A novel modified SFIA approach for feature extraction.

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A Novel Modified SFTA Approach for Feature Extraction

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***Abstract*—To increase the efficiency of conventional Segmentation Based Fractal Texture Analysis (SFTA), we propose a new approach on SFTA algorithm. We use an optimum multilevel thresholding hybrid method of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), called HGAPSO with the optimization technique for classification based on grey level range to get more accurate output. Experimental results show that proposed approach exhibits average 2% higher classification accuracy than conventional SFTA for our tested dataset.**

Keywords—SFTA (Segmentation Based Fractal Texture Analysis), multilevel thresholing, HGAPSO, Otsu function.

I. Introduction

Preprocessing step, feature extraction, making the database of feature and matching the assigned image with the created database; these four steps can draw a solution for retrieval problem of images. Here; feature extraction plays a very important role as it defines the unique features of images. A number of researchers work on development of efficient feature extraction methods [1-4]. In [2], Costa *et el* proposed a new feature extraction method, called SFTA (Segmentation based Fractal Texture Analysis). On this conventional SFTA technique, the total process has two steps. One is two threshold Binary decomposition and another one is feature extraction.

On binary decomposition step, conventional SFTA uses multilevel Otsu algorithm for thresholding. It takes exponential time [6] to perform the trial and test for finding out the best number of threshold values to do the feature extraction technique, which is not efficient. Moreover the threshold values are not that much efficient to perform more accuracy. Again SFTA has a problem on finding out the number of binary images from binary decomposition portion. Conventional method is not actually well formed to find out the exact number of decomposed images for the creation of feature vector. In addition, conventional method creates dimensional mismatch.

To overcome the limitations; we propose our new model. We have also compared the classification accuracy of our novel modified SFTA approach with the conventional SFTA for our tested dataset.

The remainder of the paper is organized as follows - Section II displays how the conventional SFTA algorithm works. Section III describes the overview in depth of our proposed novel SFTA approach. The results of the experiments carried out and their analysis are included in Section IV and finally Section V concludes the paper.

II. Literature review

To avoid the limitations of the conventional SFTA, in our novel approach, we use hybrid multilevel threshold method; defined as HGAPSO; for finding out significant threshold values with less time based on trial and test. After that; we have used optimization technique for classification based on grey level range; defined as OCGR; to attain more accurate threshold values from the collected ones from first step.

Ghamisi *et al.* proposed the HGAPSO method[3,4]; consisting of two main portions: one is for combining the standard velocity and another is for updating the rules of PSOs (Particle Swarm Optimization) with the ideas of collection, crossover and transfiguration from GA (Genetic Algorithm) [5]. We have used HGAPSO instead of Otsu because for an obvious reason. When Otsu method is comprehensive to solve multilevel thresholding, it is not efficient to define the ideal threshold values as for multilevel Otsu; because performing the trail and test to get the attained number of threshold will increase exponentially [6] along with increasing the number of thresholds. So we propose our new approach based on HGAPSO and OCGR in section III to get better accuracy on attained threshold values and avoid the exponential time necessity to obtain those values.

Conventional SFTA is a proficient texture feature extraction method; proposed by Costa *et el.* [2]; consisting of two parts. The first part performs the decomposition technique for the input grey scale images to convert it into set of binary images by using Two-Threshold Binary Decomposition (TTBD). Then the second part is to compute the fractal dimension form its region margins for each subsequent binary image.

For the first step of the whole procedure, the TTBD considers a grayscale image as an input and we get a set of binary images as result. By using multilevel Otsu threshold algorithm, TTBD gives the resulting set *T* of threshold values; as the first step. Recursively; this Otsu algorithm is functional to each region of image till the preferred digit of thresholds is not attained.

The following step of the TTBD algorithm involves in disintegrating the grayscale image *I(x,y)* which are measured as input; into a set of binary images; and it is accomplished by choosing couples of thresholds from that attained set of threshold values and relating a two-threshold segmentation [2]. Figure 1 demonstrate SFTA extraction process overview.

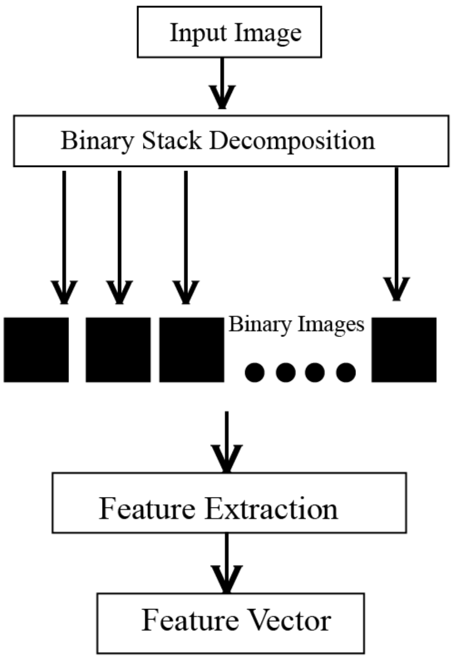

Fig. 1. SFTA Extraction Process Overview

According to the conventional SFTA; the number of causing binary images is $2n_t$ [2]; where n_t means number of thresholds; but here is a problem regarding the number of the subsequent binary images. On practical work, the number is not $2n_t$, it is $(2n_t\text{-}1)$. With relating the two threshold segmentation to the input image; the set of binary image is obtained; and this process use all pairs of adjoining thresholds from $T \cup \{n_l\}$ and all pairs of thresholds $\{t,n_l\}$, $t \in T$, where n_l corresponds to the maximum possible gray level in $I(x, y)$. Here n_l stands for gray level range; T for threshold. This way, finally, the number of resulting binary images is $2n_t$ -1. For example; if the number of threshold value is 4, on the conventional SFTA; the causing binary image would be 8; but according to the correct and practical approach it would be 7. Figure 2 shows the detail process of this [23].

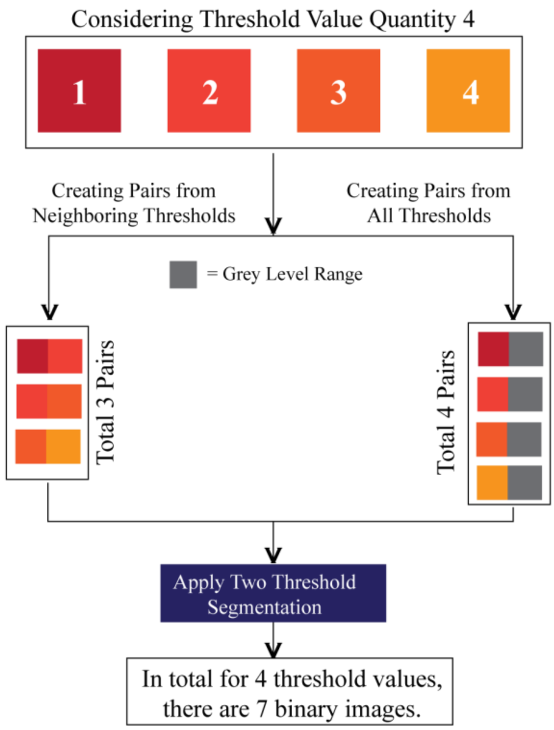

Fig. 2. Exact Binary Image Formation Process from Threshold.

III. PROPOSED MODEL

Figure 3 reveals a detailed implementation of our proposed model. This section demonstrates how the algorithm is set up.

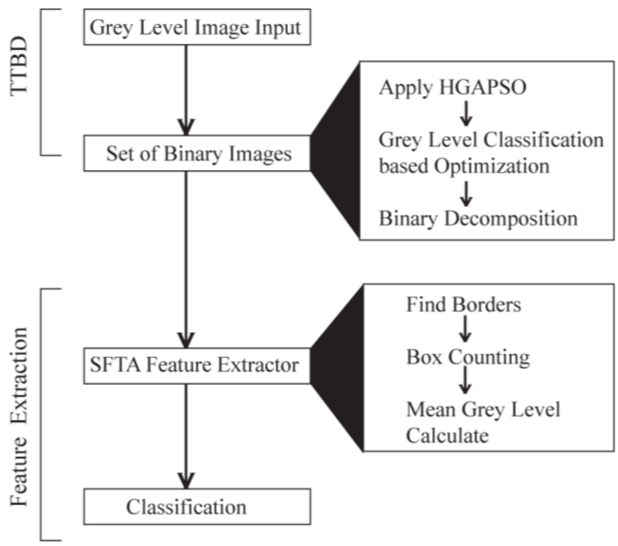

Fig. 3. The Proposed Model of Novel SFTA Method.

A. Apply HGAPSO

GA (Genetic Algorithm) and PSO (Particle Swarm Optimization) theorem [15-17] can perform together to obtain a better optimization results [3,4]. In [3,4], Ghamisi *et al.* proposed the HGAPSO method; which has two main parts. One is to the association of the standard velocity and with the planning of selection, crossover and mutation from GA [5]; another one is to update the procedure of Particle Swarm Optimization.

Swarm or population is the set of solutions from PSO; in which each solution consists of a set of parameters and represents a point in the multidimensional space, denoted as a particle [21]. Having a predisposition of winged to a better search area over the pursuit crossways [17]; the rapidity of the particles are familiar based on the chronological behavior of each one and its neighbors. The velocity of the i-th particle in the k-th iteration is resolute as follows:

$$V_{id}^{k+1} = WV_{id}^{k} + c_1 r_1 \left(pb_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(gb_{id}^{k} - x_{id}^{k}\right) \quad (1)$$

Where c_1 and c_2 are defined as acceleration constants and r_1 and r_2 have random values ranging from 0 to 1. Here W stands for inertia weight [5]; which displays the location of each particle in the d-dimensional search space by the parameter x_{id}^{k} [5, 23].The best previous position of each particle is represented by pb_{id}^{k} and considered as particle best position. gb_{d}^{k} is the best position of all particles, being denoted as global best particle [5,23]. The *i*-th particle position is updated by:

$$x_{id}^{k+1} = x_{id}^{k} + V_{id}^{k} \quad (2)$$

Then again, GA; based on the genetic process [5, 20]; is able to find an ideal solution by not exploring the whole search space [5]. Chromosome or individual is the optimization technique of GA which has several solutions. These chromosomes are consisting of several different valued genes [5]. The fitness value of the chromosome represents by the attributes of each individual; supported by these genes.

In our proposed method, to get the attained threshold value; by reducing the steps of exponential calculation of multilevel Otsu [6], we are using HGPASO and then again from those values; to select more significant threshold values we have used our own OCGR technique.

B. Optimization Technique for Classification based on Grey Level Range

From the previous step A, we get a number of threshold values. After that, we use those values to get more accurate number of threshold values. At the very beginning, we correspondingly categorize the grey level density 0 to 255 into equivalent classes. Then from all attained threshold values from previous step A, we calculate their incidence number on those classes. Then; from each class range, the mean values of thresholds are considered. If no incidence on any class, then we simply add the class range start point and class range end point and divide the attained summation by two, to consider the threshold value [23]. Thus our proposed OCGR process supports to attain the preferred number of improved threshold values. By using pseudo code, the whole algorithm of our proposed model is given below.

Algorithm 1 HGAPSO & OCGR Based SFTA extraction algorithm.

Requirement: I; the greyscale image and n_t the number of thresholds

01.	*Threshold, T*	←	***Hybrid GAPSO*** *(I,n_t)*
02.	*Set of Improved Threshold, T_{op}*	←	***OCGR*** *(T, number of threshold obtained occurrence on each Grey Level Class)*
03.	*Threshold Set 1 from binary images, A*	←	*{{ t_j, t_{j+1}}: t_j, t_{j+1} ∈ T_{op}, j ∈ [1..| T_{op} | − 1]}*
04.	*Threshold Set 2 from binary images, B*	←	*{{t_j, n_l}: t_j ∈ T_{op}, j ∈ [1...| T_{op} |]}*
05.	*j*	←	*0*
06.	*for {{lower threshold, upper threshold}: {lower threshold, upper threshold} ∈ A U B}*		*do*
07.	*Binary Image*	←	***TwoThresholdSegmentation*** *(I, lower threshold, upper threshold)*
08.	*Border Image(x, y)*	←	***Border Find*** *(Binary Image)*
09.	*SFTA Feature Vector[j]*	←	***Count Box*** *(Border Image)*
10.	*SFTA Feature Vector [j + 1]*	←	***GrayLevelMean*** *(I, Binary Image)*
11.	*SFTA Feature Vector [j + 2]*	←	***Count Pixel*** *(Binary Image)*
12.	*j*	←	*j+3*
13.			*end for*
14.	*return*		*SFTA Feature Vector*

IV. EXPERIMENTAL RESULT ANALYSIS

Figure 3 demonstrates how the proposed algorithm is set up. We applied our proposed algorithm on two publicly available dataset: KTH-TIPS [8] and Texture Surface [9]. On these two different dataset, we apply the original SFTA algorithm and our proposed novel SFTA algorithm. Like the conventional SFTA approach [2], we did not notice any major changes on classification accuracy increasing phase after the threshold value reached to 14. Till 14, the accuracy was significantly in increasing order. The interesting fact is our proposed novel SFTA algorithm gave more accuracy on different number of threshold values till 14 than the original SFTA algorithm. Mainly after 14, no additional texture patterns has been identified by our proposed TTBD phase. For individual training on each dataset for each image, we use SVM (Support Vector Machine).

The KTH-TIPS (Textures under varying Illumination, Pose and Scale) consist of 810 grayscale images [8] with 10 texture classes [2]. The Textured Surfaces Dataset [9] has numerous surfaces such as wood, marble and fur; these materials; under varying viewpoints, scales and illumination conditions [2].

A. Accurecy Measurement

Figure 4 shows the accuracy percentage for dataset KTH-TIPS [8] for number of threshold values. From here, it is clearly visible that our proposed algorithm can give more accuracy than SFTA [2] algorithm. Here from the figure 4, it is visible to us that our experimental result shows the detailed comparison between the performance of SFTA and our proposed model. When the number of threshold value is 2,4,6,8,10,12 and 14, we get a much better accuracy than SFTA. For 16, 18, 20 numbers of threshold values also giving us the higher accuracy than conventional SFTA, but not that much in percent like the previous mentioned threshold number does. So till the number of threshold values 14, our proposed model can bring a significant improvement on classification accuracy.

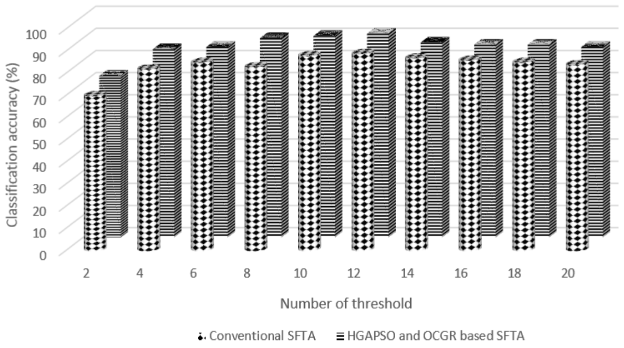

Figure 4: For **KTH-TIPS Dataset**; Classification Accuracy Comparison in Percentage between Conventional SFTA and Proposed Model.

Similarly Figure 5 shows the accuracy percentage for Texture Surfaces Dataset [9] for number of threshold values. From figure 5, along with better accuracy for our proposed model; we can also see that when the number of threshold value is 2, 4,6,8,10,12 and 14, we get a far better accuracy than SFTA. For 16, 18, 20 numbers of threshold values also giving us the higher accuracy than conventional SFTA, but not that much in percent like the previous mentioned threshold number does. So till the number of threshold values 14, for both experimented case, our proposed model can bring a significant improvement on classification accuracy.

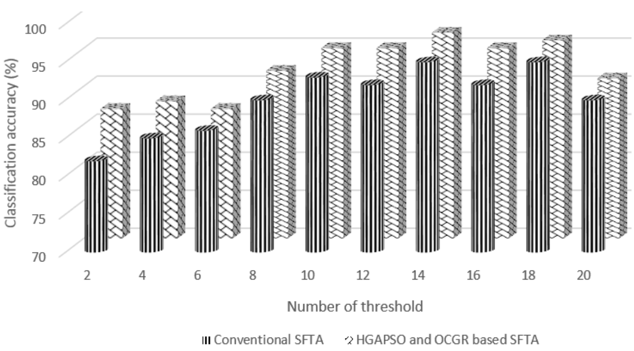

Figure 5: For **Texture Surface Dataset**; Classification Accuracy Comparison in Percentage between Conventional SFTA and Proposed Model.

V. CONCLUSION

This paper presents a HGAPSO and OCGR based SFTA texture feature extraction method. In this method, we used HGAPSO and OCGR to select the best number of threshold values and reduce steps of trail and test for the best number of feature selection. Which significantly impact on performance of conventional SFTA algorithm. Experimental results show average 96% classification accuracy for our tested dataset, where conventional Otsu based thresholding SFTA displays 94% classification accuracy. On average for different number of testing and training images our proposed method gives 2% more accuracy than the conventional one.

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