Multi-texture classification using optimized Gabor Filter by Artificial Bee Colony

Alsadegh Saleh Saied Mohamed,[a] Joan Lu [b] Qiang Xu [c]
[a] School of Computing and Engineering, University of Huddersfield, U K
alsadegh.mohamed@hud.ac.uk
[b] School of Computing and Engineering, University of Huddersfield, U K
j.lu@hud.ac.uk
[c] School of Computing and Engineering, University of Huddersfield, U K
Q.Xu2@hud.ac.uk

Abstract. Texture classification is an important topic which is used in many applications of computer vision. The Gabor Bank is one of the well-known feature extraction methods for texture classification. However, Gabor Bank suffers from high dimensional features which can be solved by finding a suitable filter for a particular task and that is the concern of this research. This paper introduces a new optimization method (Artificial Bee Colony (ABC)) to automatically select the proper values of the Gabor Filter parameters in order to design the optimal filter and avoid high dimensional features. The parameters values are tuned according to texture groups for classification. The texture groups have been prepared from standard database of University of Maryland Database (UMD). In experimental results, the average classification rate was comparable with 88.0438% of Gabor Bank against 82.7938 % of optimal filter. The optimal GF can be improved by integrating with other optimized methods.

Keywords: Texture Classification; Gabor Filter Optimization; Artificial Bee Colony Algorithm.

1 INTRODUCTION

The texture appears in many natural scenes with diversity arrangement of the pixels intensity of the image and mostly it takes repeated pattern [1]. Texture analysis methods extracts features from the texture in the images for discrimination between them, which was beneficial to be applied in many fields such as remote sensing images, aerial and satellite images, defect detection in the images and medical images [2]. There are four main types of analysis techniques for extracting features from the texture, and they are [3]: geometrical or structural approach, statistical approaches model based approaches and single processing approaches.

Gabor Filter is one of single processing methods which has the ability to decompose the image which contain the texture [4] [5]. There are two methods of Gabor Filter have been applied in previous studies for texture applications which are: Filter Bank method and Filter design method [5] [6]. Gabor Bank does not need advance information about the texture in the image, but it has high computational costs [1] [7] [8]. On the contrary, Gabor Filter design is based on a particular filter or number of filters. Here, the parameters taken into consideration for finding appropriate filters for defined application [6] [8]. Here, we consider to design Gabor Filter with optimal parameters for multi- texture classification.

There are methods used to optimize the Gabor Filter such as Genetic Algorithm (GA) [9], Simulated Annealing (SA) [10], and Particle swarm [11]. The contribution of the proposed method is the optimization of a GF parameters by the most recent method, artificial bee colony (ABC), for multi-texture classification. The optimization method will extract the optimum Gabor filter that is most effective on patterns of the image.

The rest of this paper is organized as follows: Section 2 introduces the related work; Section 3 illustrates the involved theories for automatic optimization method; Section 4 proposes the optimized method for multi-texture classification; Section 5 the results and discusses; finally Section 6 concludes the findings and describes future work.

2 RELATED WORK

There have been many automatic optimization techniques used to improve feature extraction methods, such as, Genetic Algorithm, Simulated Annealing and Particle Swarm. A genetic algorithm has been applied by Afshang [9] to optimize a set of Gabor filter parameters for texture classification. On many texture images, the genetic algorithm have achieved nearly eighty percent in an attempt to get optimized parameters for a Gabor filter. The parameters have been selected based on every image set in a database. Another study has been done by Pakdel [12] using a genetic algorithm for the selection of a suitable value set of filter parameters, which include smooth parameters of a Gaussian envelope, as well as orientations and frequency number. The accuracy ranged from 97.5% to 96.9% for 16 and 6 filters respectively. Zehang Sun [13] proposed a genetic method with clustering algorithm for filter selection, where the clustering algorithm groups the filters to remove redundant information from similar filters.

In [10] Tsai studied the performance of Simulated annealing to obtain optimum Gabor Filter design to separate the single image into different regions based on the texture. He separated between classes of textures based on maximize the minimum energy response of different regions. Fei He in 2014 [14] introduced method to cope on environmental condition such as illumination variation when dealing with iris recognition, this method used support vector regression to combine many local features by Gabor Filters. The particle swarm used to obtain the effective Gabor Filters automatically to extract the features from the databases.

3 UNDERPINNING THEORY

3.1 Gabor Filter (GF)

The two dimensional Gabor filter introduced by Daugman in 1985 [15] which development of communication theory by Dennis Gabor in 1946 [16]. In the spatial domain the Gabor filter is a sinusoid wave modulated by a Gaussian function (Eq. 1) [17].

$$\psi(x, y; f_0, \theta) = \frac{f_0^2}{\pi\gamma\eta} e^{-\frac{f_0^2}{\gamma^2}x'^2 + \frac{f_0^2}{\eta^2}y'^2} e^{j2\pi f_0 x'} \quad (1)$$

$$x' = x\cos\theta + y\sin\theta \qquad y' = -x\sin\theta + y\cos\theta$$

where is the central frequency of the filter, is the angle between sinusoidal wave direction and x-axis, are Gaussian envelop values in the wave direction of major axis and orthogonal to wave direction respectively (the minor axis). Optimal Filter design selected by proper values of the central frequency, orientations and Gaussian envelop.

3.2 Artificial Bee Colony (ABC)

The Artificial Bee Colony (ABC) is swarm of bees with self-organization intelligence method introduced by Karaboga in 2005 [18]. The swarm consist of three types of bees which are: the employed bees, the onlooker bees and the scout bees. The colony is divided equally between the employed bees and the onlooker bees. The employed bees exchange the information about the quality of food sources with onlookers by special dancing call a waggle. The food source with richest nectar will be visited by the largest number of onlookers [19]. If the food source is exhausted, the employed bees converted into scouts and memorize the food source with higher nectar [18] [20].

4 ABC AS OPTIMIZER BASED ON GF

The ABC algorithm will be applied to find the optimal Filter from the set of filters in the Gabor Bank for specific texture. The main stages of ABC algorithm are: initial stage, employed bee stage, onlooker bee stage and scout bee stage. In first stage, the initial values parameters (scales, orientation and Gaussian envelop values) will be selected randomly which are the initial solutions of GF parameters. The selected parameters will be evaluated by the objective function which are here the accuracy of image classification by ANN.

Employed stage searching in neighborhood area of initial parameters values and new parameters values will be evaluated by ANN as well, and applying greedy selection between initial and new parameters values based on the better accuracy between them. Next, Onlooker stage starts by finding highest probability and then searching in neighborhood area to improve the obtained solutions from the employed stage.

The employed bees become scouts if there is not further improvement in discovered places, where the aim is to leave the exhausted solution to find others.

5 EXPERIMENTAL RESULTS AND DISCUSSION

The main objective of the experimental results is to investigate the influence of GF parameters, which optimized by ABC algorithm, on the discriminatory power of optimum GF for analyzing the texture as the main stage for image classification.

5.1 Experimental Preparation

The program of new optimization method code, which are GF to be optimized by ABC, was developed in MATLAB 2014b and applied on a Windows 7 i5 Core Processor machine. Three layers neural network trained by back-propagation has been used for texture feature classification [21]. K fold has been used as a cross validation technique, in order to enhance the classification when dealing with a random distribution of data [22].

This method has been tested by the UMD (University of Maryland, College Park Database) [23] which consists of texture classes with high resolution 1280*900 pixels. The images in the database have a variety of texture types such as floor, shelves, fruits and others with different viewpoint scales and illumination. The textures have been divided into sixteen different groups, where each group consists of two classes of non-overlapping sub-images for bi-classification as in Figure 1.

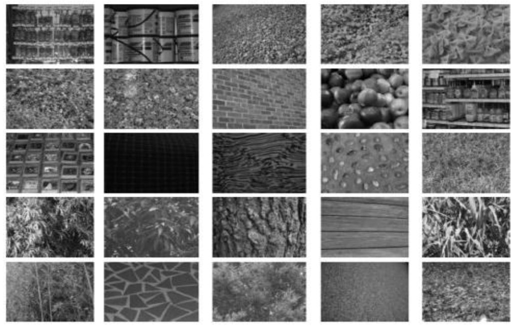

Fig. 1. The selected images groups from UMD database for binary classification of multi-texture

5.2 Results

The optimal filter has been designed by tuning the values of its parameters based on particular texture in the image groups for classification. Table 1 gives the parameters values that produced the highest possible accuracy for every group. Each image group in the data sets obtained the best available classification accuracy by different values of parameters. Most image groups recorded classification accuracy more than 82 % using single filter. The highest classification accuracy was in group 15 (G15) with 93.4%, whereas the group 7 (G07) recorded the lowest classification accuracy with 65.9%.

Table 1 The resulted Gabor parameter values by using the optimized method

Dataset	Accuracy (%)	The obtained parameters Values				
		Scale No	Orient No	Center of Frequency	Orientation Value	Gaussian Envelop
G01	83.8	4	6	0.088388	1.963495	0.832468
G02	90.5	1	7	0.25	2.356194	0.880732
G03	82.8	2	6	0.176777	1.963495	0.788737
G04	81.8	1	7	0.25	2.356194	0.870401
G05	80	5	5	0.0625	1.570796	7.071972
G06	73.5	2	6	0.176777	1.963495	6.54674
G07	65.9	2	4	0.176777	1.178097	0.758112
G08	87.8	1	8	0.25	2.748894	0.919063
G09	92.2	3	8	0.125	2.748894	0.6
G10	95.3	4	3	0.088388	0.785398	0.992078
G11	83.5	2	5	0.176777	1.570796	1.800896
G12	69.8	1	6	0.25	1.963495	1.259524
G13	77.6	4	4	0.088388	1.178097	1.320091
G14	84.1	4	3	0.088388	0.785398	0.785622
G15	93.4	1	4	0.25	1.178097	0.6
G16	82.7	3	5	0.125	1.570796	0.6

5.3 Analysis and Discussion

The initial vector values of GF parameter is based on previous studies [24]. The optimal filter have been compared with the Filter Bank consisting of 40 sub-filters. Figure 2 shows that, on average the optimal Gabor filter can be efficient with some image groups for classification such as groups 3, 4 and 15 (G03, G04, and G15, respectively). The rest groups indicates that there is no significant difference in the classification accuracy between the optimum filter and the bank which consist of 40 filters although in most of them the accuracy by Gabor Bank was slightly better than optimal filter. The redundant information from the filters in the Gabor Bank can cause a decrease in the classification rate, as many filters may capture similar features [25]. In multi-texture classification, there are techniques which can be used to improve the accuracy of image classification by texture and avoid the complications in the execution of Gabor filters such as integrate the optimal filter with other effective analyzing methods of texture.

6 CONCLUSION AND FUTURE WORK

This paper proposed a new optimization method which has been implemented for parameter selection of GF. The ABC involved automatically selecting the optimum filter for multi-texture classification.

6.1 Achievements

The method for multi-texture classification based on extracting the optimal Gabor filter using recent optimization approach instead of Gabor Bank in order to reduce the computation cost. The classification rate of the optimal filter with low dimensional features outperformed the high dimension of filter bank consists of 40 filters with different scales and orientation in some texture groups. However, the Gabor bank exceed single optimal filter with overall classification rate down 5.5 %.

6.2 Future work

In future work, it is recommended to improve the optimal filter by integrating with other feature extraction methods. The selected method may extract complementary features of GF in order to increase the accuracy of multi-texture classification.

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