Semantic rewiring mechanism of neural cross-supramodal integration based on spatial and temporal properties of attention

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Abstract

This paper proposes cross-supramodal integration system which is hypothetically dedicated by a neuronal network where prefrontal cortex is interacted with hippocampus and cortical areas in human brain. The substrate of the network is basically computed by rewiring mechanism consisting of a bidirectional processing network dedicated by PFC. The computational meaning of the rewiring allows the bidirectional network to learn cross-supramodal integration among different sensors. The cross-supramodality is represented by possible attention classes across space and time. We speculate the rewiring mechanism may particularly be crucial as consolidating of spatial and temporal attention based on the bidirectional processing network where PFC integrates expected reward outcomes and accurate representations of spatial information together to attain accurate behavior. Conclusively, the leverage on the nature of human rewiring mechanism may essentially relate to cognitive issues such as semantic priming and langueage acquisition.

Key words: Spatiotemporal attention; Rewiring mechanism; Cross-supamodal integration; PFC-based bidirectional network, Cognitive function

1 Introduction

Cross modal integration is the one of remarkable issues in brain computations because it allows us to contribute to endanger adaptive and flexible behavior in various forthcoming events of our daily life. It is however still not elucidated about neural mechanism of how underlying cross-supramodal integration can be taken in account of attention mechanisms as well as behavior tasks. With respect to the neuronal network of attention mechanisms, [1,2] showed neurobiologically the attention demanding and modulation process. In CNS*2001, we suggested the computational model of Anterior Cingulate (AC)-Prefrontal (PF)-Posterior Parietal (PP) Cortex in relation to attention demanding and modulation mechanism [3]. In human object recognition, PP is important for encoding object locations while Temporal Cortex (TC) is for object shape. The computational work also suggested such attention mechanism could be processed by bottom-up and top-down mechansims of attention in order to enhance visual responses and of guiding accurate behavioral sequences at any given time. From neuronal evidence, reward information from behavior assessment and spatial information are integrated as working memory in the PFC so that spatial information becomes more accurate when reward outcome is expected. Fig 1. shows presumably a neuronal network which is related to spatial and temporal characteristic of attention. We infer the role of the network centered by PF might consolidate both spatial and temporal characteristic of attention by interacting with Hippocampus (HC), where the appropriate relationship between behavior sequences and different modalities is learned to come out indelible memory. Indeed, HC encodes both the spatiotemporal relationship by involving PP and PF cortex for example to see [4]. We in this paper aim to provide the computational model of spatiotemporal attention in accordance with the cross-supramodal integration. Although Sharma et al, suggested neurophysiologically the relationship between the rewiring mechanism and cross-modal integration in ferret [5], we attemp in this paper, the learning scheme of the rewiring mechanism as well as its meaning presumably. In summary, we postulate the rewiring mechanism may play the crucial role to train the nonlinearity of cross-supramodal integration by a bidirectional processing network with respect to spatiotemporal attention, which is attained by PFC-HC interaction.

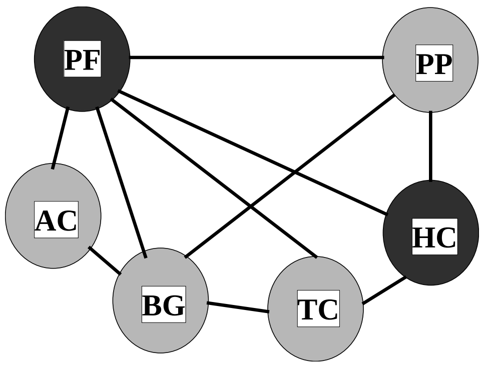

Fig. 1. Schematic connection of hypothetical network

2 Computational model across cross-supramodal integration

In this section, we present the computation model based on the cross-supramodal integration. Fig. 2 (right) illustrates the learning architecture of the cross-supramodal integration system. The system is mainly comprised of the three parts, namely rewiring mechanism, attentive reinforcement learning and behavior control. Essentially, it contains bayesian selective attention (BSA) with sensorimotor system [6]. That is, the system as shown in Fig. 2 (right) is derived from the bidirectional processing network where PF presumably generates the top-down information processing for selecting the attention classes Ω, which are computed by the bottom-up information processing based on the reinforcement learning at basal ganglia (BG). To deal with the cross-supramodal integration, the rewiring mechanism is especially taken account with the BSA's sensorimotor system. In the rewiring mechanism each sensory modality allows

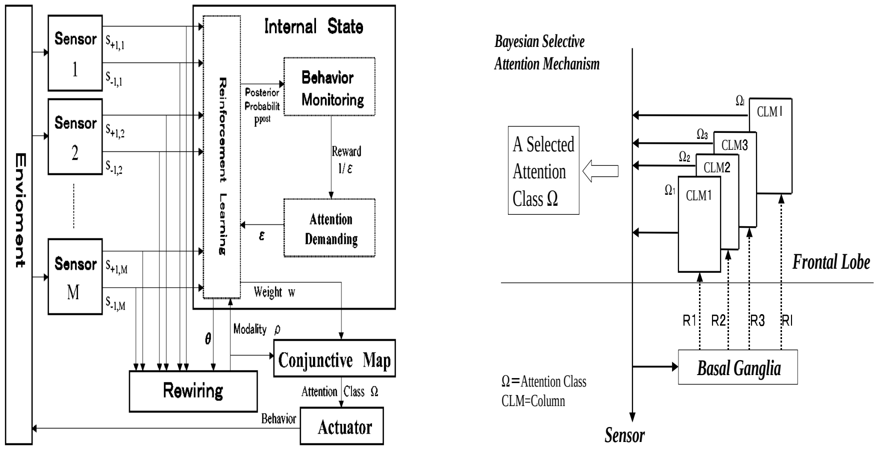

Fig. 2. Cross-supramodal rewiring system (Left) and BSA model (Right)

to be weighted by the (symmeric/asymmetric) parameter w through the bidirectional processing network (Fig.2, (left)). In addition, the cross-supramodal integration system employs an attentive reinforcement learning scheme, which trains the parameter (θ) of each attention class across the visual shape and visual motion modalities.

Now, we assume the attention class Ω_i^t of *i-th* supramodality consisting of visual shape (i=-1) and visual motion (i=+1) is mathematically modelled as follows,

$$\Omega_i^t \propto \rho_i(\mathbf{q}_i^t;\ \theta_i) \tag{1}$$

where, sensory vector over i supramodality $\mathbf{q}_i$ belongs in $\mathcal{R}^M$. The probability density function $|\rho|$ quantifies the number of population of $\mathbf{q}_i$, which is parameterized by θ, which is comprised of the mean and standard deviation of density ρ. Let ρ be gaussian distribution function as follows,

$$\rho_i(\mathbf{q}_i^t;\ \theta_i) = y_i(\mathbf{q}_i^t)\Sigma_k^M \gamma_{i,k} exp(-\frac{\|\mathbf{q}_{i,k} - \mu_{i,k}\|^2}{2\sigma_{i,k}}) \tag{2}$$

where, the probabilistic parameter θ=(γ, μ, σ) is computed by Expectation Maximization (EM) algorithm [6]. γ denotes mixing coefficient.

$$\Omega_i^t = \int_{\mathcal{S}} {w_i}^t \rho_i(\mathbf{q}_i^t;\ \theta_i) d\mathbf{q}^t \tag{3}$$

Where the weight value w_i^t of the rewiring mechanism is optimaized by Allen-Cahn (A-C) equation [8]. $\mathcal{S}$ denots the whole sensory space where the velocity component V_x, V_y is obtained from the *first-order* differentiation of the position component x, y. Assume, $\mathcal{S}$=$\mathcal{S}(x,y) \bigcup \mathcal{S}(V_x, V_y)$. The A-C equation is basically applied for phase trasitions whose solution is provided by minimizing the following cost fucntion:

$$\mathcal{E}(\mathbf{q}^t) = \int_{S} \phi(w_i^t) d\mathbf{q}^t + \epsilon^2 \int_{S} |\nabla w_i^t|^2 d\mathbf{q}^t \tag{4}$$

The quantity $\mathcal{E}$ can be derived from the double-well potential function, which is illustrated by Fig.3 (left). Here, we suggest the kind of potential function may be endowed by HC. Then, the updating equation of w_{ij}^t is can be resolved by the above equation: Notably the solution of A-C equation becomes the tangential sigmoidal typed function (Fig.3 (right))

$$w_i \equiv tanh(\rho_i(\mathbf{q}_i^t;\ \theta_i)/\epsilon) \tag{5}$$

where ϵ is the parameter minimized to *zero*. Eq.5 shows the predictive weights

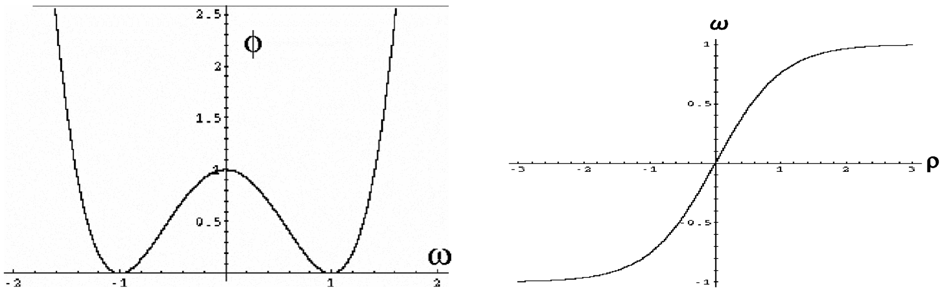

Fig. 3. Potential function (Left) and weight value (Right)

$w_{i,j}^t$, which is trained throughout the perturbation across supramodal densities ρ_i.

Since the elicitaion of attention demanding depends on the expectation posterior probability ϵ, which is predictive for expeted reward outcomes based on the synchronization in the cross-supramodal rewiring system.

$$\epsilon = |log[\frac{1}{M}\Sigma_{k=1}^{M}\{\frac{\int_{S(x,y)} P_{-1,k}^{post} dxdy}{\int_{S(V_x,V_y)} P_{+1,k}^{post} dV_x dV_y}\}]| \tag{6}$$

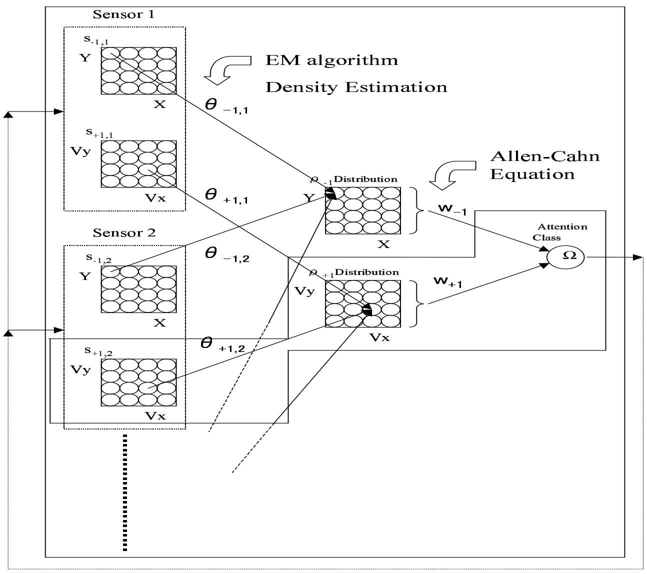

Fig. 4. Learning phase of cross-supramodal mapping

Fig. 5. Hypothesized network (Left), singular weights (ϵ=0.01) (Right)

where, P^{post} denotes the posterior probability in conditional to supramodality i and sensory modality k.

We assume the expectation posterior errors are bounded by the following exponential function because of 'cumulative' aspects of the prior probability:

$$\epsilon \approx \lambda exp(-\lambda\tau), \epsilon \geq 0 \tag{7}$$

where, λ is positive constant and τ denotes the learning feedback iteration in cross-supramodal rewiring system. λ implicates amplitude of the expectation posterior error where the curvature of expectation posterior errors monotonically decrease according to Eq.7.

Fig.4 shows the learning architecture where all the sensor information can be organized into the supramodality. Some comments would be appropriate upon the training and memory processes of the cross-supramodal mapping shown in Fig.4. It allows sensory information to be mapped by $N \times N$ matrices for both the supramodal space. In summary, the proposed scheme can effectively be constrained the the calculation by $O(2MN^2)$ as well as the memory by $O(N^2)^2$ now matter how the number of sensors are addictive. As a virture, $O(N^2)^{2M}$ is required in the both training and memory processes unless the cross-supramodal mapping is incorporated with the learning scheme shown in Fig.4.

3 Conclusion

In this paper, our computational model suggest how the spatial and temporal properties of attention can be taken into account of cross-supramodal integration system.That is, our neuronal network in relation to PFC-HC shows the two different modalities such as visual shape and visual motion, which are eventually bound by the spatiotemporal attention. Accordingly, the semantic role of rewiring mechanism may be to approximate the underlying nonlinearlity between the cross-supramodality through the spatiotemporal attention mechanism that induces the bidirectional processing network mediated from PF. This also implicates such visual processing can be attained by other sensory modalities such as tactile and audition, based on the rewiring mechanism. In other words, this made it possible to mediate the tactile sensor cortex for visual shape but the auditory sensor cortex for visual motion.

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