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Texture Classification System Based on 2D-DOST Feature Extraction Method and LS-SVM Classifier

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Feature extraction

Abstract: In this paper, a new 2D-DOST (Two-Dimensional Discrete Orthonormal Stockwell Transform) and LS-SVM (Least Squares Support Vector Machines) based classifier system is proposed for classification of texture images. The proposed system contains two main stages. These stages are feature extraction and classification. In the feature extraction stage, the distinguishing feature vectors which represent descriptive features of texture images are obtained by using a 2D-DOST based feature extraction method. In the classification stage, the texture images are classified by the LS-SVM since this classifier has high success rate and accuracy. The training of LS-SVM is performed on the distinguishing feature vector of each texture component. Texture samples are recognized by the test data applied to the input of trained LS-SVM classifier. Performance evaluations of the proposed method are carried on different datasets obtained from sub-images. These datasets include both the normal texture images and noise added images. Sub-images into datasets are derived from Brodatz and Kylberg texture images database. Gaussian and Salt & Pepper noise with different levels are used for creating noisy datasets. According to the study results, the proposed 2D-DOST and LS-SVM based classifier has a capability of classifying texture images with high success rate and noise robustness.

2D-DOST Özellik Çıkarımı Yöntemi ve LS-SVM Sınıflandırıcı Tabanlı Doku Sınıflandırma Sistemi

Anahtar Kelimeler
Doku sınıflandırma,
Görüntü işleme,
Özellik çıkarımı

Özet: Bu çalışmada, doku görüntülerinin sınıflandırılması için 2D-DOST (İki Boyutlu Ayrık Orthonormal Stockwell Dönüşümü) ve LS-SVM (En Küçük Kareler Destek Vektör Makineleri) tabanlı yeni bir sınıflandırıcı sistemi önerilmiştir. Önerilen sistem, özellik çıkarımı ve sınıflandırma olmak üzere iki ana bölümden oluşmaktadır. Özellik çıkarımı aşamasında, görüntüleri temsil eden ait ayırt edici özellik vektörleri 2D-DOST tabanlı özellik çıkarım yöntemi ile elde edilmektedir. Sınıflandırma aşamasında ise yüksek başarım oranı ve doğruluğa sahip olan LS-SVM sınıflandırıcısı ile doku görüntüleri sınıflandırılmaktadır. LS-SVM'nin eğitimi her bir doku görüntüsüne ait ayırt edici özellik vektörleri üzerinde gerçekleştirilmiştir. Test verisi olarak hazırlanan doku görüntüleri eğitilmiş LS-SVM sınıflandırıcının girişine uygulanmıştır. Önerilen yöntemin performans testleri için alt-görüntüler ile elde edilen farklı veri setleri üzerinde gerçekleştirilmiştir. Bu veri setleri hem normal doku görüntülerini hem de gürültülü doku görüntülerini içermektedir. Veri setleri içerisindeki alt görüntüler Brodatz ve Kylberg doku veri tabanlarından türetilmiştir. Gürültülü verilerin oluşturulmasında, farklı seviyelerde Gaussian ve Tuz&Biber gürültüsü kullanılmıştır. Çalışma sonuçları, önerilen 2D-DOST ve LS-SVM tabanlı sınıflandırıcının doku görüntülerini yüksek başarım oranı ile sınıflandırabildiğini ve gürültüye karşı gürbüz olduğunu göstermektedir.

1. Introduction

Analysis of texture images is a common research topic in the field of computer vision and image processing. Textures are frequently used in the fields of machine vision such as surface examinations, scene classification, surface orientation and object recognition [1]. The classification process of texture

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images is a popular field of study in texture analysis. Texture analysis methods generally consist of feature extraction and classification stages. At feature extraction stage, feature vectors are generated by obtaining a set of distinguishing characterizations for each texture images. These feature vectors that contain significant information about texture samples are used in the classification process. Therefore, an effective feature extraction substantially affects the performance of classification stage.

The approaches used in extraction of texture image features are generally divided into three categories. These categories are statistical, model-based and signal processing [2]. In statistical-based approaches, some statistical methods are applied on the image pixels and certain portions of the image. Co-occurrence matrix method is one of the most important statistical methods used in texture images [3]. Another important statistical method is Local Binary Pattern method [4, 5]. Model-based methods function according to probability distributions in random fields in characterizing the texture images. The commonly used model-based methods are Autoregressive Model (AR) [6, 7], Markov Chains and Markov Random Fields (MRFs) [8, 9], Wold decomposition model [10] and spatial auto-correlation function model [11]. Many various filtering techniques are used for decomposition of texture images in the methods based on signal processing technique. Gabor filters [12-14] and wavelet transform [15-17] are frequently-used signal processing techniques in texture analysis. In Gabor filtering, image data are decomposed by filter bank set to various spatial-frequencies and orientations by covering the suitable spatial frequency domain. Decomposed image coefficients are used for generating feature vectors. Wavelet transform method is also similar to the Gabor method. Wavelet-based method has Discrete Wavelet Transform (DWT) filters instead of Gabor filters. Another feature extraction method used in the literature is DOST [18]. The DOST has been successfully applied in signal analysis to channel instantaneous frequency analysis. It has also been recently applied to image processing such as image texture analysis [19], image restoration [20] and image compression [21].

In the classification stage of the texture analysis, some basic classifiers are used effectively. Generally, these classifiers are trained with image feature vectors and then texture images are automatically recognized. Backes et al. [22] presented a complex network theory for classification of texture images. In the study of [2], classification and segmentation of texture samples were performed by applying the Gaussian-mixture model based classifier on texture features obtained from the feature extraction. Sengur et al. [23] proposed a Wavelet Packet Neural Network method for classification of texture samples. They used Multi-Layer Perceptron classifier on the features obtained from the wavelet packet feature extraction. SVM based texture classification works are conducted in the studies [24-26]. Avcı et al., [27], performed the algorithm called GDWNN which uses the combinations of Genetic Algorithm, DWT, and Neural Network in classification of texture images. Celik and Tjahjadi [28] proposed a Dual-Tree Complex Wavelet Transform-based classifier method for classification of texture images. Karabatak et al., [29] suggested a wavelet domain association rules based classification method to classification of texture images.

In this study, a new 2D-DOST and LS-SVM based classifier algorithm for classification of texture images has been proposed. Due to its multi-resolution nature and effective time-frequency representation, 2D-DOST method is used in the feature extraction stage of this algorithm. Horizontal and vertical frequency-time components of the texture images are obtained from 2D-DOST method. In the classification stage, the LS-SVM classifier is used on the feature vector that obtained from the feature extraction.

The main aim of this study is to generate distinctive feature of texture images using a new algorithm based on 2D-DOST feature extraction method. Thus this algorithm can be a new approach for the recognition of the texture images. The performances of the proposed classifier algorithm on both normal and noisy data are evaluated separately. The performance results are showed that 2D-DOST and LS-SVM algorithm can be effectively used in the texture classification. Proposed algorithm gives reasonable success rate for modern texture samples as Kylberg dataset. When the classification results in this article compared to the various feature selection, classifier and other similar literature studies, our proposed method has a higher classification performance than other.

2. Proposed Texture Classification Method

In this study, we proposed a 2D-DOST and LS-SVM based method in classification of texture images. In this classification algorithm, 2D-DOST method is used for extraction distinctive features of the texture images. A number of statistical methods are applied on the horizontal and vertical coefficient components obtained by means of the 2D-DOST methods. The outputs of statistical methods are used to generate feature vectors. These feature vectors involve distinguishing information about the texture images. The feature vectors are applied to the LS-SVM classifier as input data and the texture images are classified. The block scheme showing the operating structure of the proposed 2D-DOST and LSSVM classifier system is given in the Figure 1.

The steps of the proposed classifier system can be defined as follows:

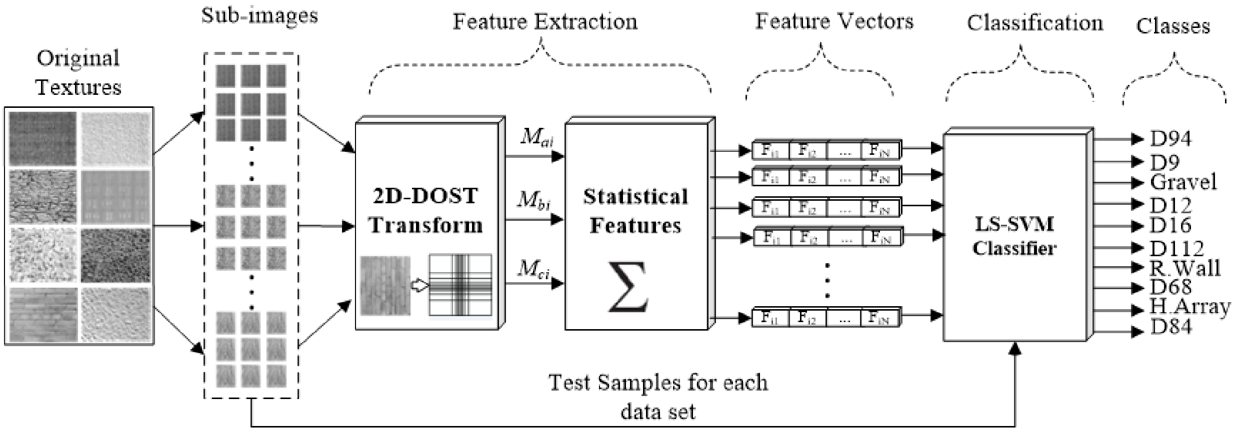

Figure 1. Block scheme showing the structure of the proposed texture classification system.

Step 1: Sub-images of sizes 128 *x* 128 derived from the original texture database randomly. These derived sub-images are used as input data of the classification algorithm.

Step 2: dimensional coefficient matrices (M_a, M_b, M_c) are obtained by using the 2D-DOST method on the sub-images. These coefficient matrices involve the values in the specified ranges of time-frequency bands belonging to the transformed texture images. The voice frequencies band widths are in the form. For this study we specified three different bandwidths that determined coefficient matrices. These bandwidths were defined as β=4, 16 and 32. The bandwidths were selected by considering low and high frequency components. In Figure 2 is shown the some sample texture images and its 2D-DOST transform results.

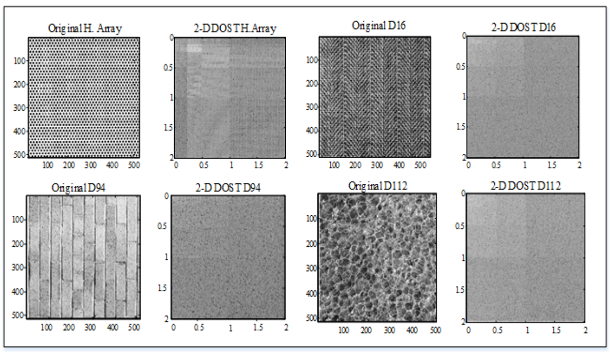

Figure 2. Images of some texture samples and its 2-D DOST results.

Step 3: Some basic statistical methods such as energy, mean, standard deviation, entropy, contrast and homogeneity are applied on the M_a, M_b and M_c coefficient matrices. The values calculated from the statistical methods for each of the texture image are used for building feature vectors. The dimensions of the feature vectors are 18 (6 methods *x* 3 matrices). Equations associated with some basic statistical methods are as follows:

$$Entropy = -\sum_i \sum_j M[i,j] \log M[i,j] \quad (1)$$

$$Energy = \sum_i \sum_j M^2[i,j] \quad (2)$$

$$Contrast = \sum_i \sum_j (i-j)^2 M[i,j] \quad (3)$$

$$Homogenity = \sum_i \sum_j \frac{M[i,j]}{1+|i-j|} \quad (4)$$

Step 4: The training of classifier is performed with the feature vectors of training datasets. These feature vectors are applied on the input of LS-SVM classifier. LS-SVM classifier has some kernel function such as RBF, linear, polynomial. In this study, RBF kernel is used as the kernel function for the LS-SVM classifier. A linear search method is employed to determine the optimum range of Gamma (ϒ) and Sigma (σ^2) values the parameters of kernel function. The performance of classifier is obtained for all determined range of values of ϒ and σ^2 in the linear search algorithm. The ϒ and σ^2 values at highest classifier accuracy are determined as classifier parameters.

Step 5: At this step, test data are applied on the trained LS-SVM classifier input. The class information formed as a result of classification for each test data is transferred to the output. The performance evaluations are carried out by comparing the obtained output data and the actual data. Finally, correlation matrices are generated for each texture images. Correct and incorrect classification results are used for evaluating performance of the classifier algorithm.

2.1 Datasets

In this study, two different texture dataset are used. First dataset consist of 10 textures that selected from the Brodatz [30] texture images. Second dataset includes 10 different textures that selected from Kylberg [31] texture images dataset. Brodatz texture images in the sizes of 512 *x* 512 are given in the Figure 3 and Kylberg texture images in the sizes of 576 *x* 576 are given in the Figure 4. Random sub-images are created in different quantities in the sizes of 128 *x* 128 for each texture image. Brodatz dataset involves normal, Gaussian noise, Salt & Pepper noise and mixed data. Gaussian and Salt & Pepper noises are added at α=0.1, 0.2 … 0.5 levels (10 texture *x* 20 sub-images *x* 5 noisy level). Kylberg dataset involves only normal datasets. Performance evaluation of the proposed algorithm is performed on these dataset both separately and hybrid. The numerical distribution information regarding the datasets prepared under the study is given in Table 1.

3. Experimental Results

For the experimental results, classification processes are performed separately on the training and test data given in Table 1. The features obtained from feature extraction for each texture set are applied on the input of LS-SVM classifier. Classifier is trained with these distinctive features and successfully learned each texture images. Then, the classifier is automatically recognized test data and classifies each test data. LS-SVM kernel parameters are optimally determined to improve performance of the classification. It is ensured that highest rate of classification is obtained by applying the kernel parameters in the range of Υ= {1:10:1000} σ^2= {0.1:0.1:10} on the classifier. The results of classification studies on the Brodatz dataset are given in Table 2. Proposed method achieved a success rate as high as 98.7% on the normal dataset. The success rates for the noisy datasets are 82.00% for Gaussian noise and 81.50% for Salt & Pepper noise. Also, it can be seen that the classifier has a high success rate as 98.37% on the mixed datasets which have noisy and normal data together.

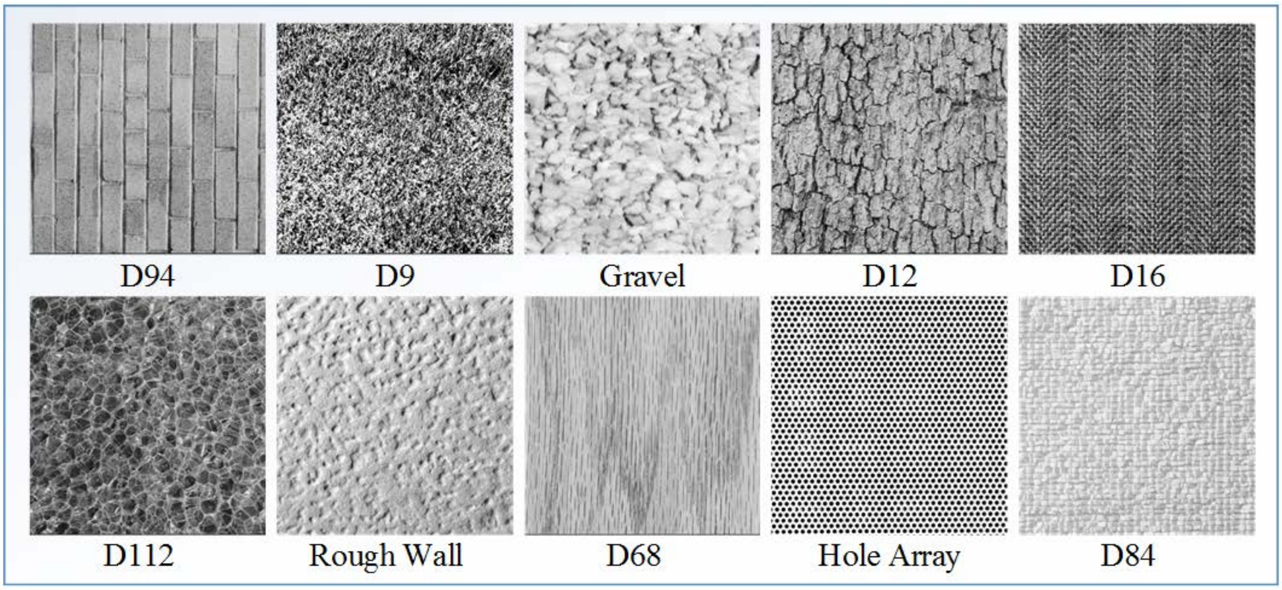

Figure 3. Brodatz texture images gallery used in the study.

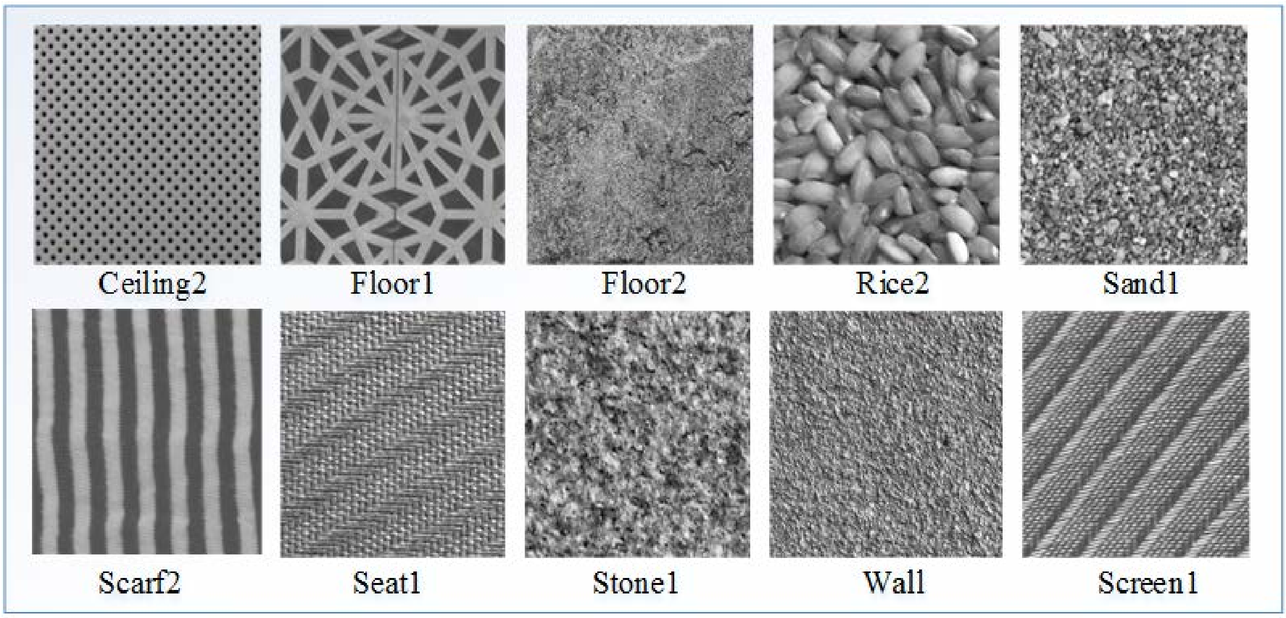

Figure 4. Kylberg texture images gallery used in the study.

Table 1. Numerical distribution table of datasets.

Data Set	Type	Number of Train Data Set	Number of Test Data Set	Number of Total Data Set
Brodatz	*Normal Dataset*	10*T* x 100*S*=1000	10*T* x 100*S*=1000	2000
	Gaussian Noisy	10*T* x 20*S* x 5*α* =1000	10*T* x 20*S* x 5*α* =1000	2000
	Salt & Pepper Noisy	10*T* x 20*S* x 5*α* =1000	10*T* x 20*S* x 5*α* =1000	2000
	Mixed Dataset	990	990	1980
Kylberg	*Normal*	10*T* x 100*S*=1000	10*T* x 100*S*=1000	2000
T: Texture *S*: Sub-image *α:* Noisy level				

Table 2. Experimental results of the proposed 2D-DOST and LS-SVM classifier system on the Brodatz dataset.

	Normal Data Set			Gaussian Noisy Dataset			Salt & Pepper Noisy Data Set			Mixed Data Set		
Textures	*Kernel Parameters Υ=210, σ²=8.1*			*Kernel Parameters Υ=10, σ²=7.0*			*Kernel Parameters Υ=10, σ²=6.0*			*Kernel Parameters Υ=200, σ²=5.2*		
	Correct	**Miss**	**Success**	**Correct**	**Miss**	**Success**	**Correct**	**Miss**	**Success**	**Correct**	**Miss**	**Success**
D94	100	0	100%	100	0	100%	100	0	100%	99	0	100%
D9	100	0	100%	100	0	100%	100	0	100%	99	0	100%
Gravel	100	0	100%	65	35	65%	65	35	65%	99	0	100%
D12	98	2	98%	80	20	80%	80	20	80%	94	5	94.94%
D16	96	4	96%	45	55	45%	45	55	45%	98	1	98.98%
D112	100	0	100%	95	5	95%	95	5	95%	98	1	98.98%
R.Wall	95	5	95%	80	20	80%	85	15	85%	95	4	95.95%
D68	100	0	100%	100	0	100%	100	0	100%	99	0	100%
H.Array	98	2	98%	60	40	60%	50	50	50%	95	4	95.95%
D84	100	0	100%	95	5	95%	95	5	95%	98	1	98.98%
	Mean Success = 98.70%			***Mean Success = %82.00***			***Mean Success = 81.50%***			***Mean Success =98.37%***		

Table 3. Experimental results of the mixed model on the test datasets.

	Normal Data Set			Gaussian Noisy Dataset			Salt & Pepper Noisy Data Set		
Textures	*Kernel Parameters Υ=80, σ²=5.2*			*Kernel Parameters Υ=50, σ²=7.0*			*Kernel Parameters Υ=90, σ²=8.0*		
	Correct	**Miss**	**Success**	**Correct**	**Miss**	**Success**	**Correct**	**Miss**	**Success**
D94	95	5	95%	100	0	100%	100	0	100%
D9	100	0	100%	100	0	100%	100	0	100%
Gravel	99	1	99%	100	0	100%	100	0	100%
D12	89	11	89%	100	0	100%	100	0	100%
D16	87	13	87%	100	0	100%	100	0	100%
D112	93	7	93%	100	0	100%	100	0	100%
R.Wall	81	19	81%	95	5	95%	95	5	95%
D68	100	0	100%	100	0	100%	100	0	100%
H.Array	94	6	94%	100	0	100%	100	0	100%
D84	96	4	96%	100	0	100%	100	0	100%
	Mean Success = 93.4%			***Mean Success = %99.50***			***Mean Success = 99.50%***		

The proposed method correctly classified D94, D9, Gravel, D112, D68 and D84 texture images within the normal dataset 100% without any error. Similarly, the recognition rate of D94, D9, D68, D112, D68 and D84 texture images inside both the noisy datasets and normal datasets is quite high. It is clearly seen that the performance of 2D-DOST and LS-SVM-based classifier is high on the mixed dataset. It is also seen that the result of the classification for the noisy data shows variations and give lower values compared to the data without imposed noise. D16 is most affected texture from the imposed noise for the recognition performance with the lowest value of 45%.

When the results belonging to mixed dataset are analyzed in Table2, it is seen that the proposed method with mixed dataset is reasonably robust against noise. To validate these observations additional experimental studies are performed on the texture dataset. For this aim, classifier is trained with mixed dataset and then tested with Normal, Gaussian noisy and Salt & Pepper noisy datasets. Experimental results of classifier obtained on these test datasets are given in Table3. Classifier has a high success rate of 93.4% on the normal test dataset and 99.5% on the both Gaussian noisy and Salt & Pepper noisy test dataset. According to these results, it can be said that proposed recognition system trained with mixed dataset provides an effective model for recognition process.

Other experimental study is performed on Kylberg texture database. The results of classification studies on the Kylberg dataset are given in Table 4. Proposed method achieved a success rate as high as 92.3% on the Kylberg dataset. Proposed algorithm is recognized Floor2 and Scarf2 textures without any error. The lowest success rate is obtained from the Screen1 texture with 83%. These results are lower than the results in Brodatz classification datasets. The Kylberg textures involve more challenging dataset when compared with Brodatz. Therefore, our method gives reasonable results as 92.3% success rate for a modern data set.

Table 4. Experimental results of the proposed classifier on the Kylberg dataset.

Textures	*Kernel Parameters $\Upsilon=120$, $\sigma^2=6$* Correct	Miss Class	Success
Ceiling2	97	3	97%
Floor1	92	8	92%
Floor2	100	0	100%
Rice2	89	11	89%
Sand1	89	11	89%
Scarf2	100	0	100%
Seat1	93	7	93%
Stone1	90	10	90%
Wall	90	10	90%
Screen1	83	17	83%
Mean Success = 92.3%			

The comparison of the classification method proposed in this study with other similar studies available in the literature is given in Table 5. The performances that the reference studies on Brodatz database are taken into consideration. It is seen that our proposed method has better results when compared to other methods.

Table 5. Comparison of algorithm of the study with the similar ones in the literature.

Reference Study	Success
Reference [23]	95.00%
Reference [27]	93.25%
Reference [19]	91.70%
Reference [29]	97.00%
Reference [22]	95.27%
Our Proposed Method	**98.70%**

4. Conclusion

In this study, a new method using the 2D-DOST feature extraction and LS-SVM based classifier algorithm for classification of texture images is proposed. At the feature extraction stage, a set of statistical methods are applied on the coefficients of each texture image transformed by means of 2D-DOST method. The feature vectors of texture images are used as the inputs of LS-SVM classifier. Performance evaluations of the proposed algorithm are performed on Brodatz textures in the size 512 *x* 512 and Kylberg textures in the size 576 *x* 576 datasets. 10 different textures are selected from these datasets. The training and test data are separately evaluated by obtaining sub-images, in the size 128 x 128, from the original texture samples. When the performances of the trained LS-SVM classifier on the test data are evaluated, it is seen that the proposed method has a higher rate of success in classification of texture data. Classification results have high success rate as 98.7% on the Brodatz dataset and 92.3% on the Kylberg dataset. Moreover, the performance evaluation results of the proposed method on the datasets with Gaussian and Salt & Pepper noise added are also presented in the study. Having efficient feature extraction and classification methods, 2D-DOST and LS-SVM classifier is presented to the literature as an effective method that can be used in texture analyses. It is very difficult to analyze correctly the complexity of the LS-SVM classifier which is dominant in the proposed method. Depending on various factors computation complexity is between O (n^2) and O (n^3). This study also presents many important information about the using 2D- DOST feature extraction method in the image processing field.

5. Future Works

In the future works, different classifiers will be implemented on the proposed model and performance comparisons with LS-SVM classifier will be obtained. Furthermore, the performance for the texture images with rotations will be investigated which could be a feasible task to evaluate the performance of the proposed model.

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