Neurocomputing 116 (2013) 157–164

Contents lists available at SciVerse ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

# Feature extraction through contourlet subband clustering for texture classification

Yongsheng Dong [a,b], Jinwen Ma [a,*]

[a] Department of Information Science, School of Mathematical Sciences and LMAM, Peking University, Beijing 100871, China
[b] Electronic Information Engineering College, Henan University of Science and Technology, Luoyang 471023, China

ARTICLE INFO

Available online 11 October 2012

*Keywords:*
Texture classification
Contourlet transform
Feature extraction
$c$-Means clustering

ABSTRACT

Feature extraction is an important processing procedure in texture classification. For feature extraction in the wavelet domain, the energies of subbands are usually extracted for texture classification. However, the energy of one subband is just a specific feature. In this paper, we propose an efficient feature extraction method for texture classification. In particular, feature vectors are obtained by $c$-means clustering on the contourlet domain as well as using two conventionally extracted features that represent the dispersion degree of contourlet subband coefficients. The $c$-means clustering algorithm is initialized via a nonrandom initialization scheme. By investigating these feature vectors, we employ a weighted $L_1$-distance for comparing any two feature vectors that represent the corresponding subbands of two images and define a new distance between two images. According to the new distance, a $k$-Nearest Neighbor (kNN) classifier is utilized to perform texture classification, and experimental results show that our proposed approach outperforms five current state-of-the-art texture classification approaches.



## 1. Introduction

Texture classification is one of the fundamental issues in computer vision and image processing. Various approaches for texture feature extraction as well as classification have been proposed during the last two decades [1–17], but the texture analysis and classification problem remains difficult and needs intensive research.

As a multiresolution analysis tool, the wavelet transform has been widely used for texture classification, which can be divided into model-based approaches and feature-based approaches. In the model-based approaches, the used models include the generalized Gaussian density (GGD) model [4], the bit-plane probability (BP) model [7], the refined histogram (RH) [8], the generalized gamma density (GΓD) model [9], and the like. These models are all under the assumption that wavelet subband coefficients follow some previously given parametric probability distributions. Texture classification is further performed by utilizing the parameters in the models which are estimated according to the subband coefficient. However, it can be found that for some texture images the parameters of the given parametric distribution of wavelet subband coefficients is difficult to be estimated. So, it is an alternative for us to utilize a nonparametric method to model or cluster the coefficients.

On the other hand, in feature-based approaches, the total energy of each high-pass wavelet subband is a commonly used statistical feature for texture classification [11]. Moreover, the local energy features in each high-pass subband can also be extracted and used to perform texture classification [12,13].

Recently, the contourlet transform was developed by Do and Vetterli [18] to get rid of the limitations of wavelets. Moreover, the contourlet expansion can achieve the optimal approximation rate for piecewise smooth functions with $C^2$ contours in some sense [18]. Therefore, it is valuable to utilize the contourlet transform to perform texture classification. Considering the advantage and disadvantage of the two kinds of wavelet-based methods, we attempt to combine nonparametric modeling with extracting features from the contourlet domain to perform texture classification.

As well-known, a typical nonparametric modeling method is to cluster the data in a given data set and represent them by the converged cluster centers. Among clustering algorithms [19–24], the $c$-means (or $k$-means) algorithm is a simple and popular clustering algorithm [19–21]. However, its performance heavily depends on the initial setting.

In this paper, by investigating the distribution of coefficients in each contourlet subband, we propose an efficient feature extraction approach for texture classification, which combines cluster features obtained by a $c$-means clustering algorithm using a nonrandom

* Corresponding author. Tel.: +86 10 62760609; fax: +86 10 62751801.
*E-mail addresses:* dongyongsheng93@163.com (Y. Dong), jwma@math.pku.edu.cn (J. Ma).

0925-2312/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.neucom.2011.12.059

initialization approach with conventional features extracted from contourlet subbands. In particular, we use a $c$-means clustering algorithm to cluster the contourlet coefficients, and the converged cluster centers are served as the features to represent the contourlet subband coefficients. Meanwhile, two conventional features representing the dispersion degree of contourlet subband coefficients are also extracted. In this way, a feature vector is formed for each contourlet subband by combining these two kinds of features together. Then, we employ the weighted $L_1$ metrics for measuring the feature vectors. Finally, we utilize a $k$-Nearest Neighbor (kNN) classifier based on the total distance obtained by summing up all the weighted $L_1$ metrics to perform the supervised texture classification, and experimental results on large texture datasets reveal that our proposed method outperforms five current state-of-the-art texture classification methods.

The rest of the paper is organized as follows. Section 2 introduces the contourlet transform. Section 3 presents the new texture classification method based on our proposed feature extraction approach. Experimental results are conducted in Section 4 to demonstrate the efficiency of our proposed feature extraction approach for texture classification. Finally, we conclude briefly in Section 5.

## 2. Contourlet transform

The primary goal of the contourlet construction was to obtain a sparse expansion for a typical image that is piecewise smooth [18]. Two-dimensional wavelets are only good at catching the point discontinuities, but do not capture the geometrical smoothness of the contours [25].

To get rid of the limitations of wavelets, the contourlet transform was constructed by utilizing a double filter bank structure in which at first the Laplacian pyramid is used to capture the point discontinuities, and then a directional filter bank (DFB) is used to link point discontinuities into linear structure [18]. Due to its cascade structure accomplished by combining the Laplacian pyramid with a DFB at each scale, multiscale and directional decomposition stages in the contourlet transform are independent of each other. Therefore, one can decompose each scale into any arbitrary power of two's number of directions, and different scales can be decomposed into different numbers of directions. Moreover, it can represent smooth edges with close to optimal efficiency. More recent developments and applications on the contourlet transform can be found in [25–27].

Fig. 1 shows an example of the contourlet transform on the "Lena" image. For the visual clarity, only two-scale decompositions are shown. The image is decomposed into a lowpass subband and 16 bandpass directional subbands with 8 subbands at each scale.

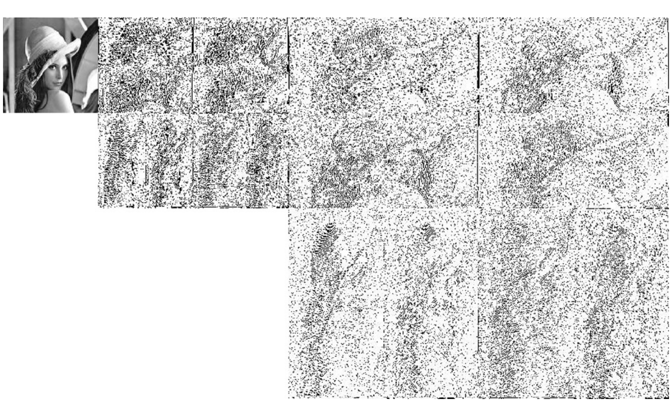

**Fig. 1.** Contourlet transform of the "Lena" image. The image is decomposed into a lowpass subband and 16 bandpass directional subbands with eight subbands at each scale. Small coefficients are colored black while large coefficients are colored white.

## 3. New texture classification method

For a texture image, denoted by a matrix $\mathbf{a}_0$, we can decompose it via the discrete contourlet transform into a set of coefficients, which are also denoted by matrixes $\{\mathbf{a}_L, \mathbf{c}_{i,j}^{(l_i)}\}$, $i = 1,2,\ldots,L$ and $j = 1,\ldots,2^{l_i}$. Note that the indexes $i$ and $j$ specify the scale and direction, respectively. $L$ is the number of scales, while the number of DFB decomposition levels varies with the scale $i$, being denoted by $l_i$. For simplicity, we set the number of DFB decomposition levels at each scale as 3 ($l_i = 3$, $i = 1,2,\ldots,L$), that is, the number of directional subbands at each scale is 8.

For $L$-scale contourlet decompositions of a given texture image, the average amplitude of the coefficients increases almost exponentially with the scale $i$ ($i = 1,2\ldots,L$). So, to uniformly measure the contourlet coefficients at different scales, we regularize them by multiplying the factor $1/4^i$ to those in the high-pass directional subbands at the $i$-th scale, and multiplying the factor $1/4^L$ to those in the low-pass subband. For the sake of clarity, the contourlet coefficients in the following will represent the regularized coefficients without explanation.

### 3.1. Proposed feature extraction method

Feature extraction is very important for the purpose of pattern recognition such as texture classification [11–14], handwritten numeral recognition [25], face recognition [28–31], and so on. In this subsection, some important features are extracted from contourlet subbands for texture classification.

#### 3.1.1. Features extracted by c-means clustering

Consider a particular contourlet subband with $N$ coefficients $S = \{x_1, x_2, \ldots, x_N\}$. As an important approach in data mining, clustering analysis has its advantage in mining valuable information from a number of data. Actually, many statistical methods need to model the data by a previously assumed parametric distribution. However, clustering analysis does not need any parametric assumption. In this paper, we attempt to mine the essential information by employing a clustering algorithm and define some features representing the contourlet subband for classification. Various algorithms have been established to solve the clustering problem [19–24]. Among them, the $c$-means algorithm is a simple and popular one. Its idea is to partition this data set into $J$ disjoint subsets (clusters) $C_1, \ldots, C_J$ such that a clustering error criterion is optimized [20]. The criterion is the sum of the squared Euclidean distances between each data point $x_i$ and the centroid $f_j$ (cluster center) of the subset $C_j$ which contains $x_i$, which is called clustering error and given by

$$E(f_1,\ldots f_J) = \sum_{i=1}^{N}\sum_{j=1}^{J} I_{C_j}(x_i)\|x_i - f_j\|^2, \tag{1}$$

where $I_C(x) = 1$ if $x \in C$ and 0 otherwise.

However, the $c$-means clustering algorithm suffers from the serious drawback that its performance heavily depends on the initial setting [19]. For the purpose of clustering on the contourlet subband with $N$ coefficients, we let $\delta = [N/2J]$, where $[z]$ denotes the largest integer less than or equal to $z$. In this way, we divide the $N$ coefficients into $J$ subsets:

$$[\tilde{x}_1, \tilde{x}_{2\delta+1}), [\tilde{x}_{2\delta+1}, \tilde{x}_{4\delta+1}), \ldots, [\tilde{x}_{2(J-1)\delta+1}, \tilde{x}_N)], \tag{2}$$

where $\tilde{x}_i$ denotes the $i$-th order statistic of the coefficient sample $S = \{x_1, x_2, \ldots, x_N\}$. Moreover, the centers of these subsets, $f_j$,