Robust characteristics for texture classification

AYOUB ABDERRAZAK MAAROUF[1], FELLA HACHOUF[1]

[1] *Université des frères Mentouri Constantine 1 Algerie, Département d'Electronique, l'aboratoire d'Automatique et de Robotique*

Abstract

In this paper, an exhaustive search for relevant characteristics for automatic texture classification has been carried out. These features have been extracted from different cooperative methods dealing with texture characterization. An optimal features vector has been constructed using genetic algorithms (GA) to avoid characteristics redundancy . Then texture classification has been performed using multi-class SVM, k-nearest neighbors, and random forest classifier algorithms. Obtained results on three texture databases are very satisfying against those produced by existing methods.

Keywords

texture, classification, genetic algorithms, optimal features, machine learning

1. Introduction

Texture is one of the most relevant characteristics used to identify objects or regions of interest in an image. Also, texture analysis is one of the central concepts in computer vision [1]. One can identify four major issues on texture analysis: texture synthesis, classification, segmentation, and shape from texture. This work is concentrated on texture classification problems. It consists on the issue of distinguishing objects by there different textures [2, 3]. Thus, the given technique's target is to assign any unknown or test image to at least one of the set of previously known texture classes. Previous works found that the majority of the machine vision-based texture classification techniques have combined texture features with classifiers to supply reasonably good classification accuracy for various images [4, 5]. Texture features provide important information about the primitives that constitute a texture and relationship[6]. Several approaches have been proposed to represent texture. statistical features including co-occurrence matrices [7, 8], Weber Local Descriptor (WLD) [9], Local Binary Pattern (LBP) [10],autocorrelation-based and registration-based features[11]. Structural features include primitive measurements [12], edge measure [13], and morphological operation features. Filter features consist in spatial domain filtering [14], frequency domain analysis [15], and common spatial-frequency methods [16]. Additionally, model-based features include fractal models [17] and auto-regressive models [18].(FIg.1)

In this work, discriminating feature extraction methods have been considered: statistical, structural, model-based, and graph-based approaches. A judicious characteristics vector has been constructed and optimized using genetic algorithms. Because the relevant used features

ICCSA 2021: The 2nd International Conference on Computer Science's Complex Systems and their Applications, May 25–26, 2021, Oum El Bouaghi, Algeria.

ayoub.maarouf@umc.edu.dz (A. A. MAAROUF); hachouf.fella@gmail.com (. F. HACHOUF)
0000-0002-0992-546X (A. A. MAAROUF)

Classes	Methods
Statistical approaches	- Grey level co-occurrence matrix - Grey level run-length matrix - Autocorrelation-based approaches - Histogram of gradient magnitudes - Local mapped patterns-based approaches - Local energy pattern - Variogram - Tamura features - Local binary pattern and variants - Shape index histograms - Weber local descriptor - Deterministic walk
Structural approaches	
Transform-based approaches	- Filter banks: Law's texture features - Fourier transform-based approaches - Gabor decomposition-based approaches - Wavelet-based approaches - Shearlet-based approaches - Contourlet-based approaches - Locally encoded transform feature histogram (LETRIST)
Model-based approaches	- Complex network-based approach - Mosaic models - Random field models - Fractal-based measures - Gravitational models - Wold decomposition
Graph-based approaches	- Local graph structures - Graph of tourist walk approach - Shortest paths in graphs
Learning-based approaches	- Vocabulary learning methods - Extreme learning machine-based methods - Deep learning methods
Entropy-based approaches	- Two-dimensional sample entropy - Two-dimensional distribution entropy - Two-dimensional multiscale entropy

Figure 1: texture features classes.

are issued from different methods, their effects cooperate to characterise a texture, yielding to an optimal features vector. Local binary feature Pattern(LBP), histogram of oriented Gradient (HOG), a two random coefficient auto-regressive model(2D-RCA), and the weber descriptor (WLD) have been chosen to construct our characteristics vector because of the different texture information they provide. A multi-class SVM, K-NN and Random Forest algorithms have been used to classify various texture images. Performances of each classifier using the same constructed vector have been estimated and discussed. This study aims to search the utility of mixing various texture features with different kind of information to classify image databases.

The remainder of this paper is as follows: Section 2 presents the texture features. Section 3 is dedicated to the different used classifiers. Experimental results carried out on three databases are discussed in section 3. Section 4 concludes the paper and offers future work.

2. Texture features

In this section, A brief description of the used parameters is given.

2.1. Local binary Pattern (LBP)

Local Binary pattern is a standard feature descriptor used for texture classification[10]. since its presentation by Ojala methods in 1994, LBP have shown a strong ability to describe a region . A 3x3 window is used in opposition to the local pixels to plot an exciting surface and think about a close-by double example (LBP).

The LBP approach uses a binary pattern to represent each image pixel qc. It is dependent on the difference between the pixel qc's grey level value and the radius R of its circular neighborhood centered at qc. As a result, the LBP codes are calculated as follows.

$$LBP_{P,R}\left(q_c\right) = \sum_{p=0}^{P-1} s(x)2^p \tag{1}$$

where x=qp-qc is the difference between the intensity levels of the neighboring pixels (qp) and the central pixel (qc),s(x) is:

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

for more detail see [10].

2.2. 2D RCA PARAMETERS

This calculation's initial step comprises characterizing the texture with the 2D-RCA models presented by equation.3. The 2D-RCA model is an expansion of the 2D-AR model presented to show some non-Gaussian spatial informational collection, for example, image digitization. Its development was enlivened by the renowned 1D-RCA model broadly utilized in econometric displaying and designing applications. A 2D stochastic cycle follows a 2D-RCA model. The 2D-RCA models proposed in [19] have been drawn on a standard network. The more significant part of the image we measure is made of matrices with sporadic pixels. Luckily, In a few circumstances, information with sporadically divided pixels can be supplanted by an ordinary network utilizing image insertion methods and re-testing programs.

$$X(t) = \sum_{\mathbf{s} \in]\mathbf{0};P]} a_{\mathbf{s}}(\mathbf{t}) x(\mathbf{t} - s) + e(\mathbf{t}), \mathbf{t} \in Z^2 \tag{3}$$

Under stationary conditions, the estimation of the 2D RCA model given by Equation (3) is achieved by the generalized method of moments (GMM) [20]. Based on the observations the GMM estimator of

$$\theta = (\alpha, \beta, \gamma) \tag{4}$$

is:

$$\hat{\theta}_n = \sum_{i=1}^{n} \sum_{j=1}^{m} \lfloor \underline{x}(i,j) \underline{x}'(i,j) \rfloor^{-1} \times \sum_{i=1}^{n} \sum_{j=1}^{m} \lfloor \underline{x}(i,j) X(i,j) \rfloor \tag{5}$$

Where:

$$\underline{\mathrm{x}} = (X(i, j-1); X(i-1, j); X(i-1, j-1)) \tag{6}$$

for more details see [19]

2.3. Weber Local Descriptor

Weber's law (a psychological law) is the foundation for the Weber local descriptor (WLD) [9]. There are two sections of this descriptor. As a result, two components of the WLD function are calculated for each pixel of the image under research: differential excitation and gradient orientation.

$$\begin{aligned} \xi\left(I_c\right) &= \arctan\left[\sum_{i=0}^{p-1}\left(\frac{i_i^{-} l_c}{I_c}\right)\right] \\ \theta\left(I_c\right) &= \operatorname{median}\left\{\frac{I_{R(i+4)}-I_i}{I_{p(i+1)}-I_{p(i+2)}}\right\}; i=0,1,\ldots p-1 \end{aligned} \tag{7}$$

Ic is the central pixel of a given neighborhood, and Ii is an Ic's neighbor.

The ratio between the relative intensity differences of a current pixel against its neighbors and the current pixel's intensity determines the differential excitation variable. The gradient orientation of the current pixel is the orientation variable. As a result, the descriptor is influenced by both the local intensity difference and the size of the intensity of the middle pixel. Then, WLD concatenates these two components of all pixels to construct a final histogram.

2.4. Histogram of oriented Gradient (HOG)

Histogram of oriented Gradient features is one of the most descriptors of images. The hog features consist to describe an image by a set of local histograms. Then, the occurrences of gradient orientation are assembled in a small spatial localized part of the image. The subsequent concatenation of 1-D histograms produces the features vector. Let the image's intensity value be analyzed is L. If the image is divided into N x N cells of size. The orientation θx,y of the gradient in each pixel is calculated using Equation (7).

$$\theta_{x,y} = \tan^{-1} \frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)} \tag{8}$$

The successive orientation θ_i^j, i=1…….N2 belonging to the same cell j is quantized and accumulated into an M-bins histogram. Then, the histograms accumulated into a single HOG histogram.

2.5. FILTER BANKS: LAW'S TEXTURE FEATURES

The application of basic filters to digital images is used in this feature extraction process. It consists of two stages[21]. To generate twenty-five 3×3 or 5 ×5 masks, multiple 1D arrays are convolved together in a combinatorial way . The texture field is then convolved with the latter to emphasize its micro structure. This yields to an image from which the micro structure's energy (and other statistics) can be calculated. Second, macrostatistic characteristics are derived from data collected over time. Five 1D arrays (size of 5) have been specified by Laws:

- Level L5 D [1 4 6 4 1]
- Edge E5 D [-1 - 2 0 2 1]
- Spot S5 D [-1 0 2 0 - 1]
- Wave W5 D [-1 2 0 - 2 1]
- Ripple R5 D [1 - 4 6 - 4 1].

Steerable filters have also been proposed for directed textures. They are a group of orientation-selective filters created by combining a linear combination of basis filters. Unser and Eden [22] have suggested a nonlinear transformation and an iterative Gaussian smoothing algorithm to create an analogous filter bank. At the performance of this analogous filter bank, the local statistics (texture energy measures) are computed. Mellor et al. [23] suggested a system based on invariant linear filter combinations in 2008. This method consists of two steps: the first is to compute two descriptors for each point in the image. The polar-separable filters form the Hessian matrix, and the eigenvectors (principal directions) and eigenvalues (principal curvatures) of the matrix are then computed. These eigenvectors and eigenvalues are then converted to local phases and energies. Contrast transitions, intensity shifts, rotations, and scaling have little impact on these descriptors locally. They're also resistant to skewing. The texture is then interpreted using these descriptors' first order statistics.

2.6. LOCAL GRAPH STRUCTURES

The characteristics of local graph structures are derived from the texture. A graph of points is used to represent the image [24]. Local graph systems are involved by a specific function on a pixel's six neighbors. As a threshold, the target pixel I(x; y) is selected. By rotating anti-clockwise at the left region of I(x; y), the neighbors pixels of I(x; y) are "visited" (x; y). If the neighbor pixel has a higher (or equal) grey value than (as) I(x; y), the edge separating the two vertices is given a binary value 1, otherwise a binary value 0 is assigned. When the left region is completed. The same procedure is repeated in an horizontal (clockwise) direction on the graph's right side. The decimal value is then calculated using the generated string. The expanded local graph form was suggested in 2016. In order to collect more spatial detail, the latter takes into account both the vertical and horizontal graphs. As a result, we have two descriptors. For each descriptor, an histogram is generated independently. The attributes of the two histograms are then combined to create a global descriptor.

3. Feature selection using GA

the amount of information carried out by the feature vector is too huge, for large images execution time and required memories space are increased. A solution to resolve this problem is to optimize the number of features.hence irrelevant features are taken of the characteristics vector avoiding data redandinding and time and space consuming.thus GA have been used to optimize this vector.

The next step after extracting features involves the combination of all features extracted to get more accurate results. The dimensions for the fused feature vector are 1×44 for each image. The high dimensional features increase the system execution time and space requirement for processing. For that, the feature selection techniques are used to find a subset of most relevant features from irrelevant data, where not pertinent denotes the redundant features, these fused features are fed to GA for feature optimization[25]. Here a GA approach is utilized for feature selection having cost function mean squared error (MSE). The best-selected features are fed to all classifiers used in the presented method for classification. In the presented work, a feature selection technique is used to improve the classification accuracy's performance to remove the redundancy between features.

The essential components of Genetic algorithms are:

1. Initial population of chromosomes: Let m be the number of features. The size of population is N. To create random population P of N number of chromosomes is given below: P = [C1, C2, ... CN]
2. Fitness function: mean squared error is used to evaluate the fitness of each individual population.
3. Selection: Select two parents from population according to their best fitness, which can generate new offspring. It assures that only the best fittest solutions made to generate offspring.
4. Recombination or Crossover: Recombinant the parents to form new offspring from two parents string, by copying selected bit of each parents.
5. Mutation: after the performance of crossover, mutate the new offspring from single parent. It reduces local optimum.

4. TEXTURE CLASSIFICATION

The above-presented characteristics have been extracted from textured images. efficiency of each feature has been tested using three machine learning classifiers (multiclass SVM, K-NN, Rf algorithms). Then, the classification has been performed using the concatenation of these features as a data vector for each classifier; the proposed method is presented in fig 2.

4.1. SUPPORT VECTOR MACHINE (SVM)

Support vector machine is a supervised machine learning models. The objective is to find the optimal hyper plane to separate sets of feature vectors into two classes[26]. The SVM training rule devises a model that appends new samples (test data) to one of the two classes.

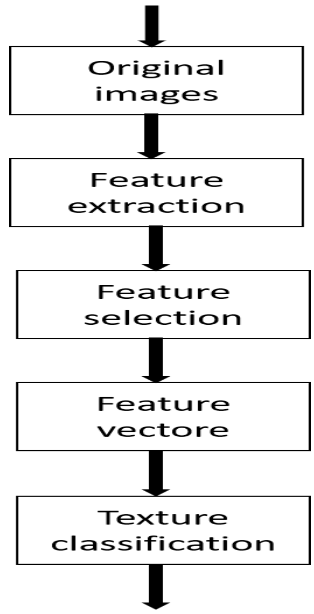

Figure 2: proposed method.

Another significant advantage of exploitation SVM is that it will effectively perform nonlinear classifications by exploiting applicable kernel performance. The rule uses a nonlinear kernel function rather than each real number. The Gaussian radial basis (RBF) is employed because of this paper's kernel function. The radial basis performs on two samples xi, and xj is of the form:

$$K\left(\mathrm{x}_i, \mathrm{x}_j\right) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{9}$$

Support Vector Machines designed for binary classification. When it addresses many categories, as in object in image classification, one needs an appropriate multi-class method. Different possibilities include: Modify the design of the SVM, as in, to incorporate the multi-class learning directly in the quadratic solving algorithm. x Combine several binary classifiers: "One-against one" (OAO) applies wise pair comparisons between classes, while "One-against-All" (OAA) compares a given class with all the others put together.

4.2. K NEAREST Neighbors

A popular non-parametric technique employed for classification and multivariate analysis is the k-Nearest Neighbors (k-NN) algorithm [27]. The k-NN algorithm measures the distance between an objective purpose and a collection of points in the data set. It assigns the target (test) purpose to the most specific category between its k nearest neighbors around it. Discussion associated with neighbors implies that there should be a distance or unsimilarity measurement that may be computed between samples victimization the freelance variables. The instances concerned within the paper consider the only accepted measure of distance, i.e., Euclidean distance. The Euclidean distance between any two points x and y is:

$$d(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{10}$$

4.3. Random Forest

Random Forest (RF) is an ensemble of classification trees.Every tree contributes with one vote for the assignation of the foremost frequent category to the input file [28]. RF uses the most effective split of a random subset of input features or predictive variables within each node's division, rather than mistreatment the most effective split variables, which reduces the generalization error. Besides extending the variety of the trees, RF uses Bagging or bootstrap aggregating to grow from totally different training information subsets. Bagging could be a technique used for training information creation by resampling the first dataset with replacement, i.e., with no deletion of the input sample's information for generating a succeeding subset. Thus, every set selected mistreatment bagging to form every individual three grow containing a precise proportion of the standardization dataset. The samples that do not seem to be a gift within the calibration set are included as a part of another collection referred to as out-of-bag (OOB). Note that a particular OOB set is made for every three of the ensembles, from the bootstrapping method's non-selected parts. The tree will classify these OOB parts that do not seem to be thought-about for the the-tree coaching to evaluate his performance.

5. Results and Discussion

Various tests have been executed on three databases with several classes, including, Broadatz Database [29], KTH-TIPS [30] and the UIUC [31]. Broadatz Dataset is yhe well-known texture dataset. This dataset is devoted to rotation-invariant texture recognition.It consists of thirteen texture categories from the initial Broadatz album and contains 1248 Pictures of dimensions 128×128 pixels. Textures are given in six different rotation angles (0^o, 30^o, 60^o, 90^o, 120^o, 150^o). The number of samples per category and Orientation is sixteen images.

KTH is the abbreviation for Kungliga Tekniska Högskolan University and TIPS. It stands for textures under Varying illumination, pose and scale. Images have been taken at nine different scales spanning two octaves. At the significant scale, the distance between the camera and the target was 28 cm. In this study, we used nine different types, with 81 images for each class. The considered textures are sandpaper, crumpled aluminum foil, styrofoam, sponge, corduroy, linen, cotton, brown bread, orange peel, and cracker.

UIUC database contains 25 texture classes. Each class contains 40 samples. All images are in greyscale JPG format at 640×480 pixels. Figures 2–4 show samples from each database

To evaluate the performance of the proposed method, a 5-fold cross-validation technique has been computed. The three texture image databases have been used to collect training and test sets. each fold is divided into an 80% train set and a 20 % test set. The training and testing are conducted five times. This process guarantees that each data point ends up in the 20 % test set exactly once. The model has achieved good performance among the five distortions.

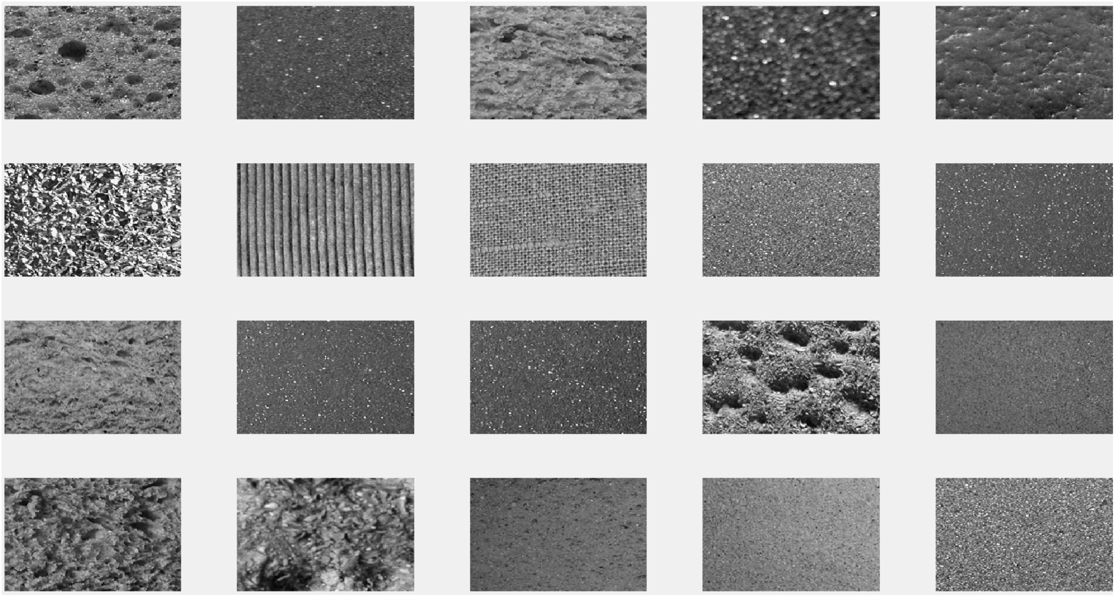

Figure 3: image database.

GA is performed to reduce the number of features. The feature set containing six characteristics is used as entries of the three classifiers. A population of 30 chromosomes has been randomly generated. Each chromosome contains 44 genes (One gene for each feature). One-point crossover and mutation genetic operators have been used. The crossover rate has been set to 90%, and the mutation rate to 10%. The Tournoi selection method has been used to select the mating pool.

Classification results are presented in three different steps. In the first step, classification is performed on each feature. Then, in the second step, a fused features vector has been used.

The best features selection method fitted by the GA is performed. Classification results have obtained with 40/50 training and testing sets.

Table 1 presents each feature's performance in each dataset with several classifiers and the fusion of texture features results.It is noticed that combining the four classes of features is the best method among all. It remarkably outperforms all others in all datasets. Then the classification results are calculated for feature selection In the first test, training/ testing part 40/60 has been selected. It achieves a classification accuracy of 98.4 %. It is clear from this table that the proposed selection method gives better results than the first two ones.

Another constructive and useful approach to evaluate the performance of the classifier is the confusion matrix. Such a matrix aims to show the number of class A elements that are assigned to class B. For instance, we chose to show the confusion matrices for the three datasets.

We can observe from table 1 and figure 2 and 3 that the best classification result has been obtained using the random forest classifier to combine the four classes of features. This is due to:

- It is unexcelled in exactness among current calculations.

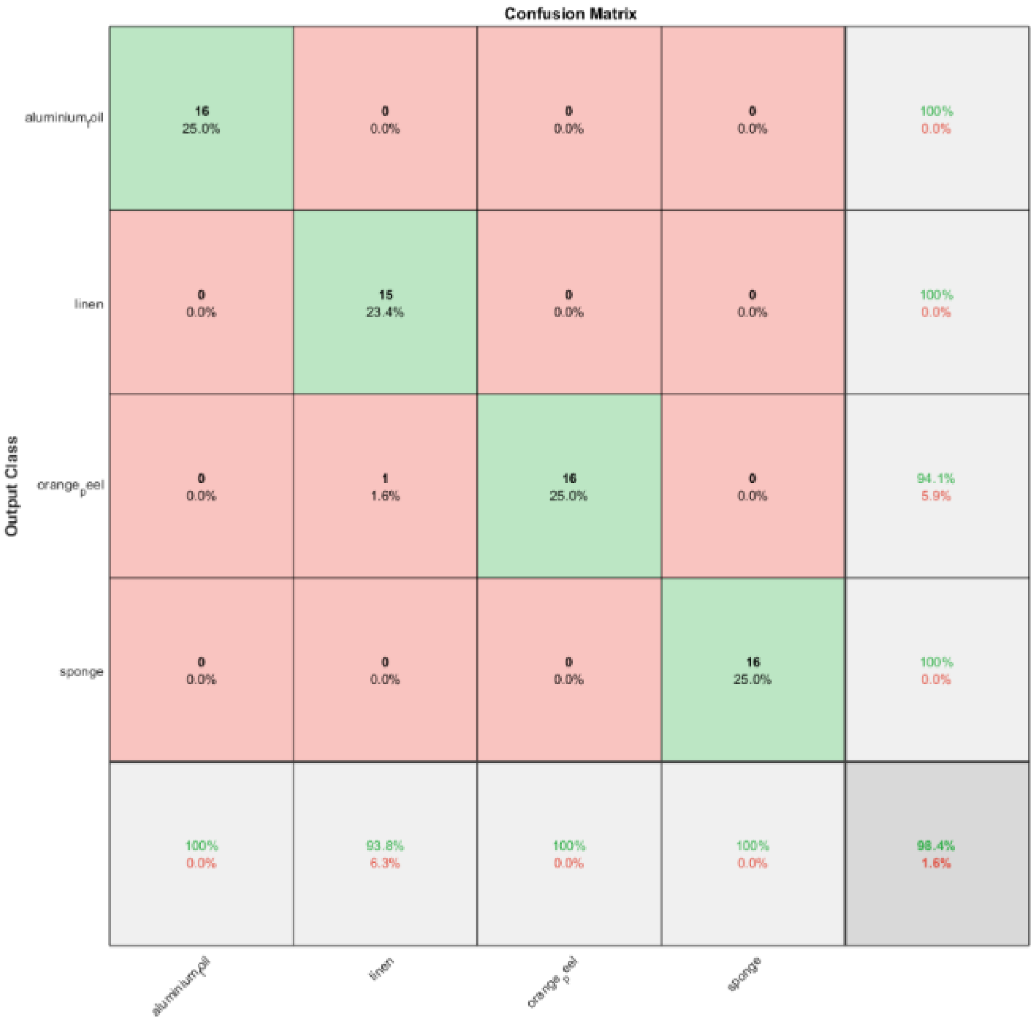

Figure 4: confusion matrix using four classes with Rf classifiers.

- It runs effectively on enormous information bases.
- It can deal with a large number of information factors without variable erasure.
- It is computationally faster than other tree troupe strategies

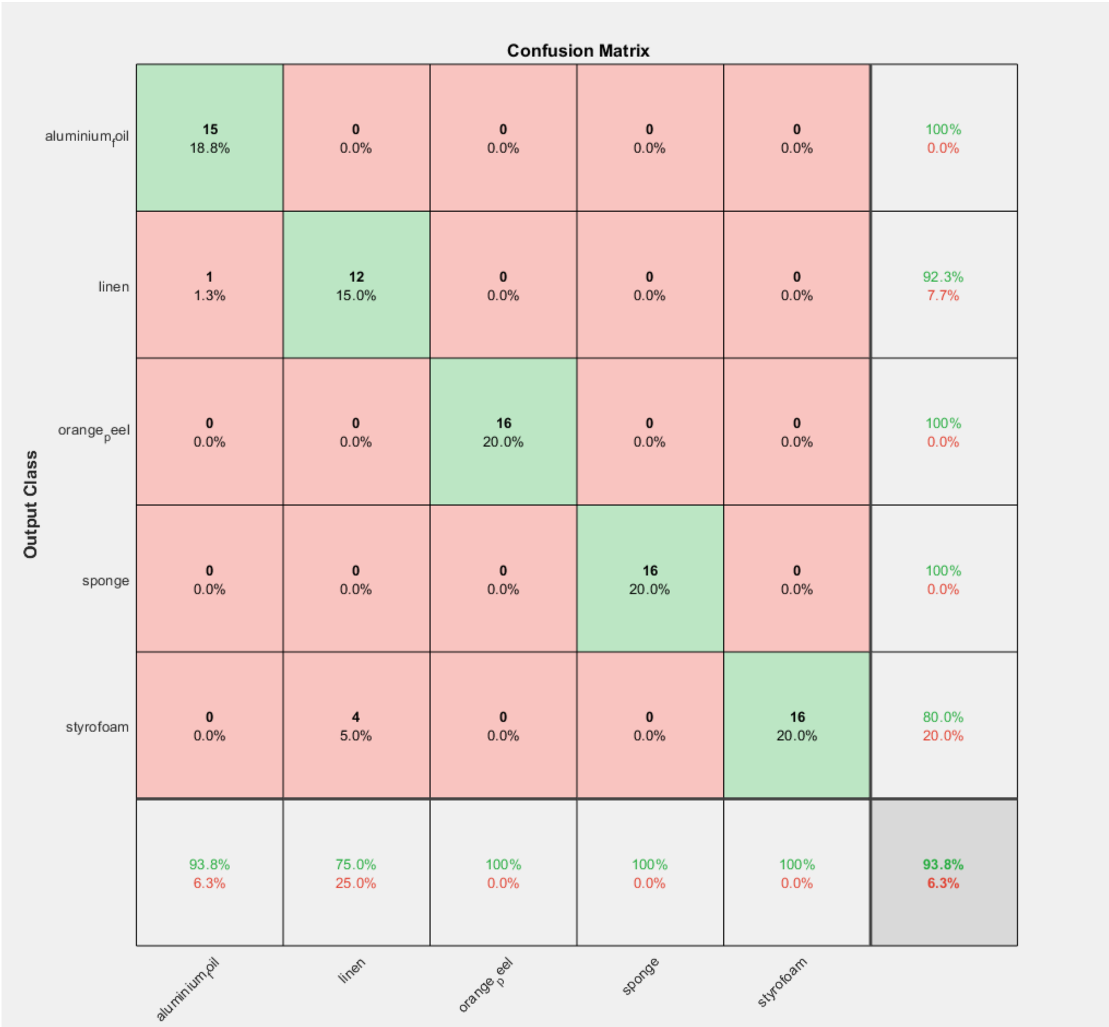

Figure 5: confusion matrix using five classes with Rf classifiers .

Table 1
Texture classification accuracy

Classification accuracy									
features	Brodatz database			Kh tips			UIUC database		
classifiers	SVM	KNN	RF	SVM	KNN	RF	SVM	KNN	RF
FILTER BANKS	77.652	72.45	77.5	79.123	78.463	79.402	79.8	78.45	79.652
LOCAL GRAPH STRUCTURES	78.45	75.785	78.516	78.45	76.45	77.45	78.45	75.45	79.4
2DRCA parameters	89.45	89.45	88.5	89.45	89.45	89.45	73.8	89.45	87.4
HOG	86.75	84.125	86.45	81.5	80.450	82.45	80.4	79.05	82.2
WDT	85.75	81	85.25	82.67	80.125	83.5	79.45	70.75	82.4
LBP	8.45	89.45	87.5	81.02	75.8	80.3	85.8	84.7	85.8
Combination of for features	92.5	88.3	98.2	90.4	80.1	96.32	88.8	84.3	90.75
Combination of for features using gA	94.5	90	**99**	91.4	80.1	**98.4**	91.8	86.3	**93.75**

6. Conclusion

in this paper, an unique combination of features extraction methods for texture classification is proposed .Genetic algorithms have been used to pick the best features from a fused vector which are then fed to three machine learning classifiers for classification: multi-class support vector machine, K-nearest neighbors and random forest. The proposed approach has been validated on three data sets. The proposed technique's classification accuracy is substantially higher than most current approaches, according to the experimental results. As a result of the above discussion, it can be concluded that combining different types of texture features with the best selection algorithm yields better results than using a random combination of features. As a future work, we are planning to extend this work to color images classification.

References

[1] H.-C. Lin, L.-L. Wang, S.-N. Yang, Regular-texture image retrieval based on texture-primitive extraction, Image and Vision Computing 17 (1999) 51–63. Publisher: Elsevier.

[2] F. Lopez, F. Acebron, J. Valiente, E. Perez, A study of registration methods for ceramic tile inspection purposes, in: Proceedings of the IX Spanish symposium on pattern recognition and image analysis, volume 1, 2001, pp. 145–150.

[3] J. Y. Tou, Y. H. Tay, P. Y. Lau, A comparative study for texture classification techniques on wood species recognition problem, in: 2009 Fifth International Conference on Natural Computation, volume 5, IEEE, 2009, pp. 8–12.

[4] S. Das, U. R. Jena, Texture classification using combination of LBP and GLRLM features along with KNN and multiclass SVM classification, in: 2016 2nd International Conference on Communication Control and Intelligent Systems (CCIS), IEEE, 2016, pp. 115–119.

[5] O. Aiadi, M. L. Kherfi, Image classification using texture features and support vector machine (svm) (2019).

[6] A. Humeau-Heurtier, Texture feature extraction methods: A survey, IEEE Access 7 (2019) 8975–9000.

[7] R. M. Haralick, Statistical and structural approaches to texture, Proceedings of the IEEE 67 (1979) 786–804. Publisher: IEEE.

[8] G. Srinivasan, G. Shobha, Statistical texture analysis, in: Proceedings of world academy of science, engineering and technology, volume 36, 2008, pp. 1264–1269.

[9] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikäinen, X. Chen, W. Gao, Wld: A robust local image descriptor, IEEE transactions on pattern analysis and machine intelligence 32 (2009) 1705–1720.

[10] T. Ojala, M. Pietikäinen, D. Harwood, A comparative study of texture measures with classification based on featured distributions, Pattern recognition 29 (1996) 51–59.

[11] T. Toyoda, O. Hasegawa, Texture classification using extended higher order local autocorrelation, in: International Workshop on Texture Analysis and Synthesis, Citeseer, 2005, pp. 131–136.

[12] A. Mehnert, R. Moshavegh, K. Sujathan, P. Malm, E. Bengtsson, A structural texture approach for characterising malignancy associated changes in pap smears based on mean-

shift and the watershed transform, in: 2014 22nd International Conference on Pattern Recognition, IEEE, 2014, pp. 1189–1193.
[13] K. Mikolajczyk, A. Zisserman, C. Schmid, Shape recognition with edge-based features, in: British Machine Vision Conference (BMVC'03), volume 2, The British Machine Vision Association, 2003, pp. 779–788.
[14] J. M. Coggins, A. K. Jain, A spatial filtering approach to texture analysis, Pattern recognition letters 3 (1985) 195–203.
[15] A. W. Lohmann, Image rotation, wigner rotation, and the fractional fourier transform, JOSA A 10 (1993) 2181–2186.
[16] T. P. Weldon, W. E. Higgins, D. F. Dunn, Efficient gabor filter design for texture segmentation, Pattern recognition 29 (1996) 2005–2015.
[17] G. R. Cross, A. K. Jain, Markov random field texture models, 1983.
[18] J. Anděl, Autoregressive series with random parameters, Mathematische Operationsforschung und Statistik 7 (1976) 735–741.
[19] A. Boulemnadjel, F. Hachouf, S. Kharfouchi, Gmm estimation of 2d-rca models with applications to texture image classification, IEEE Transactions on Image Processing 25 (2015) 528–539.
[20] H. H. Kelejian, I. R. Prucha, A generalized moments estimator for the autoregressive parameter in a spatial model, 1999.
[21] R. Shenbagavalli, K. Ramar, Classification of soil textures based on laws features extracted from preprocessing images on sequential and random windows, Bonfring International Journal of Advances in Image Processing 1 (2011) 15–18.
[22] M. Unser, M. Eden, Multiresolution feature extraction and selection for texture segmentation, IEEE Transactions on Pattern Analysis and Machine Intelligence 11 (1989) 717–728.
[23] M. Mellor, B.-W. Hong, M. Brady, Locally rotation, contrast, and scale invariant descriptors for texture analysis, IEEE Transactions on pattern analysis and machine intelligence 30 (2007) 52–61.
[24] E. E. Abusham, H. K. Bashir, Face recognition using local graph structure (lgs), in: International Conference on Human-Computer Interaction, Springer, 2011, pp. 169–175.
[25] D. E. Golberg, Genetic algorithms in search, optimization, and machine learning, Addion wesley 1989 (1989) 36.
[26] J. A. Suykens, J. Vandewalle, Least squares support vector machine classifiers, Neural processing letters 9 (1999) 293–300. Publisher: Springer.
[27] L. E. Peterson, K-nearest neighbor, Scholarpedia 4 (2009) 1883.
[28] L. Breiman, Random forests, Machine learning 45 (2001) 5–32. Publisher: Springer.
[29] F. Díaz-Pernas, M. Antón-Rodríguez, J. Díez-Higuera, M. Martínez-Zarzuela, D. González-Ortega, D. Boto-Giralda, Texture classification of the entire brodatz database through an orientational-invariant neural architecture, in: International Work-Conference on the Interplay Between Natural and Artificial Computation, Springer, 2009, pp. 294–303.
[30] B. Caputo, E. Hayman, P. Mallikarjuna, Class-specific material categorisation, in: Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1, volume 2, IEEE, 2005, pp. 1597–1604.
[31] S. Lazebnik, C. Schmid, J. Ponce, A sparse texture representation using local affine regions, IEEE transactions on pattern analysis and machine intelligence 27 (2005) 1265–1278.