A New Conception of Image Texture and Remote Sensing Image Segmentation Based on Markov Random Field

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Abstract The texture analysis is often discussed in image processing domain, but most methods are limited within gray-level image or color image, and the present conception of texture is defined mainly based on gray-level image of single band. One of the essential characters of remote sensing image is multidimensional or even high-dimensional, and the traditional texture conception cannot contain enough information for these. Therefore, it is necessary to pursuit a proper texture definition based on remote sensing images, which is the first discussion in this paper. This paper describes the mapping model of spectral vector in two-dimensional image space using Markov random field (MRF), establishes a texture model of multiband remote sensing image based on MRF, and analyzes the calculations of Gibbs potential energy and Gibbs parameters. Further, this paper also analyzes the limitations of the traditional Gibbs model, prefers a new Gibbs model avoiding estimation of parameters, and presents a new texture segmentation algorithm for hyperspectral remote sensing image later.

Keywords hyperspectral; multispectral; MRF; Gibbs model; texture; segmentation

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Introduction

As one of the important attributes of remote sensing image, texture has a special function in image analyzing. The classic analyzing methods of texture mostly aimed at single-band image or color image, and the research of multispectral and hyperspectral texture should be strengthened. Literature[1] brought forward a new texture conception of remote sensing image, which regarded the texture as a reflection model of surface objects from multidimensional spectral-space to two-dimensional image space. The new conception has more abundant connotation and better physical meaning. However, how to implement this extended conception and build up the algorithm of texture segmentation need more research.

Markov random field (MRF) shows a well capability in expressing the spatial distribution character of gray pixel. In 1984, Geman and Geman pointed out...
the equivalent relationship between the Gibbs distribution and MRF, which pushed forward the applicative research work of this model. In the domain of texture segmentation, Derin and Elliott\(^2\) did early research based on Gibbs model, and the subsequent bivalency and gray image texture research based on Gibbs model was widely developed\(^3, 4\). The paper described how to make the merit of MRF to be applicable in multidimension even high-dimension data and combine MRF with the new conception of texture.

This paper explained the new conception of texture and has in view of spatial relationship character in terms of the new conception. First, we extended the scalar quantity MRF model to vector MRF model (VMRFM) and then analyzed the texture of multispectral and hyperspectral image. The results show that the new model has the ability of characterizing multidimensional texture with exposing many problems while dealing with high-dimension data. Then, aiming at the problem of the previous stage, we have improved upon the core content of MRF—Gibbs distributive model (GDM) and finally brought forward the nonparameter Gibbs model (NPGM)). Moreover, based on the NPGM, we proceed to hyperspectral texture analysis in combination with the spectrum code measure (SCM).

1 Conception of remote sensing image texture

The multidimensional remote sensing image is a kind of special dataset that is orderly arrayed in two-dimensional space by pixels, and this reveals its nature of image-space character. At the same time, each pixel represented a spectral feature. In view of ground objects’ features, the co-occurrence of the pixels’ spectral feature has more meaningful information of objects than the spectral feature itself. For normal gray-level image, the spatial distributive feature of pixels’ gray value is commonly analyzed by texture.

The classic texture analyzing methods are mostly based on single-band image or color image. While dealing with multidimensional or high-dimensional remote sensing images, the normal methods are often based on one representative image that was produced by prior band selection. However, the “representative” image cannot really represent every band. Concerning hyperspectral image with hundreds of bands, this problem is more acute. In order to describe the distribution of the pixels’ spectral features in the two-dimensional image space, the new conception of texture, which should be more suitable for remote sensing image, must be built.

In terms of remote sensing images, the new extended texture conception this paper used can be expressed as follows:

The texture is a pattern or an expressing mode of reflection from the ground objects’ (or other objects’) denotative points in spectral space to two-dimensional image-space, where the ground objects (or other objects) are distributed. The nontexture region is a special type of texture region, and the single-band image texture can be regarded as a special situation of multidimensional image texture.

The extended texture conception can be explained concretely. Taking the three-band images for example, we can see that Fig.1 demonstrated the reflection relationship of the conception. Each pixel in image space maps a token point in the multidimensional spectral space, and the token points makes up of different spectral groups. Reflecting into image space, the spectral groups revealed a certain two-dimensional spatial distributive characteristics. The describing and analyzing for the spatial distributive characteristic that contains reflection relationship are the main studying contents of the new extended texture conception research. In following section, the multidimensional images texture analyzing based on MRF will be discussed.

Fig.1 Reflection relationship of the extended texture conception

2 MRF and multidimensional images texture

As described above, most of the texture analyzing methods was based on single-band image including the type of MRF model. In this section, we have im-
proved the MRF model in order to fulfill the new conception texture. First, we will discuss the vector MRF texture model.

2.1 Vector MRF texture model

For multiband remote sensing image, this paper gives the following definition of MRF.

The remote sensing image is defined in a limited points’ data array \( L = \{(i_1, i_2) : 1 \leq i_1 \leq N_1, 1 \leq i_2 \leq N_2\}\). The size of \( L \) is \( N = N_1 \times N_2 \), and each point \( i \) of \( L \) denotes a pixel’s position in the image, where \( i = (i_1, i_2) \) denotes the position at row \( i_1 \) and column \( i_2 \). We denote \( X_i = (X_{i1}, X_{i2}, \ldots, X_{im}) \) as the status random vector of point \( i \), where \( M \) is the count of bands, and \( X_{ip}(1 \leq p \leq M) \) is the gray value of point \( i \) at band \( p \). Thus, the \( N \) random vectors constitute a discrete vector random field \( X = \{X_1, X_2, \ldots, X_N\} \). One realization of \( X \) can be noted as \( x = \{x_1, x_2, \ldots, x_N\} \), and all possible realizations composed \( \Omega \).

The points having interaction-relationship with point \( i \) constitute the neighborhood \( \eta_i \), and set \( \eta = \{\eta_i : i \in L, i \notin \eta, \eta_i \subset L\} \) is the neighborhood-system of \( L \). \( \eta_i \) will be called the first-order neighborhood if it contains the nearest four-neighbor points of \( i \), and the second-order neighborhood contains the nearest 8-neighbor points of \( i \). Higher order neighborhood can be defined similarly.

In view of the above definition, if \( P(X = x) > 0 \) is valid for any \( x \in \Omega \), the Markov characteristic of image random field \( X \) can be formulated as follows:

\[
P(X = x_i | X_j = x_j, j \in L \text{ and } j \neq i) = P(X_i = x_i | X_j = x_j, j \in \eta_i)
\]  

(1)

The substance of Eq. (1) is that the effect on the status of point \( i \) by the overall situation of the image is equal to the effect of neighborhood \( \eta_i \).

The above Markov characteristic can be expressed by the following Gibbs distributive function:

\[
P(X = x) = \frac{1}{Z} \exp\{-U(x)\}
\]  

(2)

\[
Z = \sum_x \exp\{-U(x)\}
\]  

(3)

\[
U(x) = \sum_{c \in \mathcal{C}} V_c(x)
\]  

(4)

In the above formulas, \( U(x) \) is called energy function. Note that \( c \) is clique that is the set that contained the point itself or points in its neighborhood. \( C \) is the set of total cliques, and the cliques of second-order neighborhood are shown in Fig.2. \( V_c(x) \) is called potential function, which are dependent on the status of points in clique \( c \).

![Fig.2 Type of second-order neighborhood cliques](image)

2.2 Potential function and Gibbs parameters

2.2.1 Potential function

The potential function is the key part of Gibbs distribution. For common gray-level image, clique’s potential function is often defined as follows:

\[
V_c(x) = \begin{cases} 
-\theta, & \text{if all pixels in clique } c \text{ have same gray value} \\
+\theta, & \text{other cases}
\end{cases}
\]  

(5)

In Eq. (5), \( \theta \) denotes the Gibbs parameter corresponding to clique \( c \).

For remote sensing image with \( M \) bands, the status vector of each point is \( M \)-dimensional. We extend the definition of potential function as follows:

\[
V_c(x) = \begin{cases} 
-\theta, & \text{if } \sigma_c \leq \sigma_0 \\
+\theta, & \text{other cases}
\end{cases}
\]  

(6)

In Eq. (6), the potential energy was valued in terms of the conforming of points’ status vectors. \( \sigma_c \) denotes the difference of points in clique \( c \), and \( \sigma_0 \) is a threshold. \( \sigma_c \) is defined as follows:

\[
\sigma_c = \frac{1}{n_{\leq p, k \leq n}} \sum d_c(X_p, X_k)
\]  

(7)

where \( X_p \) and \( X_k \) are the \( p \)th and the \( k \)th points’ status vectors, respectively, and \( n \) is the count of points in clique \( c \). \( d_c(X_p, X_k) \) is a function measuring the spectral differentness between \( X_p \) and \( X_k \), which can be calculated as follows:

\[
d_c(X_p, X_k) = \sqrt{\frac{1}{M} \sum_{j=1}^{M} (x_{pj} - x_{kj})^2}
\]  

(8)

Where \( x_{pj} \) and \( x_{kj} \) denote the value of \( X_p \) and \( X_k \) at band \( j \), respectively.

The definition of potential function above is aimed at multiband image, and for single band image, the measuring of spectral differentness is simplified to the measure of gray value difference.
Established vector potential function, we can estimate the Gibbs parameters based on multiband image texture and also can proceed the texture segmentation of multiband image in the light of Gibbs parameters.

2.2.2 Estimation of Gibbs parameters

Gibbs parameters described the texture feature by means of quantitation. Each type of texture corresponded to a group of parameters denoted as vector $\theta$.

Eq.(2) shows that the right side of the formula is a complex vector nonlinear expression, which discommoded the calculation. This problem can be solved by the following method:

Assuming that there are two different spectral vectors $x_1$ and $x_2$, whose neighborhood $\eta_1$ and $\eta_2$ are the same. Referring to Eq.(2), we can give the expression $P(X=x_1)$ and $P(X=x_2)$. Dividing $P(X=x_1)$ by $P(X=x_2)$ and getting the logarithm at both sides of the formula, we can derive the following:

$$\ln(P(X = x_1)/P(X = x_2)) = -\sum_{c \in C} V_c(x_1) + \sum_{c \in C} V_c(x_2)$$

The left of Eq. (9) can be attained by the statistic of texture data, and the right is linear calculation of $\theta$. Thus, based on Eq. (9), the estimation of $\theta$ can be performed through Least Square Method (LSM) properly.

In practical operations, for a certain texture type, we can first get the statistic of every point’s neighborhood $\eta_n$, and find out the neighborhood $\eta_m$ whose frequency is most. Then, we can record two higher-frequency vector $x_1$ and $x_2$, and construct functions as Eq. (9). Next, we should find new neighborhood $\eta_m$, $x_1$ and $x_2$, and construct functions until the count of functions satisfied the demand of LSM.

2.3 Nonparameter Gibbs model

In the section above, we gave the form of potential function and the estimation of Gibbs parameters based on vector MRF, which was defined in light of the extended texture conception mentioned in Section 2. Our research work showed that the threshold $\sigma_0$ is very important for subsequent operation.

On one hand, larger $\sigma_0$ may deliberate the ability of Gibbs parameters in describing texture and even makes us unable to get convergence results. On the other hand, smaller $\sigma_0$ may lead the condition of finding functions discussed in Sections B2 to be too strict to achieve, and Gibbs parameters even cannot be estimated successively while dealing with small area texture. Especially while processing high-dimension data, the stability of Gibbs parameters’ estimation is worse, and the practicability of our algorithm becomes more oversensitive about $\sigma_0$. Thus, for hyperspectral images’ segmentation, the above algorithm is hard to be executed well.

Based on the above research, this section prefers the nonparameter Gibbs model, which abandons the manner for characterizing texture feature by Gibbs parameters. NPGM takes a new measure in potential function, which is closer to the essential of Gibbs distribution and favorable to precede texture segmentation of hyperspectral image.

In texture segmentation, there are mainly two parts impenetrated in the whole procedure, which are “Estimating parameters based on texture data—Texture’ recognizing rely parameters.” The relation of the two parts in remote sensing image texture analysis is shown in Fig.3.

![Fig.3 Classic parameter Gibbs model](image)

In Fig.3, we can see that the parameters’ estimation is based on the statistic of texture neighbor cliques, and the role of parameters is to affect the result value of potential function $V(x)$. Therefore, if the direct relationship between the statistic of texture neighbor cliques and potential function $V(x)$ was built, the complex step of Gibbs parameters’ estimation can be deleted. Considering these, this paper’s NPGM brought forward the nonparameter Gibbs model, as shown in Fig.4.

One of the characters of NPGM is that the spec-
trum code measure (SCM) takes as preparation of texture segmentation. The continue analysis of MRF is based on this one-dimensional code map. SCM can be regarded as the reflection in extended texture conception.

It is the nonparameter method performed that makes the MRF based on code map possible. Because in classic parameter Gibbs model (as Gauss-MRF model), the numeric computation of pixel’s value mostly cannot be avoided, while the spectral code is just a type of mark that cannot be calculated as a number.

In Eqs. (2) to (4), we know that the essential role of potential function \( V_c(x) \) is to quantify the central point’s dependence on neighbor cliques (classic model expressing the dependence by Gibbs parameters). If the central point’ status coincide with the neighbor cliques’ status well, the potential \( V_c(x) \) will be low, which leads to smaller energy function \( U(x) \) and results in larger Gibbs probability. Otherwise, higher \( V_c(x) \) lead to higher \( U(x) \) and smaller Gibbs probability.

Based on the above analysis, we prefer a new type of potential function definition as follows:

\[
V_c(x) = f(P_c(x))
\]

For one realization of image random field \( X = x \), the central point’s neighbor clique \( c \) has a realization \( R_c(x) \). Corresponding with \( x \in \Omega \), all the possible realization of clique \( c \) is noted as \( R^a_c \) (\( R_c(x) \in R^a_c \)).

In a certain texture data, the probability of clique \( c \) realized as a form of \( R_c(x) \) is noted as \( P_c(x) \).

\( f() \) is a reflection function conforming following conditions:

1) Define area is \((0,1)\), and the range of values is \((-\infty,\infty)\);

2) Continuous monotone descending in interval \((0,1)\).

In these conditions, if \( P_c(x) \) is larger, then the potential \( V_c(x) \) will be lower, energy \( U(x) \) will be lower too, and Gibbs probability in Eq. (2) will be larger. This new type of potential function expresses the essence of Gibbs distribution. In practice, \( f() \) can be taken to a proper form, and in this paper,

\[
f(P_c(x)) = \text{ctg}(P_c(x) \cdot \pi)
\]

While the potential function’s calculation was finished, the energy \( U(x) \) and Gibbs probability can be calculated refer to Eq. (2) to Eq. (4).

NPGM takes the cliques’ frequency as indicators while characterizing texture. This method completely avoids the solution process of Gibbs parameters in traditional models, and then, NPGM is very suitable for texture segmentation based on maximum posterior probability (MAP).

The more important thing is that the NPGM can divide the whole process into two steps, i.e., the analysis based on spectral space and the analysis based on an image’s two-dimensional space. NPGM combines the two spaces involved in extended texture conception properly and reduces the complexity of the problem at the same time. The texture segmentation of multidimensional remote sensing images based on NPGM will be discussed below.

3 Texture segmentation algorithm

3.1 MAP segmentation model

Because SCM was applied, two kinds of new random fields are defined on the condition of NPGM: spectrum code random field \( S = (S_1, S_2, \cdots, S_n) \) and texture code random field \( Y = (Y_1, Y_2, \cdots, Y_n) \). \( S \) and \( Y \), which have the same scope size, are random fields of scalar quantity defined on \( L \). \( s = (s_1, s_2, \cdots, s_n) \) is recorded as a realization of the random field \( S \), and for the meantime, \( y = (y_1, y_2, \cdots, y_n) \) is recorded as a realization of the random field \( Y \). If there are \( K \) types of texture in the image, then \( Y_i = k (k = 1, 2, \cdots, K) \) as a mean point \( i \) corresponds to texture \( k \).

In this paper, the spectrum code of hyperspectral images is the first step of texture segmentation. That is, mapping the spectral vector random field \( X \) onto the spectrum code random field \( S \). This coding process is a
kind of spectrum code based on pixel position referring to the spectral space, which can be achieved by spectrum space clustering algorithm, such as K-Means.

After the mapping, there is a realization that $S = s_0$. Since the result of the texture segmentation is unknown, the process of texture segmentation is to estimate $Y$ based on $S$.

According to the MAP law, we can seek for an optimal realization of $Y$, which should make $P(Y = y \mid S = s_0)$ to be maximum, from the random field $S$:

$$P(Y = y \mid S = s_0) = \max P(Y = y \mid S = s_0) \quad (12)$$

According to Bayes formula:

$$P(Y = y \mid S = s_0) = \frac{P(S = s_0 \mid Y = y) \cdot P(Y = y)}{P(S = s_0)} \quad (13)$$

In this formula, $P(S = s_0)$ is a constant because the spectral coding random field $S$ has a certain completion $s_0$ after the accomplishment of spectrum coding.

Therefore, when

$$P^* = P(S = s_0 \mid Y = y) \cdot P(Y = y) \quad (14)$$

becomes to the maximum, it meets the largest posterior probability criteria.

In the formula above, $P(Y = y)$ described the probability that a pixel of the random field belongs to any texture types. Once a segmentation model is finalized, there will be $K$ types of texture produced. For each type of texture, we can obtain the statistics of probability of each clique’s realization and define the clique-probability table of the $K$ texture type as $P_k (k = 1, 2, \ldots, K)$. The conditional probability $P(S = s_0 \mid Y = y)$ describes the probability of $S = s_0$, which is on the condition of a certain clique-probability statistical table set $P = \{P_k : k = 1, 2, \ldots, K\}$ and calculated based on NPGM.

### 3.2 Multilevel SCM

Actually, we could not obtain a perfect result if the MAP texture segmentation model based on NPGM discussed above was brought into operation directly due to the following problems.

As depicted in Fig.2, there are 10 types of cliques in the second-order neighborhood system. If there are a total of $n$ types of label in spectral coding random field $S$, in the second-order neighborhood, each single-point clique has $n$ kinds of realization, and there are $n^2, n^3, n^4$, kinds of realization owned individually by double-point clique, triple-point clique, and quadruple-point clique. As a result, there are $n + 4 \times n^2 + 4 \times n^3 + n^4$ types of realizations of potential energy cliques. For example, if $n$ is equal to 50, there are as many as 6760050 types of realization forms. Marking too many may bring huge statistics of clique’s probability. At the same time, a large amount of clique form will appear with zero probability, which can affect the neighborhood’s sanction to center pixel’s status and weaken Gibbs model’s validity to depict texture.

We plan to introduce the multilevel SCM to solve the problem above, that is, we can adopt a multilevel measure for mapping from spectral vector random field to spectrum code random field. The subtle spectrum code is divided to four levels, which are also four levels of realization forms of the spectrum code random field $S$: $s^0_0, s^1_0, s^2_0, s^3_0$. Among them, the higher the level is, the more precise the segmentation is. We denote the number of classes of codes is $n_1, n_2, n_3, n_4$ ($n_1 < n_2 < n_3 < n_4$), which respectively correspond to $s^0_0, s^1_0, s^2_0, s^3_0$.

When we are working on the probability statistic of cliques, there are different spectrum code random fields that correspond to different types of clique’s form. From single-point to quadruple-point, the cliques’ statistic are respectively according to $s^0_0, s^1_0, s^2_0, s^3_0$. Single-point cliques are according to the most delicate spectrum code map, double-point cliques’ rougher, and quadruple-point cliques’ roughest. Therefore, the total realization number of potential energy groups is $n_1 + 4 \times n_2^2 + 4 \times n_3^3 + n_4^4$. Selecting proper $n_1, n_2, n_3, n_4$, we are able to avoid the problem of very large statistics.

### 3.3 Algorithm flow

The process of NPGM-MAP algorithm is described as follows:

1) Take multilevel spectral code measure by means of $K$-means method and then get $s^0_0, s^1_0, s^2_0, s^3_0$.

2) Chose the highest level code map $s^3_0$, calculate the entropy within windows of $7 \times 7$ size, and get the primary segmentation $y = y_0$ based on every pixel’s entropy.

3) According to the current $y$, the statistical table of the $k$th texture’s clique probability is noted as $P_k$. Finish the statistics of all $K$ types of texture, and complete
statistical table set $P = \{P_k : k = 1, 2, \cdots, K\}$.

4) Calculate the potential energy and $P^*$ by Eqs. (4) and (14) for point $i (i = 1, 2, \cdots, N)$ in line with $P_i (k = 1, 2, \cdots, K)$. Note that $P^*_q = \max \{P^*_k : k = 1, 2, \cdots, K\}$ and sort the point $i$ to the $q$th type of texture.

5) Finish all points, then refresh the segmentation pattern $y$, and note the count of changed point of the entire $N$ points as $N_r$.

6) If $N_r / N$ is less than given threshold, turn to step 7, otherwise, return to step 3.

7) Output the result $y^* = y$.

4 Experiment and analysis

4.1 Multispectral image texture segmentation

The experiment was carried out based on the two methods discussed in this paper, in order to test the texture characterizing ability of MRF dealing with multidimensional remote sensing images. The data we used are MAIS data of Chinese Poyang Lake area, and TM and ASTER data of Wuhan. TM data contains seven bands. ASTER data contains 14 bands, and we chose six bands of SWIR type (band 4 to band 9) for testing. MAIS data contains 30 bands, and we chose six bands from them.

In Fig. 5, (a) and (c) are K-means segmentation results of TM and MAIS data, and (b) and (d) are corresponding results of vector MRF model.

Observing the whole image in Fig. 5, VMRFM is able to undertake segmentation for both texture areas and "nontexture areas," where the spectral feature is uniform. These verified the validity of VMRFM and the broad sense of extended texture conception in this paper. Compared with (a) and (b), the fractionary segments in (b) and (d) were reduced and unified as connected domains in the sense of texture.

Fig. 6 (a) is an ASTER image of Band 4, Fig. 6 (b) is texture segmentation of VMRFM, and Fig. 6 (c) is texture segmentation of NPGM. The segmentation in terms of texture lays emphasis on the spatial regularity of ground objects’ distribution; in this connection, NPGM exhibited better capability than VMRFM. It would seem that NPGM-MAP works well. For the farmlands in the upper left corner and lower right corner of the image, NPGM contained more integral of objects. Similarly, the inhabited areas in the middle of the upper part of the image and the flood land in the lower part of the image were depicted more clearly.

4.2 Hyperspectral image texture segmentation

In this section, the experiment used all the 30 bands of MAIS data, in order to test the algorithms’ stability for high-dimensional data.

As in Table 1, VMRFM has worse stability in iterating. When the count of band was more than 8,
VMRFM could not converge, and it failed. Why NPGM-MAP is more stable than VMRFM-MAP? Because NPGM-MAP includes SCM and texture segmentation two stages. High-dimensional data was transformed into one-dimensional spectral code map by SCM. The following MRF analysis is based on the spectral code map and has nothing to do with band count. Therefore, the two-stage framework makes the hyperspectral image segmentation free from the limitation of dimension.

| Count of band | VMRFM-MAP iterating times | NPGM-MAP iterating times |
|---------------|---------------------------|--------------------------|
| 1             | 4                         | 9                        |
| 3             | 6                         | 8                        |
| 5             | 9                         | 10                       |
| 8             | 9                         | 9                        |
| 10            | 8                         | 8                        |
| 18            | 10                        |                          |
| 22            | 8                         |                          |
| 26            | 10                        |                          |
| 30            | 9                         |                          |

5 Conclusion

The main work of this paper is the texture segmentation in light of new extended texture conception of remote sensing image. Based on retrospection of traditional method of gray image texture, this paper emphasized on the multidimensional and high-dimensional characteristic of remote sensing image, brought forward a new extended conception of texture in analyzing, and then preferred the vector MRF model, which mainly discussed the potential function and Gibbs parameters’ estimation. The subsequent testing showed that the VMRFM could be used to analyze multispectral image but failed for hyperspectral image. Finally, based on above researches, this paper improved Gibbs distribution, present NPGM-MAP combined with SCM, and proceeded hyperspectral image texture segmentation. The experiment revealed that NPGM was able to analyze the texture feature of code map and cope with high-dimensional data.

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