깁스확률장의 공간정보를 갖는 조건부 모멘트에 의한 패턴분류

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요 약

본 논문에서는 패턴을 효과적으로 분류하기 위하여 화상자료의 특성인 이웃 화소 간의 종속성을 잘 표현해주는 깁스확률장의 크리크를 바탕으로 2차원 조건부 모멘트를 제안하였다. 이 알고리즘 구축은 공간정보를 갖는 조건부 모멘트를 이용하여 특징벡터를 추출하는 과정과 패턴을 분류하는 과정으로 분리하여 생각한다. 특징벡터를 추출하는 과정은 하나의 패턴에 대해 깁스분포의 크리크로 표현된 파라미터를 추정한 다음, 2차원 조건부 모멘트들을 계산하여 특징벡터를 추출한다. 이 제안된 모멘트들은 화상의 크기, 위치, 회전에 대해서 불변하다. 패턴 분류 과정은 추출된 특징벡터로부터 제안된 판별거리함수를 계산하여 여러 원형 패턴 가운데 최소거리를 산출한 미지의 패턴을 원형패턴으로 분류한다. 제안된 방법의 성능을 검증하기 위하여 대문자와 소문자 52자로 된 훈련 데이타를 만들어 486 PC 66Mhz에서 실험을 한 결과 97.5%이상의 분류성능이 있음을 밝혔다.

Conditional Moment-based Classification of Patterns Using Spatial Information Based on Gibbs Random Fields

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ABSTRACT

In this paper we propose a new scheme for conditional two dimensional (2-D) moment-based classification of patterns on the basis of Gibbs random fields which are well suited for representing spatial continuity that is the characteristic of the most images. This implementation contains two parts: feature extraction and pattern classification. First of all, we extract feature vector which consists of conditional 2-D moments on the basis of estimated Gibbs parameter. Note that the extracted feature vectors are invariant under translation, rotation, size of patterns. Next, in the classification phase, the minimization of the discrimination cost function for a specific pattern determines the corresponding template pattern.

In order to evaluate the performance of the proposed scheme, classification experiments with training document sets of characters have been carried out on 486 66Mhz PC. Experiments reveal that the proposed scheme has high classification rate over 94%.

1. Introduction

Pattern Classification is an essential part of the high level image analysis system. In the recent computer vision literature there has been increasing interest in use of statistical techniques for classifying and processing image data. Statistical image analysis concerns

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the measurement of quantitative information from an image to produce a probabilistic description.

The goal of a typical computer vision system is to analyze images of a given scene and classify the content of the scene. Most of these systems share a general structure, which is composed of four building blocks[1]. The first building block is image acquisition-converting the scene into an array of numbers that can be manipulated by the computer. The second building block is preprocessing, which involves removing noise, enhancing the picture. The third building block is feature extraction, whereby the image is represented by a set of numerical "features" to remove redundancy from the data and reduce its dimension because of computational burdens. Finally, the fourth building block is to recognize an object regardless of its orientation, size and location. Selection of "good" features is a crucial step in the process. "Good" features are those satisfying the following requirements: (i) small interclass invariance-slightly different shapes with similar general characteristics should have numerically close values; (ii) large interclass separation-features from different classes should be quite different numerically. These features (or shape descriptors) may be divided into five groups as follows [2]:

- Visual features(edges, texture and shape);
- Transform coefficient features(Fourier descriptors);
- Algebraic features(based on matrix composition of the image);
- Statistical features(moment invariants);
- Differential invariants(used especially for curved objects).

Since statistical features are invariant under translation, rotation, size of the patterns, the moments are very useful features for pattern classification. In [1, 3, 4], their proposed moments that provide features for classification of patterns have been used for a number of image classifying applications. Their proposed moments are calculated by using the intensity at each point. However, their performance for pattern classification is poor since the moments did not included spatial information which is the characteristic of the most images.

In order to overcome the drawback of their pattern classification methods, we propose a new scheme for conditional 2-D moment-based classification of patterns using spatial information based on Gibbs random field (GRF). Gibbs random fields are well suited for representing statistical dependence (or spatial continuity) of the pixel value at a lattice point on the those of its neighbors [5, 6]. Previously, Derin and Won [7], Geman and Geman [5], Schunichiro [8], and Tekalp and Pavlovic [9] considered image processing using Gibbs random field. However, their works are concerned with only both restoration and segmentation.

We propose a method for pattern classification using spatial information based on Gibbs random fields. This implementation contains two parts: feature extraction and pattern classification. First of all, we estimate the parameters of Gibbs random fields to model a pattern image. And then we obtain feature vector which consists of the calculated conditional 2-D moments. Note that the extracted feature vectors are invariant under translation, rotation, size of patterns. In the classification phase, the minimization of the discrimination cost function for a specific pattern determines the corresponding template pattern.

2. Gibbs Distribution for Pattern Classification

In this section we review the basic definition and the properties of GRF. And we also present a particular class of Gibbs distribution that is used in the image model of this paper.

2.1 Gibbs Random Fields

We focus our attention on discrete 2-D random fields defined over a finite $N_1 \times N_2$ rectangular lattice of points(pixels) defined as $L=\{(x, y): 1 \leq x \leq N_1, 1 \leq y \leq N_2\}$. Suppose $Q=\{q_{xy}\}$ represents a image, where

q_{xy} measures the grey-level(or intensity) of the pixel in the x-th row and y-th column. Let η be neighborhood system defined over the finite L. A random field $Q=\{Q_{xy}\}$ on L has Gibbs Distribution (GD) or equivalently is a Gibbs Random Field with respect to η if and only if its joint distribution is of the form [6, 10]

$$P(Q=q)=\frac{1}{Z}\ \exp\{-E(q)\} \qquad (1)$$

where $Z=\sum_{q}\ \exp\{E(q)\}$ is a normalizing constant, called the partition function; $E(q)=\sum_{c\in C}\ V_c(q)$ is energy function; c is a clique, a set of sites(including single sites) such that any two elements in the set are neighbors of each other; C is the set of all cliques of a lattice-neighborhood pair (L, η); and $V_c(q)$ is the potential associated with clique c, arbitrary except for the fact that it depends only on the restriction of q to c. Let η^m be the mth order neighborhood system. Clique types for the first-order and second-order neighborhoods systems are depicted in Figure 1. The source of the revived interest in GD, especially in the context of image modeling and processing, is an important result known as the Hammersley-Clifford theorem. Besag [10] derives an expression for the joint probability $P(Q=q)$ in terms of the conditional probabilities(local characteristics) $P(Q_{xy}=\eta_{xy})$.

Equivalently, $P(Q_{xy}=q_{xy}\,|\,\eta_{xy})\propto\exp\{-E(q_{xy})\}$ where $E(q_{xy})$ is the energy function for pixel site (x, y). The GD is basically an exponential distribution. However, by choosing $V_c(q)$ properly, a wide variety of distributions both for discrete and continuous random fields can be formulated as GD. The GD characterization in some applications provides a more workable spatial model [11].

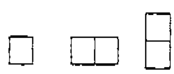
2.2 Gibbs distribution for Pattern Classification

In this subsection, we present a particular class of GD, which is used to estimate the parameters of Gibbs distributed image. We assume that the random field Q consists of binary-valued discrete random variables $\{Q_{xy}\}$ taking values in $\Omega=\{\omega_1, \omega_2\}$. To define GD it suffices to specify the neighborhood system η, the associated cliques and the the clique potentials $V_c(q)$'s. Here, it is assumed that the random field is homogeneous, that is the clique potentials depend only on the clique type and the pixel values in clique, but not on the position of the clique in L. The distribution is specified in terms of the second order neighborhood system η^2. Figure 2 shows the parameters associated with clique types, except for the single pixel clique.

The clique potentials associated with η^2 are defined as follows.

	$(x-1, y)$	
$(x, y-1)$	(x, y)	$(x, y+1)$
	$(x+1, y)$	

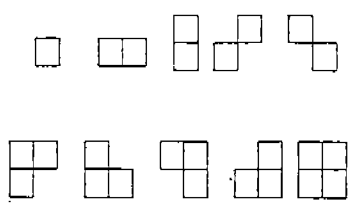
(a) η^1-neighborhood system



(b) Cliques in η^1

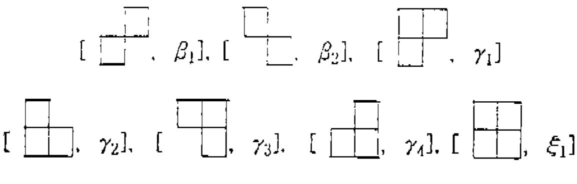
$(x-1, y-1)$	$(x-1, y)$	$(x-1, y+1)$
$(x, y-1)$	(x, y)	$(x; y+1)$
$(x+1, y-1)$	$(x+1, y)$	$(x+1, y+1)$

(a) η^2-neighborhood system



(b) Cliques in η^2

(Fig. 1) Neighborhood systems η^1 and η^2, and their associated clique types.



(Fig. 2) The parameters associated with clique types.

$$V_c(q_{xy}) = \begin{cases} -\zeta & \text{if all } q_{xy}\text{'s in c are equal} \\ \zeta & \text{otherwise} \end{cases} \tag{2}$$

where ζ is the parameter specified for the clique type c. For the single pixel cliques, the clique potential is defined as

$$V_c(q_{xy}) = \alpha_k \ \text{ for } \ q_{xy} = \omega_k. \tag{3}$$

The parameters α_k control the percentage of pixels in each site, that is the marginal distribution of the single random variables Q_{xy}'s, while the other parameters control the size and direction of clustering.

3. Proposed Moment and Classification Scheme

In this section, we describe a parameter estimation method of Gibbs distributed image since calculation of conditional 2-D moment requires the estimated parameters of Gibbs distribution. And then we propose a conditional 2-D moment that contains the spatial information based on GD and construct feature vector which is composed of the proposed moments. Finally, we proposed discrimination distance function for pattern classification.

3.1 Estimation of Parameters in a Gibbs Distributed Image

In this subsection our aim is to estimate the parameters of Gibbs distributed image. The most commonly used parameter estimation method to date is the so-called "coding method", first presented by Besag [10]. It requires the solution of a set of nonlinear equations. Therefore, it is cumbersome and difficult to use reliably.

In view of the practical difficulties involved in using the coding method [12], we describe an alternative parameter estimation scheme for finite range space GRF, which consists of histogramming and a standard, linear, least squares estimation as its components. We present the formulation in terms of a second order neighborhood system η^2, although its extension to any order is possible.

Suppose Q is a GD of the class described in Section 2.2, with a discrete range space of $\Omega = \{\omega_1, \omega_2\}$. A realization q of this random field is available to be used in estimating the parameters of the distribution. Consider a site (x, y) and its neighborhood η_{xy}. For convenience of notation, let s represent q_{xy} and t' represent the vector of the neighboring values of q_{xy}, that is,

$$t' = [u_1, u_2, u_3, u_4, v_1, v_2, v_3, v_4]^T \tag{4}$$

where the location of u_i's and v_i's with respect to s are shown in Figure 3.

v_1	u_2	v_2
u_1	s	u_3
v_4	u_4	v_3

(Fig. 3) q_{xy} and η_{xy}.

We define indicator functions

$$I(h_1, h_2, \ldots, h_k) = \begin{cases} -1 & \text{if } h_1 = h_2 = \cdots = h_k \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

and

$$J_m(s) = \begin{cases} -1 & s = \omega_m \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

We can express the potential functions of the GD in terms of these quantities. Let $V(s, t', \theta)$ be the sum of the potential functions of all the cliques that contain (x, y), the site of s. That is $V(s, t', \theta) = \sum_{c:s \in C} V_c(q)$ where θ is the parameter vector

$$\theta = (\alpha_1, \alpha_2, \beta_1, \beta_2, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \xi_1). \tag{7}$$

Using the clique potentials for this class of GD we can write $V(s, t', \theta)$ as $V(s, t', \theta) = \rho^T(s, t')\theta$ where

$$\begin{aligned}\rho(s, t) = [&J_1(s), J_2(s), (I(s, v_2) + I(s, v_4)), (I(s, v_1) + I(s, v_3)),\\ &(I(s, u_2, v_2) + I(s, u_4, u_3) + I(s, u_1, v_4)),\\ &(I(s, u_4, u_3) + I(s, u_2, u_3) + I(s, u_1, v_1)),\\ &(I(s, u_2, v_1) + I(s, u_1, u_4) + I(s, u_3, v_3)),\\ &(I(s, u_1, u_2) + I(s, u_4, v_4) + I(s, u_3, v_2)),\\ &(I(s, u_1, v_1, u_2) + I(s, u_2, v_3, u_3) + I(s, u_3, v_3, u_4)\\ &+ I(s, u_4, v_4, u_1))]^T.\end{aligned} \tag{8}$$

Now suppose $P(s, t')$ is the joint distribution of the random variables on the 3×3 window centered at (x, y) and $P(t')$ is the joint distribution of the random variables on η_{xy} only. Then the conditional distribution $P(s|t')$ is given by the ratio of $P(s, t')$ to $P(t')$. It follows from the GRF-MRF equivalence and the resulting local characteristic that

$$P(s|t') = \frac{P(s, t')}{P(t')} = \frac{e^{-V(s, t', \theta)}}{Z(t', \theta)} \tag{9}$$

where $Z(t', \theta)$ is the appropriate normalizing constant. Hence

$$\frac{e^{-V(s, t', \theta)}}{P(s, t')} = \frac{P(t', \theta)}{P(t')} \tag{10}$$

is obtained. Note that the right-hand side of (10) is independent of s. Considering the left-hand side of (10) for any two distinct values of s, e.g., $s = j$ and $s = k$, we have

$$(\rho(k, t') - \rho(j, t'))^T \theta = \ln \frac{P(j, t')}{P(k, t')} \tag{11}$$

where $\rho^T(k, t')\theta = V(k, t', \theta)$. Consideration of all possible triplets (j, k, t'), $j < k$, generates from equation (11) a large set of linear equations, which may be solved for θ by least squares procedures. The question that remains to be answered, now, is how to determine or estimate $P(s, t')$ for all (s, t') combinations using a single or a few realizations. We propose to estimate $P(s, t')$ using histogram techniques.

3.2 Proposed conditional 2-D moment based on GD

The basic and classical moment, A regular 2-D moment of order $(k + l)$ is defined by [1, 13]

$$m_{kl} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^k y^l f(x, y), \tag{12}$$

where $f(x, y)$ is the intensity at a point (x, y) in the image and $k, l = 0, 1, 2, \cdots$. Since this two dimensional integration can be viewed as if the image irradiance function $f(x, y)$ is projected to onto the moment kernel $\{x^k y^l\}$, the regular moment will be referred as geometric moment (GM). The moments proposed by many researchers [1, 2, 4, 13] have not included spatial information which is the characteristic of most images.

An an alternative to cope with the drawback of geometrical moments, however, we propose conditional 2-D moments which include spatial information by using the estimated conditional Gibbs distribution, instead of $f(x, y)$. Let $\hat{\theta}$ be the estimated parameter vector of Gibbs distributed image described in Section 3.1. The parameter vector $\hat{\theta}$ measures the strength of interaction between pixels. Also, the clique potentials $\{V_c(q_{xy})\}$ specify the local characteristics $P(Q_{xy} = q_{xy} | \eta_{xy})$, that is $P(Q_{xy} = q_{xy} | \eta_{xy}) \propto \exp\{V_c(q_{xy}, t', \hat{\theta})\}$. By the MRF property we see that $P(Q_{xy} = q_{xy} | \eta_{xy}) = P(Q_{xy} = q_{xy} | L \backslash (q_{xy}))$ where $L \backslash (q_{xy})$ is denotes the set $\{q_{kl} : (k, l) \neq (i, j)\}$. In the general 2-D form and for binary-valued images, the corresponding conditional 2-D moments is given by the following steps.

- Step 1) Calculate the centroids $\bar{x}$, $\bar{y}$ of the considered shape as follows. Let $I(\cdot)$ be the indicator function.

$$\bar{x}=\sum_{x=1}^{N_1}\sum_{y=1}^{N_2} x\hat{P}(Q_{xy}=q_{xy}\mid\eta_{xy}) \quad (13)$$

$$\bar{y}=\sum_{y=1}^{N_2}\sum_{x=1}^{N_1} y\hat{P}(Q_{xy}=q_{xy}\mid\eta_{xy}) \quad (14)$$

where $\hat{P}(Q_{xy}=q_{xy}\mid\eta_{xy})$ that is proportion to $\exp\{-V_c(q_{xy}, t', \hat{\theta})\}$ is estimated conditional probability of the site (x, y) in the Gibbs distributed image described in Section 2.3.

• Step 2) Calculate σ_x and σ_y are the standard deviation of the image with respect to the coordinates x and y, given by

$$\sigma_x=\sqrt{\sum_{x=1}^{N_1}\sum_{y=1}^{N_2}(x-\bar{x})^2\,\hat{P}(Q_{xy}=q_{xy}\mid\eta_{xy})} \quad (15)$$

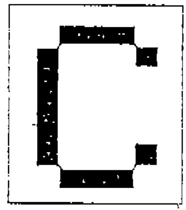
$$\sigma_y=\sqrt{\sum_{y=1}^{N_2}\sum_{x=1}^{N_1}(y-\bar{y})^2\,\hat{P}(Q_{xy}=q_{xy}\mid\eta_{xy})}. \quad (16)$$

• Step 3) Calculate the 2-D conditional moments from (15) and (16) for $k=0, 1, 2, \ldots$, and $l=0, 1, 2, \ldots$. And then, we store these moments to a feature vector.

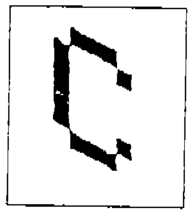
$$m_{kl}=\sum_{x=1}^{N_1}\sum_{y=1}^{N_2}\left(\frac{x-\bar{x}}{\sigma_x}\right)^k\left(\frac{y-\bar{y}}{\sigma_y}\right)^l\hat{P}(Q_{xy}=q_{xy}\mid\eta_{xy}), \quad (17)$$

The required number of moments depends on: (i) the level of the existing noise on the application and (ii) the form of the considered shapes. The above moments are invariant under translation and magnification of the image, but not under rotation. Thus, In order to use them as classification features we have to normalize with respect to rotation.

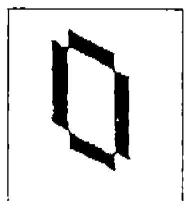
The normalization is a simple operation, since only a multiplication of the coordinates of the image by $e^{-j\phi}$, where ϕ is the rotation change of the object. Table 1 shows the conditional 2-D normalized moments of template letter C, as well as two similar letters(distorted C and O) of Figure 4.



(a) template



(b) shape 1



(c) shape 2

(Fig. 4) The template and the shapes to be tested.

<Table 1> The proposed moments of letter C and two similar letters.

Moments / Shapes	m_{30}	m_{40}	m_{50}	m_{60}	m_{70}	m_{80}	m_{03}	m_{04}	m_{05}	m_{06}	m_{07}	m_{08}
Template	1.02	2.55	1.29	4.11	3.97	7.08	1.11	2.92	1.02	3.00	1.59	3.09
Shape 1	1.06	2.67	1.31	4.15	3.97	7.26	1.04	2.83	1.22	3.13	3.02	3.18
Shape 2	1.01	2.44	1.01	2.04	1.08	5.72	−1.10	3.20	−1.93	4.20	−2.91	7.94

3.3 Classification

In order to classify patterns, we define a the discrimination cost function (DCF) $F(i, v)$ which is defined by

$$F(i, v) = \sum_{j=1}^{d} [T_{vj} - U_{ij}]^2 \qquad (18)$$

where T_{vj} denotes the $j\text{-}th$ feature of the $v\text{-}th$ template, U_{ij} denotes the $j\text{-}th$ feature of the $i\text{-}th$ shape under consideration and d is the dimension of the feature vectors. The minimization of the index $F(i, v)$, $v = 1, 2, \ldots$ for a specific shape i determines the corresponding template v.

The proposed DCF is a kinds of Euclidean distance between an arbitrary pattern vector U_{ij} and the $v\text{-}th$ prototype vector T_{vj}. Since the discrimination cost function (18) is a function of the proposed conditional 2-D moments, it is invariant under translation, scaling and rotation of the considered shape. Furthermore, Since the proposed DCF only require some simple analytic algebraic calculations, It is characterized by low computation cost. The ideal discrimination of a shape corresponding exactly to a template, without any noise and computational error, the index $F(i, v)$ should be zero. However, in practice, the discrimination is clear if $F(i, v)$ is sufficiently smaller in comparison with the other templates, as well as small enough itself.

〈Table 2〉 The DCF of the shapes of Fig. 4.

F (template "C", shape 1 "C") = 2.17
F (template "C", shape 2 "O") = 80.53

Table 2 shows the discrimination functions of the letters of Figure 4. In Table 2 it is seen that $F(i, v)$ is sufficiently smaller for the distorted C.

4. Experimental Results

In order to illustrate the performance of the proposed moment for pattern classification, we carried out the following experiments was carried out. The training document consists of 10 lines of 52 characters each. Figure 5 shows the first line of the training document. Two documents were created for testing the performance of the proposed classification method on the basis of the extracted feature vector. Each document consists of 24 lines 52 characters each. Figure 6 shows the overall block diagram of the proposed method for classification of patterns based on the conditional 2-D moment, where it is shown that a document to be processed is at first scanned. Then the classification feature vectors are extracted by formulae (13) through (17). These features are sent to a classifier, which is described by formula (18), for a decision in order to identify the input character.

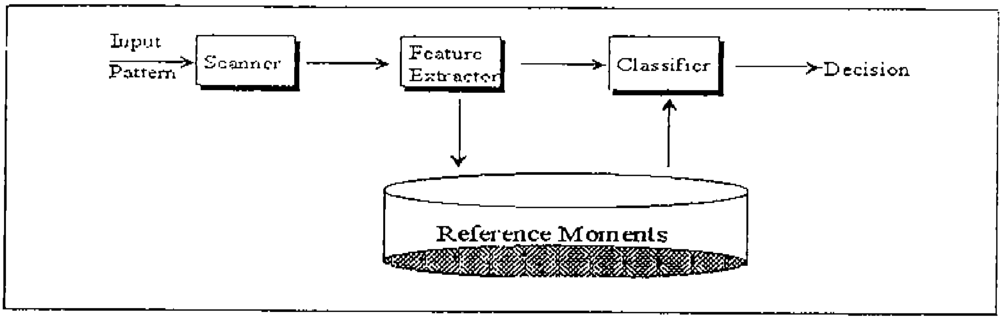
The gross structural features of the shape can be better characterized by the proposed moments derived from the silhouette. In our experiments we use only silhouette moments since these moments are less sensitive to noise. The used feature vector M_p for the templates is considered to be $M_p = [m_{03}, m_{04}, m_{05}, m_{06}, m_{07}, m_{08}, m_{30}, m_{40}, m_{50}, m_{60}, m_{70}, m_{80}]^T$.

A classification simulation was run six times. The first simulation used a library set of 52 feature vectors derived from the first line of characters of the training

q w e r t y u i o p a s d f g h j k l z x c v b n m

Q W E R T Y U I O P A S D F G H J K L Z X C V B N M

(Fig. 5) The first line of the training document.



(Fig. 6) Overview of the proposed method for classification of patterns, which is based on the proposed conditional 2-D moments.

document. The second simulation used two library sets derived from the first two lines of the training document. The third, fourth, fifth and sixth simulations used four, six, eight and ten library sets, respectively. The classification rates resulting from these simulations are presented in Table 3. As Table 3 reveals, we can achieve better than 94% increase in classification rates when we use eight or ten library sets. Since the proposed 2-D conditional moments have properties of the affine or geometric moments, as well as spatial information which describe dependance between pixels, our proposed method was superior to other methods using the affine moments and the geometric moments, respectively.

⟨Table 3⟩ The classification rates

No of library sets	Flusser's method using the affine moments (%)	Tsirikolias's method using the geometric method (%)	Proposed method(%) using the conditional moments
1	73	72	75
2	82.5	81	84
4	84	85	88
6	90.5	89	92
8	93	91	94
10	95	94.5	97.5

In our method, the incorrected classification of pattern is caused by the insufficient clique function $V(s, t', \theta)$ described in equation (8). Since the clique parameter vector $\hat{\theta}$ is a measure which is the strength of interaction between pixels, the clique potentials $V(s, t', \theta)$ affect the Gibbs distribution $\hat{P}(Q_{xy}=q_{xy} \mid \eta_{xy})$ which is used in calculation the proposed conditional 2-D moments. Thus, the method for pattern classification which is based on the proposed moments depends only the clique function. In other words, the success of pattern classification depends on how good the used clique parameter $\hat{\theta}$ fits characteristic of the image. So, we will focus our efforts on further development of the clique functions in order to complete of the pattern classification.

5. Concluding Remarks

In this paper we propose a new scheme for conditional two dimensional (2-D) moment-based classification of patterns on the basis of Gibbs random fields which are well suited for representing spatial continuity. This implementation contains two parts: feature extraction and pattern classification. First of all, we extract feature vector which consists of conditional 2-D moments on the basis of estimated Gibbs parameter. Note that the extracted feature vectors are invariant under translation, rotation, size of patterns. Next, in the classification phase, the minimization of the discrimination cost function for a specific pattern determines the corresponding template pattern.

Upon completion of the pattern classification, we will focus our efforts on further development of the clique functions.

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