

Top-Down Anticipatory Control in Prefrontal Cortex

Hualou Liang & Hongbin Wang

School of Health Information Sciences
University of Texas at Houston
Houston, TX 77030, USA

Corresponding author:

Hualou Liang
School of Health Information Sciences
University of Texas at Houston
7000 Fannin St, Suite 600
Houston, TX 77030, USA
Tel: 713-500-3914
Fax: 713-500-3915
E-mail: Hualou.liang@uth.tmc.edu

Abstract

The prefrontal cortex has been implicated in a wide variety of executive functions, many involving some form of anticipatory attention. Anticipatory attention involves the pre-selection of specific sensory circuits to allow fast and efficient stimulus processing and a subsequently fast and accurate response. It is generally agreed that the prefrontal cortex plays a critical role in anticipatory attention by exerting a facilitatory "top-down" bias on sensory pathways. In this paper we review recent results indicating that synchronized activity in prefrontal cortex, during anticipation of visual stimulus, can predict features of early visual stimulus processing and behavioral response. Although the mechanisms involved in anticipatory attention are still largely unknown, we argue that the synchronized oscillation in prefrontal cortex is a plausible candidate during sustained visual anticipation. We further propose a learning hypothesis that explains how this top-down anticipatory control in prefrontal cortex is learned based on accumulated prior experience by adopting a Temporal Difference learning algorithm.

Keywords: Anticipation; Synchronization; Event-related potential; Conditioning; Temporal Difference Learning

Introduction

A large body of evidence has shown, at both anatomical and functional levels, that the prefrontal cortex (PFC) is involved in a wide range of executive functions (Fuster 2000; Miller & Cohen 2001). One important aspect of such executive functions is anticipatory attention, a form of attention that is essential for the temporal organization of behavior (Brunia 1999). It is generally agreed that PFC plays a central role in anticipatory attention by exerting top-down control over the selection and integration of perceptuomotor processing in other cortical areas (Miller 2000).

Anticipatory attention involves a change of internal alertness to become prepared for the upcoming stimulus (Posner & Dehaene 2000; Posner & Petersen 1990). This state change prior to the appearance of the actual stimulus may reflect a feature of organized behavior. While it has been believed that anticipatory attention typically facilitates subsequent information processing and improves performance (Nobre 2001; Liang et al. 2002), the details of how the facilitation works in the brain remain elusive.

It has been suggested that anticipatory attention might be implemented as a brain process that could reduce the threshold levels of neurons in cortical areas pertinent to the modality of the anticipated stimulus (Brunia 1999). Such a threshold decrease could improve the speed and precision of perceptual processing, resulting in faster and more accurate responses. Facilitatory threshold regulation may utilize various physiological mechanisms that produce slow and long-lasting depolarization of cortical neurons, including activation of NMDA receptors (Miller et al. 1989) and persistent sodium channels (McCormick 1990). These mechanisms are expected to have profound effects at the systems level that are observable in field potential dynamics. Phase synchronization of neuronal populations in executive areas such as PFC may play an important

role in allowing these areas to exert top-down facilitatory effects that increase the effective synaptic gain of neurons in target sensory populations (Fries et al. 2001).

'Bottom-up' and 'top-down' are heuristic terms used to describe the interplay of exogenous (feedforward) and endogenous (feedback) neuronal activities within the cortex. Onset of a visual stimulus initiates a flow of activity along the geniculostriate pathway, which induces a state change from anticipation to active processing of the stimulus pattern features. The stimulus-driven bottom-up processing is largely subserved by sensory association cortexes. The traditional approaches that emphasize this bottom-up processing have been remarkably successful in our understanding of sensory processing in the brain, yet it becomes apparent that key features in cortical processing are neglected considering sensory processing as strictly bottom-up (Engel et al. 2001). An alternative view is that predictions or hypotheses about the features of environmental stimuli and goals about the current tasks are expressed by signals traveling along top-down connections from higher to lower cortical areas. As opposed to the bottom-up activity, the top-down activity is a highly selective process based on cognitive expectations and is typically subserved by the frontal systems of the brain. According to this view, therefore, the sensory and perceptive process is not just a passive bottom-up process, but is also directly influenced by higher-order internal brain processes like preparation, expectation, attention or planning, to name a few, which are necessarily active at the same time as the sensory flow (Desimone & Duncan 1995).

Neuroanatomical studies have firmly established the pervasiveness of top-down projections (Felleman & Van Essen 1991), and a number of theoretical formulations have been proposed to explain the functions of these projections (Zeki 1993; Mumford 1994; Ullman 1995). Many experimental studies, using either single-unit recordings in animals or event-related potentials

and functional imaging in humans, have shed light on the effects of top-down influences such as attentional state on the neural processing of stimulus-related information (Chelazzi et al. 1993; Martinez et al, 1999; Kanwisher and Wojciulik 2000;). Recent work has turned to address the further question of how this is mediated in the brain, by studying the control processes and preparatory states that may produce attentional modulation of sensory response (Luck et al. 1997; Kastner et al. 1999; Hopfinger et al. 2000; Chawla et al. 1999; Corbetta et al. 2000; Monsell and Driver, 2000). Much evidence has shown that attentional shifts can influence neuronal activation levels (see Engel et al. 2001 for a review), leading to elevated responses to attended locations, and suppressed responses to unattended locations, respectively. It has not yet been determined, however, if the attention-related increase in baseline activity reported in these studies is actually relevant to behavior. One of our goals is to review data available so far that establish a relationship between baseline shifts and behavioral performance.

A critical issue concerning the brain's mediation of anticipatory attention is how expectancy and predictions are coded by neural signals. In other words, what are the mechanisms that select and coordinate the brain activity that precedes the appearance of the to-be-attended stimulus? Clearly, any mechanisms for neural integration must involve interactions between the participating local networks, but the specific nature of such interactions is still unresolved. One candidate mechanism of top-down anticipatory control might be neuronal synchronized oscillation (Fries et al. 2001; Liang et al. 2002). Direct evidence supporting synchrony as a basic mechanism for neural integration has been provided by extensive studies of visual binding (Singer and Gray 1995; Bressler 1996; Gray 1999; Varela et al. 2001). Recent work supports a critical role for synchronization in sustained motor output (Baker et al. 1999; Feige et al. 2000),

and synchronization is also being revealed as a major factor in attention (Roelfsema et al. 1997; Von Stein et al. 2000, Steinmetz et al. 2000, Fries et al. 2001; Niebur 2002).

Most studies so far have concentrated on the function of synchronization underlying the selective processing that occurs after attentionally relevant stimuli arrive. Much less is known about top-down biasing signals that precede the appearance of the to-be-attended target. There is considerable evidence that prestimulus phase synchronization is an important aspect of the anticipation of visual stimuli, and may have important effects on the subsequent processing of stimulus information (Brandt et al. 1991; Haig & Gordon 1998; Basar et al. 1998; Makeig et al. 2002). We describe recent experimental evidence from monkey studies (Bressler et al. 2001; Liang et al. 2002) on the role of synchronized activity and its temporal pattern in anticipatory attention.

The principal goal of this paper is to explore the mechanisms underlying the anticipatory control in PFC. We first review some experimental evidence that clearly demonstrates that synchronized activity in PFC prior to stimulus appearance can predict features of early visual stimulus processing and motor response, and that there is significant prestimulus top-down influence from PFC to visual cortical areas. These results directly support our hypothesis that the synchronized activity may subserve the top-down anticipatory control function of the PFC. We then investigate how the prefrontal anticipation is acquired in the first place. There is a large body of research on the brain foundations of learning that suggests that anticipation is a learned alerting process. In particular, we argue that Temporal Difference learning mechanism, which is commonly adopted in the mesencephalic dopamine system with projections to frontal cortex, plays a critical role in learning to anticipate and influence the forthcoming stimulus processing.

Experimental Evidence

Recently, evidence has accumulated that the neural activity preceding the presentation of a stimulus is far from being just noise. In fact, it may provide the neuronal substrate for the dependence of sensory information processing on context and on behavioral and conscious states.

The perpetually changing ongoing activity that presumably reflects varying brain states has first been illustrated by Arieli and co-workers (Arieli et al. 1996; Tsodyks et al. 1999), who combined real-time optical imaging and electrophysiological recordings in the cat visual cortex. Their studies showed that ongoing activity is endowed with highly structured patterns that reflect the functional architecture of the underlying networks.

Specific patterns of coherence in ongoing activity have also been reported by recent studies on highly trained monkeys performing a GO/NO-GO visual pattern discrimination task (Ding et al. 2000; Bressler et al. 2001; Liang et al. 2002). When the monkey anticipates the presentation of a visual stimulus - but before the stimulus actually appears - there is a highly structured large-scale prefrontal network synchronized in the beta frequency range (Fig. 1). Specifically, three of the five prefrontal sites are significantly coherent with each other, as shown by lines, indicated that they participated in a synchronized prefrontal network established prior to stimulus presentation. The synchronized oscillations continued until the approximate onset of early visual stimulus processing (~90 ms after stimulus onset), at which time they underwent a rapid decline in strength. Characteristic patterns of endogenous synchrony before stimulation were also found in frontal areas of human in a simple visual task (Lutz et al. 2002). Therefore, ongoing activity may have an important role in cortical function and cannot be ignored in exploration of cognitive processes.

Figure 1 near here

There are now many demonstrations that the top-down influence can operate before stimulus appearance, or during states of expectancy or anticipation, as shown by single-cell recordings in animals, and by event-related potentials and functional imaging in humans (Luck et al. 1997; de Oliveira et al. 1997; Kastner et al. 1999; Hopfinger et al. 2000; Chawla et al. 1999; Corbetta et al. 2000; Ress et al. 2000; Monsell and Driver, 2000). The most striking finding from these studies is that activity in sensory brain regions can show attentional modulation even in the complete absence of any external stimulus. These investigations provide evidence that the prestimulus neuronal activity can be modulated by purely intrinsic, self-induced factors, unlike stimulus-locked activity, which is driven exogenously by external events.

The evidence regarding the ‘baseline shifts’ in attentional research has been repeatedly reported (e.g., Driver and Frith 2000). However, the mechanism that explains the biased attentional effects remains elusive. The search for the mechanisms of top-down control becomes equivalent to the investigation of the influence of ongoing activity in higher cortical areas such as PFC on the processing of sensory signals in lower cortical areas such as primary visual cortex, and, in particular, on the behavioral performance. It is essentially the question as to how the anticipatory attention, prestimulus cortical activity and behavioral performance are linked. Our hypothesis is that the PFC exerts top-down modulatory biased signals in terms of oscillatory patterns and synchronization before stimulus appearance, which leads to variability in performance. We describe a recent experimental study (Liang et al. 2002) that supports this hypothesis.

In that study local field potentials (LFPs) were simultaneously recorded from 14 chronically implanted electrodes in prefrontal and visual cortical areas (see Fig. 1) as a highly trained macaque monkey performed a visual pattern discrimination task (Bressler et al. 1993). The

monkey initiated each trial by depressing a lever with the right hand and attending to a computer screen in anticipation of a visual pattern stimulus (line or diamond), which would appear after a random delay between 500 and 1250 ms. The monkey responded by a GO (lever release) response to one stimulus type and a NO-GO (pressure maintenance) response to the other. A water reward was given after the lever release on GO trials. LFPs collection started about 115 ms prior to the stimulus onset and continued until 500 ms post-stimulus.

The experimental results led to three major findings. First, a distributed synchronized oscillatory network in the PFC coordinated at the beta frequency range was identified before the stimulus onset. The establishment of this synchronized network suggests that some coherent activities occurred in the PFC even before the stimulus onset.

If there exists any prestimulus top-down anticipatory influence from the PFC to the posterior visual cortex, one would expect a correlation between the prestimulus prefrontal cortical activities and the post-stimulus visual cortical activities and the behavioral performance. This was confirmed by the second major finding: the strength of synchronization predicted the amplitude and timing of early visual stimulus processing components and response time (RT). Prefrontal network strength, measured by spectral peak power and coherence, had significant correlations with response time for all network sites and site pairs (Fig. 2). Pre-stimulus network power and coherence were highly correlated the amplitude and latency of event-related potential (ERP) component (Fig. 3). These results suggest that the anticipatory prefrontal network plays a priming role, and that the degree of priming can be indexed by the strength of this prestimulus network activity.

Figure 2 & 3 near here

A number of studies have suggested that top-down attentional effects may bias different parts of the visual cortex to selectively enhance their processing of visual information (Duncan et al. 1997; Desimone 1998; Reynolds et al. 1999; Gilbert et al. 2000; Hopfinger et al. 2000). However, evidence available so far regarding the top-down attentional effects is only correlative. Detection of prefrontal top-down influences explicitly on stimulus processing would provide a direct “proof of concept” in support of the idea that visual cortical areas can be selectively biased in anticipation of stimulus processing. Lesion studies can adequately address whether the neural sources or control structures produce baseline shifts when preparing to attend. However, the electrophysiology in combination with appropriate techniques of data analysis may shed new light on this issue, as demonstrated (Liang et al. 2000) by a statistical measure – the directed transfer function (DTF). DTF, a concept closely related to Granger causality (Granger 1969), is a statistical index of directional influence that is derived from the adaptive multivariate autoregressive modeling (Ding et al. 2000). The third major finding of the study was that the strength of the prestimulus top-down DTF from PFC to a site in prestriate cortex was significantly correlated with the amplitude and latency of the ERP component at that site following stimulus presentation (Bressler et al. 2001). This result provides direct evidence on an effect of prestimulus top-down influences upon subsequent visual stimulus processing in visual cortex, indicating that PFC exerts anticipatory bias on visual cortical areas to facilitate their stimulus processing.

A Learning Hypothesis

While the results discussed so far support the hypothesis that the anticipatory synchronized activity may subserve the top-down control function of the PFC, it also raises the crucial question about how the anticipation is formed in the first place. A meaningful and functional anticipation requires the capacity of precisely predicting when the event of interest is going to

occur so as to start the anticipation and preparation in time. To gain a better understanding of the top-down anticipatory function of the PFC, a learning theory of the anticipation formation is needed.

We hypothesize that the learning of accurate predictions plays an important role in the formation of the anticipatory function of the PFC and thus offers an insightful explanation about why there exists coherent and influential neural activities in the PFC prior to the stimulus onset. There is a large body of evidence in diverse fields such as experimental psychology, artificial intelligence, and control theory that suggests that learning to predict is a fundamental form of learning. Our hypothesis is not only consistent with this body of evidence but also supported by more recent findings, suggesting that some frontal areas of the brain are particularly associated with learning prediction (Holroyd & Coles 2002; Braver & Cohen 1999). In what follows, we review some relevant evidence on how learning to predict occurs as a function of prior experience and how it might be implemented in the frontal areas of the brain.

Conditioning

Conditioning is a basic type of human and animal learning. In a typical classical conditioning scenario, an organism learns, based on experience, to associate the appearance of a conditioned stimulus (CS, e.g., the sound of a bell) with the appearance of an unconditioned stimulus (US, e.g., food). As a result, the CS will later begin to elicit behavior (conditioned response or CR, e.g., salivation) that is not characteristic of CS' inherent response but is characteristic of US' response (Mackintosh 1983; Miller & Escobar 2002). In other words, the organism learns a stimulus-stimulus association. The operational conditioning differs from the classical conditioning in that in a typical operational conditioning scenario the organism learns a stimulus-response-reinforcement association. Specifically, a discriminative stimulus is presented to the

organism to signal the availability of reinforcement. The organism then needs to perform an appropriate response which, in turn, influences the delivery of the reinforcement (Dayan 2002).

Despite the difference between the various schemes of conditioning, one common aspect in various conditionings is the role of prediction learning (Sutton & Barto 1998). Following conditioning it seems that the organism has learned the predictive relation between CS/response and US/reinforcement. This learned prediction, if reliable, helps the organism to be better prepared and properly motivated. Various empirical laws that well fit the behavior are consistent with this hypothesis. For example, the law of contingency postulates that the degree of conditioning is a positive function of the cue-outcome contingency, which refers to the probability that the outcome can be reliably predicted given the availability of the cue (see Miller & Escobar 2002 for a review).

Empirical support for the hypothesis that conditioning is based on prediction learning is provided by findings showing how the learning is affected by the temporal relation between the cue and outcome. While the well-documented law of contiguity suggests the temporal contiguity of the cue and outcome is a powerful and direct determinant of conditioning, several observations complicate the issue. It has been found that simultaneous presentation of the cue and outcome (therefore a perfect temporal contiguity) results in weaker conditioned response than when the cue slightly precedes the outcome. Similar weaker or even inhibiting conditioning is observed when the cue appears slightly after the outcome. Both observations are consistent with the prediction learning hypothesis in that prediction reflects a need for anticipation and it is often of little use for an organism to display an anticipatory response when an outcome is already present (see Miller & Escobar 2002). A further support for this anticipatory function of conditioning comes from the following finding. While in classical conditioning, after training, a

CR will often immediately follows a CS, it has also been found that the CR sometimes is invoked just prior to the time at which US would appear based on the training experience (see Church 2002 for a review). This finding not only indicates that the organism has learned the temporal and predictive relationship between the CS and US, but also supports an anticipatory and preparatory function of conditioning – it makes little sense to be prepared far before a relevant stimulus is to appear.

Prediction learning as a basic learning mechanism has been explored extensively in computational modeling frameworks. The well-known Rescorla-Wagner learning rule (Rescorla & Wagner 1972) can be thought as a mathematical description on how an organism learns to predict the outcome given the cue and has been widely applied to explain human and animal learning. Specifically, it uses the difference between the predicted and the actual outcome value as a training error to systematically improve the prediction. Its equivalent form in machine learning domain, the delta rule, has been the cornerstone in training artificial neural networks to perform nontrivial learning tasks.

Temporal Difference (TD) learning (Sutton 1988; Sutton & Barto 1998) is an extension of the Rescorla-Wagner rule to the continuous time domain. In the TD learning, instead of using the difference between the predicted and the actual outcome value as the train error, it uses a TD error which is the difference of the predicted values at time t and time $t+1$. As a result, in order to learn, the organism does not have to wait until the final outcome is available – it can learn at any instant within the trial simply by comparing the predicted values at any two successive time points. The process is a simple bootstrapping strategy. More complex bootstrapping strategies can be adopted, such as comparing the prediction at time t with an average of the predictions at

all later time points, which results in different types of TD error. A parameter, γ , can be used to represent this family of TD error and leads to a family of TD learning typically called TD(γ).

TD learning as a general computational formulation of human, animal, and machine reinforcement learning and sequential decision making has been generally supported (Sutton 1988; Sutton & Barto 1998). Recent advances in cognitive neuroscience have shown that there might exist suitable mechanisms in the brain, particularly in the frontal systems, which implement a similar TD type learning. These findings are quite consistent with the top-down anticipatory bias hypothesis of the PFC we discussed in previous sections and therefore offer interesting insight on how the anticipatory function is developed computationally in the brain. We briefly review some relevant findings next.

Temporal Difference Learning in the Brain

In addition to the well-documented involvement of the PFC in executive control, there is evidence that the entire frontal systems of the brain, including the PFC, the anterior cingulate cortex (Posner & DiGirolamo 1998; Posner & Raichle 1994), and the basal ganglia (Brown et al. 1997), contribute to executive control. It has been known that activity in these areas is modulated by the mesencephalic dopamine system (see Berridge & Robinson 1998 for a review), which is closely related to the realization of similar temporal difference learning in the brain (O'Reilly & Munakata 2000; Holroyd & Coles, 2002).

The mesencephalic dopamine system is composed of a collection of nuclei including the substantia nigra (SN) and the ventral tegmental area (VTA). These nuclei project widely to the basal ganglia and other midline frontal areas including the anterior cingulate cortex and PFC (Berger et al. 1991). The system has long been believed to represent a “hedonia” center in the brain and thus may contribute to reinforcement learning (see Wickelgren 1997 for a review).

However recent neural recording results about the activity from monkeys' mesencephalic dopamine cells in various delayed response tasks suggest that these cells may broadcast important reward-prediction related signals (Schultz 2000). In a typical task, a monkey learns a predictive association between a stimulus (which cues an arm movement) and a later reward (a drop of juice). A typical firing pattern of the recorded dopamine cells shows that during training they fire only at the delivery of the reward but after training they fire only at the cue stimulus. These results seem to indicate that dopamine cells fire when there is a prediction error, which occurs only at the reward delivery in early training but only at the cue stimulus presentation after learning.

Considerable computational exploration has been conducted to simulate the firing patterns of these dopamine cells (e.g., Montague et al. 1996, O'Reilly & Munakata 2000; Dayan & Abbott 2001; Holroyd & Coles 2002). It has been found that computational models based on TD learning can explain the data remarkably well. Though details are often different, these models more or less all assume that the mesencephalic dopamine cells carry a TD error signal, which summarizes the difference in reward value prediction at different time points and is broadcasted to other frontal areas for control and tuning purposes.

These models have gained considerable explanatory power due to the wide projection from the mesencephalic dopamine system to other frontal brain areas. For example, Holroyd and Coles (2002) study the link between the dopamine TD error to the anterior cingulate cortex and argue that when an organism commits an error, a TD error is generated in the dopamine system, which is then sent to the anterior cingulate cortex for further error-related processing. This model explains well the error-related negativity (ERN), a well-documented observation of the negative deflection in electroencephalogram when an error is committed. It has been believed that ERN is

generated in the anterior cingulate cortex (Gehring et al. 2000). A similar connection has been made between the dopamine TD error to motor action control in the basal ganglia (e.g., O'Reilly & Munakata 2000). We believe that the prefrontal prestimulus synchronization we discussed previously may also be driven by a prediction related TD error originated in the mesencephalic dopamine system. This error signals the incoming of an event of interest and primes the proper preparation. We illustrate this hypothesis in Fig. 4. Further empirical and computational studies are clearly needed to test this hypothesis.

Figure 4 near here

General Discussion

The data reviewed above lead us to hypothesize that the PFC exerts top-down modulatory biased signals in terms of oscillatory patterns and synchronization upon sensory cortex during anticipation of visuomotor processing. This hypothesis was supported by the results that the strength of prefrontal synchronization (peak power and coherence) was highly correlated with the amplitude and latency of early visual stimulus processing components and subsequent response time, and that there was significant prestimulus top-down DTF from PFC to visual cortical areas (Bressler et al. 2001; Liang et al. 2002). The results are compatible with the argument that top-down factors can lead to states of expectancy or anticipation, which can be expressed in the temporal structure of activity patterns before the presentation of stimulus (Engel et al. 2001).

We discussed the crucial question as to how the synchronized anticipatory activity in PFC is developed. We argued that the neuronal synchronization may be acquired during the course of learning, and then used to temporally modulate behaviorally relevant sensory processes. Our hypothesis was that prediction learning plays an important role in the formation of the

anticipatory function of the PFC and the brain possesses particularly suitable mechanisms in the frontal systems to implement this type of learning. In particular, we suggested that the mesencephalic dopamine system, which has been widely believed to carry out reward-prediction related learning, may provide critical driving signals that trigger PFC synchronization. This hypothesis offers a computational explanation to important issues such as how the top-down anticipatory control in PFC is learned based on accumulated experience and why there exist structured and predictive neural activities in PFC before the appearance of the stimulus.

It should be noted that the prefrontal cortex is not the only region where this selectivity is evident. Indeed, selectivity is a hallmark of attention and it is evident throughout the visual cortex (Miller and Cohen 2001). There is striking agreement among many studies that frontal and parietal regions have been consistently activated when attention is achieved through top-down control processes (See Frith 2001 for a review).

Neuronal synchronization has been suggested as a mechanism of attentional modulation by which a neuronal population in one area may increase the effective synaptic of target neurons in another area (Fries et al. 2001). A number of theoretical formulations (e.g., Tononi et al. 1992) have also been proposed to explain the relationship between top-down influences and synchronous oscillations. Consistent with the data reviewed, these theories predict that self-induced activity should have a distinct spatiotemporal pattern that would bias the dynamics of stimulus-triggered responses and their binding into functionally coherent assemblies. Therefore, oscillatory synchronization may be considered as a possible agent or representation in carrying out top-down biased signals originated in PFC that prime stimulus-evoked response, thereby permitting a rapid selection among multiple events or inputs.

The evidence reviewed has mostly been focused on anticipatory attention in which subjects are waiting for a stimulus to come. Control of other kinds of expectancy such as motor preparation (Donoghue et al. 1998; Riehle et al. 2000), the activation of motor and premotor structures that precedes the execution of specific movement, may be organized in a similar way. Both types of control involve internally generated states of anticipation, and both are related, at least partly, to common sources of modulation such as PFC.

Studies of synchronization in PFC before stimulus onset (Bressler et al. 2001; Liang et al. 2002) have provided further evidence that the highly structured patterns of coherence are predictively related to features of early visual stimulus processing and motor response. Significant top-down anticipatory influences of PFC upon stimulus processing in visual cortex have been observed at the same frequency. However it could also be possible that the influences occur at different frequencies. Therefore, it would be of interest to study mutual influences between oscillations in different frequency bands. Finally, systematically manipulating the anticipated sensory attributes of stimuli and motor responses will be useful to determine the brain circuits that participate in the attentional control.

Acknowledgement

We thank our collaborators on these experiments: Steven Bressler, Mingzhou Ding and Richard Nakamura. We would also like to thank the referees for the detailed comments and valuable suggestions.

References

- Arieli, A.; Sterkin, A.; Grinvald, A.; Aertsen, A. (1996) Dynamics of ongoing activity: Explanation of the large variability in evoked cortical responses. *Science* 273 (5283): 1868-1871.
- Baker, S.N.; Kilner, J.M.; Pinches, E.M.; Lemon, R.N. (1999) The role of synchrony and oscillations in the motor output. *Exp. Brain Res.* 128:109-17.
- Basar, E.; Rahn, E.; Demiralp, T.; Schurmann, M. (1998) Spontaneous EEG theta activity controls frontal visual evoked potential amplitudes. *Electroenceph. Clin. Neurophysiol.* 108: 101-109.
- Berridge, K. C.; Robinson, T. E. (1998) What is the role of dopamine in reward: Hedonic impact, reward learning, or incentive salience? *Brain Res. Rev.* 28: 309–369.
- Brandt, M. E.; Jansen, B. H.; Carbonari, P. (1991) Pre-stimulus spectral EEG patterns and the visual evoked response. *Electroenceph. Clin. Neurophysiol.* 80: 16-20.
- Braver, T. S.; Cohen, J. D. (1999) Dopamine, cognitive control, and the gating model. In J. A. Reggia, E. Ruppin, & D. Glanzman (Eds.), *Progress in brain research*. Amsterdam: North-Holland: pp 327-349.
- Bressler, S. L. (1996) Interareal synchronization in the visual cortex. *Behav. Brain Res.* 76: 37-49.
- Bressler, S. L.; Coppola, R.; Nakamura, R. (1993) Episodic multiregional cortical coherence at multiple frequencies during visual task performance. *Nature* 366: 153-156.
- Bressler, S. L.; Liang, H.; Ding, M. (2001) Top-down influence on early visual processing by an anticipatory large-scale network in macaque prefrontal cortex. *Soc. Neurosci. Abstr.* 27, 533.1.
- Brown, L. L.; Schneider, J. S.; Lidsky, T. I. (1997) Sensory and cognitive functions of the basal ganglia. *Curr. Opin. Neurobiol.* 7: 157-163.
- Brunia, C.H. (1999) Neural aspects of anticipatory behavior. *Acta. Psychol.* 101:213-42.
- Chawla, D.; Rees, G.; Friston, K.J. (1999) The physiological basis of attentional modulation in extrastriate visual areas. *Nat Neurosci.* 2 (7): 671-676.
- Chelazzi, L.; Miller, E.K.; Duncan, J.; Desimone, R. A (1993) neural basis for visual-search in inferior temporal cortex. *Nature* 363 (6427): 345-347.
- Church, R. M. (2002) Temporal learning. In R. Gallistel (Ed.), *Stevens' handbook of experimental psychology (Third edition): Learning, motivation, and emotion*. New York: Wiley.

- Corbetta, M.; Kincade, J. M.; Ollinger, J. M.; McAvoy, M. P.; Shulman, G. L. (2000) Voluntary orienting is dissociated from target detection in human posterior parietal cortex. *Nat. Neurosci.* 3 (3): 292-297.
- Dayan, P. (2002) Reinforcement learning. In R. Gallistel (Ed.), *Stevens' handbook of experimental psychology (Third edition): Learning, motivation, and emotion*. New York: Wiley.
- Dayan, P.; Abbott, L. F. (2001) *Theoretical neuroscience*. Cambridge, MA: MIT Press.
- De Oliveira, S.C.; Thiele, A.; Hoffmann, K.P. (1997) Synchronization of neuronal activity during stimulus expectation in a direction discrimination task. *J. Neurosci.* 17(23): 9248 – 9260.
- Desimone, R. (1998) Visual attention mediated by biased competition in extrastriate visual cortex. *Philos. Trans. Royal Soc. Lond. Series B-Biol. Sci.* 353:1245-1255.
- Desimone, R.; Duncan, J. (1995) Neural mechanisms of selective visual-attention, *Annu. Rev. Neurosci.* 18 : 193-222.
- Ding, M.; Bressler, S. L.; Yang, W.; Liang, H. (2000) Short window spectral analysis of cortical event-related potentials by Adaptive MultiVariate AutoRegressive (AMVAR) modeling: Data preprocessing, model validation, and variability assessment by bootstrapping. *Biol Cybern* 83: 35-45.
- Donoghue, J.P.; Sanes, J.N.; Hatsopoulos, N.G.; Gaal, G. (1998) Neural discharge and local field potential oscillations in primate motor cortex during voluntary movements. *J. Neurophysiol.* 97(1): 159 – 173.
- Driver, J.; Frith, C. (2000) Shifting baselines in attention research. *Nat Rev Neurosci.* 1: 147-148.
- Duncan, J.; Humphreys, G.; Ward, R. (1997) Competitive brain activity in visual attention. *Curr. Opin. Neurobiol.* 7:255-261.
- Engel, A.K.; Fries, P.; Singer, W. (2001) Dynamic predictions: Oscillations and synchrony in top-down processing. *Nat. Rev. Neurosci.* 2 (10): 704-716.
- Feige, B.; Aertsen, A.; Kristeva-Feige, R. (2000) Dynamic synchronization between multiple cortical motor areas and muscle activity in phasic voluntary movements. *J. Neurophysiol.* 84:2622-9.
- Felleman, D.; Van Essen, D. (1991) Distributed hierarchical processing in the primate cerebral cortex. *Cereb. Cortex.* 1:1-47.
- Fries, P.; Reynolds, J.H.; Rorie, A.E.; Desimone, R. (2001) Modulation of oscillatory neuronal synchronization by selective visual attention, *Science*, 291: 1560-1563.

- Frith, C. (2001) A framework for studying the neural basis of attention. *Neuropsychologia*. 39: 1367 – 1371.
- Fuster, J.M. (2000) Executive frontal functions. *Exp. Brain Res.* 133:66-70.
- Gehring, W. J.; Himle, J.; Nisenson, L. G. (2000) Action-monitoring deficits in obsessive-compulsive disorder. *Psychol. Sci.* 11: 1-6.
- Gilbert, C.; Ito, M.; Kapadia, M.; Westheimer, G. (2000) Interactions between attention, context and learning in primary visual cortex. *Vision Res.* 40:1217-1226.
- Granger, C.W.J. (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37:424-438.
- Gray, C.M. (1999) The temporal correlation hypothesis of visual feature integration: Still alive and well. *Neuron* 24 (1): 31-47.
- Haig, A. R.; Gordon, E. (1998) Prestimulus EEG alpha phase synchronicity influences N100 amplitude and reaction time. *Psychophysiol* 35: 591-595.
- Holroyd, C. B.; Coles, M. G. H. (2002) The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychol. Rev.* 109: 679-709.
- Hopfinger, J. B.; Buonovore, M. H.; Mangun, G. R. (2000) The neural mechanisms of top-down attentional control. *Nat Neurosci* 3: 284-291.
- Kanwisher, N.; Wojciulik, E. (2000) Visual attention: Insights from brain imaging. *Nat. Rev. Neurosci.* 1 (2): 91-100.
- Kastner, S.; Pinsk, M. A.; Weed, P. D.; Desimone, R.; Ungerleider, L. G. (1999) Increased activity in human visual cortex during directed attention in the absence of visual stimulation. *Neuron* 22: 751-761.
- Liang, H.; Ding, M.; Nakamura, R.; Bressler, S. L. (2000) Causal influence in primate cerebral cortex during visual pattern discrimination. *NeuroReport* 11: 2875-2880.
- Liang, H.; Bressler, S. L. Ding, M.; Truccolo, W.; Nakamura, R. (2002) Synchronized activity in prefrontal cortex during anticipation of visuomotor processing. *NeuroReport* 13: 2011-2015.
- Lutz, A.; Lachaux, J-P.; Martinerie, J.; Varela, F.J. (2002) Guiding the study of brain dynamics by using first-person data: Synchrony patterns correlate with ongoing conscious states during a simple visual task. *Proc. Natl. Acad. Sci. USA* 99:1586-1591.
- Luck, S. J.; Chelazzi, L.; Hillyard, S. A.; Desimone, R. (1997) Neural mechanisms of spatial selective attention in areas V1, V2, and V4 of macaque visual cortex. *J. Neurophysiol.* 77 (1): 24-42

- Mackintosh, N. J. (1983) *Conditioning and associative learning*. Oxford: Oxford University Press.
- Makeig, S.; Westerfield, M.; Jung, T. P.; Enghoff, S.; Townsend, J.; Courchesne, E.; Sejnowski, T.J. (2002) Dynamic brain sources of visual evoked responses. *Science* 295 (5555): 690-694.
- Martinez, A.; Anllo-Vento, L.; Sereno, M. I.; Frank, L. R.; Buxton, R. B.; Dubowitz, D. J.; Wong, E. C.; Hinrichs, H.; Heinze, H. J.; Hillyard, S. A. (1999) Involvement of striate and extrastriate visual cortical areas in spatial attention. *Nat. Neurosci.* 2 (4): 364-369.
- McCormick, D.A. (1990) Membrane properties and neurotransmitter actions. In: Shepard, G.M. (Eds) *The Synaptic Organization of the Brain* (3rd Ed.). New York: Oxford University Press.
- Miller, E.K. (2000) The prefrontal cortex and cognitive control. *Nat. Rev. Neurosci.* 1:59-65.
- Miller, E.K.; Cohen, J.D. (2001) An integrative theory of prefrontal cortex function. *Annu. Rev. Neurosci.* 24:167 - 202.
- Miller, K.D.; Chapman, B.; Stryker, M.P. (1989) Visual responses in adult cat visual cortex depend on N-methyl-D-aspartate receptors. *Proc. Natl. Acad. Sci. USA* 86:5183-5187.
- Miller, R.; Escobar, M. (2002) Learning: Laws and models of basic conditioning. In R. Gallistel (Ed.), *Stevens' handbook of experimental psychology (Third edition): Learning, motivation, and emotion*. New York: Wiley.
- Monsell, S.; Driver, J. (2000) *Control of Cognitive Processes*. Cambridge, MA: MIT Press.
- Montague, P. R.; Dayan, P.; Sejnowski, T. K. (1996) A framework for mesencephalic dopamine systems based on predictive Hebbian learning. *J. Neurosci.* 16: 1936-1947.
- Mumford, D. (1994) Neuronal architectures for pattern-theoretic problems. In: Koch, C.; Davis, J.L. (Eds.) *Large-Scale Neuronal Theories of the Brain*. Cambridge, MA: MIT Press, pp 125-152.
- Niebur, E. (2002). Electrophysiological correlates of synchronous neural activity and attention: A short review. *BioSystems* 67: 157-166.
- Nobre, A.C. (2001) Orienting attention to instants in time. *Neuropsychol.* 39: 1317 – 1328.
- O'Reilly, R. C.; Munakata, Y. (2000) *Computational explorations in cognitive neuroscience*. Cambridge, MA: MIT Press.
- Posner, M. I.; Dehaene, S. (2000) Attentional networks. In M. S. Gazzaniga (Ed.), *Cognitive neuroscience: A reader*. Malden, MA: Blackwell Publishers.
- Posner, M. I.; DiGirolamo, G. J. (1998) Executive attention: Conflict, target detection, and cognitive control. In R. Parasuraman (Ed.), *The attentive brain*. Cambridge, MA: MIT Press.

- Posner, M. I.; Petersen, S. E. (1990) The attention systems of the human brain. *Ann. Rev. Neurosci.* 13:25-42.
- Posner, M. I.; Raichle, M. E. (1994) *Images of mind*. New York: Scientific American Library.
- Rescorla, R. A.; Wagner, A. R. (1972) A theory of Pavlovian conditioning: The effectiveness of reinforcement and non-reinforcement. In A. H. Black & W. F. Prokasy (Eds.), *Classical conditioning II: Current research and theory*. New York: Appleton-Century-Crofts.
- Ress, D.; Backus, B.; Heeger, D. (2000) Activity in primary visual cortex predicts performance in a visual detection task. *Nat Neurosci.* 3:940 – 945.
- Reynolds, J.H.; Chelazzi, L.; Desimone, R. (1999) Competitive mechanisms subserve attention in macaque areas V2 and V4. *J. Neurosci.* 19:1736-1753.
- Riehle, A.; Grammont, F.; Diesmann, M.; Grun, S. (2000) Dynamical changes and temporal precision of synchronized spiking activity in monkey motor cortex during movement preparation. *J. Physiol. (Paris)* 94: 569 – 582.
- Roelfsema, P.R.; Engel, A.K.; Konig, P.; Singer, W. (1997) Visuomotor integration is associated with zero time-lag synchronization among cortical areas. *Nature* 385:157-161.
- Schultz, W. (2000) Multiple reward signals in the brain. *Nat Rev Neurosci* 1:199 – 207.
- Singer, W.; Gray, C.M. (1995) Visual feature integration and the temporal correlation hypothesis. *Ann. Rev. Neurosci.* 18: 555-586.
- Steinmetz, P. N.; Roy, A.; Fitzgerald, P.J.; Hsiao, S.S.; Johnson, K.O.; Niebur, E. (2000) Attention modulates synchronized neuronal firing in primate somatosensory cortex. *Nature* 404:187–190.
- Sutton, R. S. (1988). Learning to predict by the methods of temporal differences. *Mach. Learn.* 3: 9-44.
- Sutton, R. S.; Barto, A. G. (1998) *Reinforcement learning: An introduction*. Cambridge, MA: MIT Press.
- Tononi, G.; Sporns, O.; Edelman, G.M. (1992) Reentry and the problem of integrating multiple cortical areas: simulation of dynamics integration in the visual system. *Cereb Cortex* 2:310–335.
- Tsodyks, M.; Kenet, T.; Grinvald, A.; Arieli, A. (1999) Linking spontaneous activity of single cortical neurons and the underlying functional architecture. *Science* 286 (5446): 1943-1946.
- Ullman, S. (1995) Sequence seeking and counter streams: A computational model for bidirectional information flow in the visual cortex. *Cereb. Cortex.* 5:1-11.

Varela, F.; Lachaux, J-P.; Rodriguez, E.; Martinerie, J. (2001) The brainweb: phase synchronization and large-scale integration. *Nat. Rev. Neurosci.* 2:229 – 239.

Von Stein, A.; Chiang, C.; Konig, P. (2000) Top-down processing mediated by interareal synchronization. *Proc. Natl Acad. Sc. USA* 97: 14748 – 14753.

Wickelgren, I. (1997) Getting the brain's attention. *Science*, 278: 35-37.

Zeki, S. (1993) *A Vision of the Brain*. Oxford: Blackwell Scientific.

Figure Legends

Fig. 1. A large-scale prefrontal network, synchronized in the beta frequency range before the appearance of stimulus, plotted on a representative three-dimensional cortical surface reconstruction. Approximate recording sites are marked by disks, and the pairs of sites having significant peak coherence are connected by lines. The picture is adapted from the study described in Liang et al. (2002).

Fig. 2. Scatter plots showing strong correlation of prestimulus prefrontal network power (A) and coherence (B) with response time. Each point represents a group of 200 GO trials rank ordered by response time. Linear least-squares best fits to the data are superimposed, with Spearman rank correlation coefficients for all three network sites (A) and three site pairs (B) indicated in the legends. The data is adapted from Liang et al. (2002).

Fig. 3. Relation between prestimulus prefrontal network strength and early visual stimulus processing. Example of prefrontal network coherence between PF1 and PF2 (A, left) and the ERP at a striate cortex site ST1 (A, right), showing the greater prefrontal coherence and striate ERP amplitude of the fastest (solid) RT trials as compared to the slowest (dashed). (B) Scatter plots are shown of prestimulus prefrontal network peak power and coherence correlated with the amplitude and latency of the second ERP component C2. Just above each plot shows the correlation coefficient. The data is adapted from Liang et al. (2002).

Fig. 4. How the prediction related temporal difference (TD) learning may be implemented in the frontal systems of the brain. The mesencephalic dopamine system takes control input from PFC (prefrontal cortex), ACC (anterior cingulate cortex), and BG (basal ganglia), generates a predicted related TD error signal, and broadcasts the signal back (including itself) for control and tuning purposes.

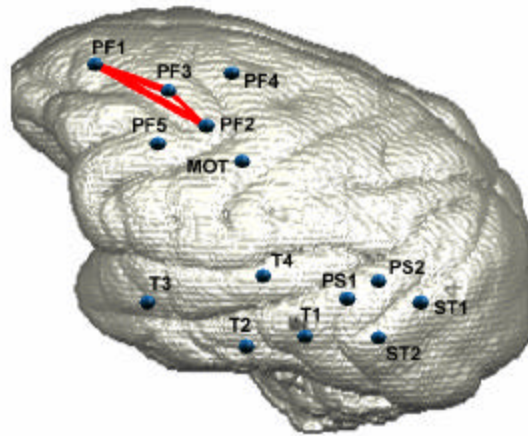
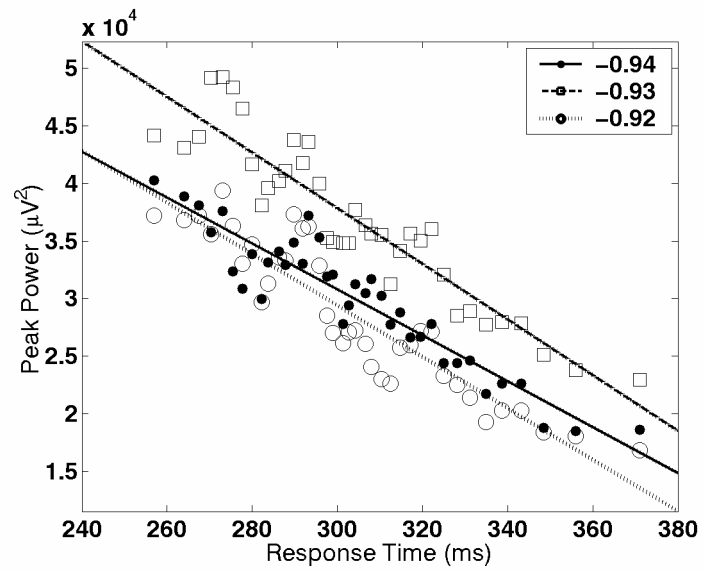


Fig. 1

A



B

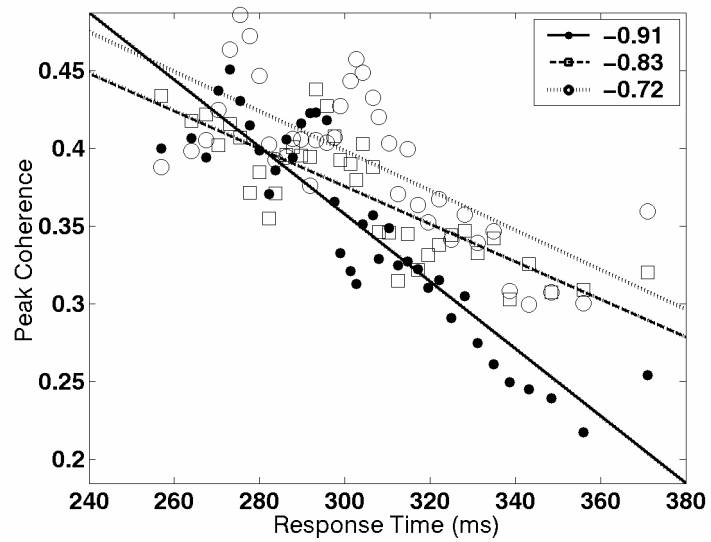
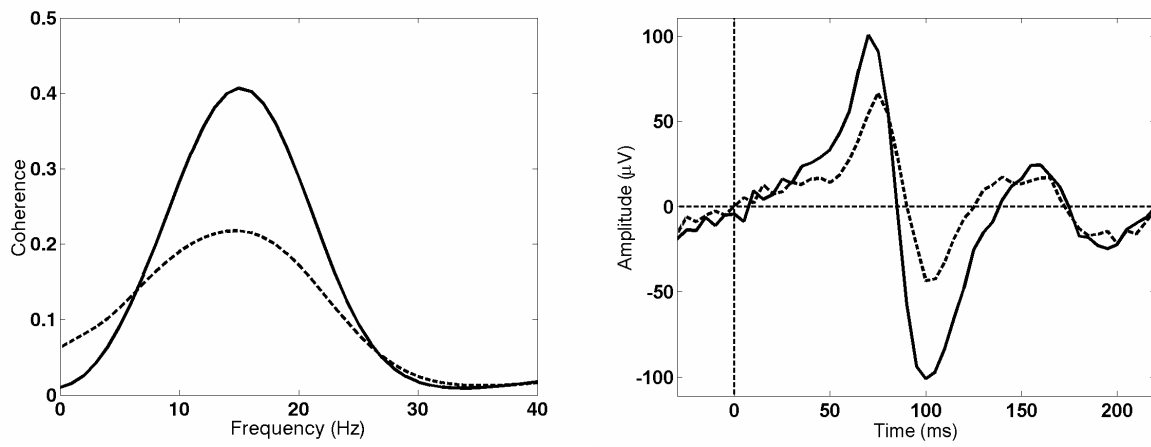
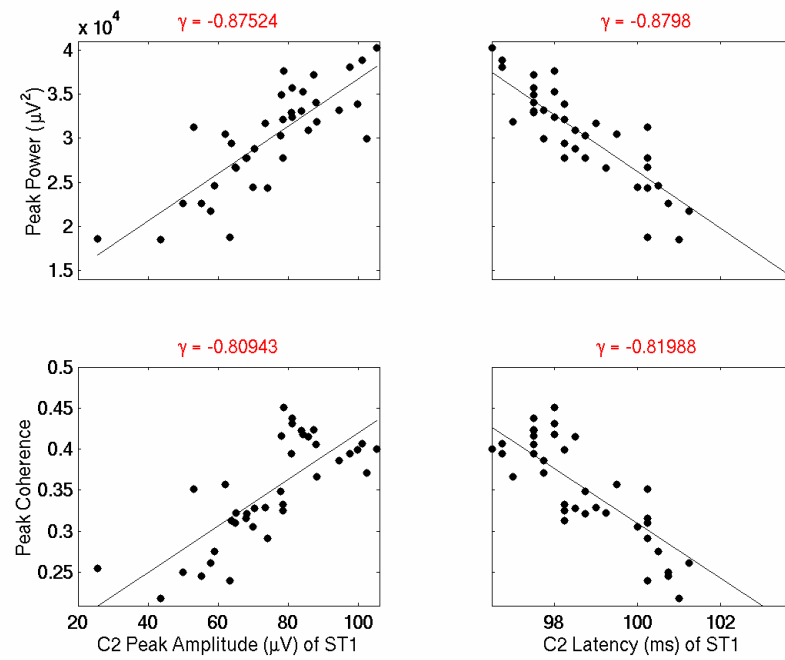


Fig. 2

A**B****Fig. 3**

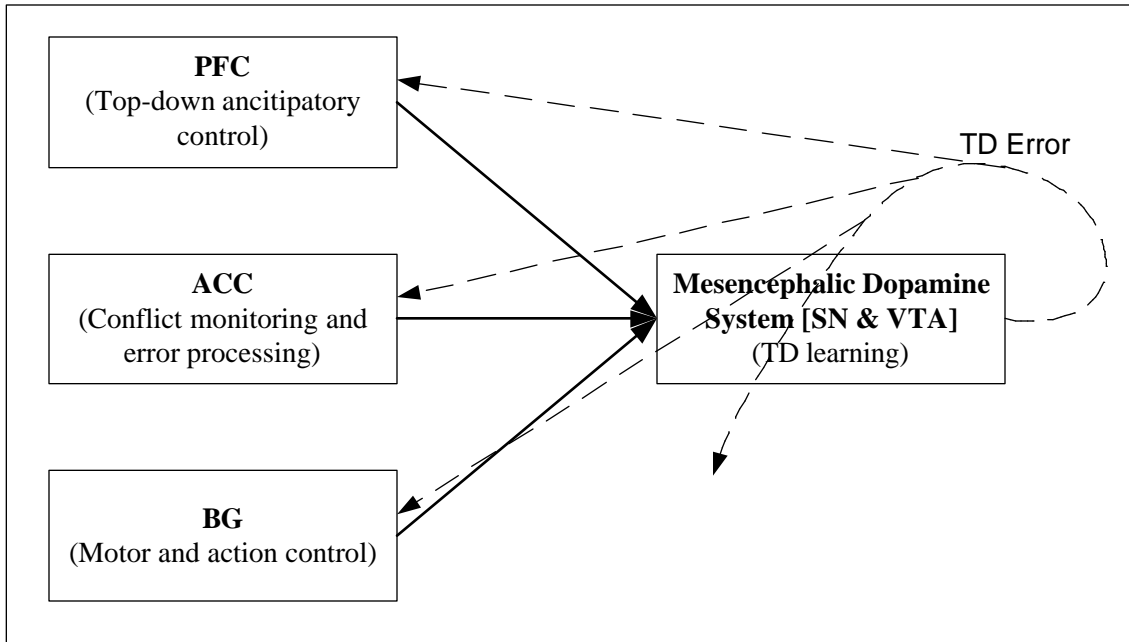


Fig. 4