An Improved Two-Dimensional OTSU Segmentation Method for Nvshu Character Image

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Abstract—For the structural characteristics of Chinese NvShu character, this paper proposes an improved two-dimensional (2-D) OTSU segmentation method based on the lateral inhibition network for Nvshu character image. A 2-D histogram with the gray level and the lateral inhibition level of the image was established and the maximum between-cluster variance was chosen as the criterion to select the optimal threshold. Experimental results show that the proposed method not only successfully reduced the effect of background noise, but also improved the accuracy of the character image segmentation, especially for NvShu character images with low contrast, uneven gray level of character strokes and uneven background.

Index Terms—Nvshu Character Image; Lateral Inhibition Network; Two-Dimensional Histogram; OTSU Method

I. INTRODUCTION

Nvshu, also called female scripts, is a mysterious symbol created by women which derived from the valley of the Xiaoshui River in Jiangyong County of Hunan Province, China. It is only used and circulated among women and is the unique female characters in the world. Nvshu is the tool of cultural communication for local women and is the unique female characters in the world. As an endangered language, Nvshu is in poor state of information processing in which the disconnection of character strokes and the high background noise, which are mainly resulted from the

there are two different aspects of thresholding: global thresholding and local thresholding. As the global thresholding methods are easy to be implemented, they are preferred to local thresholding methods especially in machine applications.

Many global thresholding techniques were developed over the past years. Among them, OTSU method [4] is one of the best threshold selection methods for general real world images, which selects a global threshold value by maximizing the separability of the classes in gray levels. To improve the adaptability of OTSU method, many modified OTSU methods had been proposed, such as the range-constrained OTSU method [5], the valley-emphasis OTSU method [6], and the two-stage OTSU method [7]. Generally speaking, OTSU method can obtain satisfied segmentation results in many cases. However, due to the influence of objective conditions and artificial actions, the gray level histogram may not show obvious peaks and valleys. In those cases, only using the one-dimensional histogram to determine the threshold is difficult to obtain satisfactory segmentation results. For this reason a two-dimensional (2-D) OTSU method which employs point pixel information and the local average gray level of the neighborhood pixels was presented in [8]. Although the 2-D OTSU method has stronger noise robustness, it gives rise to the exponential increment of computation time. Given this, many fast 2-D OTSU methods [9–13] had been proposed to reduce the time complexity of 2-D OTSU method. However, there is a main assumption in the above 2-D OTSU algorithms that the sum of probabilities of main-diagonal distinct in 2-D histogram is approximately one, which is contrary to realism sometimes. So many post-processing OTSU methods were presented, such as the curve 2-D OTSU method [14], the oblique 2-D OTSU method [15] and the precise 2-D OTSU method [16], which reclassify the boundary region pixels to improve the segmentation results. However, in our experiments, we found that the segmentation results often have many defects by using the traditional OTSU method, such as the fuzziness, the disconnection of character strokes and the high background noise, which are mainly resulted from the
complex textures of Nvshu materials and the high noise comes from the image acquisition equipment.

Consequently, this paper proposes an improved two-dimensional OTSU segmentation method based on the lateral inhibition network for Nvshu character image. A two-dimensional histogram with the gray level and the lateral inhibition level of the image was established and the maximum between-cluster variance was chosen as the criterion to select the optimal threshold. Experimental results show that the proposed method not only successfully reduced the effect of background noise, but also improved the accuracy of the character image segmentation, especially for NvShu character images with low contrast, uneven gray level of character strokes and uneven background.

The reminder of this paper is organized as follows. In Section II, some related works, such as the structural characteristics of Nvshu character image, the lateral inhibition network and the traditional 2-D histogram are briefly introduced. The proposed modified OTSU method is presented in detail in Section III. In Section IV, experimental results are shown. Finally, the conclusion is given in Section V.

II. RELATED WORKS

A. Structural Characteristics of the Nvshu Character Image

The original Nvshu materials are hand-written, which are usually written on manuscripts, fans, handkerchiefs and pieces of paper. In order to use the information technology to salvage and protect Nvshu, we need to scan the carriers of Nvshu and preserve them in the form of digital image. However, most of the Nvshu materials have a long history and are lack of protection, so the Nvshu character image is of low quality, which increase the difficulty of image segmentation. The structural characteristics of the Nvshu character image are listed as following: (1) the proportion of the object(Nvshu character) is relatively smaller than the background; (2) the object is composed of strange strokes with a complex background; (3) font overall tilt with the diamond structure; (4) dot strokes transformed from relatively short strokes; (5) the transformed neat lines strokes, only horizontal and vertical strokes with relatively short length could be retained, other strokes are transformed into oblique strokes with declining long lines [17]. All of these features of Nvshu character image must be taken into consideration to improve the quality of segmentation.

B. Lateral Inhibition Network

Lateral inhibition is one of the basic principles in the process of information processing of the visual neural system. It is a general mechanism in the visual and tactile sensations of living things such as limuloid and human beings. Hartline and his colleagues [18] firstly found the phenomenon of lateral inhibition in their electrophysiological experiment on limuloid eyes. If every little eye in the limuloid’s compound eyes is regarded as a receptor and all the eyes are exposed to the illumination, the experimental results demonstrated that the frequency that each eye transmits is less than what it transmits when it is under the light alone. The results of experiments also indicated that the response of a certain eye is influenced not only by the stimulation it receives but also by the inhibition affects comes from the surrounding eyes. Generally, when a neuron receives stimulation and becomes excited, it will enhance the neurons closed to it and exert an inhibition influence on the distant ones, which is expressed as "enhance center and suppress neighborhood”.

In image processing, the lateral inhibition network has the following functions [19]: 1) detecting the edges of image, highlighting the borders and enhancing the contrast; 2) high-pass filter by compressing the large input range of the network to its dynamic range; 3) compensating the fuzzy image caused by refraction system; 4) fitting the blind breaks in the image [20].

Since the lateral inhibition network was discovered by the researchers, many mathematical models had been proposed to express it. Generally, the mathematical models can be divided into cyclic models and non-cyclic models based on the inhibitory effect is from the input or the output of surrounding units. Besides, the mathematical models can be classified as subtraction models and shunt models based on the inhibitory effect is implemented by the summation or the shunt of surrounding units. In order to apply the lateral inhibition network to digital image processing, Chen and OuYang [21] proposed three 2-D lateral inhibition network models based on different classification rules.

2-D subtraction non-cyclic model:

\[ r_{p,q} = e_{p,q} + \sum_{i=R}^{n} \sum_{j=R}^{n} k_{m,q} e_{i,j} \]  

2-D shunt non-cyclic model:

\[ r_{p,q} = e_{p,q} \times \frac{e_{p,q}}{\sum_{i=R}^{n} \sum_{j=R}^{n} k_{m,q} e_{i,j}} \]

2-D subtraction cyclic model:

\[ r_{p,q} = e_{p,q} + \sum_{i=R}^{n} \sum_{j=R}^{n} k_{p,q} r_{i,j} \]

where, \( e_{p,q} \) and \( r_{p,q} \) are the input and the output of the visual receptor, respectively. \( k_{p,q} \) is the inhibition coefficient from receptor \( (p,q) \) to receptor \( (i,j) \). \( R \) is the radius of lateral inhibition field.

C. Traditional 2-D Histogram

An image is defined as a 2-D light-intensity function, which contains \( M \times N \) pixels each with a value of brightness, i.e. gray level, from 0 to \( L-1 \), where \( L \) is the number of gray levels. The traditional 2-D histogram contains the gray level of an image and its local average gray level. The gray level of a pixel with
coordinate \((m,n)\) is denoted as \(f(m,n)\). Let \(g(m,n)\) be the function of the local average gray level, then
\[
g(m,n) = \left\lfloor \frac{1}{9} \sum_{i=1}^{4} \sum_{j=1}^{4} f(m+i,n+j) \right\rfloor
\]  
(4)
where \(\lfloor \ \rfloor\) represents rounding.

For an image, let \(c_{x,y}\) be the total number of the occurrence of the pair \((x,y)\), which represents pixel \((m,n)\) with \(f(m,n) = x\) and \(g(m,n) = y\), then the joint probability mass function \(p_{x,y}\) is given by
\[
p_{x,y} = \frac{c_{x,y}}{M \times N}, \quad x, y = 0, 1, \cdots, L-1
\]  
(5)
where \(\sum_{x=0}^{L-1} \sum_{y=0}^{L-1} p_{x,y} = 1\).

\(\{p_{x,y}\}\) is the 2-D histogram of the image. By means of the threshold vector \((s,t)\), the histogram can be divided into four quadrants.

![Traditional 2-D histogram](image)

where quadrants 0 and 1 contain the distributions of object and background classes, whereas the quadrants 2 and 3 are the distributions of edge pixels and noise pixels. However, there is a main assumption in the above 2-D histogram that the sum of probabilities of quadrants 0 and 1 is approximately one because of that most of the pixels are located in these two areas.

### III. Modified 2-D Otsu Method

#### A. Gray Level and Lateral Inhibition Level (GLLIL) 2-D Histogram

In order to simulate the lateral inhibition network and use it to serve Nvshu character image segmentation, we design a 2-D lateral inhibition network with a radius of 3:

\[
\begin{align*}
r_{p,q} &= -e_{p,q} + \sum_{i=0}^{4} \sum_{j=0}^{4} k_{pq} e_{i,j} = -e_{p,q} + k_1 \left( \sum_{i=0}^{4} \sum_{j=0}^{4} e_{i,j} \right) \\
&\quad - k_2 \left( \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(q-2)j} + \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(q+2)j} + \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(p-2)i} + \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(p+2)i} \right) \\
&\quad - k_3 \left( \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(q-2)j} + \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(q+2)j} + \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(p-2)i} + \sum_{i=0}^{4} \sum_{j=0}^{4} e_{(p+2)i} \right)
\end{align*}
\]  
(6)
where \(k_w (w=1,2,3)\) is the lateral inhibition intensity coefficient and the definition of other parameters in the equation can refer to (1). Then, equation (6) can be merged as follows:

\[
r_{p,q} = -e_{p,q} + k_1 \sum_{i,j} e_{p,q} \\
- k_2 \sum_{i,j} e_{p,q} \\
- k_3 \sum_{i,j} e_{p,q}
\]  
(7)
where \(N_s(p,q)\) is the 8 neighborhood of \((p,q)\), \(N_{16}(p,q)\) is the 16 neighborhood of \((p,q)\), \(N_{24}(p,q)\) is the 24 neighborhood of \((p,q)\), respectively.

The lateral inhibition intensity coefficient is defined as:
\[
k_w = \frac{d_w}{s_w}, \quad w = 1, 2, 3
\]  
(8)
where \(d_w\) is the attenuation coefficient, \(s_w\) is the area of neighborhood.

By substituting \(k_w\) into (7), we obtain

\[
r_{p,q} = -e_{p,q} + \frac{d_1}{s_1} \sum_{i,j} e_{p,q} \\
- \frac{d_2}{s_2} \sum_{i,j} e_{p,q} \\
- \frac{d_3}{s_3} \sum_{i,j} e_{p,q}
\]  
(9)
and we can integrate (9) as follows:

\[
r_{p,q} = -e_{p,q} + d_1 \bar{e}_s - d_2 \bar{e}_{16} - d_3 \bar{e}_{24}
\]  
(10)
where \(\bar{e}_s\), \(\bar{e}_{16}\) and \(\bar{e}_{24}\) are the average lateral inhibition value of 8 neighborhood of \(e_{p,q}\), 16 neighborhood of \(e_{p,q}\) and 24 neighborhood of \(e_{p,q}\), respectively.

By using the lateral inhibition network which is shown in (10), we can establish the GLLIL 2-D histogram. The steps can be summarized as follows:

Step 1. calculate the lateral inhibition matrix based on (10);

Step 2. filter the image by using the lateral inhibition matrix and obtain the lateral inhibition image;

Step 3. normalize the lateral inhibition image and denote it by \(h(m,n)\);
Step 4. establish the GLLIL 2-D histogram. By letting \( f(m,n) = i \) and \( h(m,n) = j \), a certain coordinate \((i,j)\) in the GLLIL 2-D histogram is denoted, i.e., the abscissa is the gray level of a pixel and the ordinate is lateral inhibition level of a pixel, respectively. \( p_{i,j} \) represents the frequency of the occurrence of the pair \((i,j)\). It is given by

\[
p_{i,j} = \frac{c_{i,j}}{M \times N} \quad i, j = 0, 1, \cdots, L-1 \tag{11}
\]

where \( c_{i,j} \) is the total number of the occurrence of the pair \((i,j)\) and \( \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{i,j} = 1 \).

Fig. 2 is the comparison of the traditional 2-D histogram and the GLLIL 2-D histogram. We can see that the GLLIL 2-D histogram has a large density and the distribution of gray level is more even. Besides, comparing to the traditional 2-D histogram, the 2-D histogram proposed in this paper has more pixels at the peaks and valleys, which can enhance the contrast of image and highlight the features.

![Figure 2](image)

**Figure 2.** The comparison of traditional 2-D histogram and GLLIL 2-D histogram: (a) traditional 2-D histogram (b) GLLIL 2-D histogram

**B. 2-D OTSU Method Based on GLLIL**

By obtaining the GLLIL 2-D histogram, we choose the maximum between-cluster variance as the criterion to select the optimal threshold. Suppose that all the pixels in an image can be divided into two classes \( \mathcal{W}_0 \) and \( \mathcal{W}_1 \) by a threshold \((s,t)\), then the probabilities of class occurrence are given by

\[
\mathcal{W}_i = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{i,j} = \mathcal{W}_i(s,t) \tag{12}
\]

and the corresponding class mean levels are

\[
u_0 = \left( u_{00}, u_{01} \right) = \left( \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{i,j}}{W_0}, \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j p_{i,j}}{W_0} \right)^T \tag{14}
\]

\[
u_1 = \left( u_{10}, u_{11} \right) = \left( \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{i,j}}{W_1}, \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j p_{i,j}}{W_1} \right)^T \tag{15}
\]

the total mean level vector of the 2-D histogram is

\[
\mathcal{U}_T = \left( u_{T0}, u_{T1} \right) = \left( \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{i,j}}{W_0 + W_1}, \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j p_{i,j}}{W_0 + W_1} \right)^T \tag{16}
\]

Based on the assumption that the occurrences of image pixels in off-diagonal quadrants of 2-D histogram can be neglected, it is easy to be verified that

\[
W_0 + W_1 \approx 1, \quad \mathcal{U}_T = \mathcal{W}_0 u_0 + \mathcal{W}_1 u_1 \tag{17}
\]

The between-cluster variance scatter matrix can be formulated as

\[
\mathcal{G}_B = \mathcal{W}_0 \left[ (u_0 - \mathcal{U}_T) (u_0 - \mathcal{U}_T)^T \right] + \mathcal{W}_1 \left[ (u_1 - \mathcal{U}_T) (u_1 - \mathcal{U}_T)^T \right] \tag{18}
\]

The trace of the scatter matrix is expressed as

\[
tr\mathcal{G}_B = \mathcal{W}_0 \left[ (u_0 - \mathcal{U}_T)^2 + (u_0 - \mathcal{U}_T)^2 \right] + \mathcal{W}_1 \left[ (u_1 - \mathcal{U}_T)^2 + (u_1 - \mathcal{U}_T)^2 \right] \tag{19}
\]

so the optimal threshold \((s^*, t^*)\) is selected by maximizing \(tr\mathcal{G}_B\)

\[
(s^*, t^*) = \arg \max_{s, t \in \mathbb{N}} \{ tr\mathcal{G}_B(s, t) \} \tag{20}
\]

then convert the image to the binary one

\[
f_t(m,n) = \begin{cases} 0, & f(m,n) \leq s^* \text{ and } h(m,n) \leq t^* \\ L-1, & f(m,n) > s^* \text{ and } h(m,n) > t^* \end{cases} \tag{21}
\]

where \( f_t(m,n) \) is the binary image.

However, in the process of calculating optimal threshold, it takes too much repetitive calculation to obtain every \( \mathcal{W}_0, \mathcal{U}_0 \) and \( \mathcal{U}_1 \). So we use the recursive method to eliminate redundant computation and improve the computing speed of the algorithm.

Equations (14) and (15) can be rewritten as follows:

\[
u_0 = \left( u_{00}, u_{01} \right) = \left( \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{i,j}}{W_0}, \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j p_{i,j}}{W_0} \right)^T \tag{22}
\]

\[
u_1 = \left( u_{10}, u_{11} \right) = \left( \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{i,j}}{W_1}, \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j p_{i,j}}{W_1} \right)^T \tag{23}
\]
\[ u_t = (u_{i0}, u_{i1})^T = \left( \frac{\sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j} W_1}{W_t}, \frac{\sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j} W_1}{W_t} \right)^T \]  
\[(23)\]

\[ \text{let} \]
\[ X_0 = \sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j}, Y_0 = \sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j} \]
\[ X_1 = \sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j}, Y_1 = \sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j} \]
\[ \text{so} \]
\[ u_0 = (u_{i0}, u_{i1})^T = \left( \frac{X_0, Y_0}{W_0} \right) \]
\[ u_t = (u_{i0}, u_{i1})^T = \left( \frac{X_1, Y_1}{W_t} \right) \]

then establish three lookup tables

\[
\begin{align*}
P(m, n) &= \sum_{i=0}^{m} \sum_{j=0}^{n} p_{i,j} \\
X(m, n) &= \sum_{i=0}^{m} \sum_{j=0}^{n} ip_{i,j} \\
Y(m, n) &= \sum_{i=0}^{m} \sum_{j=0}^{n} jp_{i,j}
\end{align*}
\]
\[(28)\]

so

\[
\begin{align*}
W_0 &= P(s, t) \\
X_0 &= X(s, t) \\
Y_0 &= Y(s, t) \\
W_1 &= P(L-1, L-1) - P(L-1, t) - P(s, L-1) + P(s, t) \\
X_1 &= X(L-1, L-1) - X(L-1, t) - X(s, L-1) + X(s, t) \\
Y_1 &= Y(L-1, L-1) - Y(L-1, t) - Y(s, L-1) + Y(s, t)
\end{align*}
\]
\[(29)\]

By figuring out the optimal threshold using the three lookup tables in (28) and 6 formulas in (29), we can reduce the time consumption of the proposed algorithm. Three lookup tables can be established through the following three iterative formulas:

\[
P(m, n) = P(m-1, n) + P(m, n-1) - P(m-1, n-1) + p_{m,n} \]  
\[(30)\]

where \( P(0,0) = p_{0,0} \).

\[
X(m, n) = X(m-1, n) + X(m, n-1) - X(m-1, n-1) + m \times p_{m,n} \]  
\[(31)\]

where \( X(0,0) = 0 \times p_{0,0} \).

\[
Y(m, n) = Y(m-1, n) + Y(m, n-1) - Y(m-1, n-1) + n \times p_{m,n} \]  
\[(32)\]

where \( Y(0,0) = 0 \times p_{0,0} \).

IV. EXPERIMENTAL RESULTS

To evaluate the performances of the proposed method and demonstrate its effectiveness, the results are compared with the 2-D OTSU method and the curve 2-D OTSU method. Four NvShu character images with different typical characteristics were selected in our experiments, such as low contrast, uneven gray level of character strokes, uneven background and high noise. In the experiments, by setting \( d_w = 1/2^w \) (\( w = 1,2,3 \)) and putting \( d_w \) into (10), we obtain the lateral inhibition matrix:

\[
\begin{bmatrix}
-0.005 & -0.005 & -0.005 & -0.005 & -0.005 & -0.005 & -0.005 \\
-0.005 & -0.016 & -0.016 & -0.016 & -0.016 & -0.016 & -0.005 \\
-0.005 & -0.016 & 0.0625 & 0.0625 & 0.0625 & -0.016 & -0.005 \\
-0.005 & -0.016 & 0.0625 & -1 & 0.0625 & -0.016 & -0.005 \\
-0.005 & -0.016 & 0.0625 & 0.0625 & -0.016 & -0.005 \\
-0.005 & -0.016 & -0.016 & -0.016 & -0.016 & -0.016 & -0.005 \\
-0.005 & -0.005 & -0.005 & -0.005 & -0.005 & -0.005 & -0.005 \\
\end{bmatrix}
\]

Besides, all the experiments are performed on a common PC with MATLAB 2010b (Intel Core2 Duo, CPU-2.2GHZ with 2GB RAM).

A. Nvshu Character Image with Low Contrast

NvShu character image with low contrast shown in Fig. 3 was chosen in our experiments. As can be seen from Fig. 3(b) and (c), the 2-D OTSU method and the curve 2-D OTSU method failed in this case. Fig. 3(d) presents the segmentation result using our method in this paper. We can see that the proposed method can get a fairly clear segmentation result which is easy to be observed by human eyes. It has been further demonstrated that our method is well adapted to the low contrast of Nvshu character image.

![Image](a) ![Image](b) ![Image](c) ![Image](d)

Figure 3. Segmentation results for a Nvshu character image with low contrast: (a) original image (b) segmentation result using 2-D OTSU method (c) segmentation result using curve 2-D OTSU method (d) segmentation result using the proposed method.

B. Nvshu Character Image with Uneven Gray Level of Character Strokes

In the next experiment a NvShu character image with uneven gray level of character strokes shown in Fig. 4...
was chosen to demonstrate the robustness of our method. As is shown in Fig. 4(d), the proposed method has the capability to fit the strokes. However, the writer’s writing habits result in the uneven distribution of character strokes’ gray level. Since our method added the lateral inhibition information into the 2-D histogram, it effectively broadened the 2-D histogram which makes the distribution of gray level more even. As a result, our method obtains the satisfying segmented characters.

![Figure 4](image1)

**Figure 4.** Segmentation results for a Nvshu character image with uneven gray level of character strokes: (a) original image (b) segmentation result using 2-D OTSU method (c) segmentation result using curve 2-D OTSU method (d) segmentation result using the proposed method

**C. Nvshu Character Image with Uneven Background**

A Nvshu character image with uneven background is shown in Fig. 5. The uneven background is resulted from the paper texture of the old Nvshu materials. As are shown in Fig. 5(b)-(d), the 2-D OTSU method and the curve 2-D OTSU method performed poorly on this image while our method successfully extracted all the Nvshu characters. This is mainly because that the proposed method utilizes the function of lateral inhibition network which can enhance the difference between the character strokes and the background. However, our method not only avoids the loss of the character image information, but also improves the accuracy and robustness of the character image segmentation. Experimental results further demonstrated its capability to overcome the effect of uneven background on character image segmentation.

**D. Nvshu Character Image with High Noise**

In this section, we studied the anti-noise capability of the proposed method. The experiment was carried out on a Nvshu character image by adding salt & pepper noises with a density of 0.08 shown in Fig. 6(a). Figure 6(b) and (c) present the corresponding results using the 2-D OTSU method and the curve 2-D OTSU method. The segmentation result provided by our method is shown in Fig. 6(d). As can be seen from Fig. 6, the satisfying segmented characters can be obtained by using the proposed method compared with the 2-D OTSU method and the curve 2-D OTSU method. Furthermore, in the noise image, the total number of object pixels is 2259. In the segmentation results of each method, the object pixels number of the 2-D OTSU method, the curve 2-D OTSU method and the proposed method are 24632, 27576 and 1027, respectively. Misclassification rate of each method is 79.8%, 90.3% and 4.4% respectively. Our method’s misclassification rate is significantly lower than the rest two algorithms, which indicates that the proposed algorithm has the capability to reduce noise sensitivity.

![Figure 5](image2)

**Figure 5.** Segmentation results for a Nvshu character image with uneven background: (a) original image (b) segmentation result using 2-D OTSU method (c) segmentation result using curve 2-D OTSU method (d) segmentation result using the proposed method

![Figure 6](image3)

**Figure 6.** Segmentation results for a Nvshu character image with high noise: (a) original image (b) segmentation result using 2-D OTSU method (c) segmentation result using curve 2-D OTSU method (d) segmentation result using the proposed method

**V. CONCLUSIONS**

In this paper, a improved 2-D OTSU segmentation algorithm for Nvshu character image is proposed. This novel method establishes a new 2-D histogram which contains the gray level information and the lateral inhibition information of the Nvshu character image. And then, we apply it to the 2-D OTSU segmentation algorithm. Experimental results demonstrated its...
capability to reduce noise sensitivity and improve the robustness, especially for NvShu character images with low contrast, uneven gray level of character strokes and uneven background.

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