Neuroscience Letters 581 (2014) 80–84

Contents lists available at ScienceDirect

Neuroscience Letters

journal homepage: www.elsevier.com/locate/neulet

Integrative activity of neural networks may code virtual spaces with internal representations

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HIGHLIGHTS

- Spatial differentiation of fMRI activity indicates its integrative nature.
- Limitations of neuroimaging techniques preclude the direct interpretations.
- Using random numbers, we trained neural networks to integrate.
- Hierarchical networks learned faster and more efficiently than a single network.
- Spatial differentiation of the model activity reproduced the presented stimulation.

ARTICLE INFO

Article history:
Received 26 June 2014
Received in revised form 31 July 2014
Accepted 18 August 2014
Available online 23 August 2014

Keywords:
Integrative
Neural coding
Internal representations
Brain activity

ABSTRACT

It was shown recently in neuroimaging that spatial differentiation of brain activity provides novel information about brain function. This confirms the integrative organisation of brain activity, but given present technical limitations of neuroimaging approaches, the exact role of integrative activity remains unclear. We trained a neural network to integrate information using random numbers so as to imitate the "centre-periphery" pattern of brain activity in neuroimaging. Only the hierarchical organisation of the network permitted the learning of fast and reliable integration. We presented images to the trained network and, by spatial differentiation of the network activity, obtained virtual spaces with the presented images. Thus, our study established the necessity of the hierarchical organisation of neural networks for integration and demonstrated that the role of neural integration in the brain may be to create virtual spaces with internal representations of the objects.

1. Introduction

On the basis of the large number of experimental data, there is a general consensus that brain function and especially cortical function can be characterised as integrative with respect to the incoming information [1,2]. If brain activity is integrative, one can ask whether the inverse to integration method, differentiation, may help decode the incoming information [3–6]. Using spatial differentiation of the summary fMRI images, it was demonstrated recently [5] that differences of activity between the neighbouring voxels are significant at the group level even after the correction for multiple comparisons [7]; thus, they are stable between the subjects in certain loci of the brain. The resulting activity depends on specific types of stimulation, meaning that it reflects information-dependent differential coding. Even more curiously, some interesting patterns resembling visual stimulation can be found in fMRI activity by using mixed spatial differentiation [4].

However, the neuroimaging size of a voxel technically available is not a meaningful level of brain organisation. The absence of results may mean the approach is not sensitive to the adequate level of resolution. Besides, the size of the smallest information-encoding volume in the brain remains unknown; for practical purposes it can be chosen only arbitrarily on the basis of the technically available spatial resolution. The limitations of neuroimaging [8,9] necessitate the exploration of the integrative brain function using integrative neural modelling, which would imitate the patterns of brain activity.

In this study, we tested the hypothesis of whether an integrative neural network can be constructed to provide a pattern of activity similar to the patterns observed in neuroimaging and whether one can reconstruct the presented stimulation from this activity using differentiation.

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http://dx.doi.org/10.1016/j.neulet.2014.08.029
0304-3940/

We trained a neural network to integrate using random numbers and then presented different images to this network. The network organisation imitated the "centre-periphery" pattern of brain activity in neuroimaging. The resulting activity of the network was differentiated to see whether the presented images can be decoded from its integrative activity.

2. Materials and methods

The feed-forward neural network (Fig. 1) was constructed using the ffnet Python library (http://ffnet.sourceforge.net/cite.html). The hierarchical construction comprised two networks.

The first network was trained to perform integration of three numbers, the target was Simpson integration (implemented by the simps function in the Python Scipy package) performed on three pseudorandom numbers in the range of 0–255. As exact integration algorithms in neural populations are unknown and may differ between neural populations, the Simpson integration algorithm was chosen only as an example. The network consisted of two layers: (3, 1); the number of trainings were 1000.

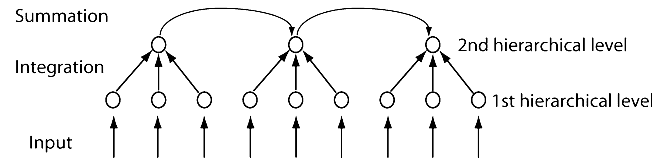

Fig. 1. Schematic representation of the integrative neural model. The first hierarchical level receives the input per pixel and performs the integration of each of the three inputs in a "three to one" way. Afterwards, the result is transmitted to the second hierarchical level where further integration is performed by the cumulative summation of the first-level values.

The second network continued the integration: using the rule that the integral of the sum equals the sum of the integrals, it summed up the results of the first network. Having received two values from the first network (Fig. 1), the model added them up so that each node of the second network had a summary value of all the preceding nodes in the row. The result was that the first integration was by rows, and then the network passed the resulting values by columns again to the first network, finally resulting

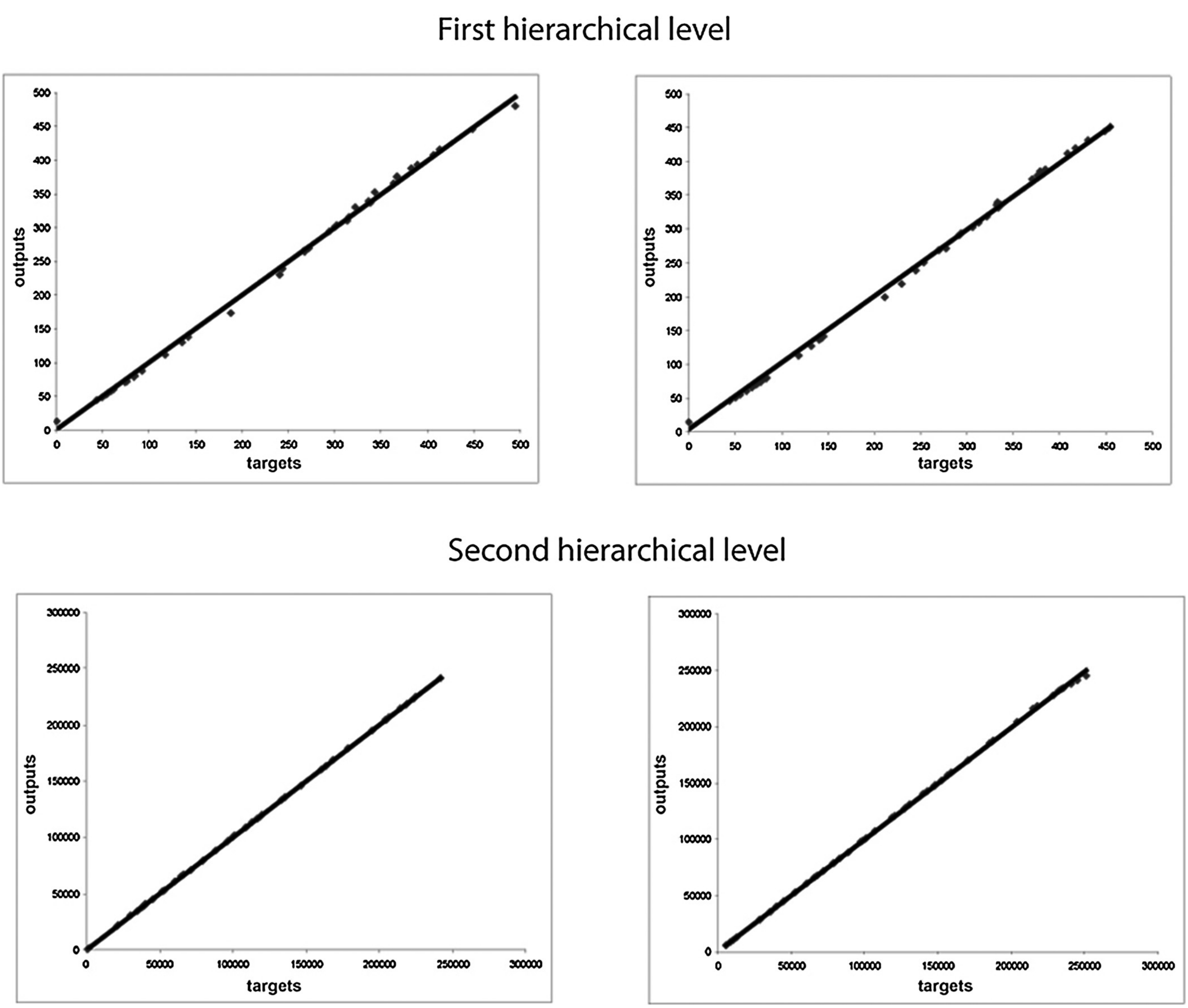

Fig. 2. Relations between the targets and the outputs of the trained model. Regressions are shown for each hierarchical level of the model, the result of the tnc training algorithm on the left and the cg training algorithm on the right ($r > 0.9$, $p < 0.01$).

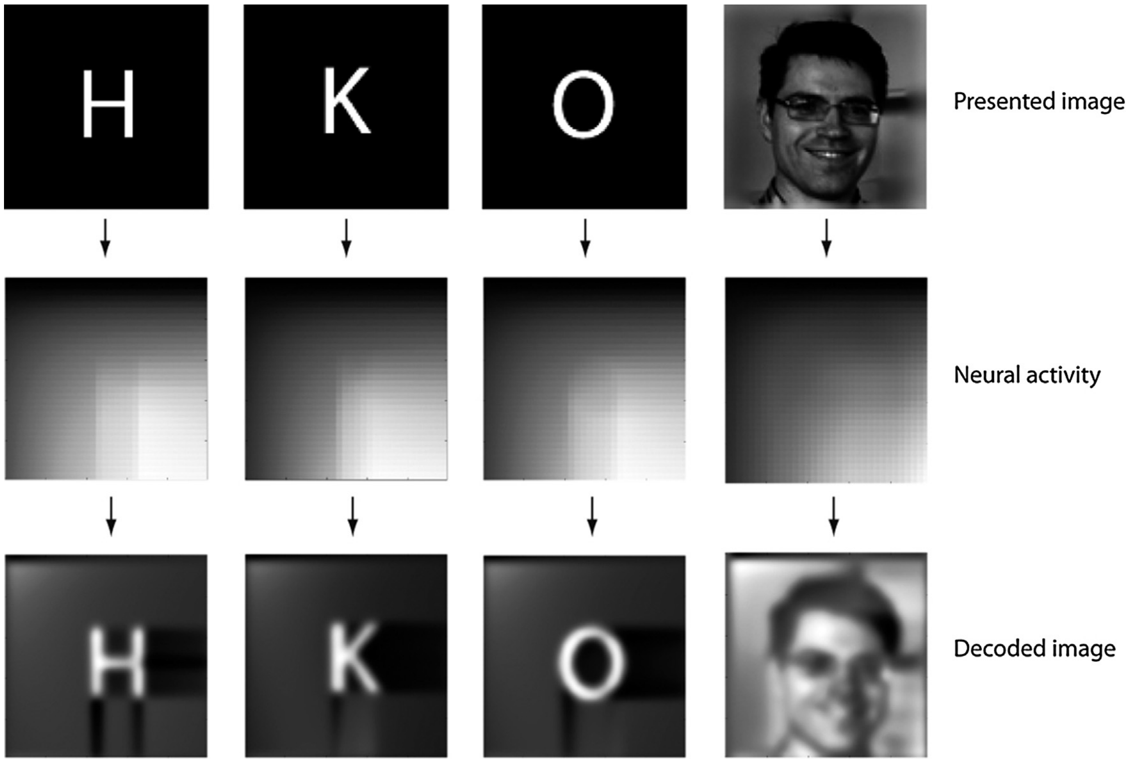

Fig. 3. Virtual spaces obtained by spatial differentiation of network activity. Different types of presented images are shown with the corresponding network activity and the results of its spatial differentiation.

in the values of two-dimensional integration in each node of the second network.

To train the network, we used two pseudorandom numbers in the range of 0:255; the first number was multiplied by the value indicating the increasing presentation number. The network consisted of seven layers: (2,2,2,2,2,2,1); the number of trainings were 1000.

Several training algorithms were tried for each of the networks (tnc, momentum, cg, rprop); for the first network, all resulted in the high correlation between outputs and targets ($r > 0.9$). Similarly, high correlations ($r > 0.9$) were observed for the second network except for the momentum algorithm, which failed to converge with the outputs being all the same number.

The constructed integrative network was able to integrate the presented images in two dimensions. The images were presented by pixels (three intensity values at a time) to the first network, which performed the first-level integration of these values and transmitted the result to the second network as described above.

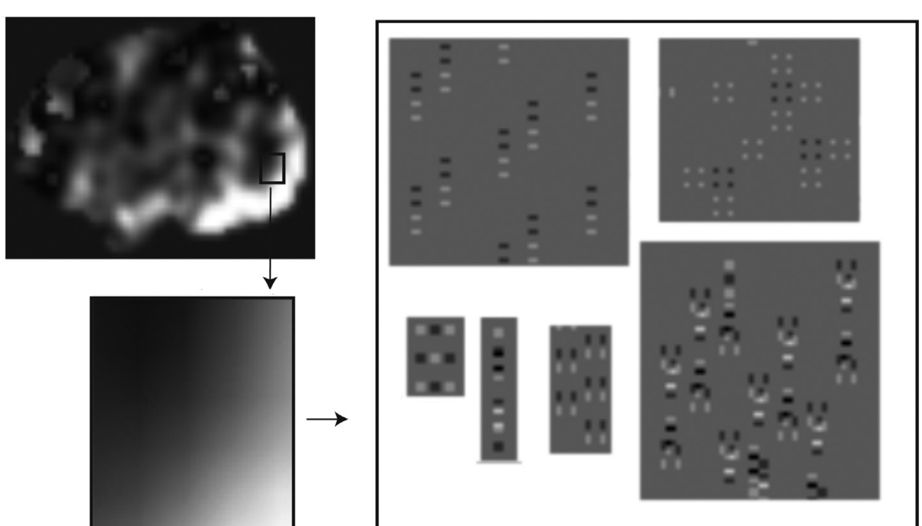

Fig. 4. Example of spatial differentiation of brain activity in fMRI data. An activity map was taken from the publicly available dataset on face perception (http://www.fil.ion.ucl.ac.uk/spm/data/face_rfx/), subject 8. The patch of activity was differentiated and various regular shapes were found in the virtual space of this hierarchical level of activity, as shown on the right.

To analyse virtual spaces in the resulting activity maps, they were differentiated taking the second-order partial derivatives according to the equation:

$$D(x, y) = \frac{\partial I(x, y)}{\partial x \partial y} \quad (1)$$

where D is the resulting differentiated matrix and I is the matrix of initial activity in the coordinates x and y.

3. Results

We found the efficient learning to integrate could not be obtained using only one neural network; it requested at least two hierarchically organised feed-forward networks. Small blocks of integrated information were passed from one network to another and were summarized to obtain the complete integration. This design permitted us to obtain surprisingly efficient and rapid learning to integrate random numbers: only a few seconds on an ordinary PC were needed to obtain the high integrative performance of the hierarchical network. While the first-level network could learn well only with two layers, the second-level network requested seven layers to obtain efficient learning. The highly efficient learning of the hierarchical network could be obtained using different training algorithms; thus, the chosen learning algorithm was not the crucial factor for the model performance (Fig. 2).

Having trained the hierarchical model with random numbers, we presented different images to the modelled network. The resulting integrative activity of the neural network was differentiated spatially to see whether the presented visual stimuli could be decoded from activity. Spatial differentiation permitted us to decode the images of various letters and even such a complex pattern as a picture of a human face (Fig. 3).

4. Discussion

Firstly, our results demonstrate the optimal way to organise integrative processing in the brain is to use multi-stage integration with hierarchical networks. The striking advantage of the hierarchical neural networks for integration explains the wide usage of the hierarchical systems in the brain [10]. As we used simplified stimulation (without colour, volume, context effects, etc.), only two hierarchical networks were sufficient. In the brain, which processes much more complex and diverse stimulation, the levels of hierarchical organisation for integration are much more numerous. Fig. 4 illustrates some regular patterns, which may be found in the virtual spaces obtained at one of the levels of integrative processing in the associative visual cortex, using fMRI. As we mentioned in Section 1, the size of the smallest information-encoding volume in the brain is unknown; the volume of one voxel in neuroimaging is imposed by technical limitations. Only when this volume is close to the physiological information-encoding volumes, meaningful results of differentiation can be obtained. The nodes of our model represent interconnected neuroglial units but their volume is not specified in the model.

As integrative information is accumulated more, there is an increase in activity towards the lower right part of the activity patches where the peak activity is observed. As activity in physiological conditions corresponds to energy turnover [8], one cannot expect infinite activity at the peaks. This energy limitation [11,12] could be another reason for the hierarchical organisation of integrative networks because integration is divided into stages and the neural network at each stage does not exceed the physiological limits of energy turnover. Besides, one can expect feedback mechanisms from the neural populations with peak activity to the other neural populations to scale down energy consumption of the whole network. Future modelling would be useful to clarify the role of feedback mechanisms in integrative hierarchical networks. We suggest some integrative capacities of the brain are inborn and some are learned during the experience.

Having differentiated the integrative neural activity, we expected to obtain virtual spaces that correspond to the presented stimulation, as differentiation is the opposite of integration operation. The observed patterns in virtual spaces are coded by the spatial organisation of stable stimulation-specific activity propagation between neuroglial structures. In our method, the patterns of integrative activity and virtual spaces were formed as the result of learning to integrate with random values. This could correspond to the inborn capacity of the brain to integrate the incoming information. However, during the lifespan, various non-random objects are encountered (e.g., human face). Interaction with such objects may create constant patterns of integrative activity in the brain with corresponding internal representations in virtual spaces. One can suggest that the most frequent patterns, such as the human face, should be the most represented in the brain and the easiest to detect (e.g., see an example of the face pattern in the virtual space of fMRI activity [4]). The already pre-wired internal representations can be activated by the stimulation at any spatial localisation, more likely by the stimulation at the site of the peak activity: the lower right corner of activity patches in our model. As glia is also involved in memory formation [13], the nodes of our model can correspond to neuroglial units in the brain.

Though we used the most convenient modality for the visualisation of results, we believe that similar integrative approaches can be used to model patterns of brain activity in other sensory modalities (auditory, proprioceptive, etc.). For example, networks in other modalities can operate with the images of the time–frequency representations of the signal.

Thus, the decoding method based on spatial differentiation permitted us to pass from patterns of integral neural activity to the virtual spaces containing the neural representations of the presented objects. Our results confirm that regular patterns observed in the differential spaces of fMRI activity can be explained by the integrative nature of this activity. They present the first principled approach to the integrative modelling of brain activity as observed in neuroimaging, and they provide a perspective to model physiologically realistic complex hierarchical networks used for integrative processing in the brain.

Acknowledgement

This work was supported by the region Midi-Pyrénées (RTT No. 10006537).

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