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Ant Lion Optimizer for Texture Classification: A Moving Convolutional Mask

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ABSTRACT Texture classification is an important issue for a number of applications in machine vision, which could be addressed through learning texture features by using a convolutional mask. However, the traditional convolutional mask has a single orientation, and the learning ability is limited. In addition, the optimization process often falls into the local optima, and the discrimination capacity of the learned mask is unsatisfactory. Thus, a novel moving convolutional mask is presented to enhance the discrimination of specific texture features in the proposed approach. Furthermore, how to achieve the satisfactory convolutional mask is considered as a combinatorial optimization problem and acquired by maximizing the texture energy by using ant lion optimizer (ALO). The proposed approach was tested on some public images, and the results were compared with those of the state-of-the-art approaches. The experimental results showed that ALO has strong optimization ability, and the proposed method is robust, adaptive and superior to the improved grey level co-occurrence matrix (GLCM), directional statistical Gabor filter and Tuned convolutional mask in terms of the fitness value and classification accuracy which has reached 27 and 91%, respectively, for all images.

INDEX TERMS Moving convolutional mask, texture classification, feature extraction, ant lion optimizer.

I. INTRODUCTION

Texture is a significant characteristic to determine the change of different targets in natural environment [1], [2]. Texture classification, the process in which texture features are extracted from images and used to assign labels for test samples [3, [4]. In the real scene, there are some of texture patterns due to the differences in orientation, scale, frequency and other visual variables; thus, a number of texture features, such as gray level co-occurrence matrix (GLCM) [5], [6], fractal theory [7], [8], local binary pattern (LBP) [9], [10], Gabor wavelet [11], [12], and run-length texture descriptor [13], have been proposed, and they could be effective in classifying textures with varying shapes, sizes and orientations to an acceptable degree. However,some traditional techniques require numerous features for texture classification, which increases the time complexity to extract valid texture features, and redundant features will also decrease the efficiency.

Convolution is a mathematical operation on two functions that produces a third function that expresses how the shape of one function is modified by the other. Convolution has been used in many image processing tasks, such as filtering, enhancement, and scrambling. The texture classification techniques based on convolutional masks have drawn considerable interest in recent years by extracting texture features efficiently and accurately [14]. Among these techniques, Law's convolutional mask is one of the important approaches to distinguish the texture features via the value of energy [15]. However, Law's convolutional mask is stationary and simplex, and cannot adapt to the change of texture features [16]. Zheng *et al.* proposed a generalized convolutional mask to extract the objects' texture in satellite images, but too many parameters need to be manually set, and the change in some parameters affects the classification accuracy [17]. You and Cohen proposed an adaptive "Tuned" convolutional mask that avoided the change in the rotation and scale of an

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image and the effectiveness has been proven [18]. However, it utilized gradient descent and heuristic learning to obtain the optimal mask, which increased the computational time and led to the algorithm falling into the local optima.

Generally, how to achieve the satisfactory convolutional mask could be seen as a combinatorial optimization problem that may be addressed by swarm intelligence algorithms, such as particle swarm optimization (PSO), honey-bee mating optimization (HBMO), gravitational search algorithm (GSA), etc. For instance, Ye *et al.* analyzed the theory and steps of training a convolutional mask with PSO, and illustrated in detail how to obtain the texture features with the process of convolution [19]. Zheng proposed a novel approach to produce a better convolutional mask using HBMO, which was utilized in the field of texture classification, and improved the quality of the convolutional mask [20]. Wan *et al.* introduced a texture classification by obtaining a convolutional mask using GSA, which was exemplified in a residential area and the performance is better than some commonly used techniques [21]. Peng *et al.* utilized CS algorithm, which had better optimization ability and could produce better mask to learn a convolutional mask and extracted the water area from an image [22]. In short, PSO, HBMO, GSA and CS algorithms can obtain good convolutional masks. However, the convolutional masks mentioned above only have a single orientation, which limits the ability to learn different textures, and it is a nondeterministic-polynomial problem with high dimensionality such that each individual is coded as a real number in wide range, that is, the algorithms above may not ensure convergence to the optimal solution.

Swarm intelligence algorithm is a metaheuristics model that mimics the behaviors of cluster to solve the combinatorial optimization problems. Numerous studies have been carried out extensively and resulted in very promising findings. In recent years, various types of bio-inspired algorithms have been proposed, and successfully applied in different fields [23]–[27]. In particular, ant lion optimizer (ALO) is a novel swarm intelligence algorithm that synthesizes global and local search [28]. Nowadays, ALO has been widely used in diverse applications, e.g., Mouassa *et al.* utilized ALO to solve the optimal reactive power dispatch (ORPD) problem building a huge-scale power system that provided near-optimal solution [29]. Kamboj *et al.* presented an application of ALO for the solution of economic load dispatch to design an electric power system, and it is revealed that ALO had the ability to enhance the exploration search and resulted in the avoidance of local optima [30]. Ali *et al.* utilized ALO to obtain the optimal allocation and designed the renewable sources in various networks, and the results verified the advantage of ALO in improving the voltage distribution under most of loading conditions [31]. Yao and Wang used ALO for the route planning of aerial survey, which was superior to other approahces in terms of reliability, converge rate and local optima avoidance [32]. Zawbaa *et al.* and Emary and Zawbaa utilized ALO to reduce the dimension of datasets and avoid curse of dimensionality that obtained the optimal feature combination independent of the initialize settings of the operators [33], [34]. The optimization ability of ALO does not rely on any parameters, and difficultly get trapped in local optima. There is a high probability that ALO will converge stably to the optimal solution. Hence, in this paper, a texture classification technique is proposed by combining a moving convolutional mask and ALO.

The rest of this paper is structured as below. Section 2 details the proposed texture classification approach using the optimal moving convolutional mask. Section 3 presents the experimental results and discussion. In the end, the paper is concluded in section 4.

II. THE PROPOSED TEXTURE CLASSIFICATION APPROACH WITH THE OPTIMAL MOVING CONVOLUTIONAL MASK

A valid texture classification technique is presented that uses the optimal moving convolutional mask to learn the mask parameters as a combinatorial optimization problem via ALO that is utilized to precisely extract the specific texture feature for several types of texture features. The main process of the proposed approach will be explained as follows.

A. THE MATHEMATICAL MODEL OF ALO

In 2015, Mirjalili introduced a swarm intelligence algorithm called ALO which imitates the hunting behavior of antlions and has no parameters to be set [28]. Essentially, exploitation is to make the best decision given current information, and exploration is to gather more information. The exploration behavior of ALO is ensured by the random walk of ants around each antlion. Additionally, the exploitation behavior of ALO is ensured by the adaptive boundary adjustment of antlions' traps. As each ant move randomly in the solving space, the random walk of them is represented as below:

$$X^t = [0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \ldots, cumsum(2r(t_n) - 1)] \quad (1)$$

where X^t is the process of random walks, n is the number of ants in the population, *cumsum* represents cumulative sum, t is the number of iteration, and $r(t)$ is a stochastic distribution function defined as below:

$$r(t) = \begin{cases} 1 & if\ rand > 0.5 \\ 0 & if\ rand \leq 0.5 \end{cases} \quad (2)$$

where *rand* is a random number produced from a uniform distribution in the interval of [0, 1].

To maintain the random walk in the scope of searching space, the positions of each ant are normalized with the min-max normalization that is explained as follows:

$$X_i^t = \frac{\left(X_i^t - a_i\right)\left(b_i - c_i^t\right)}{\left(d_i^t - a_i\right)} + c_i^t \quad (3)$$

where a_i is the minimum of the random walk of i-th variable, b_i is the maximum of random walk of i-th variable, c_i^t is the minimum of i-th variable at iteration t, and d_i^t is the maximum of i-th variable at iteration t.

Antlions build traps that are proportional in size to the fitness value and ants are moving stochastically. Moreover, antlions shoot sands outwards the center of the pit once they realize that an ant is in the trap, which maintains the trapped ant that is trying to escape. To mathematically define this behavior, the radius of an ant's random walk hyper-sphere is reduced adaptively, which is described as follows:

$$c^t = \frac{c^t}{I} \tag{4}$$

$$d^t = \frac{d^t}{I} \tag{5}$$

where $I = 10^w \frac{t}{T}$, T is the maximum number of iteration, and w is a constant variable that is defined based on the current iteration ($\omega = 2$ when $t > 0.1T$, $\omega = 3$ when $t > 0.5T$, $\omega = 4$ when $t > 0.75T$, $\omega = 5$ when $t > 0.9T$, and $\omega = 6$ when $t > 0.95T$). Basically, ω is utilized to adjust the optimization level of exploration.

For the process of ALO, there are no parameters to be set, and the random walk defined by equation (3) ensures that, in each iteration, the algorithm avoids local optima and continuously converges to the optimal solution with a high probability. In addition, ALO can be used to solve the combinatorial optimization problem with decimal encoding [33], [34]. Therefore, it is suitable for the moving convolutional mask in this paper.

B. THE FUNDAMENTALS OF THE MOVING CONVOLUTIONAL MASK

To make classification for a specific texture feature, a convolutional mask is produced that extracts various texture features at different rotation and scale. In principle, the procedure is to convolve the whole image with a convolutional mask A. The process of a 2-D convolution between the original image $I(m, n)$, and the mask $A(m, n)$ with the window size of $(2a + 1) \times (2a + 1)$is calculated as follows:

$$\begin{aligned} F(m, n) &= A(m, n) * I(m, n) \\ &= \sum_{k=-a}^{k=a} \sum_{l=-a}^{l=a} A(k, l) \bullet I(m-k, n-l) \end{aligned} \tag{6}$$

where " $*$ " represents the convolution operation, "$\bullet$" is the multiplication operator, $F(m, n)$ is the image after convolution, k and l represent the horizontal and vertical moving variables, respectively, and a is a constant that is set as $a = 2$ in this paper.

The core issue in applying ALO is the representation of the problem; that is, how to make a reasonable mapping between the problem solution and each ant in the ALO paradigm. In this paper, the search space for the convolutional mask with the size of 5×5 has 25 dimensions according to the construction of "Tuned" convolutional mask [18], and each dimension is assigned using continuous values. Zheng *et al.* suggested the structure with symmetrical and zero sums for a mask to prevent computational redundancy, and this had no effect on the classification accuracy. However, this type of mask is relatively stationary and may not adapt to different kinds of texture features [17]. Therefore, the moving convolutional mask with the zero sums and movement of the symmetric axis are defined as follows:

$$mask_i^t = \begin{cases} \begin{bmatrix} x_i^1 & x_i^2 & -2(x_i^1 + x_i^2) & x_i^2 & x_i^1 \\ x_i^3 & x_i^4 & -2(x_i^3 + x_i^4) & x_i^4 & x_i^3 \\ x_i^5 & x_i^6 & -2(x_i^5 + x_i^6) & x_i^6 & x_i^5 \\ x_i^7 & x_i^8 & -2(x_i^7 + x_i^8) & x_i^8 & x_i^7 \\ x_i^9 & x_i^{10} & -2(x_i^9 + x_i^{10}) & x_i^{10} & x_i^9 \end{bmatrix} \\ \text{if } \bmod(t,3) = 0 \\ \begin{bmatrix} x_i^1 & -2(x_i^1 + x_i^2) & x_i^2 & x_i^2 & x_i^1 \\ x_i^3 & -2(x_i^3 + x_i^4) & x_i^4 & x_i^4 & x_i^3 \\ x_i^5 & -2(x_i^5 + x_i^6) & x_i^6 & x_i^6 & x_i^5 \\ x_i^7 & -2(x_i^7 + x_i^8) & x_i^8 & x_i^8 & x_i^7 \\ x_i^9 & -2(x_i^9 + x_i^{10}) & x_i^{10} & x_i^{10} & x_i^9 \end{bmatrix} \\ \text{if } \bmod(t,3) = 1 \\ \begin{bmatrix} x_i^1 & x_i^2 & x_i^2 & -2(x_i^1 + x_i^2) & x_i^1 \\ x_i^3 & x_i^4 & x_i^4 & -2(x_i^3 + x_i^4) & x_i^3 \\ x_i^5 & x_i^6 & x_i^6 & -2(x_i^5 + x_i^6) & x_i^5 \\ x_i^7 & x_i^8 & x_i^8 & -2(x_i^7 + x_i^8) & x_i^7 \\ x_i^9 & x_i^{10} & x_i^{10} & -2(x_i^9 + x_i^{10}) & x_i^9 \end{bmatrix} \\ \text{if } \bmod(t,3) = 2 \end{cases} \tag{7}$$

Since the size of the convolutional mask is usually set as 5×5 and symmetry with zero sums is required, only 10 parameters $x_i^1, x_i^2, x_i^3, x_i^4, x_i^5, x_i^6, x_i^7, x_i^8, x_i^9, x_i^{10}$ should be encoded for a mask. In the moving convolutional mask, the symmetric axis is moving with the change in iteration. The type of decimal encoding can be directly used for ALO, and the parameters in the mask are encoded in the range of $[-50, 50]$.

Since the type of mask is assigned, it is necessary to characterize the different texture features according to a numerical value. In the paper, a statistic is calculated within the $w_x \times w_y$ (9×9 is utilized in this paper) window and the texture energy can be computed by using the mean values within the macro-window size in the process of training, which is detailed as below:

$$TE = \frac{\sum_{w_x} \sum_{w_y} F(m, n)^2}{P^2 \times w_x \times w_y} \tag{8}$$

$$P^2 = \sum_{k=-a}^{a} \sum_{l=-a}^{a} A(k, l)^2 \tag{9}$$

It the above equation, the value of the texture energy is determined by the type of mask and that the optimal moving convolutional mask can provide favorable discriminative ability. As a result, ALO is applied to generate the robust mask here, and to perform the extraction and classification of a specific texture feature in the image.

C. THE OBJECTIVE FUNCTION

To evaluate the optimization performance of ALO, it is essential to construct a reasonable objective function. Because texture classification can be regarded as a binary

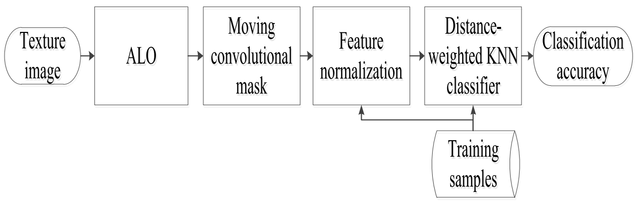

FIGURE 1. Overall scheme of the proposed texture classification approach.

TABLE 1. Parameters used in different algorithms.

Parameter	Explanation	Value
N	Population size	20
D	Dimension	10
I	Iterations for each algorithm	50
c_1,c_2	Acceleration constants in PSO	2.0
r_1,r_2	Random numbers in PSO	[0,1]
	Number of queen in HBMO	1
N_{Brood}	Number of broods in HBMO	10
α	Decreasing factor in HBMO	0.98
G_0	Gravitational value in GSA	100
α	User specified constant in GSA	10
P_a	Detecting probability in CS	0.25
α	Random number in CS	[0,1]

classification problem, each specific texture feature is considered as a category. Fisher criterion has achieved excellent performance in solving he binary classification problems by maximizing the difference of inter-class and minimizing the difference of intra-class, and thus precisely distinguishing a specific category from another [35]. Therefore, the objective function via the theory of Fisher criterion is explained as follows:

$$fit = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2} \quad (10)$$

where μ_1 and σ_1^2 are the average and variance of the eigenvalues in the former category, respectively, and μ_2 and σ_2^2 are the average and variance of the eigenvalues in the later category, respectively. Larger value of the objective function indicates better quality of the moving convolutional mask.

D. OVERALL SCHEME OF THE PROPOSED METHOD

FIGURE 1 shows the overall scheme of the proposed method. First is the encoding for each ant of ALO, the moving convolutional mask is constructed, and a feature vector is constituted. The feature vector is input into a classifier, which yields a label for each pixel of the image. The distribution of the feature vector is determined by different mask values. To bring the range become similar, the value of each vector should be normalized to a uniform magnitude. In general, the process has different stages: training and testing. Training is to seek a feasible position for each ant in the search space according to the texture energy, and the testing confirms which representative vector is the closest to the training value for each pixel.

Algorithm 1 Texture Classification Based on Moving Convolutional Mask and ALO.

Begin
Input the texture images and extract training samples from the images;
Generate the initial population of ALO;
For each ant, generate a moving convolutional mask by using equation (7), make a convolution with training samples and mask, and output the texture energy;
Normalize the variable to a uniform magnitude;
While *(The current iteration $t <$ The maximum iteration T)*
Compute the fitness value of each object using equation (10);
Trap of ants in antlion's pits using equations (4) and (5);
Random walks of ants using equation (3);
If*(The fitness value of the current position is better)*
Replace the antlion to the new position;
End if
End while
Output the optimal moving convolutional mask and conduct classification for each pixel of texture image.

It is well known that the more training samples with similar characteristics, the better accuracy will be difficultly obtained. However, as the larger of the datasets are often exclusive in time complexity, every training sample is used with different scales and rotations to avoid overfitting and to ensure a fair performance evaluation. The pseudocode for the main process of the proposed texture classification technique is ahead.

For texture classification, due to the low dimension of the datasets, we choose a distance weighted KNN classifier [36] from amount of pattern recognition models to reflect the distance difference of few texture features. The basic KNN classifier is difficult to straightly keep stable because the size of the gap between categories maybe very small, which may cause misclassifications. However, the distance-weighted KNN classifier is effective to compute the texture energy because a weight value is utilized for samples in different categories, where a large weight is assigned for the categories with a small number of samples.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed algorithm is implemented using MATLAB 2014b on a personal computer with a 2.30 GHz CPU, 8.00G RAM under Windows 8 system.

In order to assess the property of the proposed texture classification technique, 5 public images with obvious texture features are utilized in this section. Some commonly used swarm intelligence algorithms, for instance PSO [19], HBMO [20], GSA [21] and CS algorithms [22] are used to make a comparison, and the computational

TABLE 2. Results of different algorithms for public texture images.

Dataset	Meas.	PSO	HBMO	GSA	CS	ALO	"Tuned" mask
Grunge	Avg	25.2120	25.0107	26.1712	26.6071	27.2397	26.0454
	Std	1.8855	1.3129	1.0836	0.8937	0.7149	0.9224
	p-value	0.0764	0.0471	0.0306	0.0120	0.0042	0.0097
	Time	0.1766	0.1794	0.1808	0.1815	0.1780	0.1742
Rust	Avg	25.2833	25.1163	26.6810	27.2239	28.1187	25.5243
	Std	2.0386	1.8265	1.4977	1.2555	0.9940	1.5857
	p-value	0.1172	0.0719	0.0433	0.0240	0.0089	0.0161
	Time	0.1701	0.1735	0.1753	0.1762	0.1717	0.1682
Rock	Avg	24.5501	25.8634	26.7905	27.0773	27.7898	26.5882
	Std	2.1842	1.5665	1.2207	0.9621	0.8155	1.1177
	p-value	0.2539	0.1356	0.0642	0.0388	0.0119	0.0222
	Time	0.1735	0.1767	0.1794	0.1803	0.1745	0.1721
Marble	Avg	24.7489	24.3159	26.4943	27.0043	27.7298	26.5942
	Std	1.5877	1.3994	1.0501	0.9394	0.8155	1.0618
	p-value	0.0869	0.0624	0.0433	0.0204	0.0091	0.0183
	Time	0.1751	0.1785	0.1801	0.1811	0.1766	0.1736
Concrete	Avg	26.3135	26.2320	27.0287	27.3152	27.7168	26.6220
	Std	0.7520	0.7060	0.6759	0.5877	0.4295	0.6180
	p-value	0.0422	0.0295	0.0201	0.0147	0.0047	0.0092
	Time	0.1799	0.1834	0.1847	0.1854	0.1817	0.1781

complexity is O($n$ln$n$) for all of the algorithms above [37]. Furthermore, some other texture classification techniques such as modified GLCM [5], rotated LBP [10], directional statistical Gabor [12] and "Tuned" convolutional mask [18] are also used to make a further comparison. The objective function is defined as equation (10), and a higher fitness value proves better optimization ability.

To make a fair comparison, the number of function evaluations is used as the terminal criterion, that is, all algorithms will stop when the number of iterations reaches 50, and when all the algorithms make 30 independent operations. In the section, we present some contrastive experimental results, including illustrative examples and performance evaluation tables, which clearly demonstrate the merits of the proposed approach. Our primary interest is the performance of the optimal moving convolutional mask, which is shown by the fitness value, and the classification accuracy for each pixel of the image.

A. PARAMETER SETTINGS FOR SWARM INTELLIGENCE ALGORITHMS

According to the operational proceeding of ALO, the optimization ability did not rely on any parameter settings, and which prevent trapping into the local optima. Additionally, some traditional swarm intelligence algorithms are also tested for comparison in this paper. Some existing swarm intelligence algorithm based texture classification approaches, which are proposed by Ye (PSO [19]), Zheng (HBMO [20]), Wan (GSA [21]) and Peng (CS [22]) are used to make a comparison. To make a fair comparison, the standard types of PSO, HBMO, GSA and CS algorithms are used, and the primary ALO is used here. TABLE 1 shows the parameter settings of the above algorithms.

TABLE 3. Classification accuracies of common used techniques.

Dataset	GLCM	LBP	Gabor filters	"Tuned" mask	Moving mask
Grunge	55.0067	62.9721	82.7667	85.4050	91.8942
Rust	83.9342	86.1046	86.3142	89.0800	93.3438
Rock	88.9004	84.4538	91.2317	92.5083	94.6021
Marble	63.8642	78.1550	93.7417	95.1838	98.6438
Concrete	68.5600	72.9525	92.5025	96.7450	98.0288

B. EXPERIMENTS FOR DIFFERENT SWARM INTELLIGENCE ALGORITHMS

The preliminary experiments of the proposed approach on 5 images named "Grunge", "Rust", "Rock", "Marble" and "Concrete" (http://www.textureking.com/) are conducted, and the size of each image is 400×600. The texture features is changed from simplicity to complexity for 5 images. All of the training samples are extracted from the original image. TABLE 2 shows the fitness value of the moving convolutional mask used by different swarm intelligence algorithms, and the "Tuned" convolutional mask optimized by ALO is also utilized here to make a comprehensive comparison with the fitness value.

In TABLE 2, Avg and Std are respectively the fitness values in average and standard deviation obtained by performing 30 independent operations. Time is the CPU time of each iteration for different algorithms, and its unit is second. In ALO, each ant randomly walks around the ant lion with the theory of roulette wheel, and enhance the exploration ability. It is apparent that ALO has the best optimization ability compared with other 4 algorithms, its fitness value in average is straightly the maximum for all the training samples, and exceeds 27 for all of the datasets. In terms of stability, the fitness value in standard deviation is nearly lower

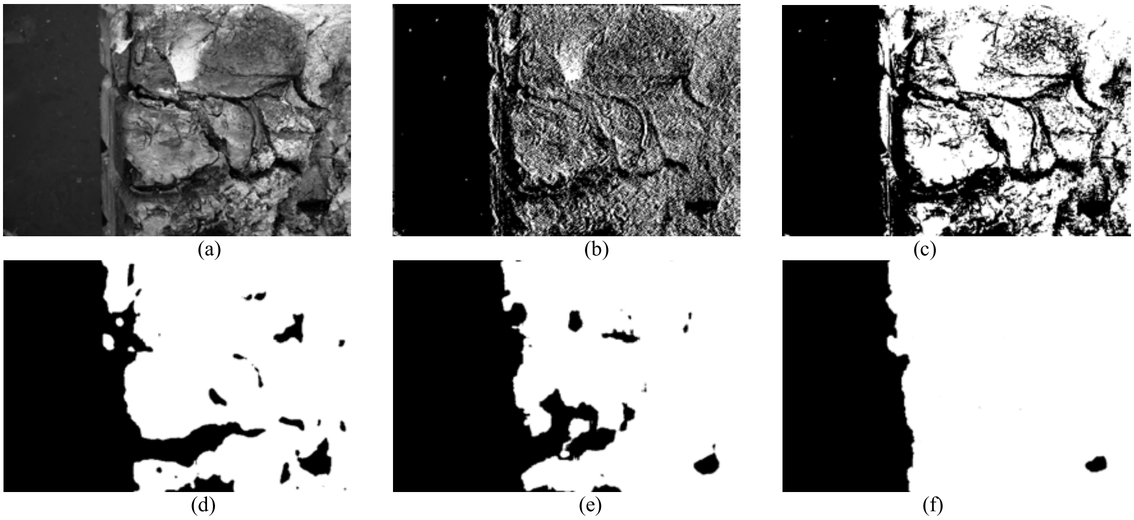

FIGURE 2. Classification results of Grunge image: (a) original image (b) result of GLCM (c) result of LBP (d) result of Gabor filters (e) result of "Tuned" convolutional mask (f) result of moving convolutional mask.

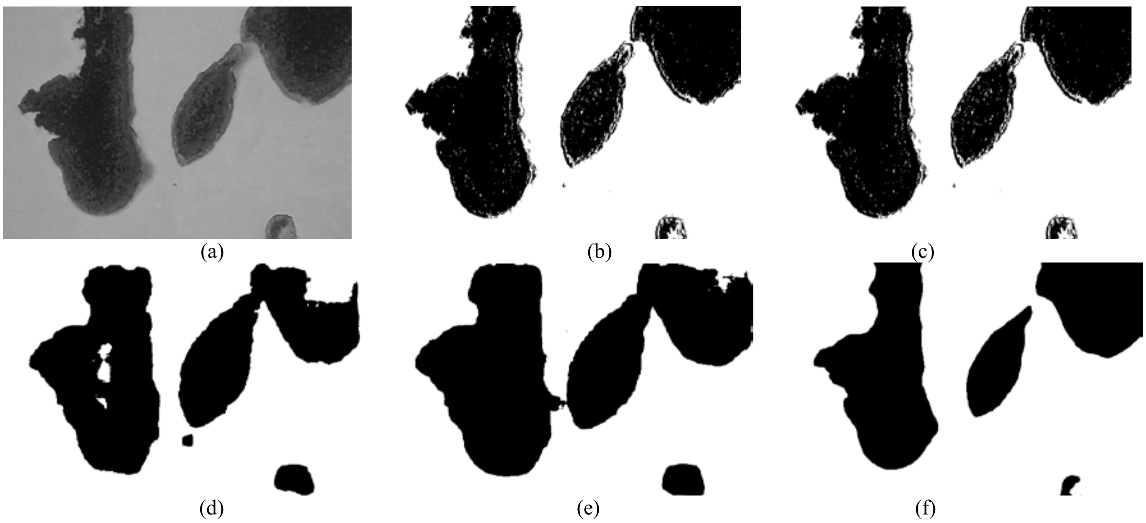

FIGURE 3. Classification results of Rust image: (a) original image (b) result of GLCM (c) result of LBP (d) result of Gabor filters (e) result of "Tuned" convolutional mask (f) result of moving convolutional mask.

than 2 for all of the swarm intelligence algorithms, and only have a mild fluctuation in the construction of the moving convolutional mask. In particular, ALO has the lowest standard deviation, and it is lower than 1 for 5 testing images. This illustrates that ALO is able to move towards the optimal solution more stably. The p-values are lower than 0.05 and even 0.009 for the proposed method, which demonstrates the significant incensement in the fitness value and even classification accuracy. The ALO retains stable classification accuracy for independent operations. In particular, the fitness value when using the moving convolutional mask is better than that when using "Tuned" convolutional mask. The moving convolutional mask increases the interclass difference by moving the symmetric axis. With the aspect of operating efficiency, PSO algorithm has a relatively fast converge rate compared with commonly used algorithms, but the difference of the CPU time compared with ALO is only 0.001-0.002s, and the fitness value obtained by ALO is apparently better than that obtained by PSO algorithm. More importantly, ALO has fewer multiplications than HBMO, GSA and CS algorithms, which demonstrates that ALO has an excellent balance between optimization ability and operating efficiency, and that is preferable for solving the texture classification problem and obtaining the optimal moving convolutional mask.

C. APPLICATION OF SPECIFIC TEXTURE CLASSIFICATION

In this section, the optimal moving convolutional mask is used to identify a specific texture feature from the original image, and the distance-weighted KNN classifier is used to

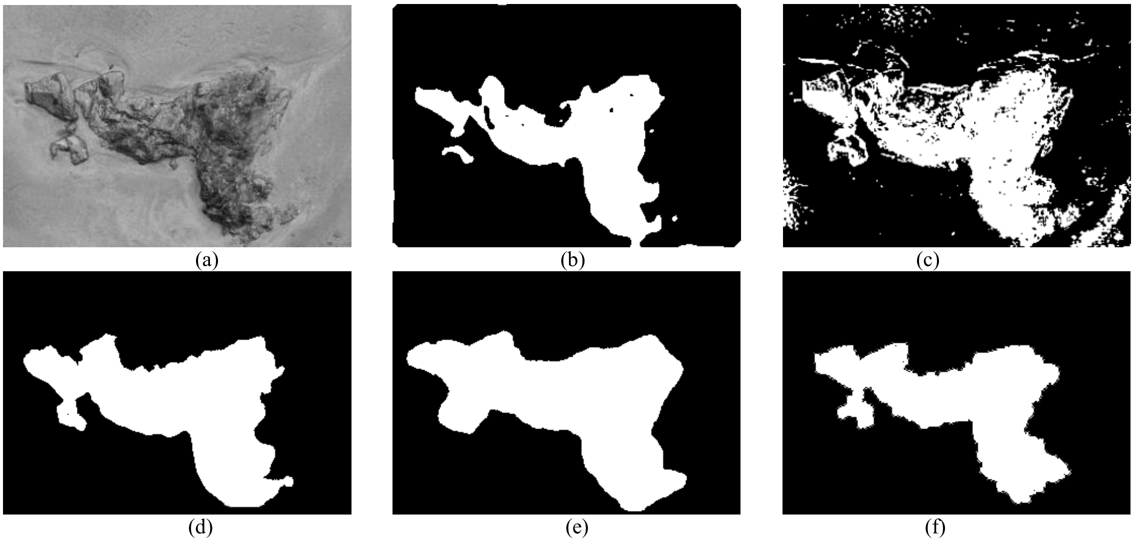

FIGURE 4. **Classification results of Rock image: (a) original image (b) result of GLCM (c) result of LBP (d) result of Gabor filters (e) result of "Tuned" convolutional mask (f) result of moving convolutional mask.**

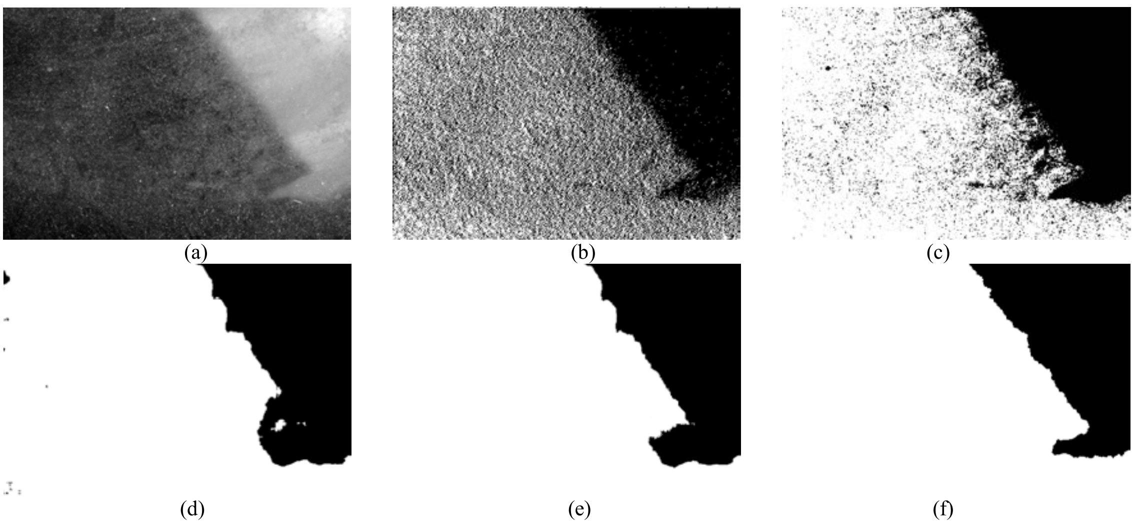

FIGURE 5. **Classification results of Marble image: (a) original image (b) result of GLCM (c) result of LBP (d) result of Gabor filters (e) result of "Tuned" convolutional mask (f) result of moving convolutional mask.**

accomplish the classification for each pixel. TABLE 3 shows the classification accuracy achieved by different texture classification approaches. The original images and experimental results are presented in FIGURES 2-6.

In TABLE 3, it is evident that the error rates obtained by improved GLCM, rotated LBP and directional statistical Gabor filters are distinctly higher than those achieved by the convolutional mask. The difference was 20% for Grunge, Marble and Concrete images, and the moving of the symmetric axis could further improve the accuracy, and coincide with the original images. According to FIGURES 2-6, the experimental results achieved by the improved GLCM, rotated LBP and directional statistical Gabor filters could do not satisfy the requirements for practical application and the misclassification is obvious. Although the "Tuned" convolutional mask achieved a relatively accurate texture classification for the whole image, the edge selection is distinctly worse than that achieved by the moving convolutional mask. The error rate is less than 2% and as low as 1.3% for the relatively pure textures such as those in Marble and Concrete images. For Grunge image, the classification accuracy also reached nearly 92% by blending the complex texture types in the right place. Moreover, the CPU time for improved GLCM method exceeds 100s for the 5 images, and it also reaches 3s for rotated LBP and directional statistical Gabor filter techniques, which proves that the proposed technique can quickly obtain satisfactory classification accuracy. Hence, it is concluded that the proposed approach could be widely used to extract a specific texture feature.

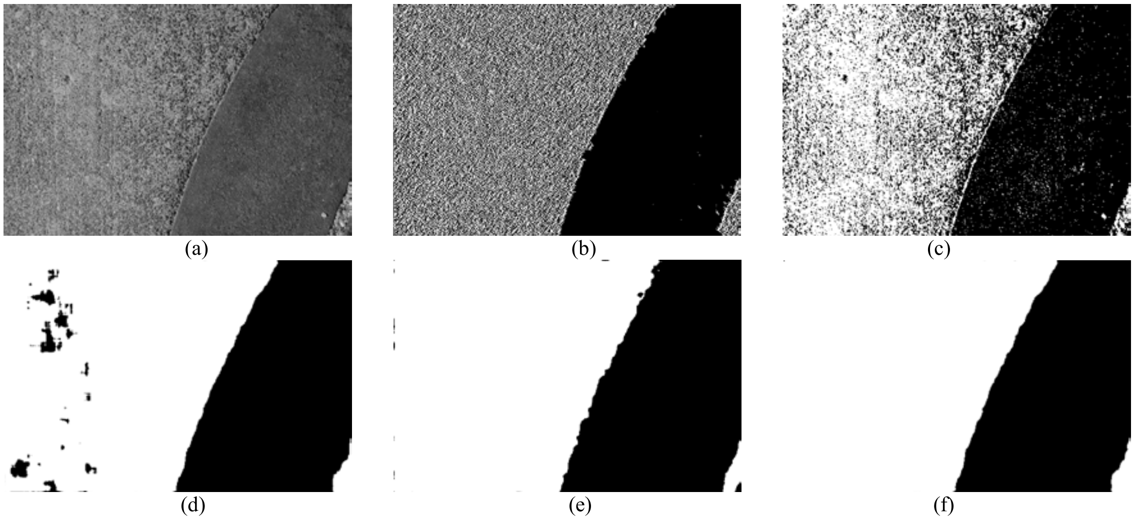

FIGURE 6. Classification results of Concrete image: (a) original image (b) result of GLCM (c) result of LBP (d) result of Gabor filters (e) result of "Tuned" convolutional mask (f) result of moving convolutional mask.

IV. CONCLUSION

In summary, a texture classification technique based on moving convolutional mask via ALO is described, and 5 public images are utilized to perform the assessment of the proposed approach. The experimental results are compared with those of traditional swarm intelligence algorithms, such as PSO, HBMO, GSA and CS algorithms; it is observed that swarm intelligence algorithm can be well used to learn the parameters of a convolutional mask. Among them, ALO has the best optimization ability, and the fitness value in average is better than that of the PSO, HBMO, GSA and CS algorithms, which indicates that it is more reasonable to be utilized to train the satisfactory moving convolutional mask. Moreover, the operating efficiency meets the requirements for real-time application. In order to develop a comprehensive comparison, texture features extracted by improved GLCM, rotated LBP, directional statistical Gabor and "Tuned" convolutional mask techniques are also used in this paper, which proves the practicability of the proposed approach. In short, the moving of the symmetric axis can enhance the discrimination ability of a specific texture feature. In addition, the problem of heavy time complexity can be addressed most effectively by applying ALO. The proposed method is able to obtain high classification accuracy with less CPU time, which shows that it is more suitable to complete the task of texture classification. In the future, it will be interesting to construct a more effective convolutional mask that can be utilized to classify for multiple types of textures.

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