A Figure-Ground Discrimination Algorithm Inspired by Border-Ownership Selective Cells

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Abstract

We developed a figure-ground discrimination algorithm that is suitable for robot vision. The algorithm is inspired by the response properties of border-ownership (BO)-selective cells, which possibly support figure-ground discrimination in the visual nervous system. The output of our algorithm is affected by spatial parameters such as the characteristics of the spatial filter used for edge enhancement and the interval of model BO-selective cells. Therefore, we investigated the relationship between the algorithm output with various spatial parameters and object sizes.

Keywords: figure-ground discrimination, border-ownership, bio-inspired.

1. Introduction

Figure-ground discrimination is one of the most important functions for image classification. Although a lot of algorithms for extracting contour has been developed in robotic vision field, it is not straightforward to extract information on which side of the contour the object is located; this information is necessary for figure-ground discrimination.

On the other hand, animals and humans have an ability to discriminate figure and ground as one of their basic visual functions, and can instantly discriminate objects of interest from other backgrounds based on visual information projected on their retina. Border-ownership (BO)-selective cells, which respond selectively to contour only on the object side, could be involved in the function of figure-ground discrimination in the visual nervous system.[1] Several neuronal network models for figure-ground discrimination have been proposed based on the response characteristics of BO-selective cells.[2], [3]

The response characteristics of BO-selective cell can play an important role in image classification. However, the computational cost of the neuronal network models themselves are expensive, and they are not suitable for real-time processing. Algorithms with less computational cost are required for real-world and real-time applications.

The purpose of this study is to develop a figure-ground discrimination algorithm inspired by BO-selective cells that is suitable for robot vision. We also investigated the relationship between the parameters used in this algorithm, such as the spatial filter, and the object's size that can be discriminated against the background by this algorithm.

2. Neuronal Model for Figure-Ground Discrimination

The algorithm developed in this study is based on a neuronal circuit model proposed to explain the figure-ground discrimination function in the visual nervous system.[2],[3] Fig. 1 shows the structure of the neuronal circuit model that consists of three layers. The first layer is the simple cell layer (S_θ in Fig. 1), in which each cell responds selectively to contours of a particular orientation. The second layer is BO-selective cell layer, in which each cell responds selectively to contours and the response of cells depends on which side the object is. The third layer is grouping cell layer, in which cells in object regions respond strongly.

The BO-selective cells receive signals from S_θ and therefore, these cells also respond selectively to contours. In the BO-selective cell layer, a pair of cells located at a position works together and one of the paired cells on a contour respond strongly depending on which side the object is. When the object is on the opposite side, the other cell of the paired cells responds strongly. Therefore, comparing the response of the paired cells tells the side of the object.

The interconnection between BO-selective cells and grouping cells enables the object-side-specific response of BO-selective cells. Each grouping cell receives input from multiple BO-selective cells to determine whether the area is enclosed by a contour. Grouping cells surrounded by a contour show a strong response. Grouping cells also send either excitatory or inhibitory feedback to BO-selective cells. The feedback enhances the response of BO-selective cells that are selective to the correct object direction and inhibits BO-selective cells that are selective to the opposite direction.

3. Figure-Ground Discrimination Algorithm

3.1. *Processing flow*

Fig. 2 shows the processing flow of the figure-ground discrimination algorithm developed in this study.

First, contour features (S_θ) of four orientations are extracted from grayscale input images using a set of Gabor filters.

Next, the contour information is sent to two types of BO-selective cells ($B_{\theta P}$ and $B_{\theta N}$ in Fig. 2 for examples) after half-wave rectification. $B_{\theta P}$ has a facilitative interconnection with grouping cells (G_L), which responds strongly to the contour of objects that are brighter than the background. $B_{\theta N}$ has a facilitative interconnection

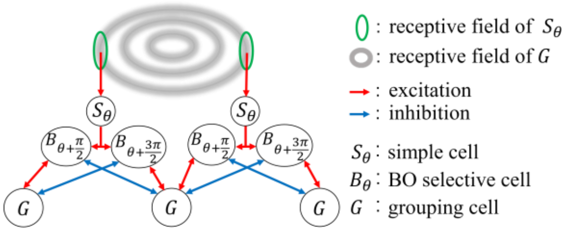

Fig. 1. Neuronal model for figure-ground discrimination.

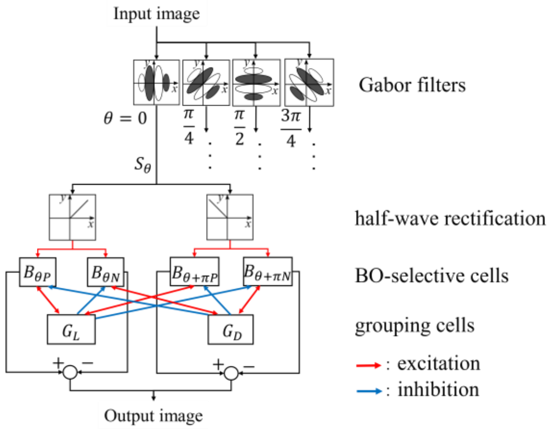

Fig. 2. Processing flow diagram of the proposed algorithm.

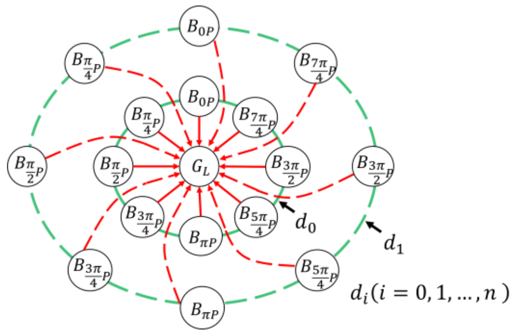

Fig. 3. Feedforward connection between BO-selective cells and grouping cells.

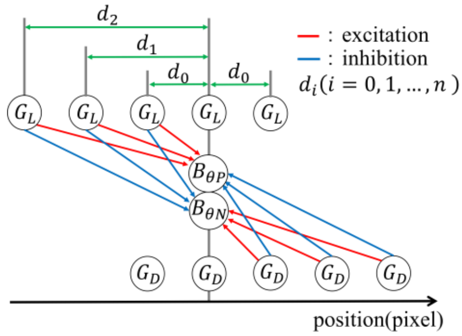

Fig. 4. Feedback connection between grouping cells and BO-selective cells.

with grouping cells (G_D), which responds strongly to the contour of objects that are darker than the background.

In the neuronal circuit model of the previous study, grouping cells are connected to BO-selective cells on their ring-shaped receptive field. In this study, the connection between grouping cells and BO-selective cells were simplified to reduce computational complexity. Each grouping cell connected to BO-selective cells that are in the eight directions whose angles are different by $\pi/4$, and are at distances of $d_i (i = 0,1, \dots, n)$ pixels.

Fig. 3 and Fig. 4 show the connections between grouping cells and BO-selective cells. Fig. 3 shows the connections of $B_{\theta P}$ at different distances d_i with respect to G_L. These connections simulate the ring-shaped receptive field of grouping cells in the original neuronal circuit models[2],[3]. The connection between $B_{\theta N}$ and G_D can be illustrated by replacing G_L and each $B_{\theta P}$ in Fig. 3 with G_D and $B_{\theta N}$. Fig. 4 shows the feedback connections between grouping cells and BO-selective cells.

Finally, an output image that indicate the direction of the figure with respect to the background is generated from the response of BO-selective cells.

3.2. *Contour extraction*

The proposed algorithm uses a set of odd-function Gabor filters for contour extraction. The contour orientation (θ) to be extracted is four orientations whose angle differences are π/4. The Gabor function is expressed by

$$\mathrm{g}(x, y, \theta, L) = A \exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) \cos\left(\frac{2\pi x'}{L} + \varphi\right), \quad (1)$$

$$x' = x\cos\theta + y\sin\theta , \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta , \quad (3)$$

where x and y represent the coordinates in the kernel, L represents the wavelength. This algorithm uses three filters whose (σ, L) sets are (2.2, 6), (3.1, 8), and (4.5, 12) pixels. The response of a simple cell (S_θ) is expressed by

$$S_\theta(x, y) = I(x, y) * \mathrm{g}(x, y, \theta, L) . \quad (4)$$

3.3. *BO-selective cells*

The contour information obtained in the previous section is used to compute the response of two types of BO-selective cells $(B_{\theta P}, B_{\theta N})$. The response of $B_{\theta P}$ is expressed by

$$B_{\theta P}(x, y) = S_\theta(x, y) \times \frac{2}{1 + \exp(-G)} , \quad (5)$$

$$G = \sum_{i=0}^{n} \frac{d_0}{d_i} \cdot (G_L(x + \Delta x_i, y + \Delta y_i) - G_D(x - \Delta x_i, y - \Delta y_i)) , \quad (6)$$

$$(\Delta x_i, \Delta y_i) = (d_i\cos\theta, -d_i \sin\theta) . \quad (7)$$

The strength of the interaction between BO-selective cells and grouping cells is represented by d_0/d_i, and reduces as distance d_i increases. The response of $B_{\theta N}$ is obtained by just replacing the coordinate of G_D with that of G_L in Eq. (6). The way of computing responses of G_L and G_D is explained in the next section.

3.4. *Grouping cells*

Responses of two types of grouping cells are computed from the responses of BO-selective cells. The response of grouping cells G_L, which respond strongly to objects that are brighter than the background, is obtained by summing $B_{\theta P}$ in the eight directions at a set of distances, as shown in Fig 3. The response of grouping cells G_D, which respond strongly to objects that are darker than background, is obtained by summing $B_{\theta N}$ in the same way as G_L.

Finally, the strengths of the responses of a set of grouping cells (G_L, G_D) at each position are compared, and the smaller one is set to 0 because an object is either darker or brighter than the background.

4. Results

4.1. *Algorithm outputs*

We examined the algorithm outputs using the input image shown in Fig. 5(a). The following parameter was used for this simulation: $d_i \in \{10,14,18,22\}$.

Fig. 5(b) shows the final output whose color indicates the object orientation. The orientation was determined by the response of BO-selective cells computed using a Gabor filter whose $L = 8$ pixels. The color circle on the upper right shows the correspondence between the color and the orientation. On most of the contour, the object orientation was correctly indicated.

Figs. 5(c), (d), and (e) show the sum of the responses of grouping cells G_L and G_D computed using Gabor filters with various values of L. In Fig. 5(d), which was used to obtain Fig. 5(b), cells only in the object region responded strongly.

Our algorithm implemented on a personal computer with an Intel(R) Core(TM) i7-8700 CPU and 16 GB RAM using Python processed one image in about 40 msec.

4.2. *Examination of grouping cell characteristics*

The object's size that can be discriminated by the proposed algorithm is roughly estimated from responses of grouping cells. Responses of grouping cells are strongly affected by the connection between BO-selective cells and grouping cells, and the spatial characteristics of the Gabor filter. Therefore, we examined the relationship between these spatial parameters and the response of grouping cells.

The input image used here has a solid white circle on a black background. The radius of the circle is between 1 to 30 pixels. We examined the response of the grouping cell at the center of the circle.

Fig. 6 shows the response of the grouping cell at the center of the circle. The following parameter was used for this examination: $d_i \in \{10,14,18,22,26\}$. Because the circle is brighter than the background, G_L (Fig. 6(a)) should always be larger than G_D (Fig. 6(b)). However, G_D has a larger value in some cases. First, G_D is larger when the radius of the circle is smaller than 8 pixels. This is because d_i was set to values that are larger than 10 pixels and the smallest object to be discriminated can be controlled by changing d_i. Second, G_D is larger when the wavelength L is 6 pixels and the radius is about 13, 17, and 20 pixels. This case is caused by constructive interference of two Gabor waves induced by contour of opposite sides. To avoid this situation, the interval of d_i has to be less than half of the wavelength L.

5. Conclusion

In this study, we developed a figure-ground discrimination algorithm based on the model of BO-selective cells in the visual nervous system. We also investigated the relationship between the spatial parameters used in the algorithm and the object's size that can be discriminated into figures and the background by the algorithm.

6. Acknowledgement

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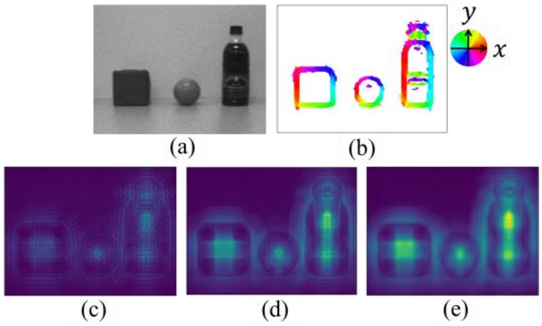

Fig. 5. Examples of input and output images of the algorithm. (a)Input image of 160 × 120 pixels. (b) Response of BO-selective cells computed using a Gabor filter whose $L = 8$ pixels. (c)(d)(e) Response of grouping cells computed using Gabor filters whose $L = 6$, 8, and 12 pixels, respectively.

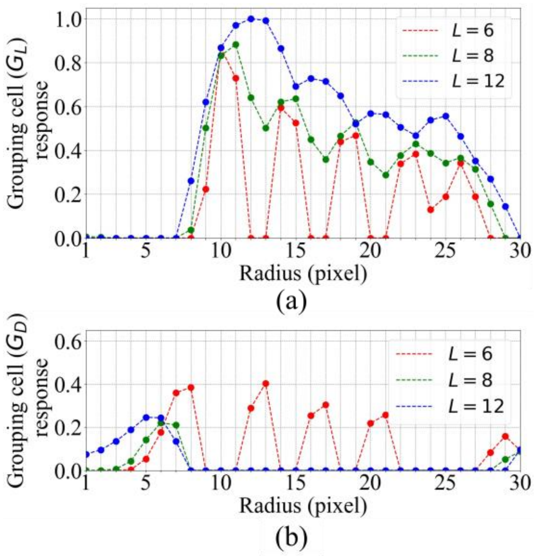

Fig. 6. The relationship between object's size and the response of the grouping cell at the center of the circle. The horizontal axis represents the radius. The red, green, and blue lines plot the response of the grouping cell computed using Gabor filters whose $L = 6$, 8, and 12 pixels, respectively. (a) Response of G_L. (b) Response of G_D.

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