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Performance Analysis of DMD and SURF Methods for Texture Classification

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Abstract:

The Texture is the crucial attribute in every image classification method as it describes the appearance of object. Today, different approaches of texture classification have been developed which focus on acquisition of image features from its texture and categorize them into different classes by using a particular classifier. This paper gives a state-of-the-art texture classification technique called Dense Micro- Block Difference (DMD). In this concept, image data representation is accomplished by capturing features in the form of micro-blocks. This method gives superior performance over already established methods in terms of processing time, accuracy and robustness and able to obtain whole image information. In this paper, we have taken UMD dataset for processing and calculated different performance parameters which gives excellent results than comparative method SURF.

I. Introduction

Texture classification is a way of grouping similar things together according to common characteristics which enables us to acquire information about the image. This information can be obtained by extracting image features. With the help of features we can describe huge amount of data accurately. Advances in digital technology have created huge collection of digital images which requires an efficient and intelligent technique of texture classification. Texture classification is the process to divide texture features into texture classes. First stage of classification is feature extraction process in which features are extracted from image by using its texture. In second stage, features are converted into texture classes by using a classifier [1].

Many texture classification methods have been introduced like Gray Level Co-Occurrence Matrices (GLCM), Gabor filters, Local Binary Pattern (LBP), wavelet transform methods, and Independent component analysis and filter banks [2], [3], [4].These earlier methods are based on simple statistics and are unable to capture the intensity variation efficiently. But Dense Micro-Block Difference (DMD) technique is superior to all these techniques and can be implemented much faster than these methods [5]. Texture classification is challenging task due to variation in scale, illumination, rotation and difference in texture patterns. These challenges have not been addressed completely by existing methods. DMD solves these problems and provides an efficient method for texture classification. It provides improvements in the field of key point description, image encoding and compressive sensing. DMD is a patch based method [6]. It captures information from image texture with the help of micro-blocks. The features captured by DMD are then encoded using Fisher vector and then processed by SVM classifier. This method is fast to compute, easy to implement.

A comparative classification method is added to compare performance with DMD i.e. Speeded Up Robust Feature (SURF). SURF is a texture detector and descriptor method which has application like object recognition, image registration, classification, reconstruction of 3D scenes and tracking objects. This method is updated version of Scale Invariant Feature Transform (SIFT) and also faster than it. SURF technique handles blurred and rotational images efficiently. Finally, performance analysis of these two methods namely DMD and SURF is given by confusion matrix [7].

A. Main Objectives

1) To provides an efficient feature extraction technique to model texture variation efficiently.

2) To provide advance classification method by giving excellent performance in the field of key-point descriptors, image encoding and compressive sensing.

3) To provide robust method that is able to deal various problems in texture classification techniques like variation in scale, illuminations, rotation and difference in texture patterns.

II. Litrature Survey

Rotation Invariant Image Description with Local Binary Pattern Histogram Fourier Features proposed by T. Ahonen et al. presented a novel rotation invariant image description computed from discrete Fourier transform. Here proposed invariants are constructed globally for the whole region to be described. The major advantage of this method is that the relative distribution of local orientation is not lost and these LBP-HF descriptors also outperform the MR8 descriptors [8].

L.D.Griffiu and M. Crosier, in 2008, proposed texture classification with a dictionary of basic image features. In this method, they had represented a multi-scale texture classification algorithm which produces state-of-art results on widely used texture dataset.BIF columns were used here to describe larger local regions of image. They have used geometrically derived dictionary of features over which images are represented, rather than pre-training of dictionary of textons. This results in simpler and more general approach. Here, more sophisticated classifiers are not used for ease of implementation. So, we can improve this method by using SVM classifier as it has higher accuracy [9].

D. Nghi and L. Chi Mai invented method, training data selection for support vector machines model in 2011. When parameters of SVM are applied to a large dataset, it requires a long time for training so the model selection task and its performance can be degraded. To reduce the time for model selection this paper has proposed a training data selection method then applied the model selection on reduced training set. Results showed that a significant amount of time for model selection can be saved without degrading the performance [10].

Efficient and robust image descriptors for GUI object classification invented by A. Dubrovina et al. in 2011.In this paper, a advanced image descriptor is implemented specifically for GUI objects which is robust to various changes in the appearance of GUI objects like various screen resolution as well as various operating system related issues. This image descriptor is further used with SVM and experiments have shown the descriptor robustness to the above transformations and its superior performance compared to existing image descriptors [11]

A. Wojnar and A. Pinheiro presented annotation of medical images using the SURF descriptors in 2012. Here, Fast Hessian matrix is used to extract features and classification is given by SVM with a quadratic kernels. The testing of developed system was performed on IRMA radiographic images. Then results of SURF features are compared with SIFT features and results showed that SURF features has better accuracy of 96%. The annotation performance will be increased by implementing multiple classifiers [12]

J. Sanchez et al. proposed image classification using Fisher vector in 2013.It is patch encoding strategy which has advantages like efficiency in computing, excellent results, and minimal loss of accuracy. Within Fisher vector framework, images are defined by first extracting a set of low level patch and then computing their deviations from a universal generative model. However being very high-dimensional and dense, the Fisher vector becomes impractical for large scale application due to storage limitation [13].

III. PROPOSED METHODOLOGIES

Proposed classification methodology is studied by two different ways which includes features extracted using DMD features extracted using SURF as follows:
i] Texture Classification using DMD feature extraction method
ii] Texture Classification using SURF feature extraction method

A. Texture Classification using DMD feature extraction method:

Figure shows block diagram of classification of texture using DMD and SVM. Input images used for experimentation are taken from UMD dataset available free on internet. Then DMD features are extracted for input image [6]. The dimensions of DMD features are reduced using Random Projection technique. Further these low dimensional features are converted into descriptors in encoding block and finally classified by SVM classifier as shown in Fig. 1.

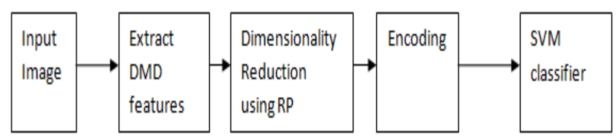

Fig.1Texture classification using DMD with SVM

1. Input Image
   Input image is taken from UMD dataset for processing. The size of each image is 1280x960. All images from the dataset are taken with different viewpoint changes and scale.

2. Extract DMD Features
   DMD features captures information by working on micro-blocks of input texture image. DMD uses intensity difference from image patch to capture the variations in it. In this method, we use small blocks in image patch instead of single pixel because individual pixels are more adaptive to noise and do not capture entire information. Here, average intensity is considered to capture data [6].

3. Dimensionality Reduction using Random Projection (RP)
   To efficiently capture the intensity difference, it is necessary to select a large number of sampling points which further increases dimensionality. This puts limitation on the size of image patch. But images are sparse in nature so we can apply compression sensing techniques to it. For reduction on dimensionality and to make it more compressed Random Projections technique is used which reduces dimensionality by preserving required information.

4. Encoding
   To convert features into descriptors encoding is used. Fisher vector technique is used for encoding [6]. Generative model for feature extraction is used by representing data by means of gradient of data log-likelihood with respect to model parameters. The Fisher vector uses the Gaussian Mixture Model (GMM) to obtain representation of compressed features. The first order and second order differences between the image descriptors and the GMM centers are obtained by encoding.

5. SVM Classifier
   Final stage of DMD algorithm is classification. Here, we have used SVM classifier which converts image features into texture classes. It compares testing set with the training set and gives proper classification of objects. SVM divides two classes by using a hyperplane. SVM gives best accuracy performance compared to ANN and nearest neighbors.

B. Texture Classification using SURF feature extraction method:
Figure shows block diagram of classification of texture using SURF and SVM. Input images used for experimentation are taken from UMD dataset available free on internet. Then SURF features are extracted for input image and feature vector is formed and finally classification is done with SVM classifier [7].

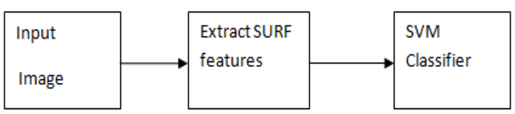

Fig. 2 Texture Classification using SURF and SVM

In this method, SURF feature extraction algorithm consists of four parts. First part is integral image computation which is very important to boost the performance speed of SURF method. Each input image is first converted into integral image and then passed for further processing. Second part is interest point detection in which point of interests are located by using determinant of Hessian matrix and points are obtained where this determinant is maximum. Third part is description in which Haar wavelet responses are used to give best description and finally these descriptors are categorized using SM classifier.

V. Results

The DMD method classification is presented by following steps-

Step 1: Test Input Image
Input image is taken from first texture class for processing. Size of an image is 1280 x 960. The result is shown below in the form of GUI.

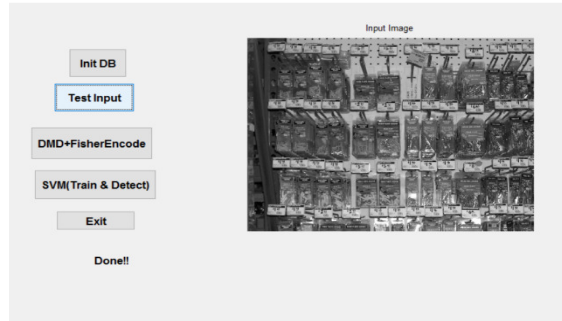

Fig.3 Input image for DMD method

Step 3: Obtain DMD features
DMD features of selected image are extracted by taking image patch of size 4 x 4. Number of sample points selected are 100 and number of co-ordinate points selected are 60. Block radius is 2. Hence output DMD vector is of size 60 x 800. This local feature vector is encoded by using Fisher encoding to obtain descriptors. Encoding uses GMM to derive probabilistic representation of local features. Here first and second order differences between the image descriptors and the GMM centers are captured. At the end of encoding, we get vector of 1x 300. Finally, these descriptors are fed to classifier to perform categorization.

Step 4: Classification
Final stage of proposed method is classification in which multilevel classifier is used which converts obtained image descriptors into texture classes. We have taken input test image from texture class 1, so at the end of classification selected image is correctly classified as 'Test set is Class 1'. This result is shown in following Fig. 4

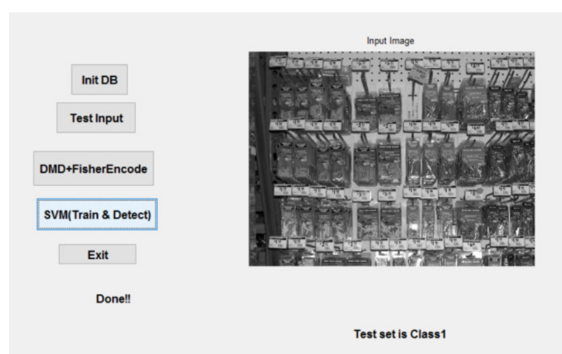

Fig.4 Texture classification of input image using DMD method

The SURF method classification is presented by following steps-

Step 1: Test Input Image
Input image is taken from texture class 1 of UMD dataset which is of size 1280 x 960.

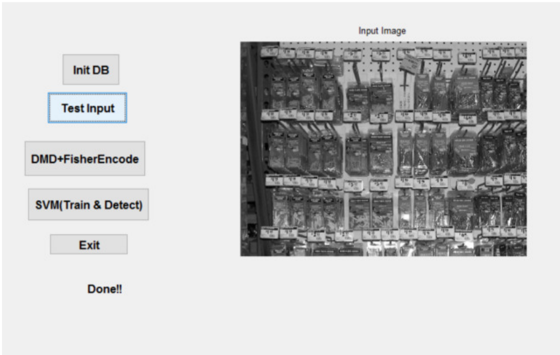

Fig.5 Input image for SURF method

Step 2: SURF feature extraction
To obtain SURF features, first stage is integral image computation which is useful for boosting the speed of performance. Further interest points are located by using Hessian matrix determinant. Extracted SURF features appear on the image as red circles called key-points. For the selected input image, obtained key-points are 395. The output image is shown in following figure.

Fig.6 Feature extraction of input image using SURF

Step 3: Classification
Extracted SURF features are finally given to the multilevel SVM classifier. SVM correctly assigns a texture class to test input. The input image taken is from texture class 1 hence classifier categorizes as 'Test set is Class 1' as shown below:

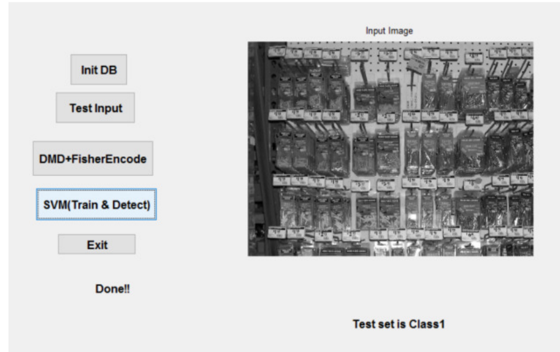

Fig.7 Texture classification of input image using DMD method

Performance Analysis using confusion matrix-
Confusion matrix is a table which is used to describe the performance of a classifier by using test data. Here first five classes of UMD dataset are used.

A. Performance analysis using DMD

N=400	**Predicted No**	**Predicted Yes**	
Actual No	TN = 0	FP = 0	0
Actual Yes	FN = 23	TP = 377	400
	23	377	

Fig. 8 Confusion matrix of DMD method

Evaluation of confusion matrix is given by following parametrs.

1. Sensitivity or True Positive Rate (TPR):

It measures the proportion of positives that are correctly identified.

$$\text{TPR}=\frac{TP}{P}=\frac{TP}{TP+FN}=\frac{377}{400}=0.9425$$

Where,

TP = True Positive= the number of samples correctly marked as positive.
TN= True Negative= the number of samples correctly marked as negative
FP= False Positive = the number of samples incorrectly marked as positive (also known as "Type I error")
FN= False Negative= the number of samples incorrectly marked as negative (also known as "Type II error")

2. Precision or Positive Predictive Value (PPV):

It is the proportion of positive results in statistics and diagnostic tests that are true positive.

$$PPV=\frac{TP}{TP+FP}=\frac{377}{377+0}=1$$

3. False Negative Rate (FNR):

It is the proportion of positives which yield negative test outcomes with the test i.e. the conditional probability of a negative test result given that the condition being looked for is present.

$$FNR=\frac{FN}{P}=\frac{FN}{FN+TP}=\frac{23}{23+377}=0.0575$$

4. Accuracy (ACC):

It is the proximity of measurement results to the true value.

$$ACC=\frac{TP+TN}{P+N}=\frac{377+0}{400}=0.9425$$

Here, values of TN and FP are not applicable for this method hence their values are zero.

B. Performance analysis using SURF

N=400	**Predicted No**	**Predicted Yes**	
Actual No	TN = 0	FP = 0	0
Actual Yes	FN = 42	TP = 358	400
	42	358	

Fig. 9 Confusion matrix of SURF method

1. Sensitivity or True Positive Rate (TPR):

$$TPR=\frac{TP}{P}=\frac{TP}{TP+FN}=\frac{358}{400}=0.895$$

2. Precision or Positive Predictive Value (PPV):

$$PPV=\frac{TP}{TP+FP}=\frac{358}{358+0}=1$$

3. False Negative Rate (FNR):

$$FNR=\frac{FN}{P}=\frac{FN}{FN+TP}=\frac{42}{42+358}=0.105$$

4. Accuracy (ACC):

$$ACC=\frac{TP+TN}{P+N}=\frac{358+0}{400}=0.895$$

VI. CONCLUSION

We have proposed an efficient and advanced method i.e.DMD which is able to acquire complete information form image, this method is very fast to compute, low in dimensionality and easy to implement. This method has wide variety of application in material classification, industrial automation, computer vision and medical diagnosis. Extensive experiments were conducted on five texture classes of UMD dataset and performance parameters are calculated with the help of confusion matrix. The results show that accuracy of DMD method is 0.9425 with fast computational time.

Another method presented is texture classification by using SURF features. In this method, points of interest are founded by determinant of Hessian matrix and description is given for each point of interest. Here Surf features are extracted in the form of key-points which appears in red circles. These obtained features are given to the multilevel SVM classifier. Experiments performed on images of UMD dataset shows that accuracy of SURF features is 0.895. From results, we can say that DMD method is better than SURF in terms of computational speed and accuracy.

REFERENCES

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[1] R. M. Haralick, K. Shanmugan, & L. Dinstein, "Texture Features for Image Classification," IEEE TSMC, vol. 3, pp. 610-621, 1973.

[2] T. Ahonen, A. Hadid, and M. Pietikalinen, "Face description with local binary patterns: Application to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037-2041, Dec. 2006

[3] J. Trefny and J. Matas, "Extended set of local binary pattern for rapid object detection," in Proc. Comput., Vis. Winter Workshop, 2010, pp. 1-7

[4] R. Cross and A. K. Jain, "Markov random field texture models," IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-5, NO.1, PP. 25-39, Jan, 1983.

[5]A. C. Bovik, M. Clark, and W. S. Geisler, "Multichannel texture analysis using localized spatial filters," IEEE Trans. Pattern Anal. Mach. Intell., vol.12, no. 1, pp. 55-73, Jan. 1990.

[6] R. Mehta and K. Egiazarian, "Texture Classification using Dense Micro-Block Difference," IEEE Transactions On Image Processing, Vol. 25, No. 4, April, 2016.

[7] Bay, T. Tuytelaars and L. Van Gool, "SURF: speeded Up Robust Features" , 9th European Conference on Computer Vision,2006.

[8] T. Ahonen, J. Matas, C. He and M. Pietikainen, "Multiresolution gray scale and Rotation invariant texture classification with local binary patterns", IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 61-70.

[9] M. Crosier & L. D. Gfiffin, "Texture Classification with a Dictionary of Basic Image Features in Computer Vision & Pattern Recognition, IEEE conference, pages 1-7, June 2008.

[10] Anastasia Dubrovina, Pavel Kisilev, Daniel Freedman, Sagi Schein, Ruth Bergman "Efficient and robust image descriptor for GUI object classification" Copyright 2011 Hewlett-Packard Development Company, L.P.

[11] Li Liu & Pawl W. Fiegnth, "Texture Classification from Random Features," IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 34, no. 3, March, 2012.

[12] Anna Wojnar and Antonio M. G. Pinheiro, "Annotation of Medical Images Using the SURF descriptor", 2012 IEEEMs.

[13] J. Sanchez, F. Perronnin, T. Mensink, and J. Verbeek, "Image Classification with the Fisher vector: Theory and Practice," Int. J. Comput. Vis., vol. 105, no.3, pp. 222-245, 2013.