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Segmentation for Fabric Weave Pattern using Empirical Mode Decomposition based Histogram

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Abstract

This paper is focused on the segmentation of the fabric weave patterns for the urgent requirement of fabric imitative design and redesign.The weave patterns related to the fabric yarn are determined by a new technology, which is called bidimensional mode decomposition based method. The proposed method first iteratively decompose the underlying fabric image into a number of intrinsic mode functions (IMFs). The first order IMF is applied to to calculate histogram and fabric weave pattern segmentation results are obtained by integrating corresponding threshold decision strategies such as double maxima algorithm or Otsu algorithm. In comparison with the original image-only based histogram segmentation method, the presented method have a high precision. Simulation results show that BEMD based method is a promising approach for the segmentation of fabric weave pattern.

Keywords: *fabric weave pattern, bidimensional empirical mode decomposition, histogram*

1. Introduction

Texture is changes of the surface color and grayscale, which can be used to distinguish different objects. Texture analysis is an important research field among image processing, image analysis, and image retrieval. The research content of texture analysis mainly includes texture classification and segmentation, texture synthesis, texture retrieval and recovery of shape from texture. The essential aspect of texture analysis is to extract texture features, which is characterized by statistical methods and structure methods. Statistical methods use local correlation operation between pixels to describe the texture, while structure methods use texture opportunities and synthesis rules to describe the texture. Classical texture analysis methods are difficult to meet the needs of complex of textures due to stationarity. The real fabric image arrangement is not ideal because of non-stationary signals arranged in the ideal model of yarn. The recently presented empirical mode decomposition (EMD) is potentially viable for nonlinear and nonstationary signal analysis, especially for time-frequency-energy representations [1]. EMD decomposition is a new data processing method possessing better adaptability compared with the wavelet analysis based methods. Extension of one-dimensional EMD to two-dimensional signal analysis yields a new way for the two-dimensional image analysis. Bidimensional empirical mode decomposition (BEMD) have been applied to the extraction of image texture and image filtering and other fields [2].

This paper deals with the recognition of fabric weave pattern using bidimensional empirical mode decomposition with histogram based thresholding. Considering the first intrinsic mode function (IMF) of BEMD results mainly consist the weave pattern information of the fabric image, the first IMF of underlying fabric image is decomposed, and then the weave patterns are segmented with the two-dimensional histogram.

2. Principle and implementation for BEMD

2.1. Sifting Process

Assume $I(m, n)$ is the underlying fabric image. The goal of sifting process for BEMD is to decompose $I(m, n)$ into multiple hierarchical components, BIMFs. A general sifting process is summarized as follows [3]:

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Step 1. Determine whether $I(m, n)$ is monotonic or not. If $I(m, n)$ is monotonic, terminate the sifting process proceeding; otherwise, set $H(m, n) = I(m, n)$.

Step 2. Use morphological operators to search the region extrema of $H(m, n)$.

Step 3. Interpolate the regional extreme points to obtain upper and lower envelope surfaces of $H(m,n)$, expressed as $e_{\max}(m,n)$ and $e_{\min}(m,n)$ respectively.

Step 4. Compute the mean between $e_{\max}(m,n)$ and $e_{\min}(m,n)$ as:

$$M(m,n) = \left[e_{\max}(m,n) + e_{\min}(m,n)\right]/2 \quad (1)$$

Step 5. Subtract $M(m,n)$ from $H(m,n)$ to obtain $\tilde{H}(m,n)$:

$$\tilde{H}(m,n) = H(m,n) - M(m,n) \quad (2)$$

Step 6. Update $H(m,n)$ by $\tilde{H}(m,n)$, and repeat Step 2 to Step 5 until the following criterion is satisfied.

$$\frac{\sum_m \sum_n \left[\tilde{H}(m,n) - H(m,n)\right]^2}{\sum_m \sum_n \left[H(m,n)\right]^2} < SD, \quad (3)$$

Where SD is a predefined threshold [4]. The resulted $\tilde{H}(m,n)$ is taken as the first IMF which represents the fabric weave pattern component. The same sifting process is then applied to the subsequent residue image to extract more IMFs.

2.2. Extreme Points Search Algorithm

Regional maxima search algorithm using morphological reconstruction can be detailed as:

Step 1. Let $I(m,n)$, $Max(I)$ be the original fabric image and the maximum value of image area respectively. Let $I-1$ be the mask image, which is represented by $Mark(I-1)$.

Step 2. Perform morphological dilation operation on $Mark(I-1)$ to obtain $P(I-1)$.

Step 3. Let $I(m,n)$ be the mask image. If there is a data of $P(I-1)$ greater than that of the original image, the corresponding data of original image is assigned to the one of $P(I-1)$.

Step 4. Compare $P(I-1)$ with $Mark(I-1)$. If they are identical, go to the next step; otherwise $P(I-1)$ is assigned to $Mark(I-1)$, and repeat Step 2 to Step 3 until $P(I-1)$ and $Mark(I-1)$ are the same.

Step 5. Subtract $P(I-1)$ from the original image to obtain regional maxima, $Max(I) = I - P(I-1)$.

Similarily, the regional minima search algorithm using morphological reconstruction can be described as:

Step 1. Let $I(m,n)$, $Min(I)$ be the original fabric image and the minimum value of image area respectively. Let $I+1$ be the mask image, which is represented by $Mark(I+1)$.

Step 2. Perform morphological erosion operation on $Mark(I+1)$ to obtain $P(I+1)$.

Step 3. Let $I(m,n)$ be the mask image. If there is a data of $P(I+1)$ less than that of the original image, the corresponding data of original image is assigned to the one of $P(I+1)$.

Step 4. Compare $P(I+1)$ with $Mark(I+1)$. If they are identical, go to the next step; otherwise $P(I+1)$ is assigned to $Mark(I+1)$, and repeat Step 2 to Step 3 until $P(I+1)$ and $Mark(I+1)$ are the same.

Step 5. Subtract $P(I+1)$ from the original image to obtain regional maxima, $Min(I)=I-P(I+1)$.

2.3. Surface Interpolation Algorithm

Surface interpolation algorithm mainly includes Delaunay triangulation [5] and cubic interpolation, which constitutes the significant two dimensional surface interpolation algorithm [6].

Assuming that the non-collinear three points $P_i(x,y)$, *i*=1,2,3 form a triangle, then any inner point $P\,(x,y)$ of the triangle can be expressed with the triangular area coordinates as:

$$P=\alpha_1 P_1+\alpha_2 P_2+\alpha_3 P_3 \quad , \tag{4}$$

Where $\alpha_i's$ are the triangular area coordinates, satisfying the conditions:

$$0 \le \alpha_i \le 1 \text{ and } \sum_{i=1}^{3}\alpha_i=1 . \tag{5}$$

Let
$$f(x,y)=\sum_{i=0}^{n}\sum_{i+j=l}\alpha_{ij}x^i y^j , \tag{6}$$

Then Bernstein-Bezier surface interpolation equation is contructed as :

$$f(x,y)=F(\alpha)=\sum_{|\lambda|=n} b_\lambda B_\lambda^n(\alpha) . \tag{7}$$

The proposed surface interpolation algorithm are as follows [7, 8]:

Step 1. Perform Delaunay triangulation.

Step 2. Arrange the triangle in the same direction, and then calculate the area of the resulting triangles and the vector products of adjacent sides.

Step 3. Compute the gradient of and the normal slope respectively in terms of the area weights.

Step 4. Compute the gradient of the gradient of each side in terms of the area weights.

Step 5. Determine the triangle adjacent to each interpolating point.

Step 6. Calculate the fitting coefficients for each interpolating point.

Step 7. Perform interpolation for each interpolating point.

3. Histogram based Segmentation with Thresholding

Assuming gray levels of the underlying image is L , and the number of pixels with gray level i is n_i, then the total number of pixels is $N=\sum_{i=0}^{L-1} n_i$. The probability of occurrence of each gray level is :

$$P_i=\frac{n_i}{N} \ , \ i=0,1,\cdots,L-1 \tag{8}$$

Assume that the threshold value is T, and then image gradation is divided into two categories A and B by T. A class contains gradation of $[0,1,\cdots,h]$; Class B contains gradation $[h+1,\cdots,L-1]$. Let the probability of each gray level be P_i, then the probability of classes A and B are shown as:

$$P_A = \sum_{i=0}^{h} P_i \ , \quad P_B = \sum_{i=h+1}^{L-1} P_i \tag{9}$$

Gradation mean of class A and B are shown as bellow:

$$\omega_A = \sum_{i=0}^{h} iP_i / P_A, \ \omega_B = \sum_{i=h+1}^{L-1} iP_i / P_B \tag{10}$$

The gray average of image is shown as below:

$$\omega = \sum_{i=0}^{L-1} iP_i \tag{11}$$

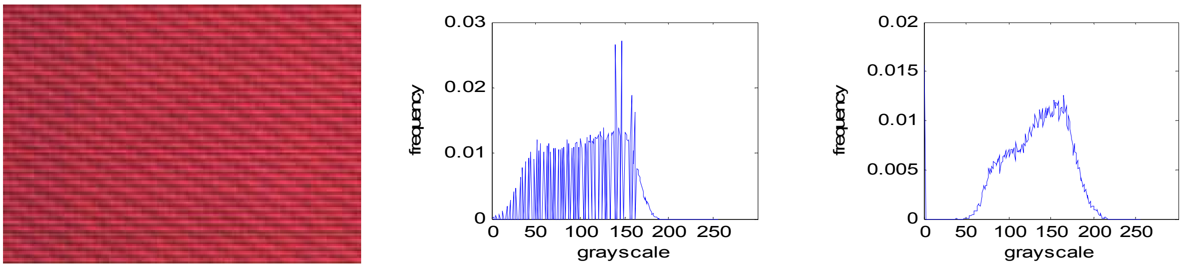
The between-class variance can be expressed as:

$$\sigma^2 = P_A(\omega_A - \omega)^2 + P_B(\omega_B - \omega)^2 \tag{12}$$

The maximum of between-class gray variance can be determined by double maxima algorithm or Otsu algorithm, which corresponds the optimal gray threshold.

4. Simulation results

BEMD is an effective method to separate the target and background from the fabric image. The histogram of decomposed first IMF is meaningful for the segmentation with thresholding. Comparison of the histogram of original fabric imge with the histogram of its decomposed first order component is shown as Figure 1, which has implied the effectiveness of BEMD based histogram segmentation algorithms.

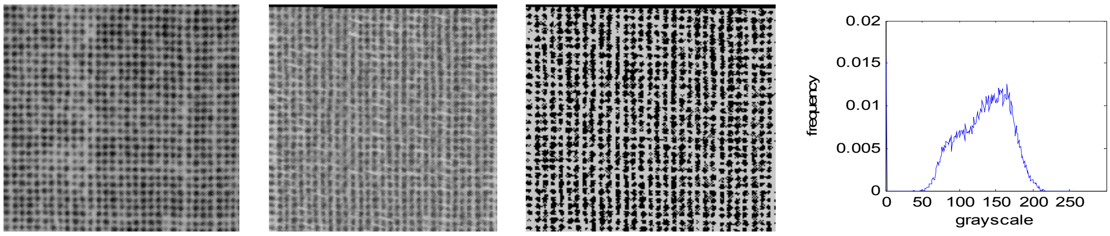


(a) (b) (c)

Figure 1. Comparison of the Histogram of Original Fabric Image with the Histogram of its Decomposed First Order Component. (a) Orginial Fabric Image. (b) Histogram of the Original Fabric. (c) Histogram of its Decomposed First Order Component

4.1. Sparse Type of Fabric

This type of fabric image renders distinct texture features. Its gray histogram is with the equalizing form with unimodal or bimodal distribution. The largest class-between variance method is proposed to segment the fabric weave pattern. The results are illustrated in Figure 2.



(a) (b) (c) (d)

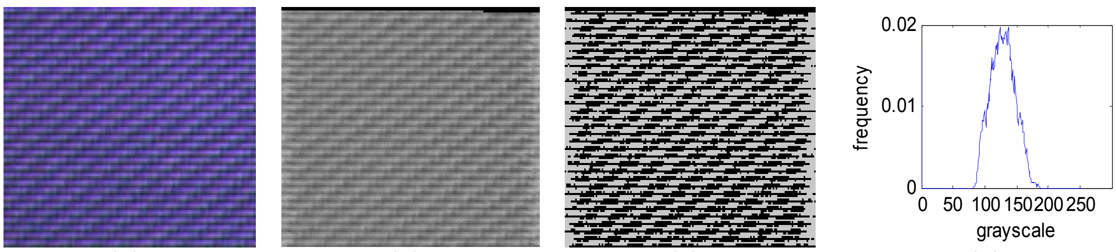
Figure 2. Segmented Results for Sparse Type of Fabric. (a) Original Fabric Image, (b) First Order IMF, (c) Segmented Textures (d) Histogram of the First Order IMF

4.2. Dense Type of Fabric

Such fabrics have no apparent backgrounds. The histogram is currently with a single peak or double peaks.

4.2.1. Single Peak Case

Segmented results of the dense type of fabric with single peak histogram are show in Figure 3.

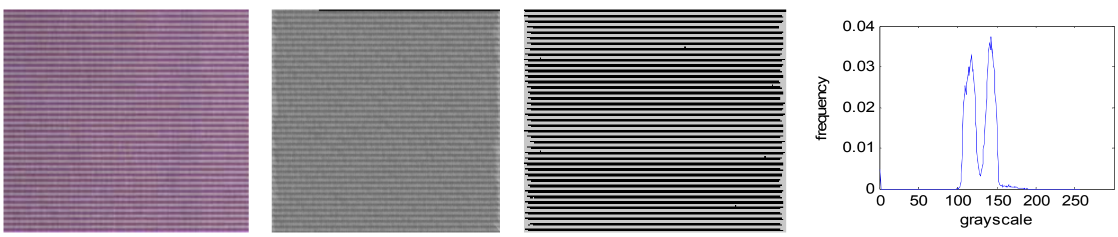


(a) (b) (c) (d)

Figure 3. Segmented Results of the Dense Type of Fabric with Single Peak Histogram (a) Original Fabric Image, (b) First Order IMF, (c) Segmented Textures, (d) Histogram of the First order IMF

4.2.2. Double peak case

If there is distinct gap between the of peaks on the histogram of the first order IMF. The segmentation of weave patterns can be performed well by choosing the value corresponding to the valley between peaks of the underlying histogram as threshold. This case is illustrated in Figure 4.



(a) (b) (c) (d)

Figure 4. Segmented Results of the Dense Type of Fabric with Double Peak Histogram (a) Original Fabric Image, (b) First Order IMF, (c) Segmented Textures, (d) Histogram of the First Order IMF

5. Conclusion

Fabric weave pattern segmentation is a key issue for fabric imitative design and redesign in order meet the new market needs. On the study of fabric pattern segmentation, this paper proposes an adaptive method based on bidimensional empirical mode decomposition. The first intrinsic mode function, which mainly implies the weave pattern of the fabric is then applied to construct the histogram. Together with double maxima algorithm or Otsu algorithm, the segmentation is performed effectively.

In comparison with the original image-only based histogram segmentation method, the presented method have a high precision. Simulation results show that BEMD based method is a promising approach for the segmentation of fabric weave pattern.

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References

[1] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen NC, Tung CC, Liu HH. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. *Proc. of the Royal Society of London*. 1998; A454: 903−995.

[2] Damerval C, Meignen S, Perrier V. A fast algorithm for bidimensional EMD. *IEEE Signal Processing Letters.* 2005; 12(10): 701−704.

[3] Cheng JS, Yu DJ, Yang Y. Research on the intrinsic mode function (IMF) criterion in EMD method. *Mechanical Systems and Signal Processing.* 2006; 20(4): 817−824.

[4] Chen Q, Norden E, Huang, Riemenschneider S. Xu Y. AB-spline approach for empirical mode decompositions. *Adv. Comput. Math*. 2006; 24: 171-195.

[5] Watson D. Computing the n-dimensional Delaunay tessellation applications to Voronoi polytopes. *Comput. J.* 1981; 24: 167-172.

[6] Isaac Amidror**.** Scattered data interpolation methods for electronic imaging systems: a survey . *Journal of Electronic Imaging.* 2002; 11(2): 157–176.

[7] Guangguo Zhang, Jing Sheng, Feng Wang. A Finite Element Analysis of The Rectangle Spline Broach. *Telkomnika*. 2012; 10(8): 2073-2082.

[8] TIAN *Qi*-chuan, CHEN Bin, WANG Da-shen, FAN Wen-guang. Virtual Slice Extraction Based on Hermite Interpolation. *TELKOMNIKA*. 2012; 10(6): 1430-1438.