Image Segmentation of Printed Fabrics with Hierarchical Improved Markov Random Field in the Wavelet Domain

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ABSTRACT
An improved MRF algorithm–hierarchical Gauss Markov Random Field model in the wavelet domain is presented for fabric image segmentation in this paper, which obtains the relation of inter-scale dependency from the feature field modeling and label field modeling. The Gauss-Markov random field modeling is usually adopted to feature field modeling. The label field modeling employs the inter-scale causal MRF model and the intra-scale non-causal MRF model. After that, parameter estimation is the essential section in the inter-scale, enhancing modeling capabilities of the pixels partial dependency. Sequential maximum a posterior criterion is applied to achieve the results of image segmentation. Comparisons with other hybrid schemes, results are indicated that performance of the presented algorithm is effective and accurate, in terms of classification accuracy and kappa coefficient, for patterned fabric images.

Keywords: Image segmentation; Feature field modeling; Label field modeling; Parameter estimation

INTRODUCTION

Printed fabric image segmentation is a very important process in textile printing and dyeing. The segmentation quality directly affects precision and accuracy of cloth printing as well as the subsequent drawing. Generally, image segmentation refers to divide into the different regions of the image that has a special significance in the division [1, 2]. These areas have mutually disjoint features, which own to gray, color, texture and other characteristics of similar principles. Image segmentation is not only a key step from image processing to image analysis, but also a basic technology of machine vision. There are numerous algorithms for image segmentation with threshold value method, the segmentation method based on edge detection, segmentation method based on fuzzy set theory, based on the random field method and other segmentation algorithms. Based on the Markov Random Field (MRF) model has attracted much attention in recent years [3, 4, 5, 6, 7, 8]. In this paper, the proposed scheme is hierarchical Gauss Markov Random Field model in the wavelet domain, to obtain given image segmentation results more accurately and reliably.

Among the method of inter-scale statistical dependencies modeling, the application of the multi-scale hierarchical Markov random field model is used widely [9]. However, due to the feature field of the images is based on the pixel level, which doesn't have a non-direction and redundancy. It is difficult to depict the non-stationary of the image. In order to overcome this defect, hierarchical Markov random field in the wavelet domain is put forward, which greatly express non-stationary in fabrics [10]. But this method is only to modeling of correlation among different scales, which doesn't deal with correlation of the same scale. There still exists the problem of insufficient local spatial information statistics, making it difficult to form large area and keep consistent in the segmentation result. Therefore, hierarchical Markov random field in the wavelet domain algorithm was further improved in some reference. The segmentation results are optimized. Therefore, we put forward wavelet domain hierarchical Gaussian Markov random field algorithm [11]. The principle of scheme is that wavelet coefficient vector of every scale represents the feature of every scale in the wavelet domain. Gaussian Markov random field model is adopted to describe feature field modeling of each scale. Potts model is adopted to depict the multi-scale label field model, which measure the intra-scale statistical dependencies. Pyramid model is put forward by Bouman, which represents the inter-scale statistical dependencies. Finally, different parameters can be calculated by maximum pseudo-likelihood and expectation-maximization method. The use of SMAP criterion can obtain the final segmentation result. Experimental results show that the proposed algorithm is effective for fabric image segmentation, with respect to classification accuracy and kappa coefficient.

The rest of the paper is organized as follow. Section 2 describes the hierarchical Markov random field model. Section 3 gives feature field modeling, which is employed wavelet transform and Gaussian Markov random field methods. Section 4 gives label field modeling, including pyramid and Potts model. Section 5 contains parameter estimation. Section 6 presents experiment procedure. Section 7 discusses the experimental results step by step, comparing the results of proposed algorithm with MRF scheme, WMRF scheme, HMRF scheme and HWMRF scheme. Final Section 8 is devoted to conclusions.

The acronyms used in the paper are listed in *Table I.*

TABLE I. Glossary.

Acronyms	Full Expressions
SMAP	Sequential maximum a posterior
EM	Expectation-maximization
MPL	Maximum pseudo-likelihood
MLL	Multi-level logistic
MRF	Markov Random Field
WMRF	Markov Random Field in the wavelet domain
HMRF	Hierarchical Markov Random Field
HWMRF	Hierarchical Markov Random Field in the wavelet domain
HWGMRF	Hierarchical Gaussian Markov Random Field in the wavelet domain

HIERARCHICAL MRF MODEL

Assuming that $S=\{1,2,\cdots,n\}$ indicates the position of each pixel in the image $Y=\{Y_s\}_{s\in S}$ stands for feature field. The image to be segmented is the samples of feature field, namely $y=\{y_1,y_2,\cdots,y_n\}$. Supposing that $X=\{X_s\}_{s\in S}$ is label field, namely $X=\{x_1,x_2,\cdots,x_n\}$, which represents segmentation result of the image. The basic framework of image segmentation is shown in *Figure 1*. In this framework, it is assumed that the feature values of each pixel location are all dependent on the corresponding to each pixel of the label field. The corresponding category could be gotten. The labeled feature values are represented by the conditional probability density function $P(y_s \mid x_s)$.

Label field is established by a causal hierarchical MRF model, [6, 12] as shown in *Figure 2*, which owns different resolutions and scales. Label field of H layers can be expressed as $X=\{X^0,X^1,\cdots,X^{H-1}\}$. X^0 indicates label field on the original resolution scales, and X^n is label field on $n-th$ scale. Pixel position set of the label field is denoted by $S=\{S_0,S_1,\cdots,S_{H-1}\}$ on each scale. Each pixel position of adjacent to the large scale corresponds to the four pixel positions on the current scale. Therefore, the size of grid position set S_{n-1} is four times to the size of S_n.

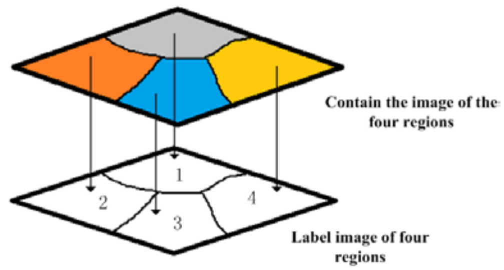


FIGURE 1. The basic framework of image segmentation.

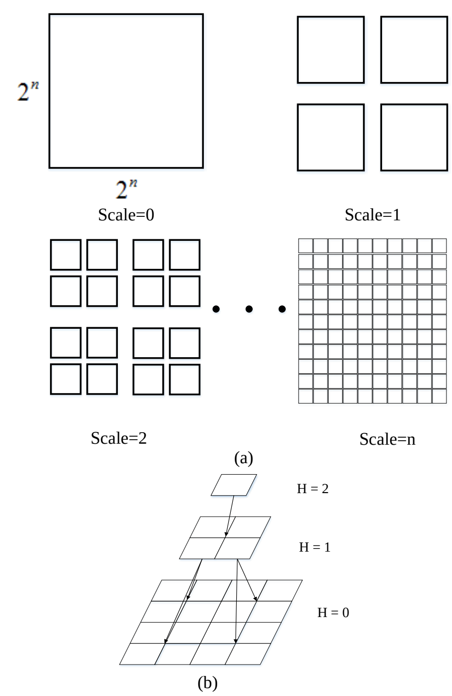


FIGURE 2. (a) Image divided into squares at different scales. Each square can be associated with Haar wavelet coefficients, (b) Hierarchical MRF model.

WAVELET TRANSFORM

To perform image segmentation based on wavelet domain MRF model, we have to make the wavelet decomposition for printed fabric image and select feature representation in every scale [13]. If a digital image y is defined in the grid S of the size of $N \times N$, $H+1$ layer wavelet decomposition of the image is denoted as W. Each of wavelet scale is represented by the corresponding level number $n(1 \le n \le H+1)$ .W contains N_P bands that are respectively wavelet coefficients image $W^{(b)}$ ($b \in \{1,2,\cdots,N_P\}$) of the wavelet transform. Each of $W^{(b)}$ structure is shown in *Figure 3*. The minimum resolution is $n = H+1$, which contains the wavelet coefficients of four bands (LL, LH, HL, HH) . Others resolutions are $n(1 \le n \le H+1)$, which correspond to the wavelet coefficients of three bands (LH, HL, HH) . Therefore, the wavelet coefficients that are each of resolution corresponding to bands of different position may be composed of vectors, forming the image corresponding to the vectors. The vectors used to express the image features in different resolutions. If the feature image that the layer number $n = 0$ regards as original resolution image, the feature sequence of the image of H resolutions is formed. The feature vector of minimum resolution scale $n = H+1$ is shown as follow:

$$w_{ij}^{n} = \left[w_{ij}^{n,(1)}, w_{ij}^{n,(2)}, \cdots, w_{ij}^{n,(b)}, \cdots, w_{ij}^{n,(N_P)}\right]^T \qquad (1)$$

where,

$$w_{ij}^{n,(b)} = \left[w_{ij}^{LL,n,(b)}, w_{ij}^{LH,n,(b)}, w_{ij}^{HL,n,(b)}, w_{ij}^{HH,n,(b)}\right] \qquad (2)$$

$w_{ij}^{LL,n,(b)}, w_{ij}^{LH,n,(b)}, w_{ij}^{HL,n,(b)}$ and $w_{ij}^{HH,n,(b)}$

represent respectively the wavelet coefficients, which are the $b-th$ band image and the position of each band (LL, LH, HL, HH) wavelet coefficients image (i, j) on $n-th$ scale. But it doesn't contain low frequency component. Eq. (2) could be improved as shown in Eq. (3).

$$w_{ij}^{n,(b)} = \left[w_{ij}^{LH,n,(b)}, w_{ij}^{HL,n,(b)}, w_{ij}^{HH,n,(b)}\right] \qquad (3)$$

The size of each feature vector at the lowest resolution is $D = 4N_P \times 1$ and the size of the feature vector at the other resolutions is $D = 3N_P \times 1$.

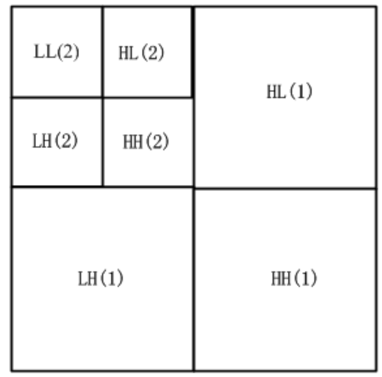


FIGURE 3. Wavelet decomposition.

PARAMETER ESTIMATION

Improved Markov random field in the wavelet domain for printed fabric is proposed in this article, the appropriate parameters are estimated firstly for the feature field modeling and label field modeling. Feature field parameters are employed to obtain $\mu_m^n, \Sigma_m^n, \theta_m^n$, which denote respectively mean vector in $m-th$ category, conditions noise covariance matrix and spatial interaction parameter matrix. Spatial interaction parameter and category have an effect on center position as shown in *Figure 4*. Each of squares represents a pixel location and the arrow indicates the relationship of the feature. Label field parameters contain α^n, β. There are the methods of parameter estimation, including the encoding method, least squares method, maximum likelihood method, MPL method [14], EM algorithm and so on [15].

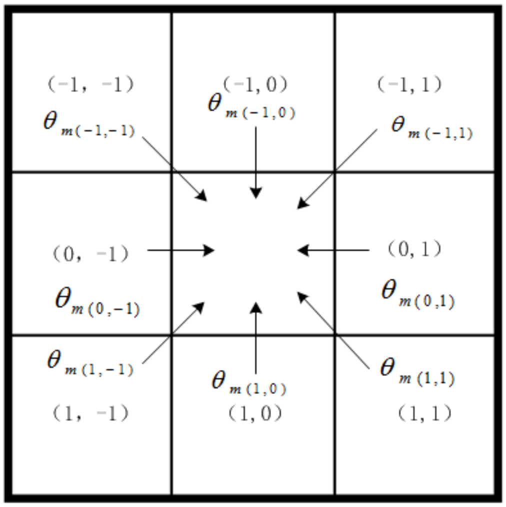


FIGURE 4. Schematic of space interaction parameter.

The MPL method is used by estimating parameters of feature field. The parameters can be calculated by the following Eq. (4) through Eq. (8):

$$u_m^{(n)(t)} = \frac{1}{N_m^{(s)(t)}} \sum_{(i,j)\in L_m^{(n)(t)}} w_{ij}^{(n)} \tag{4}$$

$$a_{ij}^{(m)(n)(t)} = col\left[w_{ij+\tau'}^{(n)} + w_{ij-\tau'}^{(n)} - 2\mu_m^{(n)(t)}, \tau' \in \eta'\right] \tag{5}$$

$$A_{ij}^{(m)(n)(t)} = \begin{bmatrix} a_{ij}^{(m)(n)(t)} & 0 & \cdots & 0 \\ 0 & a_{ij}^{(m)(n)(t)} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & a_{ij}^{(m)(n)(t)} \end{bmatrix} \tag{6}$$

$$\theta_m^{(n)(t)} = \left[\sum_{(i,j)\in L_m^{(m)(t)}} \left(A_{ij}^{(m)(n)(t)}\right)\left(A_{ij}^{(m)(n)(t)}\right)^T\right]^{-1} \times \left[\sum_{(i,j)\in L_m^{(m)(t)}} \left(A_{ij}^{(m)(n)(t)}\right)\left(A_{ij}^{(m)(n)(t)}\right)^T\right] \tag{7}$$

$$\Sigma_m^{(n)(t)} = \frac{1}{N_m^{(n)(t)}} \sum_{(i,j)\in L_m^{(n)(t)}} \left[w_{ij}^{(n)} - (A_{ij}^{(m)(n)(t)})^T \times \theta_m^{(n)(t)}\right]\left[w_{ij}^{(n)} - (A_{ij}^{(m)(n)(t)})^T \times \theta_m^{(n)(t)}\right]^T \tag{8}$$

where, m is category, and n is the scale of wavelet decomposition and t is iterations. $L_m^{(n)(t)}$ stands for the set which is lattice position of labeled m on $n-th$ scale n. $N_m^{(n)(t)}$ denotes the number of feature of labeled m on $n-th$ scale. $\eta' = \{(-1,-1),(-1,0),(-1,1),(0,1)\}$ is second-order half-plane neighborhood.

Label field parameters contain α^n, β . β is a constant with experience, which will have an influence on the segmentation result. For instance, the smaller β, the less information about the spatial connection of the feature field will be obtained. $\alpha^n \in [0,1]$ is interaction parameter of inter-scale. According to EM algorithm, that is:

$$\hat{\alpha}^n = \arg\max_{\alpha^n} \left\{E\left[\ln\left(f\left(w_d^n \mid x^n, y\right)\right)P\left(x^n \mid x^{n+1}\right) \mid w, x^{n+1}, \alpha^{n'}\right]\right\} \tag{9}$$

where, $\alpha^{n'}$ is interaction parameter of inter-scale. x^n is the scale for the wavelet vector n . w_d^n is the set of wavelet coefficient vector $w_{d(s)}^n$.

PROPOSED ALGORITHM

As mentioned above, wavelet decomposition can represent the printed fabric image at multi-resolution, providing new insight into the connection between spatial domain and the spectrum. The hierarchical MRF model is the powerful multi-resolution statistical model for analyzing the contextual dependence, which can take into account inter-scale and intra-scale information of pixels. It can acquire more information than the traditional model and obtain better segmentation results.

First, the textile image begins with wavelet transform by using Haar wavelet [16]. Then every pixel in the image turns into in the form of vector. According to these vectors, we could calculate likelihood value of vector corresponding to each location. We can represent the offset of neighborhood position relative to the center position in the second-order neighborhood system with τ as shown in *Figure 5*, According to Gauss-MRF model [16-18], wavelet coefficients vector distribution on $n-th$ scale is shown in Eq. (10):

$$f\left(w_s^n \mid \eta_s^{W^n}, x_s^n = m\right) = \frac{1}{\left(\sqrt{2\pi}\right)^B \left|\Sigma_m^n\right|^{1/2}} \exp\left\{-\frac{1}{2}\left(e_s^n\right)^T \left(\Sigma_m^n\right)^{-1} e_s^n\right\} \tag{10}$$

$$\tau \in N = \{(0,1),(0,-1),(1,0),(1,1),(-1,-1),(-1,1),(1,-1),(-1,0)\}$$

B is vector dimension. $\eta_s^{W^n}$ is the set of the second-order neighborhood corresponding to features of wavelet coefficients vector in the feature field on $n-th$ scale. x_s^n is the current labeled pixel. e_s^n is zero-mean noise vector at the position of s as shown in Eq. (11):

$$e_s^n = w_s^n - \mu_m^n - \sum_{\tau \in N} \theta_{m,\tau}^n \times \left(w_{s+\tau}^n - \mu_m^n\right) \tag{11}$$

In order to make full use of the inter-scale information, the neighborhood system should be redefined as shown in *Figure 5*. The label of a node location is only relative to its parent node, uncle node and a second-order neighborhood nodes in this scale.

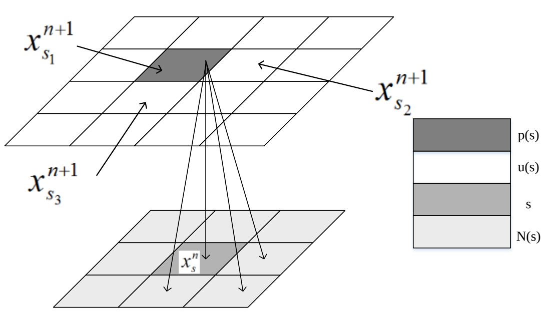


FIGURE 5. Schematic of labeled position in the label field.

In *Figure 5*, considering that the location label of second-order neighbors has an effect in the current label, MLL model is employed [19-20]. The reason is that the location label of second-order neighbors is constantly updated in the iterative process. It is the non-causal intra-scale MRF model. Expression as shown in Eq. (12),

$$P\left(x_s^n \mid x_{N(s)}^n\right) = \frac{\exp\left(-\sum_{\tau \in N} V_c\left(x_s^n \mid x_{s+\tau}^n\right)\right)}{\sum_{x_s} \exp\left(-\sum_{\tau \in N} V_c\left(x_s^n \mid x_{s+\tau}^n\right)\right)} \tag{12}$$

where, N is the offset of second-order neighborhood location and the center location. s is the current node. V_c can be represented by Eq. (13).

$$V_c\left(x_x^n, x_{x+\tau}^n\right) = \begin{cases} -\beta\left(x_x^n = x_{x+\tau}^n\right) \\ \beta\left(x_x^n \neq x_{x+\tau}^n\right) \end{cases} \tag{13}$$

where, β is a constant with experience.

Given that the label field is independent from each other on the different scales. Final segmentation result is acquired by projection from coarse resolution to fine resolution. According to the MRF and Bayesian theory, image segmentation is seeking an approximate global optimal estimation of X by the criteria of SMAP [21-22], that is

$$\left(\hat{x}\right)_s^n = \arg\max_{x_s^n}\left\{f(w_{d(s)} \mid x_s^n, w)P(x_s^n \mid x_{p(s)}, x_{u(s)})\right\} \tag{14}$$

$$\hat{x}{}_s^n = \arg\max_{x_s^n}\left\{ f(w_{d(s)} \mid x_s^n, w)P(x_s^n \mid (\hat{x})_{N(s)}^n)\right\} \tag{15}$$

$$f(w_{d(s)} \mid x_s^n, w) = f(w_s^n \mid x_s^n, \eta_s^{W^n}) \prod_{t\in c(s)} [\sum_{x_t^{n-1}} f(w_{d(s)} \mid x_t^{n-1}, w)P(x_t^{n-1} \mid x_{p(t)}^n, x_{u(t)}^n)] \tag{16}$$

where, s is node, and $p(s)$ is father node, and $u(s)$ is uncle node. $N(s)$ is second-order neighborhood node. In the process of image segmentation on each scale, the marks of parent and uncle node transmits inter-scale marks, intermediate result $\left(\hat{x}\right)_s^n$ is gotten. Then the marks of the second-order neighborhood location optimize segmentation result on $n-th$ scale, the final segmentation result $\hat{x}{}_s^n$ is obtained.

Experimental Procedure

The flow chart of proposed algorithm is shown in *Figure 6*. The optimized segmentation result on scale n will be projected to scale $n-1$ as the initial image for the new iteration. If the terminate condition, that is, iter < 3, is not satisfactory, get back to repeat intra-scale and inter-scale iterations; otherwise, stop the cycle and get the optimal segmentation result in the original resolution. The methods of hierarchical Gaussian MRF are summarized as follow:

(1) Feature field modeling. The wavelet transform is employed with Haar wavelet in fabric images firstly. Secondly, GMRF model is adopted to calculate conditional probability density function.

(2) Label field modeling. Potts and pyramid model are utilized to label the position of every pixel. Different positions of pixels in a fabric image are obtained in different scales.

(3) Parameter estimation. Feature field parameters include $\mu_m^n, \Sigma_m^n, \theta_m^n$ with MPL method. Label field parameters contain α, β with EM algorithm. After that, SMAP criterion is applied to achieve the result of image segmentation for fabrics.

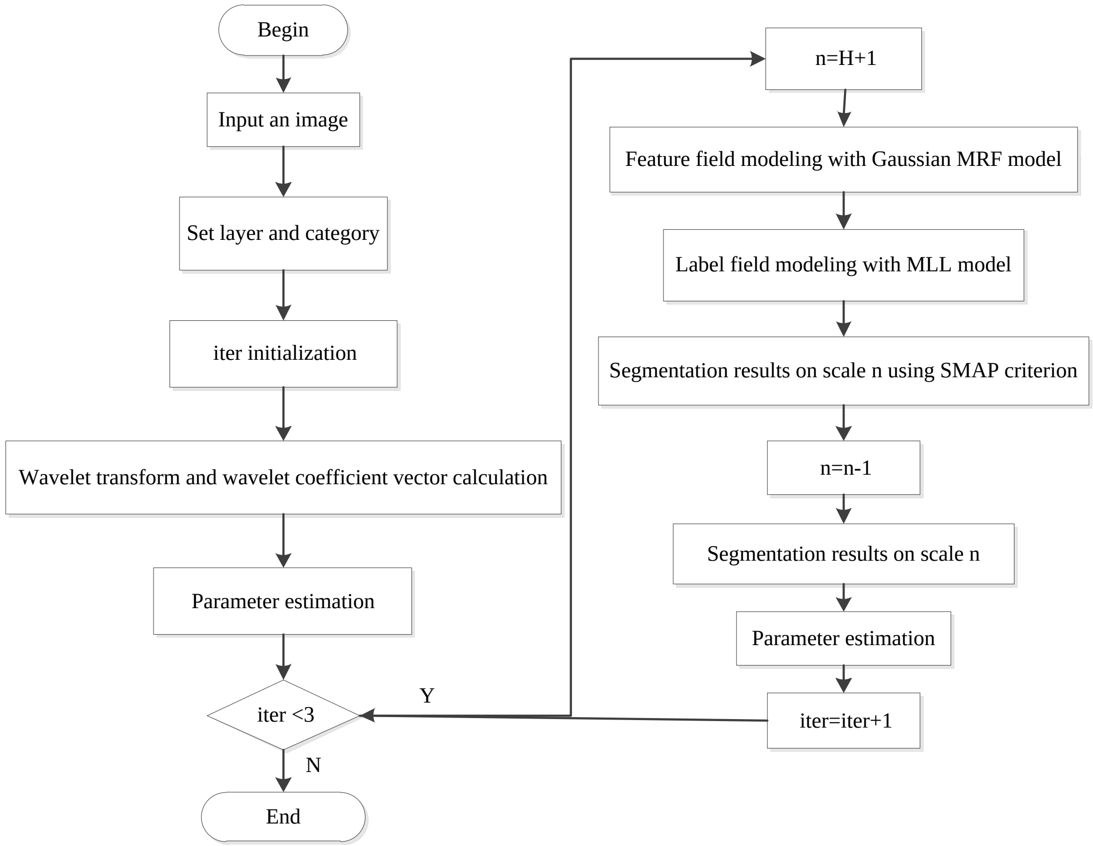


FIGURE 6. The flow chart of proposed algorithm.

RESULT AND ANALYSIS

We analyzed several types of fabric images so as to demonstrate the performance of our algorithm. Experiments are the Matlab compiling environment on personal computer with Intel 1.60 GHz processor and 1GB RAM. Fabric printing images with 256 × 256 DPI are contained by Canon 9000F scanner. It has been tested on multiple sets of experimental data to prove the effectiveness of the scheme. Parts of the typical segmentation results are selected to compare analyses from different angles.

Feature field is represented with Gaussian Markov Random Field in the domain wavelet. Label field is denoted by pyramid and Potts model in multi-scale space. In order to verify the feasibility of the proposed scheme, a number of experiments were performed on fabric images, including comparison with MRF scheme, WMRF scheme, HMRF scheme and HWMRF scheme. In *Figure 7*, the first column is original image, the second as a result of MRF, the third as a result of WMRF, the fourth as a result of HMRF, and fifth as a result of HWMRF scheme.

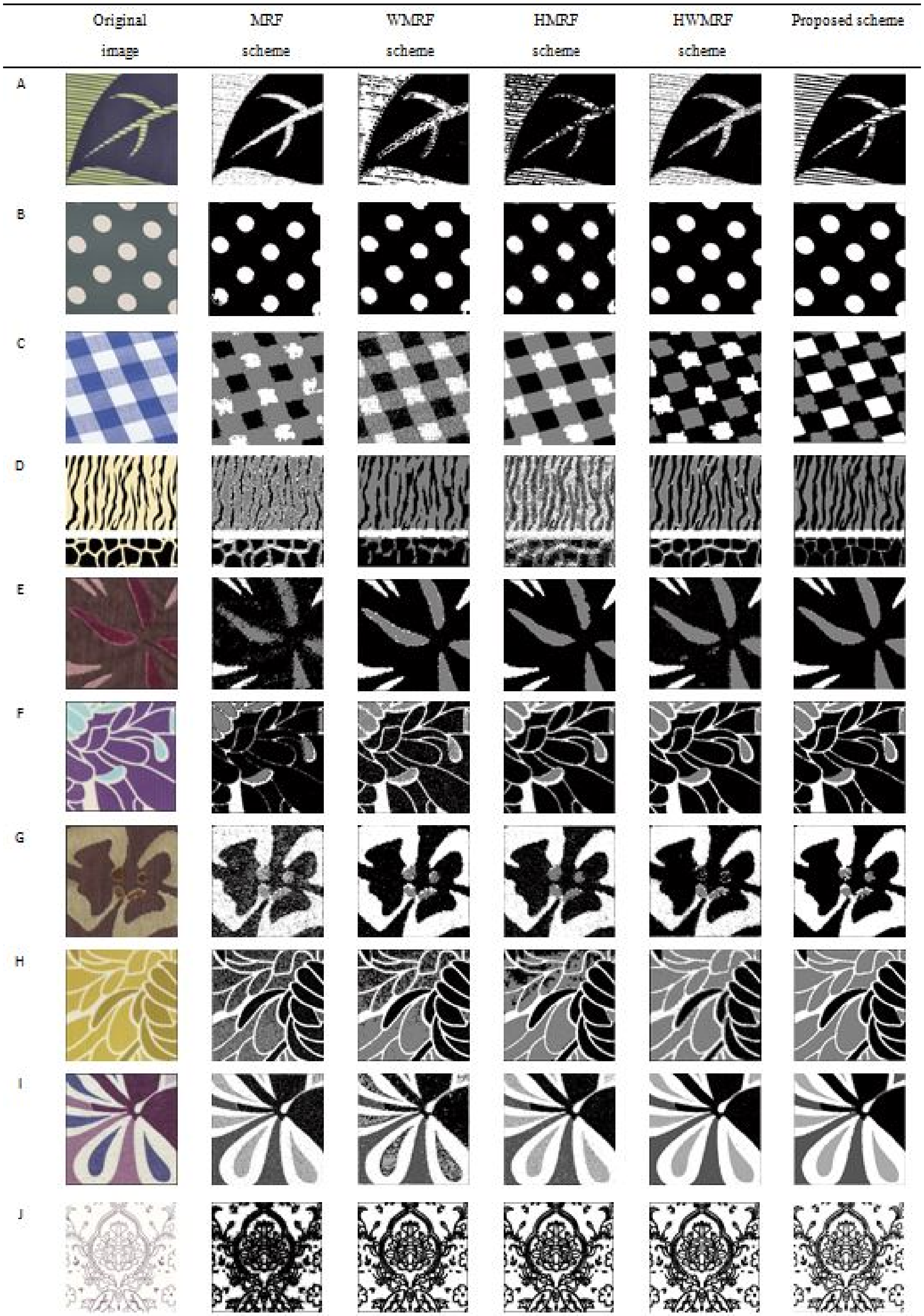


FIGURE 7. Fabric image segmentation results of classification number four.

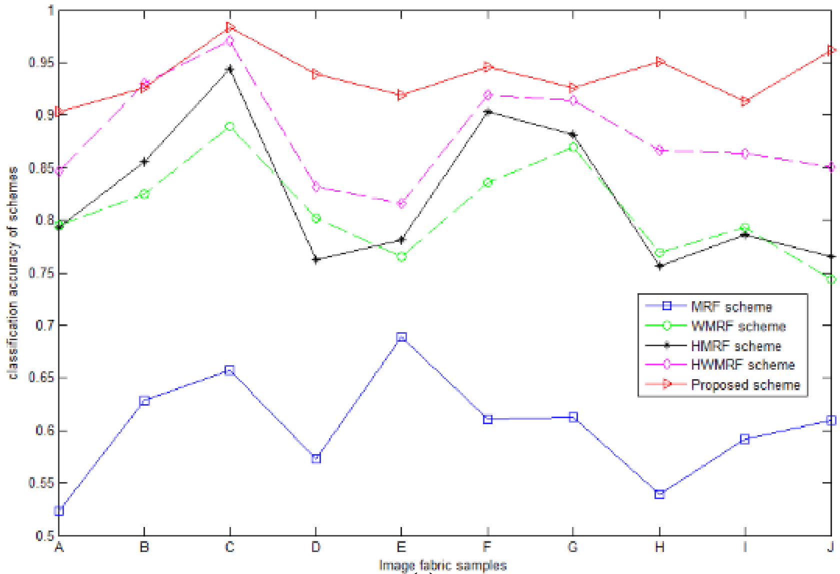
Figure 7 shows segmentation results of ten images by the proposed approach and other existing approaches. It can be shown that the proposed algorithm expresses image information comparatively better by reducing noise and solving problem of insufficient local spatial information statistics.

In current study, the equality of segmentation is weighted by visual effectiveness and quantitative indicators. Classification accuracy and kappa coefficient are calculated to measure segmentation effectiveness for fabrics, which represent the consistent probability of each random sample classification result and actual classification result. Overall classification performance is evaluated by two parameters, as shown in Eq. (17) and Eq. (18).

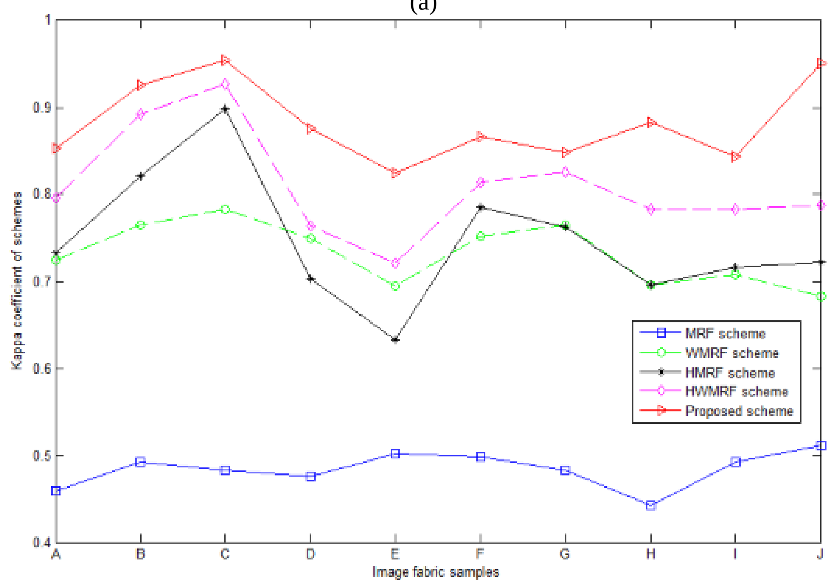
$$classification\ accuracy = \frac{\sum_{i=1}^{M} N_{ii}}{N} \tag{17}$$

$$kappa = \frac{N\sum_{i=1}^{M} N_{ii} - \sum_{i=1}^{M}(N_{i+}N_{+j})}{N^2 - \sum_{i=1}^{M}(N_{i+}N_{+j})} \tag{18}$$

where, M is the number of classification. N_{ij} represents the number of pixel that actual category i are classified as j. N shows the number of pixel. $N_{i+} = \sum_{j=1}^{M} N_{ij}$ denotes the number of pixel that classification results are divided into $i-th$ category. $N_{+j} = \sum_{i=1}^{M} N_{ij}$ expresses the number of pixel that $j-th$ category is actually contained in an image.



(a)



(b)

FIGURE 8. Curves of comparison with different methods, (a) classification accuracy of different schemes using 10 images, (b) kappa coefficient of different schemes using 10 images.

TABLE II. Average classification accuracy and kappa coefficient of five schemes.

	Average Classification accuracy (%)	Average Kappa coefficient (%)
MRF scheme	60.33	48.37
WMRF scheme	80.87	73.20
HMRF scheme	82.28	74.73
HWMRF scheme	88.09	80.91
Proposed scheme	94.03	88.28

Figure 8 denotes the classification accuracy and kappa coefficient curves of comparison with different schemes using 10 images. Average classification accuracy and kappa coefficient of approaches are shown in *Table Ⅱ*. It can be concluded segmentation results by the above: in the realization of fabric image segmentation, the number of different images for classification, segmentation results accuracy of the MRF approach is 60.33%, and kappa coefficient reaches 48.37%. We can see the outline of fabric printing design, but there are lots of noises. In the implementation section of fabric image segmentation, the number of different images for classification, segmentation results accuracy of the scheme two is 80.87%, and kappa coefficient is 73.20%.Compared with the MRF scheme, the WMRF scheme can filter out some of the noise and describe the fabric edges and regional characteristics of the image. In the realization of the fabric image segmentation, the number of different images for classification, segmentation results accuracy of the HMRF method and HWMRF method is respectively to 82.28% and 88.09%. The kappa coefficient of them is respectively to 74.73% and 80.91%. Compared with the previous two schemes, the HMRF and HWMRF algorithms could reduce noises and express spatial information accurately. Classification accuracy and kappa coefficient of proposed algorithm is to 94.03% and 88.28%. It can be demonstrated that this method filter out noise very perfectly, almost can accurately describe the fabric image edges and regional characteristics accurately. Experimental results show that proposed scheme can achieve a good segmentation performance for textile printing images.

In proposed algorithm, there are two factors that affect the algorithm performance: the potential coefficient (β) and the number of iterations (max-iter). A comparison of classification accuracy and kappa coefficient with different β and max-iter is declared in *Figure 9*. The potential coefficient (β) plays a vital role to segmentation results, but the max-iter doesn't affect the results of the segmentation, only a slight difference in time. It can be indicated that the main factor β affects the results of the fabric image segmentation.

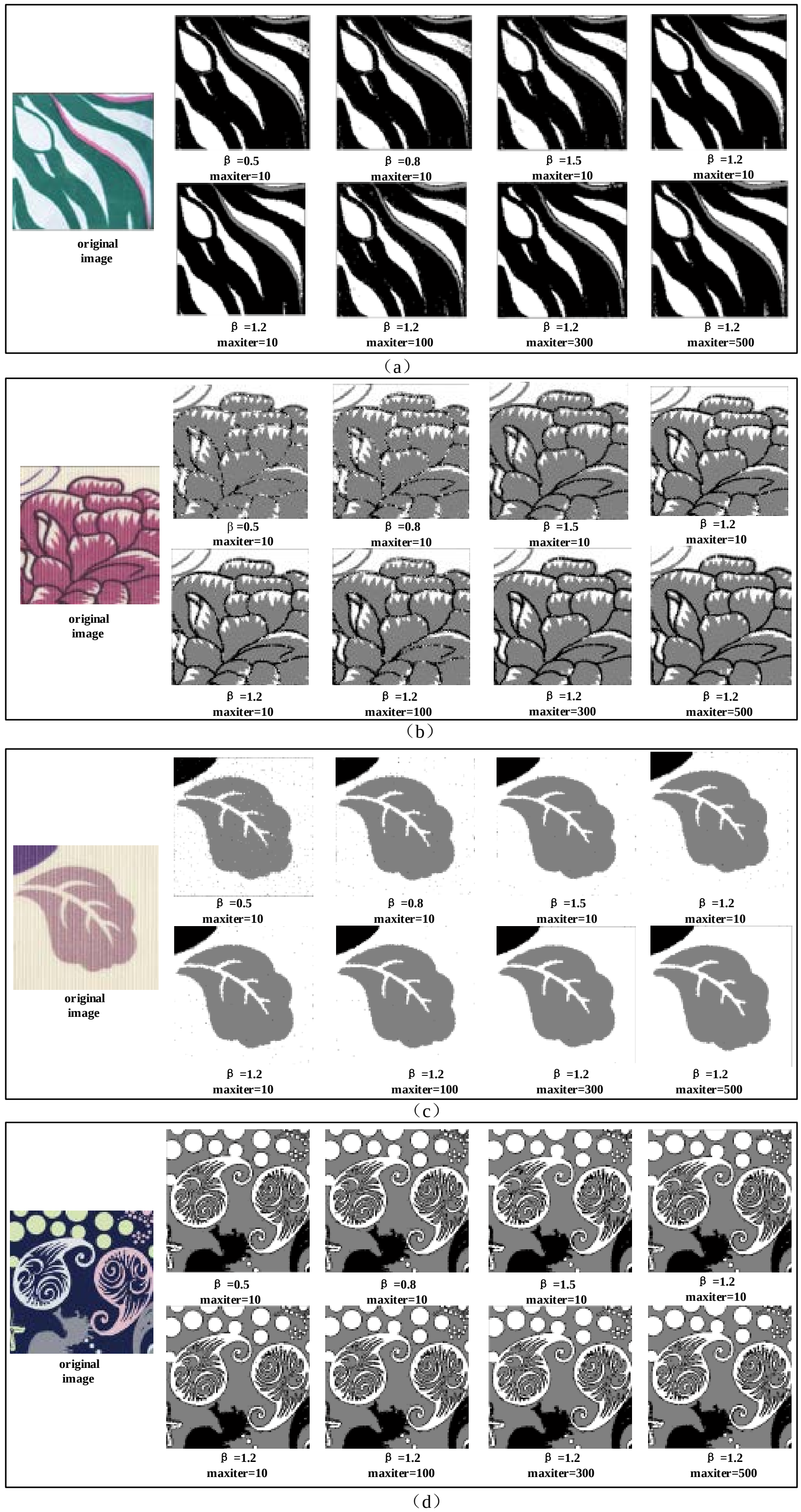


FIGURE 9. Segmentation results of four fabric images using different parameters.

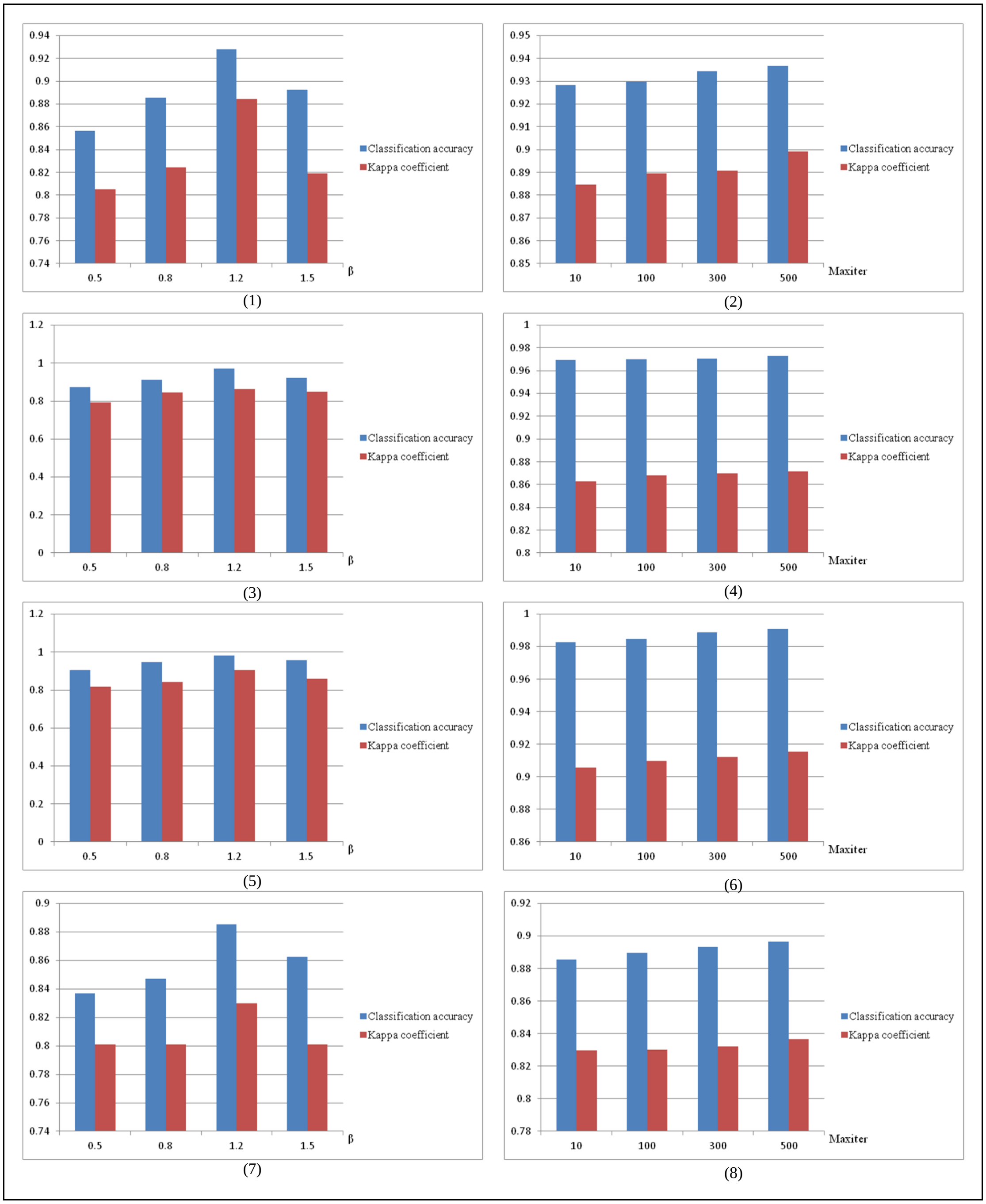


FIGURE 10. A comparison of classification accuracy and kappa coefficient using different parameters, (1)(2) by corresponding *Figure 9(a)*, (3)(4) by corresponding *Figure 9(b)*, (5)(6) by corresponding *Figure 9(c)*, (7)(8) by corresponding *Figure 9(d).*

Histogram of classification accuracy and kappa coefficient to proposed algorithm is obtained in *Figure 10 (1)(3)(5)(7)*, when max-iter is 10 and β is adopted different values. It can be concluded that the value of classification accuracy and kappa coefficient is higher than others, when β=1.2 and max-iter =10.

Figure 10 (2)(4)(6)(8) shows histogram of classification accuracy and kappa coefficient, when β is 1.2 and max-iter is used different values. It can be demonstrated that classification accuracy and kappa coefficient of image segmentation are little increased with raising the number of max-iter for fabrics.

TABLE III. Evaluation parameters of proposed scheme.

β (Maxiter=10)	Average Classification accuracy (%)	Average Kappa coefficient (%)
0.5	86.79	80.42
0.8	89.77	82.84
1.2	94.15	87.02
1.5	90.88	83.17

TABLE IV. Evaluation parameters of proposed scheme.

Maxiter (β=1.2)	Average Classification accuracy (%)	Average Kappa coefficient (%)	Time(s)
10	94.15	87.02	0.862
100	94.23	87.45	1.991
300	94.55	87.56	5.617
500	94.85	87.71	11.81

Table III indicates average classification accuracy and kappa coefficient of presented algorithm, when max-iter is 10 and β is applied different values. It can be concluded that average classification accuracy and kappa coefficient are able to achieve 94.15% and 87.02% respectively. *Table Ⅳ* declares the evaluation parameters of proposed scheme. When the number of max-iter is increasing, the results of image segmentation are improved in terms of average classification accuracy and kappa coefficient, and it has little effect. However, the higher the number of max-iter is, the longer time of the segmentation results would be. It would increase the cost in practice application. Therefore better result of image segmentation is achieved for fabrics when β employs 1.2 and max-iter is used 10.

CONCLUSION

In this paper, the traditional MRF model algorithm has been improved gradually and hierarchical GMRF in wavelet domain algorithm is proposed. In the process of the fabric image segmentation，it involves feature field modeling, label field modeling and parameter estimation. Feature field modeling is combination of wavelet transform and Gaussian MRF model algorithm. Label field modeling integrates MLL model to label the position of each pixel in fabric images. The interaction parameters are employed by MPL and EM algorithm, calculating for the likelihood value of each scale and from coarse scale to fine scale in segmentation process.

The current status of research on image segmentation point of view, two aspects of the evaluation indicators of the quality of image segmentation is usually from the visual effects and quantitative analysis. From a visual point of view, it can be decided by the naked eye whether the marginal region consistent with the original image. Quantitative analysis of indicators is used in kappa coefficient and classification accuracy. This shows that proposed method can predict the image segmentation of fabrics with acceptable accuracy. In the parameter training, a different area in the image could be selected, but the area is not the same choice every time, the result is slightly different. However, the impact is not big. That how to ensure that the same area is chosen every time continues research should be researched for no difference in the segmentation result.

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