. Those networks belong to the physical mnemonic layer of the framework. An assumption is made about categorizing the outside inputs into two groups: aware inputs and arousal inputs. The latter can only reach the recognition layer while the former can break out of the recognition layer and take part in the associative recognition in the global workspace.

2. A recognition layer is a searching tree composed of layered storage neurons positioned by their inherent frequencies. All features of an object pattern are processed in the lowest level by mnemonic layer networks before entering here. Some neurons in a particular level are grouped to form a cluster. The representative of a cluster in the nth level becomes a point in the higher-level n+1. In a given level, the neurons in a cluster have resonant frequency that is higher than a threshold value for that level. The top level of the recognition layer always has one cluster.

3. A global workspace that belongs to the abstract thinking layer of the framework can potentially interconnect multiple cerebral networks at the physical mnemonic layer through the recognition layer. When the global workspace is active for some duration, the abstract information in the thinking layer is available to a variety of processes that would be mobilized by top-down intentional projection into cerebral actions that may involve several distributed neural networks. This global availability of abstract information through workspace is defined as the conscious state of this framework.

OVERVIEW OF THE MODEL

The general consciousness framework is depicted by Fig.1, in which subsystems are responsible for vision, audio, olfactory, body movement and other functions of the human brain.

Physical mnemonic layer

Those subsystems that consist of hierarchically organized and interconnected neural networks belong to the physical mnemonic layer (PML in Fig.2). This kind of interconnection is achieved by synapses, which can be excitatory or inhibitory. Information processed by those subsystems is distributed among synapses. By adjusting the strengths of the synapses, new input is processed and added. Techniques such as PET, fMRI, EEG have enabled physiological investigations of interconnected neural networks in recent years (Kastner and Unge-

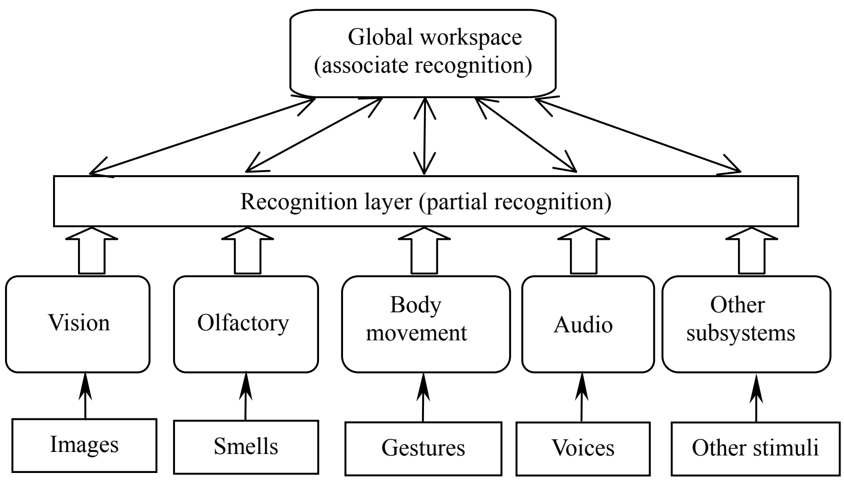

Fig.1 The general framework of consciousness

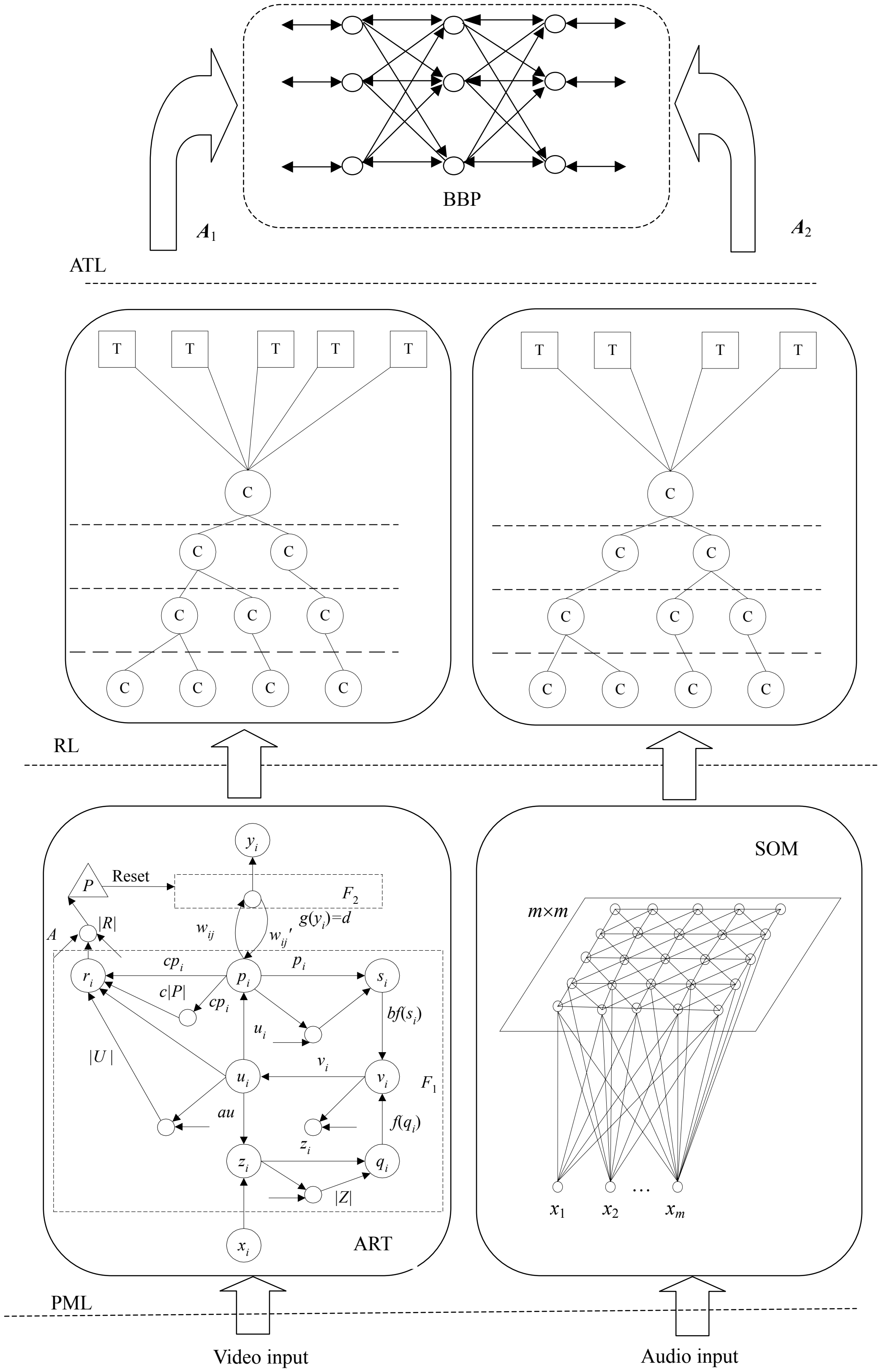

Fig.2 An artificial neural network based example

rleider, 2000; Reynolds *et al*., 1999). In the hierarchical neural network, the functionally specialized neurons of each layer process only a limited amount of information from the previous layer and the number of interconnections between neighboring layers is sparse compared with that between neighboring layers in some artificial neural networks (Rakovic, 1997). Grossberg *et al*.(1989) introduced a good model for the vision subsystem of Fig.1. Numerical simulations showed that their hierarchical parallel network could recognize even psychological illusions. Liu *et al*.(2002) introduced a model for the audio subsystem, and Yao and Freeman (1990) gave a model for the olfactory subsystem. In their model of olfactory subsystem, feedback on different hierarchical levels of the network was adopted. All of the models above are graceful but each of them only associated with one kind of brain function. The hybrid model proposed here, however, assembles those neural networks and can explain more complex cognitive phenomena.

A concrete example of the framework consisting of several human neural network models is given in Fig.2. For simplicity, only two cerebral subsystems are presented: the vision subsystem and the audio subsystem. We use an ART (Adaptive Resonance Theory) model (Carpenter and Grossberg, 1987) to describe the vision subsystem and SOM (Self-Organizing Map) model (Kohonen, 1995) for the audio subsystem. The raw data are preprocessed here to form a pattern that will be sent to the recognition layer for partial recognitions.

Recognition layer

When a new pattern is formed, it will be compared with stored patterns (knowledge) at all levels of the recognition layer (RL in Fig.2). If there are some existing clusters (circles with C in Fig.2) that are similar to the new pattern, this pattern is recognized; otherwise it belongs to the unknown group and will be saved (new storage neurons are created). We use the inherent frequency vector to measure the similarity between two patterns.

Definition 1 The inherent frequency of a pattern is a vector that contains some important features of it. We use this to represent a pattern afterward. The inherent frequency of a neuron group k that memorizes a knowledge pattern can be described by the weights from one neuron in the group to other members, as $\boldsymbol{K}=[w_1, w_2, \ldots, w_i, \ldots]$. According to this definition, we introduce the concept of resonant coefficient between two patterns.

Definition 2 The resonant coefficient of pattern a and b to measure the similarity of them (s_{ab}) can be calculated by a function $f(a_i, b_j)$:

$$R(\boldsymbol{A}, \boldsymbol{B}) = s_{ab} = f(a_i, b_j) \tag{1}$$

where $\boldsymbol{A}$, $\boldsymbol{B}$ is the inherent frequency of each, $\boldsymbol{A}=[a_1, a_2,\ldots a_i,\ldots]$, $\boldsymbol{B}=[b_1, b_2,\ldots b_j,\ldots]$. The resonant coefficient of two patterns is a kind of delta similarity relation (Klir and Folger, 1988) that satisfies the following equations:

$$R(\boldsymbol{A}, \boldsymbol{A}) = 1 \tag{2}$$

$$R(\boldsymbol{A}, \boldsymbol{B}) = R(\boldsymbol{B}, \boldsymbol{A}) \tag{3}$$

$$1-|R(\boldsymbol{A},\boldsymbol{C})-R(\boldsymbol{B},\boldsymbol{C})|\geq R(\boldsymbol{A},\boldsymbol{B}) \geq (R(\boldsymbol{A},\boldsymbol{C})+R(\boldsymbol{B},\boldsymbol{C})-1)\vee 0 \tag{4}$$

Once the pattern reaches the top-level cluster, it is projected into global workspace through transmitters (squares with T in Fig.2). If this kind of projection occurs from two or more subsystem recognitions, associative recognition may take place in the global workspace.

Abstract thinking layer

Global workspace represents a kind of working memory or central information exchange, whose contents can be “broadcast” to the nervous system of distributed modules as a whole, allowing many different specialized modules in the brain to interact, compete or cooperate for access (Rakovic, 1992). A number of models had been constructed for global workspace. Baars (1988) developed a very detailed cognitive model of consciousness by global workspace architecture. Taylor (1999) proposed a CP (Central Representation) framework and suggested its being in the inferior parietal lobes. He also gave several frameworks using monitor systems (Taylor, 2000) and some other engineering control systems (Taylor, 2001).

The abstract thinking layer (ATL in Fig.2) in the hybrid model has something different from the existing models in that, as in the example framework of Fig.2, it contains a bi-directional BP (Back Propagation) neural network with a "fusion" function. In Fig.2, $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ are both inputs of the bi-directional BP computation, as a consequence of the projection from RL. The computation is interleaved: only one-way learning is going on at a particular time interval. Parameters of the BP network are stored for different pairs of ($\boldsymbol{A}_1$, $\boldsymbol{A}_2$). As $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ may have different dimensions, the structure of the Bi-directional BP (BBP) network varies from time to time (notice that we use dash lines to indicate the boundary of ATL in Fig.2). Provided below is a structure-changing algorithm for the above BBP network: suppose vector $\boldsymbol{H}=[h_1,h_2,\ldots h_l,\ldots h_L]$ represents the collection of different number of neurons in L layers of the BBP network (h_l represents the number of neurons in layer l, $1\le l\le L$). When the kth pattern from the mnemonic layer projected onto GW, the number of neurons in layer l of the BP network can be calculated by

$$h_l^{(k)}=\left\lfloor C\left(\Delta\left|\boldsymbol{A}_1^{(k)}\right|+\Delta\left|\boldsymbol{A}_2^{(k)}\right|\right)\right\rfloor+\left|\boldsymbol{A}^{(l)}\right| \tag{5}$$

where $\left|\boldsymbol{A}_1^{(k)}\right|,\left|\boldsymbol{A}_2^{(k)}\right|$ are dimensions of the kth pattern and $\Delta\left|\boldsymbol{A}_1^{(k)}\right|,\Delta\left|\boldsymbol{A}_2^{(k)}\right|$ are variances: $\Delta\left|\boldsymbol{A}^{(k)}\right|=\left|\boldsymbol{A}^{(k)}\right|-\left|\boldsymbol{A}^{(k-1)}\right|$; C is constant. $\left|\boldsymbol{A}^{(l)}\right|$ is the average dimension of the lth pattern and can be calculated by

$$\left|\boldsymbol{A}^{(l)}\right|=\alpha\left|\boldsymbol{A}_1^{(l)}\right|+\beta\left|\boldsymbol{A}_2^{(l)}\right| \tag{6}$$

where α, β are weights of $\left|\boldsymbol{A}_1^{(l)}\right|,\left|\boldsymbol{A}_2^{(l)}\right|$ and $0\le\alpha\le1$, $0\le\beta\le1$, $\alpha+\beta=1$. The above algorithm results in fluctuations of the network boundary. A subset of neurons in the workspace is activated spontaneously in a coherent and self-amplifying manner while the rest are inhibited.

RECOGNITION LAYER ALGORITHM

This section proposes an algorithm for the RL functions in the hybrid model. As mentioned in Section 2.1, raw data from the outside form some patterns with their inherent frequencies through the PML modeled by some existing neural network models. These patterns constitute the input space of this algorithm. We shall first introduce some definitions that will be used later.

Definition 3 A knowledge cluster (also cluster) is composed of a set of patterns whose information is stored in the synapses between neurons.

Definition 4 A resonant space is a space of patterns to which any other pattern can be compared to evaluate resonant coefficient and each dimension represents the resonant coefficient between one pattern and the others.

Consider a resonant space $\boldsymbol{R}^n$ with n patterns $\boldsymbol{P}_i$ and the resonant coefficient $R(\boldsymbol{P}_i, \boldsymbol{P}_j)$ between any pair of patterns ($\boldsymbol{P}_i$, $\boldsymbol{P}_j$). A pattern $\boldsymbol{P}_m$ may be represented on $\boldsymbol{R}^n$ as:

$$\boldsymbol{P}_m=\sum_{i=1}^{n}R(\boldsymbol{P}_m,\boldsymbol{P}_i)\boldsymbol{P}_i \tag{7}$$

Suppose $\boldsymbol{P}_u$ and $\boldsymbol{P}_v$ are patterns in $\boldsymbol{R}^n$, then $R(\boldsymbol{P}_u, \boldsymbol{P}_v)$ can be limited from Eq.(4):

$$\begin{aligned}[R(\boldsymbol{P}_u, \boldsymbol{P}_i)+R(\boldsymbol{P}_v, \boldsymbol{P}_i)-1]\vee 0\le R(\boldsymbol{P}_u, \boldsymbol{P}_v)\\ \le 1-|R(\boldsymbol{P}_u, \boldsymbol{P}_i)-R(\boldsymbol{P}_v, \boldsymbol{P}_i)|\end{aligned} \tag{8}$$

Here we use the following function to calculate the resonant coefficient between patterns in $\boldsymbol{R}^n$:

$$\begin{aligned}f(u,v)&=\min_{1\le i\le n}(1-\left|R(\boldsymbol{P}_u,\boldsymbol{P}_i)-R(\boldsymbol{P}_v,\boldsymbol{P}_i)\right|)\\&=1-\max_{1\le i\le n}\left|R(\boldsymbol{P}_u,\boldsymbol{P}_i)-R(\boldsymbol{P}_v,\boldsymbol{P}_i)\right|\end{aligned} \tag{9}$$

Definition 5 The thresholds exist in RL corresponding to different levels (numbered from zero to *TOP*): $t_0>t_L>t_{L+1}>t_{TOP}$, patterns are clustered at those levels. For example, at level L, two patterns belong to the same cluster if and only if $t_L>f(u,v)>t_{L+1}$. There also exists a highest threshold

t_{max} and two patterns are recognized to be the same if $f(u,v)\geq t_{max}$.

Definition 6 The inherent frequency of a cluster C is the first pattern $\boldsymbol{P}_k$ in C.

Now we shall propose the algorithm of RL workflow. Note that massive parallelism exists among neurons, which means that the calculation and comparison in the algorithm can be performed in parallel to some extent. Hence, the recognition time will not increase exponentially with knowledge gradually learned.

Algorithm of RL workflow

The operation of RL is summarized as follows (we use C_x for cluster x, L_y for level y and t_y for threshold on level y):

(1) For each pattern $\boldsymbol{P}_u$,
    if it is the first pattern that enters RL
        put $\boldsymbol{P}_u$ in C_1 on L_0;
    else
        go to (2) with x=1, y=TOP;
(2) /*recognition process*/
  For each $\boldsymbol{P}_i$ in C_x on L_y,
    calculate the resonant coefficient $R(\boldsymbol{P}_u,\boldsymbol{P}_i)$;
    if y==0 and
        $\max_i R(\boldsymbol{P}_u,\boldsymbol{P}_i) == R(\boldsymbol{P}_u,\boldsymbol{P}_j) \geq t_{max}$
        $\boldsymbol{P}_u$ is recognized as $\boldsymbol{P}_i$, stop;
    if y>0 and $R(\boldsymbol{P}_u, \boldsymbol{P}_j)\geq t_{y-1}$
        go to (2) with x=j, y=y−1;
    else
        go to (3);
(3) /*a new pattern that is not recognized, construct knowledge entry of it*/
  if $\min_i R(\boldsymbol{P}_u,\boldsymbol{P}_i) == R(\boldsymbol{P}_u,\boldsymbol{P}_s) \geq t_y$ and $y\neq TOP$
    {
      put $\boldsymbol{P}_u$ in C_x on L_y;
      For each $L_{0\leq z\leq y-1}$,
          create C with $\boldsymbol{P}_u$;
      stop;
    }
  else
    {
      For each $L_{0\leq z\leq TOP}$,
          create C with $\boldsymbol{P}_u$;
            calculate the inherent frequency $\boldsymbol{P}_k$ of C_1 on L_{TOP};
          create L_{TOP+1} with $\boldsymbol{P}_k$, $\boldsymbol{P}_u$ in C_1;
      stop;
    }

CONSCIOUSNESS GENERATION

The global workspace in ATL only provides projection areas for those patterns that reach the top layer of RL. So the dynamic workspace states are self-sustained and follow one another in a continuous stream, without requiring any external supervision. We suppose that these states are described by the set of active or inhibited neurons. In the hybrid model, consciousness generation requires that a stable activation loop appears: active neurons in ATL send top-down responses to target cerebral subsystems, whose bottom-up pattern signals in turn are involved in maintaining the state of ATL. Fig.3 shows such a kind of loop.

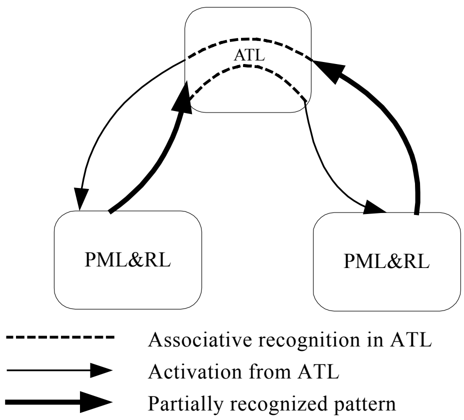

Fig.3 The maintenance loop between layers of the hybrid model

As the state of these dynamic systems consists of activation and inhibition of neurons, it is reasonable to use the weights between neurons as the dynamic network parameters. The associative recognition is done with the bi-directional learning of BBP (Fig.2) when two or more kinds of patterns emerge in ATL simultaneously. The dynamic system has an initial state $\boldsymbol{V}(0)$ at time t=0 and $\exists t\geq 0$

$$\boldsymbol{V}^* = \boldsymbol{V}(t+\Delta t) = \boldsymbol{V}(t),\ \Delta t > 0 \tag{10}$$

We say that the system enters a stable state $\boldsymbol{V}^*$, which is the so-called "attractor". Thus the associative pattern is formed in the BBP with the two-way-adjusted weights between neurons representing the associative knowledge. If this attractor can represent one result of thinking, the system running process before it appears can be called a thinking process.

Establishment of the stable state (the self-sustained loop) requires a minimal duration, thus imposing a temporal span to the successive workspace states that form the stream of consciousness. We can confirm now that except for the RL-threshold, the global workspace also has a time span threshold necessary for the ATL to be stable through the activation loop. Once the projected patterns from several subsystems appear in the GW, they may or may not be associated together. If these patterns appear in ATL for a significantly longer duration than the time span threshold (the patterns always exceed the top level of RL during this time span), a conscious state emerges; otherwise, even if the patterns go over the top level of RL and into global workspace, they will bring only minor flips of neurons and may propagate to multiple cerebral subsystems, however, they cannot establish the self-sustained activation loop. We call the latter process "sub-consciousness" in the hybrid model.

EXAMPLE

Suppose a series of four-dimension patterns $\boldsymbol{P}_i$ (i=0,1,2,…,9) formed by PML models enter RL now. For simplicity the content of $\boldsymbol{P}_i$ is the binary format of i as $\boldsymbol{P}_3$=[0,0,1,1], $\boldsymbol{P}_5$=[0,1,0,1]. According to Eq.(1), we define $R(\boldsymbol{P}_i, \boldsymbol{P}_j)$ as

$$f(a_i, b_i) = 1 - \frac{1}{4}\sum_{i=1}^{4}\left|a_i - b_i\right| \tag{11}$$

and we get the symmetric matrix with $R(\boldsymbol{P}_i, \boldsymbol{P}_j)$ on row i, column j based on Eqs.(2), (3) and (11):

$$\begin{pmatrix}
1 & 0.75 & 0.75 & 0.5 & 0.75 & 0.5 & 0.5 & 0.25 & 0.75 & 0.5 \\
0.75 & 1 & 0.5 & 0.75 & 0.5 & 0.75 & 0.25 & 0.5 & 0.5 & 0.75 \\
0.75 & 0.5 & 1 & 0.75 & 0.5 & 0.25 & 0.75 & 0.5 & 0.5 & 0.25 \\
0.5 & 0.75 & 0.75 & 1 & 0.25 & 0.5 & 0.5 & 0.75 & 0.25 & 0.5 \\
0.75 & 0.5 & 0.5 & 0.25 & 1 & 0.75 & 0.75 & 0.5 & 0.5 & 0.25 \\
0.5 & 0.75 & 0.25 & 0.5 & 0.75 & 1 & 0.5 & 0.75 & 0.25 & 0.5 \\
0.5 & 0.25 & 0.75 & 0.5 & 0.75 & 0.5 & 1 & 0.75 & 0.25 & 0 \\
0.25 & 0.5 & 0.5 & 0.75 & 0.5 & 0.75 & 0.75 & 1 & 0 & 0.25 \\
0.75 & 0.5 & 0.5 & 0.25 & 0.5 & 0.25 & 0.25 & 0 & 1 & 0.75 \\
0.5 & 0.75 & 0.25 & 0.5 & 0.25 & 0.5 & 0 & 0.25 & 0.75 & 1
\end{pmatrix}$$

The highest threshold value $t_{\max}$=0.8, other threshold on different levels: t_0=0.7, t_1=0.6, t_2=0.5. Using the RL algorithm we can get the structure in Fig.4.

In Fig.4a, after $\boldsymbol{P}_3$ is stored, RL grows to level 1 with $\boldsymbol{P}_0$ and $\boldsymbol{P}_2$ in the root cluster; in Fig.4b, the ten patterns are grouped into one cluster on level 2 with $\boldsymbol{P}_0$ and $\boldsymbol{P}_5$ in it. Accordingly two clusters are formed on level 1 and four clusters on level 0. When the stored pattern arrives next time, it will be recognized correctly. For example, when $\boldsymbol{P}_4$ compares with patterns on level 2, the maximum resonant coefficient is $R(\boldsymbol{P}_4, \boldsymbol{P}_0)$ = 0.75 (Although $R(\boldsymbol{P}_4, \boldsymbol{P}_5)$ is 0.75 too, $R(\boldsymbol{P}_4, \boldsymbol{P}_0)$ is first). So the comparison will go on to cluster 1, level 1 and next cluster 1 level 0.

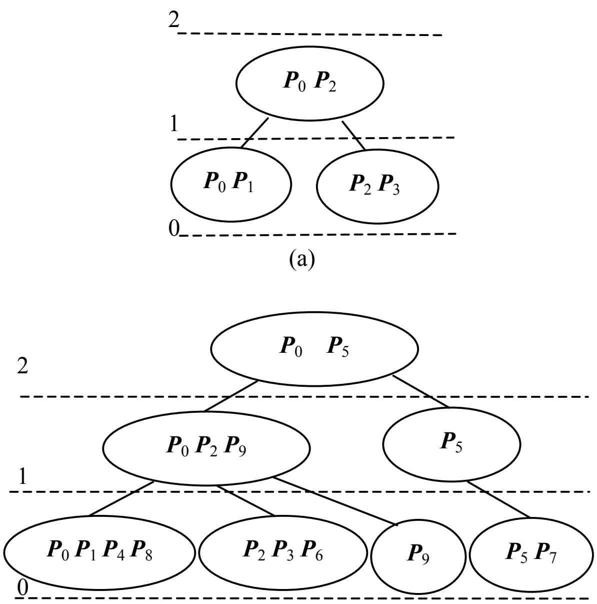

Fig.4 The structure of knowledge library using the algorithm in Section 3.2
(a) after $\boldsymbol{P}_3$ is stored; (b) after $\boldsymbol{P}_9$ is stored

We can also describe the knowledge library as a resonant space with dimension patterns in the root cluster, as in Fig.5, $\boldsymbol{P}_0$, $\boldsymbol{P}_2$ and $\boldsymbol{P}_5$ have coordinates in resonant space ($\boldsymbol{P}_0$, $\boldsymbol{P}_5$). Similarly clusters on level 1 also form sub-resonant spaces containing patterns on level 0. This schema reduces greatly the amount of storage neurons, as only the root level is required to store full data of patterns. Patterns on other levels can find a position in the resonant space created from the root level. Suppose now $\boldsymbol{P}_3$ enters RL. According to Eq.(7) and the resonant coefficient matrix mentioned earlier, we get $\boldsymbol{P}_3=R(\boldsymbol{P}_3, \boldsymbol{P}_0)\cdot\boldsymbol{P}_0+R(\boldsymbol{P}_3, \boldsymbol{P}_5)$, $\boldsymbol{P}_5=0.5\boldsymbol{P}_0+0.5\boldsymbol{P}_5$. Then $\boldsymbol{P}_3$ will be sent to cluster 1 on level 1 which is a sub-resonant space formed by ($\boldsymbol{P}_0$, $\boldsymbol{P}_2$) and $\boldsymbol{P}_3=R(\boldsymbol{P}_3, \boldsymbol{P}_0)\boldsymbol{P}_0+R(\boldsymbol{P}_3, \boldsymbol{P}_2)\boldsymbol{P}_2$. Applying Eq.(9), $R(\boldsymbol{P}_3, \boldsymbol{P}_2)=1-\max(|R(\boldsymbol{P}_2, \boldsymbol{P}_0)-R(\boldsymbol{P}_3, \boldsymbol{P}_0)|, |R(\boldsymbol{P}_2,\boldsymbol{P}_5)-R(\boldsymbol{P}_3,\boldsymbol{P}_5)|)=0.75$. So $\boldsymbol{P}_3=0.5\boldsymbol{P}_0+0.75\cdot\boldsymbol{P}_2$ and classified into cluster 2 on level 0.

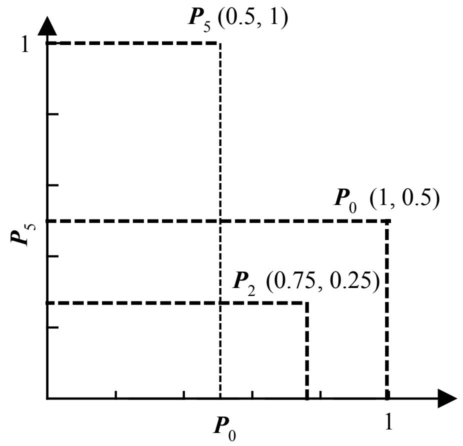

Fig.5 The resonant space formed by patterns in cluster 1 on level 2

We can see that patterns can be recognized successfully after one experience of training in RL. Now consider two patterns that reach the top-level of two different RLs are transmitted into the global workspace. Fig.6 schematizes this kind of thinking process after receiving a voice sample and a picture, taking the framework depicted in Fig.2. After the audio and vision patterns enter ATL, the dynamic thinking process (rectangles numbered from 1 to 6 in Fig.6) begins from $\boldsymbol{V}(0)$. We can see that the boundary of active neurons in ATL (interconnected black circles in rectangle 1 to 6 in Fig.6) is changing continuously, which indicates that the workspace is being driven by the loop in Fig.3 towards an "attractor". Subtle audio patterns (A, C in Fig.6) and gleaming image patterns (B, D in Fig.6) exist at unstable points (rectangle 2 to 4 in Fig.6); the system becomes stable at time t, $\boldsymbol{V}(t)=\boldsymbol{V}(t+\Delta t)$, as the boundary of active neurons is not changed after rectangle 5 in Fig.6. The associative recognition process is fully fulfilled at the stable state (E, F in Fig.6).

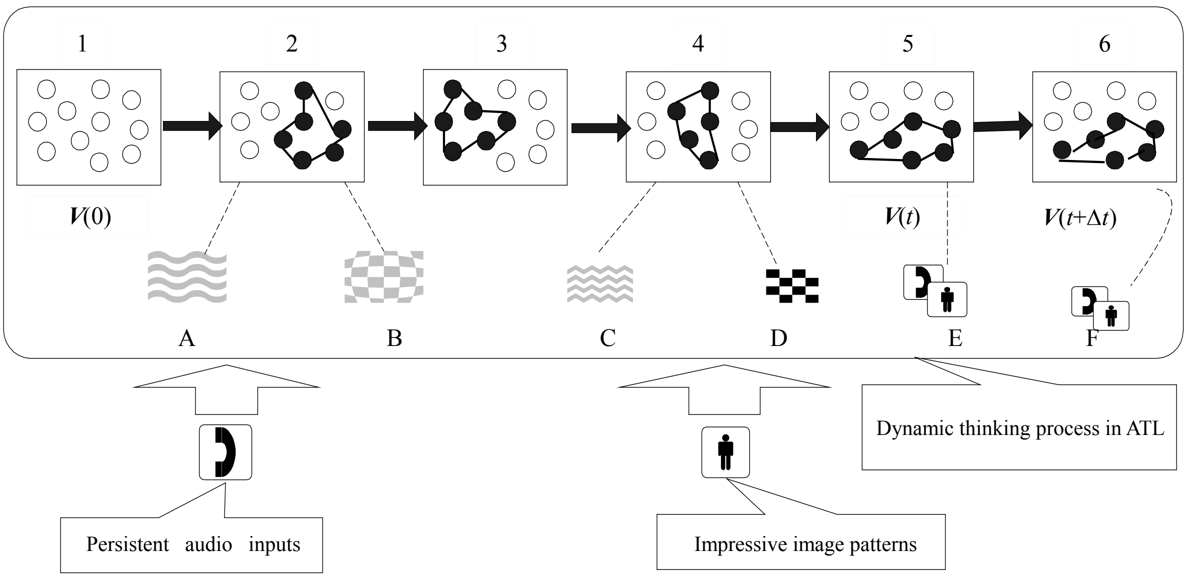

Fig. 6 The process of how identity clarified by voice and a picture

CONCLUSION

We have proposed a hybrid framework of human consciousness from functional levels and point out that a global workspace exists and has no control functions, which is different from existing models. This model reflects some routines of consciousness generation: two kinds of threshold exist for environmental stimulus; one is the partial recognition layer threshold that helps to form clusters within RL unconsciously; the other is the time span threshold that some persistently strong patterns projected into the global workspace can accomplish associative recognition, resulting in consciousness; any stimuli trapped between these two thresholds (transient strong pattern) will only bring about a kind of subliminal process.

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