Texture classification using Curvelet Statistical and Co-occurrence Features

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Abstract

Texture classification has long been an important research topic in image processing. Now a days classification based on wavelet transform is being very popular. Wavelets are very effective in representing objects with isolated point singularities, but failed to represent line singularities. Recently, ridgelet transform which deal effectively with line singularities in 2-D is introduced. But images often contain curves rather than straight lines, so curvelet transform is designed to handle it. It allows representing edges and other singularities along lines in a more efficient way when compared with other transforms. In this paper, the issue of texture classification based on curvelet transform has been analyzed. Curvelet Statistical Features (CSFs) and Curvelet Co-occurrence Features (CCFs) are derived from the sub-bands of the curvelet decomposition and are used for classification. Experimental results show that this approach allows obtaining high degree of success rate in classification.

1. Introduction

The analysis of texture in images provides an important cue to the recognition of objects. It has been recently observed that different image objects are best characterized by different texture methods. Successful applications of texture analysis methods have been widely found in industrial, biomedical, remote sensing areas and target recognition [1]. Since there are a lot of variations among natural textures, to achieve the best performance for texture analysis or retrieval, different features should be chosen according to the characteristics of texture images. A number of texture analysis methods have been proposed over the years and it is well-recognized that they capture different texture properties of the image.

Texture methods used can be categorized as statistical, geometrical, model-based and signal processing [2]. Some statistical methods used are co-occurrence matrix features [3] and autocorrelation function [4]. In geometrical methods textures are considered to be composed of texture primitives and are extracted and analyzed [5]. Several stochastic models have been proposed for texture modeling and classification such as Gaussian Markov random fields [6] and spatial autocorrelation function model [7]. The signal processing techniques are mainly based on texture filtering for analyzing the frequency contents either in spatial domain [8], [9] or in frequency domain [10]. Filter bank instead of a single filter has been proposed, giving rise to several multi-channel texture analysis systems such as Gabor filters and wavelet transforms [11]. The major disadvantage of the Gabor transform is that its output are not mutually orthogonal, which may result in a significant correlation between texture features.

In the last decade, wavelet theory has been widely used for texture classification purposes [12]-[14]. A comparative study by Randen and Husoy shows that various filtering approaches yield different results for different images [15]. The success of wavelets is mainly due to the good performance for piecewise smooth functions in one dimension. Unfortunately, such is not the case in two dimensions. In essence, wavelets are good at catching zero-dimensional or point singularities, but two-dimensional piecewise smooth signals resembling images have one-dimensional singularities [16]. Wavelets in two dimensions are obtained by a tensor-product of one dimensional wavelet and they are thus good at isolating the discontinuity across an edge, but will not see the smoothness along the edge.

To overcome the weakness of wavelets in higher dimensions, Candes and Donoho pioneered a new system of representations named ridgelets which deal effectively with line singularities in two dimensions [17]. The idea is to map a line singularity into a point singularity using the Radon transform [18]. Then, the wavelet transform can be used to effectively handle the point singularity in the Radon domain. So, Ridgelet transform allows representing edges and other singularities along lines in a more efficient way than wavelet transform, for a given accuracy of reconstruction [19].

In image processing, edges are typically curved rather than straight and ridgelets alone cannot yield efficient representations. However at sufficiently fine scales, a curved edge is almost straight, and so to

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capture curved edges, one ought to be able to deploy ridgelets in a localized manner, at sufficiently fine scales. Candes and Donoho [20], [21] proposed another multiscale transform called Curvelet transform which is designed to handle curve discontinuities well. Here, the idea is to partitioning the curves into collection of ridge fragments and then handle each fragment using the ridgelet transform.

In this paper, the curvelet transform is applied on a set of texture images and Curvelet Statistical Features (CSFs) such as mean and standard deviation and Curvelet Co-occurrence Features (CCFs) are extracted from each of the curvelet sub-bands and used for classification. The experimental result shows that the success rate is improved much when compared with traditional methods.

The paper is organized as follows: Section 2 describes the Curvelet transform and its implementation. The texture classification method is explained in Section 3. Experimental results are given in Section 4. Finally, Discussion and concluding remarks are given in Section 5.

2. Curvelet transform

Candes and Donoho developed a new multiscale transform called curvelet transform which was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e., using fewer coefficients for a given accuracy of reconstruction. Implementation of curvelet transform involves the following steps: (i) Sub-band decomposition, (ii) Smooth partitioning, (iii) Renormalization, (iv) Ridgelet analysis.

Sub-band Decomposition: The image is first decomposed into $\log_2 M$ (M is the size of the image) wavelet sub-bands and Curvelet Sub-bands are formed by performing partial reconstruction from these wavelet sub-bands at levels $j \in \{2s, 2s+1\}$. Thus the Curvelet Sub-band, s = 1 corresponds to wavelet sub-bands j = 0, 1, 2, 3, Curvelet Sub-band, s = 2 corresponds to wavelet sub-bands j = 4, 5 and so on.

Smooth Partitioning: The sub-band $s = 2$ is subdivided into an array of 64 x 64, 50% overlapping blocks, sub-band $s = 3$ is subdivided into an array of 32 x 32, 50% overlapping blocks and so on. As a result, for an image of size of 256 x 256 there will be sixty four 64 x 64 blocks for $s=2$ and two hundred and fifty six 32 x 32 blocks for $s = 3$.

Renormalization: The partitioning introduces redundancy, as a pixel belongs to 4 neighboring blocks. So, each square resulting in the previous stage is renormalized to unit scale.

Ridgelet Analysis: Ridgelet transform [17] is performed on each square resulting from the previous stage. The block diagram for the implementation of digital ridgelet transform is shown in Figure 1.

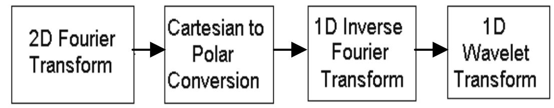

Fig. 1 Ridgelet transform flow graph.

3. Texture classification method

Texture classification involves two phases, i.e., learning and classification. In the learning phase, the original image is decomposed using Discrete Curvelet Transform (DCvT) as explained in Section 2. Features such as mean and standard deviation are calculated from each of these Curvelet sub-bands and are stored in the database for the purpose of classification. In order to improve the classification gain, co-occurrence matrix (*C)* is formed for each sub-band of DCvT, which gives the information about the spatial distribution of gray scale values. From the co-occurrence matrix, the features such as Contrast, Cluster shade, Cluster prominence and Local homogeneity are calculated [14] and are stored in the feature database.

In the classification phase, an unknown texture image is decomposed using DCvT and its features are calculated to form the feature vector similar to that of the learning phase. The feature vector derived from the unknown image is compared with the feature vectors in the database using the distance vector formula, given in Eqn. (1).

$$D(i) = \sum_{j=1}^{P} abs\left[f_j(x) - f_j(i)\right] \qquad (1)$$

where P is the total number of features used, $i=1$ *to* Q, (Q is the number of images in the database), $f_j(x)$ represents the j^{th} feature of unknown texture image *(x)* and $f_j(i)$ represents the j^{th} feature of texture belonging to i^{th} texture. In classification, the unknown texture is assigned to n^{th} texture if $D(n) < D(i)$ *for all i; i not equal to n.*

4. Experimental results

First, Classification is done for Dataset -1 containing 20 monochrome images, each of size 512 x 512, obtained from VisTex color image database using the Curvelet Statistical Features (CSF) such as mean and standard deviation. Here the image is subdivided into sixty four 64 x 64 sub image regions so that a total of 1280 sub images will be in the database. The mean is calculated over the approximation sub-bands and is averaged to a single value, whereas standard deviation is calculated over all the sub-bands (i.e., both approximation and detail) giving a total of 135 features.

Table 1 Results of Texture Classification using Curvelet Transform for 30 VisTex images (*with 2520 image regions – data set 2*)

Sl. No	Images	Classification gain (%)				Sl. No	Images	Classification gain (%)			
		F1	**F2**	**F3**	**F4**			**F1**	**F2**	**F3**	**F4**
1	Bark.0006	72.62	61.90	90.48	98.86	16	Food.0001	96.43	79.76	97.62	97.62
2	Brick.0000	98.81	71.43	100.00	100.00	17	Leaves.0003	96.43	51.19	97.62	98.81
3	Brick.0004	92.86	40.48	95.24	98.81	18	Leaves.0012	96.43	51.19	97.62	92.86
4	Brick.0005	73.81	50.00	82.14	86.90	19	Metal.0000	95.24	54.76	95.24	94.05
5	Clouds.0001	92.86	55.95	96.43	96.43	20	Metal.0002	100.00	53.57	100.00	100.00
6	Fabric.0000	92.86	73.81	97.62	96.43	21	Metal.0004	100.00	65.48	100.00	100.00
7	Fabric.0006	95.24	63.10	96.43	94.05	22	Misc.0001	100.00	51.19	100.00	100.00
8	Fabric.0007	90.48	71.43	97.62	89.29	23	Misc.0002	96.43	55.95	98.81	96.43
9	Fabric.0013	96.43	89.29	98.81	97.62	24	Sand.0000	97.62	53.57	97.62	100.00
10	Fabric.0015	84.52	46.43	97.62	86.90	25	Sand.0002	97.62	59.52	100.00	95.24
11	Fabric.0017	100.00	96.43	100.00	97.62	26	Stone.0005	95.24	57.14	98.81	94.05
12	Fabric.0019	98.81	63.10	98.81	97.62	27	Tile.0004	95.24	75.00	100.00	96.43
13	Flowers.0005	92.86	38.10	92.86	90.48	28	Tile.0008	97.62	57.14	98.81	100.00
14	Flowers.0006	98.81	72.62	100.00	98.81	29	Water.0005	100.00	84.52	98.81	100.00
15	Food.0000	100.00	47.62	100.00	98.81	30	Wood.0002	100.00	92.86	100.00	100.00
Number of Image regions correctly classified								**2390**	**1583**	**2457**	**2431**
Mean Success Rate (%)								**94.84**	**62.82**	**97.50**	**96.47**

F1 = CSFs; F2 = CCFs; F3 = CSFs + CCFs; F4 = WSFs + WCFs

The feature vector for a particular image of particular size is obtained by extracting feature vectors from all image regions of that size from the respective image and averaging over the total number of image regions. Average classification gain obtained using this feature vector is 96.25%. Since the number of sub-bands obtained from Curvelet decomposition is high and also to reduce the complexity, the partitioning and renormalization steps are skipped in the Curvelet implementation giving only 54 features and the classification gain obtained for the same dataset is 96.09% which is only 0.16% lesser. Since there is only minor difference in the classification gain this simplified implementation of Curvelet transform is used for further texture classification.

Next, Dataset-2 containing thirty 512 x 512 size monochrome images, obtained from VisTex color image database is used for analysis. Each texture image is subdivided into sixty four 64 x 64, sixteen 128 x 128 and four 256 x 256 non- overlapping image regions, so that a total of 2520 sub-image regions respectively will be in the database. The feature vector for each image is calculated from the sub-bands of DCvT decomposition. Since number of sub-bands obtained in the DRT decomposition varies with the size of an image, the number of sub-bands obtained in the DCvT decomposition also gets varied. By decomposing an image using DRT, 26, 38 and 52 sub-bands are obtained for the image size of 64 x 64, 128 x 128 and 256 x 256 respectively. Since the number of sub-band is not same for all image sizes, three separate feature databases for three different image sizes (i.e., 64 x 64, 128 x 128 and 256 x 256) were used for Dataset - 2.

Classification is done using three different feature vectors (F1 – F3). Feature vector F1 contains the Curvelet Statistical Features (CSF) such as mean and standard deviation extracted from the DCvT sub-bands. The mean is calculated over the approximation sub-bands and is averaged to a single value, whereas standard deviation is calculated over all the sub-bands (i.e., both approximation and detail) giving 54, 117, 159 features for the image regions of size 64 x 64, 128 x 128 and 256 x 256 respectively. Feature vector F2 contains Curvelet Co-occurrence features (CCF) such as Contrast, Cluster Shade, Cluster Prominence and Local Homogeneity calculated from the DRT sub-bands giving 52, 114 and 156 features for each CCF for the image regions of size 64 x 64, 128 x 128 and 256 x 256 respectively. In order to improve the classification gain the combination of feature vectors F1 and F2 is used as Feature vector F3. For the purpose of comparison, the result obtained using Feature vector F4 which contains the combination of Wavelet Statistical Features (WSF) and Wavelet Co-occurrence Features (WCF) are used [22].

The classification results obtained for the Dataset-2 which contains 30 monochrome images for three different feature vectors (F1 – F3) are given in Table 1, where each entry specifies the average classification gain (%) obtained for the 84 image regions of the particular texture image. The classification gain (*G*) is calculated using Eqn. (2).

$$G(\%) = \frac{C_{corr}}{M} x 100\% \qquad (2)$$

where, C_{corr} is the number of sub-images correctly classified and *M* is the total number of sub-images, derived from each texture image. Using the feature vector F1 (CSF) the success rate achieved is 94.84%. Then using CCF as feature vector F2 a mean success rate of only 62.82% is achieved. In order to increase the success rate the classification is done using the combination of CSF and CCF as feature vector F3 and using this, a mean success rate of 97.50% is obtained. The average classification gain obtained using the feature vector F4 which contains WSF and WCF is 96.47% which is about 1.03% less than the average classification gain obtained using feature vector F3.

5. Discussion and conclusion

Though, in overall, Curvelet features outperform Wavelet features, it is observed from the Table 1 that out of 30 texture images used for experimentation, for 7 images, such as Bark.0006, Brick.0004, Brick.0005, Leaves.0003, Sand.0000, Tile.0008 and Water.0005, Wavelet features give better results than Curvelet features. Also, for 7 other images, such as, Brick.0000, Clouds.0001, Food.0001, Metal.0002, Metal.0004, Misc.0001 and Wood.0002, Wavelet features give equal classification gain as for Curvelet features, while for the remaining 14 images, Curvelet features give better results.

From the analysis of texture classification using Curvelet transform, it is inferred that the mean success rate achieved shows good improvement, i.e., 1% improvement over the mean success rate achieved using wavelet transform for the same dataset. The improvement in success rate is due to the sparse representation of images using the Curvelet transform. In contrast the Ridgelet transform, a step in the implementation of Curvelet transform allows obtaining a sparse image representation where the most significant coefficients represent the most energetic direction of an image with straight edges. Also, ridgelet transform handles the coefficients with all possible directions. So images which contain curves can handle well using the Curvelet transform. As a result the features obtained from the Curvelet sub-bands will have powerful information compared to the features from the wavelet sub-bands, which are effectively used for texture classification.

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