A System Model for Real-Time Sensorimotor Processing in Brain

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Abstract. The present paper addresses a general diagram to investigate the real-time parallel computation mechanism in the brain, using an idea of "Gantt chart." This diagram explicitly represents the temporal relationship between the computations running in various functional modules in the brain, and helps us to understand how the brain computation proceeds along the time. The author illustrates how we can utilize this diagram, taking a motor planning model of reaching movement as an example. Moreover, the author discusses the mechanism of intra- and inter-module computations on this diagram and addresses a tentative view that can explain the relationship between the movement variability and reaction time.

1 Introduction

Every second in daily life, our brain receives vast amount of sensor information and controls the motor system with many degrees of freedom (i.e., joints and muscles). It is astonishing that our brain can accomplish this complex sensorimotor processing in a real-time manner; revealing its underlying mechanism is one of the challenging topics in computational brain research.

In the present paper, the author proposes a novel diagram for representing the parallel computation mechanism of sensorimotor processing. There, the computations in different functional modules are placed along the time axis, and their temporal relationship is explicitly represented. The author addresses how to utilize this chart, taking an on-line motor planning model as an example. Through a discussion on the mechanisms of intra- and inter-module computations, moreover, the author will give a tentative explanation how the trade-off between the movement accuracy and reaction time determines.

2 Computational Approaches to the Brain Functions

Marr[1] classified the computational approaches to brain function into three levels: "theory", "representation and algorithm" and "implementation." He somewhat put emphasis on the theory level among the three, and actually, many sophisticated theories have been proposed which successfully explained the essential features of human behavior. However, they indicate only what problem to solve for realizing a given function, and do not tell us how to solve the problem.

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For example, the hand trajectories of planer reaching movements are beautifully explained by the theories based on some optimization criteria, such as minimum torque change[2] and TOPS[3]. However, it is still unclear how our brain finds such optimal motor commands. More specifically, the theories do not discuss how the brain determines motor commands within a specific time and how much cost (e.g., time, memory and resources) the brain takes for computation. In order to discuss these issues, we inevitably have to adopt the "representation and algorithm" approach. The objective of the present paper is to provide a helpful scheme for developing and examining the representation/algorithm-level brain models.

3 System Models for Sensorimotor Mechanism

A block diagram is one of the common ways to represent the computational structure of a complex system, and this is also true in the field of brain modeling. Figure 1 shows two examples, (a) a schematic model of the feed-forward control mechanism of voluntary reaching movement[4] and (b) a control model of eye movement system[5]. A chart indicating the anatomical connections (e.g., van Essen's chart) can be regarded as a sort of this diagram.

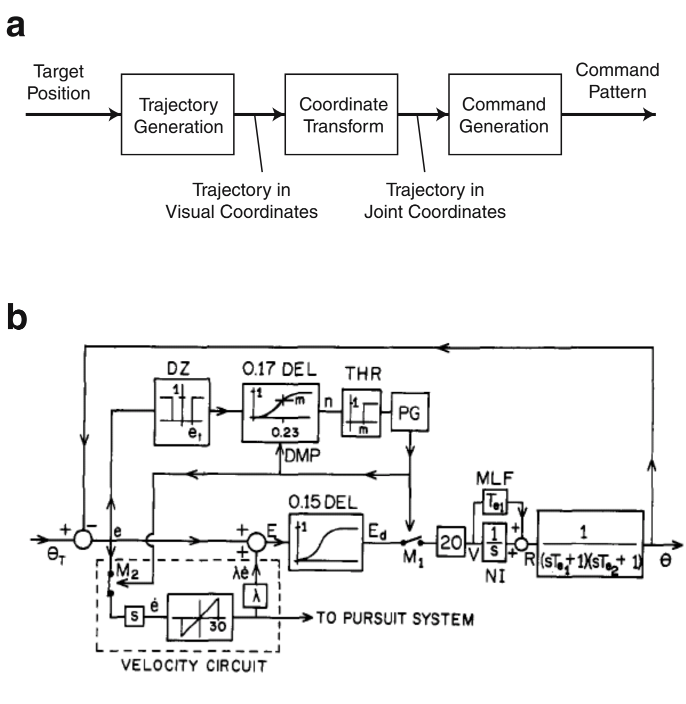

Fig. 1. Two examples of system models of motor control[4, 5]

In a block diagram, the system is represented by a set of distinct functional modules whose input-output relations are indicated by links between them. This diagram is convenient to see how the whole processing is divided into sub-processing (or modules). However, its limitation is that it cannot explicitly represent the temporal relationship between the sub-processing performed in different modules.

For example, the schematic model shown in Fig. 1(a) does not tell us the temporal orders of computations in the modules: It is unknown whether the second module starts the computation after the first module finished its computation, or computations in these modules can proceed in parallel. On the other hand, the control model in Fig. 1(b) is appropriate for representing peripheral motor system whose characteristics are time-invariant. However, it is not suitable for modeling the dynamic computational process performed in the central brain.

The point is that the processing in our brain is never uniform over either spatial or temporal dimension; some parts of the computation may be performed in a synchronized manner while other parts may be done independently. In order to represent such temporal relationship of these computations, we have to introduce the time axis to our diagram and to place them along the time axis.

Here, the author proposes to adopt "Gantt chart" [6] as a tool satisfying this requirement. Gantt chart is a graphical bar chart, originally proposed for illustrating a project schedule. It presents the start and finish timing of activities (or jobs) together with their dependency relationships. In the computer science field, actually, this chart is commonly used to show the job assignment to processing elements (PEs) in multi-processor systems (Fig. 2). Bars in this chart represent jobs of the PEs, whose left and right ends show when they start and finish, respectively. Thus, we can readily see the time spent for each job and the logical/causal relationships between different jobs. Moreover, this chart tells us how efficiently the system utilizes the computational resources: If the most parts of the chart are filled by the bars, it means that the system makes full use of the system resource.

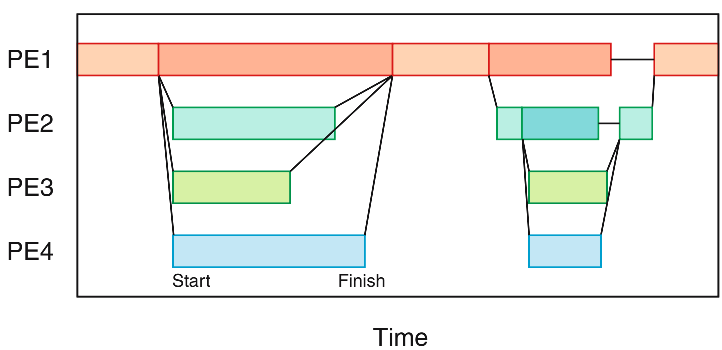

Fig. 2. A Gantt chart for a multi-processor system

The author's proposal is to make use of this chart as a tool to understand the computational structure of the sensorimotor processing. To the author's knowledge, surprisingly, this kind of chart has never been adopted to illustrate the progress in computation in the brain. Below, the author addresses how to utilize this chart for modeling the brain functioning.

4 Gantt Chart for Brain Computation

4.1 General Structure

Figure 3 (a) shows an example of the diagram. This chart consists of three parts, arranged in the vertical direction. The central part represents the inside of the brain, and a number of functional modules are placed here.[1] On the other hand, the upper and lower parts show the sensory and motor events, respectively. The time-invariant sensory/motor organs (e.g., retina and muscles) are placed in these regions.[2] The horizontal axis represents the physical time.

In more concrete, bars in the central part show the computational activities of the functional modules. Graduation in each bar represents the progress in computation, and the left and right ends roughly represents the start and finish timing (but, this point will be discussed later). On the other hand, broken ellipses show the communication (or coupling) between different modules.

Therefore, we can see how the computations in different modules are related to each other and to sensory and motor events. Moreover, we can read reaction time (the time between the sensory trigger and motor response) by measuring the interval between the sensory input and motor output. Looking at this from the other side, this chart tells us how long each module can spend for a given calculation.

Given this framework, our next task is to describe how the intra- and inter-module computations proceed in the model. Before going into this subject, however, we first see how to utilize this diagram, taking a hypothetical model of reaching movement as an example.

4.2 An Example: On-line Motor Planning of Reaching Movement

It is an interesting question how people can start reaching movement within a few hundreds milliseconds after the target's visual information is provided. How does the brain calculate the motor commands in such a short time? One possible answer to this question is that the brain keeps calculating the commands concurrently with the movement execution, rather than finishing the planning in advance of the movement onset. Here, the author would like to see how this on-line planning model works, using the proposed diagram.

[1] Each module roughly corresponds to a certain brain area, but the grain size of the modular structure can be determined according to the research target.

[2] Since sensory events and motor outputs are related by causal relationship (indicated as an arrow in the figure), it would be better to draw this chart on a cylindrical surface on which the sensory and motor parts adjoin each other.

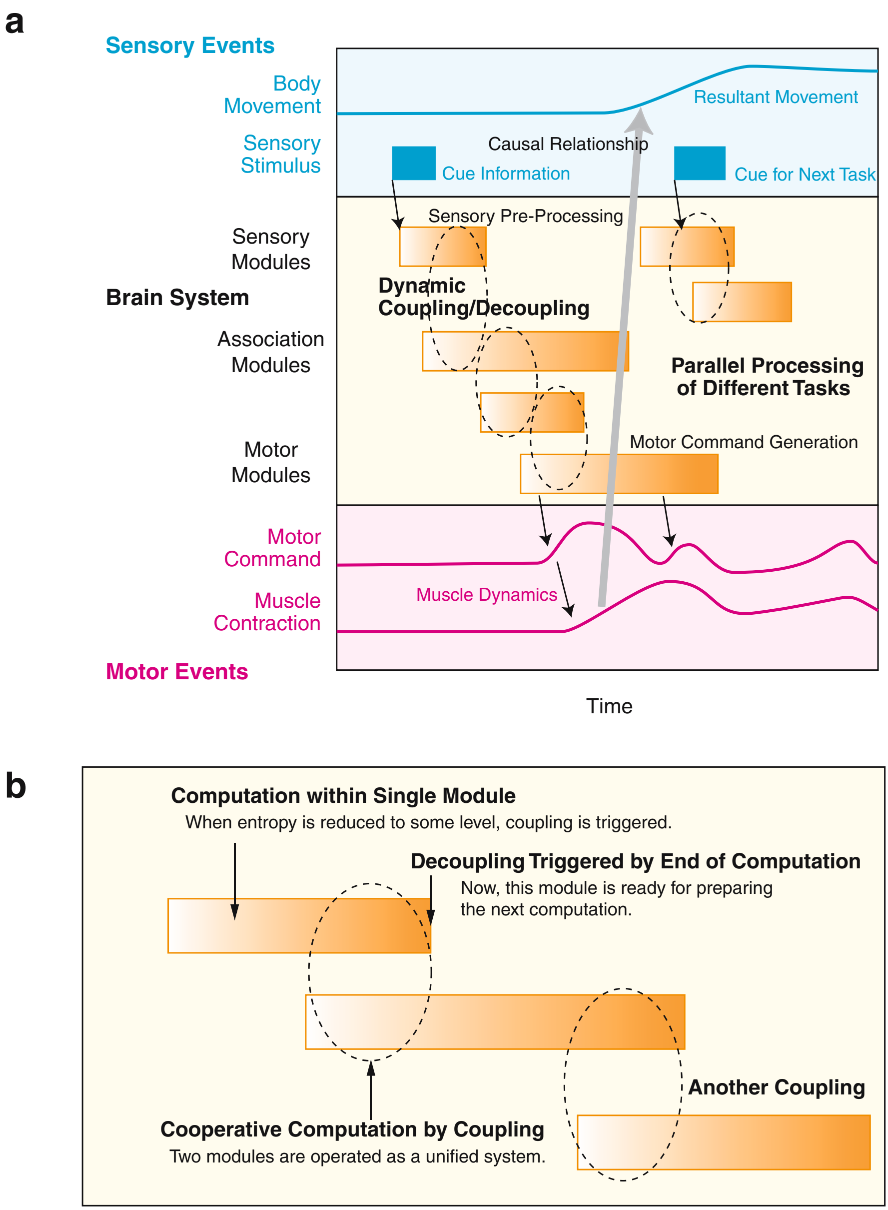

Fig. 3. An example of Gantt chart for brain computation

Figure 4 illustrates a typical scenario with this model, during the reaching movement. When a target is presented, the visual system acquires its position and creates its internal representation. Receiving this information, the command planning module starts to calculate the command pattern. From this point,

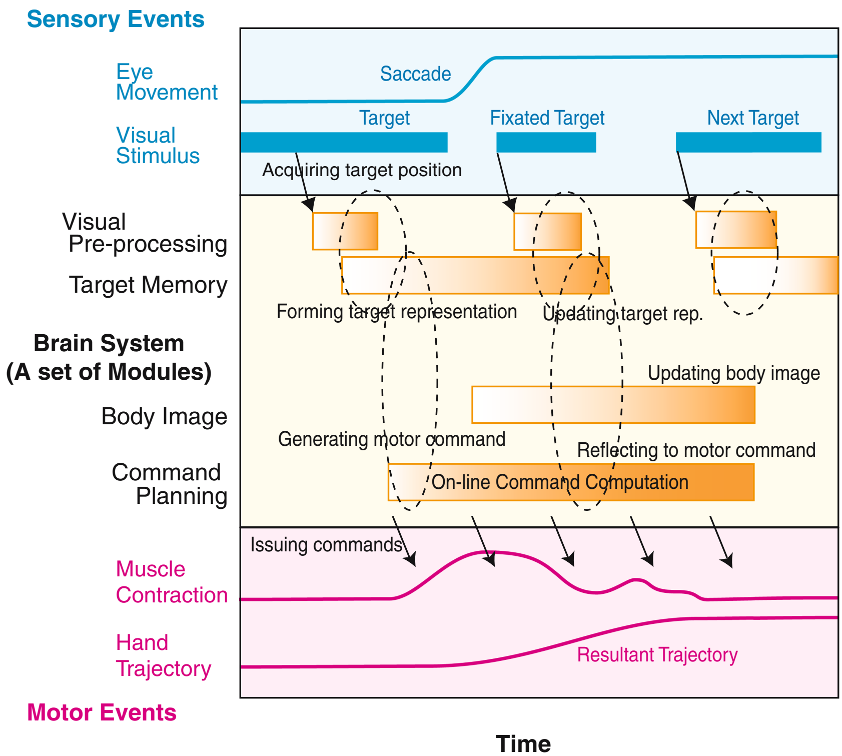

Fig. 4. A Gantt chart for an on-line command planning model of reaching movement

the planning module continues to calculate and issue motor commands towards the end of movement.[3] At the same time, the body image module updates the resultant body posture, cooperating with the planning module. On the other hand, a saccadic eye movement is triggered to capture the target within the fovea (i.e., the center of the visual field). When the saccade is done, the visual system acquires new target information and updates its internal representation. The command planning module reflects this updated information into the motor plan and later commands.

This chart, furthermore, illustrates the possibility that different modules can be engaged in different tasks in parallel. When we move the hand sequentially among multiple targets, our gaze often moves to the next target before the hand reaches the present one. This implies that the computation for the next action starts during the execution of the present action. This situation is represented

[3] Some researchers propose that motor commands are produced by central pattern generators (CPGs) in the downward pathway and that the brain need not to calculate the detailed commands [11]. Even if CPGs are essential for generating the final commands, however, it is still true that higher brain areas have to control them (i.e., activate CPGs at proper timings) for achieving purposive movements [12].

in the top-right part of the diagram: The target representation module starts to handle the information of the next target while the command planning module is still calculating the motor command for the current movement.

Therefore, the proposed diagram helps us to understand spatio-temporal structure of sensorimotor processing in human motor control.

Finally, digressing from our subject for a moment, the author would like to point out advantages of the on-line planning model introduced above, over the in-advance planning model.

From a viewpoint of efficient usage of computational resource, first, it is desirable that the command planning module keeps working throughout the movement (remember the discussion for the multi-processor system). If the planning has been finished by the movement onset, this module would have nothing to do during the movement execution, which seems inefficient. Moreover, if the commands are planned in advance, the brain has to prepare a buffer for holding the planned commands until the end of the movement. Therefore, the on-line motor planning seems more efficient than the in-advance planning.

Second, if adopting the on-line planning strategy, our brain can reflect the latest sensory information to the planning of on-going movement, as mentioned in the above scenario. Actually, this can explain why people could modify the movement without sensory feedback after making a saccade to the target: It was reported that if the target position was shifted during the saccade, the endpoint was shifted to the new target position even if no visual feedback is provided during the movement[10]. The in-advance planning model cannot explain this experimental fact.

5 Computation Flow in the Brain

Now, we go back to the detailed mechanism of the intra- and inter-module computations in the brain. In this section, the author develops some speculative discussion on these mechanisms.

5.1 Computation and Variability of Neural Activities

In a multi-processing computer system, the activity of a processing element (PE) is determined by whether a program is running or not on the PE. In the brain model, the activity of a module corresponds to neural activity in a specific brain area. In this sense, a Gantt chart may look like a time series of activity map obtained in recent neuro-imaging studies.

However, here we should also keep in mind that the computation in the neural system can proceed even if the average neural activity is maintained at an identical level: It was suggested that the variability of the activity, rather than mean activity, may reflect the progress in computation[7].[4] Below, the author

[4] The cited paper [7] showed that inter-trial variability of activity of single neurons (not population variability) of the monkey's premotor area diminished during the reaction time period and suggested that the movement was started when the variability decreased to some threshold level.

would like to discuss more about the relationship between neural computation and variability of neural activities.

The variability-based computation view is attractive in some points. First, considering that the "variability" or "uncertainty" is measured by "entropy" in the field of information theory, we can relate the neural computation to such information measures. Second, the motor planning of voluntary actions is essentially a search problem where the brain tries to choose a best command sequence for a given task from a number of possible sequences. In other words, motor planning is a process to reduce the possibilities of the motor command. Comparing the variability of neural activities and possibilities of motor commands, therefore, finding an answer of motor planning may correspond to reducing the variability of the neural activities.

This can be paraphrased as follows. The entropy of a neural module must be high when its component neurons are activated in a random manner (i.e., spontaneous firing). In this situation, no computation proceeds in this module. Once some cue signal is imposed, however, the activity would be updated into a more organized one, which reduces the entropy. When the network reaches an equilibrium state and the entropy reaches the minimum value, the network finishes the computation. That is, the progress in computation can be measured by the variability (or entropy) of the neural activities.

This view provides an explanation to a behavioral property related to reaction time (RT). RT is the time required for making an action responding to the trigger sensory signal, and it can be regarded as the time spent for solving the search problem. Accepting this view, RT should depend on the complexity (or size) of the search problem. In concrete, RT would be shortened if the number of possibilities of motor commands (i.e., the size of search space) is reduced before the trigger signal is provided. This corresponds to the empirical fact that RT is shortened when the response variety is limited and when richer task information is provided in advance.

Furthermore, the variability-based computation view can give an explanation to the relationship between the movement variability and reaction time. It is well known that movement variability increases as people are asked to make a quicker action (e.g., Fitts' law). According to the variability-based view, one possible interpretation is that this is because the brain is forced to make a motor output before the module reaches the optimal answer: Motor outputs obtained by such incomplete computation would vary trial by trial because they are generated before the variability of neural activities becomes sufficiently low. This resultantly brings larger inter-trial variability.

Therefore, the variability-based view suggests that the trade-off between the computational time and completeness determines the relationship between RT and movement accuracy of human behavior. This view is also meaningful in the point that it suggests that the computational variability can be a source of movement variability, in addition to sensory/perceptual and motor noises [3].

5.2 Information Processing through Inter-module Coupling

Finally, the author would like to discuss the inter-module interaction.

In a multi-processor computer system, PEs are operated separately and their communication are explicitly controlled by the system. In a neural system, in contrast, many brain areas are closely interconnected through bi-lateral connections and the neurons in different areas often show similar response properties. Therefore, we should think of some specific mechanism of inter-module communication applicable to brain model, which is essentially different from that for the computer system.

An important point is that the brain does not work as a statically unified network even if its component modules are closely interconnected: Some modules can be operated cooperatively while others can be operated independently, and such cooperative relations are formed and dissolved in a temporary manner. To be more specific, adjacent modules are coupled as a cooperative network to achieve a specific computation and dissolve the coupling when the computation is finished (see Fig. 3 (b)). Decoupled modules can behave independently and be engaged in different computations in parallel. A series of such coupling and decoupling mediates the information flow in brain, and finally brings an answer. This coupling/decoupling mechanism is essentially different from the communication in a multi-processor system in the point that the coupling creates a larger computational unit, not simply exchange information. In this sense, coupling is computation *per se*.[5]

Here, again, the entropy (or variability of the activity) plays a key role to indicate the progress in computation: The entropy reduces as the coupled module gets closer to the answer, and it reaches the minimum value when the computation is finished.

Therefore, the author's tentative view is that the brain achieves a complex computation with dynamic coupling/decoupling mechanism. Primary structure of coupling/decoupling is presumably set by an executive system because the primary process flow should depend on the task. However, timings of each coupling/decoupling must depend on the actual progress in computation, and this could determine the RT of the motor action. Of course, the relationship between RT and movement accuracy, discussed in the previous section, is also effective in the coupled network.

6 Concluding Remarks

In the present paper, the author first proposes a general diagram for real-time sensorimotor processing in the brain, based on the Gantt chart. Then, the author explained how to utilize this diagram by following the computational process of

[5] The idea of "cell assembly" or "dynamic cell assembly" hypothesis [8, 9] is a possible implementation of this scheme. This hypothesis says that a group of neurons forms a temporal organization and integrates information by dynamical foundation of bi-directional interactions, which corresponds to our coupling/decoupling scheme.

an on-line motor planning on the diagram. In addition, the author gave some speculative discussion on the relation between the progress in computation and the variability of neural activity, and on the relationship between reaction time and movement accuracy of human motor behavior.

The author believes that the proposed diagram be helpful to investigate the spatio-temporal computational mechanism of the brain. An ultimate goal of a computational brain research is to design the whole parts of this diagram so that the model's temporal behavior agrees with those observed in the behavioral experiments. To this end, we should link various physiological, behavioral and imaging data to this diagram, which forms a unified platform to integrate various findings on our sensorimotor functions: It is desirable that such a platform works as an environment where the experimental and computational studies are examined together.

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