TROPICAL WOOD CLASSIFICATION BASED ON LBP-LIKE DESCRIPTOR AND NEAREST NEIGHBOR CLASSIFIER
/
基于纹理特征及最近邻分类器的木材分类识别

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ABSTRACT

This paper compares the discriminative ability of six LBP-like texture descriptors for tropical wood classification, LBP, uniform LBP, rotation invariant LBP, rotation invariant uniform LBP, covariance of LBP and covariance of LBP difference were considered. Experiments on wood image dataset with 54 wood species was carried out, experimental results show that these six descriptors combined with nearest neighbour classifier achieve recognition rate of 97.50%, 96.64%, 92.84%, 88.55%, 54.40% and 56.53% respectively. LBP is the best and one of the efficient wood texture descriptors among these six LBP-like descriptors. LBP8,8 is the best and most stable wood texture feature, the recognition rate of $LBP_{8,8}$ *and* $LBP_{8,2}^{u2}$ *are 97.84% and 97.41% respectively, the time to classify one image by them is 0.28 second and 0.08 second. Compared with existing wood image classification methods, the combination of LBP descriptor with nearest neighbour classifier is very simple, it does not need the feature selection and training process, and it achieves much better time efficiency and a slightly lower recognition rate than the existing algorithms.*

摘要

本文对比了LBP、Uniform LBP、旋转不变LBP、旋转不变Uniform LBP、LBP 协方差矩阵、LBP 差协方差矩阵等6 种不同的类LBP 纹理描述算子的分类性能。分类对比实验在具有54 种木材类别的数据库上进行，实验结果证明六种类LBP 算子结合最近邻分类器分别能够得到97.50%、96.64%、92.84%、88.55%、54.40%以及 56.53% 的分类识别率。其中 LBP 具有最稳定的木材纹理描述能力， $LBP_{8,8}$ *以及* $LBP_{8,2}^{u2}$ *的识别率分别为97.84%和97.41%，两者识别一副图像所需时间分别为0.28 秒及0.08 秒。与现存木材分类方法相比，将LBP 算子与最近邻分类器结合进行木材分类方法更简单，不需要进行特征选择及训练阶段，且时间效率大大提高而分类识别率只有细微降低*

INTRODUCTION

Timbers are usually classified by their appearance and weight based on visual inspection. Whereas, wood colour may change after storing and it is hard to measure the intensity of wood pores precisely. As a unique characteristic of timber, wood textures provide an efficient way for online wood classification. Several different kinds of wood recognition system have been designed in various ways *(Khalid et al., 2008; Bremananth et al., 2009; Tang et al., 2009; Khairuddin et al., 2011; Yusof et al., 2013a; Yusof et al., 2013b; Mohan et al., 2014; Taman et al., 2014; Zhang et al., 2014; Ibrahim et al., 2015)*. GLCM (Gray-Level Co-Occurrence Matrix) has been used to classify wood image *(Khalid et al., 2008; Bremananth et al., 2009)*. Among them, Khalid used GLCM to classify wood dataset with about 20 species; they get the average accuracy of 95% *(Khalid et al., 2008)*. (2D) 2PCA was proposed to classify chordal section wood images and its classification accuracy on datasets of 60 wood classes is 76.67%.

Khairuddin et al. combined BGLAM (Basic grey level aura matrix) with distributions of wood pores under microscopy to classify the tropical wood dataset of 52 different classes; they got accuracy of 94.4% *(Khairuddin et al., 2011)*. Yusof et al. proposed a framework that uses pre-classifier to improve the recognition rate and efficiency *(Yusof et al., 2013)*. Yusof et al. combined the KDA (Kernel discriminant Analysis) and GA (genetic algorithm) to reduce the dimension of the timber database, to improve the recognition rate (98.69%) and the time efficiency (1.2 second to recognize an image of size 768×576) *(Yusof et al., 2013)*. Ibrahim et al. use pre-classifier and nonlinear feature selection to classify tropical wood, their method got lower accuracy of 98.5 but slightly faster recognition speed (1 second to recognize one image) *(Ibrahim et al., 2015)* compared to the non-linear feature selection method *(Yusof et al., 2013)*.

Time efficiency is the key factor for the wood recognition system to classify the timber online successfully. Compared to GLCM, PCA and Gabor transform, LBP (Local Binary Pattern) is with low computation complexity, resistance to light changes and has the ability to describe details *(Nanni et al., 2012)*. Since texture descriptor is one of the key factors for success texture classification, this paper compares the recognition rate and efficiency of six LBP-like texture descriptors to choose the wood texture descriptor with the promise discriminative ability and good time efficiency. These six LBP-like descriptors are LBP (Local Binary Pattern) *(Ojala et al., 1996)*, uniform LBP *(Ojala et al., 2002)*, rotation invariant LBP *(Ojala et al., 2002)*, rotation invariant uniform LBP *(Ojala et al., 2002)*, covariance of LBP difference *(Hong et al., 2014)* and covariance of LBP *(Hong et al., 2014)*.

The remaining sections are organized as follows. Section 1 introduces the definition of these six LBP-like descriptors. Section 2 introduces the dataset, the distance measure methods for histograms and covariance matrices and the proposed tropical wood recognition method. Section 3 compares the classification abilities and efficiencies of these six LBP-like descriptors, the confusion matrix of the best LBP-like descriptor is given in this section, it also compares the recognition rate and time efficiency of the optimal LBP-like descriptor with existing methods. Conclusions and possible improvements are discussed in Section 4.

1. LBP-LIKE DESCRIPTORS

1.1 LBP

LBP is a method to extract local grey level information *(Ojala et al., 1996)*. LBP sequence represents the comparison of a pixel to its neighbouring ones in a local area, it compares the feature value (usually grey value) of the middle pixel with its neighbouring pixels, if the feature value of the middle pixel is bigger than those of the neighbouring pixel, then the LBP value of the neighbouring pixel is 0, otherwise the LBP value will be 1. Calculation of LBP is described in equation (1) (Ojala et al., 1996).

$$LBP_{P,R}(x)=\sum_{p=0}^{P-1}\mathrm{S}(g_p-g_c)2^p \tag{1}$$

Where $\{g_p\}_{p\in[0,P-1]}$ is the feature value of P neighbouring pixels, with distance R to the central pixel x. g_c is the feature value of central pixel x. S(x) is the step function with S(x)=1 when x≥0 and S(x)=0 for otherwise. The bit order and example for calculating LBP *(Ojala et al., 1996)* is given in figure 1, where P equals 8 and R equals 1.

1.2 Uniform LBP

Most of texture information is represented by a small subset in LBP *(Ojala et al., 2002)*; this subset is called uniform LBP. If the number of bitwise spatial transitions (from 1 to 0 or from 0 to 1) in LBP is not bigger than 2 (including the transition from end to the beginning), then the LBP is a uniform LBP, the other LBP patterns are called the non-uniform patterns. *i.e.*, 01110000 and 10000000 are uniform LBP patterns, but 10000100 and 00100100 are non-uniform patterns. The number of LBP patterns is *P*(*P*-1)+3, *P* is the number of neighbouring points. Calculation of uniform LBP is described in equation (2) *(Ojala et al., 2002).*

$$LBP^{u2}_{P,R}=\begin{cases}\sum_{p=0}^{P-1}\mathrm{S}(g_p-g_c)2^p, & \mathrm{U}(LBP_{P,R})\le 2\\ other & ,otherwise\end{cases} \tag{2}$$

Where *P* is the number of neighbouring points, and *R* is the radius. S(*x*) =1, if *x*≥0, and S(*x*) <0 for otherwise. *u2* stands for the number of bitwise transitions(including the transition from end to the beginning) in LBP is not more than 2, U($LBP_{P,R}$) stands the number of bitwise transitions (including the transition from end to the beginning) in $LBP_{P,R}$ pattern. In Ojala's research, if (*P*, *R*) equal (8, 1), the uniform LBP represent at least 90% of the texture information, and if (*P*, *R*) equal (16, 2), the uniform LBP represent at least 70% of the texture information. Uniform LBP not only can describe the majority of the texture information, but also for dark spots, smooth region, and the light spots of the edge. It has strong classification ability with higher time efficiency compared to LBP *(Ojala et al., 2002).*

1.3 Rotation invariant LBP

The classification ability of LBP is irrelative to the binary coding order. A LBP value is a label for its pattern, numerical comparison between two LBPs is meaningless. LBP changes a lot when image rotation happens, while rotation invariant LBP has the same texture classification ability when rotation happens. Rotation invariant LBP treat the different LBPs which rotated from the same LBP as one class. Rotation invariant LBP is denoted as $LBP_{P,R}^{ri}$, its definition is given in equation (3) *(Ojala et al., 2002).*

$$LBP_{P,R}^{ri} = min\left\{\mathrm{ROR}\left(LBP_{P,R}, i\right) | i = 0,1,2,\ldots,P-1\right\} \tag{3}$$

Function ROR ($LBP_{P,R}$, i) move LBP binary sequence to the right circularly for i bits, where $i\in[0,P-1]$. Number of $LBP_{P,R}^{ri}$ patterns is 36 when P equals 8. $LBP_{8,1}^{ri}$ is *LBPROT (Pietikäinen et al., 2000)* when R equals 1.

1.4 Rotation invariant uniform LBP

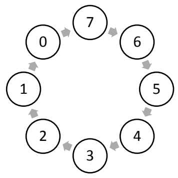
The occurrence frequencies of each patterns in $LBP_{8,1}^{ri}$ varies a lot and its crude quantization of the angular space at 45° intervals lead to a non-ideal texture recognition rate. $LBP_{P,R}^{u2}$ provides the vast majority of texture information, which includes the bright spots, flat points, dark spots and different curved edge texture information. Therefore, $LBP_{P,R}^{ri}$ and $LBP_{P,R}^{u2}$ can be combined to get the rotation invariant uniform LBP. Rotation invariant uniform LBP is denoted as $LBP_{P,R}^{riu2}$, it has P+1 different patterns, it is defined as listed in equation (4) *(Ojala et al., 2002)*:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} \mathrm{S}\left(g_p - g_c\right), & \text{if } \mathrm{U}\left(LBP_{P,R}\right) \le 2 \\ P+1, & otherwise \end{cases} \tag{4}$$

Where $\mathrm{U}\left(LBP_{P,R}\right) = |\mathrm{S}(g_{P-1}-g_c) - \mathrm{S}(g_0-g_c)| + \sum_{p=1}^{P-1} |\mathrm{S}(g_p-g_c) - \mathrm{S}(g_{p-1}-g_c)|$, and *riu2*stands for the use of rotation invariant uniform pattern, and U is less or equal to 2, function S is the same as those used in $LBP_{P,R}^{u2}$. $LBP_{P,R}^{riu2}$ has P+2 different values.

1.5 Covariance of LBP

Compared to histogram, covariance matrix of different features of one image is more compact *(Hong et al., 2014*). Covariance Matrix (CovM) not only combines several different feature channels together, but reflects the covariance of any two of the elementary features as well *(Tuzel et al., 2006*). LBP is one of the effective texture descriptors. Covariance matrix of local binary pattern is computed by different LBPs of one



7	6	5	4	3	2	1	0

125	100	95
99	**100**	60
10	99	110

1	1	0
0		0
0	0	1

Pixel-wise feature value

LBP：10010001（145）

(a) Bit order for LBP *(b) Example of LBP calculation*

Fig. 1 - LBP descriptor

image.

Covariance matrix of local binary pattern is denoted as $\mathbf{CovM}_{\mathrm{LBP}}$ and can be computed by equation (5) *(Tuzel et al.*, 2006)**.**

$$\mathbf{CovM_{LBP}}(I) = c\sum_{x\in I}(f(x)-\mu)(f(x)-\mu)^T \tag{5}$$

Put N LBPs of one pixel into an N dimensional feature vector $f(x)$, μ is the average vector of the feature vectors in one image area, I is an image area, and $\{f(x)\}_{x \in I}$. The size of $\mathbf{CovM}_{LBP}$ is $N \times N$, c is a normalization factor *(Tuzel et al., 2006)*.

1.6 Covariance of LBP difference

LBPD (Local Binary Pattern Difference) was proposed by Hong *et al. (Hong et al., 2014)*. LBPD of one pixel is the difference between its LBP and LBP mean, LBP mean is the mean vector of LBPs within an image area. LBPD is a real value. LBPD is rotation invariant and insensitive to noises since one bit difference would not contribute much difference to the LBPD. There are three steps to calculate LBPD for one image (area). Firstly, we calculate LBP for one image (area), then calculate the mean vector of this image (area) to get LBP mean vector, the last step is to calculate the difference vector between LBP and LBP mean to get the LBPD for each pixel. A covariance matrix of LBPD with size $N \times N$ of N different LBPDs for one image(area) can be calculated by equation (5) (Hong *et al.*, 2014), covariance matrix of LBPD is denoted as $\mathbf{CovM}_{LBPD}$, $f(x)$ is an N dimensional feature vector of n LBPDs, μ is the average vector of the feature vectors in one image area, and $\{f(x)\}_{x \in I}$. The size of $\mathbf{CovM}_{LBPD}$ is $N \times N$, c is a normalization factor *(Tuzel et al., 2006)*.

MATERIALS AND METHODS

2.1 Wood database

The dataset used in our experiment contains the timber images of Forest Research Institute Malaysia downloaded from the website *https://info.frim.gov.my/woodid/index.cfm#*. The dataset has images of 54 different tropical timber species, and each species has 9 images, which produce 486 images for the wood database. Resolution of images is about 500×600. Figure 2 provide some examples of the wood images from 8 different wood species in the database. We can see from figure 2 that images of some different wood species share great similarities, this would increase the difficulty of classification.

2.2 Distance measurement

2.2.1 Distance measurement for histograms

Histogram is treated as a vector, therefore, the distance measurement for vectors can be used directly to measure the dissimilarity of histograms *(Cha and Srihari, 2002).*

Suppose that A and B are histograms. Then the Euclidean distance and Chi-square distance are defined as follows. $H_i(X)$ is the value of the i-th bin of histogram X.

(1) Euclidean distance

Euclidean distance is originated in Euclidean geometry; Euclidean distance is denoted as $D_E(A,B)$, which is defined in equation (6). The bigger the $D_E(A,B)$, the bigger the distance between histograms A and B *(Cha and Srihari, 2002)*.

$$D_E(\mathbf{A},\mathbf{B}) = \sqrt{\sum_{i=0}^{b-1}(H_i(\mathbf{A}) - H_i(\mathbf{B}))^2} \tag{6}$$

(2) Chi square distance

Based on Euclidean distance, Chi-square distance considers the relative difference of bins in the same position and it pays more attention to the difference of smaller bins *(Pele and Werman, 2010)*. This is more effective for LBP distance description, especially for histogram vectors of uniform LBP, where the non-uniform pattern is usually bigger than uniform patterns, so that Chi-square pays more attention to the uniform patterns which is usually smaller than the non-uniform patterns. Hence, compared to Euclidean distance, Chi-square distance is more suitable for describing the histogram distance. Chi-square distance is denoted as $D_X(A,B)$, The bigger the $D_X(A,B)$, the bigger the distance between histograms A and B. Equation (7) gives the definition of Chi-square distance *(Pele and Werman, 2010)*.

$$D_x(\mathbf{A},\mathbf{B}) = \sum_{i=0}^{b-1}\frac{(H_i(\mathbf{A}) - H_i(\mathbf{B}))^2}{H_i(\mathbf{A}) + H_i(\mathbf{B})} \tag{7}$$

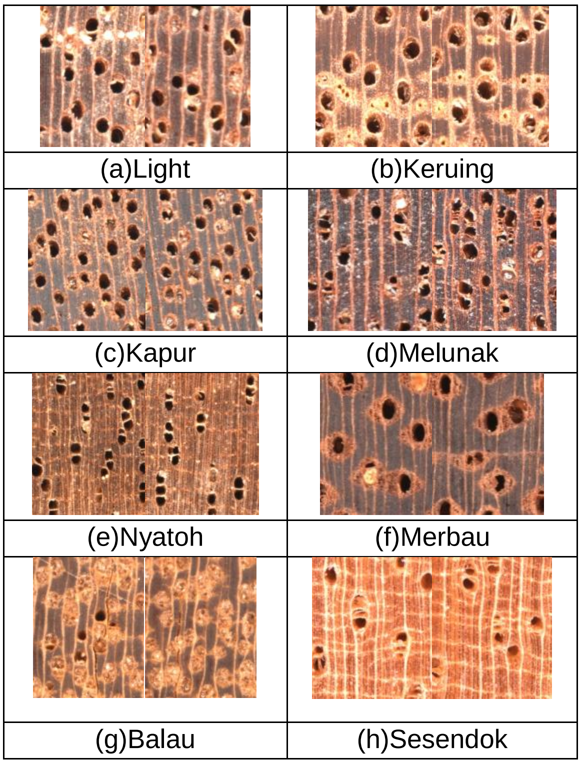


Fig 2 - Wood texture image sample

2.2.2 Distance measurement for covariance matrix

We use one of the Riemannian manifold based metric to calculate the distance of two covariance matrices $\mathbf{M}_1$ and $\mathbf{M}_2$[11]. Distance measurement of two covariance matrices is defined in equation (8).

$$d(\mathbf{M}_1, \mathbf{M}_2) = \sqrt{\sum_{i=1}^{n} \ln^2(\lambda_i(\mathbf{M}_1, \mathbf{M}_2))} \tag{8}$$

Where $\{\lambda_i(\mathbf{M}_1, \mathbf{M}_2)\}_{i=1,\dots,n}$ are the n generalized eigenvalues of two positive definite matrices $\mathbf{M}_1$ and $\mathbf{M}_2$.

Compared to most of the other feature matrices, Covariance Matrix is more compact, it always equals $N\times N$ no matter how big the image size is, where N is the number of elementary features.

2.3 Proposed method

This paper uses $LBP_{P,R}$, $LBP_{P,R}^{u2}$, $LBP_{P,R}^{ri}$, $LBP_{P,R}^{riu2}$, **CovM**$_{LBP}$, and **CovM**$_{LBPD}$ to describe wood image textures, then combines each of these descriptors with Nearest Neighbor (NN) classifier separately. Different (P, R) values for all these six descriptors are compared, where P is the number of neighbours and R is the radius. Because of memory limitation, we set P equal to 8, and R equal to 1, 2, 4, and 8 respectively, so that we get four features for each of these six descriptors, and twenty four features for one image.

Then the average recognition rates of these six descriptors are compared, the best descriptor and its best (P, R) value are selected. The recognition rate for each different feature is the average recognition rate of 10 times classification using random permutation.

(1) Random permutation

In NN classification section, K (we use 3 in our experiment) images are selected randomly as the test images, so that the left images would be the training images (for each class, number of training images is 9-K).

Then, use NN classifier to recognize the test image, compare the class of nearest neighbor with those of test image, if they are the same, then the classification rate for this test image is 100%, and 0 for otherwise. The classification rate of one random permutation experiment is the average of the classification accuracy of all test images.

Recognition rate can be calculated by the average of the classification rate of 10-times random permutation experiments; this would ensure the representativeness and reliability of the results (Micheals and Boult, 2001).

(2) Procedure for wood recognition:

There are three steps to classify the tropical wood images:

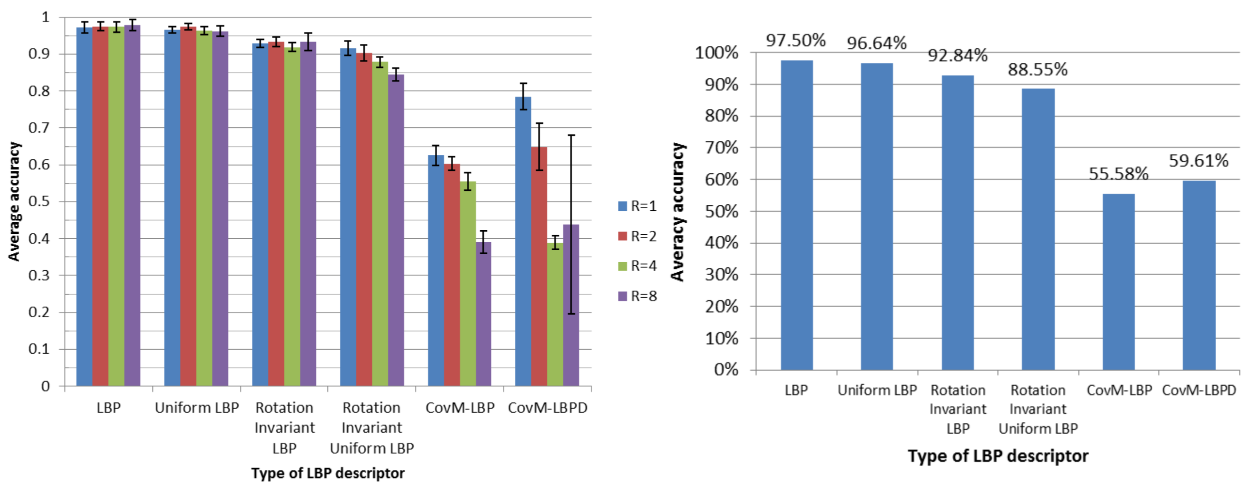
Firstly, turn the RGB image to gray image. The second step is to calculate these twenty four features for each images, using $LBP_{P,R}$, $LBP_{P,R}^{u2}$, $LBP_{P,R}^{ri}$, $LBP_{P,R}^{riu2}$, **CovM**$_{LBP}$, and **CovM**$_{LBPD}$ with four different(P,R) values. Finally, classify images by combining different features with NN classifier separately, where distances of $LBP_{P,R}$, $LBP_{P,R}^{u2}$, $LBP_{P,R}^{ri}$, $LBP_{P,R}^{riu2}$ are calculated by equation (7) and distances of **CovM**$_{LBP}$, and **CovM**$_{LBPD}$ are calculated by equation (8).

(3) Calculation of recognition rate

Take R($LBP_{P,R}^{X}$) as the recognition rate of $LBP_{P,R}^{X}$, N is the size of test set, M_t is the number of test images that have been correctly classified in the t-the random permutation experiment, and T is the times of random permutation experiment. Recognition rate of one feature can be calculated by equation (9).

$$\mathrm{R}(LBP_{P,R}^{X}) = \frac{\sum_{t=1}^{T} M_t}{T * N} * 100\% \quad (9)$$

RESULTS



(a) (b)

Fig. 3 - Comparison of accuracy of wood classification using different LBP-like descriptors
(where P equals 8)

(a) Comparison of classification accuracy and the standard deviation using different LBP-like descriptors with different (P, R) value.

(b) Accuracy of wood classification using different LBP-like descriptors. Wherein, LBP is for $LBP_{P,R}$, uniform LBP is for $LBP_{P,R}^{u2}$, rotation invariant LBP is for $LBP_{P,R}^{ri}$, rotation invariant uniform LBP is for $LBP_{P,R}^{riu2}$, CovM_LBP is for CovMLBP and CovM_LBPD is for CovMLBPD.

Figure 3 compares the classification accuracy and their standard deviation of $LBP_{P,R}$, $LBP_{P,R}^{u2}$, $LBP_{P,R}^{ri}$, $LBP_{P,R}^{riu2}$, **CovM**$_{LBP}$, and **CovM**$_{LBPD}$, where P is 8 and R is equal to 1,2,4,8 respectively, so that there are four different bars for each texture descriptors. In figure 3(a), Error bar with standard deviation shows the deviation of recognition rate from their mean, where $LBP_{P,R}^{u2}$ has the smallest standard deviation so that it has the most stable performance, and the $LBP_{P,R}$ is the second steady descriptor, **CovM**$_{LBPD}$ has the worst stability. Figure 3(b) compares the mean recognition rate of $LBP_{P,R}$, $LBP^{u2}_{P,R}$, $LBP^{ri}_{P,R}$, $LBP^{riu2}_{P,R}$, **CovM**$_{LBP}$, and **CovM**$_{LBPD}$, where each descriptor's mean accuracy are calculated by averaging the recognition rate of its four different (*P*,*R*)s. It is clearly to see that $LBP_{P,R}$ has the best average classification accuracy of 97.5%, $LBP^{u2}_{P,R}$ is the second best, where its mean recognition rate is 96.64%, recognition rate of different (*P*,*R*) values are nearly the same for $LBP_{P,R}$. $LBP_{8,8}$, with a recognition rate of 97.84%, showing the best classification ability, the second best feature is $LBP^{u2}_{8,2}$, with a classification rate of 97.41%.

Figure 4 compares the mean recognition rate of $LBP_{P,R}$, $LBP^{u2}_{P,R}$, $LBP^{ri}_{P,R}$, $LBP^{riu2}_{P,R}$ for different wood species by radar graph (for the clarity of different lines, **CovM**$_{LBP}$ and **CovM**$_{LBPD}$ with low recognition rates are not included in figure 4). There are 7 concentric circles in the radar graph, where the radius of each circles are the classification rate, and the centre of the circle is relative to the recognition rate of 30%, and the recognition rate of circles from the centre to the outer circle are 40%, 50%, 60%, 70% , 80%, 90%, 100%, respectively. Dots in the outer circle are the wood species names and their class number (*i.e.*,"1 Balau" means the wood class name is Balau, and its class number is 1). Four curves on the radar graph stands for recognition rates of $LBP_{P,R}$, $LBP^{u2}_{P,R}$, $LBP^{ri}_{P,R}$, and $LBP^{riu2}_{P,R}$ respectively. It is clearly to see that these four descriptors have 100% recognition rate for wood species Dammar, Gerutu, Kulim, Kungkur, Nyatoh, Perupok, Pulai, Resak, Tembusu, Terentang, and YellowMeranti, while the recognition rate of these four descriptors are not ideal for wood species Dark, Kapur, Kempas, Keruing, Light, Melunak, Sepetir, and WhiteMeranti.

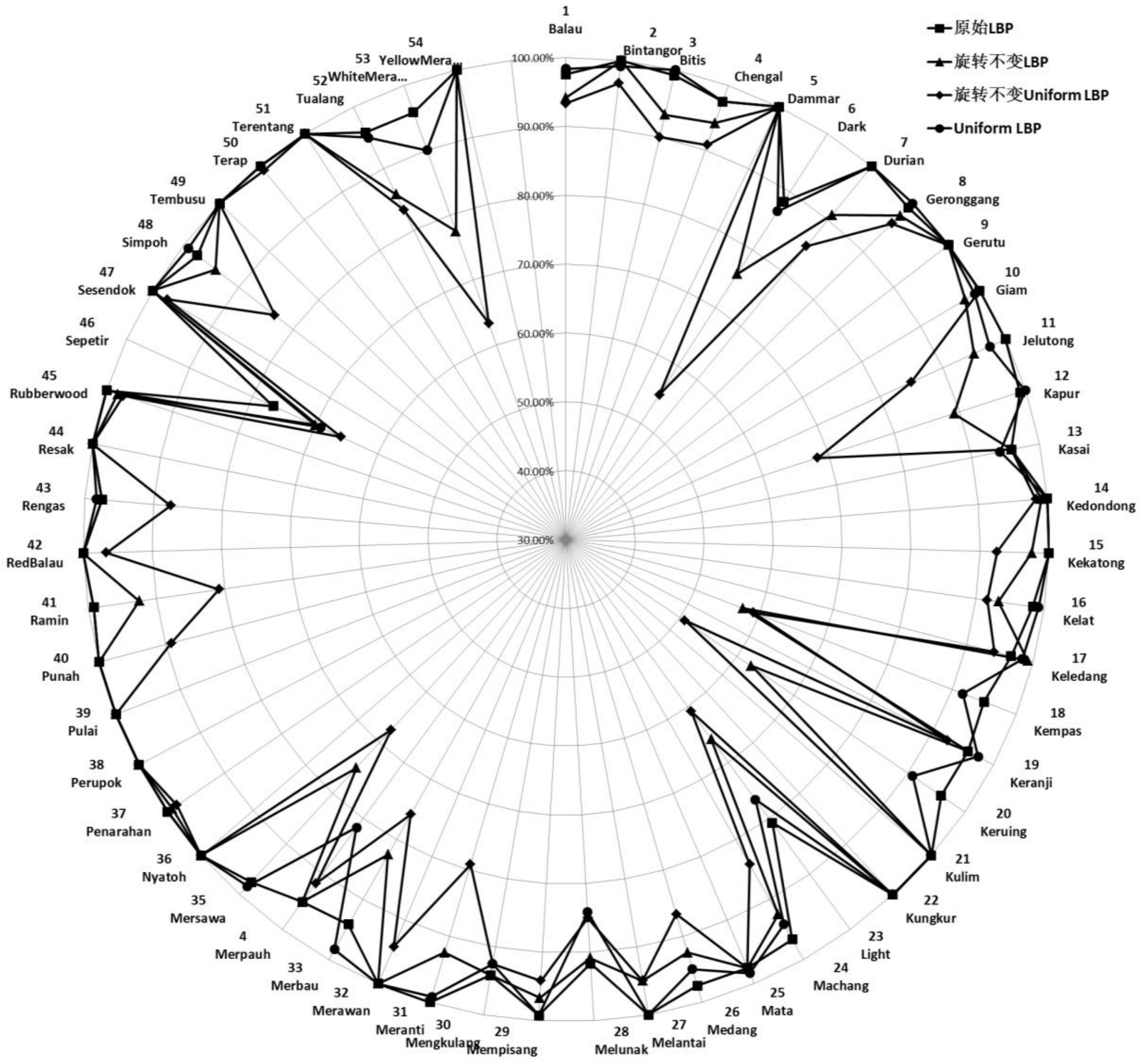


Fig. 4 - Comparison of classification accuracy for four LBP-like descriptors combined

with nearest neighbor classifier respectively

Figure 5 is the confusion matrix of $LBP_{8,8}$, numbers from 1 to 54 in figure 5 represent the wood class number in figure 4. Values in figure 4 are between [0%, 100%], white stands for 0%, standard red is the transition colour and black stands for the recognition rate of 100%. The colours of recognition rate in [0%, 33.33%] gradually change from white to standard red, while the colours of recognition rate in (33.33%, 100%] gradually change from standard red to black. The colour bar of figure 5 is shown on its right side. From the colour of diagonal line of figure 5, we can see that $LBP_{8,8}$ has very good classification ability for almost all of the wood classes, only a small portion of the test samples are misclassified to other classes, and most of the misclassified test samples are classified as the wood classes of the same wood family.

Table 1 compares the recognition rate and time efficiency of existing algorithms *(Khalid et al., 2008; Khairuddin et al., 2011; Yusof et al., 2013; Ibrahim et al., 2015)*,. The time efficiency of proposed method ($LBP_{8,8}$ combined with nearest neighbor) is 4.27 times faster than nonlinear feature selection method *(Yusof et al., 2013)*, while its recognition rate is 97.84%, which is only 0.85% lower than those of the nonlinear feature selection method. Recognition rate of $LBP_{8,2}^{u2}$ is 97.41%, which is slightly lower than those of $LBP_{8,8}$, but its time efficiency is 3.6 times of $LBP_{8,8}$.

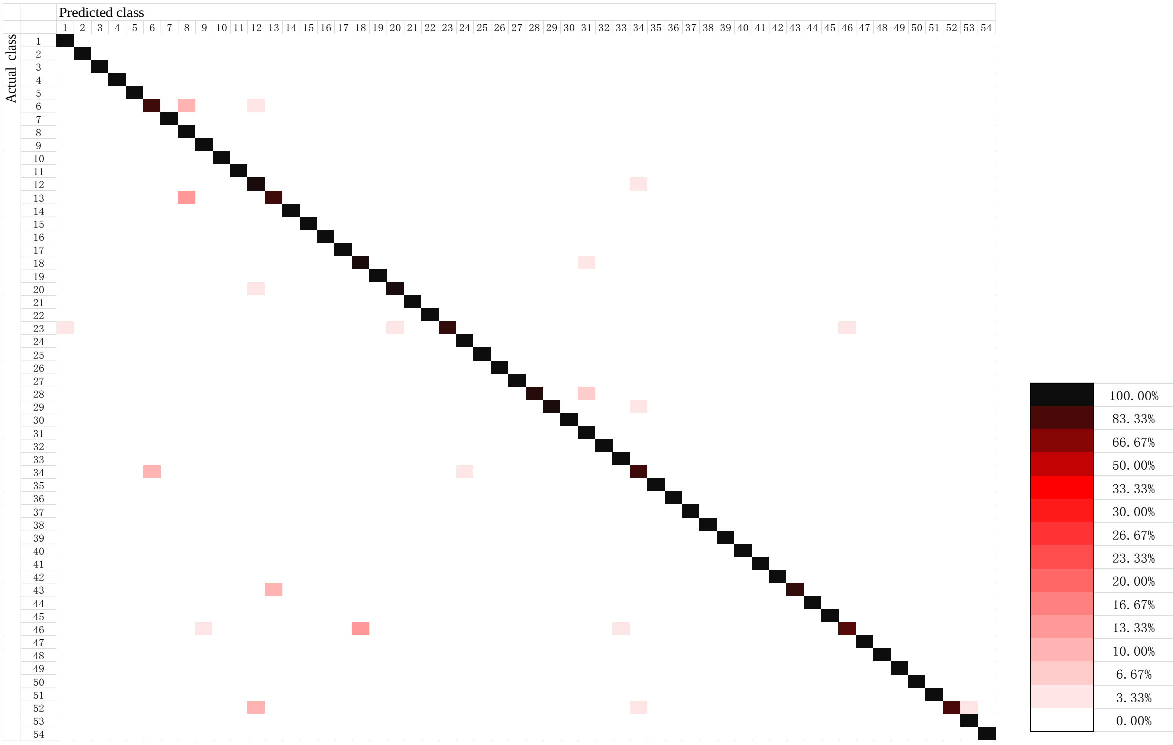


Fig 5 - Global confusion matrix for $LBP_{8,8}$

Table 1

Comparison of existing timber classification methods

Classification methods	Recognition rate	Classification speed (millisecond/image)
GLCM feature extractor *(Khalid et al., 2008)*	45%	1000
GA feature selection *(Khairuddin et al., 2011)*	94.4%	1500
Nonlinear feature selection excluding *(Yusof et al., 2013)*	98.69%	1200
Fuzzy pre-classifier with nonlinear feature selection *(Ibrahim et al., 2015)*	98.5%	1000 to 1060
$LBP_{8,8}$ with Nearest Neighbor classifier (proposed method)	97.84%	281
$LBP_{8,2}^{u2}$ with Nearest Neighbor classifier (proposed method)	97.41%	77

CONCLUSIONS

Timbers classification by visual inspection has low efficiency and is unreliable. This paper combines six LBP-like texture descriptors with nearest neighbor classifier to classify timber images from 54 wood species, and it compares the wood texture discrimination power of $LBP_{P,R}$, $LBP^{u2}_{P,R}$, $LBP^{ri}_{P,R}$, $LBP^{riu2}_{P,R}$, **CovM**$_{LBP}$, and **CovM**$_{LBPD}$. Experimental results show that $LBP_{P,R}$ is the best texture descriptor with a classification accuracy of 97.5% while $LBP^{u2}_{P,R}$ is the second best texture descriptor with a classification accuracy of 96.64%.

$LBP_{8,8}$ has the best discrimination power for wood dataset with 54 wood species, its classification accuracy is 97.84%, and the standard deviation of classification accuracy is only 1.52%. Classification rate and its standard deviation of $LBP^{u2}_{8,2}$ is 97.41% and 0.91%. Storage and time consumption of $LBP^{u2}_{8,2}$ are only 32.45% and 26.83% of $LBP_{8,8}$. Thus, uniform LBP is one of the options for wood texture description if higher storage efficiency and time efficiency are needed.

Combination of LBP with wood biological features (*i.e.*, density of wood pores) and other classifiers (*i.e.*, deep learning and SVM, etc.) would be possible methods for future works. Multi-resolution fusion of different texture features would possibly improve the classification rate. For the wood species which are difficult to classify, we need to study their properties to design a more specific targeted recognition system.

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