Modeling Percentage Change of fMRI BOLD Signal and Reaction Time of a Dual Task with a Queuing Network Modeling Approach

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Abstract

To model the percentage change of blood oxygenation level-dependent (BOLD) signal and reaction time in a dual task, we propose a new mathematical modeling approach—a queuing network approach based on queuing network theory of human performance (Liu, 1996, 1997) and current discoveries in neuroimage studies. This approach includes a queuing network architecture representing the information processing in the brain and mathematical equations to quantify the reaction time, BOLD signal and its percentage signal change (PSC). Both reaction time and the percentage change of BOLD signal in an fMRI study of the dual task are successfully modeled with analytical solutions of the mathematical equations, which demonstrates its usefulness and parsimony in modeling the brain activation pattern and human performance simultaneously. Furthermore, the current modeling approach uniquely quantifies the queuing mechanism discovered by the fMRI study and also provides a coherent and quantitative linkage between the neural signals and behavioral data. Further extension and development of the current modeling approach are discussed.

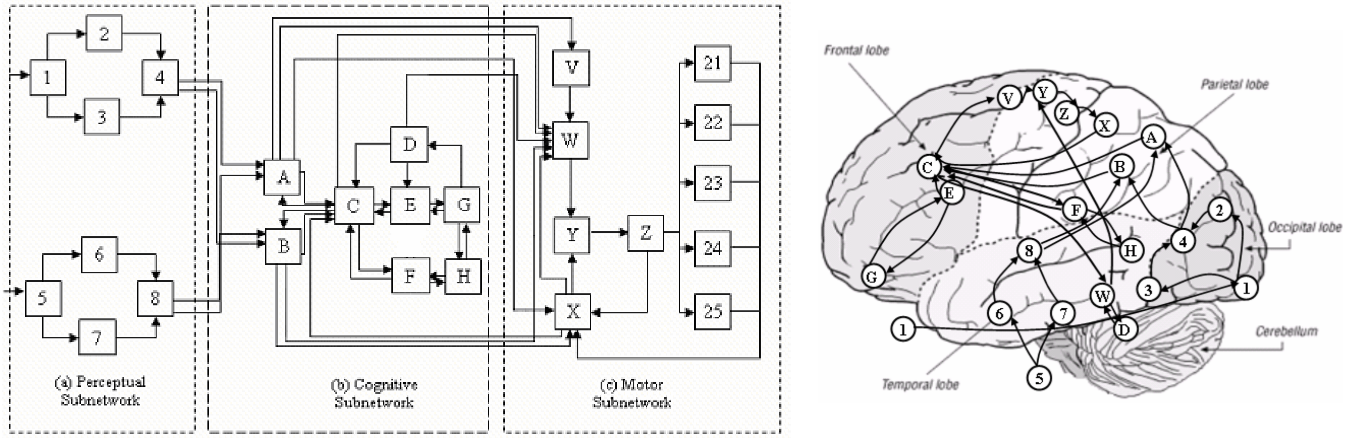
Introduction

Performing dual tasks at the same time is common in daily life. Among these dual tasks, psychological refractory period (PRP) is one of the most basic dual tasks and it has been studied at the behavioral level by psychologists for more than 50 years (Creamer, 1963). The basic PRP experiment paradigm requires subjects to perform two choice reaction time tasks called task 1 (T1) and task 2 (T2) concurrently; typically, the reaction time of T1 (RT1) is not affected but the reaction time of T2 (RT2) is delayed when the interval time between stimuli of the two tasks is relatively short. The interval between presentation of stimulus of T1 and T2 is called stimulus onset asynchrony (SOA).

To find neural correlates of the basic PRP, Jiang et al. (2004) conducted the first brain imaging experiment strictly following the procedure in the basic PRP experiment paradigm with a large number of subjects. In their experiment, both task 1 and task 2 were choice reaction task. Task 1 was a visual-manual task: square or circles were presented on a display, and subjects pressed ‘‘1’’ for a square and ‘‘2’’ for a circle with their left hands. Task 2 was also a visual-manual task: subjects were asked to press different keys on a keypad depending on different letters or different colors of crosses on the display. They collected both behavioral performance data and BOLD signal of several major brain regions.

Besides the fMRI experimental studies, two major groups of models have been established in modeling BOLD signal—statistical models and mathematical models. In the group of statistical models, Cohen (1997) proposed a statistical model of BOLD signal by fitting the data from the averaged responses to a three-parameter gamma variate function. Another important statistical modeling technique is the structural equation modeling (SEM/SEQ) (Frackowiak, Friston, Frith, Dolan, & Mazziotta, 1997) and it models the connectivity among the brain areas by determining the functional strengths of each anatomical link between regions with SEM which is widely used in social science. In mathematical models, several large-scale neuron models have been built (Husain et al., 2002; Tagamets & Horwitz, 1998). Each of these models is composed of large-scale networks of neuronal-like elements; and the brain imaging signal of certain brain region is computed by integrating synaptic input into that region. In addition, based on Cohen’s statistical model, Anderson and his colleagues proposed a mathematical model which successfully simulated the change of BOLD signal during the 0-20 sec time course (Anderson, Qin, Sohn, Stenger, & Carter, 2003; Anderson, Qin, Stenger, & Carter, 2004).

In addition to the previous research, we propose a new mathematical modeling method which can quantify the BOLD signal and reaction time simultaneously in dual task situations. In the following, first, we introduce the platform of this modeling approach—a queuing network architecture of information processing in the brain, representing the major brain regions and their connections as a network. Second, based on this network platform, a set of mathematical equations are developed to quantify the two dependent variables. Third, the modeling results are presented and validated with the experimental results of Jiang et al. (2004). Finally, we discuss the implication of this modeling approach and its further extensions to model the experimental results of electrophysiological studies.



Perceptual Subnetwork

1. Common visual processing (eyes, lateral geniculate nucleus, superior colliculus, primary and secondary visual cortex)
2. Visual recognition (dorsal system)
3. Visual location (ventral system)
4. Visual recognition and location integration (distributed parallel area including the connections among V3 , V4 and V5, superior frontal sulcus, and inferior frontal gyrus)
5. Common auditory processing (middle and inner ear)
6. Auditory recognition (area from dorsal and ventral cochlear nuclei to the inferior colliculus)
7. Auditory location (area from ventral cochlear nucleus to the superior olivary complex)
8. Auditory recognition and location integration (primary auditory cortex and planum temporale)

Cognitive Subnetwork

A. Visuospatial sketchpad (right-hemisphere posterior parietal cortex)
B. Phonological loop (left-hemisphere posterior parietal cortex)
C. Central executive (dorsolateral prefrontal cortex (DLPFC), anterior-dorsal prefrontal cortex (ADPFC) and middle frontal gyrus (GFm))
D. Long-term procedural memory (striatal and cerebellar systems)
E. Performance monitor (anterior cingulate cortex)
F. Complex cognitive function: decision and mental calculation etc. (intraparietal sulcus (IPS), the superior frontal gyrus (SFS), the inferior frontal gyrus (GFi), the inferior parietal cortex and the ventrolateral frontal cortex, the intraparietal sulcus and the superior parietal gyrus)
G. Goal initiation (orbitofrontal region and amygdala complex)
H. Long-term declarative & spatial memory (hippocampus and diencephalons)

Motor Subnetwork

V. Sensorimotor integration (premotor cortex)
W. Motor program retrieval (basal ganglia)
X. Feedback information collection (somosensoy cortex)
Y. Motor program assembling and error detecting (supplementary motor area (SMA) and the pre-SMA)
Z. Sending information to body parts (primary motor cortex)
21-25: Body parts: eye, mouth, left hand, right hand, foot

Figure 1: The general structure of the queuing network model (function of each server and corresponding brain areas)

Queuing Network Architecture

To model human performance and brain imagining data, the queuing network modeling approach regards the human cognition system as a queuing network based on several similarities between them. First, ample research evidence has shown that major brain areas with certain information processing functions are localized and connected with each other in the brain cortex via neural pathways (Bear & Connor, 2001; Smith et al., 1998; Roland, 1993), which is highly similar to a queuing network of servers that can process entities traveling through the routes serially or/and in parallel depending on specific network arrangements. Therefore, brain regions with similar functions can be regarded as servers and neural pathways connecting them are treated as routes in the queuing network (see Figure 1). Second, it has discovered that information processed in the brain are coded in spikes trains (Rieke, Warland, R.S., & Bialek, 1997); depending on different tasks and learning stages, the to-be-processed information represented by these spikes trains sometimes are processed by the brain regions (servers) immediately; sometimes they have to be maintained in certain regions to wait for the previous spike trains being processed (E. E. Smith & Jonides, 1998; Taylor et al., 2000). Hence, these spikes trains can be represented as entities in the queuing network naturally and entities are processed in the network by certain queuing process as an analogy to represent the waiting and maintaining process of spikes trains.

In modeling human performance, computational models based on queuing networks have successfully integrated a large number of mathematical models in response time (Liu, 1996) and in multitask performance (Liu, 1997) as special cases of queuing networks. Queuing network modeling approach has been successfully used to generate human behavior in real time, including simple and choice reaction time, driver performance and transcription typing (Liu, Feyen & Tsimhoni, in press; Wu & Liu, 2004a).

In modeling brain imaging pattern, previous work in queuing network modeling was focused on modeling the dynamic connectivities among brain regions. Wu and Liu (2004b) successfully modeled how brain imagining patterns change with different learning stages and different stimuli to be processed. These connectivities of brain regions were modeled as dynamic changes of routing probability (probability of entities enter one of multiple routes) in the queuing network during the learning process.

Modeling BOLD Signals and Reaction Time

To model the experiment of Jiang et al. (2004), first, it is necessary to determine the route of entities in the network; second, the reaction time can be estimated by the time for the entities spent in the routes; third, fMRI BOLD signal and its percentage signal change (PSC) are modeled by the processing process of entities in the network.

Route of Entities

The route of entities in the network is determined based on previous queuing network modeling work in modeling the connectivity of brain regions (Wu and Liu, 2004b): in general, depending on the task to be performed, servers whose function is related to the target task are included in the route of entities. Since both task 1 and 2 are visual-manual task in Jiang et al.'s experiment (2004), entities representing the visual stimuli enter the visual perceptual subnetwork first (1->2/3->4) to process its location and content information (see Figure 1); and then they are transferred to the cognitive subnetwork and go through server A, C and F, making the judgments of choice reaction task at server F. After that, they travel to the motor subnetwork (server W, Y, Z and hand server) to retrieve motor programs, assembly the motor programs, and initiate the motor response. As a result, according to the connection of these brain regions, the routes of the two tasks are:

T1: 1->2/3->4->A->C->F->C->W->Y->Z->Hand

T2: 1->2/3->4->A->C->F->C->W->Y->Z->Hand

Mathematic Modeling of Reaction Time

Independent of SOA conditions, the response time of T1 (RT1) can be predicted by the sum of servers' the processing time in the route of entities of T1 since no previous entities occupy any of the servers in the route (see T1 in Figure 2 and Equation 1).

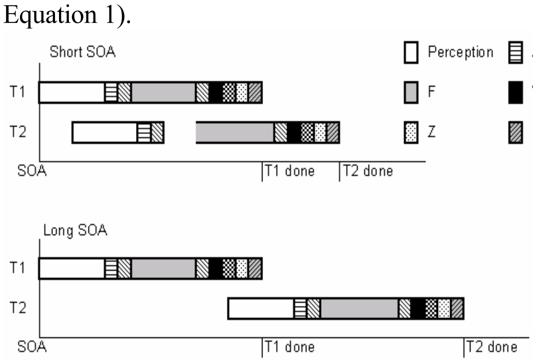


Figure 2: Illustration of reaction time in the basic PRP paradigm

$$E(RT1)= T_{1,VP}+T_{1,A}+T_{1,C}+T_{1,F}+T_{1,C}+T_{1,Y}+T_{1,W}+T_{1,Z}+T_{1,K} \quad (1)$$

where, $T_{1,VP}$ is the processing time of the visual perceptual subnetwork; $T_{1,A}$, $T_{1,C}$, $T_{1,F}$, $T_{1,Y}$, $T_{1,W}$, $T_{1,Z}$, and $T_{1,K}$ represents the processing time of server A, C, F, Y, W, Z and Hand, respectively.

The response time of T2 (RT2) depends on the comparison between a) the difference between SOA and the time point when of entities of T1 exit server F ($T_{1,VP}+ T_{1,A} +T_{1,C} +T_{1,F} - SOA$) and b) the duration of the processing time before entities of T2 enter server F (the sum of processing time at the perceptual subnetwork, server A and C, $T_{2,VP}+T_{2,A}+T_{2,C}$) (see Equation 2).

$$E(RT2)= max(T_{1,VP}+T_{1,A}+T_{1,C}+T_{1,F}-SOA,\ T_{2,VP}+T_{2,A}+T_{2,C}) + T_{2,F}+ T_{2,C}+ T_{2,Y}+ T_{2,W}+ T_{2,Z}+ T_{2,K} \quad (2)$$

Equation 2 above can be rewritten into: $E(RT2)=$

$$\begin{cases} T_{1,VP}+T_{1,A}+T_{1,C}+T_{1,F}-SOA+T_{2,F}+T_{2,C}+T_{2,Y}+T_{2,W}+T_{2,Z}+T_{2,K} & SOA< T_{1,VP}+T_{1,A}+T_{1,C}+T_{1,F}-(T_{2,VP}+T_{2,A}+T_{2,C}) \\ T_{2,VP}+T_{2,A}+T_{2,C}+T_{2,F}+T_{2,C}+T_{2,Y}+T_{2,W}+T_{2,Z}+T_{2,K} & SOA\geq T_{1,VP}+T_{1,A}+T_{1,C}+T_{1,F}-(T_{2,VP}+T_{2,A}+T_{2,C}) \end{cases} \quad (3)$$

Mathematic Modeling of BOLD Signal

BOLD Signal BOLD signal in the queuing network model is modeled based on the prior fMRI signal modeling work of Cohen (1997) and Anderson et al. (2003). Using Cohen 's model, Anderson et al. (2003, 2004) proposed that the integrated BOLD signal (*CB(t)*) in a certain brain region is mainly determined by several factors: the length of time the current buffer/server occupied throughout time *t* (*i(x):* at time *x*, if the current buffer/server is occupied, *i(x)*=1; otherwise, *i(x)*=0), latency scale *s* and magnitude scale *M* (see Equation 4) (Anderson et al., 2003; Anderson et al., 2004).

$$CB(t) = M\int_0^t i(x)B(\frac{t-x}{s})dx \quad (4)$$

where, $B(T) = kT^a e^{-T/b}$ (Cohen, 1997). In the queuing network model, assuming the length of time server *i* is being used is η, Equation 4 can be further developed into:

$$CB(t)=\begin{cases} M\int_0^\eta B(\frac{t-x}{s})dx & 0\le x\le\eta \Rightarrow i(x)=1 \\ 0 & x<0 \text{ or } x>\eta \Rightarrow i(x)=0 \end{cases} \quad (5)$$

Suppose $Y=\frac{t-x}{s}$ and combine Equation 5 with the Cohen's equation $B(T) = kT^a e^{-T/b}$, then Equation 5 can be rewritten into Equation 6:

$$CB(t)=\begin{cases} skM\int_{\frac{t-\eta}{s}}^{\frac{t}{s}} Y^a e^{-Y/b}dY & \frac{t-\eta}{s}\le Y\le\frac{t}{s} \\ 0 & \frac{t-\eta}{s}>Y \text{ or } Y>\frac{t}{s} \end{cases} \quad (6)$$

Solving the integer above, if $\frac{t-\eta}{s}\le Y\le\frac{t}{s}$, $CB(t)=$

$$\frac{kMsb}{a+1}\left(\begin{array}{l} e^{(-.5t/bs)}\left(t/s\right)^a\left(t/bs\right)^{-.5a}\text{WhittakerM}\left(.5a,.5a+.5,t/bs\right)- \\ e^{(-.5a\frac{t-\eta}{bs})}\left(\frac{t-\eta}{bs}\right)^{.5a}\text{WhittakerM}\left(.5a,.5a+.5,\frac{t-\eta}{bs}\right) \end{array}\right) \quad (7)$$

where, the result of the Whittaker function—WhittakerM (m, n, z) can be obtained by solving the following differential equation: $y'' + [-0.25 + m/z + (0.25 - n^2)/z^2]y = 0$. and η in queuing network can be quantified by Equation 8:

$$\eta = \rho_i L = \frac{\lambda_i T_i}{Cap_i} L \tag{8}$$

where, ρ_i is server i's utilization (fraction of time a server is busy in total time of each trial,); λ_i is the arrival rate (number of arrivals into sever i through L) and T_i and Cap_i is the processing time and capacity of server i, respectively.

Percentage Signal Change of CB(t) (PSC) For the same brain region, the percentage signal change (fMRI *PSC*) is the *CB(t)* of the experimental condition compared to the *CB(t₀)* of the baseline condition (e.g., fixation condition in Jiang et al. 2004) (see Equation 9) (Ben-Shachar, Hendler, Kahn, Ben-Bashat, & Grodzinsky, 2003).

$$PSC = \frac{CB(t) - CB(t_0)}{CB(t_0)} \tag{9}$$

Therefore, according to Equations 6 to 9, *PSC* at short and long SOA conditions (PSC_{long}, PSC_{short}) can be calculated if T_i, Cap_i, λ_i, *k, M, s, b, a,* and *t* at these conditions are given. For the same brain regions measured by the same fMRI techniques, *s, k, M, a,* T_i, Cap_i, and *b* are expected to be remained the same in short and long SOA conditions. Furthermore, since the length of each trial is fixed either at short or long SOA conditions, the value of *t* also remains the same in short and long SOA conditions. During each trial, the same amount of information through *t* arrived at the cognitive system; therefore, λ_i remains the same in short and long SOA conditions. Therefore, according to Equations 6-9 above, for the same brain region, the expected percentage signal change of *CB(t)* keeps constant across different SOA conditions, i.e.:

$$\therefore\ CB(t)_{long} = CB(t)_{short}$$

$$\because\ PSC_{long} - PSC_{short}$$

$$= \frac{CB(t)_{long} - CB(t_0)}{CB(t_0)} - [\frac{CB(t)_{short} - CB(t_0)}{CB(t_0)}] = \frac{CB(t)_{long} - CB(t)_{short}}{CB(t_0)}$$

$$\therefore\ PSC_{long} - PSC_{short} = 0$$

In other words, in this queuing process, since the amount of information processed by each brain region remains the same in the short and long SOA conditions, the integrated BOLD signal remains the same in the short and long SOA conditions.

Modeling Results and Validation

Using the equations derived in the previous sections, the predicted results of both reaction time and percentage change of fMRI signal are presented and validated with the target experiment results. The value of parameters of these equations is set based on a classic cognitive modeling study (Byrne & Anderson, 2001) (see Appendix).

Reaction Time

Figure 3 shows the modeling results in comparison with experimental results in reaction time: the R square of the model is .8 and the RMS=35.0 ms.

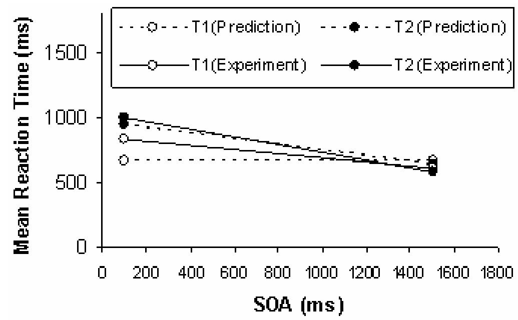
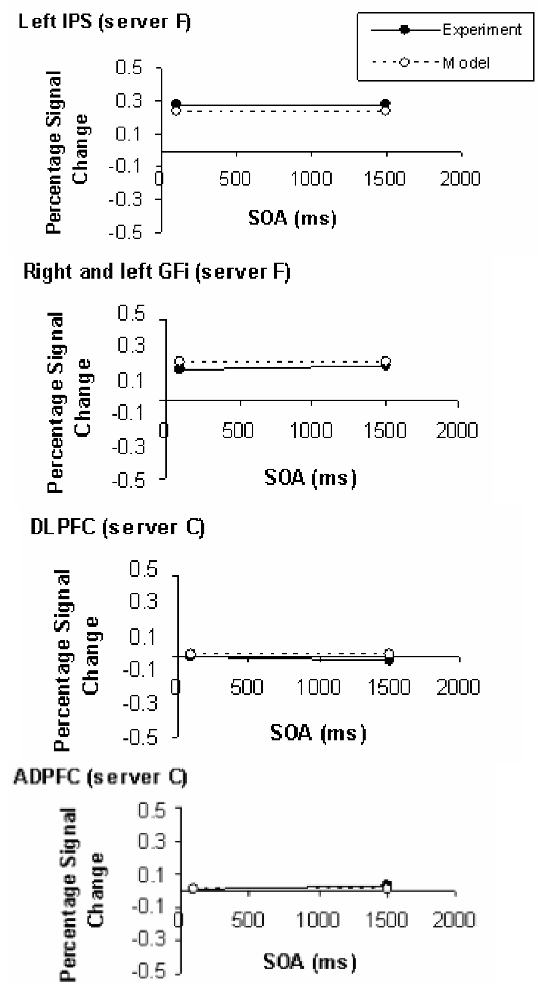


Figure 3: The reaction time in the study of Jiang et al. (2001) (solid lines) along with the queuing network modeling results (dashed lines)

Percentage Change of fMRI BOLD Signal

Figure 4 shows the modeling results in comparison with experimental results of the percentage change of fMRI signal: the R square of the model is .70 and the RMS=0.03.



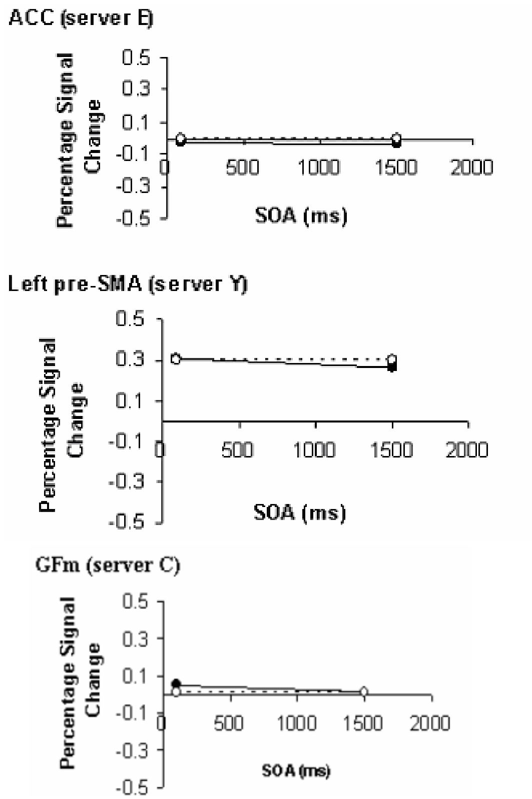


Figure 4: The percentage signal change (*PSC*) in the study of Jiang et al. (2004) (solid lines) along with the queuing network modeling results (dashed lines)

Discussion

In the present work, we described a mathematical modeling approach to model reaction time and PSC of BOLD signal in a dual task. This modeling approach includes a queuing network architecture of information processing in the brain and several mathematical equations quantifying the reaction time, BOLD signal and its PSC. Both reaction time and the percentage change of BOLD signal are successfully modeled with this queuing network approach, which demonstrates its usefulness in modeling brain activation and human performance simultaneously. With the previous work in modeling the different brain activation patterns in learning process of a visuo-motor task (Wu and Liu, 2004b), the current queuing network approach is able to model the brain activation and the dynamic connectivity among the brain regions simultaneously.

Compared with the traditional reaction time models of dual tasks focusing on behavioral performance alone, the current modeling approach provides a coherent and quantitative linkage between the neural signals (BOLD signal) and behavioral data (reaction time). The queuing network model has successfully unified several traditional major reaction time models (Liu, 1996). The current work extends the advantages of this modeling approach to unify the neural signals and behavioral data: the model's prediction is not only consistent with the external behavior of the subjects, but also in line with the experimental results of brain imaging studies. With solid neurological evidence in developing the queuing network architecture, the current modeling approach provides a new way to quantify the external behavioral data and to some extent explain how they are generated by the internal information processing in the brain.

Furthermore, with the unique feature of queuing in the current modeling approach, the queuing network modeling approach quantifies the queuing mechanism in the basic dual task found by the current fMRI study—"these data suggest that passive queuing, rather than active monitoring, occurs during the PRP" (Jiang et al., 2004, p390). In other words, our modeling approach modeled the experimental data very naturally without purposely adjusting the model's core assumption to be consistent with this queuing mechanism discovered by the experimental researchers. This unique feature makes the current approach very useful in modeling the behavioral data and BOLD signal in dual tasks since very few of existing statistical models or mathematical models regard queuing as their core assumption and quantifies the queuing mechanism in the basic dual task.

Another important feature of the current modeling approach is that the mathematical equations of BOLD signal in the approach incorporate the Cohen's statistical model and Anderson's mathematical model (see the development of these equations in this article). In other words, this queuing network modeling approach is consistent with the existing modeling approaches of BOLD signal; from the development of its mathematical equations, it can also model the experimental data quantified by the models of Cohen and Anderson. For example, by changing the value of a, s and M in Equation 5, the current modeling approach is able to model the change of BOLD response during 0-20 sec in which the peak BOLD response is observed.

Finally, the current modeling approach provides a parsimonious and accurate quantification of the BOLD signal and behavioral data, since all of the dependent variables are modeled by analytical solutions of the relatively simple mathematical equations.

The current model approach can be extended to model a wider range of behavioral and physiological measurements and their neurological mechanisms. For example, we are developing the mathematical models of event-related potential (ERP), so that the current modeling is able to not only model the spatial location where information processing occurred in the brain, but also quantify the temporal stage of information processing. Overall, the queuing network modeling approach is a useful modeling method to quantify and predict the behavioral and brain imaging data in the cognitive system; and it also gives us a better understanding of the basic mechanism underling the dual task performance.

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APPENDIX Parameter Setting in the Modeling Process

The parameter setting method in this article follows the parameter setting method in a classic cognitive modeling study (Byrne & Anderson, 2001)—a free parameter (server F's processing time) is estimated to fit the experiment data at the long SOA condition. The same value of this parameter is used in short SOA conditions to predict the RT1 and RT2 under short SOA conditions. Therefore, at short SOA conditions, there are no free parameters to fit the experiment result in the current modeling approach. Moreover, the value of the free parameter is also constrained by the nature of the task: processing time of server F for both T1 and T2 are similar since both of the two tasks are choice reaction tasks; the processing time of server F is significantly longer than the processing time of other servers because the judgment and decision process involves complex processing at server F.

Except the value of the free parameter, all of the other parameters are set based on the experimental conditions of the target experiment to be modeled (Jiang et al., 2004) as well as existing researches; and the majority of them come from the same modeling approach which models a wide range of human performance in various tasks (Liu, et al, in press) (see Table 1).

Table 1: Parameters in modeling Jiang et al (2004)'s experiment

Parameter	Value	Source
$T_{1,VP}$, $T_{2,VP}$	126 ms	Liu, et al. (in press)
$T_{2,A}$, $T_{2,B}$	18 ms	Liu, et al. (in press)
$T_{1,C}$, $T_{2,C}$	18 ms	Liu, et al. (in press)
$T_{1,F}$	408 ms	Value estimated
$T_{2,F}$	376 ms	Value estimated
$T_{1,W}$, $T_{2,W}$	24 ms	Liu, et al. (in press)
$T_{1,Y}$, $T_{2,Y}$	24 ms	Liu, et al. (in press)
$T_{1,Z}$, $T_{2,Z}$	24 ms	Liu, et al. (in press)
$T_{1,K}$	10 ms	Byrne & Anderson (2001)
Cap_i	depending on servers	Wu and Liu (2004a)
L	3 sec	Jiang (2004)
$\lambda_{i\text{-}short}$, $\lambda_{i\text{-}long}$	22 entities	Eagleman & Churchland (2005); Jiang (2004)
k_{long}, k_{short}	0.452	Cohen (1997)
M_{long}, M_{short}	2.75	Anderson et al. (2003)
s_{long}, s_{short}	0.991	Anderson et al. (2003)
b_{long}, $b_{short,}$	0.547	Cohen (1997)
a_{long}, a_{short}	8.60	Cohen (1997)
t_{long}, t_{short}	3 sec	Jiang (2004)