Comparison of Combining Methods in Invariant Color Texture Classification with Cross-Bispectral Features

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Abstract

The features of 2D images based on the bispectrum invariant to similarity transformations (shift, rotation and scaling) are applied to the classification of color image data. The invariant features are calculated with the cross-bispectra between color values, which retain information on spatial third-order correlations of color images. Three kinds of color systems (the *RGB*, $L^*a^*b^*$ and K-L like systems) are employed. Combining techniques of the distance values of the invariant features, including decision rules (average, product, minimum, maximum, median and distance of decision profiles) and voting methods (majority voting, Borda count and approval voting) are then compared. Computer experiment is done on the classification of 79 natural color texture images in the VisTex database suffering from similarity transformations by combining the cross-bispectral features. The results of computer experiment show that the classify-cation performance is improved with the use of color values when the less correlated color systems (the $L^*a^*b^*$ and K-L like systems) than the *RGB* system are used. The average and maximum rules give the highest classify-cation performance among the decision rules. Further, the Borda count is superior to the majority and approval voting.

1. Introduction

The fusion of information in pattern classification has received much attention recently and many studies have been done (e.g., Refs. 1-6 and the references therein). Combining classifiers can produce higher classification performance than any single classifier under various conditions. A lot of methods for combing the output of classifiers have been proposed and the comparison of their performance is of wide interest.

In this study the author compares several combining methods of classifiers through experiment on the classification of color texture images. The use of three kinds of color systems: the *RGB*, $L^*a^*b^*$ and K-L like system are also compared with each other. The representations of image data invariant to the similarity transformations based on the bispectra are extended to color image data. Ten different representations are then obtained and are used as the features for the classifiers. As combining methods, 6 decision rules: average, product, minimum, maximum, median and distance of decision profiles, as well as 3 voting methods: majority voting, Borda count and approval voting are considered.

The derivation of the invariant features are mentioned in **2.**. The color systems and the combining methods are explained in **3.** and **4.**, respectively. The method and results of the classification experiment with color texture images are shown in **5.**. Discussion on the performance of the combining methods is given in **6.**.

2. Invariant Features Based on the Bispectrum

Several invariant features have been derived from the third-order correlation (the bispectrum) and applied to the recognition of images.[7-17] In this study the following invariant feature based on the bispectrum[18-20] is used in the classification experiment.

Let $f(\boldsymbol{x})$ be 2D image data and $F(\omega)$ be its Fourier transform.

$$F(\boldsymbol{\omega}) = \int f(\boldsymbol{x}) exp(-j\boldsymbol{\omega}\cdot\boldsymbol{x}) d\boldsymbol{x} \quad (1)$$

When image data is rotated at an arbitrary point, the Fourier transform is rotated at the origin by the same angle. When image data is scaled, the Fourier transform is scaled at the origin by the inversely proportional amount. These rotation and scaling at the origin cause no changes in the ratio r (= $|\omega_1|/|\omega_2|$) of length and the angle θ ($\cos\theta = \omega_1\cdot\omega_2/(|\omega_1||\omega_2|)$) of any pairs of frequency vectors ω_1 and ω_2 in the function of $F(\omega_1)$ and $F(\omega_2)$ invariant to the shift of $f(\boldsymbol{x})$. Thus the following integral $I(r,\theta; g; f)$ of an arbitrary function g of the bispectrum $B(\omega_1,\omega_2)$ of $f(\boldsymbol{x})$, which is invariant of the shift, on condition that $|\omega_1|/|\omega_2| = r$, $\omega_1\cdot\omega_2/(|\omega_1||\omega_2|) = \cos\theta$ is thus invariant to similarity transformations (shift, rotation and scaling of $f(\boldsymbol{x})$.

$$I(r,\theta; g; f) = I'(r,\theta; g; f)/(\iint I'^2(r,\theta; g; f)drd\theta)^{1/2} \quad (2)$$

$$I'(r,\theta; g; f) = \iint_{r,\theta} g(B(\boldsymbol{\omega}_1,\boldsymbol{\omega}_2))d\boldsymbol{\omega}_1 d\boldsymbol{\omega}_2$$
$$(|\boldsymbol{\omega}_1|/|\boldsymbol{\omega}_2| = r,\ \boldsymbol{\omega}_1\cdot\boldsymbol{\omega}_2/(|\boldsymbol{\omega}_1||\boldsymbol{\omega}_2|) = cos\theta) \quad (3)$$

$$B(\boldsymbol{\omega}_1,\boldsymbol{\omega}_2) = F(\boldsymbol{\omega}_1)F(\boldsymbol{\omega}_2)F(-\boldsymbol{\omega}_1-\boldsymbol{\omega}_2) \quad (4)$$

Note that the feature is also invariant to linear changes in the amplitude of image data.

The invariant feature is numerically evaluated through the Fourier transform of image data without the calculation of the bispectra.[18-20]

3. Cross-Bispectra and Color Systems

Color image data consist of three (R, G, B) planes and the following 3^3 (cross-) bispectra exist.

$$B_{lmn}(\omega_1,\omega_2) = F_l(\omega_1)F_m(\omega_2)F_n(-\omega_1-\omega_2)$$
$$(l,\ m,\ n = R,\ G,\ B) \qquad (5)$$

Ten invariant features different from each other are then obtained in the RGB system: I_{RRR}, I_{GGG}, I_{BBB}, I_{RRG}, I_{RRB}, I_{RGG}, I_{RBB}, I_{GGB}, I_{GBB}, I_{RGB}.

Further, the following two color systems are used for comparison.[21]

The $L^*a^*b^*$ system:

$$\begin{aligned}
L^* &= 116(Y/Y_0)^{1/3}-16\\
a^* &= 500((X/X_0)^{1/3}-(Y/Y_0)^{1/3})\\
b^* &= 200((Y/Y_0)^{1/3}-(Z/Z_0)^{1/3})\\
X &= 0.49R+0.31G+0.20B\\
Y &= 0.177R+0.813G+0.011B\\
Z &= 0.01G+0.99B
\end{aligned}$$
X_0, Y_0, Z_0: the values of X, Y, Z of white (6)

The system based on the Karhunen-Loéve expansion:

$$\begin{aligned}
I_1 &= (R+G+B)/3\\
I_2 &= (R-B)/2\\
I_3 &= (-R+2G-B)/4 \qquad (7)
\end{aligned}$$

Ten invariant features in each system are obtained in the same way as the RGB system.

These invariant features with the cross-bispectra in the three color systems are used for the comparison of combining methods in the classification of color textures.

4. Combining Methods of Classifiers

The following decision rules and voting methods for combining classifiers are compared.

4.1. Decision Rules

The RMS distance $d_{ij}(f)$ between the ith features $I_i(r,\theta;\ g;\ f)$ of image data f and those $I_i(r,\theta;\ g;\ f_j)$ of the original image data of the jth class is used as the output of the ith classifier. A matrix $(d_{ij}(f))$ is then regarded as a decision profile.[6] In this case the distance between the features is used instead of the similarity measure. Thus the ith classifier supports that f is belong to the jth class as the value of $d_{ij}(f)$ is smaller.

The average (sum), product, minimum, maximum and median rules are used for classification.

Average: $\mathrm{argmin}_j\ (\Sigma_i\ d_{ij}(f))$
Product: $\mathrm{argmin}_j\ (\Pi_i\ d_{ij}(f))$
Minimum: $\mathrm{argmin}_j\ (\min_i\ d_{ij}(f))$
Maximum: $\mathrm{argmin}_j\ (\max_i\ d_{ij}(f))$
Median: $\mathrm{argmin}_j\ (\mathrm{med}_i\ d_{ij}(f))$

The RMS distance between the decision profiles $(d_{ij}(f))$ of f and that $(d_{ij}(f_k))$ of the original image data of the kth class is also treated.

RMS-dist: $\mathrm{argmin}_k\ (\Sigma_i\ \Sigma_j\ (d_{ij}(f),d_{ij}(f_k))^2)$

4.2. Voting Methods

The voting methods have also been used in multiple classifier systems.[1-3] The majority voting, the Borda count and the approval voting based on the decision profile are compared.[22]

Majority: $\mathrm{argmax}_j\ (\Sigma_i\ \Delta_{ij}(f))$
$\Delta_{ij}(f) = 1$ for $j = \mathrm{argmin}_j\ (d_{ij}(f))$
0 otherwise

Borda: $\mathrm{argmax}_j\ (\Sigma_i\ \mathrm{rank}_i\ (d_{ij}(f)))$

Approval: $\mathrm{argmax}_j\ (\Sigma_i\ U_{ij}(f;\ d_{th}))$
$U_{ij}(f;\ d_{th}) = 1$ if $d_{ij}(f) < d_{th}$
0 otherwise

The Borda count uses the sum of the ranked values of the output of the classifiers. The approval voting uses the number of the classifiers the output of which is less than some threshold d_{th}.

5. Experiment on Color Textures

The color systems and the combining methods of the features are compared through computer experiment on the classification of color texture images. Texture image data are taken from the Vision Texture (VisTex) database at the MIT Media Lab.[23] A total of 79 image data in 8 kinds of 24 bits RGB color texture images of 128×128 pixels in the reference textures are used. These texture image data are shown in Fig. 1 with gray-scales: 'Bark' (13), 'Brick', (9) 'Flower' (8), 'Leaves' (17), 'Sand' (7), 'Stone' (6) 'Terrain' (11) and 'Water' (8).

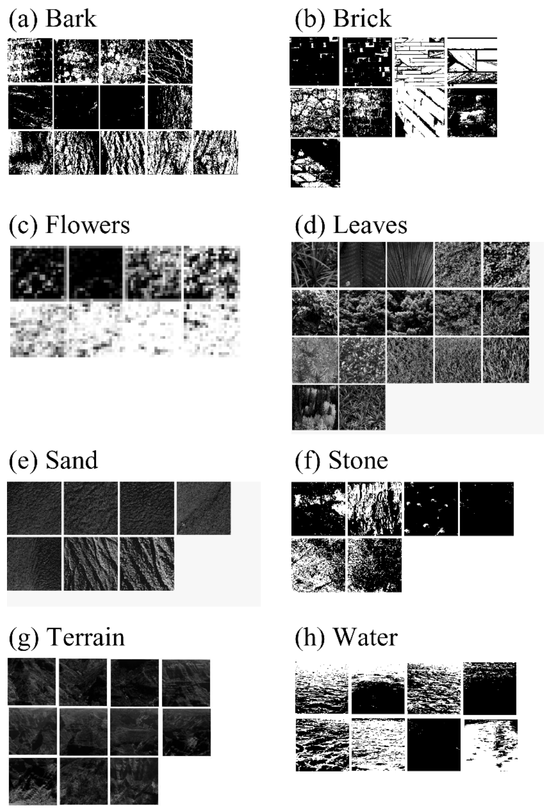
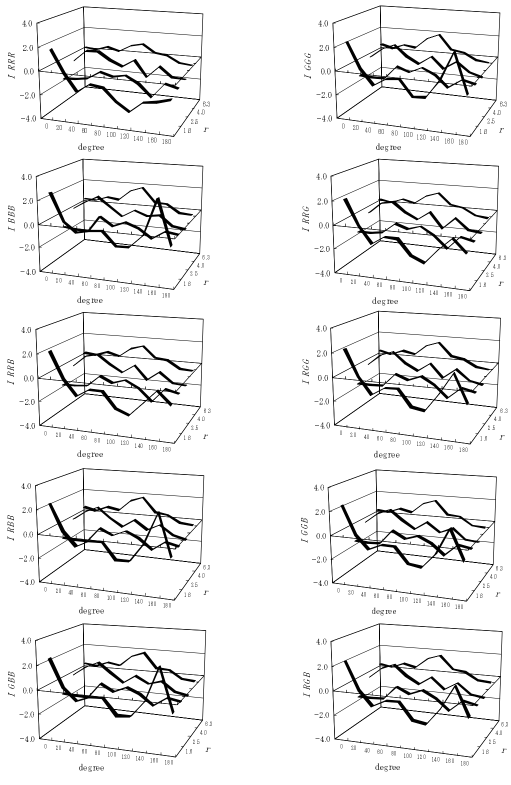
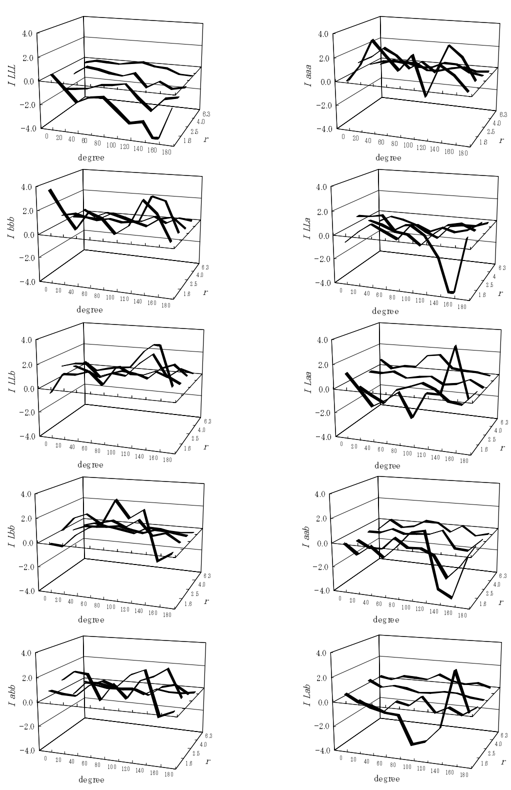


Figure 1. VisTex texture images[21]

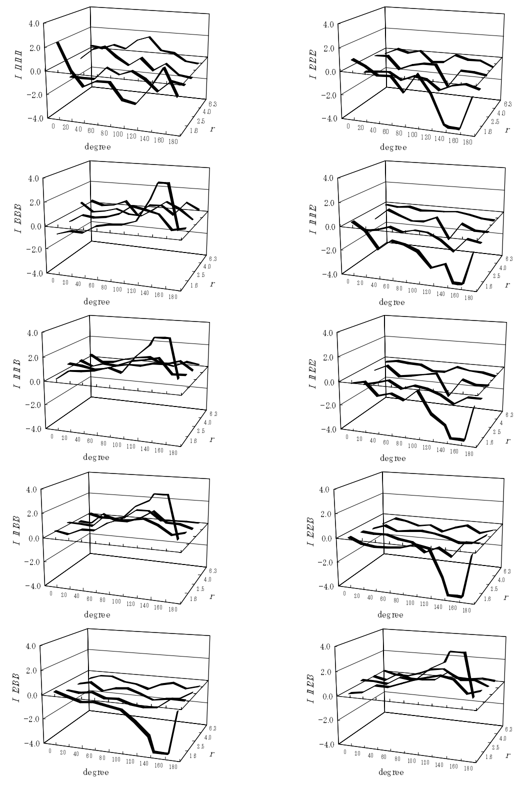


(a) f: Bark.0000, $(l, m, n) = (R, G, B)$

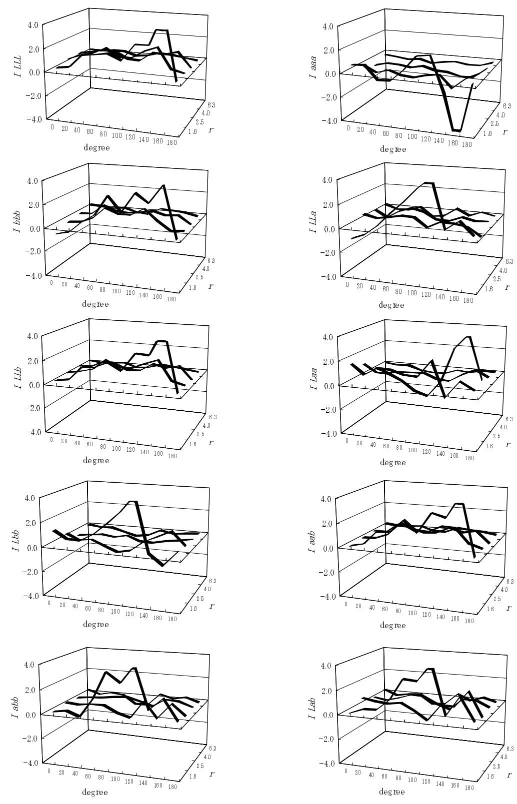


(b) f: Bark.0000, $(l, m, n) = (L^*, a^*, b^*)$

Figure 2. Invariant features $I_{lmn}(r,\theta;\ Re(B);\ f)$ of the original texture image



(c) f: Bark.0000, $(l, m, n) = (I_1, I_2, I_3)$



(d) f: Brick.0000, $(l, m, n) = (L^*, a^*, b^*)$

Figure 2. Invariant features $I_{lmn}(r,\theta;\ Re(B);\ f)$ of the original texture image (cont.)

Examples of the invariant features $I_{lmn}(r,\theta;\ \mathrm{Re}(B);\ f)$ of central parts (64×64 pixels) of the original image data are shown in Fig. 2; f: Bark.0000, $(l, m, n) = (R, G, B)$ (a), f: Bark.0000, $(l, m, n) = (L^*, a^*, b^*)$ (b) f: Bark.0000, $(l, m, n) = (I_1, I_2, I_3)$ (c), f: Brick.0000, $(l, m, n) = (L^*, a^*, b^*)$ (d). Note that $I_{lmn}(r,\theta;\ \mathrm{Im}(B);\ f) = 0$ since $F(-\omega) = F^*(\omega)$. The ratio r is ranged from 1.0 to $10^{0.8}$ by $10^{0.2}$ on a log scale and the angle θ is ranged from 0° to 180° by 20°. The graphs of the 10 kinds of the invariant features I_{RRR}, I_{GGG}, I_{BBB}, I_{RRG}, I_{RRB}, I_{RGG}, I_{RBB}, I_{GGB}, I_{GBB}, I_{RGB} of Bark.0000 in the RGB system (a) have forms similar to each other, while there are small changes. However, the invariant features I_{LLL} - I_{Lab} in the $L^*a^*b^*$ system (b) and I_{I1I1I1} - I_{I1I2I3} in the K-L like system (c) have different forms with each other. The invariant features then retain more information on the color correlation in the $L^*a^*b^*$ and K-L like systems than in the RGB system. Further, The forms of the invariant features of Brick.0000 in the $L^*a^*b^*$ system (d) differ from those of Bark.0000 (b).

In the classification experiment, 30 transformed images (scaled by 1.0, 1.5 and 2.0; rotated from 0° to 45° by 5°) are made for each image data with the bilinear interpolation. A total of 2370 images are then classified to one of 79 image data. The 10 kinds of the invariant features $I_{lmn}(r,\theta;\ \mathrm{Re}(B);\ f)$ are calculated in each color system (the RGB, $L^*a^*b^*$ and K-L like system). The RMS distance $d_{ij}(f)$ between the ith features $I_i(r,\theta;\ \mathrm{Re}(B);\ f_{jk})$ of the transformed image data f_{jk} $(1 \le j \le 79,\ 1 \le k \le 30)$ and those $I_i(r,\theta;\ \mathrm{Re}(B);\ f_j)$ of the original image data of the jth class is used as the output of the ith classifier $(1 \le i \le 10)$. Six decision rules and three voting methods are applied to the classification of the transformed image data.

The correct classification ratio (CCR) for the three color systems are shown in Fig. 3, in which the average rules is applied to the classification. In each color system, the use of one (I_{RRR}, I_{LLL}, I_{I1I1I1}), three ((I_{RRR}, I_{GGG}, I_{BBB}), (I_{LLL}, I_{aaa}, I_{bbb}), (I_{I1I1I1}, I_{I2I2I2}, I_{I3I3I3})) and all ten invariant features is compared. The use of one feature in the three color systems gives about the same CCR. The CCR with the multiple features is higher in the less correlated systems ($L^*a^*b^*$ and K-L), however, than in the RGB system. The use of the all (10) features gives the highest CCR in the $L^*a^*b^*$ and K-L like systems, while the CCR with 10 features is lower than that with 3 features in the RGB system.

Figure 4 shows the CCR with the different decision rules and voting methods. In the approval voting, the optimal values of the threshold d_{th} are used (d_{th} = 0.7 (RGB), 1.0 ($L^*a^*b^*$), 1.0 (K-L)). The highest CCR is achieved with the maximum rule, the average rule and the Borda count in the RGB (a), $L^*a^*b^*$ (b) and K-L like (c) systems, respectively. Among the decision rules, the average rule keeps high CCR in the all color systems. The maximum rule, however, gives higher CCR in the RGB system, in which the overall performance of the combining methods is worse. The performance of the RMS distance between $d_{ij}(f)$ is not better than that of the average rule. The CCR with the simple majority voting is lower than that with most decision rules. The Borda count is superior in the voting methods and is competitive to the decision rules.

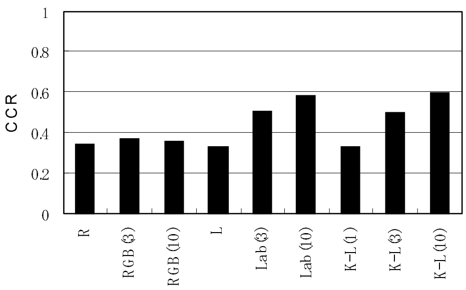


Figure 3. Correct classification ratio (CCR) using different color systems with the different number of the features

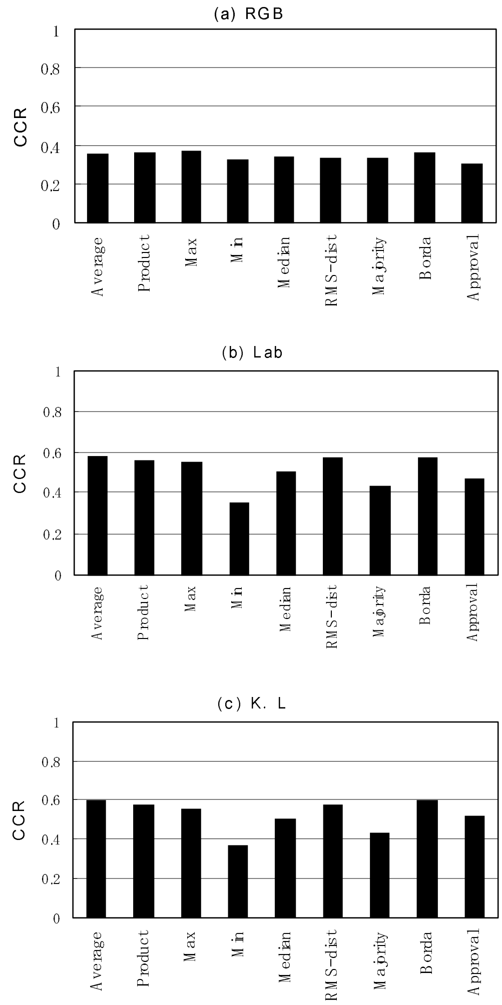


Figure 4. Correct classification ratio (CCR) with different decision rules and voting methods in the RGB (a), $L^*a^*b^*$ (b) and K-L like (c) systems

6. Discussion

It has been shown that the use of the color correlation can improve performance in the classification of color texture images.[20,24-28] In this study, the CCR was higher by using the less correlated systems ($L^*a^*b^*$ and K-L) than the RGB system. It is known that the equivalent number of dependent classifiers is considerably less than that of independent classifiers.[29] It was confirmed that the decorrelation process is useful in the features based on the third-order correlation (the bispectra).

Concerning the decision rules, the average rule was best in the $L^*a^*b^*$ and K-L like systems. This agrees with the result that the average rule can perform better than the other decision rules since it is robust to estimation errors [4]. The reason that the maximum rule was best in the *RGB* system is unclear.

Further, the Borda count was superior to the majority and approval voting. This result is attributed by the fact that the Borda count uses more information in a set of the values of the RMS distance of the features than the majority and approval voting. The highest CCR is achieved using the Borda count with the K-L like system. The normalization due to the ranking can give better performance than the averaging.

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Biography

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