Inhibition-augmented COSFIRE model of shape-selective neurons
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Inhibition is a phenomenon that occurs in different areas of the brain, including the visual cortex. For instance, the responses of some shape-selective neurons in the inferotemporal cortex are suppressed by the presence of certain shape contour parts in their receptive fields. This suppression phenomenon is thought to increase the selectivity of such neurons. We propose an inhibition-augmented model of shape-selective neurons, as an advancement of the trainable filter approach called combination of shifted filter responses (COSFIRE). We use a positive prototype pattern and a set of negative prototype patterns to automatically configure an inhibition-augmented model. The configuration involves the selection of responses of a bank of Gabor filters (models of V1/V2 neurons) that provide excitatory or inhibitory input(s). We compute the output of the model as the excitatory input minus a fraction of the maximum of the inhibitory inputs. The configured model responds to patterns that are similar to the positive prototype but does not respond to patterns similar to the negative prototype(s). We demonstrate the effectiveness of the proposed model in shape recognition. We use the Graphics Recognition (GREC2011) benchmark dataset and demonstrate that the proposed inhibition-augmented modeling technique increases selectivity of the COSFIRE model.

Introduction

Shape is of great importance for humans and animals to recognize objects. The brain processes shape information in the ventral pathway, which passes through areas V1/V2 [1, 2] and V4 [3] of the visual cortex and terminates in the inferotemporal cortex (IT) [4–6]. Shape-selective neurons are understood by neurophysiologists as integrating afferent information of multiple contour segments, such as edges [7], corners [8], and curvatures [9], to be able to selectively respond to complex shapes or objects [4, 5].

Various computational models inspired by shape-selective neurons have been proposed in the literature [10–15]. Some models [11–14] have layers of units, which have properties of simple and complex neurons in areas V1/V2 of the visual cortex. Cadieu et al. [15] propose a V4-like model that reproduces V4 selectivity through a combination of subunits. Rodríguez-Sánchez and Tsotsos [5] propose a model of shape-selective neurons that integrates end-stopping and curvature computations. It is demonstrated to be effective for the detection of two-dimensional (2D) silhouettes. Aside from shape recognition, the remarkable functionality of the brain has been a source of inspiration for other computational techniques [16, 17].

Recently, a model inspired by a specific type of shape-selective neuron [6] in area V4 of the visual cortex has been proposed [18]. This model is referred to as COSFIRE, which is an abbreviation for Combination of Shifted Filter Responses. It has been applied in various computer vision applications, including object localization and recognition [19, 20], image classification [21], retina vessel segmentation [22–24] and contour detection [25]. For a given prototype pattern, this model extracts information about the dominant orientations (edges/lines) and their mutual spatial arrangement. The response of a COSFIRE model is then computed by an AND-type function and it is greater than zero only when all the concerned contour parts are present in a local pattern. This
COSFIRE model also reacts when a pattern of interest is surrounded with additional contours, texture, or noise. While this aspect can be advantageous in certain applications, it may be less beneficial in others. For instance, Figure 1 shows two examples for which a COSFIRE model is not suitable. A COSFIRE model configured to be selective for the pattern representing the electrical symbol for a core-air inductor, encircled by a solid line in Figure 1, would also respond strongly to the pattern of a core-iron inductor that is marked by a dashed circle. This is because all contour elements contained in the core-air inductor pattern are present in the same arrangement in the pattern of the core-iron inductor. This example demonstrates that the COSFIRE model in its current form is not suitable for distinguishing objects that are contained within other objects.

The existing COSFIRE model employs the integration of multiple contour elements that only provide excitatory inputs. There is, however, neurophysiological evidence that neurons in different layers of the visual cortex also receive inhibitory input [26]. Neurons in the lateral geniculate nucleus (LGN) have center-surround receptive fields. For instance, a center-on LGN model has an excitatory central region with an inhibitory surrounding region. Such a neuron can be modeled by a difference-of-Gaussians (DoG) operator. Similarly, simple cells in the primary visual cortex have receptive fields constituted of excitatory and inhibitory regions. This property inspired the designs of Gabor filters [27], derivatives of Gaussians [28], and the CORF (Combination of Receptive Fields) model [10], all of which are models of simple cells in the visual cortex. In the later works, researchers introduced surround inhibition and push-pull inhibition to Gabor filters [29] and the CORF model [30], respectively. In both cases, inhibition suppresses responses to texture and improves the effectiveness in contour detection. Inhibition is also thought to increase the selectivity of neurons [31, 32]. It can suppress the activation of a neuron to some specific stimuli in order to be more selective for the preferred one. Shape-selective neurons [4] in the posterior visual cortex and end-stopped cells [33, 34] in the primary visual cortex are two examples. A specific type of shape-selective neuron [4] responds to complex shapes that consist of convex and concave curvature elements with a certain geometrical arrangement. The presence of some curvatures excites such a neuron, while the addition of some other specific contour elements can inhibit its response. This type of neuron in the posterior IT cortex integrates information about the relative positions of multiple contour elements, presumably by combining excitatory and inhibitory responses from afferent neurons [4].

In our work, we propose an inhibition-augmented model inspired by shape-selective neurons that receive inputs from a group of orientation-selective cells in areas V1/V2 and experience inhibition in the IT area of the visual cortex. The proposed model takes as input the responses of a group of Gabor filters. In the configuration, we use two types of prototypes, a positive prototype pattern to which the model must respond, along with one or more negative prototype(s) to which the model must not respond. The configuration automatically selects which Gabor responses provide excitatory input and which ones provide inhibitory input. We compute the response of the model as the difference between the collective excitatory input and a fraction of the maximum of the collective inhibitory inputs. The configured inhibition-augmented COSFIRE model responds to patterns that are equivalent or similar to the positive prototype but does not respond to patterns similar to any of the negative prototype(s).

The remainder of the paper is organized as follows. In the next section (“Computational model”), we explain how an inhibition-augmented COSFIRE model can be configured.
The structures of the resulting two excitatory-only COSFIRE models configured with the positive (left) and negative prototype patterns (right), respectively. The size and orientation of the ellipses illustrate the wavelengths \( \lambda \) and orientations \( \theta \) of the selected Gabor filters, and their positions indicate the coordinates \( (\rho, \varphi) \) at which their responses are used as input to the concerned COSFIRE models. The blobs superimposed on the ellipses represent Gaussian functions that are used to blur the corresponding Gabor filter responses.

Such a model takes as input the responses of Gabor filters and combines them in a geometric mean function. The parameters of the involved Gabor filters and the positions at which their responses are taken are determined in an automatic configuration procedure. This procedure determines the most dominant contour parts and extracts four parameters for each part—the scale \( \lambda \) and orientation \( \theta \) of the corresponding Gabor filter and the distance \( \rho \) and polar angle \( \varphi \) with respect to the center of the prototype. For instance, we use the pattern marked by the solid circle in Figure 1 as a prototype of interest to configure a COSFIRE model, the resulting structure of which is shown in the left image in Figure 2. These properties are represented by a set of 4-tuples \((\lambda, \theta, \rho, \varphi)\). Each ellipse in Figure 2 illustrates the wavelength and orientation of the selected Gabor filters and its position indicates the location \((\rho, \varphi)\) at which its response is taken as inputs to the concerned COSFIRE model. The small central blobs superimposed on the ellipses represent Gaussian function maps that are used to blur the corresponding Gabor filter responses in order to provide some tolerance regarding the preferred positions.

The response of a COSFIRE filter at every location of an input image is computed as the geometric mean of the blurred responses of the involved Gabor filters. For more details about the COSFIRE model, we refer the interest reader elsewhere [18].

**Configuration of an inhibition-augmented COSFIRE model**

Let us consider two example symbols encircled by solid and dashed lines in Figure 1, which we refer to as a positive and a negative prototype, respectively.

First, we apply the automatic configuration process proposed by Azzopardi and Petkov [18] to configure two excitatory-only COSFIRE models, one to be selective for patterns that are similar to the positive prototype and the other to be selective for those similar to the negative prototype pattern. The resulting COSFIRE models are represented by two sets of 4-tuples. We denote by \( P_j = \{ (\lambda_i, \theta_i, \rho_j, \varphi_i) | i \in 1..n_1 \} \) and \( N_j = \{ (\lambda_j, \theta_j, \rho_j, \varphi_j) | j \in 1..n_2 \} \) the configured
excitatory-only COSFIRE models selective for the positive and negative prototypes, respectively. The parameters $n_1$ and $n_2$ denote the number of tuples in the respective sets. The structures of the resulting two COSFIRE models are shown in Figure 2. The tuples indicated by white ellipses characterize the properties of the contour parts in the positive pattern, and those marked by black ellipses are from the negative pattern. In the configuration of these two examples, we use a bank of Gabor filters with one wavelength $\lambda = 24$ (in pixels) and eight orientations $\theta \in \{\pi i / 8 | i = 0, \ldots, 7\}$. Finally, we use $t_1 = 0.2$ to threshold their responses.

Next, we form a new set $S_f$ by selecting tuples from the two sets $P_f$ and $N_f$. We include all tuples from $P_f$ in the set $S_f$ and add a tag $\delta = +1$ to these tuples, indicating that their contributions are excitatory. Then, we identify tuples in the set $N_f$ whose coordinates are sufficiently far from the coordinates of any of the tuples in the set $P_f$. We denote by $d(N_f, P_f)$ a function that computes the minimum Euclidean distance between the coordinates given in tuple $j$ in the set $N_f$ and the coordinates of all tuples in the set $P_f$:

$$d(N_f, P_f) = \min_{i \in \{1, \ldots, |P_f|\}} \left\{ \sqrt{(\rho_i \cos\varphi_i - \rho_j \cos\varphi_j)^2 + (\rho_i \sin\varphi_i - \rho_j \sin\varphi_j)^2} \right\}$$

(1)

We include in the new set $S_f$ every tuple $N_f^j$ that has a distance $d(N_f^j, P_f)$ larger than a threshold $\zeta$. We specify the value of $\zeta$ for the experiments in the section “Experiments and results.” We add a tag $\delta = -1$ to these tuples in the set $S_f$ obtained from the negative example, as they provide inhibitory input to the concerned inhibition-augmented COSFIRE model. With this procedure, we form a new set denoted by $S_f = \{ (\lambda, \theta, \rho, \varphi, \delta) | i \in 1 \ldots n \}$, where $n$ denotes the number of tuples in $S_f$. Figure 3 shows the structure of the resulting inhibition-augmented COSFIRE model that is represented by the set $S_f$. The white and black ellipses and blobs indicate Gabor filters that provide excitatory and inhibitory inputs, respectively. The contour parts represented by black ellipses and blobs are present in the negative prototype but are absent in the positive prototype.

In applications where we have multiple negative prototypes, we apply the same method described above for the identification of inhibitory tuples. We give a unique value of tag $\delta$ to each set of inhibitory tuples originating from the same negative prototype. For example, we add the tag $\delta = -2$ to the resulting tuples from the second negative prototype whose polar coordinates are far from the positive prototype. We generalize this approach for any number of negative prototypes.

**Excitatory and inhibitory inputs**

We use the thresholded Gabor filter responses at the determined positions to compute the excitatory and inhibitory inputs of the inhibition-augmented COSFIRE model.

For each selected Gabor filter response $|g(\lambda, \varphi, \rho, \delta)(x, y)|_t$, we first shift it by $\rho_i$ pixels in the direction opposite to $\varphi_i$. In Cartesian coordinates, the shift vector is $(\Delta x_i, \Delta y_i)$, where $\Delta x_i = -\rho_i \cos\varphi_i$ and $\Delta y_i = -\rho_i \sin\varphi_i$. In this way, all Gabor filter responses described by different tuples meet at the support center of the inhibition-augmented COSFIRE model. We denote by $g(\lambda, \varphi, \rho, \delta)(x, y)$ a shifted and thresholded response of a Gabor filter in location $(x, y)$:

$$g(\lambda, \varphi, \rho, \delta)(x, y) \text{ def } = |g(\lambda, \varphi, \rho, \delta)(x - \Delta x_i, y - \Delta y_i)|_t$$

(2)

Then, we use a 2D Gaussian function $G_\sigma(x, y)$ to blur the shifted and thresholded responses of the Gabor filters in order to achieve some tolerance with respect to the preferred positions. The parameter $\sigma$ denotes the standard deviation of the Gaussian function. There is neurophysiological evidence that the diameter of receptive fields increases with the eccentricity [39]. The blobs

**Figure 3.**

The structure of the resulting inhibition-augmented COSFIRE model. The white and black pairs of ellipses and blobs indicate Gabor filters that, respectively, provide excitatory and inhibitory inputs to the inhibition-augmented COSFIRE model.
superimposed on the ellipses shown in Figures 2 and 3 represent such Gaussian functions. We denote by $s_{\lambda, \theta, \rho, \varphi, \delta}(x, y)$ the blurred and shifted response of a Gabor filter in the position $(x, y)$ that is specified by the $i$-th tuple $(\lambda_i, \theta_i, \rho_i, \varphi_i, \delta_i)$ in the set $S^x$:  

$$s_{\lambda_i, \theta_i, \rho_i, \varphi_i, \delta_i}(x, y) \overset{\text{def}}{=} g'_{(\lambda_i, \theta_i)}(x, y) * G(x, y),$$  

(3)

where $*$ stands for convolution.

Next, we combine the collective Gabor filter responses indicated by tuples that have the same value of $\delta$. We denote by $S^x_\delta$ the tuples that have tag $\delta = +1$, and by $S^{-x}_\delta$ the tuples that have $\delta = -j$: $S^x_\delta = \{(\lambda_i, \theta_i, \rho_i, \varphi_i) \mid \forall (\lambda_i, \theta_i, \rho_i, \varphi_i, \delta_i) \in S_f, \delta_i = +1\}$ and $S^{-x}_\delta = \{(\lambda_i, \theta_i, \rho_i, \varphi_i, \delta_i) \in S_f, \delta_i = -j\}$. We denote by $I^x_\delta(x, y)$ and $I^{-x}_\delta(x, y)$ the excitatory and inhibitory contributions:

$$I^x_\delta(x, y) \overset{\text{def}}{=} \left\| \left( \prod_{i=1}^{\left|S^x_\delta\right|} (s_{\lambda_i, \theta_i, \rho_i, \varphi_i, \delta_i}(x, y))_{\omega_i} \right)^\delta \right\|_{l_2},$$  

(4)

$$I^{-x}_\delta(x, y) \overset{\text{def}}{=} \left\| \left( \prod_{i=1}^{\left|S^{-x}_\delta\right|} (s_{\lambda_i, \theta_i, \rho_i, \varphi_i, \delta_i}(x, y))_{\omega_i} \right)^\delta \right\|_{l_2},$$  

(5)

where

$$\omega_i = \exp\left(\frac{\rho_i^2}{\sigma_i^2}\right).$$

Here, $\sigma'$ is the standard deviation. In this implementation, $\sigma'$ is given as a function of the maximum value of $\rho$:

$$\sigma' = \left(\frac{\rho_{\text{max}}^2}{2\ln 0.5}\right)^{1/2}$$

in which $\rho_{\text{max}} = \max_{i \in [1, \ldots, |S_f|]} \{|\rho_i|\}$. Here, $\cdot \cdot l_2$ stands for thresholding the response at a fraction $t_2$ of the maximum response value that the model achieves when it is applied to its preferred model symbol. For $1/\sigma' = 0$, the above computation becomes equivalent to the standard geometric mean.

**Response of inhibition-augmented COSFIRE model**

We denote by $r_S(x, y)$ the response of an inhibition-augmented COSFIRE model, which we define as the difference between the excitatory input $S^x_\delta$ and a fraction of the maximum of the inhibitory inputs $S^{-x}_\delta$:

$$r_S(x, y) \overset{\text{def}}{=} \left| I^x_\delta(x, y) - \eta \max_{1 \leq j \leq n} I^{-x}_j(x, y) \right|_{l_3},$$  

(6)

where $n = \max|\delta_i|$, and $\eta$ is a coefficient that we call the inhibition factor. We threshold the responses of an inhibition-augmented COSFIRE model at a fraction $t_3$ of its maximum across all locations in an image.

We apply the configured inhibition-augmented COSFIRE model, the structure of which is shown in Figure 3, to the input image in Figure 1. Figure 4 shows the output response map of this model to the input image. The red cross in the image indicates the center of the symbol where the configured filter gives the maximum response.

**Tolerance to geometric transformations**

The proposed inhibition-augmented COSFIRE model can achieve tolerance to scale, rotation, and reflection by manipulating the configured tuples $(\lambda, \theta, \rho, \varphi, \delta)$ in a similar way as proposed for the original excitatory-only COSFIRE model [18]. For rotation tolerance, we use a parameter $\psi$ to represent the rotated angle. For example, tuples $(\lambda, \theta + \pi, \rho, \varphi + \pi, \delta)$ represent a model that is rotated 180 degrees counterclockwise. Similarly for
scaling tolerance, we manipulate the original tuples by scaling them in size by a factor \(v\); for example, tuples \((v\lambda, \theta, v\rho, \varphi, \delta)\) represent a model scaled by a factor \(v\). We do not elaborate on these aspects here; a thorough explanation about tolerance to geometric transformations can be found elsewhere [18].

**Experiments and results**

**Data sets**

We use the Graphics Recognition (GREC2011) localization data set [35] to evaluate the proposed model. The data set contains 16 architectural and 21 electrical symbols. It consists of a training and a test set. In the training set, there are 40 drawing images, 20 of which are floor plans consisting of architectural symbols, and the rest are electrical diagrams. In each domain, there are four subsets, namely Ideal, Level 1, 2, and 3, of five images each. The latter three subsets have different levels of noise degradation. The test set has 160 drawing images, 80 images of which are floor plans and the rest are electrical diagrams. Similar to the training set, every domain has four subsets (Ideal, Level 1, 2, and 3) of 20 images each. In total, the test set of GREC2011 data set for localization contains 3,463 symbols in all drawing images. The lines in the ideal symbols have a thickness of 5, 9, or 12 pixels. Figure 1 shows an example of an electrical diagram taken from the Ideal subset.

**Implementation**

In the following, we explain how we apply the proposed inhibition-augmented model. First, we configure 16 inhibition-augmented COSFIRE filters to be selective for the 16 architectural symbols given in the training set. The way we configure the filters is as follows. We configure an excitatory-only COSFIRE filter as proposed by Azzopardi and Petkov [18] for a given symbol prototype and apply the resulting filter to the remaining 15 symbols. After that, we threshold each response map at a fraction \(\varepsilon\) of the maximal response that the resulting filter achieves when applied to the given prototype. We take the symbol images that elicit responses greater than \(\varepsilon = 0.1\) as negative prototype patterns and determine the inhibitory line segments. Then, the inhibition-augmented COSFIRE filter is configured to be selective for the given pattern with the method proposed in the section “Computational model.” We perform the same procedure for each of the 16 architectural symbols. For the symbols from the electrical domain, we apply the same configuration procedure as above to configure 21 inhibition-augmented COSFIRE filters. In this experiment, we use a bank of Gabor filters with eight orientations, \(\theta \in \{(\pi i)/8 \mid i = 0, \ldots, 7\}\), and three wavelengths \(\lambda \in \{10, 18, 24\}\). The wavelength of a symmetric Gabor filter is roughly twice the thickness of the preferred line.

The choice of the three wavelength values is motivated from the empirical determination of line thicknesses in the images of the training set. We threshold the Gabor responses with \(t_1 = 0.2\) and the excitatory and inhibitory inputs with \(t_2 = 0.5\). For the blurring function, we set \(\sigma\) to 4 pixels. We use a value of 12 pixels for \(\xi\), which is three times the standard deviation \(\sigma\), in order to prevent the interference of inhibitory and excitatory parts of the filter.

Next, we apply the above-configured inhibition-augmented COSFIRE filters to all training symbol images in each domain. We investigate the inhibition factor by varying the value of parameter \(\eta\) between 0 and 2 in intervals of 0.1. For \(\eta = 1\), the filters give responses only to the preferred positive prototype pattern.

Then, in order to determine the optimal value of \(t_3\) for each configured filter, we apply each filter in rotation-tolerant and scaling-tolerant mode to the drawing images in the training set (subsets Ideal, Level 1, 2, and 3). For the images in the noisy sets, we do not apply any pre-processing method. We use different values of \(t_3\) between 0 and 1 in intervals of 0.1 to threshold the response of such an inhibition-augmented COSFIRE filter to a given image. We compute the harmonic mean of the precision and recall for each value of the threshold. The optimal threshold is the minimum value that achieves the highest harmonic mean.

**Results**

We apply the resulting 16 inhibition-augmented COSFIRE filters selective for architectural symbols to the images in the subsets Ideal, Level 1, 2, and 3 of architectural domain in rotation-tolerant and scaling-tolerant mode. Similarly, we apply the 21 filters selective for electrical symbols on the corresponding subsets of electrical domain. We compare our results with the ground truth provided in the dataset. In each test drawing image, the “ground truth” provides a rectangular region in which a symbol is located. If the distance between the center of the detected symbol and the center of the provided region is less than 0.25 of the maximum of the width and the height of the provided region, we consider it as a successful localization.

We report the achieved precision, recall, and F-score in Table 1, in which we highlight (in bold font) the best results achieved among different methods. We compare the results of the proposed filters with those obtained by the original excitatory-only COSFIRE filters by setting the inhibition factor \(\eta = 0\). The method proposed by Valveny et al. [35] achieves the best recall in the architectural subsets, while on average the excitatory-only COSFIRE filters have better recall than those from the other two methods. On average, the best precision and F-score are achieved by our proposed inhibition-augmented COSFIRE filters, which have slightly lower recall (0.90) than that achieved (0.92) by excitatory-only COSFIRE filters.
Discussion
We use Gabor filters, which are the model of orientation-selective cells in area V1 and V2 of the visual cortex. Gabor filters are, however, not intrinsic to the proposed model, and other computational models of simple cells, for example, the models proposed elsewhere [10, 30], can also be used.

We use four parameters $t_1$, $t_2$, $t_3$, and $h$ to control the output of an inhibition-augmented COSFIRE model. The parameter $t_1$ regulates the threshold at which the response of a Gabor filter indicates the presence of a contour part. The choice of the value of parameter $t_1$ depends on the contrast of the image and the presence of noise. The value of $t_2$ controls the minimum valid value of the response that provides the excitatory and inhibitory inputs to the model. The parameter $t_3$ depends on the noise of an input image and it is used to suppress the responses that are below a given fraction of the maximum response value across all locations of the input image. We use the value of the parameter $\eta$ to adjust the inhibition factor. The inhibition contour parts, and the inhibition strength parameter that we propose, are determined from the training set of a given application. The generalization ability of an inhibition-augmented COSFIRE model decreases with an increasing number of inhibitory contour parts and/or with an increasing value of the inhibition strength parameter $\eta$. We determine optimal values of $t_1$, $t_2$, $t_3$, and $\eta$ for each model as the ones that contribute the best to the results on the training images.

The proposed model can be considered as a general framework for the localization of any pattern of interest such as traffic signs [18], handwritten letters [40], and music notes [41]. It automatically learns the involved excitatory and inhibitory contour parts from a positive pattern and a set of negative patterns. The presence of a symbol in an image is indicated by the locations where the corresponding model evokes strong responses.

For future work, one direction is to investigate a learning model to automatically determine optimal values of parameters for the inhibition-augmented COSFIRE model. Another direction is to further investigate the performance of the proposed approach on other data sets such as the graphics recognitions data set used in [42, 43].

Conclusion
The proposed inhibition-augmented COSFIRE model is inspired from some shape-selective neurons in the area IT of the visual cortex that experience inhibition. We demonstrated how the proposed inhibition-augmented model can be used to design an effective computer vision algorithm for localization of architectural and electrical symbols. The inclusion of the proposed inhibition mechanism in the COSFIRE models substantially improves the precision and F-score of symbol localization. The model is trainable, in that it does not use domain knowledge, and its selectivity is automatically determined in a configuration procedure. This property makes this approach suitable for various object localization and recognition applications in computer vision.

References
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