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Vicarious function in the motor cortex A computational investigation

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Abstract

This paper presents a computational investigation of the vicarious function in the motor cortex (c/o the ability to reorganise its functioning by virtue of a shift of the lost function in the surrounding cortex which becomes able to vicariate). Several experimental studies in animals and humans have shown that motor recovery after partial destruction of the motor cortex is based on adjacent motor reorganisation. This study provides phenomenological evidence of this vicarious function. We tested the hypothesis according to which the vicarious function is possible because there is a synaptic rearrangement of the weights (which are comparable to the synapses of the brain) of the lesioned layer (*unmasking of previous silent synapses* hypothesis), and our results confirm this hypothesis. We argue that functional recovery is possible only when having bidirectional connections and that it is facilitated when non-M1 areas can guide the layer to relearn the lost movement.

Keywords: Vicarious learning; Stroke; Rehabilitation; Functional recovery; Neural network model; k-Winners-Take-All

Recovery of a motor or cognitive function after a stroke can be due to several factors, including events in the first days (e.g., reabsorption of edema, tissue reperfusion), and more slow processes lasting for months such as cortical reorganisation [16]. Of great interest for the present study are the second class of mechanisms. Cross-sectional PET and fMRI studies of hand movement after full recovery have shown that patterns of activation after stroke are significantly different from those of normal individuals [see 16 for a review]. However, the reasons for such differences are not clear.

Several experimental studies in animals [4,5,10] have shown that motor recovery after partial disruption of the motor cortex is based on adjacent motor reorganisation suggesting a vicarious function in the motor cortex. In a longitudinal study, Jaillard et al. [7] examined four patients suffering from ischaemic stroke limited to the M1 area. The test comprised two motor tasks: a finger tapping and a finger extension. They reported a progressive dorsal shift of the area activated by the tasks in respect of controls, reflecting an increasing functional reorganisation of the surrounding cortex. After 2 years the four patients showed a complete recover of the finger motor tasks in the intact dorsal M1. An additional observation was that motor-related activation of supplementary motor area (SMA) correlates with faster and better motor recovery [9]. This finding has been interpreted as reflecting an adaptive response to an increased demand related to the need to relearn the motor tasks after stroke [7].

Despite the fact that motor recovery observed after lesion is well documented in the literature [3,11–13], the attempts to study the underlying neural mechanisms are very few. There are three hypotheses generated to account for the "vicarious functioning": the first namely "synaptogenesis", refers to the creation of new synapses in the surrounding area, the second "dendritic arborisation", refers to the expansion and/or creation of new dendrites, the third "unmasking of silent synaptic connections", by which the synapses that were silent up that moment, start changing and functioning. Even though imaging techniques and animal studies showed that a cortical reorganization does exist in the brain, unfortunately they cannot tell us anything about the mechanisms that permit this recovery. By means of computational simulations it is possible to study these problems with formal models in which different hypotheses can be tested to show which is the best in reproducing the effect.

In this study we tested the hypothesis whether after a lesion of the area corresponding to a movement, an artificial neural network system is able to recover the function by vicarious learning focusing on the mechanism of the "unmasking of previous silent

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synapses". We also tried to investigate the potential factors that make this relearning possible. We decided to implement the same motor tasks used in the study of Jaillard et al. [7] (finger tapping and extension). To pursue our aims we bore in mind two relevant observations derived from the literature: (1) the importance of the *time* of rehabilitative training and (2) the role of other non-M1 areas in influencing the task performance during relearning (as for example the SMA, in [9], or the same controlateral regions via transcallosal connections, in [16]).

We built a simple phenomenological model to study the vicarious learning, focusing on the mechanism of the "unmasking of previous silent synapses". This approach is contributive as a meta-model of plasticity mechanisms. However, it is not the case in which the model enables us to account for all the phenomena such as degree of ischaemia, edema, physiology of the movement.

The model is a multi-module neural network consisting of four layers [see Fig. 1 and Appendix A for technical details]. The input layer encodes both the movements schema (finger tapping and extension). This layer consists of a matrix of 2×7 units with one set of units representing *observed actions* (tapping and extension) and another *executed actions* (tapping and extension). The input layer is connected to an "action representation" (AR) layer consisting of a matrix of 2×7 units with one set of units representing observed actions and another executed actions. The latter has a bidirectional connection with the "action schema" (AS) layer (where observation and execution are effectively collapsed into schemas for each action). This layer consists of a matrix of 10×12 units in which the two movements (one representation for the observed and executed tapping, and one for the observed and executed extension) are coded. The action schema is in turn connected to the output layer (2 units).

The two motor tasks, the "finger tapping" and the "finger extension" are implemented as different attractors. Their kind of representation changes for each layer: in both the input layer and the AR layer, the two movements are represented in an abstract and more symbolic way (one unit per movement obtained by implementing a Winner-Takes-All algorithm [6,14,15]); while in the AS layer, the implementation is more realistic with 8 units that respond for each movement (obtained by a modified version of the k-Winners-Take-All in which $k = 8$ units are active). It is important to stress that in this simulation we are interested in studying the recovery of the representation which permits the execution of the movement, and not in all the parameters related to the execution of the movement itself (kinematics) such as speed, strength or angular acceleration.

The model of artificial neural network developed here [see 6 for further details], is a simple not-completely recurrent neural network which is able to reproduce finite-states attractor dynamics: once the input is given the net performs several cycles in which the weights are updated to reach the final, stable state. The *number of cycles* to reach this state can be viewed as the time of the net to perform the task.

Learning employed O'Reilly's LEABRA (Learning in an Error-driven and Associative, Biologically Realistic Algorithm: [14]) formalism. This is based on point-neuron activation function with k-Winners-Take-All inhibition (that achieves sparse distributed representations with Gaussian distribution by means of inhibitory interconnections) and a plausible version of the error-driven learning [1] in which the contrast between positive and negative phase is used to adjust the weights in a local fashion, without external teaching signal:

$$\Delta w_{ij} = (x_i^+ y_j^+) - (x_i^- y_j^-)$$

The algorithm minimises the distance between the two distributions.

The network was trained by presenting the following pairs of input–output associations: (1) finger extension movement in the

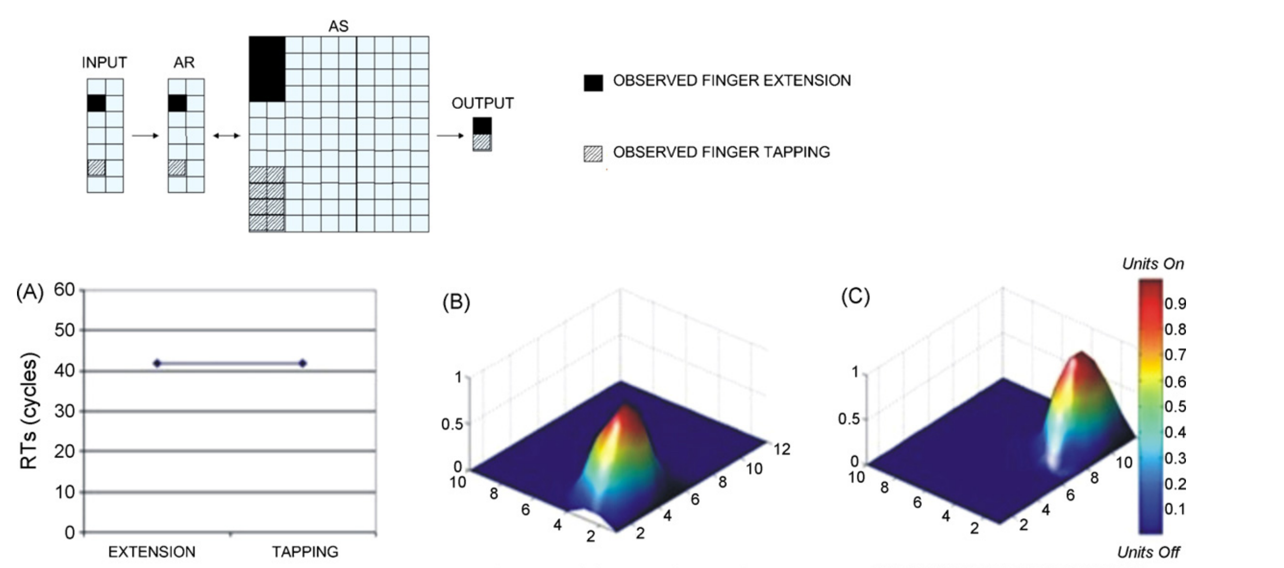

Fig. 1. Upper part: The model of the artificial neural network is shown as well as examples of movements' representation. See text for details. Lower part: Development of sparse distributed representation for finger tapping and finger extension. (A) The number of cycles the net requires to execute the two tasks (RTs). (B) The representation for the finger extension. (C) The representation for the finger tapping.