WOOD RESEARCH doi.org/10.37763/wr.1336-4561/67.4.686699
e-ISSN 2729-8906
67(4): 2022 686-699 pp.

A NOVEL WOOD FEATURE EXTRACTION METHOD BASED ON IMPROVED BLOCKED HIGHER-ORDER LOCAL AUTO-CORRELATION

ZIHAO LIU, SULAN ZHANG, XIAOJUN JIA, JUN YANG
JIAXING UNIVERSITY
P.R. CHINA

(RECEIVED DECEMBER 2021)

ABSTRACT

Traditionally, HLAC (Higher-order Local Auto-Correlation) algorithm was used to extract texture features of wood images. However, heavy memory consumption and complexity of high-order mask pattern were common in HLAC. A novel feature extraction strategy based on improved blocked higher-order local auto-correlation (IBHLAC) is proposed to circumvent these problems. Initially, sequences of the whole wood image frames, which are the grayscale treatment, were being divided into series of subdivisions vertically and horizontally. Additionally, to enhance auto-correlation ability of the proposed method, different high-order patterns of masks were rebuilt based on zero-order mask by introducing the morphology and affine transformation. Finally, time-consumption and memory occupation of related four methods were compared. Experiment results indicated IBHLAC costs less time and fewer memory consumption on the wood texture database compared with other methods, which reveal that IBHLAC is efficient.

KEYWORDS: Feature extraction, wood recognition, mask pattern, HLAC.

INTRODUCTION

Commonly, wood recognition refers to making a final decision by expert judgment according to macroscopic features and microscopic characteristics, through observation, comparison and analysis. Traditional intelligent wood recognition method has proven remarkably effective for supervised learning (Liu et al. 2013), and has also produced impressive reinforcement learning results, such as good portability and expansibility. However, low recognition rates, time-consuming also exist in the traditional methods. Besides, the existence of numerous lumbers belong to different categories, may result in great loss even catastrophic, threatening the accuracy of wood recognition.

Automatic wood recognition strategies mainly focus on using the digital image processing and pattern recognition algorithms (Liu et al. 2013). For example, various methods are proposed to extract discriminative feature information in order to improve the performance of recognition precision, and the accuracy estimated by series of databases with variations of images, such as, Multi-layer perceptron (MLP) (Ren et al. 2017), Principle Component Analysis (PCA) (Liu 2013), Independent Component Analysis (ICA) (Hofmeyr 2021), Gray Level Co-occurrence Matrix (GLCM) (Wang et al. 2010), Gabor-wavelets (Rubiyah et al. 2009), Local Binary Pattern (LBP) (Balazs et al. 2005), Higher-order Local Auto-correlation (HLAC) (Laievardi et al. 2010) has been widely adopted in the last few years.

Specially, Higher-order Local Auto-correlation (HLAC) (Laievardi et al. 2010), is a feature extraction method which achieves discriminated external characterization by incorporating adaptive mask patterns into the original images to complete the matrix convolutional operations. In the HLAC method, the problem called "Curse of Dimensionality" happens occasionally for high-dimension features with a large displacement region (Hutzenthaler et al. 2020). Hence, the extracted features become extremely numerous when the mask patterns are high-dimensional, which imposes many application limitations. Moreover, original HLAC features are restricted up to the second-order (three-point relations) and within a 3×3 displacement region. HLAC features are rarely scanned over the noisy image left to right in horizontal. However, it is a waste of shifting mask patterns in horizontal and bringing the drawbacks of low efficiency and squandering, when relate to some wood texture. Dividing the noisy image in vertical and horizontal can extract abundant features to correctly distinguish wood species for the classifiers (Wang et al. 2009).

Therefore, to circumvent above-mentioned problem, an Improved Blocked-HLAC (IBHLAC) method for feature extraction was proposed in this study. Consider the traditional HLAC, whose computation processes are complex and high-occupied storing memory in the PC system, conceived the innovation idea of using blocking partition and high-order mask reconstruction to decrease the masks of dimensions rapidly. At first, transform sequences of wood images into gray scale images, divide grayscale treatment frames into series of subdivisions. Then, mask patterns were covered and scanned from left to right over the entire image, including vertical and horizontal respectively. Furthermore, to enhance auto-correlation ability of the partition method, different high-order patterns were built upon zero-order mask model by introducing morphology transformation algorithm. Moreover, three efficient classifiers-SVM (Sadeghi 2021), Random-Forest (Gazzola et al. 2019) and SoftMax (Li et al. 2020) were also investigated to complete feature classification. Experiments achieved on the wood texture database reveals that IBHLAC is efficient compared to the traditional HLAC. The main objective of this paper is to reduce and optimize the high-order mask patterns based on zero-order masks.

MATERIAL AND METHODS

Materials

A wood image database named *WM 22* dataset was built in this section. In the *WM 22* dataset, twenty-two tree species, wildly distributed in nationwide were selected. Generally, stereogram images are captured on the cross-section surface of wood samples with Olympus

SZ61TRC stereo-microscope, and MD50 digital imaging system is applied to collect the details of wood texture images. The *WM 22* wood dataset refers to 22 species of wood with 18 wood stereograms per species, 396 different wood samples were contained in this dataset. To acquire high-quality wood images, it is necessary to intercept a rectangle region from the tree growth rings over the wood stereogram. Actually, the requirement for selecting certain region is that the corresponding width and length should be exactly extracted in one growth ring, while its texture is discriminative, excluding the fracture, scratches and other non-timber nature area. Fig. 1 shows the whole process of acquiring, selecting and normalizing one wood image (*Qiqihar poplar*).

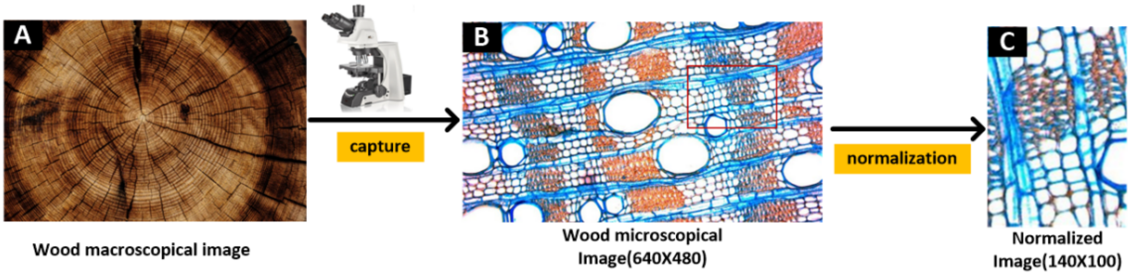


Fig. 1: Processes of acquiring, selecting and normalizing one wood image (Qiqihar poplar).

Fig. 2 shows parts of 22 species of color wood microgram, which are contained in the dataset, they are *Populus tomentosa (Beijing)*, *Picea asperata Mast*, *Liriodendron chinense (Hemsl.) Sargent*, *Magnolia officinalis var. biloba Rehder & E.H.Wilson*, *Castanopsis fissa (Champ. ex Benth.) Rehd. et Wils*, *Liquidambar formosana Hance*, *Cleyera japonica Thunb*, *Taxus wallichiana var. chinensis (Pilg.) Florin*, *Schoepfia chinensis Gardn.et Champ*, *Pseudolarix amabilis (Nelson) Rehd*, *Larix gmelinii (Rupr.) Kuzen*, *Quercus acutissima Carruth* correspondingly. From Fig. 2, the appearances between different wood species are diverse, which may be caused by different sizes, density, arrangement, and distribution of the main wood cell organizations, such as pore, ray, and axial parenchyma. However, these cells show a high certain regularity in the same tree species, which is also the main reason why experienced wood experts identify wood species quickly and accurately.

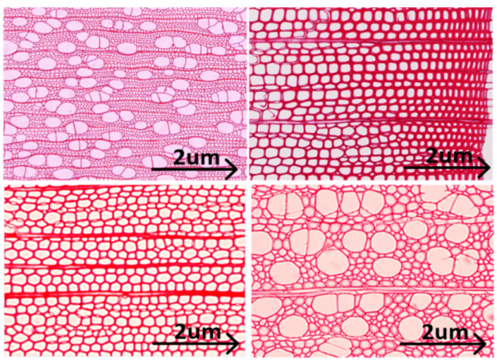


Fig. 2: Texture wood images (from left to right and top to bottom: Populus tomentosa (Beijing), Picea asperata Mast, Larix gmelinii (Rupr.) Kuzen, Liriodendron chinense (Hemsl.) Sargent correspondingly).

Image pre-processing

The feature differences distinguish among wood species may bring about confusion during subsequent image truncation and feature extraction, which will impose significant limitations in choosing adaptive wood image regions. To delete noise pollution on the wood micro-image, image pre-processing algorithm was performed to eliminate irrelevant information and superfluous wood micro-image part, such as the polluted part by effects of illumination and lighting. Furthermore, pre-processing can also strengthen the basic discrimination and detectability within the same species. Size of original image is 640×480, and 140×100 image part was chosen according to above choosing rule. The processed gray image and binarization image can be seen in Figs. 3b,c. Fig. 3 shows the image pre-processing processes.

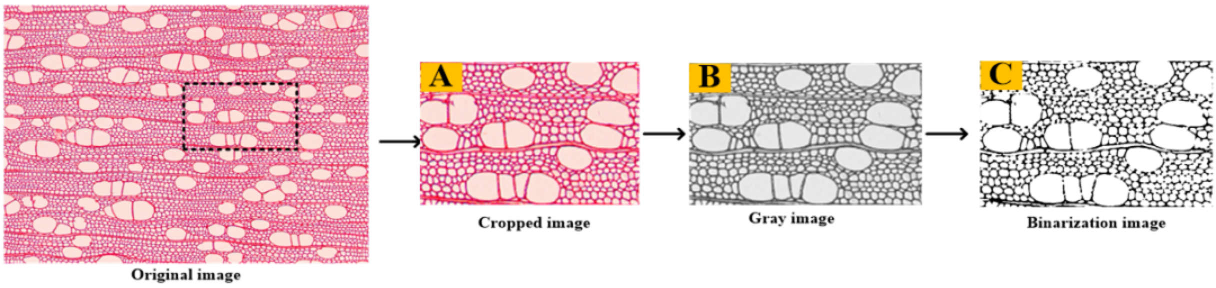


Fig. 3: 140×100 image pre-processing (from original image to binary image).

Improvements of traditional BHLAC

Higher-order local auto-correlation (HLAC) (Laievardi et al. 2010) is actually a texture feature extraction method, which was proposed to express the complex object's texture feature primitively. To support and require large effective image feature regions, the masks of different sizes and different directions were used. Traditional method for extracting image features of BHLAC is to store hundreds of mask templates into the system previously, and directly invoke the used one. In this way, the pre-stored templates occupy a large amount of system memory, which is not adaptive for industrial online implementation. Instead of storing a large number of templates in the system previously, the proposed method (IBHLAC) can directly construct a special information transformation algorithm from high-order to low-order patterns with minimal memory consumption. From above analysis, two strategies-morphological transformation upon small matrix and affine transformation upon large matrix are carried out to complete dimension reduction based on the zero-order mask template. In this way, low-memory and high-randomness of the generated templates can be built, with high mask generation efficiency. Extensions of HLAC mask patterns are shown in Fig.4.

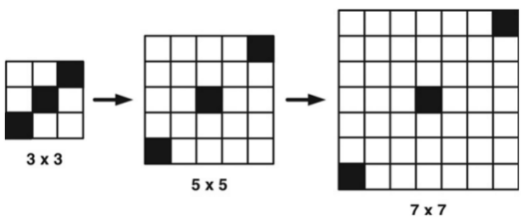


Fig. 4: Extension of HLAC mask patterns from 3×3 model.

All orders of masks of traditional BHLAC have the property of affine transformation from the entire whole image. However, from tremendous online practical applications, many masks occupy a large amount of system memory, which makes it hard to implement real-time and online application. Moreover, in the high-dimensional case of template matrix, the number of mask patterns corresponding to all orders are extremely large. For example, Ext-HLAC feature extraction methods (Suzuki 2014) proposed by Suzuki, totally 16 241567 5×5 mask templates from 1-order to 24-order were contained. Because this method has adaptive computation ability and various template styles, it was adopted as the improved basis. However, the corresponding masks of each order are different. For all the original types of masks, the numbers of each mask pattern are the results after removing repeated rotation, translation and reversal invariances. All high-order masks from 1-order to 24-order can be re-constructed through image morphology and affine transformation operations. Image morphology contains dilation transformation and linear superposition transformation, and affine transformation contains the transformation of translation, flipping and rotation. All masks are derived and multiplied with zero-order pattern, which has a good timeliness and practicality. Above-mentioned five transformations are mainly operated by mask binarization. The visualization of the five transformations is shown in Fig. 5.

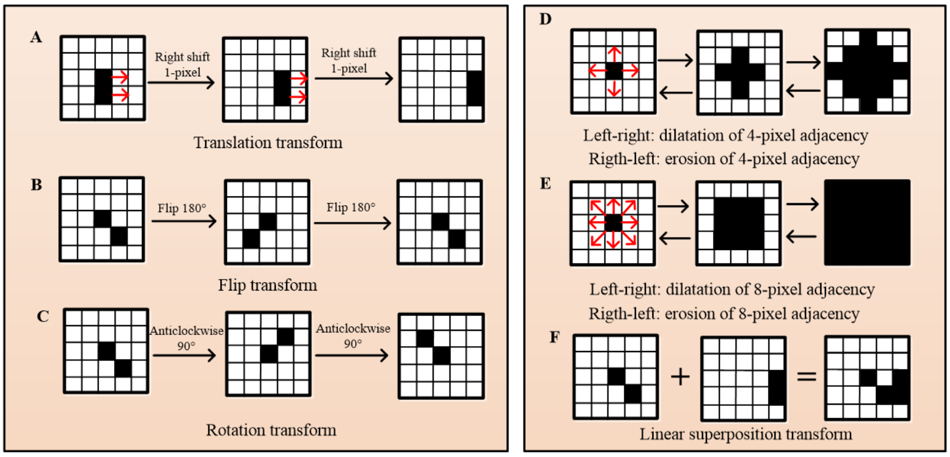


Fig. 5: The visualization processes of translation, flip, rotation, dilatation, erosion and linear superposition transformation.

Geometric transformation

Geometric transformation contains transformations of Flipping, Rotation, Dilation, Erosion, Linear superposition. Flow chart of five kinds of transformation is shown in Fig. 5. Translation transformation refers to the linear movement of a certain pixel to other point in the image, which means it can move any pixel point to any other position within the current image, to realize free moving of pixel points in the image. This transformation is mainly treated as a pre-order step of linear superposition transformation. The order ascending operation based on 0-order mask by translation transformation is a foundation step in the dimensionality reduction.

Flipping transformation is a kind of matrix transformation form that is carried out from inside to outside according to the default direction of the mask template used. The results of extracting image features before and after flipping transformation are different. As a way of reducing order, flipping transformation can decrease complexity of this algorithm. Moreover, the transformation from 0-order to high-order mask provides an important pixel reversal way, which is of great significance in the implementation and representation of Ext-HLAC 5×5 mask. The flipping transformation is mainly the special flipping process from inside to outside around a certain pixel in the image, during which the mirror image of the original image can be realized.

Rotation transformation contains 2D, 3D and other transformation ways, such as, Rotation Matrix (Theobalt et al. 2019), Quaternion (Eriksson et al. 2021) and Euler Angle (Nie et al. 2019). Rotation transformation refers to the rotation of arbitrary pixel points around a certain axis. The rotation moving around origin point is a common situation in the 2D-rotation. When the rotation around arbitrary point is necessary, from arbitrary points to the origin point in the 2D-coordinate, which can be depicted as following three steps: *(1)* translate the point that is needed to be rotated to the origin point, *(2)* perform the rotation of origin point. This method generally defaults to counterclockwise rotation and *(3)* translate the completed rotation point to the point of origin again.

Dilation transformation can be classified as four-pixel field and eight-pixel neighborhood operations. Dilation in four-pixel neighborhood means that the current pixel is used as a seed to carry out a single filling of pixel "1" to the surrounding area in the original upper, lower, left and right pixel value of "0". Dilation in eight-pixel neighborhood means that the single filling of pixel "1" takes the current pixel as a seed to the upper, upper left, lower left, lower left, left, right, upper right and lower right area with the pixel value of "0", to realize the filling of any "0" pixel value by "1" pixel value. The dilation transformation is one of the most important method at aspect of reaching the expansion from 0-order mask to high-order mask. With that expansion, some white areas of "1" are often covered multiple times, but this does not affect the change of pixel values in binary images.

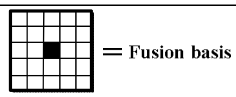
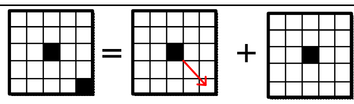
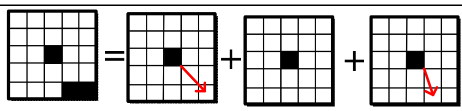
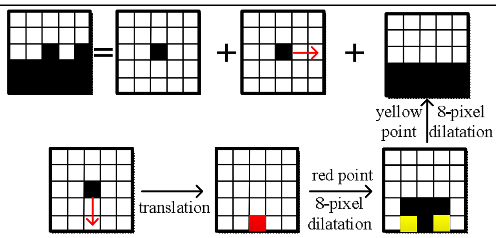
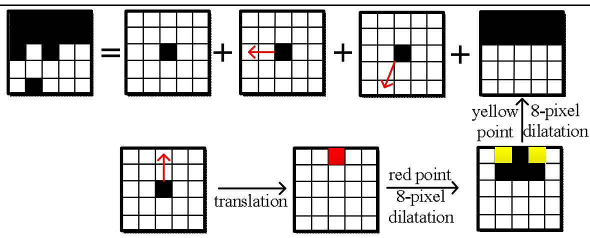
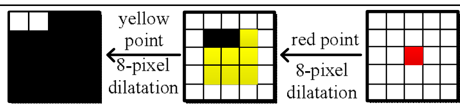
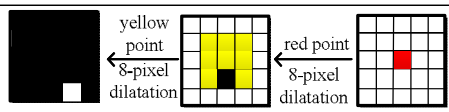
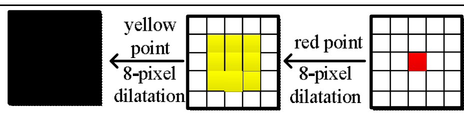
Erosion transformation is opposite to dilatation transformation, it can also be classified as four-pixel and eight-pixel neighborhood operations. Erosion in four-pixel neighborhood means that the current pixel is used as a seed to carry out substitutions from pixel value of "1" to "0" with the surrounding area in the original upper, lower, left and right pixel. Erosion in eight-pixel neighborhood means that the several substitutions of pixel value "1" takes the current pixel as a seed to the upper, upper left, lower left, lower left, left, right, upper right and lower right area with the pixel value of "0", to realize the substitutions of any "1" point by "0" point. The erosion transformation is one of the most important method in reaching expansion from complex matrix to simple matrix.

Linear superposition transformation refers to the production of various high-order mask patterns with using linear superposition of different 0-order mask based on different morphology and affine transformation. Some parameters would be combined with independent variable x and y in the traditional linear summation. However, it will simplify the processes of linear superposition by using pixel one as coefficient of variable. This manipulation can realize normalization steps with adaptive mask patterns. Linear superposition transformation is one of core step from low-order to high-order, and nearly it is frequently to be used with dilation transformation in each step.

After above-introduced six transformation methods, simplified mask patterns produce. Tab.

1 shows diagrams of mask translation processes. In Tab. 1, *n* denotes the order of mask, symbol "#" demotes numbers of transformation ways, and the last column of Tab. 1 shows the visualization of mask patterns in different orders. Therefore, the proposed six transformation methods play important roles at the dimensional decreasing from high-order mask to low-order mask.

Tab. 1: Transformation ways of mask patterns from Ext-HLAC 5×5 by using the proposed method.

n	#	Transformation visualization of mask patterns
0	1	
1	12	
2	180	
3	1449	…
4	8182	…
5	34662	…
6	114804	…
7	2408859	
8	2640680	
9	2459078	…
…	…	…
20	10626	…
21	2024	…
22	276	
23	24	
24	1	

RESULTS AND DISCUSSION

After using feature extraction upon *WM 22* database, the binary images of wood texture were acquired. 18 wood texture images correspondingly distributing in 22 species were included per species. Consider these few numbers of images, to get more intelligible and credible results, leave-one-out cross-validation method was chosen, which means treating one wood images from database randomly as predicting set and the rest was regarded as training set. Moreover, the images presented in the training set are not included in the predicting set. Sequences of training image frames are being divided into series of subdivisions from 1 to 8 both in vertical and horizontal. The proposed IBHLAC algorithm was indirectly used for extracting features. Moreover, three classic classifier-SVM, Soft-Max and Random-forest were adopted to achieve final wood recognition accuracy. The final results are the average value of the three classifiers combining with IBHLAC features.

To show superiority of the proposed method, four feature extraction methods were compared, they are HLAC (Laievardi et al. 2010), Blocked-HLAC (BHLAC) (Wang et al. 2013), Suzuki's method (Suzuki 2014) and Bulugu's method (Bulugu et al. 2017). The experiment results were displayed in Fig. 6. Figs. 6a,b suggest that the proposed IBHLAC method can achieve relatively high accuracy than the original one (baseline) (Laievardi et al. 2010). However, there are parts of fluctuations based on different species of wood image, the recognition results are consistent seen from Fig. 6c.

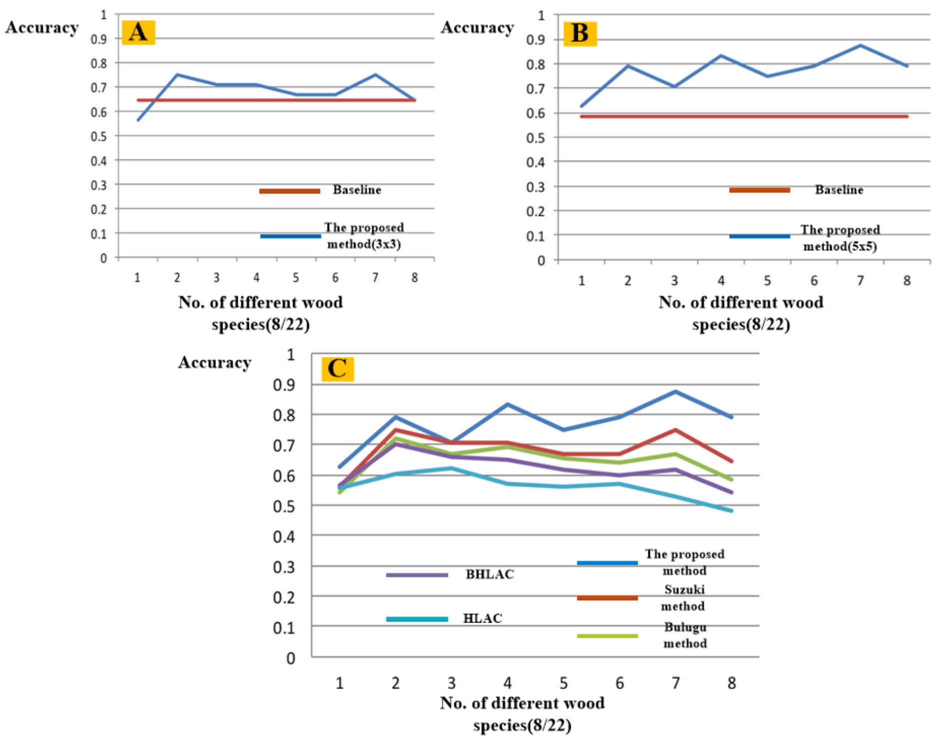


Fig. 6: Compared experiment result using HLAC,BHLAC, Suzuki's method and Bulugu's method.

To certificate well-performance at aspects of occupied memory and recognition time per image, related experiments were conducted. Tab. 2 displays the experimental results of the efficiency comparison when calling different patterns of 5×5 Ext-HLAC masks. In this table, two parameters-[*Occupied memory for all the masks*] and [*Decimal number of different mask pattern*] were calculated. The calculation method of parameter-occupied memory for all the masks (MB) is that: each 5×5 matrix occupies 25-bits of system memory, and there are a total of 16241567 masks in 5×5 patterns. The conventional method is to multiply the data 25-bits with numbers of masks, but the system space occupied by the matrix exist differences in different computers. Thus, the calculation results of each computer are also different. In the proposed method, since there is only zero-order mask, the zero-order matrix can be regarded as occupying 1-bit of system memory space. Therefore, the calculation processes are very efficient by comparing with 25-bits. The calculated results are shown in Tab. 2. The calculation processes of parameter-occupied memory for single decimal number can be explained: each result is average value of all 5×5 templates with all the numbers of masks. Since there are only 0 and 1 value for each 5×5 mask image, thus this mask can be treated as a binary sequence (25-bits).

Tab. 2: The efficiency comparison results when calling the occupied memory for the masks.

Compared methods (5x5 mask patterns)	Efficient comparison when calling the special mask pattern		
	Occupied memory for all masks (MB)	Decimal number of different mask pattern	Recognition time per wood image (ms)
HLAC (Laievardi and Hussain 2010)	112.49	5.92×10^4	68.41
BHLAC (Wang et al. 2013)	147.34	3.84×10^5	89.13
Suzuki's method (Suzuki 2014)	387.23	1.70×10^6	103.36
Bulugu's method (Bulugu et al. 2017)	143.33	2.68×10^7	122.17
The proposed method	**15.49**	$\mathbf{4.11\times10^3}$	**10.89**

Fig. 6 suggests IBHLAC method presents a better wood recognition accuracy compared with other four methods. In spite of that Suzuki's method claims it can achieve 95% accuracy based on the Portions of OUTEX database (Suzuki 2014), poor performance was achieved when importing into different species of wood database compared with IBHLAC. The same situation happens to Bulugu's method (Bulugu et al. 2017), which demonstrated that it is efficient for special image database, but these methods have weak robustness and are limited to extend into other databases. Fig. 6 also revealed that the results produced by using traditional methods, such as HLAC and BHLAC, were not a good strategy especially used in the high-precision demanding industrial factory, which would generate negative effects.

From Tab. 2, several interesting and advantage experimental results were found. For example, the occupied memory for all masks of the proposed method is least over the other four compared methods. This suggests the numbers of orders decrease from high-order to zero-order in the processes of morphological and affine transformation. When all the dimensionality of high-order masks (1 through 16,241,567) reduce, the occupied memory obviously becomes small for all the masks. Moreover, to reduce the file sizes, Ext-HLAC 5×5 masks can be represented in decimal number (Suzuki. 2014). Since each mask consists of a set of cells, these cells can be represented by using a sequence of binary numbers as shown in Fig. 7. Each sequence of binary numbers (25bits) is converted into a single decimal number. Therefore, the decimal number of different mask patterns of the proposed method can reach a small value of 4.11×10^3, which is three orders of magnitude less than Suzuki's method (Suzuki 2014). Although decimal number of different mask pattern of traditional HLAC also can achieve a relatively small value of 5.92×10^4, it is inefficient and cannot be used in the actual application scene. Based on the former analysis, recognition time per wood image can also be less than the compared methods. The reduction of recognition time per image is mainly attributed to the dimension reduction of high-order masks and the low-occupied system memory. The feature extraction time of IBHLAC also decreases when performing the linear combination of different zero-order morphology manipulation, such as pixel translation, single pixel dilation, etc. Thus, over all the compared methods, the proposed method is most superior.

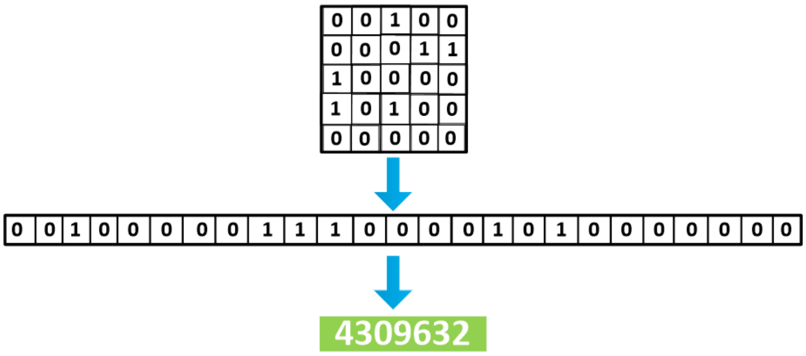


Fig. 7: Decimal number representation of 5x5 masks.

To validate the actual effects of the proposed method furthermore, different species of wood datasets were investigated. Due to space constraints, five tree species were randomly selected from 22 wood datasets, which are *Taxus wallichiana var. chinensis (Pilg.) Florin*, *Schoepfia chinensis Gardn.et Champ*, *Pseudolarix amabilis (Nelson) Rehd*, *Larix gmelinii (Rupr.) Kuzen*, *Quercus acutissima Carruth*. This experiment is conducted from following four aspects: wood accuracy, occupied memory, recognition time per image and number of different mask pattern. The results are shown by displaying three dimensional histogram (Fig. 8), where all the data results are the average of five experiments. In Fig. 8, X-coordinate denotes the sequence number of wood species, Y-coordinate denotes the used wood feature extraction algorithms displayed in Tab. 2, Z-coordinate denotes the corresponding data experimental results.

From vertical comparison of different algorithms in Fig. 8, the experimental results are basically consistent with those in Fig. 6 and Tab. 2, which indicates that the proposed method can still show superior effects and strong generalization ability in five randomly selected wood species. On the other hand, from horizontal comparison of tree species, the differences among five tree species in above four indexes (Z-coordinates) mainly related to the thinning density of appearance texture of each tree species. For example, *Quercus Acutissima Carruth* tree species has dense appearance texture, and all the used algorithms consume much time in the process of extracting wood texture features.

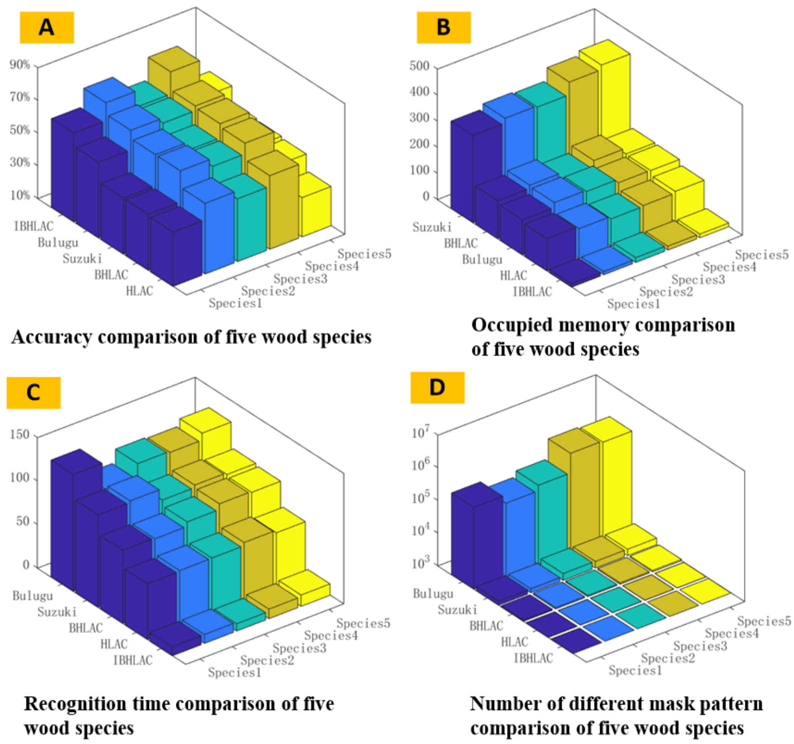


Fig. 8: Effects comparison of four indexes-accuracy, occupied memory, recognition time per image and number of different mask pattern based on five feature extraction algorithms.

Moreover, when compared with other wood species which composing of sparse texture, the difficulty of feature extraction increases, and the risk of error also increases accordingly. Therefore, the recognition time for this species will increase and the recognition rate will decrease. Even if the samples come from the same species but different individual tree, it is still prone to acquire distinct microscopic wood image containing different texture features in spite of using the same physical and chemical methods such as dyeing, interception and impurity elimination. That's why the performances of various algorithms can produce obvious differences even samples all come from the same tree source.

CONCLUSIONS

In this paper, a novel feature extraction method based on improved BHLAC was performed. Many actual on-line applications motivate us to improve the original HLAC through the ideas of blocking partition and high-order mask reconstruction. The maximal innovation point is to construct a concise method and this was inspired by the fact that, instead of presenting the image feature using high-order mask patterns, simplified masks consisting of zero-order mask are combined to represent the special wood features based on morphological and affine transformation. Experimental results indicated that the occupied memory and recognition time per image of the proposed method are all superior compared with HLAC related improvement algorithms. In the near future, the possible application scene of the proposed method may be in the large wood working factory, on-line wood external/internal quality detection or wood healthy status measurement center by acquiring dyed slice sections of different wood species rapidly, which have a great application prospect and economic profit increasing core point. This micro-image acquiring and recognizing processes depend heavily on whether the macroscopical wood is handled in a regulated and ruled ways commonly. Furthermore, we can break through the connection between microscopic chemical manipulation and macroscopic wood image processing, so as to avoid the production process of microscopic wood samples, including chemical sample preparation and bubble elimination, which can greatly speed up the processing process and improve the efficiency of image recognition. Beyond that, recognition duties of different wood species using deep learning technologies (Hu et al. 2022, Lin et al. 2022) would also be a new trend based on artificial intelligence in recent years.

ACKNOWLEDGMENTS

This work was financially supported by the Scientific Research Foundation of Jiaxing University (No. CD70519085), Public Welfare Technology Application Research Project of Jiaxing City (No. 2020AY10009), Public Welfare Technology Application Research Project of Zhejiang province (No. LGG21F030013 and No. LGG20F010010), Humanities and Social Sciences of Ministry of Education Planning Fund (No. 18YJA880032).

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ZIHAO LIU*, SULAN ZHANG, XIAOJUN JIA,JUN YANG
JIAXING UNIVERSITY
COLLEGE OF INFORMATION SCIENCE AND ENGINEERING
414# ROOM, 8# BUILDING, No.118, JIAHANG ROAD
JIAXING CITY, ZHEJIANG PROVINCE
P.R. CHINA
*Corresponding author: lzh@zjxu.edu.cn