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Application of Binary Particle Swarm Optimization in Automatic Classification of Wood Species using Gray Level Co-Occurence Matrix and K-Nearest Neighbor

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Abstract— This paper proposed an application of Binary Particle Swarm Optimization in automatic classification of wood species. The images of wood species are taken from Universiti Teknologi Malaysia's CAIRO Wood Database which consists of 25 species. The features of the images are extracted using Gray Level Co-Occurrence Matrix. Then, Binary Particle Swarm Optimization is use to optimize feature selection and parameters related to it. The result indicates that the proposed approach obtained a better result compared to previous literatures with fewer features used as input for the classifier.

Index Terms — binary particle swarm optimization; computational intelligence; gray level co-occurrence matrix; k-nereast neighbour; optimization; pattern recognition; wood recogniiton

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1. INTRODUCTION

AUTOMATIC classification of wood species is not something new, there are numerous researches has been done on the area [1-14]. Based on our literature survey, researchers in Centre for Artificial Intelligence and Robotics (CAIRO), Universiti Teknologi Malaysia (UTM) and Computer Vision and Intelligent Systems (CVIS), Universiti Tuanku Abdul Rahman (UTAR) have done extensive researches on the performance of the automatic classification of tropical wood species. In this paper, we try to experiment with the application of Binary Particle Swarm Optimization (BPSO) [15] in features selections of Gray Level Co-Occurrence Matrix (GLCM) [16]. The objective is to investigate whether there is any improvement in classification rate if the features and parameters of GLCM used for classification were chosen by using BPSO. Optimized features not only improve the accuracy rate of the classification but also reduce classification time because only features that relevant are selected as input. The model proposed is taken from a literature [17]. The result obtained indicates that there is a slight improvement in the performance of the k-Nearest Neighbor classifier.

2. STATE OF ART

As mentioned earlier that CAIRO, UTM, itself had done extensive researches on this area. A literature by M. Khalid *et al*. [2] back in year 2008 is one of the earliest literatures written in this area. The authors proposed a system that covered the entire process of wood species recognition from hardware implementation for images acquisition to software implementation for automatic classification. For images acquisition, the author used an industrial monochrome CCD camera with a magnification tube. The acquired images are transferred to computer using interface card. The raw image is then preprocessed using several methods: high pass spatial filtering, contrast enhancement and histogram equalization. Then, GLCM is used to extract features from the preprocessed images. These features are used as inputs for the Artificial Neural Network (ANN) classifier to perform classification. The wood images obtained (better known as CAIRO wood database) by the literature has becomes a benchmark of other literatures that come after it. The CAIRO wood database also increase in term of the number of wood species covered as the researches progresses.

R. Yusof *et al.* [6] proposed the use of Gabor Filter (GF) to multiply a single wood image into two images. This will create additional features for the GLCM to work with. The authors then extended the model in [10] by having a higher order GF to produce more additional images. The result obtained indicates improvement compared to [6].

Prasetiyo *et al.* [8] had done an extensive comparison of the performance of several features extraction

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methods and several classification methods. The features extraction methods used are GLCM, Linear Binary Pattern (LBP), Wavelet, Ranklet, Granulometry, and Law's Masks. The classification methods used are Artificial Neural Network (ANN), k-Nearest Neighbour (k-NN), Support Vector Machine (SVM), Linear Discrete Classifier (LCD), and Quadratic Discrminant Classifier (QDC). The authors discussed the performance from two views: computation time and classification rate.

In [13], M. Khalid *et al.* proposed an improved system based on multi-features extractor and classifier. The improved system proposed features extraction using both, Binary Gray Level Aura Matrix (BGLAM) and Statistical Properties of Pores Distribution (SSPD). The features extracted then are clustered into several clusters using K-Means and Kernel Discriminant Analysis (KDA). Two classifiers used in the literature are LCD and k-NN. In the same year, M. Khalid *et al.* [14] proposed the use of Genetic Algorithm (GA) in selecting the features as the input for the classifier. The paper test the performance of GA by using three feature extraction methods: GLCM, SSPD and BGLAM, and two classification methods: k-NN and LDA. It is proven that GA improves the performance of the system.

Other than CAIRO UTM, Computer Vision and Intelligent Systems (CVIS) Universiti Tuanku Abdul Rahman (UTAR) also actively performing researches on the wood species recognition. In year 2007, Y. T. Jing *et al.* [1] proposed a hardware model of an embedded system of a computer vision based wood recognition system. As for initial finding, the authors decided to use Matlab for executing the proposed approach. The proposed approach consists of GLCM as features extraction method and ANN as classifier. The proposed approach is test using five species of tropical wood from CAIRO wood database.

Then, Y. T. Jing *et al.* [3] proposed a one-dimensional GLCM algorithm in year 2008. Again, five species of tropical wood from CAIRO wood database are a part of the test database use by the authors. In a different literature [5], the same authors make a concise comparative study of implementation of two features extraction methods (GLCM and Gabor filters) and three classifiers (Verification-Based, k-NN and Covariance Matrix). In the same year, the authors proposed a rotational invariant GLCM algorithm for wood species recognition. The algorithm proposed that the features values are calculated based on the minimum value of the eight rotational variations of GLCM.

There are also several literatures done by other than CAIRO UTM and CVIS UTAR. In year 2009, R. Bremananth *et al.* proposed a wood species recognition system that can identify 10 species of Indian wood species. The image acquisition is done using a consumer digital camera. Then, the acquired images are resized and conversions from RGB to grayscale are done. GLCM is use to extract statistical-based features from the images. A simple correlation method is use to classify the wood species. V. Piuri and F. Scotti [9] suggested a more complex system in performing wood type classification. The authors suggested the use of spectrometer, 473nm DPSS laser and long pass filter to acquired wood information at fluorescence spectra. The proposed approach able to recognize 21 type of woods use in the Woodtechnology Gmbh.

A. Malik *et al.* [11] proposed wood species recognition by image segmentation method of the wood micrographs. Seven types of woods consist of five hardwoods and two softwoods are use as case study. The images acquired at a magnification of 1500 times from the original images. Then, several methods in pre-processing are used to enhance and prepare the images for features extraction. The methods are median filtering, histogram equalization, thresholding, edge detection and dilation. The features extracted are parameters related to the tracheids of the wood: number of tracheids, average circularity of tracheids, average rectangularity of tracheids, average area per tracheid, and average distance between tracheids. The authors used several classification methods which are LDC, Logistic Regression, Naïve Bayes, k-NN, SVM, and ANN.

L. Sun *et al.* in [12] proposed a new wood recognition method based on texture analysis. The images captured using Olympus SZ61TRC. The features extraction method proposed by the authors using Gabor wavelet while the k-NN is chosen as the classifier.

3. MOTIVATION

The motivation of having automated wood species recognition had been described in great details in [2]. In [14], GA is use to optimize the features selection process but ignore the parameters selection for features extraction and classifiers. This project attempted to use BPSO not only to optimize features selection process but also optimize parameters use in GLCM and k-NN. BPSO will find the best combination of GLCM parameters (d,bin) features and k-NN parameters (k). There are a few advantages of having optimized features and parameters of feature extraction method and classifiers. First and the most significant advantage is the performance of the proposed system is expected to improve. Second, the computation time taken should be lesser as the number of features selected is reduced to the minimal amount.

4. METHODOLOGY

The proposed model for automatic classification of wood texture is similar to [14, 17] where the model is as shown in Figure 1. The model consists of four main components: database of wood texture images, GLCM as features extraction method, k-NN as classifier, and BPSO as optimization method.

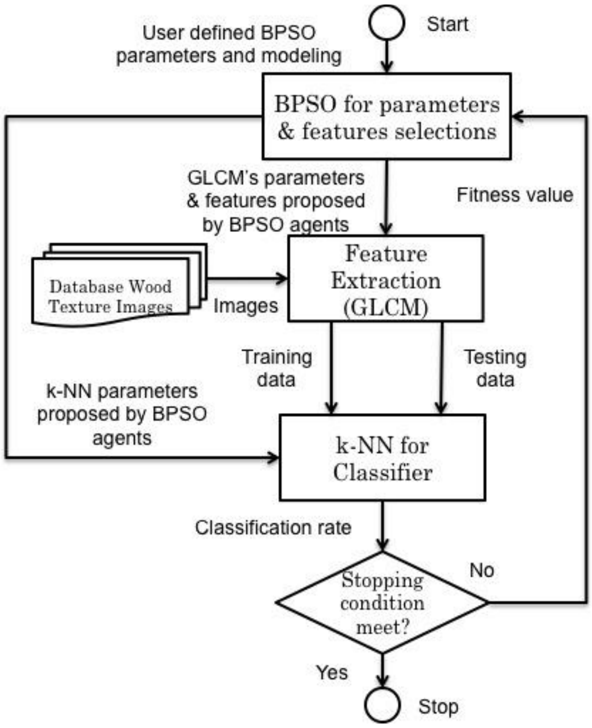
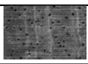
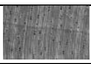
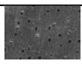
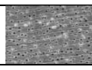


Fig 1: The proposed approach

4.1 Wood Texture Image

The wood texture images are taken from the CAIRO wood database as mentioned in [2, 6, 8, 10, 13, 14]. There are 25 types of woods consist of the images of the woods textures. Figure 1 listed the scientific name and images of the wood species. The total number of images used in the experiment is 1250 images, 50 images per wood species.

Campnosperma Auriculatum	Mangifera Foetida	Dyera Costulata	Durio Lowianus	Canarium Apertum
				
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	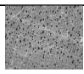	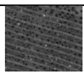	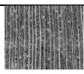	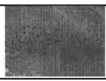
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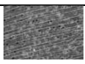	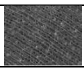	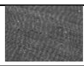	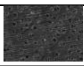	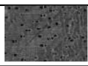
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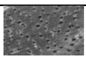	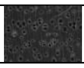	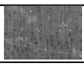	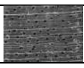	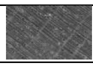
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	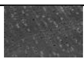	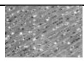	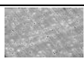	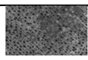

Fig 2: Example image of each wood species

4.2 Gray Level Co-Occurrence Matrix

GLCM [16, 18-19] is use as feature extraction method for the proposed approach. GLCM table is tabulated based on the transition of the gray–level between the pixel of interest and its neighbors. GLCM consists of two parameters: θ, d, and bin. θ is the angle of between the pixel of interest and its neighbor. d is the distance between the pixel of interest and its neighbor. bin is the number of gray-level use. Instead writing the Matlab source code by our own, we choose to use source code provided by [20].

Table 1: Features extracted from texture image

Feature Number	Feature (mean, range)	Feature Number	Feature (mean, range)
1, 2	Autocorrelation	23, 24	Sum of squares
3, 4	Contrast	25, 26	Sum of average
5, 6	Correlation (Matlab)	27, 28	Sum of variance
7, 8	Correlation [18, 19]	29, 30	Sum of entropy
9, 10	Cluster prominence	31, 32	Difference variance
11, 12	Sum variance	33, 34	Difference entropy
13, 14	Sum entropy	35, 36	Information measure of correlation (Info A)
15, 16	Entropy	37, 38	Information measure of correlation (Info B)
17, 18	Homogeneity (Matlab)	39, 40	Inverse difference
19, 20	Homogeneity [19]	41, 42	Inverse difference normalized
21, 22	Maximum probability [19]	43, 44	Inverse difference moment normalized

As stated earlier, BPSO is use to select optimized values of the parameters in GLCM. In this project the value of GLCM's parameters can vary based on Equation (1) and Equation (2). While all possible θ values as in Equation (3), are used in the proposed approach. Therefore, for each value of d, and bin, GLCM algorithm can extract up to 44 features (as shown in Table 1). This is based on the approach suggested by [17, 20].

$$d = \{1, 2, 3, 4, 5, 6, 7, 8\} \quad (1)$$

$$bin = \{2, 8, 64, 256\} \quad (2)$$

$$\theta = \{0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ}\} \quad (3)$$

4.3 k-Nearest Neighbour

k-NN is used as the classifier due to its simplicity. Classifier k-NN classify a test data based on the majority class of the k-th nearest neighbor of the test data. If there is more than one majority class, the average Euclidean distance is use as a tie-break where majority class with smallest value of the average Euclidean distance will be chooses as the winner. In k-NN, there is only one parameter that need to be set by the user: k. Although, each possible value of k can be attempt to identify the optimal classification performance, the process is tedious and time consuming. Instead, BPSO can be used to find optimized value of k for a suitable range of time period. The proposed approach limits the value of k from integer value of 1 to 16 (as stated in Equation (4)).

$$1 \leq k \leq 16 \text{ and } k \in \mathbb{N}^{+} \quad (4)$$

Each features selected by BPSO as input for the k-NN classifier will be normalize to the range [0, 1]. This to ensure all input features have the same weightage in the training and testing process.

4.4 Binary Particle Swarm Optimization

J. Kennedy and R. Eberhert introduce BPSO [15] in 1997 as a discrete version of Particle Swarm Optimization (PSO). BPSO had been successfully employed in numerous engineering optimization problems such as routing problem in PCB holes drilling process [21], VLSI problem [22-24], and DNA sequence design problem [30]. BPSO differs slightly from PSO in two ways: each dimension of search space in BPSO can be either in the state 0 or 1, and the particle position is updated based on the sigmoid value of the velocity. In this project, each particle in BPSO represents a candidate solution of the optimization problem as shown in Equation (5).

$$\boldsymbol{s} = [bin, d, features, k]^{T} \quad (5)$$

where:

- 1st 2 bits for bin (00 = 2, 01 = 8, 10 = 64, and 11 = 256).
- Next, 3 bits for d (000 = 1, 001 = 2, … 1111 = 8).
- Next, 46 bits for features selections (1 = select, 0 = off). Bit 6 is for the first feature number, Bit 7 is for the second feature number, and so on.
- Last, 4 bits for k in k-NN (0000 = 1, 0001 = 2, … 1111 = 16).

The fitness formulation of each agent or particle is as shown in Equation (6). This equation is better known as classification rate.

$$f(\boldsymbol{s}) = \frac{100\% \times T}{N} \quad (6)$$

where T is number of test data correctly classified, and N is the total number of test data.

The first step in executing BPSO algorithm is to set the BPSO parameters, as listed in Table 2. These values are initialized based on user's desired values, and problem-dependent. Particle's velocity, $\boldsymbol{v}$ and particle's position, **s**, are randomly assigned based on the boundary of the search space. In this case, **s** can be either 0 or 1 while $\boldsymbol{v}$ is usually clamped at the range of [-2, 2]. Each particle will propose a solution as model in Equation (5). Then, based on the proposed solution by the particles, relevant GLCM parameters value are used, and selected GLCM features are extracted from the wood texture images. These features then are normalized before use as inputs for k-NN classifier. The k-NN classifier will return the classification rate of the proposed solution by the particle. The process is repeated for all particles. After that, the particle's personal best, $\boldsymbol{p}$, and the swarm's global best, $\boldsymbol{g}$, are updated according to the condition in Equation (7) and Equation (8).

$$\boldsymbol{p}_i^{k+1} = \begin{cases} \boldsymbol{p}_i^k, & f(\boldsymbol{s}_i^k) \leq f(\boldsymbol{p}_i^k) \\ \boldsymbol{s}_i^k, & f(\boldsymbol{s}_i^k) > f(\boldsymbol{p}_i^k) \end{cases} \quad (7)$$

$$\boldsymbol{g}^{k+1} = \begin{cases} \boldsymbol{g}^k, & f(\boldsymbol{s}_i^k) \leq f(\boldsymbol{g}^k) \\ \boldsymbol{s}_i^k, & f(\boldsymbol{s}_i^k) > f(\boldsymbol{g}^k) \end{cases} \quad (8)$$

Then, $\boldsymbol{v}$ is updated for next iteration, **k** for each bit, **d**, using Equation (9).

$$\boldsymbol{v}_{id}^{k+1} = \omega \boldsymbol{v}_{id}^{k} + \boldsymbol{r_1} c_1 (\boldsymbol{s}_{id}^{k} - \boldsymbol{p}_{id}^{k}) + \boldsymbol{r_2} c_2 (\boldsymbol{s}_{id}^{k} - \boldsymbol{g}_{d}^{k}) \quad (9)$$

Algorithm 1: BPSO Algorithm for the proposed approach

Initialize all particles with a random position and velocity in the search space
while stopping condition not met
  for each particle **do**
    Calculate the fitness of the particles using Equation (6)
    if particle fitness better than previous $\boldsymbol{p}$ **then**
      Set particle fitness value as new $\boldsymbol{p}$
    end if
    if particle fitness value better than the current $\boldsymbol{g}$ **then**
      Set fitness value as the new $\boldsymbol{g}$
    end if
  end for
  for each particle **do**
    Update particle velocity according to Equation (9)
    Update the particle position according to Equation (10)
  end for
end while
Present $\boldsymbol{g}$ solution

where i is the particle's number. $\boldsymbol{r_1}$, $\boldsymbol{r_2}$, and $\boldsymbol{r_3}$, are random number of [0,1]. c_1 and c_2 are cognitive parameter and social parameter, respectively. Next, **s** is updated using Equation (10) based on the probability of the normal distribution. The process of repeated of evaluation proposed solution of the particles offered to particles position updated are repeated until maximum iteration is reached, and the global best solution is presented. This can be summarized by Algorithm 1.

$$s_{id}^{k+1} = \begin{cases} 1, & \boldsymbol{r_3} < \frac{1}{1+e^{-v_{id}^{k+1}}} \\ 0, & \boldsymbol{r_3} \geq \frac{1}{1+e^{-v_{id}^{k+1}}} \end{cases} \qquad (10)$$

5. EXPERIMENTAL RESULT AND DISCUSSION

Table 2 shows the BPSO parameters and value chosen for the proposed approach. 5-fold cross validation method for training and testing is used to measure the performance of the proposed approach. At an instance, the ratio of testing and training data is 1:4.

Table 2: BPSO parameters and their values for the proposed approach

Parameters	Value
Inertia weight, ω	0.7
Cognitive component, c_1	1.42
Social component, c_2	1.42
Random: $\boldsymbol{r_1}, \boldsymbol{r_2}$, and $\boldsymbol{r_3}$	[0, 1]
Velocity clamping, $\lvert\boldsymbol{v}\rvert$	2
Number of iteration, k	500
Number of particle, i	50

Table 3 indicates the result obtained by [8] and ours. Although, the performance cannot be compare directly due to variance of experimental methodology by [8], it can be clearly seen that the application of BPSO reduces the complexity of experimental methodology required as all the parameters of the features extraction method and classifier are chosen autonomously and efficiently by BPSO. It can be also seen that BPSO able to reduce the number of features use as input for classifier by 91.58% (assuming all possible combinations of k, d, bin, and number of features in Equation (5) are used as inputs for classification).

Table 3: Result obtained by [8] and ours

Parameter	Prasetiyo [8]						Ours
k	2	3	5	7	9	11	5
θ	$0^{\circ}, 45^{\circ}, 90^{\circ}, \& 135^{\circ}$						
d	1, 2, 3, …, 9, & 10						2
bin	256						124
Features	520 ($4 \times 10 \times 1 \times 13$)						124
Accuracy	63.5	64.3	63.5	63.5	56.3	63.5	68.4

6. CONCLUSION

This paper introduces reader to the application of BPSO to optimize the process of parameters and features selection of GLCM and k-NN. The methodology of the proposed approach is explained in great details. The result indicates that there is potential for further study due to the good result obtained. Further study can be extended using different optimization strategies and different classifiers.

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