

Response Properties of Single Neurons Predicted by Sparse Representation

Jiqian Liu, Chengbin Zeng, and Liping Xiao

Abstract—Sparse representation by neuronal populations in sensory cortex has been heavily investigated and validated. Recently, it was reported that sparse representation can predict response properties of single neurons, which gives insight into the unified understanding of the responses of both neuronal populations and single neurons. The current work takes a step forward in this regard. We simulate the response properties of simple cells with a neurally plausible sparse representation model. The model turns out to explain well the response properties of single cortical neurons, such as the sharp and contrast invariant orientation tuning as well as cross orientation suppression within the classical receptive field (CRF) and surround suppression from beyond the CRF.

Index Terms—Sparse representation, orientation selectivity, cross orientation suppression, surround suppression.

I. INTRODUCTION

Neural mechanisms of visual information processing have been intensively investigated both at the neuronal population level and the single-neuron level for several decades. In understanding the representation of sensory stimuli by neuronal population, Barlow [1] has proposed that the goal of visual information processing is to reduce statistical redundancy in the visual signals. Olshausen and Field [2] demonstrated that an algorithm maximizing the sparseness of the code for a given image can produce basis vectors which are similar to the receptive field shapes of simple cells. Sparse representation of sensory stimuli in cortex has been widely validated [3]-[7]. On the other side, although many response properties of single neurons are well characterized, there are disagreements about the neural mechanisms underlying these observations. Ever since Hubel and Wiesel [8] first proposed a feedforward model for the orientation selectivity [9] of primary visual cortex (V1) simple cells, it has been argued whether orientation selectivity originates from excitatory convergence of lateral geniculate nucleus (LGN) afferents. This simple model predicted the tuning width of orientation selectivity should widen with increasing contrast of stimuli, which on the contrary is invariant [10], a phenomenon known as the contrast invariance of orientation selectivity. Cross

orientation suppression in which the response of a V1 neuron to its preferred orientation is suppressed by null oriented stimuli [11], [12] has been thought to be responsible for the sharpness of orientation selectivity [13], [14]. But measurements with intracellular recordings [15], [16] indicated that such kind of inhibition could not be involved in cross orientation suppression. Another phenomenon known as surround suppression, that is, the presence of stimuli in the non-classical receptive field (nCRF) of neurons can suppress their spiking responses [17]-[19], has attracted much interest in the last decade. Differently from cross orientation suppression, surround suppression is strongest when the stimulus in the nCRF has a parallel orientation (iso-orientation) and exhibits contrast dependent size tuning [20]. The spatial extent seems not to support the suppression induced by far surround stimuli [21]. The lack of global information in the observations made in a very limited area could be the main reason for these disagreements.

In this paper, we simulate the response properties of simple cells with a sparse representation algorithm, demonstrating that the conflicting measurement results of single neurons may occur as a consequence of the neuronal populations performing sparse representation. Recently, some other studies have reported that several classical receptive field (CRF) and non-classical receptive field (nCRF) response properties of single neurons are well simulated by sparse representation [22]-[24]. To further testify this hypothesis, we use a neurally plausible sparse representation model to simulate the emergence of several known simple cell response properties. For a unified understanding of the responses of both neuronal populations and single neurons in early visual cortex, our work takes it a step forward.

II. THE L_0 NORM BASED SPARSE REPRESENTATION

In the model presented by Olshausen and Field [2], there were only two global objectives to be optimized: that the representation is sparse and that the representation error is small. Rehn and Sommer [25] then introduced the L_0 norm to replace the smoothness prior to force the representation to be sparse. The sparse representation problem modeled with a L_0 norm term is given by

$$\min \left\{ \left(x - \sum_j a_j w_j \right)^2 + \lambda \|a\|_0 \right\} \quad (1)$$

where x is the input signal, w_j is the basis vector corresponding to the receptive field of an active neuron, a_j is the coefficient of w_j , a is a vector whose j th component is

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a_j , and λ is the trade-off parameter.

A large number of methods have been proposed for this problem. Iterative thresholding algorithms (ITA) solve sparse representation in an iterative framework using thresholding [26]-[28]. In these methods, the input is approximated iteratively while the representation is made sparser by a thresholding mechanism at each iteration step. It is widely believed that lateral inhibition play an important role for the implementation of sparse representation in visual cortex [29]. The lateral inhibitory coefficients are consistent with those obtained from physiological data [30]. In this paper, a neurally plausible sparse representation model with lateral inhibition and thresholding is adopted. Furthermore, non-negative data processing is performed. With these modifications, the laterally inhibited non-negative sparse representation algorithm (LINSR) is proposed in Table I.

TABLE I: LATERALLY INHIBITED NON-NEGATIVE SPARSE REPRESENTATION

INPUT: the signal X and the set of basis vectors W .

OUTPUT: the approximation \hat{X} of X .

Initially, compute $y_i^{(0)} = Y_i = X \cdot W_i$ for all $w_i \in W$.

Repeat the following two steps several times for all i :

Step 1. If $y_i^{(\tau)} < 0$, set $y_i^{(\tau)} = 0$.

Step 2. Calculate $y_i^{(\tau+1)} = Y_i - \sum_{k \neq i} C_{k,i} y_k^{(\tau)}$ where $C_{k,i}$ is also set to be 0 if it is smaller than a given threshold $\mu > 0$.

In Table I, $C_{k,i}$ is the inhibitory coefficient of the k th output neuron on the i th output neuron which is calculated by $C_{k,i} = \frac{w_k w_i}{\|w_k\|^2}$ [30]. In the implementation process of LINSR,

a large initial positive response may be reduced to zero. Correspondingly, some active output neurons will be forced to be inactive by lateral inhibition resulting that only a smaller number of output neurons left for the representation of x . It means that the representation is forced to be sparser and more accurate, and thus the two global objectives of the sparse representation model are achieved.

III. EXPERIMENTAL RESULTS

A. Sparse Representation of Image Patches

We test the LINSR algorithm with a 250×250 sized "Lena" image (see Fig. 1(a)). To make the test simpler, we use a group of two dimensional trigonometric functions and two Gaussian functions illustrated in Fig. 1(b) as the basis set. The two dimensional trigonometric functions are given by

$$u(x, y) = \sin(\alpha\pi f(y \cos i\Delta\theta - x \sin i\Delta\theta) + \frac{k\pi}{2}) \quad (2)$$

where α is a scalar, $f=1+0.7n$, and $\Delta\theta=\pi/6$. Both the spatial frequency f and the value of $\Delta\theta$ are carefully selected to generate sinusoidal gratings that are slightly correlated. By doing this, the generated basis functions are neither highly correlated to avoid the redundancy in the representation nor

too dispersed to avoid the loss important information in the input. In the visual cortex, the value of $\Delta\theta$ may be a little smaller because the Gabor-like receptive fields of V1 neurons are more localized than the sinusoidal functions.

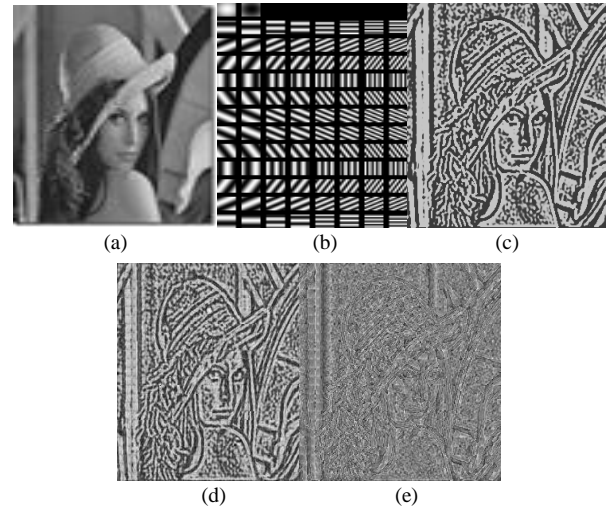


Fig. 1. Illustration of the DoG filtered "Lena" image being reconstructed by the LINSR algorithm. (a) The "Lena" image with a size of 250×250 pixels. (b) The filters used in this paper. (c) The DoG filtered "Lena" image which is cut into 25×25 patches with a size of 10×10 pixels as the inputs of the LINSR algorithm. (d) The stitched image from the reconstructed patches. (e) The error image between the DoG filtered "Lena" and reconstructed result.

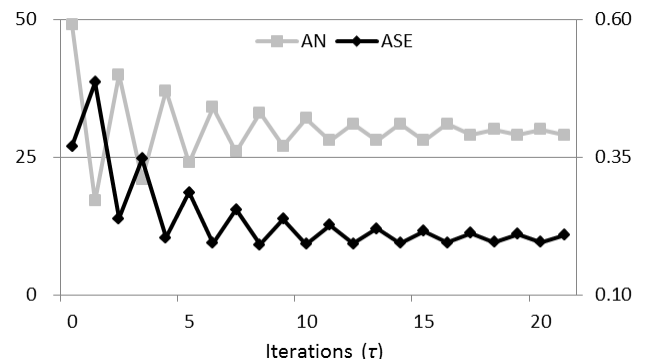


Fig. 2. Trend of the average number (AN) of selected basis functions and the average squared error (ASE) in the first iterations of the reconstruction process for the "Lena" image.

As mentioned above, the "Lena" image will be filtered with DoG at first. Then the DoG filtered "Lena" image (see Fig. 1(c)) is cut into 25×25 patches with a size of 10×10 pixels as the input data set. Each of the image patches, corresponding to x , is reconstructed by the LINSR algorithm one by one. At last, we stitch all the reconstructed image patches, corresponding to \hat{x} , back together into the new image as shown in Fig. 1(d). Comparing Fig. 1(c) with Fig. 1(d), we see that the DoG filtered image is reconstructed very well. The error image is given in Fig. 1(e).

We provide an error analysis of the first iterations of the LINSR algorithm, and the result is shown in Fig. 2 where the average number of the basis functions selected for the reconstruction of each image patch is also plotted. When to calculate the average squared error, all image patches are normalized to remove amplitude dependence. From Fig. 2 we can see that the iterative procedure tends to converge after about 15 iterations. This demonstrates the time course of reconstruction can be very short.

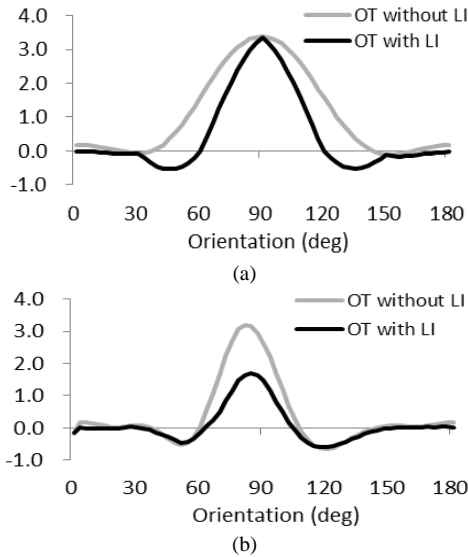


Fig. 3. Lateral inhibition sharpens orientation tuning (OT). The orientation tuning curves calculated with lateral inhibition are sharper than those without lateral inhibition. (a) The grating stimuli are not filtered before fed to the input of the network. (b) The grating stimuli are filtered.

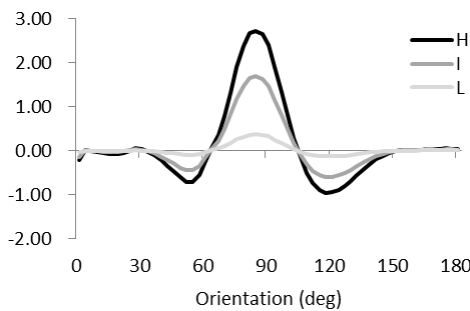


Fig. 4. Illustration of the contrast invariance of orientation tuning. The tuning width remains unchanged for stimuli at high (H), intermediate (I) and low (L) contrasts.

B. Neuronal Response Properties

We analyze the response properties of single neurons with sinusoidal gratings over the full range of orientation angles. The gratings are generated in the same way as the basis vectors to make sure they can elicit a maximum response of the output neurons as those used in physiological experiments. The simulation result shown in Fig. 3 indicates that the selected output neuron exhibits sharp orientation tuning (OT), and the tuning curve calculated only with the LGN inputs can be much broader than that with lateral inhibition. These results are consistent with the observations that orientation selectivity results mainly from broader tuning of excitation and can be reduced by blocking cortical inhibition [31], [32]. The contrast invariance of orientation selectivity is also predicted by our model (see Fig. 4). The tuning width, an interval where the neuron shows a positive response, remains unchanged with respect to contrast. The Mexican-hat appearance of some tuning curves as illustrated in Fig. 5 has been reported and modeled by Ringach *et al.* [33], [34].

As suggested by MacEvoy *et al.* [35], we use the population response properties to examine cross orientation suppression. Responses of output neurons preferring the same orientation angle are averaged. The average population response profiles are plotted in Fig. 6 where the profile obtained at low contrast for superimposed gratings maintain

the same structure as those at high contrasts. This is an important physiological observation [35] against the prediction of a purely feedforward model without lateral inhibition [36].

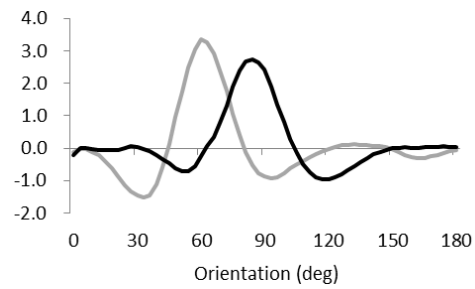


Fig. 5. Simulated orientation tuning curves of two output neurons, both of which have a Mexican-hat shape with little difference.

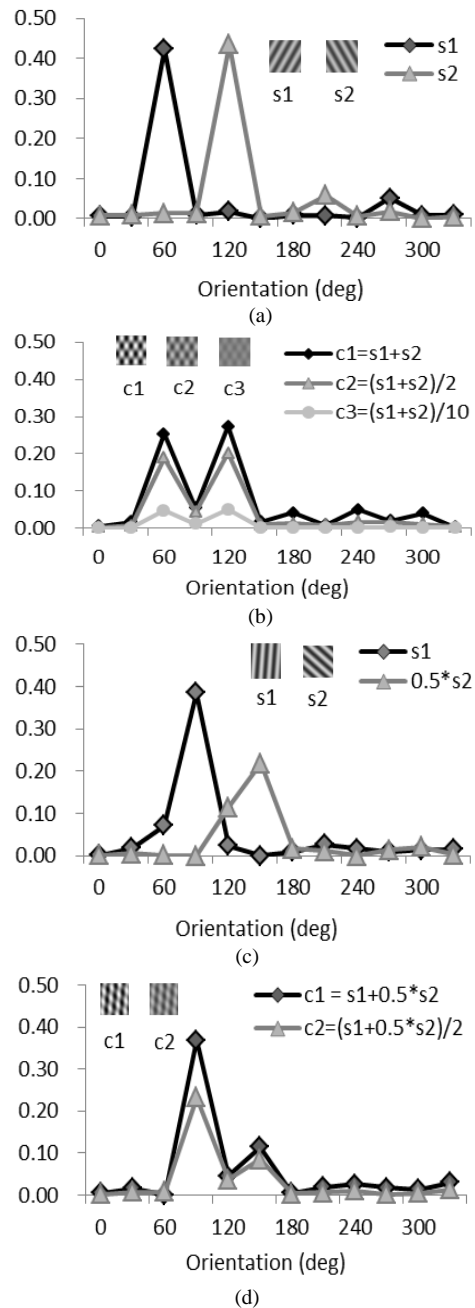


Fig. 6. Average responses of output neurons preferring the same orientation to single and superimposed gratings. Each data point represents the average response of output neurons that prefer the same orientation angle. (a, c) Average population response profiles for two single gratings s_1 and s_2 . (b, d) Average population response profiles for superimposed gratings c_1 , c_2 and c_3 at different contrasts.

IV. CONCLUSION

In this paper, we demonstrate that most response properties of simple cells may occur as a result of neuronal populations performing sparse representation in V1. To achieve this purpose, the neurally plausible sparse representation model named LINSR is proposed. The sharp and contrast invariant orientation selectivity, cross orientation suppression and surround suppression are well simulated by LINSR. Future work will focus on the development of more neurally plausible sparse representation models and the simulation of more complex response properties of single neurons.

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