Surface grading of bamboo strips using multi-scale color texture features in eigenspace

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\section*{1. Introduction}

Bamboo products have been appeared in China for at least 4000 years leading China to be the most well-known bamboo producing country in the world today. Traditionally, bamboo was only used to make primitive products such as chopsticks, chairs and tables, etc. Due to the great improvement of bamboo material processing and manufacturing technology, many bamboo product companies have extended the applications of bamboo into the construction and decorative materials field with high additional value. By virtue of the color, fiber structure, density and intensity, Mao bamboo, a special kind of bamboos, has been looked upon as the ideal green alternative materials to wood for producing various kinds of furniture and flooring. Bamboo production industry has played an important role as the agricultural cornerstone in local government’s economy.

After split and processed with more than 10 steps of treatments such as drying, carbonization, etc., the bamboo stalk becomes long narrow bamboo strips which are glued together to assemble bamboo products. The color texture appearance of the final bamboo strips can be affected by a variety of factors such as growth period, humidity, temperature of carbonization, etc. The overall visual appearance of bamboo strips, exhibits the combination of color and texture. The color characteristic is more important than the texture, as bamboo strips show almost the same pattern. However, the perception of the color is also affected by the texture. The quality of bamboo products is quantified by the variation of color texture appearance of the bamboo strips used to assemble them. Any subtle changes of color tonality will become much significant once the bamboo strips are placed together. In order to achieve high competitive quality of bamboo products, bamboo strips with naturally different color tonalities must be elaborately sorted into different classes according to their global color texture appearance. Currently, bamboo production industry in China relies heavily on the manual inspection of experts for the task of surface grading of bamboo strips. Automatic surface grading for bamboo strips is highly demanded by bamboo production industry for taking place of the subjective and inefficient process of manual inspection.
Recently many approaches to automatic surface grading have been developed mainly in the wood and ceramics tiles production industry (Kurthdthongmee, 2008; Lopez et al., 2005; Xie, 2008). Kauppinen (1999, 2000) introduced a method based on the centile features of color histograms for wood surface inspections and parquet slabs grading. Boukouvalas et al. (1997, 1999) used color histograms to grade randomly textured ceramic tiles. Although there are debates on whether color and texture should be processed jointly or separately (Maenpaa and Pietikainen, 2004), it has been demonstrated that color and texture should be combined to achieve good performance for some applications (Drimbarean and Whelan, 2001; Maenpaa et al., 2003), and a number of methods of integrating color and texture information have been proposed. Jain and Healey (1998) proposed a multi-scale representation including unichrome and opponent color features based on Gabor filters. The representation used unichrome features computed from each independent spectral band, as well as opponent features that capture the spatial interaction between spectral bands. Prats-Montalban and Ferrer (2007) illustrated the benefits of integrating color and texture information in multivariate statistical image analysis. The multivariate images, from which the multivariate image analysis extracts variable relevant information, could be constructed by shifting the image to the directions of 8 neighborhood pixels and stacking the original image with all the shifted ones. However, it is still an open field how best to integrate color and texture into a composite model for surface grading according to the global appearance.

The discrimination ability of the human to perceive color and texture appearance with great acuteness has motivated researchers to partially emulate some functions in human visual system for solving the problems in computer vision (Papathomas et al., 1997; Porat and Zeevi, 1998). The perception of human to nature of real-world objects is in a multi-scale structure, which implies that objects would be perceived in different ways depending on the scale of observation (Koenderink, 1984). Inspired from physics and biologic vision, the scale-space theory has already been developed as a framework for multi-scale image representation. Gaussian linear scale-space, as the canonical way to generate a linear multi-scale representation, is the most common type of scale-space used in image processing and computer vision (Lindeberg, 1994). It has been shown by the neuron-physiological studies that there are receptive field profiles in the mammalian retina and visual cortex, which can be well modeled by linear Gaussian derivative operators (DeAngelis et al., 1995; Romeny and Florack, 2000; Young et al., 2001). So it is the reasonable approach to represent and process the image with multi-scale representations.

Principal component analysis (PCA) has been widely used in image analysis and pattern classification as a powerful technique for extracting structure from high-dimensional data sets (Bharati and MacGregor, 2000; Haenselmann and Effelsberg, 2002). The multivariate image analysis (MIA) techniques, which are based on multi-way principal component analysis, are first introduced by Esbensen and Geladi (1989). Different works have applied the MIA to the monitoring and classification problems using spectral or spatial information for color or/and texture images (Bharati, 2002; Bharati et al., 2003; Prats-Montalban and Ferrer, 2007). Recently, Xie et al. (2006) proposed a multidimensional histogram and PCA eigenspace approach to inspect color tonality defects of ceramic tiles. PCA was performed on a 9D feature vector of color shade properties to form the reference eigenspace. The color features of unseen tiles were projected onto this eigenspace and histogram comparison was used to measure the similarity of eigenspace features between the new and the reference tiles.

The goal of our research is to develop an automatic surface grading approach to sort bamboo strips into perceptually homogenous classes in the manufacturing of high quality bamboo products for bamboo production industries in China. The contributions of this paper are: (1) to propose a method to construct multivariate image using the multi-scale representations which could be regarded as an integration of color and texture information and (2) to develop an efficient approach based on MIA to make use of multi-scale color texture eigenspace features to correctly grade the surface of bamboo strips.

This paper is organized as follows. Section 2 describes the details of the Gaussian multi-scale representations based on scale-space theory and the approach of using multivariate image analysis techniques to grade bamboo strips in eigenspace. Section 3 details the results and discussion, followed by conclusions in Section 4.

2. Materials and methods

In this paper, the Gaussian multi-scale representations for RGB color images of bamboo strips are used for image analysis and referred to as the encapsulation of spectral (color) and spatial (texture) information of observation from different scales. Fig. 1 illustrates the overall processes of the proposed surface grading approach. It can be classified into two stages: the training stage and the testing stage. During the training stage several RGB images of bamboo strips are pre-classified into some classes by experts and acting as the reference for the training images. And the characteristic images corresponding to typical classes are selected to build the model of the reference eigenspace. Then the training images are projected onto this reference eigenspace to obtain their representative feature clusters as the reference data in the testing stage. In testing stage, the novel testing image of an unknown bamboo strips is also projected onto the reference eigenspace. And the Bhattacharyya distance is used to estimate the similarity of the representative feature clusters between the testing images and the training images in the eigenspace. Then a widely used k-nearest neighbor (k-NN) classifier is adopted to classify the testing images to the given classes of training images.

2.1. Images acquisition of bamboo strips

To evaluate the discrimination effectiveness and classification accuracy of the proposed approach, a set of images of bamboo strips are used in the experiments with the known groundtruth obtained from manual classification by experts. All of the images were acquired using a 3-CCD color camera (AW-E350MC, Panasonic) with a lens of 12-mm focal length (AVENIR), a frame grabber and a PC (AMD XP3000+ processor). The camera was fixed above bamboo strip sample and was set focus on the surface. It was important to guarantee the homogeneous illumination of light during the acquisition of all the images (Bharati, 2002). Here a low-angle square LED light was used to illuminate the bamboo strips from 50 mm above. This type of light units radiates uniform diffused light from a low angle which could eliminate the reflection and provide the homogeneous illumination on a large region. Fig. 2 shows the gray levels in the image of a white paper. It can be seen that the most center field is illuminated homogeneously with the gray levels in the scope of 205–220. And we only choose the ROI of images from the red rectangle in which the illumination of light is uniform. The setup of the image acquisition system is shown in Fig. 3. The system obtained the images of bamboo strips in size of 640 × 480 pixels. In each image a 120 × 100-pixel region of interest (ROI) image was extracted to present the corresponding bamboo strip. Fig. 4 shows one image of the bamboo strips with the corresponding ROI.

The images of two set bamboo strips elaborately sorted by experts according to their global appearance were obtained and used in the experiments. The bamboo strip surface grading process could be separated into two stages: coarse grading and fine...
grading. In coarse grading stage the number of separable classes is more than those in fine grading stage. The bamboo strips in Set 1 are selected at the coarse grading stage, and the bamboo strips in Set 2 are selected at the fine grading stage. The bamboo strips in Set 1 have more classes than the bamboo strips in Set 2.

Set 1 consists of 9 classes, with 6 strips in each class, totalling 54 bamboo strips. In the first part of the experiments, the 54 ROI images of each bamboo strip in Set 1 were obtained and separated into 6 groups with 9 different class images in each group. This set of images was used to evaluate the effective discrimination of the proposed multi-scale eigenspace features by estimating the inter-class Bhattacharyya distances based on the Gaussian multi-scale representations compared with RGB and HSV color spaces.

There are less classes but large samples in Set 2. Set 2 consists of 4 classes, totalling 240 bamboo strips with 60 strips in each class. This set of images was used to estimate the classification accuracy of the proposed bamboo strip surface grading approach in the final part of the experiments.

And according to the darkness of the overall color, the classes of two set bamboo strips were respectively labeled from light to dark in sequence, $C_1, C_2, \ldots, C_9$ and $V_1, V_2, V_3, V_4$. The example ROI images of all classes in two set bamboo strips are shown in Fig. 5.

2.2. Methods

2.2.1. Gaussian multi-scale color texture representations and MIA

Human vision system has the ability to reveal features from the image whether the features come from the coarse scales or the fine scales. It implies that the multi-scale representation is essential to the understanding of perception to both natural and artificial objects. Since color and texture are the fundamental aspects of human visual perception, they are closely related with the scales of observation. In the recent research on the color and texture classifi-
provides a canonical class of image representations. For a given approach is to represent and process the data at multi-scale image analysis for deriving color texture information, the reason-

Fig. 4. One image of the bamboo strips with 120 × 100-pixel ROI.

Fig. 5. The example ROI images of all classes in Set 1 and Set 2 bamboo strips.

cation based on the perceptual vocabulary and grammar, Mojsilovic et al. (2000) proposed five perceptual criteria to measure the similarity of different color patterns. The conclusion is that, at the coarse scales of judgment, the human primarily uses the color information, such as “overall color” and “color purity”, to perceive and measure similarity. And at the fine scales, humans primarily use texture information, such as “directionality and orientation”, “regularity and placement rules” and “pattern complexity and heaviness”. So the relationships between the color texture global appearance and scales of observation could be summarized in “directionality and orientation”, “regularity and placement rules” and “pattern complexity and heaviness”. So the relationships between the color texture global appearance and scales of observation could be summarized in Fig. 6. In the image analysis for deriving color texture information, the reasonable approach is to represent and process the data at multi-scale space.

According to the scale-space theory the Gaussian multi-scale provides a canonical class of image representations. For a given image f(x, y), its Gaussian multi-scale representation is defined as

$$L(x, y; \sigma) = G_\sigma * f(x, y), \quad G_\sigma(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right)$$

(1)

$G_\sigma$ denotes the symmetric Gaussian kernel. And $\sigma^2$, i.e. the variance of this kernel is referred to as the scale parameter. And f(x, y) is a

RGB 3-channel color image and expressed as

$$f(x, y) = [R(x, y), \quad G(x, y), \quad B(x, y)]$$

(2)

With different scale parameters of the Gaussian kernel, the representation at m scale of the original color image could be written as

$$L_m(x, y; \sigma_m) = G_{\sigma_m} * f(x, y)$$

$$= [G_{\sigma_m} * R(x, y), \quad G_{\sigma_m} * G(x, y), \quad G_{\sigma_m} * B(x, y)]$$

(3)

The multi-scale color texture representations use the Gaussian convolution of different scales to include the spatial information in each independent spectral channel, and stack different spectral channels to include the inter-spectral information. So the multi-scale color texture representations with the following multivariate image analysis could be regarded as an integration of color and texture information.

In this paper the Gaussian multi-scale representations of the image are used to construct the multivariate image for image analysis. The image $f(x, y)$ is of $I \times J$ pixels in size and of 3 channels in spectrum. By stacking the different coarse-to-fine M scales representations of the RGB color image $f(x, y)$ at the spectral and scale dimension, the $I \times J \times K (K = 3 \times M)$ Gaussian multi-scale multivariate image $F(x, y)$ can be expressed as

$$F(x, y) = [L_1(x, y; \sigma_1), \quad L_2(x, y; \sigma_2), \cdots L_m(x, y; \sigma_m), \cdots L_M(x, y; \sigma_M)]$$

(4)

PCA decomposes the multivariate image into a series of principal components which recover as much variability in the data as possible. These components, orthogonal and arranged according to their eigenvalue, are linear combination of the original variables (Ledaupin et al., 2004). To apply PCA on the three-dimensional $I \times J \times K$ multivariate image data $F(x, y)$, it is required to unfold the three-dimensional data into two-dimensional matrix. The two-dimensional $I \times J$ pixel single channel image could be unfolded and reorganized by rows or columns into a one-dimensional $IJ \times 1$ long vector. The representation of color image at the m scale $L_m(m = 1, 2, \ldots, M)$ could be unfolded into a $N \times 3$ narrow matrix $I_m(N = IJ)$, as shown in Fig. 7. And the unfolding multivariate image matrix $X_{(IJ) \times K}$ is written as

$$F_{(IJ) \times K} \overset{\text{unfold}}{\longrightarrow} X_{(IJ) \times K} = [I_1(x, y; \sigma_1) \quad I_2(x, y; \sigma_2) \quad \cdots \quad I_M(x, y; \sigma_M)]_{N \times K}$$

(5)

PCA carried on the multivariate image matrix $X_{(IJ) \times K}$ leads to decomposing into a series of $A \quad A \leq K$ principal components as

$$X = \sum_{n=1}^{A} L_n p_n^T + E = TP^T + E$$

(6)
where \( t_a \) (\( a = 1, 2, \ldots, A \)) is a \( N \times 1 \) orthogonal score vector, and \( p_a \) (\( a = 1, 2, \ldots, A \)) is a \( K \times 1 \) orthonormal loading vector. And \( T = [t_1, t_2, \ldots, t_A] \) and \( P = [p_1, p_2, \ldots, p_A] \) are the scores and loading matrices for \( A \) principal components. \( E \) is the \( N \times K \) residual array and if \( A = K \) then \( E = 0 \).

Once the loading vector \( p_a \) as the eigenvectors of the matrix \( X^T X \) has been obtained by using kernel-based algorithm (Esbensen and Geladi, 1996), from Eq. (6) the scores matrix for the image can be calculated as

\[
T = XP
\]  
(7)

According to Eqs. (6) and (7), the loading matrix \( P \) as the linear coordinate transformation matrix, could project the Gaussian multi-scale representations of the image onto the new principal component space. We refer to this principal component space as the eigenspace. So the loading vector \( p_a \) as the eigenvectors is the basis vector of the eigenspace. And the scores \( T \) could be interpreted as the color texture integrated features of the original image on the eigenspace.

In order to integrate the color and texture information of bamboo strips, we use fine, median and coarse \( M = 3 \) scales of Gaussian multi-scale representation to construct the multivariate image data, respectively \( \sigma_1 = 1, \sigma_2 = 4 \) and \( \sigma_3 = 10 \) in all the experiments. With \( K = 9 \), we choose \( A = 6 \) in Eq. (7) to obtain six-dimensional feature cluster.

### 2.2.2. Modelling the reference eigenspace from characteristic images

In order to properly describe the color texture features of bamboo strips images, we use the characteristic images selected from the lightest and darkest classes in the bamboo strips, i.e. \( C_{light} \) and \( C_{dark} \), to build the model of the reference eigenspace.

For each typical class, a set of \( N_{ref} \) characteristic images \( j_{light} \) and \( j_{dark} \), \( i = 1, \ldots, N_{ref} \), are selected as the reference images to build the model of the reference eigenspace. Their corresponding Gaussian multi-scale multivariate image matrix could be obtained and, respectively expressed as \( X_{i, light} \) and \( X_{i, dark} \).

By adjoining all the pixels of these reference images by rows, their multivariate image matrix \( X_{ref} \) for the modelling of the reference eigenspace can be written as

\[
X_{ref} = \begin{bmatrix}
X_{1, light} \\
\vdots \\
X_{N_{ref}, light} \\
X_{1, dark} \\
\vdots \\
X_{N_{ref}, dark}
\end{bmatrix}_{(2 \times N_{ref}) \times K}
\]  
(8)

In Eq. (8), \( M \) is the number of scales for RGB color texture multi-scale representation, \( K = 3 \times M \) is the number of variables in multivariate images, and \( N = I \) is the number of total pixels in each image. So the resulting multivariate image \( X_{ref} \) is a \( (2 \times N_{ref}) \times K \) data matrix.

The loading matrix \( P_{ref} \) as the basis vectors of the reference eigenspace \( \Phi_{ref} \) could be obtained from the eigendecomposition of the kernel matrix \( X_{ref}^T X_{ref} \) (Geladi and Grahn, 1996).

Because the class \( C_1 \) and \( C_3 \) were the lightest and darkest classes in Set 1, we chose their images as the reference images to build the model of the reference eigenspace for the first part of experiments. All the images of Set 1 have been projected onto this reference eigenspace. In Set 2 the class \( V_1 \) and \( V_4 \) are the lightest and darkest classes, we choose their images to build the model of the reference eigenspace for the final part of the experiments.

### 2.2.3. Extraction of representative feature cluster using standard deviations

To extract the color texture integrated features of the bamboo strip image \( f(x, y) \), its Gaussian multi-scale representation \( X \) could be projected onto the reference eigenspace \( \Phi_{ref} \) to obtain the \( A \)-dimensional multi-scale color texture eigen features, i.e. the scores \( T \) from Eq. (7). The eigen feature matrix \( T \) is written in the form of...
matrix elements as

\[
T = [ t_1 \ t_2 \ \ldots \ \ t_a \ \ldots \ \ t_A ] = \begin{bmatrix}
\ell_{1,1} & \ell_{1,2} & \cdots & \ell_{1,a} & \ell_{1,A} \\
\ell_{2,1} & \ell_{2,2} & \cdots & \ell_{2,a} & \ell_{2,A} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\ell_{n,1} & \ell_{n,2} & \cdots & \ell_{n,a} & \ell_{n,A}
\end{bmatrix}
\]

(9)

Since the rows of \( T \) are \( A \)-dimensional feature vectors of \( N \) pixels of the image, \( T \) can be referred to as the \( N \)-point feature cluster for the image, where each pixel cluster point is a \( A \)-dimensional multi-scale feature vector.

To find the appropriate size of cluster points to describe the color texture features of the original image \( f(x, y) \), we extract the representative feature cluster from the \( N \)-point pixels by using a statistic linear regression method based on standard deviations (SD).

From the \( N \) pixels we extract \( R \) (\( R < N \)) pixels as the representative feature points which satisfy the dimensions at ±2SD. And we use \( t_1 \) and \( t_2 \), the first and second column vectors of the eigen feature matrix \( T \) to limit the dimensions of representative feature cluster to ±2SD. The \( R \)-point representative feature cluster written as \( T^R \) can be represented as

\[
T^R = \left\{ \begin{bmatrix}
\ell_{1,1} & \ell_{1,2} & \cdots & \ell_{1,a} & \ell_{1,A} \\
\ell_{2,1} & \ell_{2,2} & \cdots & \ell_{2,a} & \ell_{2,A} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\ell_{n,1} & \ell_{n,2} & \cdots & \ell_{n,a} & \ell_{n,A}
\end{bmatrix}
\right\}_{\bigcup_{a=1,2} \| \ell_{d,a} - \mu_a \| \leq 2\sigma_a,}
\]

where \( \mu_a, \sigma_a \) are the mean and the standard deviation of the \( a \)th column vector \( t_a \) (\( a = 1, 2 \)), respectively. They are defined from the \( N \)-point pixels as

\[
\mu_a = \frac{\sum_{n=1}^N \ell_{n,a}}{N} \tag{11}
\]

\[
\sigma_a = \sqrt{\frac{\sum_{n=1}^N (\ell_{n,a} - \mu_a)^2}{N}} \tag{12}
\]

### 2.2.4. Similarity estimation of representative feature clusters in eigenspace

For the grading of new bamboo stripes, a distance-based scheme is used to measure the similarity of the representative feature clusters. And we utilize the Bhattacharyya distance (B-distance) for the similarity estimation between two of the representative feature clusters for bamboo strips (Paschos, 2001).

For two images of bamboo strips \( f_i, f_j \), their Gaussian multi-scale multivariate image matrices could be obtained and, respectively expressed as \( X_i \) and \( X_j \). By using above method their representative feature clusters on the reference eigenspace \( \Phi_{\text{ref}} \) could be obtained and written as \( R_i \)-point \( T_{i}^{R_i} \) and \( R_j \)-points \( T_{j}^{R_j} \), respectively. The Bhattacharyya distance on the \( A \)-dimensional eigenspace \( \Phi_{\text{ref}} \) is defined as

\[
B_{\Phi_{\text{ref}}}(T_{i}^{R_i}, T_{j}^{R_j}) = \frac{1}{4} (\mu_u - \mu_v)^T [\Sigma_u + \Sigma_v]^{-1} (\mu_u - \mu_v)
\]

\[
- \frac{1}{2} \ln \frac{\det((\Sigma_u + \Sigma_v)/2)}{\sqrt{\det(\Sigma_u) \cdot \det(\Sigma_v)}}
\]

(13)

where \( \mu_u, \mu_v \) are the mean center points of the \( R_u \)-point feature clusters \( T_{i}^{R_i} \) and the \( R_v \)-point feature clusters \( T_{j}^{R_j} \), and \( \Sigma_u, \Sigma_v \) are the covariance matrices. The operation symbol \( \det(\cdot) \) denotes the matrix determinant.

B-distance is normally used to measure the pairwise separability of classes in a certain feature space. It is expected that in the most discriminating feature space, the clusters of different classes have more inter-class distances.

In order to evaluate the effective discrimination of multi-scale eigenspace features, the first part of the experiments was carried out to estimate the inter-class Bhattacharyya distances based on the Gaussian multi-scale representations compared with RGB and HSV color spaces. The similar modeling and projecting procedures are used to extract feature clusters from the representation of bamboo strip images in RGB and HSV color spaces. The images in Set 1 were used. The 54 ROI images of the bamboo strips in Set 1 were separated into 6 groups with 9 different class images in each group. In each of 6 groups the inter-class B-distances were estimated.

### 2.2.5. Grading new bamboo strip with k-NN classifier

From the training image of bamboo strips with known groundtruth, we can grade the new bamboo strip to the known classes of the training set by using the multi-scale color texture feature on eigenspace.

In each bamboo strip class \( C_i \) of the training set there are \( N_{\text{sample}} \) images \( f_{ij}, i = 1, \ldots, N_{\text{sample}}; j = 1, \ldots, N_{\text{class}} \). The color texture feature clusters \( T_{ij} \) of these training images can be obtained by projected their respective Gaussian multi-scale multivariate image matrices \( X_{ij} \) onto the reference eigenspace \( \Phi_{\text{ref}} \). And the corresponding \( R_i \)-point representative feature clusters \( T_{i}^{R_i} \), can be extracted according to the standard deviations.

In order to grade the new bamboo strip, the same procedure to construct the Gaussian multi-scale representation is performed. The corresponding multivariate image matrix \( X_{\text{new}} \) is projected onto the reference eigenspace \( \Phi_{\text{ref}} \), and the \( R_{\text{new}} \)-point representative feature clusters of the new surface image can be extracted as \( T_{\text{new}}^{R_{\text{new}}} \). The B-distances \( B_{\Phi_{\text{ref}}} (T_{\text{new}}^{R_{\text{new}}}, T_{i}^{R_i}) \) between the new representative feature clusters \( T_{\text{new}}^{R_{\text{new}}} \) and every training representative feature cluster \( T_{i}^{R_i} \) can be calculated according to Eq. (13).

A widely used k-NN classification algorithm is used to grade the new bamboo strip to the most consistent class in the training set. According to the values of the B-distances, the new bamboo strip would be assigned by a majority vote of its neighbors to the class most common amongst its k-nearest neighbors.

### 3. Results and discussion

From the first part of the experiments, the results indicate that the multi-scale representation achieves the large separability for most cases and appears to be more effective in discriminations than the representations in RGB and HSV space. The inter-class Bhattacharyya distances based on the Gaussian multi-scale representations compared with RGB and HSV color space were estimated. The results come from the experiments on the 54 ROI images in Set 1 which were separated into 6 groups with 9 differ-
ent class images in each group. The mean inter-class distances in 6 groups are shown in Table 1 with the value normalized by the B-distance between the class $C_i$ and $C_j$. It could be seen that in most cases the multi-scale representation achieves larger distance and appears to be more effective in the class separability than RGB and HSV.

In the final part of the experiments, the surface grading tests of bamboo strips have been performed on the training images in Set 2 using the proposed approach. The 240 ROI images of the training bamboo strips belonging to 4 classes with 60 strips in each class.

In order to estimate the classification accuracy rate of the proposed surface grading algorithm, the leave-one-out type testing cross validation was performed. Each sample in turn is removed from the training set of 240 ROI images as the testing image, tested against the other samples, and returned back to the set. The $k$-NN classifier with $k$ value 3 and 5 was used throughout all the tests. In this final part of the experiments we have estimated the classification accuracy 4 times by choosing the different ROI from the original images of bamboo strips in Set 2. The 4 groups of surface grading tests (ROI 1 to ROI 4) could be performed independently. The comparative results of the classification and the average accuracy rate of 4 groups are shown in Table 2. In this special classification application, bamboo strip grading, the integration of color and texture information is very important to classify the images of different bamboo strips. Although the images from the bamboo strips in Set 2 are similar in color and texture appearance, it could be seen that the proposed surface grading method achieves good accuracy in the classification of bamboo strips. So the MIA could achieve good classification results which are enough for the fine grading stage of bamboo industry.

In the first part of the experiments, the first 3 eigenvectors of $P_{ref}$ of the reference eigenspace $\Phi_{ref}$ are, respectively $p_1 = [0.3986 
0.3357 
0.2495]$, $p_2 = [0.3876 
0.213 
0.045]$, $p_3 = [0.269 
0.190 
0.223]$, $p_4 = [0.058 
0.052 
0.037]$, $p_5 = [0.234 
0.141 
0.134]$, $p_6 = [0.620 
0.410 
0.411]$, $p_7 = [0.238 
0.135 
0.122]$, $p_8 = [0.102 
0.078 
0.082]$, $p_9 = [0.030 
0.030 
0.028]$, $p_{10} = [0.061 
0.055 
0.061]$. According to Eqs. (7) and (9) and the value of $p_{ref}$, the first vector $t_1$ of the eigen feature matrix $T$ representing a kind of weighted average of all the Gaussian multi-scale color channels can be regarded as the luminance feature of the image. And similarly the other eigenspace features represent the differences of multiple scales and color spectra. These differential eigenspace features could capture the spatial interaction between spectral bands according with the opponent color features proposed by Jain and Healey (1998). And the multivariate image analysis based on PCA for surface grading closely resembles the process of human to perceive color texture appearance. These are the bionic interpretations of the proposed method.

### 4. Conclusions

In this paper, an automatic surface grading approach for bamboo strips based on Gaussian multi-scale space is proposed. The Gaussian multi-scale representations for RGB color images of bamboo strips are obtained to encapsulate the color and texture information of observation from different scales, and used to construct the multivariate image. The multivariate image analysis (MIA) techniques are used to extract multi-scale features from the resulting multivariate image data for surface grading. Comparative experimental results show that the multi-scale color texture eigenspace features based on multi-scale representations could be regarded as an integration of color and texture information, and is able to achieve rather effective discrimination. In the experiments the proposed grading method is used to classify the bamboo strips into four classes, which are enough for the current application in fine grading stage of bamboo industry. And at the fine grading stage the proposed surface grading method based on multi-scale color texture eigenspace features could effectively classify the bamboo strips with good accuracy up to 93.4%.

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### References


