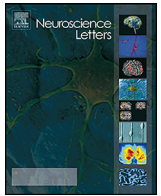




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Integrative activity of neural networks may code virtual spaces with internal representations

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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.

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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.

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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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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 ffnnet 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.

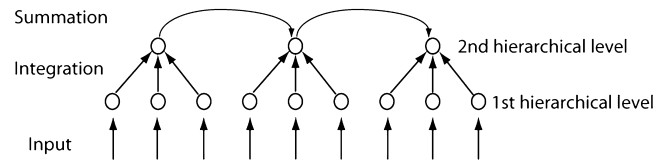
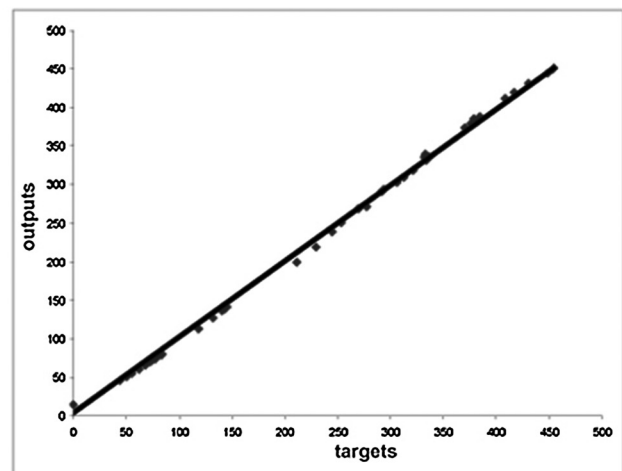
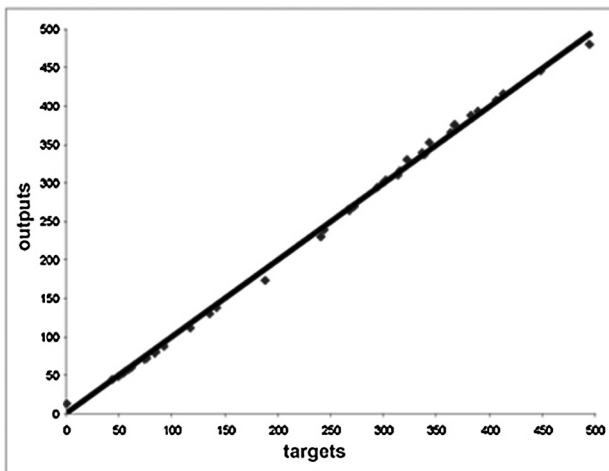


Fig. 1. Schematic representation of the integrative neural model. The first hierarchical level receives the input per pixel and performs the integration of each of the three inputs. Afterwards, the result is transmitted to the second hierarchical level where further integration is performed by the cumulative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

First hierarchical level



Second hierarchical level

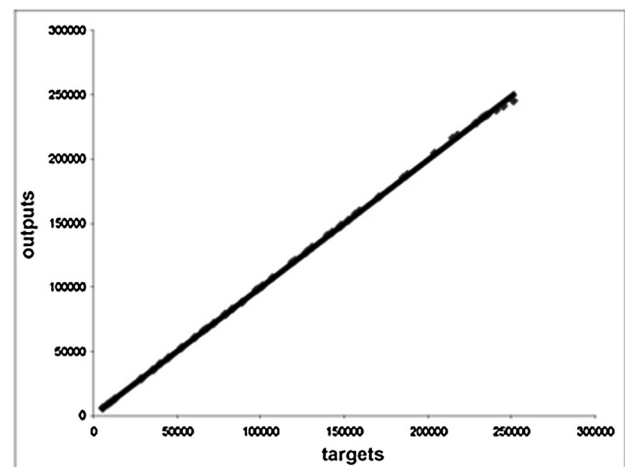
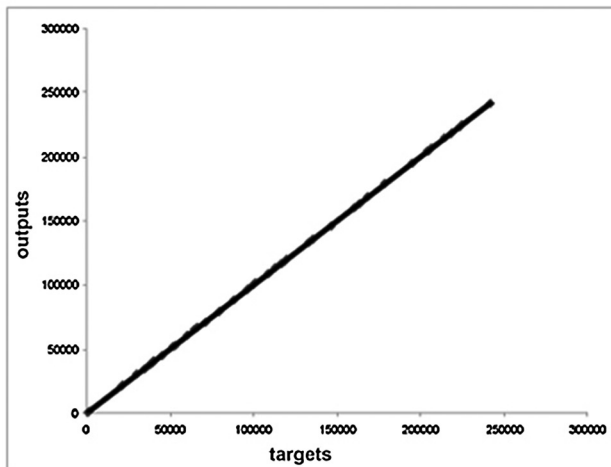


Fig. 2. Relations between the targets and the outputs of the trained model. Regressions are shown for each hierarchical level of the model, the result of the tnc training algorithm on the left and the cg training algorithm on the right ($r > 0.9$, $p < 0.01$).

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