Ergonomics

Mathematically modelling the effects of pacing, finger strategies and urgency on numerical typing performance with queuing network model human processor

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Mathematically modelling the effects of pacing, finger strategies and urgency on numerical typing performance with queuing network model human processor

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Numerical typing is an important perceptual-motor task whose performance may vary with different pacing, finger strategies and urgency of situations. Queuing network-model human processor (QN-MHP), a computational architecture, allows performance of perceptual-motor tasks to be modelled mathematically. The current study enhanced QN-MHP with a top-down control mechanism, a close-loop movement control and a finger-related motor control mechanism to account for task interference, endpoint reduction, and force deficit, respectively. The model also incorporated neuromotor noise theory to quantify endpoint variability in typing. The model predictions of typing speed and accuracy were validated with Lin and Wu's (2011) experimental results. The resultant root-mean-squared errors were 3.68% with a correlation of 95.55% for response time, and 35.10% with a correlation of 96.52% for typing accuracy. The model can be applied to provide optimal speech rates for voice synthesis and keyboard designs in different numerical typing situations.

Practitioner Summary: An enhanced QN-MHP model was proposed in the study to mathematically account for the effects of pacing, finger strategies and internalised urgency on numerical typing performance. The model can be used to provide optimal pacing for voice synthesise systems and suggested optimal numerical keyboard designs under urgency.

Keywords: cognitive modelling; numerical typing; numerical keyboard design; typing error

1. Introduction

Modelling human performance in skilled perceptual-motor tasks is a long-standing topic that provides many insights for understanding complex interactions between concurrent perceptual, cognitive and motor processes (Salthouse 1986, Wu and Liu 2008b). Among those skilled perceptual-motor tasks, typing is of researchers' particular interest because it consists of complex coordination between perception, cognition and motor process. Since Newell's idea of unified theories of cognition that applies a model of a phenomenon to lots of diverse situations (Newell 1973), many typing models have been proposed to account for phenomena observed in transcription typing (Rumelhart and Norman 1982, John 1996, John 1998, Wu and Liu 2008b). Those models well accounted phenomena observed from experienced typists in alphabetical transcription typing, summarised in Salthouse's (1986) review, but they ignored typing behaviours on non-alphabetical keys. As stated in Rumelhart and Norman (1982), varying typing rate in different situations and monitoring accuracy as a result of speed-accuracy trade-off were not examined in their typing model, and skilled typists may adopt a different mode of typing due to unfamiliarity with the number keys (Rumelhart and Norman 1982). In particular, skilled typists can possibly use single finger typing on the numerical keypad. Furthermore, typing tasks can be conducted by non-experts in a discontinuous manner in general, and their performance can be easily influenced by external and internal factors such as pacing, response complexity and urgency (Lin and Wu 2011). The variation of performance in the abovementioned situations, however, was not accounted by previous typing models. Recently, Leong *et al.* (2011) attempted to model performance time of data entry on numerical keyboards by empirical regressions. They successfully developed a performance time model derived from Gan and Hoffman's (1988) ballistic movement time model which can predict performance time in a single typing situation, but their model did not consider varying typing rates in different situations such as urgency and the model was not able to predict typing errors.

Some limitations in Rumelhart and Norman's (1982) typing model were addressed later by John's TYPIST model (John 1996, 1998); namely, the perceptual encoding of alphabetical strings was accounted by a schedule chart

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with critical path analysis. The TYPIST model covered 19 of 34 common phenomenon observed in alphabetical transcription and used only one free parameter obtained from regression of experimental data. Recently, queuing network model human processor (QN-MHP) further covered 32 of 34 phenomena in transcription typing without free parameters (Wu and Liu 2008b). However, Wu and Liu (2008b) did not model varying typing performance as a function of pacing or urgency or considered the single finger typing situation. In fact, typing performance can be easily influenced by external pacing and internal urgency when materials are presented verbally in numerical format, i.e. typists hear and type numbers. Numerical hear-and-type tasks are common in daily verbal communication schemes, such as entering contact numbers of friends into cell phones over conversation and inputting numerical information into computers when talking by phone. Typists are subject to errors because they have to react rapidly to transient verbal stimuli digit-by-digit without preview which enables them to pre-program and produce successive keystrokes independently regardless of the speed of input information (Wickens and Hollands 1999). In this situation, numerical typing performance may be degraded if multiple fingers are used due to uncertainty about finger to be used (Hutton and Tegally 2005) and well-known finger enslaving effects (Kilbreath and Gandevia 1994, Zatsiorsky *et al.* 2000, Li *et al.* 2004), making single finger typing a feasible, or even preferable, choice for typists who are not familiar with typing on numerical keyboards. How task demands (e.g. pacing), motor-control strategies (e.g. single vs. multi-finger typing) and internalised motivations (e.g. urgency) would affect human performance in numerical typing, however, received relatively less attention than alphabetical typing in both experimental and modelling literature.

The lack of information about numerical typing is dangerous because critical numerical typing errors occur in medical management, nuclear control and financial transaction systems (Gough *et al.* 1983, Arndt *et al.* 1994, Bohm *et al.* 2008, O'Hara *et al.* 2008). Fatal cases have been reported due to numerical entry errors in a popular drug delivery system used in hospitals (Thimbleby and Cairns 2010). Numerical typing errors contributed considerably to input errors in control of nuclear power plants (O'Hara *et al.* 2008). They also have been thought to be more problematic than frauds in causing financial loss in transactional systems (Bohm *et al.* 2008). The potential threats posed by numerical typing errors to our lives, safety and finance necessitate understanding humans'perceptual-motor skills and limitations in numerical typing context. As an effort towards this end, Lin and Wu (2011) conducted an experimental study to understand the effects of pacing, finger strategy and urgency on numerical hear-and-type tasks (Lin and Wu 2011). The experimental task was to type verbally presented, random 9-digit numbers under different speech rate (defined by inter-digit/inter-stimulus intervals (ISI)) and urgency (speedy responses at given accuracy level were encouraged by monetary rewards) conditions, with either single (index) finger or multiple fingers. The results demonstrated somewhat interesting effects of pacing and finger strategy, i.e. fast pacing and multi-finger typing increased both response time of keystrokes and number of errors committed in each trial, while urgency produced faster response time at the expense of increasing errors. The fast pacing results were consistent with empirical evidence in the literature that short ISI created temporal overlap of two consecutive tasks, and dual-task interference in this dual-task situation might contribute to both slower responses and more errors (Calvo and Alamo 1987, Pashler 1994a, Pashler and Christian 1994, Ulrich *et al.* 2006). Furthermore, findings in multi-finger typing supported negative effects of higher response complexity on reaction time (Schumacher *et al.* 1999) and finger enslaving effects on motor control accuracy (Kilbreath and Gandevia 1994, Zatsiorsky *et al.* 2000, Li *et al.* 2004). The urgency effects were also comparable to findings in rapid aiming tasks based on neuromotor noise theory, where faster movements as a result of higher muscle co-activations were also noisier, and, thus, caused higher endpoint variability (Van Gemmert and Van Galen 1997, 1998, Van Galen and Van Huygevoort 2000). However, the study was not able to confirm the abovementioned internal mechanisms due to lack of biophysiological measurements.

Provision of a mathematical QN-MHP typing model can help depict how quantitative relationships between proposed mechanisms in the perceptual-motor system are established based on cortical functions (represented by servers) and neurological connections (represented by links). Most of the abovementioned typing models are simulation models, i.e. the solutions of modelled outputs were generated by enumerating possible inputs. However, for the following reasons, a mathematical model is preferred over a simulation model. First, mathematical modelling provides precise solutions by analytical methods, while simulation modelling approximates feasible solutions using numerical methods (Banks *et al.* 1996). Second, a mathematical model can be easily implemented with any software with mathematical formulation capabilities, while a simulation model requires specific language for particular simulation software and programming skills for flow control and coding (Sokolowski and Banks 2009). Third, mathematical models represent a system's inputs and outputs explicitly by their mathematical relationships, but whether the results obtained from simulation models are caused by true interrelationships or randomness is hard to interpret (Banks 1999).

The goal of this study is to propose and validate a mathematical model based on the QN-MHP architecture that can account for effects of pacing, finger strategy and urgency in numerical hear-and-type tasks. Although Lin and Wu (2011) were not able to confirm the proposed mechanisms by detailed biophysiological measurements, human performance modelling may provide insights as to the validity of those assumed mechanisms. Should those mechanisms have caused effects observed in the study, a quantitative model that integrates those mechanisms must predict similar human behaviours that can be confirmed/validated by the experimental results. The model can be further used to predict human performance under conditions that were not examined in the experiment, such as different pacing and keyboard designs. Based on such a model, it may be possible to generalise how humans perform perceptual-motor skills involving external task demands, inherent motor-control strategies and internalised motivation.

2. Modelling mechanisms

Section 1 briefly introduced that fast pacing and multi-finger typing increased both response time of keystrokes and number of errors committed in each trial, while urgency produced faster response time at the expense of increasing errors in Lin and Wu (2011). They suggested that short ISI may cause temporal overlaps and dual-task interference between two consecutive keystrokes which resulted in both slower reaction time and more errors (see Appendix 1 for details). In QN-MHP, the dual-task interference is modelled through competition of visuospatial attention at Server C, and its resultant increase of background neuromotor noise at Server E. Furthermore, high response complexity and finger enslaving effects were assumed to contribute to delay of reaction time and degradation of motor control accuracy, respectively (see Appendix 2 for details). These two mechanisms are modelled by response selection at Server F and motor-related noise calculated at Server Z, respectively. Finally, rapid typing under urgency is modelled through different modes of movements to account for shorter movement time while its increased errors are associated with lack of close-loop motor control (see Appendix 3 for details). Server G plays an important role in initiating different movement modes at Server Y and in deactivating Server X's function to relay somatosensory feedback for error corrections. Implementation of the abovementioned mechanisms are summarised in Figure 1. The following sections provide an overview of QN-MHP and details of its enhancements to account for neurological and psychological phenomena found in numerical typing.

2.1. Overview of queuing network-model human processor (QN-MHP)

To model aforementioned mechanisms in numerical typing under different pacing, response complexity and motivational factors, the queuing network-model human processor (QN-MHP) was used (Feyen 2002, Liu *et al.* 2006, Wu and Liu 2008b). The QN-MHP is a computational architecture based on neurological networks in human brain and body parts. It consists of three subnetworks: perceptual, cognitive and motor (Figure 1). Each subnetwork is constructed using different servers, which are considered information-processing units in the brain, and the links among servers, which represent neurological connections between cortical areas. Each individual server is an abstraction of a brain area with specific functions, and the connections among servers represent neural pathways among functional brain areas. To illustrate how imperative stimuli are transformed into desired responses through neurological processes in different functional areas of the brain, transformation of entities passing through a pathway consisting of servers is used as an analogy in QN-MHP. In the numerical hear-and type task, the auditory stimuli of the numerical digit firstly arrive at Server 5 one by one as entities (common auditory processing). The features of the sound are then processed at Server 6 (auditory recognition) and 7 (auditory location) in parallel. They are finally integrated and recognised at Server 8 (auditory recognition and location integration). The digit, as meaningful phonological information (entities), is then stored at Server B (phonological loop) and enters Server C (central executive) for making response-selection. Since entities represent an anticipated stimulus in Server D (long-term procedural memory) that requires manual response (keystrokes), Server C routes it to Server F (complex cognitive function) to determine the response. After the response is selected, the executive command would be sent to Server C again. Because the command involves manual responses, Server C triggers Server W to retrieve motor programs based on the command. Those motor programs are then assembled at Server Y and initialised at Server Z, sending out the neural drives to the right arm, hand and finger (Server 23). The abovementioned processes are represented by the Flow of Entities in Figure 1. Detailed descriptions of servers, connections and their neurological mapping to functional brain anatomy can be found elsewhere (Wu and Liu 2008a).
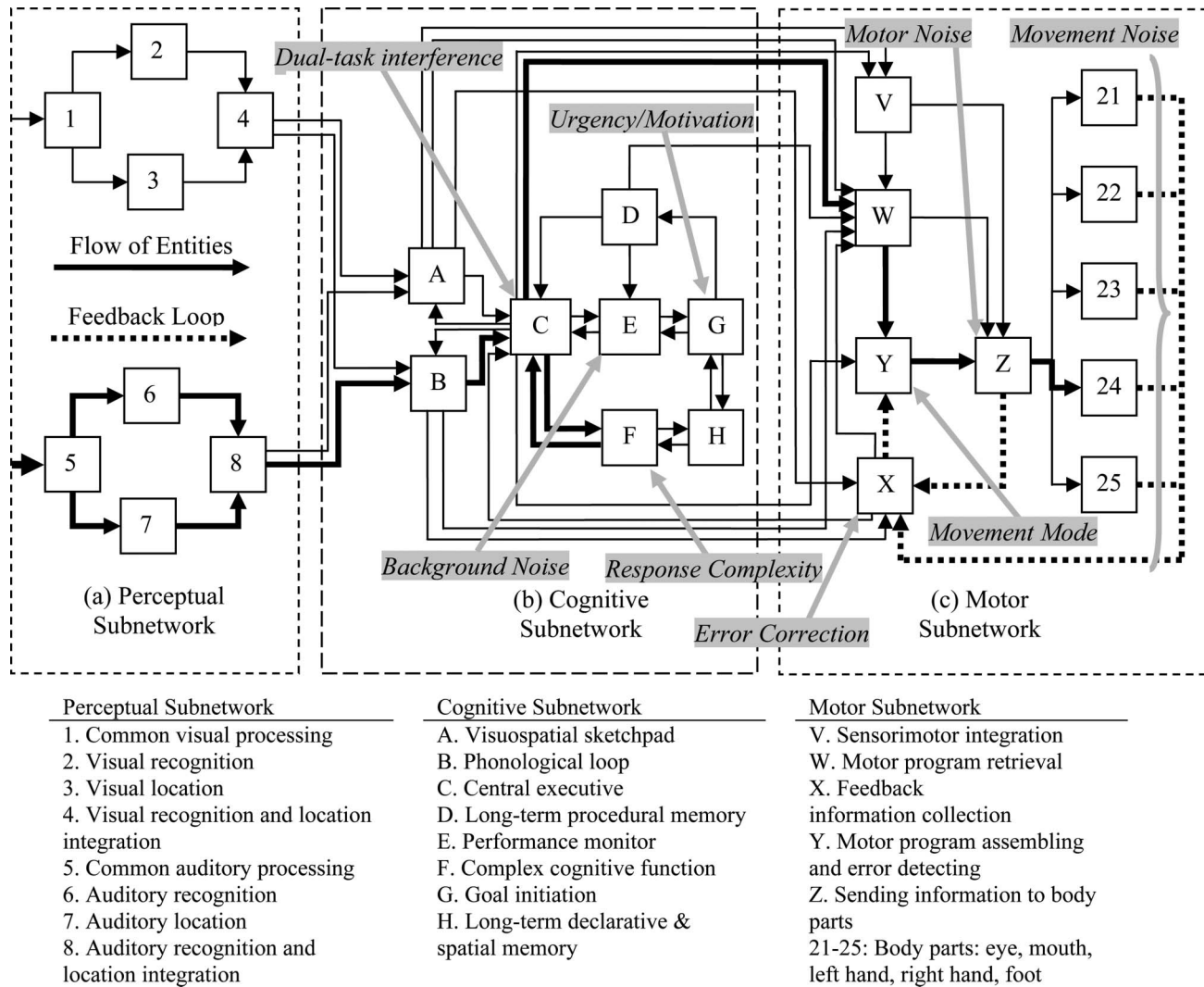
Figure 1.   Enhanced QN-MHP architecture.

Perceptual Subnetwork	Cognitive Subnetwork	Motor Subnetwork
1. Common visual processing	A. Visuospatial sketchpad	V. Sensorimotor integration
2. Visual recognition	B. Phonological loop	W. Motor program retrieval
3. Visual location	C. Central executive	X. Feedback information collection
4. Visual recognition and location integration	D. Long-term procedural memory	Y. Motor program assembling and error detecting
5. Common auditory processing	E. Performance monitor	Z. Sending information to body parts
6. Auditory recognition	F. Complex cognitive function	21-25: Body parts: eye, mouth, left hand, right hand, foot
7. Auditory location	G. Goal initiation	
8. Auditory recognition and location integration	H. Long-term declarative & spatial memory	

2.2. Enhancements of Queuing Network-Model Human Processor (QN-MHP)

Previous modelling work with QN-MHP mainly assumed that information (entities) flows were controlled by bottom-up mechanisms, i.e. processing time and capacity of servers determined the speed and regulated the flow. However, the human brain has a top-down control mechanism to facilitate processing of information, especially when the task involves rewards and multi-tasking (Paus *et al.* 1993, Pochon *et al.* 2002). This control mechanism was mainly associated with the prefrontal cortex represented by Server C and anterior cingulate cortex (ACC) represented by Server E, but they were not fully developed in previous versions of QN-MHP. Furthermore, the close-loop control mechanism was not well explored because performance of experts in alphabetical transcription typing does not rely on visual corrections (Wu and Liu 2008b). However, reliance on visual feedback is very possible for novice typists or those typists unfamiliar with the physical layout of the numerical keyboard. Finally, single finger typing condition was not considered in previous QN-MHP, and the phenomena relevant to well-known finger enslaving in multi-finger typing (Kilbreath and Gandevia 1994, Zatsiorsky *et al.* 2000, Li *et al.* 2004) cannot be explained by previous models. For non-expert typists, single finger typing is definitely a practical option, and finger-related motor control strategies may not be optimal when typing with uncertainty in verbal communication context (Hutton and Tegally 2005). The top-down control mechanism of information flow, close-loop control of movements based on visual guidance, and finger-related motor control strategy are discussed in the following as essential enhancements to capture phenomena in numerical hear-and-type tasks.

2.2.1. Top-down control mechanism to model dual-task interference

Top-down control mechanism was added to QN-MHP by utilising Server C and Server E to account for the dual-task interference in fast pacing and the increase of neuromotor noise. Fast pacing induced dual-task interference, resulting in resource competition. Firstly, the competition delayed the execution of saccadic eye movements to search the second target in two consecutive keystrokes because saccades would interfere with the execution of the first motor response that needed eye fixation (Adam *et al.* 2000, Godijn and Theeuwes 2002). Secondly, target searching is associated with visuospatial attention (Hoffman 1995, Adam *et al.* 2000), so the competition would raise the activation level of ACC which is sensitive to attentional demands. The ACC activation level was assumed to increase background neuromotor noise in response-selection stage which, in turn, increased endpoint variability in motor execution. In QN-MHP, Server C was responsible for routing information and suppressing automatic responses to enforce a cognitive bottleneck. During numerical typing in fast pacing, the following stimulus might arrive at Server B before the on-going key is pressed. In the meantime, the on-going movement was still under execution and thus needed visual information from fixation. Server C, therefore, would not allow the entities of the second task to enter into Server F and trigger another saccadic eye movement that interrupts the execution of the on-going movement. Such a competition also increased noise level calculated at Server E which is sensitive to resource competition. The connection between Server C and Server E in QN-MHP (Figure 1) signifies that ACC (Server E) is sensitive to resource competition caused by information regulation by prefrontal cortex (Server C).

2.2.2. Close-loop control mechanism to model movement modes

Close-loop control of movements was accounted by the functions of Server G, Server Y and Server X to implement different movement modes under urgency. In urgent condition where monetary rewards were applied to encourage fast responses, a different goal in which speedy reactions outweighed accuracy would be supposedly adopted due to activation of specific cortical areas that are sensitive to the context value of tasks (Pochon *et al.* 2002, Williams *et al.* 2004). In QN-MHP, such a 'speedy' goal is initiated by Server G which works closely with Server E and Server C to assure the achievement of the goal. When there is no urgency, the somatosensory cortex represented by Server X can send afferent copies of motor executions from the primary motor cortex (Server Z) and sensory information from body parts (e.g. eyes) to the supplementary motor area (SMA) and pre-SMA (Server Y) so that corrective movements can be made (close-loop mode). This on-line control mechanism was also supported by cortical representations of movement accuracy in neurological research (Gomez *et al.* 2000). However, the feedback loop of Server 21/24 → Server X → Server Y → Server Z (Figure 1) would be deactivated through the connection from Server C to server Y when the speedy goal is initiated by Server G in urgent condition. The iterative corrections (Crossman and Goodeve 1983) are, thus, no longer possible, and the open-loop mode movements increase endpoint variability, despite their shorter movement time.

2.2.3. Finger-related motor control strategy to model multi-finger typing

Finger-related motor control strategy is associated with response-selection at Server F and motoric activation at Server Z (Figure 1). As suggested by Rumelhart and Norman (1982), typists may adopt different typing strategies on unfamiliar numerical keyboards. When single finger is used, the response selection at Server F is less complex because there is no uncertainty about which finger to be used. In multi-finger typing, however, the reaction time should increase due to an additional cognitive cycle needed at Server F to choose from more stimulus-response (S-R) pairs (Schumacher *et al.* 1999, Schedlbauer 2006). Furthermore, finger enslaving effects are expected to produce force deficit when multiple fingers are simultaneously recruited (Latash *et al.* 2002), and more motor units were assumed to be recruited at Server Z (the primary motor cortex) to compensate for this deficit (Hager-Ross and Schieber 2000). Since the signal dependent neuromotor noise was proportional to motoric activation level and the extent of neuromotor noise increased endpoint variability (Van Beers *et al.* 2004), multi-finger typing is, therefore, slower and error-prone because of uncertainty (complex response-selection at Server F) and high cortical activation (noisy neuromotor system).

3. Mathematical formulation of modelling mechanisms

The following sections describe how mathematical equations are formulated based on QN-MHP architecture to quantify relationships between model inputs and outputs. The model inputs are one continuous variable, ISI (I_v in units of milliseconds), and three discrete variables: order of response (*i*, representing i[th] response), finger strategy

($\alpha = 0 \rightarrow$ single finger typing; $\alpha = 1 \rightarrow$ multi-finger typing) and urgency ($\beta = 0 \rightarrow$ non-urgent condition; $\beta = 1 \rightarrow$ urgent condition). The model outputs are two continuous variables: response time to i[th] stimulus in the 9-digit number (PT_i) and number of errors in the jth coded condition (see Appendix 4 for the coding of experimental conditions). Sections 3.1 and 3.2 introduce the modelling of response time and number of errors, respectively.

3.1. *Modelling response time of numerical typing*

The nature of numerical hear-and-type tasks is a combination of choice reactions and rapid aiming tasks. A typist needs to decide which key to press based on the auditory stimulus and choose a proper finger to use in the case of multi-finger typing. The response selection is a choice reaction rather than a simple reaction because the S-R pair presents a certain extent of uncertainty (Wickens and Hollands 1999). After the reaction is determined, the typist needs to press the key with the finger accurately and quickly. The execution is both spatially and temporally constrained as required in rapid aiming (Meyer *et al.* 1988). Thus, to model the response time (PT) of this numerical typing task, factors that affect reaction time (RT) of response selection and movement time (MT) of rapid aiming need to be considered. Here, the reaction time (RT) is defined as the temporal lapse from the arrival of the stimulus (e.g. the arrival of the sound) to the initiation of the corresponding response (e.g. the initiation of the typing movement). The movement time (MT) is the duration needed to finish the movement. In the case of depression of keys, the measured response time should include key closure time (K_s): a small portion of time lapse from the touch of the key to the end of depression. That is:

$$PT = RT + MT + K_s \tag{1}$$

Furthermore, when two consecutive keystrokes are close in time, dual-task interference may cause an extra delay in reaction time due to a top-down control mechanism to regulate information flow. Such a delay also needs to be considered in Equation (1). Therefore, the general equation of response time can be modified into:

$$PT_{i(\alpha,\beta)} = RT + DL + MT + K_s \tag{2}$$

where
$PT_{i\,(\alpha,\,\beta)}$: Response time to i[th] stimulus with α finger strategy under β urgency condition.
DL: Delay time caused by dual-task interference.
RT: Reaction time.
MT: Movement time.
K_s: Key-closure Time.
The following demonstrates how each component in Equation (2) is modelled.

3.1.1. *Modelling baseline response time in numerical typing*

Since numerical typing with single finger under slow pacing without urgent condition is the simplest typing situation, the response time in this condition $PT_{i(0,0)}$ is modelled as baseline. Based on Figure 1 (Flow of Entities), the common pathway of entities in the numerical hear-and-type tasks in baseline condition can be modelled as:

$$5 \rightarrow 6/7 \rightarrow 8 \rightarrow B \rightarrow C \rightarrow F \rightarrow C \rightarrow W \rightarrow Y \rightarrow Z \rightarrow 23 \tag{3}$$

As entities travel through the network, they are processed at different servers on this pathway and gradually transformed into responses. The time they spend in a particular server is called 'processing time,' signifying the time needed for the information to be processed by certain cortical areas. This is compatible with the notion that neuron assemblies need considerable time to accumulate enough excitatory inputs to reach a state of self-sustaining firing (Wickens *et al.* 1994). The routing, however, is relatively quick and the conduction time can be ignored (Feyen 2002). The QN-MHP also assumes that processing time of an individual server is independent of arrivals of entities and that routing is independent of the state of the system. Therefore, the reaction time of a choice reaction task can be modelled by summarising processing time of all servers on the route where a stimulus is transformed into a response. Consequently, the baseline reaction time ($RT_{(0)}$) in single finger typing is modelled as:

$$RT_{(0)} = T_{AP} + T_B + T_C + T_{F(0)} + T_C + T_W + T_Y + T_Z \tag{4}$$

where $RT_{i(0)}$ is the reaction time for single finger typing and T_k is the processing time of ith stimulus at Server k (or AP signified auditory perception time). All T_k are estimated based on parameter settings in QN-MHP (Appendix 5) except for $T_{F(0)}$ (the processing time of ith stimulus at Server F for single-finger typing). $T_{F(0)}$ is estimated based on the processing time for making a keystroke in the numerical typing task at Server F modelled by the Natural GOMS Language (NGOMSL) (Appendix 6). The resultant $RT_{(0)}$ was 554 ms for single finger typing.

In addition, baseline movement time ($MT_{(0)}$) is modelled by Fitt's law because, under non-urgent condition, typists are assumed to adopt close-loop controlled movements based on visual guidance to obtain higher movement accuracy. A Fitts'law model modified for numerical typing on a calculator is used (Welford 1968, Card *et al.* 1983):

$$MT_{(0)} = I_M \times \log_2(D/S_e + 0.5) \tag{5}$$

where D and S_e are travel distance and effective target size in millimetres based on dimensions of a standard numerical keyboard in Figure 2. The effective target size (S_e) is calculated based on the maximal target width that can be utilised without touching adjacent keys (Drury and Hoffmann 1992), i.e.:

$$S_e = 2KD - S - PS \tag{6}$$

where KD and S are key distance and key size on a standard numerical keyboard (Figure 2). PS is the average finger pad size measured in Drury and Hoffman (1992). $I_M = 100$ is used as it was suggested in the original study (Card *et al.* 1983). Movement time between repetitive digits (e.g. $0 \rightarrow 0$) is assumed to be zero, and the probabilities of moving between different keys are assumed to be identical. The average $MT_{(0)}$ to press a key for all possible combinations of keys (e.g. $1 \rightarrow 2$, $2 \rightarrow 6$, etc.) is computed as about 133 ms. The total response time of single finger, non-urgent typing to the ith stimulus is thus:

$$PT_{i(0,0)} = RT_{(0)} + MT_{(0)} + K_s = 554 + 133 + 10 = 697 \text{ (ms)} \tag{7}$$

where K_s means key-closure time $= 10$ ms (Appendix 5).

3.1.2. *Response time in fast pacing*

Based on mechanisms discussed in Section 2 and Appendix 1, reaction time is assumed to delay due to dual-task interference when two consecutive stimuli arrive closely in time, i.e. a delay of one task to perform another first as a top-down control mechanism of information flow. The arrival of the following stimulus at Server C is assumed to delay until the depression of the on-going key because exogenous eye-fixation (at the first target) was found to inhibit saccades (for the second target) (Godijn and Theeuwes 2002) and the initiation of the second saccade coincided with the initiation of the second movement in pressing two consecutive buttons (Adam *et al.* 2000). The processing time needed at Server C can be calculated by:

$$\begin{aligned} T'_{i,C} &= \lceil [PT_{i-1} - (I_v + T_{AP} + T_B)]/T_C \rceil \times T_C; && \text{IF } PT_{i-1} - (I_v + T_{AP} + T_B) > 0 \\ &= T_C; && \text{IF } PT_{i-1} - (I_v + T_{AP} + T_B) < 0 \end{aligned} \tag{8}$$
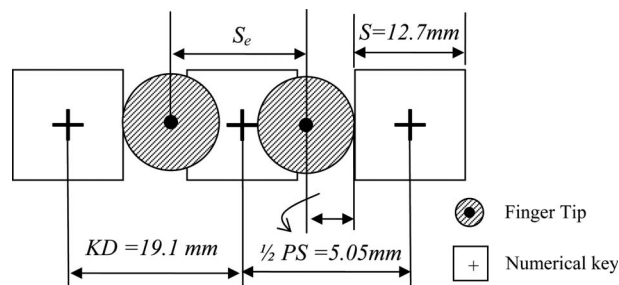

Figure 2. Key distance, key size and effective target size on a standard numerical keyboard.

where PT_{i-1} is the lapse for the previous key to be pressed ($PT_0 = 0$) and Iv is the ISI. ($Iv + T_{AP} + T_B$) is the lapse for the entity of the on-going stimulus to leave Server B. The difference $PT_{i-1} - (Iv + T_{AP} + T_B)$ yields the least duration that the current stimulus needs to wait at Server C. The duration is then divided by the cycle time of Server C (T_C) and rounded up to decide the actual number of the cycle time needed to assure completion of the on-going keystroke. Therefore, the delay time can be calculated as:

$$DL_i = T'_{i,C} - T_C \tag{9}$$

The reaction time to the first stimulus (RT_1, RT_4 and RT_7) of every 3-digit set should have no delay ($DL_1 = DL_4 = DL_7 = 0$) because there was a small blank (no stimulus for 300 ms) in-between every three digits in Lin and Wu's (2011) experiment, during which the delay of the previous response was absorbed. The concept of this delay is depicted in Figure 3.

3.1.3. Response time in multi-finger typing and urgency

In multi-finger typing, one cognitive processing cycle is added to the processing time at Server F due to decision of finger to use (Appendix 6). That is:

$$RT_{(1)} = T_{AP} + T_B + T_C + T_{F(1)} + T_C + T_W + T_Y + T_Z = 715 \ ms \tag{10}$$

In urgent situation, ballistic movements are assumed to be adopted instead of visually-guided movements. The following equation is used to predict ballistic movement time (Gan and Hoffmann 1988):

$$MT_{(1)} = A + B \times \sqrt{D} \tag{11}$$

where A and B are experimental parameters and D is travel distance in centimetre. Specific values of parameters A and B for movements of different Fitts' indices of difficulty are provided in Gan and Hoffman (1988), and travel distance D from the centre of one numerical key to another can be derived from Figure 2. The resultant $MT_{(1)}$ is about 105 ms on average for all possible key combinations on the standard numerical keyboard.
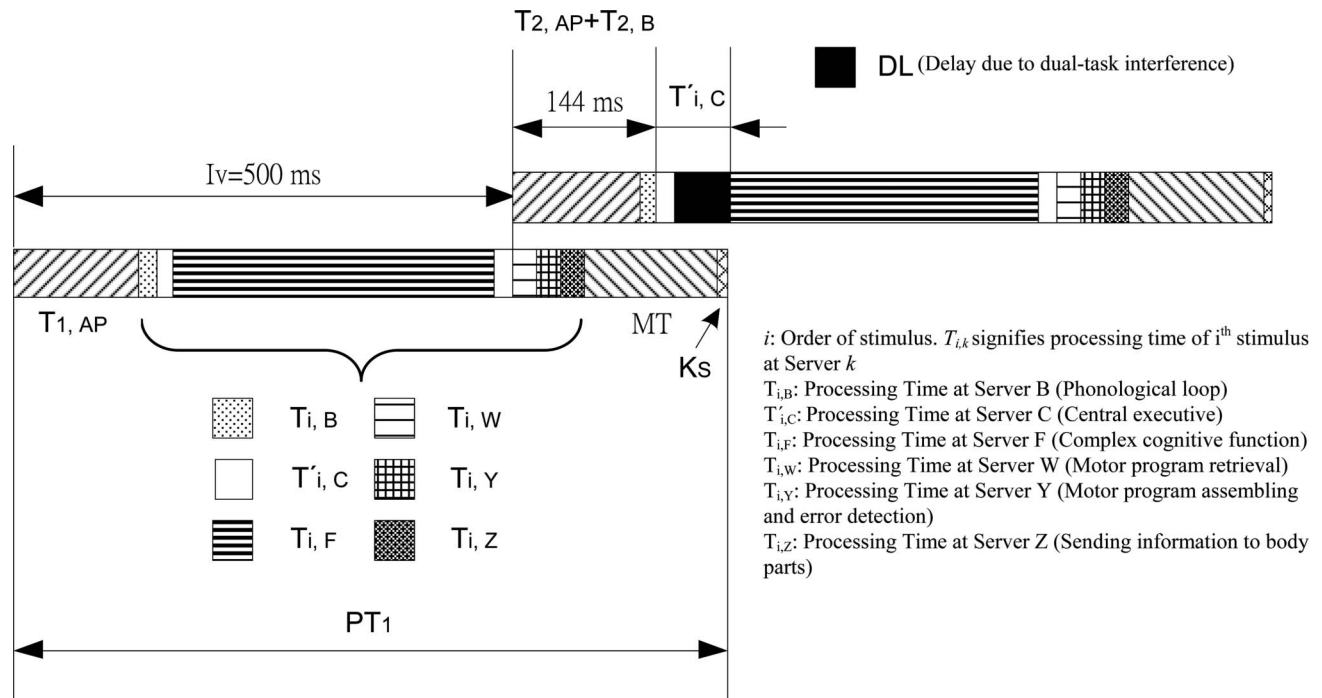

Figure 3.   Delay at Server C.

In summary, the response time of numerical typing is modelled by the following general equation:

$$PT_0 = 0$$

$$PT_{i(\alpha,\beta)} = RT_{(\alpha)+}DL_i + MT_{(\beta)} + Ks \tag{12}$$

where

i: notation of response order. $i = 1$ → first response in 9-digit number, and so on.
α: notation of finger strategy. $\alpha = 0$ → Single finger typing; $\alpha = 1$ → Multi-finger typing.
β: notation of urgency. $\beta = 0$ → *non*-urgent condition; $\beta = 1$ → urgent condition.

$RT_{(0)}$ and $RT_{(1)}$ can be found in Equations (4) and (10) respectively. The calculation of DL_i is presented in Equations (8) and (9), while $MT_{(0)}$ and $MT_{(1)}$ are modelled in Equations (5) and (11) respectively. Ks is a constant (10 ms) adopted from original QN-MHP model and can be found in Appendix 5. The integrated equation for modelling response time is therefore:

$$
\begin{aligned}
PT_{i(\alpha,\beta)} = {} & \left[T_{AP} + T_B + T_C + T_{F(\alpha)} + T_C + T_W + T_Y + T_Z \right] \\
& + \left\{ \begin{array}{ll} \left[\left\lceil \frac{PT_{i-1}-(I_v+T_{AP}+T_B)}{T_C} \right\rceil - 1 \right] \times T_C; & \text{IF } PT_{i-1} - (I_v + T_{AP} + T_B) > 0 \\ 0; & \text{IF } PT_{i-1} - (I_v + T_{AP} + T_B) < 0 \end{array} \right\} \\
& + \left[\begin{array}{l} I_M \times \log_2(D/S_e + 0.5); IF\beta = 0 \\ A + B \times \sqrt{D}; IF\beta = 1 \end{array} \right] + K_s
\end{aligned}
\tag{13}
$$

The average reaction time for the *n*- digit number can be calculated accordingly as:

$$PT_{AVG} = \sum_{i=1}^{n} PT_{i(\alpha,\beta)} \bigg/ n; n = 9 \ \text{ in Lin and Wu (2011)} \tag{14}$$

3.2. *Modelling errors of numerical typing*

The expected number of typing errors is modelled through two mechanisms: neuromotor noise (Van Beers *et al.* 2004) and open/close-loop control (Figure 1). Van Beers *et al.* (2004) conducted an experiment in which participants were asked to perform rapid aiming by their index fingers as quick as possible in different directions without visual feedback about the hand position. The single finger movements were ballistic in nature under urgency, but no pacing was presented between two successive movements. The results showed that endpoint variability formed scatter ellipses oriented with moving directions. They suggested that the endpoint variability was caused by neuromotor noise and successfully modelled it as a function of neuromotor noise level. The current study implemented the conceptual neuromotor noise model proposed by Van Beers *et al.* (2004) at Server E, Z and Server 23 in QN-MHP (Figure 1) and combined it with a visual correction mechanism (Crossman and Goodeve 1983) to predict the number of errors produced in numerical hear-and-type tasks.

3.2.1. *Modelling baseline errors in numerical typing*

First of all, the neuromotor noise is assumed to include three components: signal-dependent noise (SDN) calculated at Server Z, background noise (CN) computed at Server E and temporal noise (TN) accumulated at Server 21 through 25. SDN is scaled by muscle activation level (*u*) that is proportional to recruitment of motor units in primary motor cortex, M1 (represented by Server Z in QN-MHP). CN represents background noise in the neuromotor system during response selection (processing time at Server C and Server F) and is independent of *u*. Whenever there is cognitive task interference, more CN is assumed to be added as a function of the duration of interference (calculated by Server E). Finally, TN signifies noise added during execution of movements and is scaled by movement time (accumulated during motor execution at Server 21-25). Furthermore, to account for the observation that movements with a longer duration tended to have a lower peak velocity (and thus lower *u*), when TN is scaled by *c*, *u* should be simultaneously scaled by $1/c^2$ as suggested in Van Beers *et al.* (2004). That is,

$$\sigma_u = \sqrt{k_{SDN}^2 \cdot \frac{u^2}{c^2} + k_{CN}^2 \cdot l^2 + k_{TN}^2 \cdot c^2} \tag{15}$$

where σ_u is the extent of SDN added with muscle activation level u; I was an interference index (see Equation (28)) accounting for the relative extent of the dual-task interference in background noise (CN). c is the extent of TN which accumulates as movement time increases. k_{SDN}, k_{CN} and k_{TN} are experimental constants for weighting three components. They were set to the values (Appendix 5) as provided in Van Beers *et al.* (2004).

In order to extend this model to cover eight experimental conditions in Lin and Wu (2010), a coded notation j is added to Equation (15) to signify the jth experimental condition (Appendix 4) so that u, I and c level can be calculated accordingly. That is:

$$\sigma_{u,j} = \sqrt{k_{SDN}^2 \cdot \frac{u_j^2}{c_j^2} + k_{CN}^2 \cdot I_j^2 + k_{TN}^2 \cdot c_j^2}; j = 0 \text{ to } 7 \tag{16}$$

Later on, u_j, I_j and c_j will be scaled or modified based on mechanisms discussed in section 2, but, initially, $u_0 = 0.5$, $I_0 = 1$ and $c_0 = 1$ are used respectively in baseline condition ($j = 0$) to keep the relative weightings of SDN, CN and TN identical with original settings in Van Beers *et al.* (2004).

Now, the averaged total endpoint variability ($S_{t,0}^2$) for single finger, ballistic movements in urgent condition without pacing is determined by the following equation:

$$S_{t,0}^2 = S_0^2 (MT_{(1)}/MT_0) \tag{17}$$

where S_0^2 (68 mm^2) is the averaged total endpoint variability in Van Beers *et al.* (2004), and it is scaled by a ratio of the average ballistic movement time in numerical typing ($MT_{(1)}$, Appendix 5) predicted by Equation (11) to the average movement time ($MT_{0} = 420$ ms) in the experiment of Van Beers *et al.* (2004). The endpoint variability is scaled by movement time[1] because endpoint variability in ballistic movements is more associated with peak velocity (Messier and Kalaska 1999) and peak velocity is found to be highly correlated with movement time in Van Beers *et al.* (2004). The resultant endpoint variability in baseline condition is $S_{t,0}^2 = 17$ mm^2. In non-baseline condition, however, the endpoint variability can be quantified as:

$$S_{t,j}^2 = S_{t,0}^2 (\sigma_{u,j}/\sigma_{u,0}); j = 0 \text{ to } 7 \tag{18}$$

where $S_{t,j}^2$ signifies endpoint variability in j^{th} experimental condition ($j = 0$ to 7 signified eight experimental combinations of three factors, see Appendix 4) and $\sigma_{u,j}$ is the neuromotor noise level in the jth condition (to be further developed in Equation (29)). $\sigma_{u,0}$ and $S_{t,0}^2$ are the neuromotor noise level and baseline endpoint variability calculated from Equations (16) and (17), respectively.

Finally, to estimate the number of errors produced as a function of endpoint variability, the deviation of keystrokes from the target (the centre of the key) needs to be calculated. The total endpoint variability ($S_{t,j}^2$) is assumed to be composed of variations in two orthogonal directions along movement directions (Figure 4). The extent of these two variation components are assumed to follow normal distribution with mean $m_0 = 0$ and standard deviation $S_{v,j}$ and $S_{h,j}$, respectively. Their relationship is determined by aspect ratios (AR) in different movement directions (θ) so that the orientation of resultant scatter ellipses would be compatible with experimental results of Van Beers *et al.* (2004). That is:

$$S_{h,j}^2 = \frac{S_{t,j}^2}{[AR^2(\theta) + 1]} \tag{19}$$

and

$$S_{v,j}^2 = AR^2(\theta) \cdot S_{h,j}^2 \tag{20}$$

$AR(\theta)$ are provided in Van Beers *et al.* (2004). Resultant $S_{v,j}$ and $S_{h,j}$ can be used to calculate aiming shift in X and Y coordinates, i.e.

$$\Delta x_j = S_{v,j} \cdot \cos(\theta) + S_{h,j} \cdot \sin(\theta) \tag{21}$$

and

$$\Delta y_j = S_{v,j} \cdot \sin(\theta) - S_{h,j} \cdot \cos(\theta) \tag{22}$$

A criterion to avoid typing errors needs to be set based on physical constraints of standard numerical keyboards (Figure 2) and average finger pad size (10.1 mm) (Drury and Hoffmann 1992). Figure 5 shows relationships among key size (S), key distance (KD), finger pad size (PS) and shift (SF) from centre of the key. In any case, if the typist intended to touch the left key but ended up with his/her finger pad touching the right key, i.e.:

$$SF + 0.5 \times PS > KD - 0.5 \times S \tag{23}$$

then an error would result. Given $KD = 19.1$ mm, $S = 12.7$ mm, and $PS = 10.1$ mm, it can be calculated that any SF exceeding 7.7 mm ($SF_{\max}$) would produce numerical typing errors. Given that SF is assumed to be normally distributed, the probability of errors in X-direction during j^{th} experimental condition can be calculated based on:

$$P(Err_{j(X)}) = 2 \times \left\{ 1 - \Phi \left[(SF_{\max} - m_0) \middle/ \sqrt{\frac{AR^2(\theta) \cdot \left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{\mu,0}) \right]}{AR^2(\theta) + 1}} \cdot \cos(\theta) + \sqrt{\frac{\left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{u,0}) \right]}{AR^2(\theta) + 1}} \cdot \sin(\theta) \right] \right\} \tag{24}$$

where $\sigma_{u\ j}$ signifies the extent of neuromotor noise in j^{th} experimental condition in Equation (16) and will be further developed in Equation (29). $\Phi[z]$ is the inverse cumulative normal distribution function that gives probability of z-score greater than value z. The probability of errors in Y-direction can be modelled similarly:
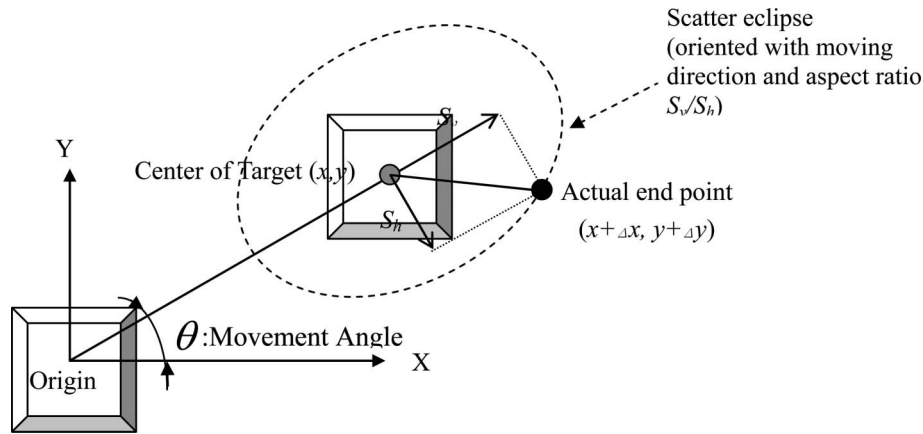

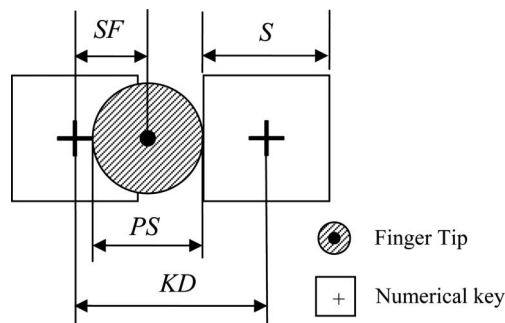Figure 4.   Endpoint variability in two orthogonal directions.

Figure 5.   Key size (S), key distance (KD), finger pad size (PS) and shift (SF).

$$P(Err_{j(Y)}) = 2 \times \left\{ 1 - \Phi \left[(SF_{\max} - m_0) \middle/ \sqrt{\frac{AR^2(\theta) \cdot \left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{\mu,0}) \right]}{AR^2(\theta) + 1}} \cdot \sin(\theta) - \sqrt{\frac{\left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{u,0}) \right]}{AR^2(\theta) + 1}} \cdot \cos(\theta) \right] \right\}$$

(25)

If any Δx and Δy exceeding $SF_{\max}$ would result in an error, the expected error rate would be 3.9% at baseline (about 10.6 errors for 270 keystrokes). This error rate represents the baseline accuracy in single finger numerical typing under slow pacing and urgent condition.

3.2.2. Endpoint variability in different conditions

The baseline errors modelled in setion 3.2.1 represent endpoint variability in a single finger typing, slow pacing and urgent condition. However, in multi-finger typing, muscle activation level (u) needs to be adjusted because more motor units are assumed to be recruited to compensate force deficit. To compute how many more motor units need to be recruited, the extent of motor unit recruitment is firstly determined by the equation (Selen 2007):

$$F = e^{R\% \times ln(MVC)}$$

(26)

where $R\%$ is proportion of M1 motor units recruited and F is the corresponding force produced. The increment of $R\%$ in multi-finger typing then is calculated based on keying force data reported in the literature (Martin *et al*. 1996), and the finger force deficit needs to be compensated (Latash *et al*. 2002). That is, because the maximal voluntary contraction (MVC) in Equation (26) was reduced in multi-finger typing, the $R\%$ must increase, and the u also increased proportionally:

$$u_j = u_0 \cdot \frac{\ln(MVC_0)}{\ln(MVC_j)}$$

(27)

The resultant muscle activation level (u) is calculated to be 111% in multi-finger typing ($j = 2$, 3, 6, and 7) to generate the same reaction force as in single finger typing.

Furthermore, in fast pacing condition, more CN is assumed to be added to an extent proportional to the interference index (I) calculated in the following equation:

$$I_j = I_0 + DL_j/(T_{j,C} + T_{j,F} + T_{j,C})$$

(28)

where I_j represents the extent of perceptual-motor interference in j$^{\text{th}}$ condition on any entity relative to total time it spends in the cognitive subnetwork. Finally, the TN component and u were also scaled by any change in movement time based on movement time models: Equations (5) and (11) for close-loop controlled and ballistic movements, respectively. In summary, the extent of neuromotor noise can be represented as a function of abovementioned scalars and modifiers:

$$\sigma_{u,j} = \sqrt{ k_{SDN}^2 \cdot \frac{\left[u_0 \cdot \frac{\ln(MVC_0)}{\ln(MVC_j)} \right]^2}{\left(c_0 \cdot \frac{MT_j}{MT_{(1)}} \right)^2} + k_{CN}^2 \cdot \left[I_0 + \frac{DL_j}{(T_{j,C} + T_{j,F} + T_{j,C})} \right]^2 + k_{TN}^2 \cdot \left(c_0 \cdot \frac{MT_j}{MT_{(1)}} \right)^2 }$$

(29)

However, the abovementioned adjustments cannot account for reduction of endpoint variability by visual guidance and corrections. It is assumed that visual guidance and corrections are subject to an initial delay (DL_v) because the visual feedback needs to go through $21 \rightarrow X \rightarrow Y \rightarrow Z$ (Feedback Loop in Figure 1) so that it can be transformed to corrective signals. The initial delay can be computed as the following based on the parameter settings in Appendix 5.

$$DL_v = T_{21} + T_X + T_Y + T_Z = 24 + 24 + 24 + 24 = 96 \; (ms)$$

(30)

Then, the endpoint variability under ballistic movements before the time of correction would be corrected iteratively, leaving only variability occurring after the correction point. That is, if the movement was supposed to last MT ms, the uncorrected portion of endpoint variability will be:

$$
\begin{aligned}
S_{r,j}^2 &= S_{t,j}^2 \cdot [MT_{(0)} - DL_v]/MT_{(0)}, MT_{(0)} > DL_v \\
&= S_{t,j}^2, MT_{(0)} \leq DL_v
\end{aligned}
\tag{31}
$$

Thus, any movement shorter than the initial delay will not be corrected. Equations (24) through (31) combined would allow estimations of error rates ($Err\%$) in j[th] typing conditions:

$$
E(Err\%_j) = P(Err_{j(X)}) \cup P(Err_{j(Y)})
\tag{32}
$$

where

$$
P(Err_{j(X)}) = 2 \times \left\{ 1 - \Phi \left[(SF_{\max} - m_0) \middle/ \sqrt{\frac{AR^2(\theta) \cdot \left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{\mu,0}) \right]}{AR^2(\theta) + 1}} \cdot \cos(\theta) + \sqrt{\frac{\left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{u,0}) \right]}{AR^2(\theta) + 1}} \cdot \sin(\theta) \right] \right\}
$$

$$
P(Err_{j(Y)}) = 2 \times \left\{ 1 - \Phi \left[(SF_{\max} - m_0) \middle/ \sqrt{\frac{AR^2(\theta) \cdot \left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{u,0}) \right]}{AR^2(\theta) + 1}} \cdot \sin(\theta) - \sqrt{\frac{\left[S_{t,0}^2 \cdot (\sigma_{u,j}/\sigma_{u,0}) \right]}{AR^2(\theta) + 1}} \cdot \cos(\theta) \right] \right\}
$$

if $j = 0,2,4,6$ (ballistic without corrections); and

$$
P(Err_{j(X)}) = 2 \times \left\{ 1 - \Phi \left[(SF_{\max} - m_0) \middle/ \sqrt{\frac{AR^2(\theta) \cdot \left[S_{t,0}^2 \cdot \frac{\sigma_{u,j} \cdot [MT_{(0)} - DL_v]}{\sigma_{u,0} \cdot MT_{(F)}} \right]}{AR^2(\theta) + 1}} \cdot \cos(\theta) + \sqrt{\frac{\left[S_{t,0}^2 \cdot \frac{\sigma_{u,j} \cdot [MT_{(0)} - DL_v]}{\sigma_{u,0} \cdot MT_{(0)}} \right]}{AR^2(\theta) + 1}} \cdot \sin(\theta) \right] \right\}
$$

$$
P(Err_{j(Y)}) = 2 \times \left\{ 1 - \Phi \left[(SF_{\max} - m_0) \middle/ \sqrt{\frac{AR^2(\theta) \cdot \left[S_{t,0}^2 \cdot \frac{\sigma_{u,j} \cdot [MT_{(0)} - DL_v]}{\sigma_{u,0} \cdot MT_{(0)}} \right]}{AR^2(\theta) + 1}} \cdot \sin(\theta) - \sqrt{\frac{\left[S_{t,0}^2 \cdot \frac{\sigma_{u,j} \cdot [MT_{(0)} - DL_v]}{\sigma_{u,0} \cdot MT_{(0)}} \right]}{AR^2(\theta) + 1}} \cdot \cos(\theta) \right] \right\}
$$

if $j = 1,3,5,7$ (visually guided and corrected)

$AR(\theta)$ are provided in Van Beers *et al.* (2004); $\sigma_{u,0}$ and $S_{t,0}^2$ are baseline neuromotor noise and endpoint variability that can be calculated from Equations (16) and (17), respectively. $MT_{(0)}$ is estimated from Equation (5). The detailed calculation of $\sigma_{u,j}$ can be found in Equation (29). Here $P(Err_{j(X)})$ is assumed to be independent of $P(Err_{j(Y)})$ because they are probability of errors in two orthogonal directions, i.e.

$$
E(Err\%_j) = P(Err_{j(X)}) \cup P(Err_{j(Y)}) = P(Err_{j(X)}) + P(Err_{j(Y)}) - P(Err_{j(X)}) \times P(Err_{j(Y)})
\tag{33}
$$

In order to transform error rates into number of errors, the dependent variable used in Lin and Wu (2011), the following equation is used:

$$
NE_j = E(Err\%_j) \times N_j; j = 0 \text{ to } 7
\tag{34}
$$

where NE_j is the number of errors predicted in the jth conditions and N_j is the number of keystrokes to be produced. In the current study $N_j = 270$ because Lin and Wu (2011) asked each participant to type 30, 9-digit, random numbers in each trial ($30 \times 9 = 270$ keys).

4. Results and model applications

4.1. Response time

The model predictions for response time in different typing conditions are shown and compared to experimental data in Figure 6. To validate modelling results using experimental data in Lin and Wu (2011), the comparability of model predictions and experimental results were quantified by Pearson correlation coefficient as well as the root-mean-squared error percentage (RMSE%).[2] The overall RMSE% was 3.68% with a correlation of 95.55%.

The abovementioned results can be further factorised into pacing (speech rate defined by ISI), finger strategy, and urgency. Table 1, 2, and 3 show factorised results for pacing, finger strategy and urgency respectively. For pacing factor, the model predicted a delay of 54 ms for fast speech while it was 38 ms in the experiment, resulting in 1.20% RMSE.

For finger strategy factor, the model predicted an increase of 27 ms in response time for multi-finger typing while 22 ms was added in the experiment. The resultant RMSE% was 0.94%.

For urgency/motivational factor, the model predicted a 37 ms decrease in urgent typing, 7 ms less than 44 ms revealed in the experiment. The RMSE% was 0.96%.

4.2. Typing errors

The model predictions of accuracy can be found in Figure 7 in comparison with experimental results of Lin and Wu (2011). The overall RMSE% was 35.10% with a correlation of 96.52%.

Similarly, the results can also be factorised into pacing (speech rates), finger strategies and urgency, and they are shown in Table 4, 5 and 6 respectively. For pacing, the effect of fast speech was predicted as an increment of 2.1
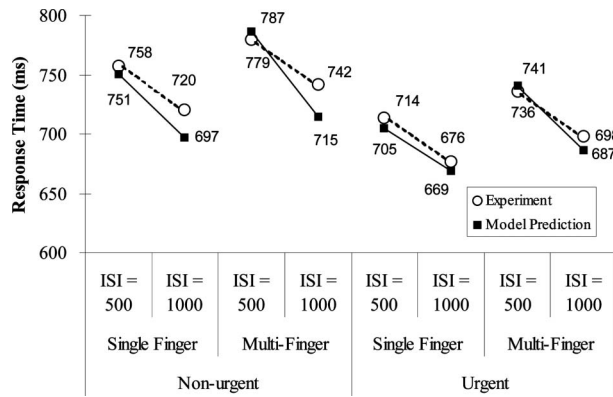

Figure 6. Comparison of model predictions of response time with experimental data.

Table 1. Factorised results for pacing factor in response time.

Pacing	Fast	Slow	Effect
Exp	747	709	−38
Mod	746	692	−54
RMSE %	1.20		

Table 2. Factorised results for finger strategy in response time.

Finger	Single	Multiple	Effect
Exp	717	739	22
Mod	705	732	27
RMSE %	0.94		

Table 3. Factorised results for urgency in response time.

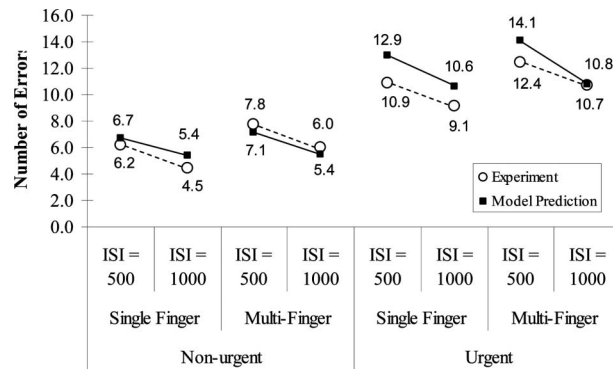| Urgency	Non-urgent	Urgent	Effect
Exp	750	706	−44
Mod	737	700	−37
RMSE %	0.96		

Figure 7. Comparison of model predictions of errors with experimental data.

Table 4. Factorised results for pacing factor in errors.

Pacing	Fast	Slow	Effect
Exp	9.3	7.6	−1.8
Mod	10.2	8.1	−2.1
RMSE %	6.17		

Table 5. Factorised results for finger strategy in errors.

Finger	Single	Multiple	Effect
Exp	7.7	9.2	1.6
Mod	8.9	9.4	0.4
RMSE %	7.53		

Table 6. Factorised results for urgency in errors.

Urgency	Non-urgent	Urgent	Effect
Exp	6.1	10.8	4.7
Mod	6.2	12.1	6.0
RMSE %	8.03		

errors (6.17% RMSE in comparison with experimental data). For finger strategies the model predicted an effect size of 0.4 increment of errors in multi-finger tying (7.53% RMSE). For urgency the model predicted an increase of 6.0 errors in urgent condition (8.03% RMSE). In general, QN-MHP successfully modelled the extents and trends of effects on typing performance with lower than 10 RMSE% and high correlation.

4.3. Model applications

4.3.1. Determination of optimal speech rates for synthesised voice systems

Based on abovementioned modelling results, the model predicted that errors and response time would be reduced with slower speech rate (longer ISI). There is, however, a trade-off between speech rate and task duration, i.e. the slower the speech rate, the longer the task duration. Obviously none of the speech rates tested in Lin and Wu (2011) were the optimal pacing. It is, therefore, of research interests to ascertain how the model would help in determining such an optimal pacing in different situations. In order to quantify productivity under different accuracy and typing speed, the following object function is defined:

$$\text{Maximise } DPM = (60 \times 10^3/PT_j) \times (1 - Err\%_j) \tag{35}$$

where DPM is number of correct digits typed per minute. Figure 8 shows model prediction results from $ISI = 500$ ms to $ISI = 600$ ms (the productivity from $ISI = 600$ ms to $ISI = 1000$ ms is constant so the graph is trimmed). When optimal pacing is adopted, productivity of single finger typing improves from 78 DPM to 86 DPM in non-urgent condition and from 81 DPM to 90 DPM in urgent condition (in comparison with $ISI = 500$ ms). For multi-finger typing, using optimal pacing increases productivity from 74 DPM to 84 DPM and from 77 DPM to 87 DPM in non-urgent and urgent condition respectively. On average, the optimal pacing could increase productivity by 9 DPM.

4.3.2. Assistance towards optimal keyboard design for urgency

We may also wonder what might be the optimal keyboard design when the pacing cannot be optimised and may cause interference. Here we choose $ISI = 500$ ms, the fast pacing condition in Lin and Wu's experiment, as an example. Optimisation should be subject to the following constraints: size of the optimised numerical keyboard should be less than or equal to the original numerical keyboard (space efficiency) and key size should be at least the finger pad size. Therefore we could rewrite the object function with the constraints as follows:

$$\text{Maximise } DPM = (60 \times 10^3/PT_j) \times (1 - Err\%_j)$$

$$\text{Subject to } (S + K_G) \leqq 19.1 \text{(keyboard size constraint)} \tag{36}$$

$$S \geqq 10.1 \text{(finger pad constraint)}$$
$$K_G \geqq 0$$

where S and K_G are key size and key gap (distance between edges of two adjacent keys) respectively. If $S + K_G$ is greater than key distance ($KD = 19.1$ mm) on a standard numerical keyboard, then the resultant numerical
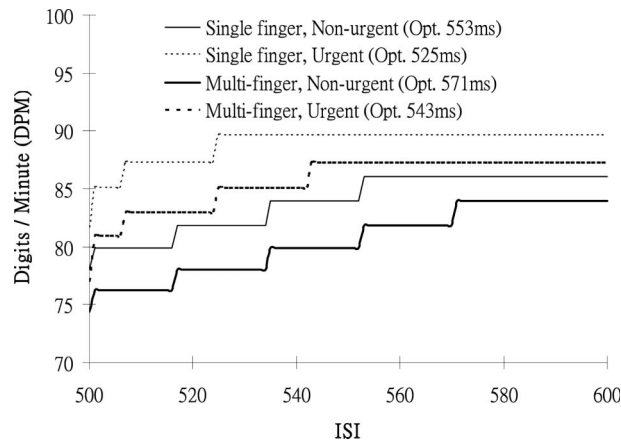

Figure 8. The optimal speech rate defined by ISI.

keyboard would exceed the size of the standard numerical keyboard (Figure 2). Given Equation (36), the DPM can be optimised, and the results are shown by contour plots in Figure 9. Based on the results, the standard numerical keyboard (12.7 mm in key size and 6.4 mm in key gap) is not an optimal design at fast pacing regardless of urgency. A larger key size (17.5 mm) with a smaller key gap (0.5 mm) is needed to maximise the productivity. The optimisation is expected to improve productivity of single and multiple-finger typing by 10.2 *DPM* on average. For urgent typing, however, a smaller key size (10.1 mm) with a larger key gap (9 mm) is needed to maximise the productivity, and the optimal design is expected to increase productivity by 1.7 *DPM* on average. In general, smaller keys with a larger gap are preferred by numerical typing under urgency, while typing in non-urgent situation requires larger keys with a smaller key gap (Figure 10).

Practically, the keyboard design can be optimised based on the situation of real usage. For example, in military combat systems, the operators may need to respond to auditory commands as soon as possible. Because both reaction time and accuracy is critical in wartime, under urgent situation, the numerical keyboard used in the military combat system may consider adopting smaller key size with larger key spacing as suggested in Figure 10 (right). In contrast, older people or physically challenged individuals may have slower response time in movements and need more time in error correction when public kiosks are used. In that case, the designer may consider adopting the design at the centre of Figure 10 to maximise reaction time and reduce errors.
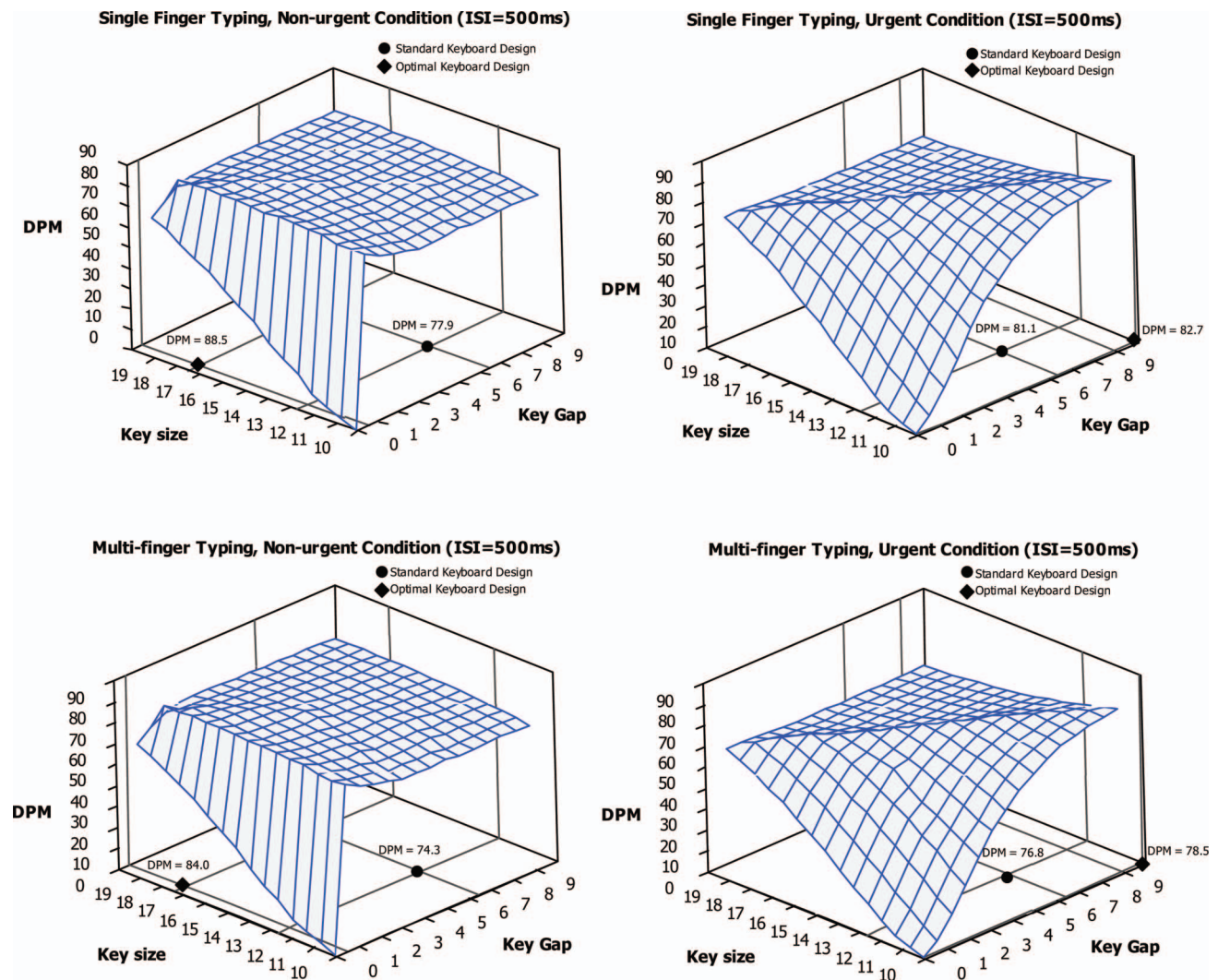

Figure 9. Contour plots of effects of key size and key gap on typing productivity.
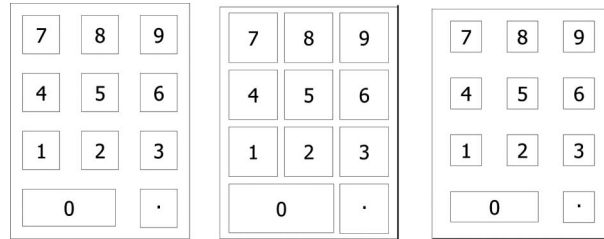
Figure 10.   Keyboard designs (left: standard; centre: for use without urgency; right: for use in urgency)

5.   Discussion

In this modelling work, Queuing Network Model Human Processor (QN-MHP) was used to predict numerical typing performance in terms of typing speed (response time) and accuracy (number of errors) in different pacing, finger strategies and urgency conditions. Typing performance under different task conditions was never modelled by previous typing-related models (Rumelhart and Norman 1982, John 1996, 1998, Wu and Liu 2008b). QN-MHP was proved able to model typing performance in those conditions, with low root-mean-squared error percentage and high correlation when the model predictions were compared to experimental data (Lin and Wu 2011). The speech rate represented an external task demand while urgency was associated with rewards and internal motivation. Both could be influential factors in general perceptual-motor tasks in addition to motor control strategies used to perform the task, e.g. finger strategies in typing. Modelling those task-related factors associated with performance of perceptual-motor tasks is one step towards Newell's unified cognitive theory that can model a phenomenon in diverse situations where the phenomenon occurs.

The current work also contributed to enhancing QN-MHP in that previous QN-MHP modelling studies did not incorporate top-down control mechanism and the information flow was mainly regulated by bottom-up phenomena such as queuing, waiting, and processing of entities. Such a push system, i.e. entities were pushed into servers by continuous arrivals, is likely to have congestions and may not be representative of cognitive processes in multi-tasking or resource competition. The human brain indeed has some embedded top-down control functions to regulate information flow based on the importance of the task and to mediate cognitive system by activating extra brain areas and/or suppressing affective brain areas under stress (Paus *et al.* 1993, Pochon *et al.* 2002). The enhancement of QN-MHP related to top-down control mechanism enabled QN-MHP to also model a pull system in which the flow of entities were controlled by servers so that processing of multiple entities competing for the same route or resource can be optimised, as revealed in fast speech condition in the current study. Furthermore, the current work improved QN-MHP by enhancing its capability to account for error-variability produced by different task situations. Previous QN-MHP modelled endpoint variability by population size which is a constant within individuals. However, an individual can recruit different motor areas to execute motor tasks in various situations, and, in multi-finger typing, additional brain areas could be recruited to increase muscular co-activation so that finger force deficit would be compensated (Hager-Ross and Schieber 2000). The variation of recruitment in motor units has not been covered by previous QN-MHP studies. Since motor recruitment was associated with neuromotor noise and the noise level was associated with endpoint variability in rapid aiming (Van Beers *et al.* 2004), the neuromotor noise was integrated to the current model to account for endpoint variability in different finger strategies. Without this enhancement, the model would not be able to explain the reduction of errors in single finger typing as endpoint variability would not change by assuming a constant standard deviation of normal distribution in previous QN-MHP (Wu and Liu 2008b).

The model predicted different optimal speech rates in different situations, and those results could be easily applied to the design of human computer interface in multi-tasking. For example, in cases where visual channels are occupied by the primary tasks, e.g. daily driving or radar monitoring in war time, verbal signals may be necessary to provide drivers or operators numerical information to be input into the system, e.g. dialling on a touch screen cell phone or entering target coordinates via physical numerical keyboards. The tasks may be performed in different situations, e.g. non-urgent typing with single finger in cell phone dialling versus urgent typing with multiple fingers in radar monitoring, but, during multi-tasking, drivers or operators are likely to react rapidly to the verbal stimuli instead of memorising them and typing at a later time. In those cases, an optimal speech rate can help design the voice synthesise system to output verbal information at an appropriate pace so that the numerical typing performance can be maximised. The model also predicted that, in non-urgent numerical typing, the key size should

be larger (about 17–18 mm) while the key gap may be sacrificed (1–2 mm is enough) without impeding typing performance. This result is compatible with previous keyboard design study showing that people performed better on larger keys (20 mm in size), implying their greater than normal requirement for accuracy, while they are relatively insensitive to key gaps (Colle and Hiszem 2004). To the authors' knowledge, systematic efforts have not been made to compare numerical typing performance in urgent and non-urgent situation. However, the model prediction that smaller keys with larger gaps are needed for numerical typing in urgency makes sense because faster responses in urgent typing are supposed to result in greater endpoint variability that is scaled by target size, i.e. the larger the target size, the greater the variability. By using smaller keys with a larger gap, the greater endpoint variability is expected to be dealt with by both inherent scaling (typists naturally produce smaller variance with smaller target) and by external buffering (a larger gap allows greater variability without making errors). Whether this prediction is correct, however, needs to be confirmed by further user experimentation.

It is noticed that the overall root-mean-squared error (RMSE) of the model predictions for typing accuracy was relatively high (35.10%) when it is compared to the RMSE of the model predictions for typing speed (3.68%). Although factorised results showed that the model could predict the effects of pacing, finger strategy and urgency on typing accuracy with 6.17%, 7.53%, and 8.03% RMSE respectively, the enhanced QN-MHP modelled typing errors mainly through spatial variability of typing movements; other cognitive or motor processes could also produce typing errors. For example, typists could forget numbers to be typed or transpose their positions due to memory failure, resulting omission or transposition errors. Omission could be also caused by insufficient depression force due to force production variability (Wu and Liu 2008b). Omission and transposition errors, however, constituted less than 10% of errors and were thus not emphasised in the current model (Lin and Wu 2011). In addition, when typists touched the wrong key or two adjacent keys simultaneously as predicted by the model due to excessive spatial deviation, errors did not necessary registered because there was certain mechanical allowance of depression before the key was activated. Typists might manage to correct the keystroke after the key was touched without the error being registered. This mechanical buffer was not modelled by the enhanced QN-MHP and might contribute to the discrepancy between theoretical accuracy and accuracy measured in reality.

So far, QN-MHP has successfully modelled various types of perceptual-motor tasks including basic steering tasks and dual tasks in vehicle driving (Liu *et al.* 2006, Wu and Liu 2007), transcription typing (Wu and Liu 2008b) and numerical typing (the current study). It was also used to account for psycho-physiological phenomena observed in perceptual-motor tasks such as mental workload (Wu and Liu 2007), event-related potential (ERP)(Wu *et al.* 2008), and psychological refractory period (PRP) (Wu and Liu 2008a). However, no high level cognitive operations, such as problem solving, reading comprehension and complex reasoning, are covered by any QN-MHP model (Wu and Liu 2008b). This limitation is partially attributable to the NGOMSL task description used in the cognitive network. The task analysis is completed beforehand and the steps are deterministic, making the execution of cognition static, i.e. procedural steps are followed with only elementary comparisons and computations of information. To solve problems, QN-MHP needs to adopt a dynamic process and a more flexible structure so that servers may modify connections and take novel steps to accommodate new situations. A learning process through change of routing probability and processing time has been implemented in previous QN-MHP (Wu and Liu 2008b). Further study may extend this process into a more powerful mechanism that is able to generate new connections and processing steps in cognitive networks. Furthermore, current QN-MHP did not model individual differences, but they may significantly contribute to model applications. For example, although the model predicted optimal speech rates and keyboard designs in urgent and non-urgent situations, anthropometry (e.g. finger pad size, hand size), personality (e.g. vulnerability to stress) and typing expertise may affect typists' ability to cope with urgency. Optimal pacing may vary based on their expertise and personality, while keyboard design may be adjustable to individual anthropometry if touch screen keyboards are used. Customisation of task demands and keyboard designs based on individual differences should improve user performance and preference as compared to provision of only one optimal task and keyboard type. Ideally, future QN-MHP should consider individual differences and provide different system design suggestions according to individuals' characteristics instead of an average typist's.

6. Conclusion

An enhanced Queuing Network Model Human Processor (QN-MHP) architecture was proposed in this study to account for mechanisms of pacing, response complexity and urgency factors in numerical typing. Dual task interference regulated by a top-down control mechanism, complexity of fingering strategy dealt with by multi-stage response selection, and alternation of movement modes associated with close-loop control were added to the existing Queuing Network Model Human Processor (QN-MHP) architecture to model response time in numerical

typing. A derived neuromotor noise model and a visual guided correction mechanism were utilised to quantify spatial variability of typing movements and thus typing errors could be estimated based on physical constraints of standard numerical keyboards. After model predictions were validated by the experimental data in Lin and Wu (2011), the results showed that the model successfully predicted the effects of pacing, finger strategy and urgency with low root-mean-squared errors (3.68% for response time and 35.10% for typing accuracy) and high correlations (95.55% for response time and 96.52% for typing accuracy). Manipulation of continuous pacing rate inputs and keyboard design parameters rendered different typing performance under different typing conditions, and, therefore, the model can be utilised to provide design suggestions for optimal pacing in voice synthesis system and for the best layout design in terms of key size and spacing. Modelling human perceptual-motor skills in different task conditions has thus advanced with the enhanced QN-MHP model as it visualised complicate mechanisms in numerical typing and predicted human performance in response time and accuracy under different task pacing, typing strategies and urgency conditions.

Acknowledgements

Notes

1. Some experimental studies found ballistic movement variability was proportional to either movement amplitude (e.g. Lin and Drury 2011) or squared movement amplitude (e.g. Beggs *et al.* 1972). The ballistic movements in their experiments were either controlled in movement time by a metronome or performed without emphasis on rapid responses. Since the rapid typing movements were encouraged in both Lin and Wu (2011) as well as in van Beers *et al.* (2004) but their time were not controlled, the results in those experiments might not apply to the current modelling work.
2. The root-mean-squared error percentage is computed by:

$$RMSE(\%) = 100 \times \sqrt{\frac{\sum_{j=1}^{n}(E_j - M_j)^2}{n} \bigg/ \frac{\sum_{j=1}^{n} E_j}{n}}$$

where E_j and M_j were experimental observation and model prediction in condition j, respectively, n was total number of observations/predictions to be compared.

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Appendix 1. Empirical evidence for the effects of dual-task interference

Unlike continuous transcription typing, the numerical hear-and-type task requires typists to react rapidly to transient stimuli in a digit-by-digit manner. No visual and permanent information allows typists to preview so that serial keystrokes can be pre-programmed and produced independently regardless of the speed of input information. In this situation, the pace is regulated by the inter-stimuli interval (ISI), and short ISI can produce temporal overlaps between processing of consecutive stimuli, resulting in dual-task interference (Pashler 1994a). When two consecutive auditory-manual tasks were required closely in time, the second response was found to be delayed as a function of ISI even though they were performed by different hands (Pashler and Christian 1994). Typing performance was also found to be affected by concurrent auditory recognition tasks (Calvo and Alamo 1987). The delay due to short ISI has been speculated to be a result of competition for general and specific attentional resources (Calvo and Alamo 1987), bottleneck in response-selection (Pashler 1994b) or even response execution (Ulrich *et al.* 2006). Given that saccadic eye movements are limited but necessary for obtaining target information and they cannot be made without visuospatial attention (Hoffman 1995, Adam *et al.* 2000), the dual-task interference is supposed to cause a delay to reconcile visual resource competition between execution of the on-going aiming task that needs eye-fixation and the coming auditory stimuli that triggers saccades.

The competition for attentional resources may further degrade motor accuracy through activation of the anterior cingulate cortex (ACC). ACC is a cortical region where cognitive and motor commands are funnelled to the motor system, and electrical stimulation of the ACC can elicit movements. Positron emission tomography (PET) study showed that regional cerebral blood flow (rCBF) within the ACC significantly changed with high attentional demands (Pochon *et al.* 2002). Since there is somatotopic organisation that connects the ACC and the primary motor cortex (M1), competitions in the ACC were assumed to increase activation level in M1, raise neuromotor noise and, thus, decrease movement accuracy.

Appendix 2. Empirical Evidence for the Effects of High Response Complexity and Finger Enslaving

Multi-finger typing is associated with higher response complexity (Schumacher *et al.* 1999) and subject to finger enslaving effects (Kilbreath and Gandevia 1994, Zatsiorsky *et al.* 2000, Li *et al.* 2004). Multi-finger numerical typing required matching five (fingers) to eleven (keys), and, thus, produced greater stimulus-response (S-R) numerosity than matching one (finger) to eleven (keys) in single finger typing. Greater S-R numerosity would increase reaction time for response-selection (Schedlbauer 2006). Furthermore, peripheral constraints (e.g. coupling between soft tissues of adjacent fingers and interconnections between tendons of extensor and flexor digitorum) and central mechanisms (e.g. overlaps of M1 cortical areas innervating to different finger muscles) suggested that individualisation of finger movements is limited. Involuntary force would be produced on uninstructed fingers while maximal voluntary force of the instructed finger would be reduced if multiple fingers were recruited simultaneously (Latash *et al.* 2002). To keep uninstructed movements stable and counteract force deficit from finger-enslaving, additional cortical motor areas must be recruited (Hager-Ross and Schieber 2000). It is speculated that this additional recruitment of motor area would also increase neuromotor noise and degrade accuracy of movements.

Appendix 3. Empirical evidence for the effects of urgency

Neurological studies showed that monetary rewards activated specific cortical areas that are independent of task difficulties, e.g. Brodmann area 10 in the ventral medial prefrontal cortex (Pochon *et al.* 2002). The area is strongly connected to the hypothalamus which projects to the sympathetic motor system associated with 'flight-or-fight' response. In addition, the monetary rewards also deactivated the limbic and paralimbic system that is associated with behaviour adaptation to maximise performance level. It is thus assumed that a monetary reward system facilitates ballistic movements due to its time efficiency.

Furthermore, aiming movements are not perfect and subject to endpoint variability (Elliott *et al.* 2001, Van Beers *et al.* 2004). The endpoint variability is an innate nature of human motor behaviours because the perceptual-motor system is an inherently stochastic and noisy system (Van Galen and Van Huygevoort 2000). Neuromotor noise could be added throughout the execution of motor behaviour (Van Beers *et al.* 2004), and the endpoint variability would be related to the signal-noise ratio (Van Galen and Van Huygevoort 2000). To counteract endpoint variability, visual guidance is needed for on-line correction of aiming movements despite their being pre-programmed (Smiley-Oyen 1996, Elliott *et al.* 1999). Fitts' law (1954) described the movement time of visual-guided movements as a function of movement amplitude and target width (Fitts 1954) and has been verified as an effective modelling method to predict movement time in both rapid aiming (Soukoreff and MacKenzie 2004) and typing under visual control (Drury and Hoffmann 1992). However, Gan and Hoffman (1988) found that movements with lower Fitts' difficulty indices were likely ballistic and their movement time was related to the square root of the movement amplitude without considering target widths as much as visually guided movements (Gan and Hoffmann 1988). Therefore, the movement time of a typing task could possibly be modelled as either ballistic or visual-controlled. When quick responses were required under urgent situation, ballistic movements were more likely to be adopted because they can be prepared in advance regardless of target size and produce shorter movement duration without later corrective phase (Donkelaar and Franks 1991). Although ballistic movements are expected to reduce movement time, the endpoint variability would be relatively large due to lack of on-line corrections.

Appendix 4. Coding for eight experimental conditions in modelling errors

When response time is modelled, single finger typing under slow pacing *without* urgency is considered to be baseline. However, in modelling errors, single finger typing under slow pacing <u>with</u> urgency is used as baseline for compatibility with the original experiment in Van Beers *et al.* (2004). This discrepancy necessitates a new notation system to code experimental conditions. Since, single finger typing under slow pacing <u>with</u> urgency is defined as baseline, this condition is noted as $j = 0$. Using 3 digits of 1-bit codes to note urgency, finger strategy and pacing, we can have the coding system as shown in Table A–1.

Table A–1. Coding system for modelling errors in different experimental conditions.

Condition	Bit			Code (j)
	2^0 (Urgency)	2^1 (Finger strategy)	2^2 (Pacing)	
Urgent, single finger, slow pacing	0	0	0	$j = 0$
Non-urgent, single finger, slow pacing	1	0	0	$j = 1$
Urgent, multi-finger, slow pacing	0	1	0	$j = 2$
Non-urgent, multi-finger, slow pacing	1	1	0	$j = 3$
Urgent, single finger, fast pacing	0	0	1	$j = 4$
Non-urgent, single finger, fast pacing	1	0	1	$j = 5$
Urgent, multi-finger, fast pacing	0	1	1	$j = 6$
Non-urgent, multi-finger, fast pacing	1	1	1	$j = 7$

Table A–2. Parameter settings in QN-MHP.

Parameter	Mean value (ms)	Description	Source
T_{AP}	126	Time for auditory perception (42 ms at Server 1, 2/3 and 4; i.e. $42 \times 3 = 126$)	Wu and Liu (2008a)
T_B	18	Average cycle time at Server B	
T_C	18	Average cycle time at Server C	
T_F	18	Average cycle time at Server F	
$T_{F(0)}$	302	Estimated processing time at Server F for single finger typing	See Appendix 6
$T_{F(1)}$	320	Estimated processing time at Server F for multi-finger typing	
$T_{1,W}$	24	Average cycle time at Server W	Wu and Liu (2008a)
$T_{1,Y}$	24	Average cycle time at Server Y	
$T_{1,Z}$	24	Average cycle time at Server Z	
$T_{1,21}$–$T_{1,25}$	24	Average cycle time in motor subnetwork	Feyen (2002)
$MT_{(0)}$	133	Estimated movement time for Fitt's law tasks	Drury and Hoffmann (1992)
$MT_{(1)}$	105	Estimated movement time for ballistic movements	Gan and Hoffmann (1988)
Ks	10	Key closure time	Wu and Liu (2008a)

Table A–3. Parameter settings in neuromotor noise model.

Parameter	Value	Unit	Description	Source
MT_0	420	ms	Average movement time in the original rapid aiming experiment.	Van Beers *et al.* (2004)
k_{SDN}	0.185	–	Relative weighting constant for signal dependent noise	
k_{CN}	0.103	–	Relative weighting constant for background noise	
k_{TN}	0.083	–	Relative weighting constant for temporal noise	
u_0	0.5	–	Initial extent of signal dependent noise	
I_0	1	–	Initial extent of background noise	
c_0	1	–	Initial extent of temporal noise	
$S_0{}^2$	68	mm^2	Average end point variability in the original rapid aiming experiment.	
m_0	0	mm	Assumed mean for the shift from the centre of the key	–
DL_v	96	ms	Initial delay for visual correction	Figure 1
N_j	270	–	Number of keys to be produced	Lin and Wu (2011)

Appendix 5. Parameter settings in QN-MHP and neuromotor noise model

See Tables A–2 and A–3.

Appendix 6. Estimation for processing time at Server F

Making a keystroke in numerical typing task can be modelled by NGOMSL-style description as shown in Table A–4, and individual steps in the task require Server F to perform phonological judgment (what the digit is), multiple-choice decision (which finger to use), spatial working memory operations (where the key is) and visuomotor choices (where to look). Each step in the task is assumed to take one average cognitive cycle time in QN-MHP (18 ms) to complete, except for <watch for> operator. This operator involves waiting for saccadic eye movements to obtain visual information and processing of visual information. Average eye movement time (230 ms) in Card *et al.* (1983) is adopted as the time lapse for 'Watch for' operator. Processing time of step 6 and step 9 are not included in reaction time because they are accumulated after completion of the response. For single finger typing, four cycles ($18 \times 4 = 72$ ms) plus one <watch for> process (230 ms) are needed, resulting in 302 ms of processing time ($T_{F(0)}$). For multi-finger typing, an additional cycle (step 7) is needed and causes the processing time to increase ($T_{F(1)} = 302 + 18 = 320$ ms).

Table A–4.   NGOMSL-style task procedure for numerical typing at Server F.

GOAL: Do numerical typing task
   Method for GOAL: Press <key> at <location> with <finger>
   Step 1 Retrieve <location> of <number> on a numerical keyboard from LTM
   Step 2 Watch for <label> around <location>
   Step 3 Recall <finger strategy> from LTM
   Step 4 Decide if <finger strategy> matches <single finger>
   IF MATCH go to step 5
   ELSE go to step 7
   Step 5 Press <key> at <location> with <index finger>
   Step 6 Return with goal accomplished
   Step 7 Decide <finger to use> based on <location>
   Step 8 Press <key> at <location> with <finger to use>
   Step 9 Return with goal accomplished