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MACHINE VISION ALGORITHMS ON A COLOR BLINDNESS PLATE

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ABSTRACT

This paper presents a new approach including passive and active processes to deal with the image segmentation and pattern recognition to a color blindness plate (CBP). The CBP is well-known satisfactory way of testing the degree of color blindness happened in the human visual system. The image of CBP is very complex. It includes not only the colors but also the disconnected size-varied dots. It is very difficult by using a conventional machine vision algorithm to recognize the meaningful pattern (*e.g.*, a figure) from such a CBP image. The proposed machine vision algorithms provide a new solution to this problem.

1 INTRODUCTION

The random problem [1] addressed by Abu-Mostafa and Psaltis may be applied to the optical character recognition (OCR). So far, various OCR systems have been proposed and widely used [2-4]. Usually an OCR system can be divided into preprocessing, feature extraction, and matching. The major processing techniques available are smoothing, normalizing, thinning, and line-segment approximation. However, these procedures are only effective on the well-defined characters and can be readily performed by a traditional approach. If a dotted image containing a meaningful dotted pattern such as a color blindness plate (CBP for short) shown in Fig. 1(a) (which also conducts a random problem) is concerned, its recognition using a conventional computer algorithm will become difficult since the dotted pattern is disconnected and the segmentation of the meaningful dotted pattern is not easy. This introduces to our researches on the CBP image.

The CBP is a satisfactory way of testing the color blindness. For example, one test consists of a card with brilliant purplish-red dots arranged in such a way as to form a number (see Fig. 1(a). A colored dot in a CBP is composed of a circular region of pixels having approximately the same color with red, green, and blue components.) A normal person can see the number immediately because its color contrasts vividly with the background. But individuals with certain types of color deficiency cannot read it because to them the dots all seem to be the same color.

To simulate the computer vision on the CBP image, a "passive-active model" based on the human visual perception is presented. This model is the extended version of our early model which can recognize the meaningful dotted pattern from a dotted image [5]. It consists of passive and active processes. The passive process performs the image segmentation for a CBP [6]; and the active process performs the pattern recognition.

In the following, the machine vision algorithms on a CBP image is briefly presented. Then the results are shown and a conclusion is given.

2 MACHINE VISION ALGORITHMS

2.1 Passive Process: CBP Segmentation

The CBP image can be represented as a 2-D color intensity function $[\mathbf{f}]$ whose (i,j)th element is pixel $\mathbf{f}(i,j)$, where i and j denote spatial coordinates and the vector of $\mathbf{f}$ at any point (i,j) is represented by triples of numbers representing the strengths of their red, green, and blue components, and can be denoted by a 3-element color vector of the form $\mathbf{f}(i,j) = (r_{i,j}, g_{i,j}, b_{i,j})^T$. According to [6], the segmentation of CBP is performed by classifying color planes into pattern and background, and written as

$$[\mathbf{f}] \approx [\mathbf{f}]_{pattern} + [\mathbf{f}]_{background}, \quad (1)$$

where $[\mathbf{f}]_{pattern}$ and $[\mathbf{f}]_{background}$ are respectively expressed by

$$[\mathbf{f}]_{pattern} = \sum_{k \in pattern} [\mathbf{f}]_k, \quad (2)$$

and

$$[\mathbf{f}]_{background} = \sum_{k \in background} [\mathbf{f}]_k. \tag{3}$$

If there are several clusters, say C clusters, appeared in the set of color planes, then the segmentation of CBP can be further expressed as the general form

$$[\mathbf{f}] \approx \sum_{c=1}^{C} [\mathbf{f}]_{cluster(c)}, \tag{4}$$

where

$$[\mathbf{f}]_{cluster(c)} = \sum_{k \in cluster(c)} [\mathbf{f}]_k. \tag{5}$$

And the two clusters, pattern and background, can be regarded as a special case of this general expression.

2.2 Active Process: CBP Recognition

Let each segmented cluster be regarded as a binary image since only two types of pixels (zero and nonzero pixels) in a segmented image are applied to the pattern recognition. Two major problems will be encountered while the segmented clusters are recognized. One is that the pattern information in each segmented cluster is dotted and disconnected, it is impossible to extract the "features" from the pattern using a conventional scheme. The other is that the size of the meaningful pattern (e.g., a figure) is unknown, and which segmented cluster contains the meaningful pattern is also unknown. According to the suggestions of Abu-Mostafa and Psaltis [1] and the psychovisual supports, the solution to the first problem therefore lies essentially in memorizing all possible solutions, and the solution to the second problem lies in selecting the reasonable attended range [7]. Because memorizing all possible solutions may result in impracticability for a computer vision, we develope a useful procedure to make these solutions feasible. All the algorithms in the recognition stage are selective filter, long-term memory, generalization, and neural matching.

2.2.1 Selective filter

To realize the selective attention in our model, at each time, one of the segmented clusters is regarded as a pattern, then the others are regarded as background. If only one cluster is recognized as a meaningful figure, then the model perceives an unique interpretation. If more different clusters are recognized as different meaningful figures, then the model perceives multiple interpretations. If no cluster is recognized as a meaningful figure, then no interpretation is perceived by the model. Thus, it is reasonable to select every segmented cluster for pattern recognition.

When the cth segmented cluster $[\mathbf{f}]_{cluster(c)}$ is selected, only the region containing the pattern is allocated. This will output the effective size and location of the region. This is similar to the function of the selective filter in psychology. Note that, after the selective filter stage, we still use the notation $[\mathbf{f}]_{cluster(c)}$ to represent the located region for the further use of pattern recognition and regard it as a binary image.

(a)

(b)

(c)

Figure 1: Illustration. (a) A CBP image used in [6]. (b) Segmented pattern $[\mathbf{f}]_{pattern}$ (or the first segmented cluster $[\mathbf{f}]_{cluster(1)}$). (c) Segmented background $[\mathbf{f}]_{background}$ (or the second segmented cluster $[\mathbf{f}]_{cluster(2)}$).

2.2.2 Long-term memory

To make the proposed model feasible, in our current presentation, the vectorization of a figure is represented as a template base. For each vector in a template, the first two elements are defined as starting point, and the last two elements are defined as ending point. They are easily reconstructed to be an image form.

2.2.3 Generalization G

For a binary image, the generalization is a growing process for stimuli so that the pattern is thick enough to tolerate all deformations and scalings [7]. But where is the boundary of the growing? It depends on the complexity of pattern. The presented generalization algorithm is composed of three parts: dilation, thinning, and distance computation. The first is used for thickening the vectorized template. The second is used for thinning the thickened pattern. And the last is used for computing the spatial distance between the original vectorized template and the thinned one. The generalized pattern $[\mathbf{g}]_{lc}$ may be expressed as

$$[\mathbf{g}]_{lc} = G([\mathbf{v}]_l | [\mathbf{f}]_{cluster(c)}),\ l = 0 \sim 9. \qquad (6)$$

Where G is the so-called generalization process [7]. It means that according to the effective size, the vector template $[\mathbf{v}]_l$ is converted to a generalized pattern $[\mathbf{g}]_{lc}$ since the generalized pattern is induced from the effective size of the segmented cluster $[\mathbf{f}]_{cluster(c)}$.

2.2.4 Neural matching M

To compute the matching scores, the selected pattern ($[\mathbf{f}]_{cluster(c)}$) will be matched to all the generalized patterns (which can be stored in the interconnections among the neurons). Because the selected pattern is dotted and disconnected, we define the following expression to effectively compute the matching score s_{lc} between $[\mathbf{f}]_{cluster(c)}$ and $[\mathbf{g}]_{lc}$.

$$\begin{aligned} s_{lc} &= M([\mathbf{f}]_{cluster(c)}, [\mathbf{g}]_{lc}) \\ &= \sum_{\forall i,j} W(\mathbf{f}_{cluster(c)}(i,j), \mathbf{g}_{lc}(i,j)),\ l = 0 \sim 9. \end{aligned} \qquad (7)$$

According to the closure property in human visual perception having the tendency to complete in perception what in physically an incomplete pattern or object, we define that the matching weights W's depending on not only the nonzero pixel ("1") but also the zero pixel ("0") in both $[\mathbf{f}]_{cluster(c)}$ and $[\mathbf{g}]_{lc}$. For each location (i,j), we have a matching weight. Hence, we have four types of matching weights, W_{00}, W_{01}, W_{10}, and W_{11} as follows.

Type 1 $W_{00} = \frac{1}{G_0}$, denotes the matching weight in which the selected pattern pixel $\mathbf{f}_{cluster(c)}(i,j) = 0$ and the generalized pattern pixel $\mathbf{g}_{lc}(i,j) = 0$.

Type 2 $W_{01} = \frac{C_{ij}}{G_1}$, denotes the matching weight in which the selected pattern pixel $\mathbf{f}_{cluster(c)}(i,j) = 0$ and the generalized pattern pixel $\mathbf{g}_{lc}(i,j) = 1$.

Type 3 $W_{10} = \frac{-1}{G_0}$, denotes the matching weight in which the selected pattern pixel $\mathbf{f}_{cluster(c)}(i,j) = 1$ and the generalized pattern pixel $\mathbf{g}_{lc}(i,j) = 0$.

Type 4 $W_{11} = \frac{1}{G_1}$, denotes the matching weight in which the selected pattern pixel $\mathbf{f}_{cluster(c)}(i,j) = 1$ and the generalized pattern pixel $\mathbf{g}_{lc}(i,j) = 1$.

Where G_0 is the total number of the pixels whose value is 0 in the generalized pattern, and G_1 is the total number of the pixels whose value is 1 in the generalized pattern, respectively. And C_{ij} depending the location (i,j) is the closure weight related to the selected pattern $[\mathbf{f}]_{cluster(c)}$.

The closure weight is constructed as follows. In physiology, every neuron is not isolated from the others. The lateral function often meeting in neural network is made to depend on neural distance [8]. The degree of lateral interaction is usually described as having the form of Mexican hat. The form of 2-D lateral interaction usually used in stimulation can be defined as

$$\begin{aligned} L_{ij}(x,y) &= \frac{\sin(\sqrt{(x-iM/N)^2+(y-jM/N)^2})}{\sqrt{(x-iM/N)^2+(y-jM/N)^2}}, \\ & -M \le x,y \le M, 1 \le i,j \le N, \end{aligned} \qquad (8)$$

where $N \times N$ is the size of the selected pattern, and $M \times M$ is the the desired range of the 2-D lateral interaction. In our experiments, we set $M = N$. Therefore, the closure weight C_{ij} may be expressed as

$$C_{ij} = \sum_{\forall x,y} L_{ij}(x,y)\mathbf{f}_{cluster(c)}(x,y),\ 1 \le i,j \le N. \qquad (9)$$

Hence the Eq. (7) can be rewritten as

$$\begin{aligned} s_{lc} = & \sum_{\text{Type 1}} W_{00} + \sum_{\text{Type 2}} W_{01} + \\ & \sum_{\text{Type 3}} W_{10} + \sum_{\text{Type 4}} W_{11}. \end{aligned} \qquad (10)$$

3 RESULTS

In the following, the results of the CBP image shown in Fig. 1(a) are given. After the image segmentation in the passive process [6], the original CBP image shown in Fig. 1(a) is classified into two clusters (see Fig. 1(b) and 1(c)). The two segmented clusters are individually performed by the pattern recognition in the active process. The matching results are shown in Table 1. By the specified threshold ($T_m = 0.6$), we have a maximum score ($s_{51} = 1.269$) and get the recognition result 5. In this case, $[\mathbf{f}]_{cluster(1)}$ is the segmented pattern, and $[\mathbf{f}]_{cluster(2)}$ is the segmented background, respectively.

4 CONCLUSION

A new approach including passive and active processes to deal with the image segmentation and pattern recognition to a CBP image has been presented. The passive process performs the image segmentation for a CBP, and the active process performs the generalization and matching for the pattern recognition. The results have confirmed the feasibility of the proposed algorithms.

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Table 1: The matching score s_{lc}, for $c = 1 \sim 2$, $l = 0 \sim 9$. The found maximum value is 1.269 in s_{51}, i.e., the recognition result is figure 5.

matching score	$l=1$	2	3	4	5
s_{l1}	0.555	0.717	0.913	0.833	1.269
s_{l2}	-3.231	-0.194	-0.089	-0.798	-0.607
matching score	$l=6$	7	8	9	0
s_{l1}	0.974	0.481	0.853	0.790	0.543
s_{l2}	0.145	-1.085	0.222	-0.018	0.357

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