# SUPPLEMENTARY MATERIAL FOR:

# THE ORGANIZATION OF THE MONKEY EXTRASTRIATE VISUAL CORTEX RE-EXAMINED USING THE PRINCIPLE OF SPATIAL CONTINUITY OF FUNCTION

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## METHODS DETAILS FOR THE OPTIMIZED FOUR-STREAM MODEL

### *Match metric for the optimized four-stream model*

To produce the optimized four-stream model, we begin with an information structure, rendered it onto the model cortex using the Kohonen algorithm, assessed how closely the resulting map resembled the actual map in the monkey brain, and then systematically refined the information structure to optimize the map. Through an iterative search, we obtained a form of the information structure that mapped to the cortex in a fashion almost exactly conforming to the topography in the monkey brain. To perform this search, it was necessary to quantify the degree of match between the map produced by the model (the derived map) and the actual map of the monkey cortex (the real map). Two metrics were combined: node matching and inter-areal distance correlation.

*Node Matching.* The similarity between the derived map and the real map was assessed by counting the number of matching nodes. The model of the visual cortex contained 1892 nodes. Each node could represent a match (if the node represented the same visual area in the derived map and the real map) or a mismatch (if the node represented a different visual area in the derived map than in the real map). We measured the degree of match as the percent of matching nodes. A perfect match would score 100% and a total mismatch would score 0%.

*Inter-areal distance correlation.* It may be possible for the derived map and the real map to be offset or rotated from each other and yet still be similar in the topological relation of areas to each other. In this case, a node-matching score would not necessarily accurately reflect the degree of match. We therefore constructed a second value function based on the relative positions of visual areas. The centroid of each visual area was calculated and all pair-wise distances between these centroids were computed. This distance matrix was calculated for the derived map and for the real map. A correlation was taken between the two distance matrices to measure similarity. If the inter-areal distance matrices were identical between the two maps than a correlation value of 1 would result. If the inter-areal distance matrices were randomly mis-matched between the two maps than a correlation value of 0 would result.

Both match functions (node-matching and inter-areal distance correlation) captured different useful aspects of the similarity between maps. To take advantage of both approaches, we used the product of the two. The final value function was therefore the node-matching score times the inter-areal distance correlation. If the derived map and the real map were identical, then the value function would be 1. A total mismatch would result in a value function of 0. The purpose of this match value function was to enable us to modify the model systematically in order to optimize the match.

### ***Genetic algorithm for the optimized four-stream model***

We systematically modified the parameters of the information structure in order to optimize the match between the derived map and the real map. The goal was to find the particular values of parameters (the hierarchy value, the values of dimensions A through D, and the number of data points for each of 15 visual areas) such that the information structure would map to the cortex in a manner that fit the actual monkey brain. Because the information structure included a large number of parameters, finding an optimal fit involved searching an extremely large parameter space. Therefore, normal methods of data fitting were not applicable to this task. We used a genetic algorithm, since such algorithms have been found to successfully find good solutions within a large search space. Differential evolution (based on the method in Price et al. 2005; Storn and Price 1997) was used to find the set of parameters for the information structure that maximized the match value function. Briefly, a population of randomly varying information structures was created. For each information structure, the match value function (described in the previous section) was computed. The information structures with the highest value functions were chosen and combinations of those information structures were used to construct a new population according to the differential evolution scheme. This updating of the population was performed over repeated generations.

*Stage 1:* We first optimized the dimensions of A through D for each data cluster. With 15 data clusters, this search space was 60-dimensional. We generated an initial population of 1200 members (following the standard method of using 20x the number of parameters). We allowed the differential evolution algorithm to run for 100 generations. Thus 120,000 variants were tested.

*Stage 2:* We then optimized the hierarchical value assigned to each data cluster. With 15 data clusters, this search space was 15-dimensional. We generated an initial population of 300 members by randomly varying the optimal solution obtained in stage 2. We allowed the differential evolution algorithm to run for 100 generations. In this stage, 30,000 variants were tested.

*Stage 3:* We then optimized the number of data points within each data cluster. With 15 data clusters, this search space was 15-dimensional. We generated an initial population of 300 members by randomly varying the optimal solution obtained in stage 2. We allowed the differential evolution algorithm to run for 100 generations. In this stage, 30,000 variants were tested.

*Stage 4:* The final stage was to simultaneously adjust all parameters. With 15 data clusters and 6 parameters per data cluster (hierarchy, dimensions A through D, and number of data points per visual area), this 90 dimensional space would normally be difficult to search for an optimal solution. However, the goal of the first three stages was to find a solution that was close to optimal, such that we could then use that approximate solution as a starting point for the final search through the full parameter space. For the final stage we therefore generated an initial population of 1800 members by randomly varying the optimal solution obtained in stage 3. We allowed the differential evolution algorithm to run for 100 generations. In this stage, 180,000 variants were tested.

In total, the differential evolution algorithm generated and tested 360,000 information structures. This large number of runs was expected, given the highly dimensional search space. As a result of the search, the algorithm converged on an information structure that, when mapped to the model cortex, resulted in a topography that closely resembled the actual topography of the monkey visual cortex.

### ***Pinning the orientation of the map***

The present method involves arranging a data set onto a model cortical sheet such that cortical continuity is optimized. Visual areas that are near each other in information space are mapped to locations near each other in cortical space, as much as possible given the multi-dimensional nature of the problem. The method tends to produce an internally consistent map, but has no intrinsic reason for orienting the map one way or another. The constraint of optimal continuity could be satisfied whether the map is flipped or rotated. How is it possible to produce a map that is consistently in the correct orientation on the model cortex?

As described in the main article, we were able to fix the anterior-posterior orientation of the map by pinning the location of V1. We assigned the cortical location of V1 to contain low hierarchy values, and in this way seeded the map such that hierarchy would always progress roughly in a posterior-to-anterior direction. We used this method of pinning the anterior-posterior orientation of the map for all three models, including the two-stream model, the four-stream model, and the optimized four-stream model.

For the optimized four-stream model, we also pinned the dorsal-ventral orientation of the map in the following manner. These models included the D stream, comparable to the action stream in the actual monkey visual cortex. Area 5 in the superior parietal lobe, just outside the borders of the traditionally recognized extrastriate visual system, is known to contain neurons that are responsive to somatosensory stimuli and that are also active in association with voluntary movement (Buneo et al. 2002; Kalaska et al. 1983; Seal et al. 1982). Therefore, if the extrastriate cortex contains any movement-control functions, and if functions are arranged to maximize local continuity, then action processing in the visual system should be attracted to the parietal lobe, especially to the cortex adjacent to area 5. To mimic this edge effect, we added 5 nodes at the anterior edge of the inferior parietal lobe, adjacent to area 5, that we initialized to a high level of property D. The map therefore was fixed in two places: V1 was assigned to the lowest hierarchical level, and the border with area 5 was assigned to the highest values of property D. In this way, though we did not pin the map of the extrastriate cortex itself, we initialized the bordering areas that then constrained the anterior-posterior and the dorsal-ventral polarity of the map between.

### *References for Supplementary Material*

Buneo CA, Jarvis MR, Batista AP, Andersen RA. Direct visuomotor transformations for reaching. Nature 416: 632-636, 2002.

Kalaska JF, Caminiti R, Georgopoulos AP. Cortical mechanisms related to the direction of two-dimensional arm movements: relations in parietal area 5 and comparison with motor cortex. Exp Brain Res 51: 247-260, 1983.

Price K, Storn RM, Lampinen JA. Differential Evolution: A Practical Approach to Global Optimization. Secaucus, NJ: Springer-Verlag, 2005.

Seal J, Gross C, Bioulac B. Activity of neurons in area 5 during a simple arm movement in monkeys before and after deafferentation of the trained limb. Brain Res 250: 229-243, 1982.

Storn R, Price K. Differential evolution — a simple and efficient heuristic for global optimization over continuous spaces. J Glob Optim 11: 341–359, 1997.