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Multi-channel chromatic transformations for nonlinear color pattern recognition

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Abstract

We present a new approach for color pattern recognition based on multi-channel nonlinear correlations. High discrimination capability is obtained in comparison with common linear multi-channel detection methods. We apply the nonlinear morphological correlation to different color channel decompositions as RGB and ATD channels. Moreover, in order to improve the discrimination we have introduced a new color transformation. When a high selectivity is required, the combination of the nonlinear correlation and the new color decomposition yields to detect the object using just a single channel. Simulation results are provided. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

Color is one of the most powerful and important information to be considered for image processing, in particular for pattern recognition. From the optical pattern recognition point of view, the linear correlation is one of the most useful tool [1]. In fact, optical correlation can be extended to polychromatic images. The first color detection process was introduced by Yu and Chao [2]. In that work, they used three coherent light sources (red, green and blue, RGB) and a diffraction grating. An extensive method to study color pattern recognition is the multi-channel correlator [3–5]. With this approach the input scene and the color target are decomposed into three color channels and then processed separately. Finally, the correlation outputs are combined to give a final detection using arithmetic or logical point-wise operations. Much work has been devoted for the multi-channel processing in order to improve the process [6–9].

Nevertheless, color pattern recognition has not been studied only with multi-channel methods. There are methods based on preprocessing the input scene and the color target in order to combine the color information in a unique image. Those are the single-channel approaches and some work has been done based on its application to two-dimensional [10,11] and tri-dimensional im-

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ages [12]. However, in spite of the advantages of a reduction in the number of channels, those methods imply an important loss of information.

In a previous paper, a nonlinear correlation, called morphological correlation (MC) [13] was introduced for pattern recognition. The MC is defined by thresholding the input and the target into many binary slices. Then, different linear correlations are performed between the thresholded slices of the input and the target, and finally the correlation outputs are added. MC can be optically realized by a conventional joint transform correlator (JTC) [14]. MC provides higher discrimination between similar patterns in recognition systems when compared with the linear correlation (LC) [13,14].

The MC has been applied satisfactorily to color pattern recognition using the multi-channel approach and the RGB color channel decompositions [15]. However, the RGB color components are frequently correlated one from the other. This mutual information will degrade the recognition process and false color objects may be detected as correct ones.

In order to solve this inconvenience, we have extended the application of the morphological correlation to other color channels defined using different chromatic transformations. These new transformations are based on human visual models [16,17]. The ATD models consist of an achromatic (A) bright–dark channel that can be considered as the luminance channel, a T channel (tritan channel) that corresponds to the opponent response red–green, and a D channel (deutan channel) that corresponds to the opponent response yellow–blue. Although the discrimination capability of the recognition was improved in comparison with the RGB transformation, equal shape objects but different in color are still detected as the same.

To achieve better results, we introduce a new tri-dimensional color transformation inspired by the mathematical expression of ATD transformation. Note that the new transformation has nothing to do with visual parameters. Despite the loss of physical meaning of the decomposition, the discrimination capability of the process is significantly improved. We call the color transformation as color discrimination method (CDM). After the decomposition, we have used the morphological correlation as the pattern recognition operation. The method consists of performing a morphological correlation on the three CDM channels separately. Then, we combine the correlation results using a logical decision. The results are presented in terms of a well-known discrimination parameter which we have revised in Section 3.

2. The morphological correlation

The linear correlation has been widely and successfully applied for optical pattern recognition using a Vander Lugt matched filter [1]. In a correct detection process, the analysis of the maximum in the correlation plane indicates the presence and position of the target. The linear correlation, between two real discrete functions f and g, is given by

$$\mathrm{LC}_{fg}(x,y) = f(x,y) \otimes g(x,y) = \sum_{u,v} f(u+x, v+y) g(u,v), \tag{1}$$

where $\otimes$ denotes the correlation symbol.

The morphological correlation is defined as

$$\mathrm{MC}_{fg}(x,y) = \sum_{u,v} \min\,[f(u+x,v+y), g(u,v)]. \tag{2}$$

The latter definition can be expressed in terms of a thresholding function and linear correlations [13,14]

$$\begin{aligned}\mathrm{MC}_{fg}(x,y) &= \sum_{q=1}^{Q} \mathrm{MC}_{f_q g_q}(x,y) \\ &= \sum_{q=1}^{Q} \mathrm{LC}_{f_q g_q}(x,y) \\ &= \sum_{q=1}^{Q} [f_q \otimes g_q](x,y),\end{aligned} \tag{3}$$

where Q is the total number of gray levels of images and

$$f_q(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geqslant q \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \quad g_q(x,y) = \begin{cases} 1 & \text{if } g(x,y) \geqslant q, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

The optical implementation of the MC [14] is carried out by means of a JTC scheme [18]. The nonlinearity provides as a bonus the detection of low-intensity images in the presence of high intensity patterns.

3. A color discrimination method for color pattern recognition

As we have pointed out in Section 1, the RGB decomposition has been applied for multi-channel pattern recognition. The multi-channel algorithm implies the application of an operation to each channel separately and then to combine the result using a decision theory. However, the RGB decomposition is not appropriated for discriminating between similar color objects. For this reason, other color transformations have been studied. One of these transformations is the ATD. It is possible to transform the primary RGB components into the new ATD components allowing a reduction of similarity degree between the color channels. If we call $[M]$ the transformation matrix, we have

$$\begin{bmatrix} A \\ T \\ D \end{bmatrix} = [M] \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \tag{5}$$

Some models have been defined to transform RGB color space into ATD. The usual transformations proposed by Guth et al. [16] and Boynton [17] are two examples.

$$[M]_{\text{Guth}} = \begin{bmatrix} 0.5967 & 0.3654 & 0 \\ 0.9553 & -1.2836 & 0 \\ -0.0248 & 0 & 0.0483 \end{bmatrix}, \quad [M]_{\text{Boynton}} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & -2 & 0 \\ 1 & 1 & -1 \end{bmatrix}. \tag{6}$$

Millan et al. [7] applied those transformations to common multi-channel pattern recognition using linear correlation. They reduced the number of channels needed for the recognition of the correct color object, passing from the three RGB channels to the T and D channels. Although, they reduce the number of channels from three to two, the discrimination was not substantially improved.

In this paper we give two ideas to improve the discrimination. First we apply the MC which is more selective than linear methods used for recognition, and second we introduce a new $[M]$ matrix to decorrelate as much as possible the common RGB color channels. In Eq. (7) is shown the CDM transformation.

$$\begin{pmatrix} C \\ D \\ M \end{pmatrix} = \begin{pmatrix} 1 & -2 & -1 \\ -1 & 1 & 2 \\ 2 & -1 & 1 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}. \tag{7}$$

This color transformation is very efficient for the recognition process providing better discrimination between similar color objects. The motivation to define such a transformation matrix must be understood in the sense to achieve higher discrimination capability using higher degree of decorrelation between channels in comparison to previous ATD decompositions [16,17]. Although the visual interpretation of this color transformation is lost, it is not an important issue for the possible optical implementation of the method. Also, we would like to point out that although the transformation is *heuristic* because there is neither mathematical nor physiological justification, it gives good results in discrimination capability for color pattern recognition.

Those decorrelated CDM channels will improve the discrimination process for images with the same external shape but different internal color information. When the CDM components for the input scene and the reference object are obtained, we apply the morphological correlation. Finally, we combine the results of the morphological correlation using a logical decision table to obtain the final result.

In order to evaluate the discrimination capabilities of the recognition we used the discrimination capability (DC) parameter as follows:

$$\mathrm{DC}(\%) = \left(1 - \frac{\mathrm{Max(CC)}}{\mathrm{AC}}\right) \times 100, \tag{8}$$

where AC represents the auto-correlation peak intensity and CC is the cross-correlation peak intensity.

As we can see from Eq. (8), a high value for DC will indicate that the color reference object will be detected with a high discrimination and at the same time the others will be rejected. If the DC value is high then objects that are similar to the reference object will be rejected.

4. Results

The color input scene is made up of four butterflies (Fig. 1). Three of them have the same shape but they are different in color (P_1, P_2 and P_3), whereas the fourth one (P_4) has different shape and color. In this scene we want to detect the first butterfly (P_1). In order to show the influence of the morphological correlation in any pattern recognition method, we show in Figs. 2(a)–(c) the linear correlation for the three red, green and blue channels, respectively. As we see from the figure, the linear correlation is not very discriminant and

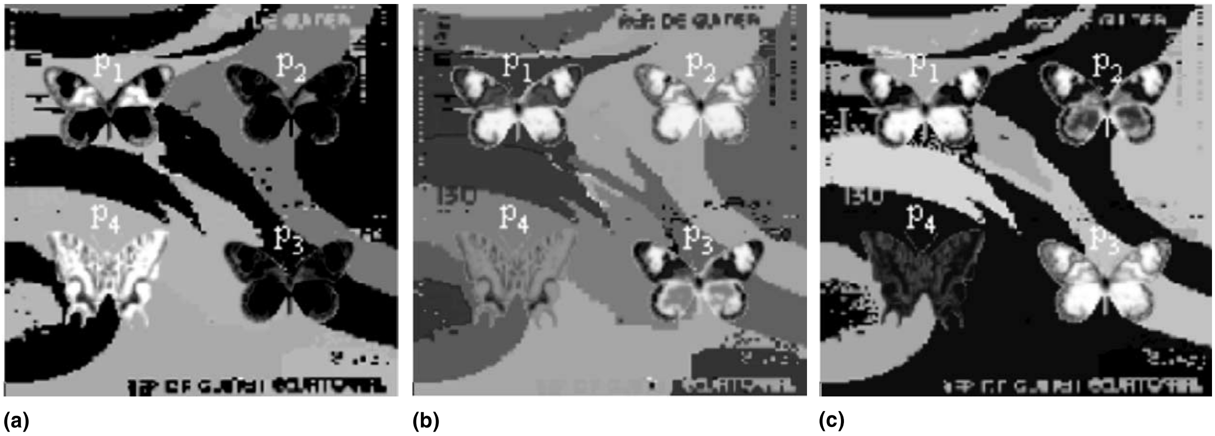

Fig. 1. Color input image. (a) R channel; (b) G channel; (c) B channel.

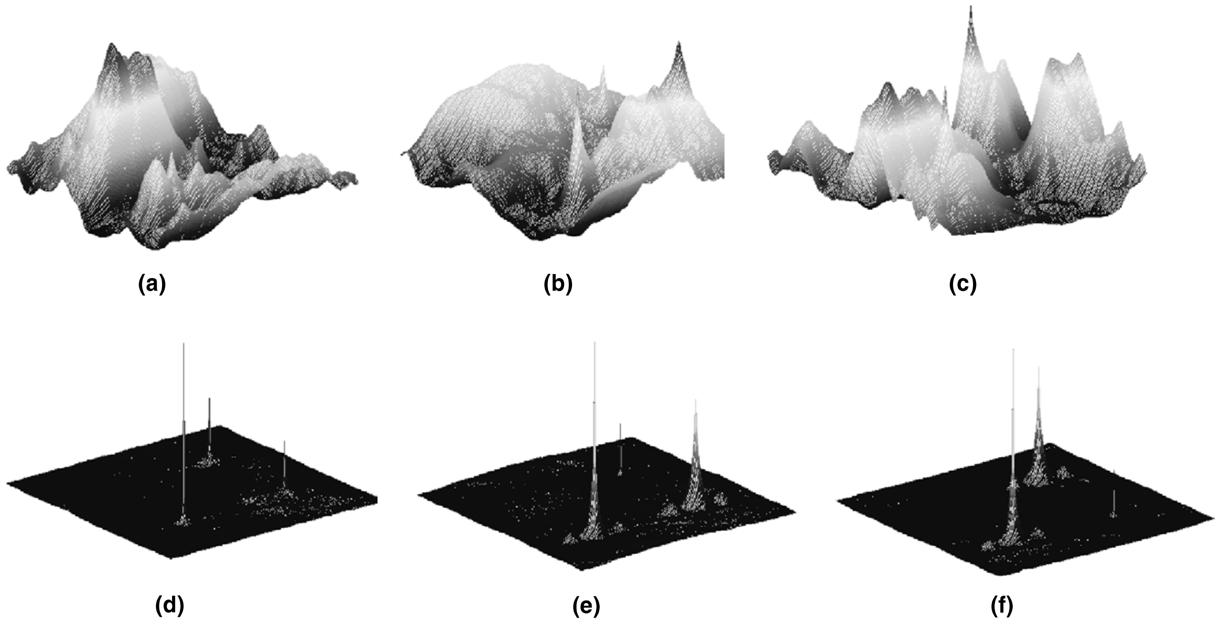

Fig. 2. Tri-dimensional representation of the linear correlation for the red channel (a), green channel (b) and blue channel (c). Correlation plots for the morphological correlation, red channel (d), green channel (e) and blue channel (f).

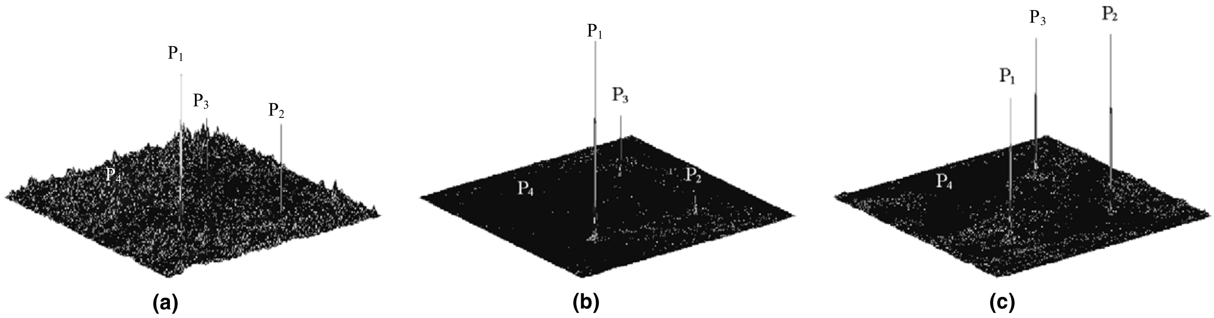

Fig. 3. Correlation plots for the phase only filter (POF) case, red channel (a), green channel (b) and blue channel (c).

false alarms have appeared. On the contrary, in Figs. 2(d)–(f) we have used the morphological correlation applied again on the three color components R, G and B. The color channels have 16 gray scale levels. Although we might have false alarms the discrimination has basically improved and correlation peaks are sharper than the linear case.

In order to compare the morphological correlation with common filters, like phase only filters (POF) Fig. 3 shows the results obtained with POF. As we observe, there are false alarms for the three color channel. These results justify the application of a more discriminant operation as the morphological correlation.

As the results obtained with MC depend on the color object decomposition, Table 1 shows the values of the correlation peaks obtained for every channel when MC is applied to RGB, ATD and CDM decompositions. In a column, we have shown the DC for all of the different color channels used. We notice that when we combine the MC and the DCM decomposition, the system presents higher discrimination capabilities than any other color decomposition.

In order to give a final detection decision we combine the information of the three correlation outputs. We assume that for each channel the object is detected if the correlation peak is higher than a certain fixed recognition threshold. Depending on the threshold chosen the information of all the three channels will be needed generally to take the final decision. However, in some cases depending on the threshold values, two or even one channel will be enough. As examples, we have considered two threshold values: 50% and 20% of the highest peak.

In Table 1, the correlation values that exceed 50% of the auto-correlation are marked in bold writing. From the table, we observe that we detect the reference object for all the channel systems. In some cases, in order to obtain the correct detection we need to combine the information of only two channels, for instance G–B for the RGB decomposition. Moreover, for the ATD Boynton's model and the CDM transformation, just one channel, any of them, is enough to detect the correct object. However, for a certain recognition process may be this 50% threshold could be too high and it would be interesting to decrease the recognition threshold because a lower value of the threshold implies a higher selectivity in the recognition process. Let us assume the value of 20% of the auto-correlation as the recognition threshold. In the same table, the correlation values that exceed this 20% of the auto-correlation are underlined. Note that neither with the RGB nor with the ATD decompositions we detect the correct object without false alarms. Only when we use the combination of the morphological correlation and the CDM transformation, the P_1 object is isolated. Moreover, as was mentioned before, this detection decision can be achieved using a single channel. For the sake of clarity, in Fig. 4 we show the correlation outputs obtained applying the MC to the CDM channels.

As we see from the results, for a certain threshold of discrimination, the combination of the CDM transformation and the morphological correlation will allow the possibility of using simply a single channel to isolate the correct object.

Table 1
Correlation results for the recognition of object and P_1, P_2, P_3 and P_4 with different color channel decompositions

Channel system		P_1	P_2	P_3	P_4	DC (%)
MC with RGB channels	R	$\mathbf{6.5397 \times 10^5}$	2.0574×10^5	2.3673×10^5	0.2451×10^4	64
	G	$\mathbf{6.9510 \times 10^5}$	$\mathbf{3.9638 \times 10^5}$	1.8416×10^5	0.8289×10^4	43
	B	$\mathbf{6.9510 \times 10^5}$	1.6672×10^5	$\mathbf{4.1687 \times 10^5}$	0.3342×10^4	40
	Decision, Thr = 50%	**Detected**	**Rejected**	**Rejected**	**Rejected**	
	Decision, Thr = 20%	Detected	Detected	Detected	Rejected	
MC with ATD Boynton's model	A	$\mathbf{10.8368 \times 10^5}$	$\mathbf{7.8203 \times 10^5}$	1.2124×10^5	0.2200×10^4	28
	T	$\mathbf{6.6673 \times 10^5}$	1.9965×10^5	0.62428×10^5	0.3898×10^4	70
	D	$\mathbf{6.2008 \times 10^5}$	1.5507×10^5	0.72000×10^5	0.3801×10^4	75
	Decision, Thr = 50%	**Detected**	**Rejected**	**Rejected**	**Rejected**	
	Decision, Thr = 20%	Detected	Detected	Rejected	Rejected	
MC with ATD Guth's model	A	$\mathbf{19.5172 \times 10^5}$	9.5547×10^5	2.9576×10^5	0.6037×10^4	51
	T	$\mathbf{7.1760 \times 10^5}$	2.0177×10^5	0.8178×10^5	0.4149×10^4	72
	D	$\mathbf{48.6904 \times 10^5}$	$\mathbf{45.3264 \times 10^5}$	$\mathbf{45.3264 \times 10^5}$	2.3919×10^5	7
	Decision, Thr = 50%	**Detected**	**Rejected**	**Rejected**	**Rejected**	
	Decision, Thr = 20%	Detected	Detected	Rejected	Rejected	
MC with color discrimination method	C	$\mathbf{6.5291 \times 10^5}$	0.4261×10^5	0.8469×10^5	0.2144×10^4	87
	D	$\mathbf{6.4462 \times 10^5}$	0.4675×10^5	0.4853×10^5	0.2017×10^4	92
	M	$\mathbf{5.3098 \times 10^5}$	0.4115×10^5	0.6815×10^5	0.2772×10^4	87
	Decision, Thr = 50%	**Detected**	**Rejected**	**Rejected**	**Rejected**	
	Decision, Thr = 20%	Detected	Rejected	Rejected	Rejected	

Decision when the threshold used is 50% of the highest correlation peak value is marked bold. Decision when the threshold used is 20% of the highest correlation peak value is underlined.

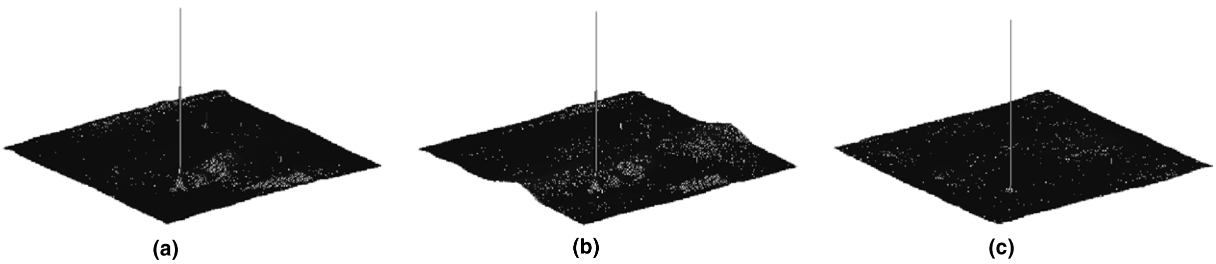

Fig. 4. Tri-dimensional representation of the morphological correlation for the C channel (a), D channel (b) and M channel (c).

This is an important result because other comparable methods shown in the paper require more than one correlation output to take the final decision.

5. Conclusion

In this paper we have combined two approaches for color pattern recognition. The first approach is to use a nonlinear correlation, the morphological correlation, which is more selective than linear correlation. In a second step, in order to work with channels as much decorrelated as possible we have introduced a new transformation matrix to decompose the primary RGB channels into the new CDM components. So, the discrimination capability for color pattern recognition is improved. The motivation to decorrelate the color channels is to distinguish among objects which are similar in shape but different in color. We show different results provided from the application of the morphological correlation to different color channel decompositions, which can be seen from Table 1. We notice that the combination of morphological correlation and the CDM decomposition gives better results than applying the MC to other color channel decompositions. Although the matrix choice is heuristic, one of the main advantages of the method is the possibility of a reduction of the number of channels involved in the final detection process. This reduction is related with the detection threshold chosen. Another improvement is the high values for the discrimination capability obtained.

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