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Evaluation of Robust Feature Descriptors for Texture Classification

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Abstract**—**Texture is an important characteristic in real and synthetic scenes. Texture analysis plays a critical role in inspecting surfaces and provides important techniques in a variety of applications. Although several descriptors have been presented to extract texture features, the development of object recognition is still a difficult task due to the complex aspects of texture. Recently, many robust and scaling-invariant image features such as SIFT, SURF and ORB have been successfully used in image retrieval and object recognition. In this paper, we have tried to compare the performance for texture classification using these feature descriptors with k-means clustering. Different classifiers including K-NN, Naive Bayes, Back Propagation Neural Network , Decision Tree and Kstar were applied in three texture image sets－UIUCTex, KTH-TIPS and Brodatz, respectively. Experimental results reveal SIFTS as the best average accuracy rate holder in UIUCTex, KTH-TIPS and SURF is advantaged in Brodatz texture set. BP neuro network works best in the test set classification among all used classifiers.

Keywords**—**Texture classification, texture descriptor, SIFT, SURF, ORB.

I. Introduction

TEXTURE has been found a powerful cue for structure analysis in real scene, which give rise to certain similar patterns. Texture classification is an important topic in image and video processing and has been widely used in many applications including automated optical inspection (AOI), medicine image analysis, natural object recognition. The goal of texture classification is to match a query image with reference images in a pre-defined image database. The process of texture classification methods usually consist of four steps:pre-processing, feature extraction, feature selection and classification.

Maani et al. [1] divide the texture classification methods into four groups: statistical, structure, probability, and filter-based approaches. In statistical approaches, the co-occurrence matrix proposed by Haralick and Shanmugam [2] is one of the generally used statistical method. Besides co-occurrence matrix, some statistical features such as run-length matrix [3], higher order statistics [4], fractal dimension [5]. Recently, Local Binary Pattern [6] has been regarded as one of the most successful statistical method. The structure approach decomposes textures into elements known as privatives of texels. The primitives and their spatial arrangements are used to recognize textures [7], [8]. In the probability approach, Markov random field (MRF) [9], [10] is one of the popular method to texture analysis. The main concept about probability models is how to efficiently map a texture into the selected probability model. For instance, MRF assume that the probability of each pixel in textures depends on its neighbors. In the filter-based approaches, texture features can be extracted from Fourier transform [11], Gabor transform [12] or wavelet transform [13]. The main advantage of these methods that uses frequency components is the capability of handling noise.

Different to the above traditional approaches of texture classification. In order to achieve good robustness necessary for semantic classification, robust local feature descriptors have been developed recently, such as SURF [14], SIFT [15] and ORB [16] features. The gradient orientation histograms of these robust features have been widely used in many recognition and image classification applications. In this paper, we focus on the comparison of performances for texture classification using these three robust features. In our experiments, K-means clustering method [17] is applied to convert the extracted key-point features from a texture used these three descriptors into distinguished histograms for classification.

The paper is organized as follows. The review of three robust features and k-means clustering is in Section 2. The design of evaluation of texture classification is presented in Section 3. Experimental results and Conclusion are described in Section 4 and Section 5, respectively.

II. Review of Related Robust Features

A. SURF

SURF (Speeded Up Robust Features) key-point detection is based on the Hessian matrix approximation. The detection process lends to the use of integral images to reduce the computation time. Given a point x in an image I, the Hessian matrix H(x,) in x at scale is defined as follows.

$$H(x,\sigma) = \begin{pmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{pmatrix} \quad (1)$$

where Lxx(x,σ) is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in point x, and similarly for Lxy(x,σ) and Lyy(x,σ). In the case of SURF, 9x9 box filters are used to approximate the Hessian matrix roughly. The box filters are approximations of a Gaussian with σ=1.2 and represent the

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lowest scale for computing the blob response maps the determinant is denoted as follows:

$$\det(\mathrm{H}_{\mathrm{approx}}) = \mathrm{D}_{\mathrm{xx}}\mathrm{D}_{\mathrm{yy}} - (\mathrm{wD}_{\mathrm{xy}})^2 \quad (2)$$

The approximated determinant of the Hessian represents the blob response in the image at location x. These responses are stored in a blob response map over different scales and local maxima are detected.

The responses to Haar wavelets are used for orientation assignment, before the keypoint descriptor is formed from the wavelet responses in a certain surrounding of the keypoint. The standard descriptor vector has a length of 64 floating point numbers. Finally, a query image q is matched with all the images in the sub-class using these descriptor vectors. The image which has the maximum matching points is displayed as the top best match for the given query image.

B. SIFT

SIFT (the Scale Invariant Feature Transform) consists of four major stages: (a) scale-space detection, (b) keypoint localization, (c) orientation assignment and (d) keypoint descriptor. The first stage used difference-of-Gaussian (DOG) function to identify potential interest points, which were invariant to scale and orientation. DOG was used instead of Gaussian to improve the computation speed.

Given a texture image I(x,y), its linear scale-space $\mathrm{L}(x, y, \sigma)$ is obtained by convolving I(x,y) with an Gussian smoothing kernel of standard deviation σ:

$$\mathrm{L}(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (3)$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (4)$$

$$\mathrm{D}(x, y, \sigma) = \big(G(x, y, k\sigma) - G(x, y, \sigma)\big) * I(x, y)$$

$$= \mathrm{L}(x, y, k_i\sigma) - \mathrm{L}(x, y, k_j\sigma) \quad (5)$$

where * is the convolution operator, G(x, y, σ) is a variable scale Gaussian, D(x, y, σ) is Difference of Gaussians with scale k times. Only scale-space extreme of D(x, y, σ) that have strong contrast are choosen as keypoints. This is done by computing the quadtatic Tayor expansion of D(x, y, σ) around candidate kepoints.

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \quad (6)$$

A keypoint descriptor based on local gradient directions and magnitudes is used. The descriptor is invariant to image rotations since the bin of orientation histograms are normalized relative to the dominant gradient direction in the vicinity of the keypoint. In addition, the scale of analysis, and hence the size of the local region whose features are being presented, corresponds to the scale at which the given keypoints was found to be a stable extremism.

C. ORB

ORB (Oriented FAST and Rotated BRIEF) is basically a fusion of FAST keypoint detector and BRIEF descriptor with many modifications to enhance the performance. First, it uses FAST to find keypoints, then apply Harris corner measure to find top N points among them. It also use pyramid to produce multiscale-features. To overcome the orientation problem of FAST, it computes the intensity weighted centroid of the patch with located corner at center. The direction of the vector from this corner point to centroid gives the orientation. If pixel location (x, y) is one keypoint obtained by FAST， one can obtain the orientation information about the region R with a radius r surrounded the center (x,y) using the following equations:

$$m_{pq} = \sum_{x,y \in R} x^p y^q \, I(x, y) \quad (7)$$

$$\mathrm{C} = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}\right) \quad (8)$$

$$\theta = \tan^{-1}\left(\frac{m_{01}}{m_{10}}\right) = \tan^{-1}\left(\frac{\sum_{x,y} yI(x,y)}{\sum_{x,y} xI(x,y)}\right) \quad (9)$$

Now for feature descriptors, ORB use BRIEF descriptors. For any feature set of n binary tests at location (x, y), define a 2 ×n matrix, S which contains the coordinates of these pixels. Then using the orientation of patch, θ, its rotation matrix is found and rotates the S to get steered(rotated) version Sθ. ORB discretize the angle to increments of 2π/30 (12 degrees), and construct a lookup table of precomputed BRIEF patterns. As long as the keypoint orientation θ is consistent across views, the correct set of points Sθ will be used to compute its descriptor.

D. K-Means Clustering

K-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. K-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. Given a set of observations (x_1, x_2, …, x_n), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets (k ≤ n) G = {G_1, G_2, …, G_k} so as to minimize the within-cluster sum of squares:

$$\sum_{i=1}^{k} \sum_{x_j \in G_i} ||x_j - \mu_i||^2 \quad (10)$$

The most common algorithm uses an iterative refinement technique. Due to its ubiquity it is often called the k-means algorithm; it is also referred to as Lloyd's algorithm, particularly in the computer science community.

III. Texture Datasets and Texture Histograms

A. Image Datasets for Comparative Texture Analysis

The UIUCTex texture database [18] (Fig. 1), developed and maintained by the Ponce Group at the University of Illinois at

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Urbana-Champaign, features 17 texture classes with 40 image per class of natural and artificial materials such as bark, wood, glass, marble, fabric, etc.

The KTH-TIPS dataset [19] (Fig. 2) is another dataset selected for texture classification. There are 9 texture classes, and each image is captured at nine scales spanning twooctaves. Each is viewed under three illumination directions and three poses, giving a total of 45 images per material including aluminum foil, brown bread and so on.

The Brodatz texture dataset [20] (Fig. 3) is one of the most widely used texture benchmarks. The dataset contains 60 images extracted from the Brodatz album. In our experiments, each image is divided into 25 sub-images for classification experiments.

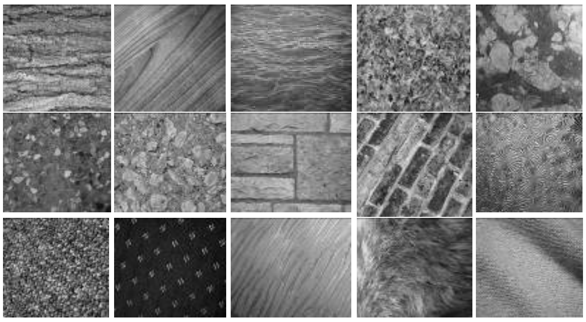

Fig. 1 15 different textures in UIUCTex dataset

Fig. 2 9 different textures in KTH-TIPS dataset

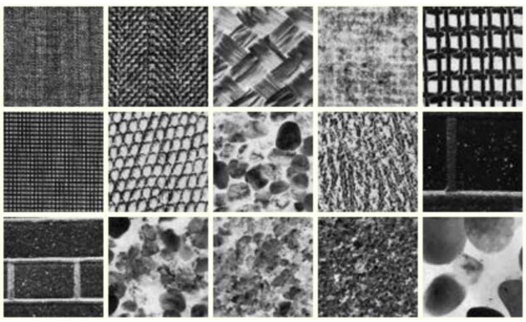

Fig. 3 15 different textures in Brodatz dataset

B. Texture Feature Histograms

The evaluation of texture classification can be divided into two stages: the training process and the test process. The textures in different datasets are also divided into two parts for the experiments. In the training process, texture feature histogram is constructed to represent the corresponding texture of each texture per dataset. First, we extract the keypoints for all textures in training set using a specified feature point detection method (like SURF, SIFT or ORB). These keypoint vectors are used as input to perform the clustering using k-means clustering algorithm. Then, we can obtain k cluster centers and these center vectors will be employed as the reference features. Finally, for each texture T in the training set, each extracted keypoint vector is compared to all reference cluster centers and find the closest center then vote one for it and the corresponding texture histogram of T is constructed. The process of building texture histograms are shown in Fig. 4. Fig. 5 shows the constructed texture histogram with SIFT descriptor and k-means clustering (k=50). Note that, these cluster center vectors will also be employed in the test process as the reference features.

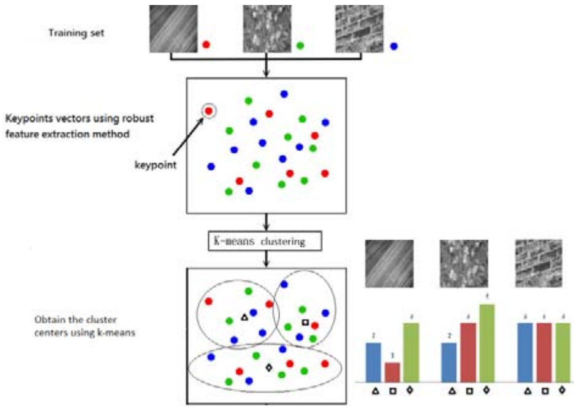

Fig. 4 The texture histogram construction using k-means in the training process

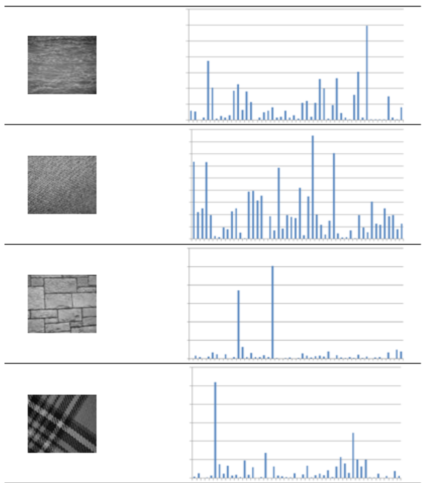

Fig. 5 Texture histograms for 4 test textures using the proposed method

IV. Experimental Results and Discussion

To evaluate the performance of various texture descriptors, we present the results on texture classification using the datasets described in the previous Section. Table I shows the amount of textures in different datasets used under the training and test process, respectively. There are 17 classes, and 25 and 15 images for each class selected from UIUCTex in training and test sets, respectively. There are 9 classes, and 27 and 18 images for each class selected from KTH-TIPS in training and test sets, respectively. There are 60 images, and 15 and 10 subimages segmented from each image selected from Brodatz in training and test sets, respectively.

TABLE I
THE AMOUNT OF TEXTURE USED IN DIFFERENT DATASETS

dataset	Training	test
UIUCTex	425	255
KTH-TIPS	243	162
Brodatz	900	600

In our experiments, different classifiers including KNN, Naïve Bayes , BP Neuro Network, decision tree and Kstar are used and utilized the default Weka settings.

TABLE II
CLASSIFICATION RATE (%) ON UIUCTEX USING DIFFERENT FEATURE DESCRIPTORS

UIUCTex						
descriptor / classifier	SIFT		SURF		ORB	
	Training set	Test set	Training set	Test set	Training set	Test set
KNN	100	93.7	100	72.15	100	78.43
Naïve Bayes	92.94	84.31	89.41	72.54	91.52	77.25
BP NN	99.05	90.19	96.47	76.07	99.52	85.49
Decision Tree	96.47	70.98	94.35	58.43	93.88	62.74
Kstar	100	89.80	100	70.98	100	77.25
Average	**97.69**	**85.80**	96.05	70.03	96.98	76.23

TABLE III
CLASSIFICATION RATE (%) ON KTH-TIPS USING DIFFERENT FEATURE DESCRIPTORS

KTH-TIPS						
descriptor / classifier	SIFT		SURF		ORB	
	Training set	Test set	Training set	Test set	Training set	Test set
KNN	100	52.46	100	64.81	100	54.93
Naïve Bayes	81.89	56.17	76.95	54.93	71.19	59.87
BP NN	99.58	61.72	93.41	53.08	97.53	55.55
Decision Tree	93.82	50	94.65	53.70	93.41	43.82
Kstar	100	32.71	100	43.20	100	58.02
Average	**95.06**	50.61	93.00	53.94	92.43	**54.44**

V. CONCLUSION

In this paper, we performed a comparison of three robust texture feature extraction techniques, SURF, SIFT and ORB, when applied to several popular texture datasets. The texture descriptors were analysed using different classifiers to perform classification. Experimental results show that SIFTS has the best average accuracy rate in UIUCTex, KTH-TIPS and SURF is advantaged in Brodatz texture set. BP neuro-network works best in the test set classification among all used classifiers.

TABLE IV
CLASSIFICATION RATE ON BRODATZ USING DIFFERENT FEATURE DESCRIPTORS

Brodatz						
descriptor / classifier	SIFT		SURF		ORB	
	Training set	Test set	Training set	Test set	Training set	Test set
KNN	100	55	100	71.16	100	43.66
Naïve Bayes	89.77	67.66	92.77	77.5	82.66	55.33
BP NN	93.88	65.5	96.88	75.5	89.88	51.5
Decision Tree	86.44	42.16	89.22	48.83	83.55	23.83
Kstar	100	50.16	100	60.5	100	38.66
Average	94.02	56.10	**95.77**	**66.70**	91.22	42.60

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[20] Brodatz dataset: http://www.ux.uis.no/~tranden/brodatz.html

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