A dual processing theory of brain and mind: Where is the limited processing capacity coming from?

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(1998). Y. Bar-Yam (ed.), New England Complex Systems Institute (1997).
InterJournal of Complex Systems, 98, 169.

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I thank my advisor Scott Gronlund for his help on previous versions of this manuscript.

Dynamical neural activity, which involves oscillatory and activity synchronization in neural firing, seems to have significant implications for understanding how the brain produces cognitive behavior. Computations based on dynamical activity require much more feedback information than is employed in traditional neural network approaches. The traditional neural network approach typically involves computation based on feed-forward mathematical mapping from input to output. Several findings, including the limited correlational dimensionality of EEG activity, suggest that if dynamical neural activity contributes to information processing in the brain, than its processing capacity is very limited. I review the evidence suggesting that dynamical neural activity might be responsible for the limited processing capacity observed in voluntary/conscious processes in human cognition and propose the following hypothesis: the brain changes its information processing strategy from heavily relying on dynamical activity toward processing that relies on unidirectional mapping as learning and the development of skills increase (i.e. processing becomes more automatic). This transfer results in a decrease in the need for limited dynamically-based resources. Computations based on such a transfer might provide powerful information processing properties that optimize the complexity of the computational tasks in the brain.

1 Introduction

Our understanding of how the cognitive behavior of the brain emerges from its computational elements (neurons) has profited from theoretical work using neural network simulations. Research on neural networks has had considerable success in recent decades. Neural nets have provided us with explanations of several brain/mind problems as well as a commercial technology that provides information processing based on the computational power of the brain. Perhaps, the most important mechanism employed in neural networks is the ability of several layers of units to provide mathematical *mapping* functions between input and output. A proper mapping between input and output is achieved by the synaptic weights between the units.

However, the neural networks did not succeed in providing answers to all the questions about the brain and mind that we wish to answer. Although almost any phenomena on the behavioral level has at least one corresponding model on the neural level, neural network models still are not sufficiently powerful theoretical tool for neuropsychological research. They still do not govern most of the research in either neurophysiology or psychology. One possible reason is that they do not include all the important neural mechanisms that the brain utilizes.

This paper suggests a possible important role of dynamical neural activity for information processing in the brain. However, there is a need for caution regarding the use of the term 'dynamical' when referring to neural activity. There is a long tradition of studying the dynamics of neural networks that is describable by dynamical system theory [35, 36, 37]. However, I will use the term 'dynamical' to refer to mechanisms that involve both oscillations and synchrony in neural firing. In this way, I broaden the definition of dynamical neural activity. Through this paper, I attempt to contrast dynamical neural activity with mapping in neural networks. I assign to them different processing roles in the brain's adaptive mechanisms.

2 Mapping in neural networks

The proof that neural networks have powerful mapping capabilities follows from Kolmogorov's theorem which shows that a three-layer feed-forward neural network with *n* input units, *2n+1* hidden units and *m* units in the output layer can implement any continuos function of a type:

$$f:[0,1]^n \rightarrow \mathrm{R}^m$$

f:[0,1]^n -> R^m

Later, it was shown that some neural networks can perform mapping from $\mathbf{R}^n$ to $\mathbf{R}^m$ with a sufficient number of units and/or hidden layers [10]. A particular mapping function is provided by fine tuning of the weights of connections between the units. In this respect, the brain is typically viewed as a highly parallel, multi-layered, mapping machine that maps input to output. In models that attempt to explain brain mechanisms, this mapping power is typically accompanied with many additional mechanisms that provide additional computational power. One example is the adaptive resonance theory [8]. The adaptive resonance theory includes top-down feedback connections, orienting and gain control mechanisms. The dynamical activity of the brain, as defined here was, in most of the cases, neglected or considered an epiphenomena.

For such a highly parallel mapping machine, as the brain was viewed to be, there does not seem to be any obvious reason why the processing would be limited in capacity. In other words, the architecture is such that a bottleneck in information flow does not exist [22]. The only reason for limited capacity in processing could be a need for sharing the same processing resources [16]. This paper, however, suggests that interesting information processing advantages that might emerge from the dynamical neural activity *must* have a very narrow bottleneck. In other words, unlike mapping, the brain is probably not able to perform information processing based on the dynamical neural activity in a highly parallel fashion.

3 Oscillations and synchrony in neural firing

Oscillatory neural activity has been observed for more than a century but until recently has been considered as an important processing mechanism by only a few scientists [13, 6]. The synchrony in neural firing, on the other hand, is a much more recent finding [28, 29, 30, 34], and only recently has been the importance of both oscillatory and synchronous activity seriously recognized [20, 21, 7, 11]. Although it is not clear how much the oscillatory and synchronous activity are related, in this paper it is assumed that there is a correlation between the firing rhythm and the oscillatory activity observed in EEG [28]. The relevance of synchrony in neural firing for information processing has been demonstrated by showing that the neurons that code for properties of the same object have a high level of synchronization of action potentials. It has also been found that just before a motor response on a visual stimulus is executed, cells in the visual, parietal, and motor cortex synchronize [25]. The best explanation of the binding problem in human perception is the synchrony in firing [4, 34].

3.2. Computational advantages of dynamical activity

One advantage of synchronous input to a cell is that the input becomes more effective (see Fig. 1). If cells A and B are synchronized and cell C fires with the same intensity but off-synchrony, than cell D could win the competition with cell E although cell E has stronger connections [28]. It has been also proposed and shown that synchrony in firing might enhance the synaptic learning process [28, 14].

An important computational advantage of the process depicted in Fig. 1 is that a specific pattern in synchrony in neural firing could temporarily override the learned synaptic weights and redirect the information flow in a new direction that has not been experienced or trained before. This effect is also a characteristic of voluntary or conscious processes that often provide new behavior that has never before been experienced.

4 Controlled and automatic processes in the brain

The difference between controlled and automatic processes in psychology has been known for long time [31, 32] and is closely related to conscious versus unconscious processes [12]. It could be exemplified by comparing the cognitive processes while driving a car for the first time and driving it after years of experience. When doing it for the first time, most of the actions are consciously controlled and the processing has very limited capacity. After prolonged training, the processing becomes in large part unconscious (i.e. automatic) and the demand on the limited processing capacity significantly decreases. This enables the driver to conduct other activities in parallel while driving (e.g., conversation). In this case, the processing moved from conscious or controlled to unconscious or automatic. The result of making processing unconscious is the freeing-up of processing capacity so that additional activities could be performed.

It is hard to provide a good measure of the size of the capacity space that is available for controlled processes. The best estimate of the capacity size, that psychologists have, is probably the Miller's ‘magic’ number 7 +/- 2 [17]. This number pertains to the number of items that one can hold in working memory, the number stimuli that one can attend to at the same time, and the number of categories that one can distinguish in absolute judgments. It has also been shown that with extensive practice people can overcome this limitation. Significant increases in processing capacity with practice have been shown for memory of numbers [2], restaurant orders [5], chess pieces [3], and serial search [9].

Besides the amount of the occupied processing capacity, controlled and automatic processing differ in other respects. The response time for automated reactions is much shorter than for controlled actions. A skilled driver, for example, reacts much faster to a new, possibly dangerous, event than a novice. Controlled processes seem to take more of capacity, and are slower to execute. The disadvantage of automatic processes is that they are much less adaptive than controlled ones. This means that it takes relatively long time to develop automatic processing and a long time to unlearn them when they need to be changed. Conscious processes, on the other hand, are very adaptive and they allow us to perform behavioral actions that we have no previous experience with.

A simple stimulus-response learning situation can demonstrate the difference between automatic and controlled processes. Both processes can result in similar behavior, say, closing an eyelid after a tone. One way to acquire an automatic response is classical conditioning where the tone could be paired with an air-puff. In this case, several hundreds of parings are necessary to establish the response on the stimulus. On the other hand, one can give an instruction to a person: `close your eyelid whenever you here the tone'. Both manipulations will lead to the same result: the eyelid will close after the tone. However, these two processes are fundamentally different. The first difference is in the time it takes to establish each. Whereas the automatic processes employing conditioning need hundreds of repetitions, the controlled process needs only one instruction or decision. Thus, the adaptability of the controlled process is obvious: one can quickly produce new behavior that has never been experienced before. This is not the case with the automatic processes. Controlled processes have the same adaptability advantage if the behavior has to cease. Again, a simple instruction to quit responding is sufficient for controlled processes whereas automatic processes need again a number of extinction trials.

Finally, controlled processes can control automatic processes. Controlled processes can trigger automatic ones, shut them off, or retrieve them into consciousness when the situation requires it (i.e. novel situation). This adaptive feature of controlled processes is probably one of the most powerful computational mechanisms that the brain has.

5 Is dynamical neural activity responsible for controlled processes?

A comparison of dynamical processing in the brain with the mapping shows the same three basic differences in controlled and automatic processes: speed, adaptability and limited capacity.

5.1. Adaptability

The patterns of oscillatory activity and synchrony in neural firing change quickly [29]. A new oscillatory pattern can be produced in several hundred milliseconds. Structural changes, on the other hand, take much longer time. They could take anywhere from several minutes to several days [27]. Therefore, the fast changes in behavior due to controlled processes are more likely to be caused by changes in some dynamic oscillatory patterns rather than by structural synaptic changes. In contrast, the relatively slow changes in behavior, due to the development of an automatic process, will likely result in structural changes in the synapses.

5.2. Speed in processing

The processing that takes place in a dynamical system includes feedback information. Processing with feedback information is slower than one-directional, feed-forward processing that takes place in mapping processing. Therefore, the slow processing in controlled processes could be attributed to the time needed for a dynamical system to reach a new pattern of oscillations or synchrony patterns after a stimulus is presented.

5.3. Limited processing capacity

Mapping processing does not have an obvious limitation on processing capacity. In other words, many separate neural network modules can receive input from the same input and process it in parallel, without disturbing each other. They can also submit their results to the same output module without slowing down each other [22]. On the other hand, there are several sources of evidence that suggest that the dynamically based processing is narrowly limited in its processing capacity. In other words, it seems that there is always a small number of separate neural, concurrently existing, groups which contain synchronized neurons. Attempts to simulate synchronous neural firing result in a small number of separate groups [11]. More direct evidence is provided from EEG recordings. This evidence comes from the phase space reconstruction of EEG time series and the estimation of the embedding dimension. The embedding dimension represents the minimal number of differential equations necessary to reproduce the time series. In our case, a group of neurons that oscillate together could be regarded as one differential equation in the system. The embedding dimension, therefore, gives a rough estimate of the number of separate neural groups oscillating at the same time. Analyses have shown that the embedding dimension varies between 3 and 10 [1, 26]. If one group of oscillating neurons provides a temporary change in overall processing, than the number of those changes in the same time is limited to a one-digit number. It is interesting to note that the embedding dimension for EEG is in the same range as the psychological measure for the maximum capacity for controlled processes (i.e., 7 +/- 2).

From the comparison of the processing characteristics of controlled and automatic processes on the behavioral scale and mapping and dynamical processing on the cell scale of brain's behavior it follows that: controlled/conscious processes rely more on the dynamical neural activity than do automatic/unconscious processes.

6 Derived hypothesis

There are several hypotheses that follow from the proposed role of dynamical activity for controlled processes.

6.1. Harder tasks have larger dimensionality

The tasks that are more difficult require more voluntary effort, and should require more temporary changes in the neural nets implemented by dynamical processes. The embedding dimension of the underlying activity (e.g., the number of oscillating neural groups) should therefore be larger for more difficult tasks. There is indirect support for this hypothesis that comes from recent research on the embedding dimension of the reconstructed phase space of repetitive hand movements. Mitra et al. [18] have shown that repetitive hand movements produce chaotic activity with embedding dimension between 3 and 4. Swinging a heavier stick produces a smaller dimension than swinging a light stick. The participants, however, judge swinging the heavier stick as being a much easier task than swinging the light stick [24]. This finding provides only indirect support for the hypothesis because dynamical neural activity was not measured (they only measured the dynamical activity of hand movements). The notion that the brain couples with the environment through its dynamical activity [7, 15, 33] suggests that the complexity of the dynamical activity of the movements reflects the complexity of the neural activity that produces those movements.

6.2. Transfer from dynamical to mapping processing

Because controlled processes rely more on dynamical processing, and automatic processes rely more on mapping, during practice when controlled processing becomes automatic, the dynamical processing should be replaced with mapping. In other words, with automation of an activity, the ratio of involvement of dynamical and mapping processing should change so dynamical processing becomes involved to a lesser extent. Greater reliance on mapping frees the limited processing capacity of dynamical processing for additional parallel processes. This prediction receives, albeit indirect, support from the hand movement research. Mitra at al. [19] have found that with practice the dimensionality of repetitive hand movements decreases.

6.3. Automatic processes that are under conscious control

Some automatic processes are under voluntary control, meaning that they can become conscious if it is necessary. Eye-blink and breathing are examples of processes that are very automatic but that can be brought under conscious control and therefore be controlled by a conscious decision. Other automatic processes (like patellar reflex, many processes in autonomous nervous system (ANS) and emotional responses) cannot be directly under conscious control.

There also probably is a difference in the neural processes that underlay consciously controllable and not controllable automatic processes. The view on the controlled and automatic processes proposed here suggests an explanation: If voluntary processes perform control through dynamical activity than automatic processes that can be consciously controlled should employ, to some extent dynamical activity (i.e. oscillations and synchrony in neural firing). If they employ dynamical processes, than they should be subjected to the limited processing capacity, at least to a small extent. The support for this prediction comes from eye-blink research. It has been found that the eye-blink reflex decreases its activity if a second hard task is given to participants. Stern [23] had participants hold six digit numbers in working memory while eye-blinks were recorded. The average time between two eye-blinks significantly decreased compared to a situation where participants had to memorize only two items. The eye-blink reflex is therefore subjected to limited processing capacity. However, the reflexes that are not under conscious control, should not be affected by a secondary task. There are no experimental data that I am aware of that would suggest and answer to this prediction.

7 Conclusions

The differences in some of the processing characteristics between one-directional mapping in neural networks and the dynamical activity in the brain seem to match the difference in processing characteristics between automatic and voluntary processing. In addition, experimental support exists for several hypotheses derived from an assumption that this match is not coincidental. It appears, therefore, that the brain uses heavily dynamical processing of information in novel situations where conscious processing is necessary. Familiar, previously experienced, processing on the other hand seems to rely much less on dynamical activity but more on the learned one-directional mapping.

The transfer from dynamical to mapping processing with experience has implications on the optimization of computational complexity: The brain adapts so that in familiar situations it executes computations by involving a small amount of resources. In novel situations, however, the brain seems to use larger amount of resources by combining the already learned mappings with the flexibility of the dynamical processing.

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