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Computational neuroergonomics

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ABSTRACT

Neuroergonomics merges neuroscience and ergonomics for the study of brain and behavior in natural and naturalistic settings. Together with the rapid development of neuroergonomics concepts, technologies, and related data, there is an urgent need to develop computational models of neuroergonomics that can help integrate and interpret empirical findings and make predictions for scientific research and practical application. This article discusses the relationship between computational neuroscience and computational neuroergonomics, and describes a queuing network based computational neuroergonomic architecture and its applications. These discussions illustrate the mission and challenges of computational neuroergonomics and future research needs.

Introduction

Neuroergonomics merges neuroscience and ergonomics for the study of brain and behavior at work in relation to every day environments, technologies and settings in the real world (Parasuraman and Rizzo, 2008; Parasuraman and Wilson, 2008). As a rapidly developing field, it is accumulating a large amount of empirical data, developing a fast growing body of concepts and technologies, and opening up new frontiers of theoretical inquiries and practical applications. As in all fields of science and applications, researchers also see the importance and necessity to develop computational models of neuroergonomics in addition to data collection, concept formation, and technology development.

Computational modeling can help researchers and practitioners organize and summarize empirical data, provide unique perspectives to examine and interpret the data, guide and generate hypotheses for new experiments to obtain data in a systematic fashion, and make extrapolations and predictions to situations in which empirical data collection is not feasible or undesirable. Scientifically, computational modeling help advance the understanding of the brain and behavior; practically, it may help guide system design by comparing different design alternatives and predicting human behavior in operational contexts that cannot be easily covered by experimental or simulation studies.

One may ask “don't we have many computational models in neuroscience?” and “can't we simply use them in neuroergonomics?” The answer is that we do have many outstanding computational models in neuroscience, which can be used to inform and inspire computational neuroergonomics models; but in the same sense that neuroscience is not synonymous with neuroergonomics, computational neuroscience is not synonymous with computational neuroergonomics. In the same sense that neuroscience provides a rich soil for neuroergonomics to grow and also benefit from it, computational neuroscience models will support and hopefully benefit from computational neuroergonomics models.

In the following section (A brief summary of some related computational neuroscience models), we first summarize some of the major existing models of computational neuroscience, with a focus on models of neuroimaging data. This summary shows the strengths of these models and their limitations for direct application in neuroergonomics. In the section “A queuing network architecture of computational neuroergonomics”, we discuss the unique challenges faced by computational neuroergonomics models, and describe one example of a computational neuroergonomic architecture called the queuing network architecture. In Neuroergonomic applications of the QN architecture section, some example applications of the queuing network architecture in neuroergonomics are described. The last section concludes this article by emphasizing the unique mission of computational neuroergonomics and its relation to computational neuroscience.

A brief summary of some related computational neuroscience models

Computational neuroscience is an extremely active field of research, and many outstanding computational models in neuroscience have been developed, from neural networks models, to statistical regression models, to causal network models, among others. It is neither feasible nor the intention of the present paper to offer a

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comprehensive review of these models. Rather, this paper focuses on a sample of computational models and data analysis techniques that attempt to infer the function and network structure of brain regions using neural imaging techniques. We select these models for discussion here because neuroimaging is arguably the most widely used method in neuroscience and neuroergonomics, and it is so fitting that this special issue on neuroergonomics is scheduled for publication in *NeuroImage*. As discussed later, a network and integrated view of brain function is crucial for models to be valuable and applicable for neuroergonomic purposes.

In neuroimaging research some researchers focus on a particular brain region to identify its role in particular psychological or behavioral functions, while others take a "network" view of the brain and examine the interactions or coactivations between several brain regions in psychological activities and develop hypotheses about how these regions interact with each other and form networks. Each approach has its strengths and limitations, praises and criticisms, successes and failures (Cabeza and Nyberg, 2000; Friston, 2009). While not attempting to go into the debate on the pros and cons of the various approaches, we emphasize that for useful and meaningful neuroergonomic developments and applications, the network view of exploring brain region interactions is indispensable. Human behavior in real world settings – its understanding and analysis are the goals of neuroergonomics – involves the participation of multiple psychological and neural functions, no matter how simple and primitive the real world task is. This statement does not logically imply the lack of value in studying the functions and roles of specific brain regions, in the same sense that emphasizing the importance of looking at trees does not automatically ignore the beauty of the flowers and fruits on the trees and the necessity of healthy branches and strong invisible roots. Both the modular and the network approaches are important, but this paper will focus on the network approach.

Several major techniques and methods have been developed and widely applied in network analyses of neuroimaging data as a way to examine possible interaction patterns between brain regions, including partial least squares (McIntosh et al., 1996), structural equation modeling (Nyberg and McIntosh, 2001), dynamic Bayesian networks (Labatut et al., 2004), topological inference based on random field theory (Taylor and Worsley, 2007), support vector machines (Laconte et al., 2005), self-organizing maps (Peltier et al., 2003), and canonical variates analysis (Friston, 2009).

The Partial Least Squares (PLS) technique (McIntosh et al., 1996) is a multivariate extension of the pairwise interrelations method, which represents perhaps the earliest method of analyzing brain region interactions. The pairwise interrelations method examines the correlations in activations between a selected brain region (called a seed region) with other selected regions of interest. PLS extends this examination of correlations to more than one experimental conditions and more than one seed regions. PLS is a technique for identifying functional connectivity (namely correlations) between brain regions, not for hypothesizing any causal relationships about which region may cause another region to be activated in certain ways.

Structural equation modeling (SEM) and dynamic Bayesian networks (DBN) are both statistical causal modeling methods widely used in many fields of psychology, econometrics, and social sciences for inferring possible causal relationships among variables of interest, and they are used to identify possible causal connections among brain regions in the case of neural data modeling. As in all applications of SEM, researchers start with a hypothesized causal relationship among the brain regions, which may or may not be supported by the computed "path coefficients" based on interregional covariances shown in the related neural data. The path coefficients represent the hypothesized causal influence between the regions. DBNs are directed graphical models of stochastic processes, where the nodes of the graphs represent brain regions and the arcs (or lack of) represent dependence (or conditional independence) assumptions. Directed arcs are used to represent "causal" relations, in the sense that a directed arc from A to B is regarded as indicating A causes B. An example of using DBNs is the work of Labatut et al. (2004). A summary and discussion of the topological inference based on random field theory (Taylor and Worsley, 2007), support vector machines (SVM) (Laconte et al., 2005), statistical parametric mapping (SPM) (Friston et al., 1995), and canonical variates analysis (CVA) (Worsley et al., 1997) can be found in Friston (2009).

All the models and techniques summarized above are important mathematical or statistical methods of identifying possible roles of and interactions among brain regions and the possible brain networks. They are valuable neuroscience models, whose findings can be used to inform and develop neuroergonomic models but they cannot be directly applied to neuroergonomics applications for analyzing operator performance of complex real world tasks and evaluating design alternatives. In this regard, it is important to note the recent development of ACT-R in its efforts toward establishing stronger neuroscience connections (Anderson, 2007). Unlike the neuroscience models summarized above that are mathematical or statistical in nature, ACT-R has been developed for about three decades mainly as a symbolic cognitive model based on production rules and symbolic processing. ACT-R is now capable of modeling a wide range of cognitive tasks. Its recent neuroscience inspired work focuses on identifying the neurophysiological basis for its cognitive processing modules. ACT-R uses mathematical equations extensively to specify the rules and functions of some of its modules, but its overall architecture is a symbolic rather than mathematical one. Its relation to computational neuroergonomics will be discussed later in this paper, in comparison to the queuing network architecture summarized in the following section.

To support the design and analysis of complex human–machine systems, neuroergonomic models of human performance should meet the following five criteria. They should be not only neuroscience based, but also mathematical, computational, comprehensive and application-relevant. Pure mathematical models such as those reviewed above do not allow real time simulation of human performance and human–machine interaction. Pure computational symbolic models lack mathematical representations of their overall structures at the macro architectural level. Comprehensive models are needed to capture the whole range of concurrent processing activities, affective states, and neural mechanisms. They should be application-relevant, suitable for tackling practical design problems (Liu, 2009).

A queuing network architecture of computational neuroergonomics

In this section we summarize a queuing network architecture of computational neuroergonomics that aims to meet simultaneously the five ergonomic modeling criteria mentioned above: mathematical, computational, neural-science driven, comprehensive, and application-relevant. It is an approach to modeling human performance based on both neuroscience findings and neuroergonomic objectives.

To model human performance and neurophysiological activities of the brain, the queuing network architecture represents the human behavioral and brain system as a queuing network (QN). A QN is a network of service stations (called servers), each of which provides a particular kind of service to the demanders for service (called customers or entities), either immediately or after a delay (called queuing or waiting). QN theories and methods represent a family of the most commonly used mathematical and simulation tools in system performance analysis in a wide range of applications such as telecommunications, internet, traffic systems, and manufacturing. It is an active field of mathematical research and it supports precise mathematical analysis as well as simulation and symbolic computations.

It is also easy to see, at least at the conceptual level, the similarities between a QN and a human brain. Both are networks of distributed but connected processing units that work together to allow complex behaviors to emerge. Both QN servers and brain modules have a processing aspect (i.e., time is needed to perform their specific functions) and a "waiting" (or queuing) aspect (i.e., entities may need to wait for a processing unit to become available). It should be noted that the QN architecture is an abstraction or representation of the brain, which can be done in different ways and at different levels of granularity, depending on the purpose of modeling and analysis. For example, neural network models represent and analyze the brain at the level of neurons, while the SEM and DBN models represent the brain activities as regional networks.

Over the past 15 years, we have developed a QN architecture for the behavioral and brain system. The QN architecture is a relatively fixed computational structural representation (Newell, 1990) with detailed specifications of its servers, network connections, entity arrival, processing, and routing mechanisms based on existing psychological and neuroscience findings. This relatively fixed QN architecture can be used as a shared platform to develop and implement specific QN models for particular tasks, all of which share the same set of general QN assumptions, parameters, and mechanisms that are not task specific.

Using the same QN architecture and exercising the *mathematical* power of QN, mathematical QN models have been successfully developed to integrate a large number of mathematical models in response time (Liu, 1996), speed–accuracy tradeoff (Liu, 2007), and multitask performance (Liu, 1997) as special cases of queuing networks. Exercising the power of QN to support *symbolic* computations, the cognitive modeling and task analysis method called MHP-GOMS (Model Human Processor—Goals, Operators, Methods, and Selections) (Card et al., 1983) has been implemented in a QN simulation software. This specific QN architectural development and implementation is called Queuing Network-Model Human Processor (QN-MHP), which has been used for both mathematical modeling and computational generation of human performance and mental workload in real time, including driver performance (Liu, et al., 2006) and driver subjective workload (Wu and Liu, 2007), transcription typing (Wu and Liu, 2008b), visual manual tracking performance and mental workload measured by the event-related potential (ERP) techniques (Wu et al., 2008a), and neuroimaging findings associated with performing the psychological refractory period task (Wu and Liu, 2008a).

The QN architecture consists of perceptual, cognitive, and motor subnetworks (shown in Fig. 1 and Fig. 2), which are summarized in the following sections.

Perceptual subnetwork

The perceptual subnetwork currently includes a visual and an auditory perceptual subnetwork, each of which is composed of four servers. In the visual perceptual subnetwork, Server 1 represents the eye, the lateral geniculate nucleus, the superior colliculus, the primary visual cortex, and the secondary visual cortex. Visual stimulus entities are first processed by Server 1 and then transmitted in parallel visual pathways—the parvocellular stream (Server 2) and the magnocellular stream (Server 3) where the object content (e.g., color, shape, labeling) and location features (e.g., spatial coordinates, speed etc.) are processed. These information features from the two parallel pathways are integrated in Server 4 before transmitted to the cognitive subnetwork; Server 4 represents the distributed parallel areas including the neuron connections between V3 and V4, the superior frontal sulcus, and the inferior frontal gyrus. These brain regions also serve as the visual sensory memory storage (Bear, et al., 2001; Ohbayashi, et al., 2003; Smith and Jonides, 1998; Ungerleider and Haxby, 1994).

The auditory perceptual subnetwork also consists of four servers: the middle and inner ear (represented by Server 5) transmits auditory information to the parallel auditory pathways, represented by Server 6 (the neuron pathway from the dorsal and ventral cochlear nuclei to the inferior colliculus) and Server 7 (the neuron pathway from the ventral cochlear nucleus to the superior olivary complex) where location, pattern and other aspects of the sound are processed. The auditory information in the auditory pathways is integrated at the primary auditory cortex and the planum temporale (Server 8), which also serve as the auditory sensory memory storage (Bear et al., 2001; Mustovic et al., 2003). Upon existing the auditory subnetwork, auditory information is transmitted to the left-hemisphere posterior parietal cortex (Server B) as well as the right-hemisphere posterior parietal cortex (Server A), in accordance with the working memory mechanisms proposed by Baddeley (1992) and the functions of multimodal areas (neuron pathways between the primary auditory cortex and the posterior parietal cortex, and the angular and supramarginal gyri) (Faw, 2003).

Cognitive subnetwork

The cognitive subnetwork consists of a working memory system, a long-term memory system, a goal execution system, and a complex cognitive processing system. Following Baddeley (1992)'s working memory model, QN contains four components in the working memory system. Server A and Server B represent the visuospatial sketchpad (the right-hemisphere posterior parietal cortex) and the phonological loop (the left-hemisphere posterior parietal cortex), respectively, where visuospatial and phonological information are stored and maintained in working memory. Server C stands for the

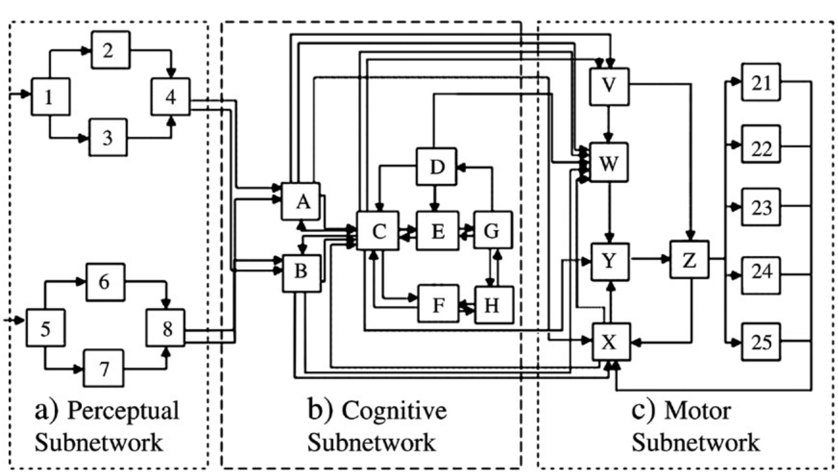

Fig. 1. The queuing network (QN) cognitive architecture.
Adapted from Liu, Feyen, and Tsimhoni, 2006; Wu and Liu, 2008a.

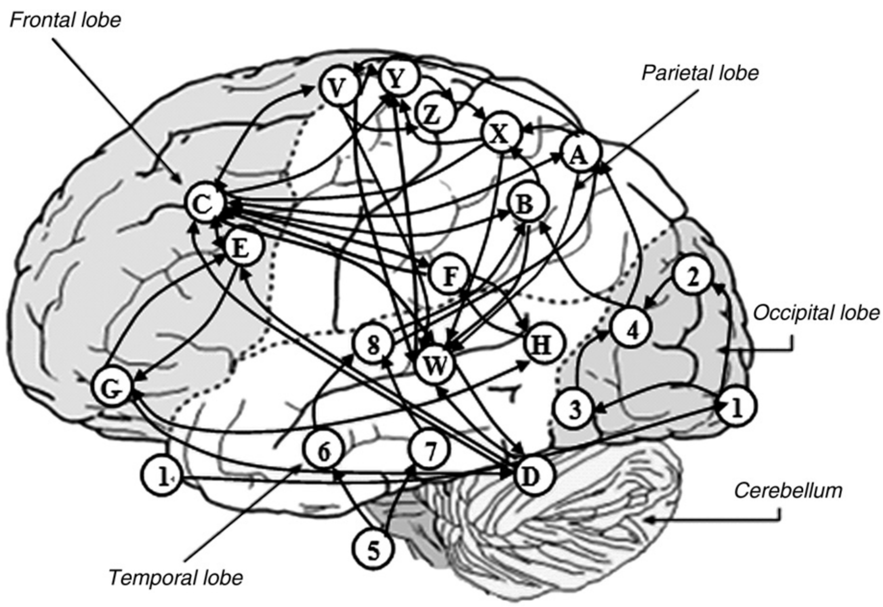

Fig. 2. Approximate mapping of the servers in the Queuing Network architecture onto the human brain. Adapted from Wu and Liu, 2008a.

central executor, which plays a crucial role in suppressing automatic responses (Burle, et al., 2004; Smith and Jonides, 1998; Koski and Paus, 2000) and for categorization of information (Grossman et al., 2002; Shafritz, et al., 2005; Vartanian and Goel, 2005). It represents the dorsolateral prefrontal cortices (DLPFC), the anterior–dorsal prefrontal cortices (ADPFC), the right ventral frontal cortex and the middle frontal gyrus (GFm). Server E can be called the performance monitor, representing the anterior cingulate cortex (ACC) responsible for performance monitoring and error detection (Smith and Jonides, 1998).

Two types of long-term memory are currently represented in the QN with two servers. Server D stands for procedural memory and motor programs (non-declarative memory), representing the striatal and the cerebellar systems where all the task procedure steps and motor programs are stored. Server H represents declarative (facts and events) and spatial memory (the medial temporal lobe including the hippocampus and the diencephalons), which stores various kinds of production rules in choice, judgment, decision making, and long-term spatial information (Bear, et al., 2001). The goal execution system (Server G) represents the orbitofrontal region and the amygdala complex, which are typically involved in goal initiation and motivation (Rolls, 2000).

An important feature of QN is its hybrid structure of the cognitive subnetwork, which includes both serial processing at Server F (responsible for complex cognitive processing) and parallel processing in the other servers in the cognitive subnetwork. Based on Byrne and Anderson's (2001) experimental finding that humans cannot perform two arithmetic operations at once, Server F is assumed to perform complex cognitive functions in a serial manner. Server F represents brain areas including the 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. These areas are responsible for complex cognitive functions such as mental calculation, phonological judgment, spatial working memory operations, anticipation of stimuli in simple reaction task, multiple-choice decision, (excluding information categorization and automatic response suppression, which are the functions of Server C) (Fletcher and Henson, 2001; Manoach et al., 1997; Kazui, et al., 2000; Smith and Jonides, 1998).

Motor subnetwork

The motor subnetwork consists of 5 servers, representing the major brain areas responsible for the retrieval, assembling, and execution of motor commands as well as sensory information feedback. Server V represents the premotor cortex in Brodmann Area 6, which plays an important role in sensorimotor and sensory cue detection and in processing spatial working memory information after practice (Kansaku et al., 2004; Mitz et al., 1991; Roland, 1993). The basal ganglia (Server W) retrieve motor programs and long term procedural information from long term procedural memory (Server D) (Cook and Woollacott, 1995; Gilbert, 2001; Bear et al., 2001). The supplementary motor area (SMA) and the pre-SMA (Server Y) perform functions of assembling motor programs and ensuring movement accuracy (Gordon and Soechting, 1995). The primary motor cortex (Server Z) addresses the spinal and bulbar motorneurons and sends the neural signals to different body parts as motor actuators. Motor information from the primary motor cortex (Server Z) and sensory information from the body parts are collected at S1 (the somatosensory cortex, Server X) and then relayed to the prefrontal cortex (Server C) as well as the SMA (Server Y).

Neuroergonomic applications of the QN architecture

This section describes several illustrative examples of neuroergonomic applications of the QN architecture, focusing on multitask modeling. Modeling of multitask performance is one of the major challenges of cognitive and ergonomic modeling, since performing multiple tasks at the same time is common in daily life and has significant safety and design implications; for example, drivers can steer a car and at the same time talk with friends in the car, and telephone operators can answer customer phone calls and type textual information into a computer.

Among the wide range of multiple task situations, the psychological refractory period (PRP) is one of the most basic and simplest forms of a dual-task situation. In a PRP experiment, two reaction time (RT) tasks are presented close together in time and participants are asked to perform the two tasks as quickly as possible. Typically, participants' response to the second of the two RT tasks (T2) is performed more slowly than to the first (T1) when the interval between the presentation times of these two tasks – called stimulus onset asynchrony (SOA) – is short. PRP has been studied in laboratories for over 100 years from the behavioral (Solomons and Stein, 1896; Welch, 1898; Creamer, 1963; Oberauer and Kliegl, 2004; Schumacher et al., 1999) to the neurological level (Jiang et al., 2004; Sommer et al., 2001).

Using the QN architecture and solely relying on closed form mathematical equations, Wu and Liu (2008a) successfully modeled a large number of PRP effects, two of which are of most relevance to the present article and thus briefly described below. One is the brain imaging patterns discovered by Jiang et al. (2004) and another is the lateralized readiness potential (LRP) findings discovered by Sommer et al. (2001). Jiang et al. (2004) conducted the first fMRI study that followed the experimental paradigm of PRP and tested a large number of participants in an effort to find neural correlates of the basic PRP with the fMRI techniques. They did not find any increase in activation in the brain regions corresponding to "executive control" in the short SOA conditions compared with the long SOA conditions. In their experiment, both T1 and T2 were visual–manual two-choice RT tasks. In T1 squares or circles were presented on a display, and participants pressed "1" for a square and "2" for a circle with the left hand. T2 involved two groups of participants. Participants responded to a letter "A" or "B" (for the first group) or to a red or green cross (for the second group) by pressing the number "3" or "4" on a keypad, respectively. Jiang et al. (2004) measured the activation of all of the brain areas related to the possible executive control, including the DLPFC (dorsal lateral prefrontal cortex), the ACC (anterior cingulate cortex), the GFi (inferior frontal gyrus), the ADPFC (anterior–dorsal prefrontal cortex), the SPL (superior parietal lobule), and the GFm (middle frontal gyrus). However, they found virtually no increase in activation in these brain regions in the short SOA conditions compared with the long SOA conditions.

The detailed modeling process and results are presented in Wu and Liu (2008a) and it is important to mention that the integrated BOLD (blood oxygen level dependent) signal (CB(t)) is modeled in the QN based on the prior fMRI signal modeling work of Cohen (1997) and Anderson et al. (2003). Their findings are integrated into the queuing network by considering the server utilization level (the fraction of time during which a server is busy in the total trial period), stimulus arrival rate, and server capacity. For the same brain region, the percentage signal change (PSC) is the CB(t) of the experimental condition compared to the $CB(t_0)$ of the baseline condition (e.g., the fixation condition in Jiang et al. (2004)). Through detailed mathematical derivations that integrates queuing network server utilization and the prior work of Cohen (1997) and Anderson et al. (2003), Wu and Liu (2008a) show that the integrated BOLD signal remains the same in the short and long SOA conditions, as reported by Jiang et al. (2004) and that no assumption of an executive process is needed in modeling this finding.

Sommer et al. (2001) used the event related potential (ERP) technique to measure the lateralized readiness potential (LRP) in a PRP experiment that replicated Karlin and Kestenbaum's PRP experiment (1968). In this experiment, T1 required the participants to perform a visual–manual task by pressing their left-hand fingers corresponding to the digits (1–5) on a visual display. T2 was an auditory–manual task, which asked the participants to use their right-hand index and middle fingers to respond to high- and low-pitched tones, respectively, and T2 had two difficulty levels. Karlin and Kestenbaum (1968) demonstrated a subadditive difficulty effect in RT: the difference in RT2 between the easy and the hard T2s in the short SOA condition is smaller than that in the long SOA condition. Sommer et al. (2001) found not only the same subadditive difficulty effect in RT but also an early onset of LRP (15-msec) before S2 (the stimulus for T2) was presented, suggesting that the motor component of the psychological system had started to prepare the processing of S2 before it was presented. This early onset was observed only when T2 was an easy simple RT task, and the percentage of early onsets increased with an increase in the SOA, which was consistent with a similar finding in another study (Van Selst and Jolicoeur, 1997). This early onset of LRP was not observed when T2 was a hard choice RT task.

Using the same QN architecture that was used to model all the other PRP findings, Wu and Liu (2008a)were able to account for this pattern of LRP mathematically by incorporating the neuroscience findings that the premotor cortex (Server V) and the primary motor cortex (Server Z) are both generators of LRP (Leuthold and Jentzsch, 2002; Ulrich et al., 1998) but not equally involved in simple and choice RT tasks. More specifically, since Server V is located in front of Server Z (Fig. 1) in the route for simple RT task entities, the entity arrival time at Server V determines the LRP onset time. However, for choice RT tasks, the entity arrival time at Server Z decides the LRP onset time because Server V is not in the route of entities. The corresponding mathematical derivation and modeling work are presented in detail in Wu and Liu (2008a).

The main lesson here is that QN is able to account for the fMRI and LRP neuroscience findings about their mechanisms and implement them in the QN, provide a coherent explanation of a diverse range of findings in a unified framework, as well as supply support/evidence for certain theoretical arguments (e.g., executive control processes might not be needed in multitask performance of PRP). This is an example that illustrates the value of using computational neuroscience findings to inform and strengthen neuroergonomic models. In this modeling work, the same modeling methods were used to model reaction time and other behavioral findings as well as the fMRI and LRP data.

Another neuroergonomic application of the QN architecture is the modeling of transcription typing, which was chosen as a target of modeling since transcription typing is one of the basic and common activities in human–machine interaction. Of unique value to modeling work is that 34 robust and quantitative transcription typing phenomena have been discovered, including 29 phenomena reviewed by Salthouse (1986) and 5 phenomena not included in the Salthouse review (see, Wu and Liu, 2008b). These phenomena involve many aspects of human performance-interkey time, typing units and spans, typing errors, concurrent task performance, eye movements, and skill effects. Transcription typing involves intricate and complex interactions of concurrent perceptual, cognitive, and motor processes. The availability of a wide range of experimental data and an extensive list of phenomena make transcription typing one of the best candidate tasks to test theories and models of human performance. Modeling this rich and coherent set of behavior data and quantitative phenomena with the same set of assumptions and mechanisms is an important challenge to any theory or model of human performance (Newell, 1990).

Using the specific implementation of the QN architecture called QN-MHP that integrates QN and MHP as mentioned above, Wu and Liu (2008b) successfully modeled 32 of the 34 behavioral phenomena with the exception of two phenomena that involve reading and comprehension, whose modeling requires the use of complex symbolic processing and is beyond the scope of the modeling capacity of QN-MHP. Later in this article, we discuss the current work of integrating QN and ACT-R to model complex cognitive processing. Of most interest and relevance to the present discussion is that much of the modeling work was based on careful analyses of related neuroscience findings in selecting modeling mechanisms and parameters. For example, modeling the typing errors in transcription typing is based on the firing variability of neurons at the primary cortex in the brain. The distribution of movement distance is estimated based on the findings in neurological studies that the movement direction of body parts can be predicted by the action of motor cortical neurons in the primary motor cortex (Georgopoulos et al., 1993). When individual cells in the primary motor cortex are represented as vectors, they make weighted contributions along the axis of their preferred direction and the resulting vector (population vector) is the sum of all of these cell vectors. Tanaka (1994) quantified the RMSE (root-mean-square error) of the movement direction of a certain body part as a function of the population size of corresponding brain area in the primary motor cortex. This RMSE provides the input to the QN architecture in predicting the distribution of movement distance of each finger on average, and then producing the estimated typing errors.

The third application of the QN architecture we would like to summarize here is the work of Wu et al. (2010), which integrated queuing network and reinforcement learning (RL) methods to model human behavioral and brain activation patterns related to the learning process of transcription typing and the PRP. The work uses the QN as the static aspect of the brain structure and RL as the dynamic algorithm to quantify the learning process. Reinforcement learning is a computational approach that is able to quantify how an agent tries to maximize the total amount of reward it receives in interacting with a complex, uncertain environment. The learning process of a perceptual–motor task is modeled by entities in the QN architecture traversing the network to maximize information processing speed and minimize error. The model makes testable predictions about QN server utilizations, which were verified with two important fMRI experimental findings. First, it has been found that at the beginning stages of learning a visuomotor control task, including transcription typing, the dorsal lateral prefrontal cortex (DLPFC), the basal ganglia, and the pre-SMA are highly activated (Sakai, et al., 1998). After practice, activation of the DLPFC disappears and strong activation is observed in the supplementary motor area (SMA), the basal ganglia, and the primary motor cortex (M1) in addition to slight activation in the somatosensory cortex (S1). Second, in the well-learned stages of typing (skilled typist reported in (Gordon and Soechting, 1995)), when the stimuli to be typed are repetitive letters (e.g., AAA…), M1 is strongly activated; however, when the stimuli to be typed are multiletter sentences (e.g., JACK AND…), M1 is still strongly activated, but there is more robust activation in the SMA, the basal ganglia, and S1. The QN model produced the same pattern of server utilizations at the various servers corresponding to the related brain structures. By assuming that server utilization is positively correlated with brain activations, the model results are consistent with the empirical findings (Wu et al., 2010).

Discussion

Computational neuroergonomic models are needed to organize, examine, and interpret empirical data, to guide and generate hypotheses for new experiments, and to make extrapolations and predictions to situations in which empirical data collection is not feasible or undesirable. These needs for computational neuroergonomics demonstrate both their importance and the challenges they face.

As discussed in this paper, the queuing network architecture aims to address these challenges by serving as a unifying structure that simultaneously tackles the five modeling criteria mentioned in the introduction section of the paper. The goal is to bring disparate theories and findings in diverse fields into a single framework so that their relationships and joint implications can be examined quantitatively, both for theoretical advancements and for informing ergonomic design decisions. In this regard, the QN architecture has made significant progress in addressing computational neuroergonomics challenges, but it faces more questions and challenges ahead than what it has accomplished. The architecture needs to evolve to accommodate new findings in psychology and neuroscience. For example, the current 3-Server memory system may need to be modified to take into account the possible existence of episodic buffer as the fourth working memory component (Baddeley, 2000).

In the following, rather than focusing on the specific future modifications of the QN architecture, we discuss two general types of challenges computational neuroergonomics faces: one is more theoretical and methodological, pertaining to the synergy between computational neuroscience and computational neuroergonomics, and the other more practical, dealing with neuroergonomic applications in the real world.

For theoretical and methodological advancements, it is important to achieve greater synergy between computational neuroscience and computational neuroergonomics to benefit the development of both areas. For example, how can the QN methods be used fruitfully to model neuroscience data in a way that relates to but goes beyond the existing methods summarized in the second section (A brief summary of some related computational neuroscience models) of this paper. How can the QN methods be used to develop fundamental neuroscience concepts and theories? Thus far, the QN work has mainly focused on incorporating existing neuroscience findings to develop the QN architecture for psychological or ergonomic applications and explain related empirical data, but the QN has not produced a set of new tools for neuroscience data analysis and theory development.

We do see some promising beginnings along this direction of reverse inference, namely the QN architecture and methods might inform neuroscience and psychology. For example, the work summarized above on using the QN and reinforcement learning together to model brain activation patterns related to the learning process of transcription typing and the PRP (Wu et al., 2010) have implications for some fundamental issues in understanding brain functions such as whether any underlying process is an optimization process and whether brain activations represent levels of utilizations.

Another related work that attempts to explore the value of QN in informing neuroscience is the development of a simple 3-server QN to model a set of neuroimaging findings (Berman et al., 2007). In contrast to the QN architecture with two dozens of servers shown in Fig. 1 that represents a “top-down” approach of starting with a comprehensive structure (necessary for real world ergonomic applications, as stated earlier), the 3-server QN represents a “bottom-up” approach of starting with the most basic networks. A 3-server network is the simplest non-trivial network. Encouragingly, the 3-server QN model made testable predictions regarding the processes that may underlie different neural areas. For example, the models produced plausible and testable quantitative relationships between gray matter volume and neural processing and between white matter anisotropy and neural processing. The model suggests that these changes in processing might explain when certain neural areas are recruited to perform a task. The model was used to account for the experimental findings of Reuter-Lorenz et al. (2000) that young participants showed substantial left lateralized frontal activation for a verbal working memory task but substantial right lateralized frontal activation for a spatial working memory task. Older participants, on the other hand, showed bilateral frontal activation for both spatial and verbal working memory tasks, suggesting that older participants may be recruiting other brain areas to compensate for neural declines. By setting the server service rates according to the equation provided by Zimmerman et al. (2006) about how gray matter volume in lateral frontal areas decreases with increased age, the 3-Server QN model generated the same pattern of results observed by Reuter-Lorenz et al. (2000). While there have been some conceptual models that make some similar but qualitative predictions (e.g., Reuter-Lorenz and Cappell, 2008, the CRUNCH model), the QN model accounted for the data quantitatively (Berman et al., 2007).

The QN approach is certainly not the only computational approach that can inform neuroscience and make predictions about neural activations, and one corresponding challenge is how to integrate and unify these approaches. For example, Anderson and Qin (2008) used an ACT-R model to account for neural activities in the fusiform gyrus, pre-frontal cortex, and the anterior cingulate cortex during a complex arithmetic task. As in the QN, these different brain regions reflected processing modules in the ACT-R model.

The QN architecture and ACT-R are highly complementary, as discussed in detail in Liu (2009). As mentioned earlier in this paper, ACT-R is a symbolic, production rule based model at its macro architectural level, and its recent development focuses on finding neural mechanisms for the related modules and functions. At the macro level, its overall architecture is not a mathematical one, although mathematics is used extensively at many local or subsymbolic levels to specify the related rules and functions. In contrast, the QN architecture is mathematical at all its levels, while supporting symbolic computation and simulations at any level needed. It goes without saying that the importance of mathematical reasoning is emphasized in all fields of science, and it is illustrative to point out that the value of a mathematical overall macro-architecture is demonstrated in many of the QN modeling work. For example, all of the PRP modeling work (Wu and Liu, 2008a) was performed with closed form mathematical equations, rather than computer simulations, which are not as rigorous as mathematical equations. However, QN needs sophisticated symbolic processing tools at its local levels to perform complex cognitive simulations, which ACT-R does the best.

Clearly, QN and ACT-R are complementary, and one of the current focuses of our computational neuroergonomics research is to integrate the two approaches. The first integration phase has been completed, through which we have developed an ACTR-QN simulation software (Cao and Liu, 2011). ACTR-QN represents ACT-R as a QN and can perform ACT-R tasks in exactly the same way as ACT-R and generate exactly the same simulation results, but ACTR-QN goes beyond ACT-R by allowing modelers to visualize the flow of information in the simulated brain network in real time while the model is running. Because ACTR-QN represents ACT-R as part of the QN, all the modeling capabilities and findings of ACT-R constitute integral components of ACTR-QN.

From the perspective of neuroergonomic applications, it is instructive to use the four applications of neuroergonomics described in Parasuraman and Wilson (2008) to illustrate the challenges of the QN architecture. This illustration pertains to computational neuroergonomics in general as well. Parasuraman and Wilson (2008) described four applications of neuroergonomics, namely the assessment of operator workload and vigilance, implementation of real-time adaptive automation, neuroengineering for people with disabilities, and design of selection and training methods. In this regard, the QN has successfully modeled a variety of subjective and ERP-based workload data (Wu and Liu, 2007) and an adaptive automation system has been developed for driver interface design (Wu et al., 2008b), while no other computational neuroscience or neuroergonomic model has tackled these two issues. However, the QN has not been applied to neuroengineering for people with disabilities, nor to the design of selection and training methods. Conceptually, it is feasible for the QN to explore these and related issues. For example, genetics and individual differences as well as people with disabilities can be represented in the QN as different service routes, different service rates at corresponding servers, or other parameters and values. Testing the various modeling methods while absorbing and predicting related findings, however, remains a challenge ahead. Meeting this challenge requires a systematic and disciplined approach.

In the same sense future research in neuroergonomics and neuroscience will go hand in hand, it is hoped that computational neuroergonomics and computational neuroscience can both reach a higher theoretical and methodological level by further informing and enriching each other through complementary and synergistic efforts. The practical value of computational neuroergonomics will be best demonstrated when it produces specific and practical benefits to the design and improvement of human–machine system.

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