A Neurocomputing Model for Ganglion Cell’s Color Opponency Mechanism and Its Application in Image Analysis

Hui Wei, Heng Wu
Lab of Cognitive Model and Algorithm
School of Computer Science
Fudan University
Shanghai 200433, China
Email: weihui@fudan.edu.cn

Abstract—The vision system of primates could process colorful scenes very efficiently. This is because, in biological retina, there are three types of cone cells and several types of ganglion cells that possess highly complicated receptive fields. The central and the surrounding areas of a receptive field are usually composed of different types of cones. Typically, they form two classes, namely the red-green opponency and the blue-yellow opponency. In order to develop a new representation schema for colorful images, we simulated some physiological mechanisms in retina, such as the opponent color theory. Based on anatomical and electrophysiological findings of ganglion cells, we proposed a bio-inspired color processing method. We designed a neural network simulating retinal ganglion cells (GCs) and their classical receptive fields (CRF), and also raised a dynamic procedure to control receptive field’s self-adjustment according to the characteristics of an image. A great number of experiments were conducted on natural images. The results showed that this new method could reserve crucial structural information of an image and suppress trivial information at the same time. Depending on these new representations, some up-coming processing, such as image segmentation, could be improved significantly. Image segmentation is very critical to ultimate image understanding. However, actual image stimuli are a little bit far from biological studies. Our work integrated them together and explained how the physiological opponent-color theory could facilitate image processing in real applications.

I. INTRODUCTION

At present, color information processing, to some extent, is simple. The typical methods dealing with the color information in the natural image include graying the chromatic colors and the statistical treatment to the number of pixels of the same color. Meanwhile, it is known to all that advanced primates’ eyes have effective mechanisms to process the color information and represent natural images. With thousands of years’ evolution, advanced primates are able to capture the significant information of a meaningful object from the scene using one kind of descriptor with minimum costs. And these biological mechanisms inspired researchers a lot when designing image processing algorithms.

In recent decades, many scholars began to shift their sights to the mechanism of our eyes. Fortunately, with the development of science and technology, biologists have got some scientific advances in the working mechanism of the human visual system after considerable studies. Researchers integrated the known neurobiological knowledge with computer technology to simulate the mechanism of our visual system and have fulfilled various computer vision tasks. In 1965, Rodieck et al. [1] first raised a mathematical model, named as Difference of Gaussian (DoG), to describe the concentric classic receptive field (CRF). In 1985, Daugman et al. [2] proposed a way to use the Gabor basis function to simulate the receptive fields (RFs) of simple cells. Furthermore, Ghosh et al. [3] used a model of a combination of three-Gaussian at three different scales to describe the non-classical receptive field (nCRF). Grigorescu et al. [4] used the nCRF inhibition property to detect edges. Wei et al. [5] built an array of retinal ganglion cells with their non-classical receptive field, which could expand and shrink automatically depending on the characteristics of the image. In addition, he [6] also proposed a non-classical receptive field based model, which would integrate the information in a multi-scale way. They used this model to process and represent image. As color-opponent theory is crucial in the receptive field, some researchers started to use it. Lambrecht et al. [7] proposed a computational metric that incorporated the opponent colors theory and human color perception to assess the quality of color coded images. Huang et al. [8] enhanced natural color images by converting the color information from RGB signals to opponent-color signals. Nadenau et al. [9] compressed images based on the opponent color space. Debashis et al. [10] proposed a new method of measuring image contrast based on local band-limited approach and the center-surround retinal receptive field model. In [10], when conducting quantitative evaluation of his novel contrast enhancement algorithm, the color-opponent organization was applied into his evaluation method.

It is a wonderful idea to use the computational model to simulate the retinal ganglion cell and its receptive field, taking the output of the model to represent images. This kind of method applied the mechanism of human visual system to digital image processing, having achieved great performance with high efficiency. As mentioned above, a great many of scholars have done much on it. However, nowadays many of them like to use nCRF, not the CRF which is the original
model of the receptive field. Though there were some researchers applying the color opponency mechanism to image processing, seldom did they use this mechanism when representing the image. In fact, the “color opponency” is an efficient representation of spectral properties in natural scenes. Such opponency mechanism could reduce redundant information and help achieve a highly efficient encoding of natural chromatic signals [11]. Therefore, it encourages us to take the CRF and the color opponency mechanism into consideration, seeking a novel way to represent images.

Our paper proposed an image representation method involving a neural network consisting of retinal ganglion cells inspired by the biological mechanism. In our model, the retinal ganglion cells’ classical receptive fields could dynamically self-adjust depending on the characteristics of the scene. Besides, the opponent color theory was applied to help interpret information about color in real images. To prove our model has a strong image representing ability, we have conducted a lot of experiments on the Berkeley Segmentation Dataset and Benchmark (BSDS300) [12]. The famous image segmentation algorithm gpB-OWT-UCM [13] had much better performance based on the result of our representing method than the original image.

This paper is organized as follows. Section II briefly introduces the basic knowledge of retinal ganglion cells, the classical receptive field and their neurophysiological mechanism. Our human visual system’s color opponency mechanism and the fixation eye movements would also be included in this part. Section III elaborates our model design and the whole image representation algorithm. Section IV shows the experimental results and Section V concludes the paper.

II. PHYSIOLOGICAL BASIS

A. Neurophysiological Mechanism of RF of Retinal GC

The human vision system is a pyramid hierarchical structure. Visual Information is mainly perceived and transformed from the retina through the lateral geniculate nucleus to the visual cortex. In the early phase, the retina obtains illumination, color and spatial information, and then transfers them to higher processing stages. The ganglion cell (GC), which lies on the inner surface of the retina, is the final output neuron in retinal information processing. The GC receives visual information from receptor cells (RCs) via bipolar cells (BCs) and amacrine cells (ACs). A group of retinal RCs form the CRF center of the BC. At the same time, more RCs are indirectly connected to the BC through horizontal cells (HCs), and they form the CRF surround of the BC. BCs with antagonistic center-surround RFs send their outputs to a GC, and they collectively form the antagonistic center-surround CRF of the GC. Furthermore, the retinal GC’s RFs, which are sensitive to contrast and brightness, pass the stimuli they perceived to their own GC, then the GC would merge and integrate all these signals. The output of the retinal GC complex network would be applied to represent images or other further uses.

B. The Structure of Classical Receptive Field (CRF)

By studying cats’ retinal ganglion cells’ spatial distribution of the response sensitivity, Kuffler [14] expounded to the public that the classical receptive field of the ganglion cell had a structure of antagonistic concentric circle. It means the CRF consists of CRF center which is the excitatory and the CRF surround which is the inhibition. The CRF center and the CRF surround are functionally antagonistic. Fig. 1 shows the structure of the classical receptive field. In different parts of the retina, the size of the RF of GC varies from one to another. In most cases, the RF of the GC locating in the peripheral zone of the retina is larger than the one locating in the central part. Moreover, the RFs which are next to each other may overlap.

Fig. 1. The structure of the CRF

The CRF’s antagonistic concentric structure makes GC very sensitive to the light falling in the CRF, which provides the neurophysiological basis for the visual system to distinguish the spatial contrast and to extract spatial shape information.

C. Color Opponency Mechanism

The color opponency mechanism [15] is a color theory stating that the human visual system interprets information about color by processing signals from cones and rods in an antagonistic manner.

Bipolar cells (BCs) and ganglion cells (GCs) make great contribution to this opponent mechanism. The bipolar cells transform the information from cones to ganglion cells in the retina during the opponent process. There are two major classes of the ganglion cells: parvocellular and magnocellular. The majority of the color information is processed by parvocellular, which could be divided into two groups. One group of cells are responsible for processing the red-green differences. The other group handle the blue-yellow differences [16].

Shown in Fig. 2, the center-surround retinal receptive field is characterized by the red, green, blue and yellow components [17]. There are four types of retina receptive field: a red CRF center with an antagonistic green CRF surround, a green CRF center with an antagonistic red CRF surround, a blue CRF center with an antagonistic yellow CRF surround, a yellow CRF center with an antagonistic blue CRF surround.

During the perception of chromatic signals, all these four types of center-surround retinal receptive fields are formed in
the retina. When chromatic signals come, these four types of CRF would distribute automatically according to the signals. Each type of the CRF has its own most sensitive chromatic signal range. Consequently when processing the image information, the CRF would choose to process the chromatic signal which it is most sensitive to. In this way, they would automatically locate in the right place. Furthermore, these receptive fields would automatically expand or shrink to achieve most excellent performance and well utilize themselves. As shown in Fig. 3, after locating in the right place with the most applicable sizes, these four types of CRF would pass the signals they have processed to their GCs. Then their GCs would immediately integrate the information from different components and pass them to the upper layer for subsequent processing.

![Fig. 3. GCs integrate the information processed by these components](image)

D. Fixation Eye Movements

Fixation eye movements [18] are unconscious eye movements in the state of fixation. It has been found in a number of species, including humans, other primates and some mammals.

The fixation eye movement is an indispensable information extraction mechanism in the visual information processing. It has a great value of instruction in the field of computer vision. There are three types of fixation eye movements: tremor, slow drift and microsaccades. The tremor transforms a static image into alternating current signals, and, in this way, the information could be got through the visual channel. The low drift has a close relationship with the microsaccades. It is generally believed that the low drift moves the target object away from the center of the fovea, while the microsaccades correct this displacement. So the fixation eye movements shift retinal image position and in order to rectify this, GC’s RF produces a series of small displacement. All these are the physiological basis for us to use the fixation eye movements to adjust the GC’s response.

III. MODELS AND ALGORITHMS

A. The Model of Retinal GCs’ Responses to Light

As foresaid, there are four types of the classical retina receptive field. Each type of the CRF has a range of chromatic signals that it is most sensitive to. In the pre-processing procedure of our algorithm, we needed to construct a model to measure and present the response of retinal GCs with different kind of CRFs to the visible light.

In the retina, light is one kind of physical stimulus that could fire cone cells. Meanwhile, the response of the cells when receiving the stimulus depends on wavelength of the light. Thus it is urgent to get the wavelength of the chromatic signals which come into our eyes. In most cases, a digital image, however, is based on RGB color model. All the pixels in this kind of image are defined by the three chromaticities of the red, green, and blue (RGB) additive primaries. Hence we aimed to convert the RGB values into its corresponding wavelength value. Equation (1) is used by us to convert the color from RGB space to XYZ space, according to [19]. After getting the value of the color in XYZ space, we could get its corresponding wavelength also by the curve graph in 1931CIE [19].

\[
\begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix} = \begin{bmatrix}
0.49 & 0.31 & 0.20 \\
0.17697 & 0.81240 & 0.01063 \\
0.00 & 0.01 & 0.99
\end{bmatrix} \begin{bmatrix}
R \\
G \\
B
\end{bmatrix} \tag{1}
\]

Given the wavelength of every color in the space of RGB, we designed three curves to simulate responses of red cones, blue cones and green cones based on the response curves and peak spectral sensitivities of these three primate cone types in the primate retina [20]. However, there is a yellow component in the color opponency mechanism of the GC. Regarding the fact that there is no yellow cone in the photoreceptor layer and our visual perception is formed by complicated information reconstruction in the middle layers, in order to simplify the computational models, we set a phantom cone-response curve corresponding to the yellow component as an auxiliary. Here, we supposed the yellow curve reflected the sensitivity of the fictitious yellow-cone when receiving light in image processing.

Fig. 4 shows the sensitivity of the red cone, green cone blue cone and the fictitious yellow-cone to the light. Studies [21] show that the wavelength of the visible light ranges from about 370 nm to 780 nm, but a typical eye could only have strong responsiveness to the light with the wavelength from about 380 nm to 680 nm [21]. In our paper, we only took the light whose wavelength is between 380 nm and 680 nm into consideration. Furthermore, the red cone, green cone, blue cone and the fictitious yellow-cone get the most excited status when the light with the wavelength of around 655 nm, 505 nm, 405 nm and 580 nm respectively. The X-axis in Fig. 4 is the wavelength of the colors and the Y-axis in Fig. 4 is the sensitivity of the different cones to the light with different wavelength. Below are the definition equations for these four curves. For the red cone, the sensitivity when stimulated by the light with the wavelength ranging from 380 nm to 680 nm:

\[
r' = \exp(-k_i^2 \frac{(\text{wavelength} - 380)}{680 - 380} - \frac{704}{255 \times 3 + 2}) \tag{2}
\]

where \( k_i = 5.0 \)
For the green cone, the sensitivity when stimulated by the light with the wavelength ranging from 380 nm to 680 nm:
\[ g' = \exp\left(-k'_g\left(\frac{\text{wavelength} - 380}{680 - 380} - \frac{320}{255 \times 3 + 2}\right)^2\right) \]
where \( k'_g = 5.0 \)

For the blue cone, the sensitivity when stimulated by the light with the wavelength ranging from 380 nm to 680 nm:
\[ b' = \exp\left(-k'_b\left(\frac{\text{wavelength} - 380}{680 - 380} - \frac{64}{255 \times 3 + 2}\right)^2\right) \]
where \( k'_b = 5.0 \)

For the fictitious yellow-cone, the sensitivity when stimulated by the light with the wavelength ranging from 380 nm to 680 nm:
\[ y' = \exp\left(-k'_y\left(\frac{\text{wavelength} - 380}{680 - 380} - \frac{512}{255 \times 3 + 2}\right)^2\right) \]
where \( k'_y = 5.0 \)

Shown in Fig.5, in order to make the area of the inner circle equal the area of the ring between the inner circle and the outer circle, we solved Equation (6):
\[ \pi \times r^2 = \pi \times R^2 - \pi \times r'^2 \]
Then we got \( R = \sqrt{2}r \).

When processing images, these four types of CRFs would locate in the place where their computing units would give relatively high outputs. After determining the place where to locate, the CRF would change its size to reach the best status, at the same time the computing units in CRF center and in the CRF surround would give corresponding outputs. Then the integration of the outputs was regarded as the response of GC.

Table I illustrates the way how to calculate the response of the individual component and the GC for the four types of CRF. And there are also four columns. The first column is the CRF type. In the second column, there are equations for calculating the output of the computing unit for the each CRF center. The third column shows the equations for the calculation of the output of the computing unit for the each CRF surround. And in the last column, the way how the outputs were integrated for the response of the GC is explained. In these equations, \( \sigma_r \) stands for the region of CRF center, \( \sigma_s \) stands for the region of CRF surround, \( p \) and \( p(x, y) \), where \( (x, y) \) are the coordinates, represent the pixel in the image. And the parameters \( k_r, k_p, k_b, k_s \) all equal the value of 5.0. The function \( \text{waven}(p) \) was used to get the wavelength of a pixel described in RGB color space model. We made it offline, which has been described at the beginning of this section.

In our model, the maximum output of the each component was set to 1 and the minimal output was set to 0, which could also be seen from Fig.4. So the response value of GC would vary from -1 to 1.

Table III gives the all the possibilities of the stimulus, i.e. the light, from the outside, for different types of CRF. Here the CRF with red component in the center and an antagonistic green component in the surround was taken as an example to illustrate the mechanism. When the relative-long-wavelength light came, the output of the computing unit for the CRF center would be relatively high, while the output of the computing unit for the CRF surround would also have a positive value, but would not be so high. As a result, the response of the GC, using the method described in Table I, would be much closer to 1 than to 0. It meant there was no big color difference, and there was no distinct edge. When the relative-long-wavelength light shined in the CRF center and the relative-short-wavelength light shined in the CRF...
surround, both the outputs of the computing unit for the CRF center and the CRF surround would be relatively high, hence the response of the GC would be close to 0. It meant some great color differences existed there, a distinct boundary also much likely existed there. While the relative-short-wavelength light shined, the output of the computing unit for the CRF center would be relatively low, but still a positive value. Meanwhile, the output of the computing unit for the CRF surround would have a relatively high value. In this way, the response of the GC would be much closer to -1 than to 0, which meant there was no big color difference, no distinct edge existed. When the relative-short-wavelength light shined in the CRF center and the relative-long-wavelength light shined in the CRF surround, both the outputs of the computing unit for the CRF center and the CRF surround would be relatively low, so the response of the GC would be close to 0. It meant some great color differences existed there and a distinct edge also existed there in a great probability.

C. The Mechanism of Dynamic Change of all the CRFs in the GC array

In our method, there was a concept of GC array which was an array consisting of 5*5 GCs. When processing an image, the 5*5 GC array would shake a lot of times in order to cover the whole image. As mentioned above, the CRF in our model would expand or shrink to cover the most appropriate area of the image, making the best use of themselves and outputting the most meaningful computing results.

Table II shows the algorithm for the mechanism of dynamic change of all the CRFs in the GC array.

<table>
<thead>
<tr>
<th>CRF Type</th>
<th>Output of the Computing Unit for CRF Center</th>
<th>Output of the Computing Unit for CRF Surround</th>
<th>Response of GC</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRF Center - Red = ( \sum_{p \in I} \exp(-k_1 \frac{\text{wavelet}(p, x, y) - 380}{300}) \frac{1}{\pi \times r^2} )</td>
<td>CRF Surround - Green = ( \sum_{p \in I} \exp(-k_2 \frac{\text{wavelet}(p, x, y) - 380}{300}) \frac{1}{\pi \times r^2} )</td>
<td>GC Red-Green = ( \text{CRF Center-Red} - \text{CRF Surround-Green} )</td>
<td></td>
</tr>
<tr>
<td>CRF Center - Green = ( \sum_{p \in I} \exp(-k_2 \frac{\text{wavelet}(p, x, y) - 380}{300}) \frac{1}{\pi \times r^2} )</td>
<td>CRF Surround - Blue = ( \sum_{p \in I} \exp(-k_3 \frac{\text{wavelet}(p, x, y) - 380}{300}) \frac{1}{\pi \times r^2} )</td>
<td>GC Green-Red = ( \text{CRF Center-Green} - \text{CRF Surround-Red} )</td>
<td></td>
</tr>
<tr>
<td>CRF Center - Yellow = ( \sum_{p \in I} \exp(-k_1 \frac{\text{wavelet}(p, x, y) - 380}{300}) \frac{1}{\pi \times r^2} )</td>
<td>CRF Surround - Yellow = ( \sum_{p \in I} \exp(-k_3 \frac{\text{wavelet}(p, x, y) - 380}{300}) \frac{1}{\pi \times r^2} )</td>
<td>GC Yellow-Blue = ( \text{CRF Center-Yellow} - \text{CRF Surround-Blue} )</td>
<td></td>
</tr>
</tbody>
</table>

**Table II**
The algorithm for dynamic change of all CRFs in the GC array

- **Input:** An image with RGB pixels. **Output:** A representation for the image
- **foreach** RGB pixel in original image
  - Get its wavelength according to 1931CIE
  - Calculate the four components’ response to it by Equation (2)-(5)
- **end**
- **repeat** set 5*5 GC array until they cover the whole image
  - **foreach** GC in the array
    - for the area CRF center covers from 200 pixels to 1 pixel
      - Choose the proper type for this CRF according to the area it covers
      - Get the output of the computing unit for CRF center & surround
      - Integrate these outputs for the response of the GC
      - Insert the type of the CRF and the response of the GC into Array Z
    - end
  - Choose the response of the GC which is most close to 1 or -1 in Z
  - Set its corresponding type to CRF
  - The final response of this GC \( \leftarrow -1 \) [original response of the GC]
- **end**
- Shake the GC array
- **end**

Here, we took an image for example and Fig.6 shows a sketch map of the whole process.

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**Fig. 6.** The sketch map of the whole procedure when processing an image
TABLE III
RESPONSE IN DIFFERENT TYPES OF CRFS TO THE STIMULUS AND ITS CORRESPONDING EXPLANATION

<table>
<thead>
<tr>
<th>CRF Type</th>
<th>Stimulus to CRF Center</th>
<th>Stimulus to CRF Surround</th>
<th>Response in CRF Center</th>
<th>Response in CRF Surround</th>
<th>Response of GC</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>L</td>
<td>High</td>
<td>Low</td>
<td>+</td>
<td>No Distinct Edge</td>
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<tr>
<td>L</td>
<td>S</td>
<td>High</td>
<td>High</td>
<td>—</td>
<td>Distinct Edge Exists</td>
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<tr>
<td>S</td>
<td>L</td>
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</tbody>
</table>

“L” stands for the stimulus of the light with relative long wavelength; “S” stands for the stimulus of the light with relative short wavelength; “—” stand for the degree of the response in the CRF center or the CRF surround; “+” means the response in CRF center and the response in its antagonistic CRF surround are balanced, while “—” means not balanced.

At first, the results of computing units for the CRF center and CRF surround respectively would be calculated. The four intermediate results lying from the left to the right are the outputs of computing units for a red CRF center with an antagonistic green CRF surround, a green CRF center with an antagonistic red CRF surround, a yellow CRF center with an antagonistic blue CRF surround, a blue CRF center with an antagonistic yellow CRF surround respectively. Then the GC would integrate these outputs from each type of CRF to get the final response. After some mathematic transformation, the original image would be represented in our way eventually. Fig.7 also gives some samples with our bio-inspired methods. In each row, the leftmost image is the original image and the other 5 images are the outputs.

![Fig. 7. Four sample outputs with our methods](image)

IV. EXPERIMENTS

Based on the foregoing neural computational model and algorithm, we conducted a large number of experiments to test and evaluate the efficiency of our model. In our model, GCs constructed a network of different-size RFs according to the input image. The responses of GCs were used for image representation. This section would present our representation results of some images from database BSDS300. We also ran the famous image segmentation algorithm gPb-OWT-UCM on the original images and the results showed that our image representation method could enhance the segmentation performance.

In each row of Table IV, the leftmost image is the original image, which is also the input of our algorithm. The following four images are the results of computing units for four kinds of CRF and the fifth one is the integrated result. The last two images in the rows of Table IV are the segmentation results with the well-known algorithm, gPb-OWT-UCM, based on our outputs and the original images. From Table IV, we could find that by our algorithm, almost all the important elements, such as edges, were reserved while most detailed information, such as textures, was filtered out. Then we ran the famous gPb-OWT-UCM segmentation method based on original images and outputs of our model with the results in the last two columns. We could see that, in most cases, the gPb-OWT-UCM has much better or at least the same performance on our results than on the original images, proving that our image representation way could also significantly facilitate image segmentation.

V. CONCLUSION

Representing visual stimuli efficiently always lies at the heart of many image processing tasks, such as image representation, compression, denoising and feature extraction [22]. In this paper, for example, it helped improve the performance of image segmentation. As the neighboring pixels in a natural image are highly correlated [23], segmentation would never be just contrast detection in terms of physical features. Before making decision, a segmentation algorithm needs to take the information in a continuous area of the image into account. Our approach exactly met this demand by using a dynamic receptive field. In this receptive field, the color opponency mechanism was modeled.
<table>
<thead>
<tr>
<th>Input: Original Image</th>
<th>Outputs (Outputs of Computing Units for 4 kinds of CRF and the Integrated Result)</th>
<th>Segmentation Results Using ( \text{gPb-OWT-UCM} )</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 1" /></td>
<td><img src="image2.png" alt="Image 2" /> <img src="image3.png" alt="Image 3" /> <img src="image4.png" alt="Image 4" /> <img src="image5.png" alt="Image 5" /></td>
<td><img src="image6.png" alt="Image 6" /> <img src="image7.png" alt="Image 7" /></td>
</tr>
<tr>
<td><img src="image8.png" alt="Image 8" /></td>
<td><img src="image9.png" alt="Image 9" /> <img src="image10.png" alt="Image 10" /> <img src="image11.png" alt="Image 11" /> <img src="image12.png" alt="Image 12" /></td>
<td><img src="image13.png" alt="Image 13" /> <img src="image14.png" alt="Image 14" /></td>
</tr>
<tr>
<td><img src="image15.png" alt="Image 15" /></td>
<td><img src="image16.png" alt="Image 16" /> <img src="image17.png" alt="Image 17" /> <img src="image18.png" alt="Image 18" /> <img src="image19.png" alt="Image 19" /></td>
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</table>
A great number of experiments have been done, and the improved segmentation results showed that this method could represent images more faithfully, simply and efficiently.

Our future work will focus on the application of this method, including applying it in object recognition, scene understanding etc.

**ACKNOWLEDGMENT**

This work was supported by the 973 Program (Project No. 2010CB327900), the NSFC major project (Project No. 30990260) and the National Twelfth 5-Year Plan for Science & Technology (Project No. 2012BAI37B06).

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