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A feedforward architecture accounts for rapid categorization

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Primates are remarkably good at recognizing objects. The level of performance of their visual system and its robustness to image degradations still surpasses the best computer vision systems despite decades of engineering effort. In particular, the high accuracy of primates in ultra rapid object categorization and rapid serial visual presentation tasks is remarkable. Given the number of processing stages involved and typical neural latencies, such rapid visual processing is likely to be mostly feedforward. Here we show that a specific implementation of a class of feedforward theories of object recognition (that extend the Hubel and Wiesel simple-to-complex cell hierarchy and account for many anatomical and physiological constraints) can predict the level and the pattern of performance achieved by humans on a rapid masked animal vs. non-animal categorization task.

Object recognition in the cortex is mediated by the ventral visual pathway running from the primary visual cortex (V1) (1) through extrastriate visual areas II (V2) and IV (V4), to the inferotemporal cortex (IT) (2–4), and then to the prefrontal cortex (PFC), which is involved in linking perception to memory and action. Over the last decade, a number of physiological studies in nonhuman primates have established several basic facts about the cortical mechanisms of recognition. The accumulated evidence points to several key features of the ventral pathway. From V1 to IT, there is an increase in invariance to position and scale (1, 2, 4–6) and in parallel, an increase in the size of the receptive fields (2, 4) as well as in the complexity of the optimal stimuli for the neurons (2, 3, 7). Finally, plasticity and learning are probably present at all stages and certainly at the level of IT (6) and PFC.

However, an important aspect of the visual architecture, i.e., the role of the anatomical back projections abundantly present between almost all of the areas in the visual cortex, remains a matter of debate. The hypothesis that the basic processing of information is feedforward is supported most directly by the short time spans required for a selective response to appear in IT cells (8). Very recent data (9) show that the activity of small neuronal populations in monkey IT, over very short time intervals (as small as 12.5 ms) and only ~100 ms after stimulus onset, contains surprisingly accurate and robust information supporting a variety of recognition tasks. Although this finding does not rule out local feedback loops within an area, it does suggest that a core hierarchical feedforward architecture may be a reasonable starting point for a theory of visual cortex aiming to explain immediate recognition, the initial phase of recognition before eye movements and high-level processes can play a role (10–13).

One of the first feedforward models, Fukushima’s Neocogniton (14), followed the basic Hubel and Wiesel proposal (1) for building an increasingly complex and invariant object representation in a hierarchy of stages by progressively integrating convergent inputs from lower levels. Building on several existing neurobiological models (5, 15–19, †), conceptual proposals (1, 2, 20, 21), and computer vision systems (14, 22), we have been developing (5, 23, ‡) a similar computational theory (see Fig. 1) that attempts to quantitatively account for a host of recent anatomical and physiological data.

The model is a simple and direct extension of the Hubel and Wiesel simple-to-complex cell hierarchy: It takes as an input a gray-value image (256 × 256 pixels, ~7° × 7° of visual angle) that is first analyzed by a multidimensional array of simple $S_1$ units which, like cortical simple cells, respond best to oriented bars and edges. $S_1$ units are modeled as half-rectified filters consisting of aligned and alternating “on” and “off” subregions, which share a common axis of elongation that defines the cell-preferred orientation [see supporting information (SI) Text for details]. $S_1$ units come in four orientations and several different scales (see SI Fig. 9) and densely cover the input image. The next $C_1$ level corresponds to striate complex cells (1). Each of the complex $C_1$ units receives the outputs of a group of simple $S_1$ units with the same preferred orientation (and two opposite phases) but at slightly different positions and sizes (or peak frequencies): The result of the pooling over positions and sizes is that $C_1$ units become insensitive to the location and scale of the stimulus within their receptive fields, which is a hallmark of cortical complex cells (1). The parameters of the $S_1$ and $C_1$ units (see SI Table 1) were adjusted so as to match as closely as possible the tuning properties of V1 parfoveal simple and complex cells (receptive field size, peak frequency, frequency, and orientation bandwidth; see ref. 24 for details).

Feedforward theories of visual processing, like the model described here, consist of extending these two classes of simple and complex cells to extrastriate areas. By alternating between S layers of simple units and C layers of complex units, the model achieves a difficult tradeoff between selectivity and invariance: Along the hierarchy, at each S stage, simple units become tuned to features of increasing complexity (e.g., from single oriented bars to combinations of oriented bars forming corners and features of intermediate complexities) by combining afferents (C units) with different selectivities (e.g., units tuned to edges at different orientations). For instance, at the $S_2$ level (respectively $S_3$), units pool the activities of retinotopically organized afferent $C_1$ units (respectively $C_2$ units) with different orientations (different feature tuning), thus increasing the complexity of the representation: From single bars to combinations of oriented bars forming contours or boundary conformations. Conversely, at each C stage, complex units become
increasingly invariant to 2D transformations (position and scale) by combining afferents (S units) with the same selectivity (e.g., a vertical bar) but slightly different positions and scales.

The present theory significantly extends an earlier model (5). It follows the same general architecture and computations. The simple S units perform a bell-shaped tuning operation over their inputs. That is, the response $y$ of a simple unit receiving the pattern of synaptic inputs $(x_1, \ldots, x_{n_k})$ from the previous layer is given by

$$y = \exp \left( -\frac{1}{2\sigma^2} \sum_{j=1}^{n_k} (w_j - x_j)^2 \right), \quad [1]$$

where $\sigma$ defines the sharpness of the tuning around the preferred stimulus of the unit corresponding to the weight vector $w = (w_1, \ldots, w_{n_k})$. That is, the response of the unit is maximal ($y = 1$) when the current pattern of input $x$ matches exactly the synaptic weight vector $w$ and decreases with a bell-shaped tuning profile as the pattern of input becomes more dissimilar. Conversely, the pooling operation at the complex $C$ level is a max operation. That is, the response $y$ of a complex unit corresponds to the response of the strongest of its afferents $(x_1, \ldots, x_{n_C})$ from the previous $S_k$ layer:

$$y = \max_{j=1\ldots n_C} x_j. \quad [2]$$

Details about the two key operations can be found in SI Text (see also ref. 23).

This class of models seems to be qualitatively and quantitatively consistent with [and in some cases actually predicts (23)] several properties of subpopulations of cells in V1, V4, IT, and PFC (25) as well as fMRI and psychophysical data. For instance, the model predicts (23), at the $C_1$ and $C_2$ levels, respectively, the max-like behavior of a subclass of complex cells in V1 (26) and V4 (27). It
also shows good agreement (23) with other data in V4 (28) about the response of neurons to combinations of simple two-bar stimuli (within the receptive field of the S2 units), and some of the C2 units in the model show a tuning for boundary conformations which is consistent with recordings from V4 (29) (C. Cadieu, M. Kouh, A. Pasupathy, C. Connor, and T.P., unpublished work). Readout from C2b units in the model described here predicted (23) recent readout experiments in IT (9), showing very similar selectivity and invariance for the same set of stimuli. In addition, plausible biophysical circuits may implement the two key operations (5) assumed by the theory within the time constraints of the experimental data (8).

Because this feedforward model appears to agree with physiological data while performing well in the recognition of natural images, it is natural to ask how well it may predict human performance in complex object-recognition tasks. Of course as a feedforward model of the ventral stream pathway, the architecture of Fig. 1 cannot account for our everyday vision which involves eye movements and top-down effects, which are mediated by higher brain centers and the extensive anatomical back projections found throughout the visual cortex, and are not implemented in the present feedforward model. Thus, a natural paradigm for comparing the performance of human observers in an object-recognition task to that of a feedforward model of visual processing is ultra-rapid categorization, a task for which back projections are likely to be inactive (30, 31). A well established experiment is an animal- vs. non-animal-recognition task (30–34).

**Results**

Animals in natural scenes constitute a challenging class of stimulus because of large variations in shape, pose, size, texture, and position in the scene (see SI Text for the performance of several benchmark systems). To vary the difficulty of the task, we used four sets of balanced image categories (150 animals and 150 matching distractors in each set, i.e., 1,200 total stimuli; see Materials and Methods), each corresponding to a particular viewing distance from the camera, from an animal head to a small animal or groups of animals in cluttered natural backgrounds (i.e., “head,” “close-body,” “medium-body,” and “far-body” categories; see Fig. 2a and Materials and Methods).

When testing human observers, we used a backward-masking protocol (1/f noise image with a duration of 80 ms; see Fig. 2b) with a long 50-ms stimulus onset asynchrony [SOA; 50-ms SOA corresponding to a 20-ms stimulus presentation followed by a 30-ms interstimulus interval (ISI)]. It was found (31) that increasing the SOA on a similar animal- vs. non-animal-categorization task above 44 ms only has a minor effect on performance (accuracy scores for longer SOA conditions were not significantly different). At the same time, we expect the mask to block significant top-down effects through the back projections (see Discussion and SI Text). In the present version of the model, processing by the units (the nodes of the graph in Fig. 1) is approximated as essentially instantaneous (see, however, possible microcircuits involved in the tuning and max operation in ref. 23). All of the processing time would be taken by synaptic latencies and conduction delays (see SI Text). The model was compared with human observers in three different experiments.

A comparison between the performance of human observers (n = 24, 50-ms SOA) and the feedforward model in the animal classification task is shown in Fig. 3a. Performance is measured by the d’, a monotonically increasing function of the performance of the observers which combines both the hit and false-alarm rates of each observer into one standardized score [see Materials and Methods; other accuracy measures such as error rates or hits gave similar results (see SI Text)]. The task-specific circuits of the model from IT to PFC were trained for the animal- vs. non-animal-categorization task in a supervised way using a random split procedure (see Materials and Methods) on the entire database of stimuli (i.e., in a given run, half of the images were selected at random for training and the other half were used for testing the model). Human observers and the model behave similarly: Across all four animal categories, their levels of performance do not show significant differences (with overall correct = 80% for human observers and 82% for the model). It should be noted that no single model parameter was adjusted to fit the human data (all parameters apart from the supervised stage from IT to PFC were fixed before all tests by taking into account the physiology data from V1 to IT). The accuracy of the human observers is well within the range of data previously obtained with go/no-go tasks on similar tasks (30, 31, 33).

Most importantly, both the model and human observers tend to produce similar responses (both correct and incorrect; see Fig. 3). We measured quantitatively the agreement between human observers and the model on individual images. For each image in the database, we computed the percentage of observers (black values above each panel) who classified it as an animal (irrespective of whether the image contains an animal). For the model, we computed the percentage of times the model (green values) classified
each image as an animal for each of the random runs (during each run, the model is trained and tested on a different set of images and therefore, across several runs the same test image may be classified differently by the model). A percentage of 100% (50%) means that all (half) the observers (either human observers or random runs of the model) classified this image as an animal. The overall image-by-image correlation between the model and human observers is high (specifically 0.71, 0.84, 0.71, and 0.60 for heads, close-body, medium-body, and far-body, respectively, with $P < 0.01$). Together with the results of a “lesion study” performed on the model (see SI Fig. 4), the data suggest that it is the large, overall set of features that underlies such a human-like performance in this task.

To further test the model, we measured the effect of image rotation (90° and 180°) on performance. Recent behavioral studies (34)** suggested that the animal categorization task can be performed very well by human observers on rotated images. Can the model predict human behavior in this situation? SI Fig. 5 shows indeed that the model (Right) and human observers (Left) show a similar pattern of performance and are similarly robust to image rotation. The robustness of the model is particularly remarkable as it was not retrained before being tested on the rotated images. It is likely due to the fact that an image patch of a rotated animal is more similar to an image patch of an upright animal than to a non-animal.

Finally, we replicated previous psychophysical results (31) to test the influence of the mask on visual processing with four experimental conditions, i.e., when the mask follows the target image (20-ms presentation): (i) without any delay (“immediate-mask” condition), (ii) with a short ISI of 30 ms (50-ms SOA) as in the previous experiments, (iii) with an ISI of 60 ms (80-ms SOA), or (iv) never (“no-mask” condition). For all four conditions, the target presentation was fixed to 20 ms as before. As expected, the delay between the stimulus and the mask onset modulates the level of performance of the observers improving gradually from the 20-ms SOA condition to the no-mask condition (see SI Fig. 6). The level of performance of human observers reached a ceiling in the 80-ms SOA condition (except when the animal was camouflaged in the scene, i.e., far-body group). The model predicts human-level hit rate very well between the 50- and the 80-ms SOA conditions. For SOAs longer than 80 ms, human observers outperform the model (the performance for the 50-ms SOA condition, however, is only ∼5% lower than the ceiling performance in the no-mask condition). It remains an open question whether the slightly better performance of humans for SOAs longer than 80 ms is due to feedback effects mediated by the back projections (35).

**Discussion**

The new model implementation used in this study improves the original model (5) in two significant ways. The major extension is a new unsupervised learning stage of the units in intermediate stages of the model (23, 34). A key assumption in the new model is that the hierarchy of visual areas along the ventral stream of the visual cortex, from V1 to IT, builds a generic dictionary of shape-tuned units which provides a rich representation for task-specific categorization circuits in prefrontal areas. Correspondingly, learn-
ing proceeds in two independent stages: First, during a slow developmental-like unsupervised learning stage, units from V1 to IT become adapted to the statistics of the natural environment (see SI Text for details). The resulting dictionary is generic and universal in the sense that it can support several different recognition tasks (23) and in particular, the recognition of many different object categories. After this initial unsupervised learning stage, only the task-specific circuits at the top level in the model, possibly corresponding to categorization units in PFC (25), have to be trained from a small set of labeled examples and in a task-specific manner (see Materials and Methods) for the “mature” model to learn a categorization task (e.g., animal vs. non-animal).

Additionally, the new model is closer to the anatomy and the physiology of the visual cortex in terms of quantitative parameter values. For instance, the parameters (see SI Table 1) of the $S_1$ and $C_1$ model units were constrained by physiology data (1, 36, 37) so that their tuning properties would agree with those of cortical simple and complex cells (see SI Text). In addition to the main routes through the V4 to the IT cortex (4), the model also accounts for the bypass routes (38) from V2 to the posterior inferotemporal cortex and from V4 to the anterior inferotemporal cortex (Fig. 1) [unlike the original model (5)]. A more detailed description of the model can be found in SI Text, and a software implementation is accessible from our supplementary online material at http://cbcl.mit.edu/software-datasets/serre/SerreOlivaPoggioPNAS07/index.htm and includes, in particular, a basic software implementation for the model, the animal-/non-animal-stimulus database, as well as supplementary data including a summary of different error measures for both the model and human observers (e.g., roc curves).

Stimulus Data Set. All images were gray-value $256 \times 256$ pixel images. The stimulus database contains a total of 600 animal stimuli (a subset of the Corel database as in ref. 30; $256 \times 256$ image windows were cropped around the animal from the original $256 \times 384$ pixel images with a random offset to prevent the animal from always being presented in the center of the image) and 600 non-animal stimuli. Animal images were manually grouped into four categories with 150 exemplars in each; that is, head, close-body, medium-body, and far-body.

A set of distractors with matching mean distance from the camera (300 from natural and 300 from artificial scenes) was selected from a database of annotated mean-depth images (53). We selected images with a mean distance from the camera $<1$ m for close-body, between 5 and 20 m for close-body, between 50 and 100 m for medium-body, and $>100$ m and panoramic views for far-body. The database is publicly available at http://cbcl.mit.edu/software-datasets/serre/SerreOlivaPoggioPNAS07/index.htm.

Human Psychophysics. All participants (18–35 years old; $n = 24$ in the first experiment with a fixed 50-ms SOA; $n = 14$ in the second experiment with 0°, 90°, and 180° rotated stimuli; $n = 21$ in the last experiment with variable SOAs) gave a written informed consent. There was approximately the same number of male and female observers in each experiment and none participated in more than one of the three experiments. Participants were seated in a dark room, 0.5 m away from a computer screen connected to a computer [Intel Pentium IV processor (2.4 GHz), 1 GB RAM]. The monitor refresh rate was 100 Hz, allowing stimuli to be displayed with a frame duration of 10 ms and a resolution of 1,024 × 768.

We used MATLAB software (MathWorks, Natick, MA) with the psychophysics toolbox (54, 55) to precisely time the stimulus presentations. In all experiments, the image duration was 20 ms. In all experiments except the last one (see below), the mask appeared after a fixed ISI of 30 ms (corresponding to a SOA of 50 ms). In the last experiment, we randomly interleaved different ISI conditions: 0-ms ISI (SOA = 20 ms), 30-ms ISI (SOA = 50 ms), 60-ms ISI (SOA = 80 ms), or infinite (i.e., never appeared). The mask following the picture was a (1/f) random noise mask, generated (for each trial) by filtering random noise through a Gaussian filter.

The stimuli were presented in the center of the screen ($256 \times 6428$ | www.pnas.org/cgi/doi/10.1073/pnas.0700622104 Serre et al.
Categorization by the Model. To train the PFC classification unit in the model, we used a random splits procedure, which has been shown to provide a good estimate of the expected error of a classifier (56). The procedure was as follows.

1. Split the set of 1,200 (animal and non-animal) images into two halves; denote one half as “training” and the other as “test.”
2. Imprint \( S_i \) units with specific examples of animal and non-animal images from the training set of images (25% selected at random). Like units in lower stages become tuned to patches of natural images (see SI Text); \( S_i \) units become tuned to views of the target object by storing in their synaptic weights the patterns of activity of their afferents during a presentation of a particular exemplar. This finding is consistent with a large body of data that suggests that the selectivity of neurons in IT depends on visual experience (see ref. 23 for a review).

3. Train a PFC classification unit on the labeled “training” set of images. The response \( y \) of a classification unit with input weights \( c = (c_1, \ldots, c_{100}) \), when presented with an input pattern \( x = (x_1, \ldots, x_{100}) \) from the previous layer (\( S_i \) unit \( j \) denoted \( x_j \) is tuned to the \( i \)th training example), is given by

\[
y = \sum_{j=1}^{100} c_j x_j. \tag{[3]}
\]

The unit response \( y \in \mathbb{R} \) is further binarized (\( y \leq 0 \)) to obtain a classification label \((-1, 1)\). This supervised learning stage involves adjusting the synaptic weights \( c \) so as to minimize the overall classification error \( E \) on the training set. In this article, we used one of the simplest types of linear classifier by computing the least-square-fit solution of the regularized classification error evaluated on the training set(15):

\[
E = \sum_{i=1}^{n} [y_i - y(i)]^2 + \lambda \| c \|^2,
\]

where \( y \) corresponds to the classification unit response for the \( i \)th training example, \( y(i) \) is the true label of the \( i \)th training example, and \( \lambda \) is a fixed constant. To solve Eq. 1, we used the nonbiological MATLAB left division operation for matrices, but we obtained similar results with a more biologically plausible stochastic gradient learning approach using weight perturbations modified from ref. 57, i.e., \((x(i), y(i))\) pairs, where \( x(i) \) denotes the \( i \)th image in the training set and \( y(i) \) is its associated label (animal or non-animal).

4. Evaluate the performance of the classifier on the “test” set. We repeated the overall procedure \( n = 20 \) times and computed the average model performance. Note that the error bars for the model in Fig. 3 correspond to the standard errors computed over these \( n = 20 \) random runs.

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