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Texture Segmentation via Scattering Transform

Huajuan Wu[1,2], Mingjun Li[3],Mingxin Zhang[1,2], Jinlong Zheng[2] and Jian Shen[2]

[1]College of Computer Science and Engineering,
Northwest Normal University, 730070 Lanzhou, China
[2]College of Computer Science and Engineering,
Changshu Institute of Technology, 215500 Changshu, China
[3]School of Computer and Information Engineering, Harbin University of Commerce,
Harbin, 150028, China
wuhuajuan1986@163.com,mxzhang163@163.com

Abstract

Texture contains high and low frequency information which could be hierarchically extracted by scattering the texture along multiple paths, with a cascade of wavelet modulus operators implemented in a deep convolutional network, which builds a scattering energy distribution network. Therefore, the scattering transform is used, in this paper, to get texture energy features. Besides, the classification of scattering energy feature matrix at all levels is done by using the Ostu global threshold processing method. Experimental results indicate that high accuracy can be achieved for both texture segmentation and license plate location with the proposed methods.

Keywords: *texture segmentation; wavelet transform; scattering operator; scattering convolution network; license plate location*

1. Introduction

Image segmentation is an important foundation of object recognition, classification and retrieval, and also the basic starting point and one of the key works in those research areas such as image processing, machine vision, and pattern recognition. Because texture is an important attribute of image regions, naturally, texture segmentation becomes the focus of image segmentation, which has drawing the attention of many researchers. At present, texture descriptor has been developed for many aspects: foreground detection [i], biometric pattern recognition [ii], and medical images [iii]. Texture segmentation has two critical points: one is texture feature extraction, whose main purpose is to obtain the feature vectors of pixels which can distinguish different texture; the other is consistency segmentation based on the feature vector, whose aim is to distinguish different texture by using the feature vector [iv]. In the past thirty years, researchers have proposed many kinds of texture analysis methods. In 1989, texture analysis based on wavelet transform was raised by S. Mallat, and then texture segmentation based on wavelet transform was highly concerned by the majority of researchers. In 2011, S.Mallat advanced scattering operator theory based on wavelet transform [v], which could compute an affine transformation invariant image representation, was stable to elastic deformation, and not sensitive to illumination. Scattering operator keeps translation invariance and deformation stability, meanwhile, preserves the lost high frequency and extracts image symbiosis information--- scattering coefficient, and thus better able to

Corresponding author: Mingxin Zhang, E-mail: mxzhang163@163.com
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extract invariant image representations for affine transformation and elastic deformation. Scattering operator has made a very good classification results for handwritten digit recognition and texture discrimination [vi].

In this paper, the novel approach proposed by S. Mallat is applied to texture segmentation of singles image, which advanced a texture segmentation based on wavelet scattering convolution network. Firstly, the scattering energy feature of each sub-image block is obtained with wavelet scattering convolution network, as texture feature which is used to distinguish between different textures. Secondly, the method adds up the scattered energy values of each sub-image block by output level to obtain eigenvalues which form eigenvalue matrixes. And then the coarse segmentation result is obtained with a global threshold processing (Ostu) which is classifiable to eigenvalue matrixes. Finally, the spurious spots of coarse segmentation are removed to get fine segmentation results by applying morphological techniques.

2. Wavelet Scattering Convolution Network

The Fourier transform, which reflects global energy of image, is a global transformation, so its energy spectrum cannot splendidly describe the local features of image. The wavelet transform, which reflects the local feature of image, is a local transformation. The selection of wavelet function is different, extracted features is also different. Wavelet transform can obtain multiscale and multidirectional frequency characteristics of image, resulting in multiscale and multidirectional energy distribution characteristics of image.

First, wavelet scattering convolution network uses wavelet transform to obtain high-frequency information of image (the detailed information of image) at each network layer, and then transforms high-frequency to low-frequency by applying average operator, thus maintain the stability of high-frequency information. High frequency lost during the process can be recovered at the next network layer. Therefore, high frequency information at different levels can be extracted by wavelet scattering convolution network.

2.1. Wavelet Modulus

The essence of wavelet transform is a filtering process to the original signal [vii]. Scaling and rotating band-pass filtering function ψ can get two-dimensional direction wavelet function. Binary scaling and rotating filtering function ψ can obtain multi-resolution wavelet function:

$$\psi_{\lambda}(x) = 2^{2j}\psi(2^{j}r^{-1}x) \tag{1}$$

With $\lambda = 2^{j}r \in \Lambda = G\times□$, $j\in□$, $r \in G$ （G is a discrete and limited rotation group in $□^{2}$）, j decides the scale of $\psi(x)$ and r decides the direction of $\psi(x)$. So the wavelet transform of texture $f(x)$ as follows:

$$W_{\lambda} f(x) = f * \psi_{\lambda}(x) \tag{2}$$

Therefore, the wavelet modulus is

$$U_{\lambda} f(x) = \left| f * \psi_{\lambda}(x) \right| \tag{3}$$

The modulus operator acts on wavelet transform, which can capture low-frequency information, so the high-frequency coefficients of wavelet transform could be mapped to the low-frequency form by using the modulus operator[viii].

The result of the convolution of texture $f(x)$ and zoom function $\phi_J(x)$ is low frequency information.

$$A_J f(x) = f(x) * \phi_J(x)\text{, with } \phi_J(x) = 2^{-2J}\phi(2^{-J}x) \tag{4}$$

The resulting wavelet modulus operator $\overline{U_J}$ is

$$\overline{U_J} f = \{A_J f = f * \phi_J, U_\lambda f = |f * \psi_\lambda|\}_{\lambda \in \Lambda} \tag{5}$$

2.2. Scattering Operator

The modulus operator acts on the wavelet transform, which lose some high-frequency information. It could be recovered by further iterating on U_λ [v]. The diverse information of texture is scattered to different paths $p = \{\lambda_n\}_{1 \le n \le |p|}$ in the iterative process. Resulting in the scattering propagator as follows:

$$U(p) f = |...| f * \psi_{\lambda_1} | * \psi_{\lambda_2} | ... | * \psi_{\lambda |p|} | \tag{6}$$

The wavelet modulus operator is iteratively applied to progressively map high signal frequencies to lower interference signals. The resulting scattering operator is defined from $A_J f = f * \phi_J$ and $U_\lambda f = | f * \psi_\lambda |$ [v].

Definition (scattering operator): A wavelet path is an index sequence $p = \{\lambda_n\}_{1 \le n \le |p|}$. A scattering operator at the scale 2^J is defined over a set P_J of paths $p = \{\lambda_n = (j_n, \gamma_n)\}_{1 \le n \le |p|}$ for which $\max_n \ j_n < J$:

$$S_J(p) f = A_J S(p) f\text{, with } S(p) f = \prod_{n=1}^{|p|} U_{\lambda_n} f \tag{7}$$

For $p = 0$, $S(0) f = f$ and $S_J(0) f = A_J f$.

The scattering operator S_J implements a sequence of wavelet convolutions and modulus, followed by a convolution with ϕ_J :

$$S_J(p) f = |...| f * \psi_{\lambda_1} | * \psi_{\lambda_2} | ... | * \psi_{\lambda |p|} | * \phi_J \tag{8}$$

2.3. Scattering Convolution Network

The key property of the scattering operator depends on the scattering propagator $U(p) f$, which implements a multi-level convolution network. Therefore, the wavelet scattering transform process could be described by a deep convolution network [ix], as shown in Figure 1. But a scattering transform appears to be a deep convolution network with some particularities. As opposed to most convolution networks, a scattering network output coefficients $S_J[p] f$ at all layers, not just at the last layer. Related theory has proved that the energy of the deepest layer converges quickly to zero as the length of path increases [v], and most of the energy is concentrated in $|p| \le 3$ [vi]. A second distinction is that filters are not learned from data but are predefined wavelets.

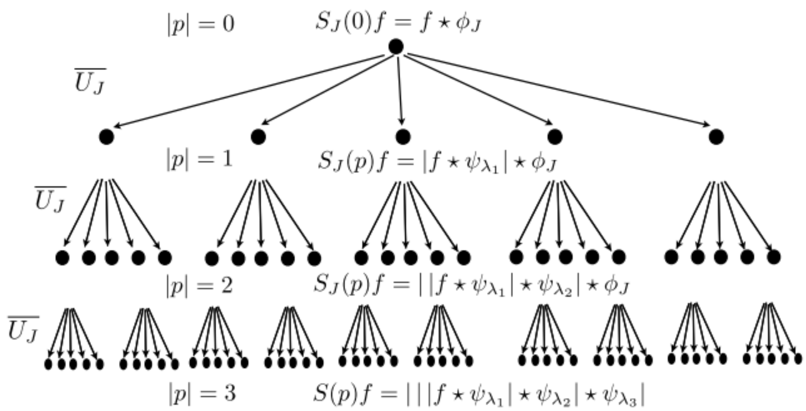

Figure 1. Scattering convolution network

3. Texture Segmentation Based on Wavelet Scattering Convolution Network

In this paper, the scattering energy coefficients of wavelet scattering convolution network at the former three levels are chosen to measure texture similarity. Figure 2 shows the scattered energy distribution of two different texture in Brodatz, (a) is the original texture image, (b) is the second layer output of scattering energy distribution, (c) is the third layer output scattering energy distribution.

As you can see in Figure 2, the distribution of image energy is closely related to the distribution of its texture, the main direction of the texture above is horizontal and vertical direction, its energy also concentrates in the horizontal and vertical direction; the main direction of the one below is diagonal direction, whose energy mainly concentrates in the diagonal direction. Further, it is clear that the total scattering energy of the texture bellow is greater than the one's above at the second and third levels. Therefore, the energy distribution characteristics of texture, obtained by scattering convolution network, can be applied to segment texture.

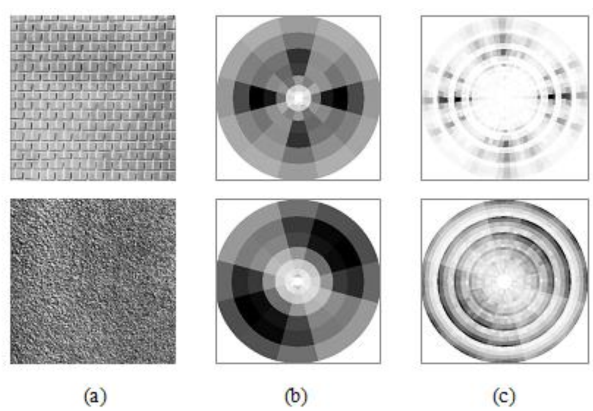

Figure 2. Scattering display of two images. (a) Texture $f(x)$. (b)Scattering $S_J(p)f$ for $|p|=1$. (c) Scattering $S_J(p)f$ for $|p|=2$

Texture segmentation algorithm:

Input: Texture image of size $N \times N$.

Output: Texture segmented image.

Step 1: Read texture image and obtain $S \times S$ sub-image blocks.

Step 2: Apply wavelet scattering transform to extract scattering energy distribution SE_i of each sub-image block.

$$\mathrm{SE}_i = \| S_J(p)x \|^2 \tag{9}$$

Where $i = 1, 2, ..., K$, K is the number of scattering energy.

Step 3: Calculate the total scattering energy of sub-image block according to convolution network of different levels, and the percentage SER_m of it from the total energy of sub-image block. The percentages compose $M \times M$ eigenvalue matrixes.

$$SER_m = \frac{\sum_{i \in m} SE_i}{\|x\|^2}, \text{ with } m = 1, 2, 3 \tag{10}$$

Step 4: Obtain the thresholds of eigenvalue matrixes by applying the Ostu method of global threshold processing and use the thresholds to get coarse segmentation.

Step 5: Apply the dilation and erosion mathematical morphology to remove spurious spots in the coarse segmentation, which gets fine segmentation.

Step 6: Apply the dilation and erosion mathematical morphology to get the edge of fine segmentation image, and then map it back to original mage.

4. Experimental Results and Discussion

4.1. Artificial Texture Segmentation

The first experiment is an artificial image of dimension 256×256 that contains two textures in Figure 2, and is divided into 8×8 sub-image blocks. The goal of this experiment is to validate and illuminate the validity and feasibility of the proposed method. The image and its experimental results are shown in Figure 3. The coarse segmentations are shown in Figure 3 (b), from left to right, which are the scattering energy characteristics, obtained by applying the Ostu method of global threshold processing, at the $|p| = 1$, $|p| = 2$ and $|p| = 3$. We can observe that the left side of the first image in Figure 3(b) is white and the right is black (In the diagram, the white parts indicate value is larger than the black parts indicated), the second and third one are just the opposite. The result shows that the energy of texture on the left mainly concentrates on low-frequency, while on the right mainly concentrate on high-frequency, which is consistent with the scattering energy distribution illuminated in Figure 2. Figure 3(c) shows the thinned segmentation, from left to right; the three images are obtained by applying morphology algorithm to the three coarse segmentations. Obviously, the first and second thinned segmentations are better than the third one, because of influence of spurious spots in the coarse segmentation. The best thinned segmentation is chosen, from Figure 3(c), to get the final segmentation, as shown in Figure 3(d). In addition, other three images are patched with the textures chosen at random in Brodatz to further validate the suggested method, as shown in Figure 4. All test images are 8-bits per pixel grayscale images of dimension 256×256 and are divided into 8×8 sub-image blocks.

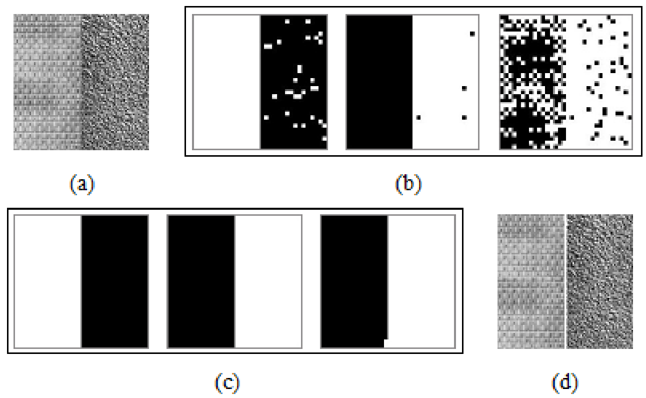

Figure 3. Texture segmentation example. (a) Original texture. (b) Coarse segmentation. (c) Fine segmentation. (d) Final segmentation

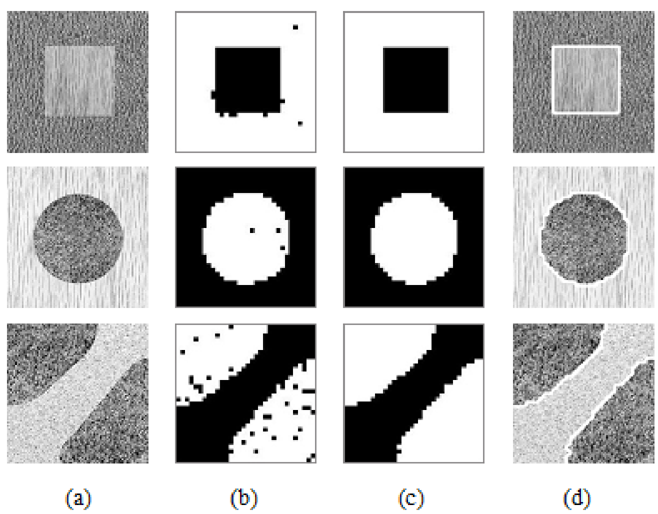

Figure 4. Texture segmentation example. (a) Original texture. (b) Coarse segmentation. (c) Fine segmentation. (d) Final segmentation

4.2. License Plate Location

At present, license plate location algorithm is mainly based on texture feature, color feature or combining them [x]. The license plate region, whose texture is particular, only contains Chinese characters, English letters and numbers. It has more plentiful edge information than the other regions. Hence, the suggested method is equally applicable to the license plate location. The results of the license plate location by applying the proposed method are show in Figure 5.

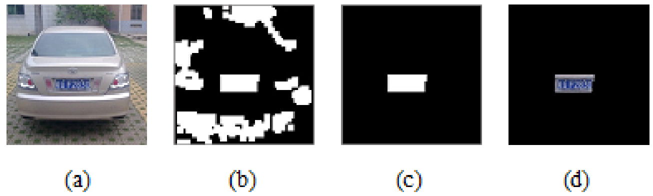

Figure 5. License plate location. (a) Car. (b) Fine segmentation. (c) Region of interest. (d) License plate

In order to test the robustness and adaptability of the algorithm for the license plate location, 646 pictures were captured in different background, different weather, and different light to make experiments. Image classification and experimental statistical results are shown in Table 1. Based on the data in Table 1, environmental complexity and light brightness have little impact on the license plate location with 98.9 percent accuracy. Figure 6 shows the renderings of three pictures in different environment, different illumination, and different perspective. Differing from other method [xi] [xii] which may require specific conditions, the proposed method has no such requirement.

Figure 6. Location results in different situation

Table 1. The statistical results

Illumination	Number of images	False Location	Accuracy rate of location (%)
Lighter	152	3	98
Light	274	3	98.9
Dark	191	1	99.5
Darker	29	0	100

5. Conclusion

In this paper, the concept of wavelet scattering convolution network is applied to texture segmentation. Scattering energy distribution characteristics, computed with wavelet scattering convolution network, reflect sparsity and edge characteristics of image. The basic idea of the proposed method is that using the scattering energy distribution characteristics as texture similarity metric to distinguish between different textures. The results show that the proposed method can be well applied to texture segmentation and license plate location. However, in the coarse segmentation stage, the proposed method only apply single threshold to segment the image consists of two types of textures. If you want to split an image consists of many types of textures, you need multiple thresholds or to use statistical classification methods. In addition, scattering convolution network can extract the multiscale and multidirectional energy distribution characteristics of image. However, in this paper, eigenvalue matrixes are constituted just from the point of view of convolution network level. Hence, the future research direction is that using scattering energy feature from multiscale and multidirection.

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Authors

Huajuan Wu is a postgraduate at College of Computer Science and Engineering, North West Normal University, China. Her research interests include pattern recognition and image processing.

Mingjun Li, associate professor, received the B.S degree in computer science from the Northeastern University, Shenyang, China, in 1982. His research interests include pattern recognition; The main research directions: information management, business automation, ERP systems, logistics and distributed computing.

Mingxin Zhang received the B.S degree in computer science from the Northeastern University, Shenyang, China, in 1982, the M.S degree in general traffic design from the Xi'an University of Architecture and Technology, Xi'an , China, in 1990, and the Ph.D. degree in software and theoretical science from the Xi'an Jiaotong University, Xi'an, China, in 2008. He has taught Computer Science at Northwest Normal University and Gansu Agricultural University as a professor. He is currently a professor of Computer Science at Changshu Institute of Technology, China. His research interest include database and system integration , intelligent control system based on network, graphic image and video information retrieval , data mining and knowledge discover.

Jinlong Zheng received the B.S degree at College of Computer Science and Engineering, Northwest Normal University. His research interests include pattern recognition and image processing.