# Research on Feature Extraction for Character Recognition of NaXi Pictograph

Hai Guo
Dalian Nationalities University, Dalian, China
Email: dlguohai@gmail.com

Jing-ying Zhao*
Dalian Nationalities University, Dalian, China
Email: dalianzjy@gmail.com

***Abstract*—Character recognition is one of important applications for pattern recognition. Feature extraction is the most important problem in character recognition. In this paper, we have researched on feature extraction for character recognition of NaXi pictograph. The characteristics of NaXi pictograph are firstly analyzed. Four kinds of features, including permeability number, coarse grid, directional line element, and invariant moments, and 6 kinds of computation distances, including Lidean distance, Standardized Euclidean distance, Minkowski metric, Chebychey distance, City distance, and Correlation distance will be applied to classify characters of NaXi pictograph, based on its characteristics. We have built a sample database containing 21000 samples for 2120 NaXi characters. The results of experiments suggest that coarse grid and directional element are more suitable for character recognition of NaXi pictograph, while invariant moments is not advisable for this task.**

***Index Terms*—Character recognition, pattern recognition, Feature extraction, NaXi pictograph, NaXi characters**

## I. Introduction

Automatic recognition of characters by computer technology is one of the important areas in pattern recognition. In production and life, people need deal with lot of words, statements and texts. In order to alleviate people’s labors and improve the processing efficiency, people began to research on the general methods of character recognition in 1950’s, and have developed the recognition reader of optical character. In 1960’s, practical machines appeared, in which magnetic ink and special fonts are used. In the late 1960’s, recognition reader of multifold fonts and handwriting character appeared, whose precision and machine performance can satisfy requirements basically. For example, the recognition reader for handwritten digitals in mail sorting, and the recognition reader for printed English numbers. In 1970’s, basic theory of character recognition was studied and character recognition readers in high performances were developed. At the same time, the research on Chinese character recognition is focused on. [1]

Generally, character recognition includes text information collection, information analysis and processing, information classification and discrimination, and so on. Information collection means that gray of characters on paper will be converted into electrical signals, which can be input into computers. Information collection is based on paper feeding mechanisms and photoelectric conversion devices in character recognition reader, flying-spots scanners, video camera, photosensitive components, laser scanners, and other photoelectric conversion devices. Information analysis and processing eliminate the noises and disturbance caused by printing quality, paper quality, writing instruments and other factors. It can normalize size, deflexion, shade and thickness. Information classification and discrimination can remove the noises, normalize the character information, classify the character information and output the recognition results. [2-6]

Feature extraction is a crucial part of character recognition. It will affect the recognition accuracy greatly if features are not suitable for this task. [7] In this paper, we research on the feature extraction for character recognition, especially for the feature extraction of Naxi pictograph characters, which are graphic characters. This paper consists of seven main sections. Section I is the preface. Section II is introduction related to the characteristics of NaXi characters. Section III is the presentation for developed Naxi recognition pretreatment. Section IV is vital part in the paper, in which feature extraction of NaXi pictograph characters are introduced and 4 methods of feature extraction are given. In section V, classification methods of NaXi character recognition are described. In section VI, features that are most suitable for NaXi character recognition are given. Section VII summarizes the paper.

## II. The Characteristics of NaXi Pictograph and Current Situation of Information Processing

NaXi pictograph belongs to Tibeto-Burman languages, and Yi branch of the Naxi language. It is the only one of circulated, living and ancient scripts so far, and it is of great reference value for studying the development history of scripts in the world. Last century, people at home and abroad began to study the NaXi pictograph. Nowadays, universities in American, Japan and Europe

*Corresponding author: Jing-ying Zhao Email: dalianzjy@gmail.com


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begin to study the NaXi pictograph further. The manual ways of manually-drawing, manually-scanning, manually-plating and so on, are used in traditional processing technology of NaXi pictograph. The morphology of NaXi pictograph is extremely complicated. For example, “ ”, “ ”, “ ”, “ ”, “ ” and some other scripts have many writing patterns. So, it will take at least 10 years to learn to write the 2010 common words. The poor efficiency of manually-processing is not suitable for the need of the current script information processing.

### *A. Characteristics of NaXi pictograph*

As a special language, NaXi pictograph is different from English, Chinese and other languages in aspects of word formation, spelling, and typesetting. Therefore its recognition is very different from that of Chinese and English. As the pictograph of initial stages in script evolutionary history, NaXi pictograph has some relations with Chinese, English and some other national characters. But there are still lots of differences.[8]

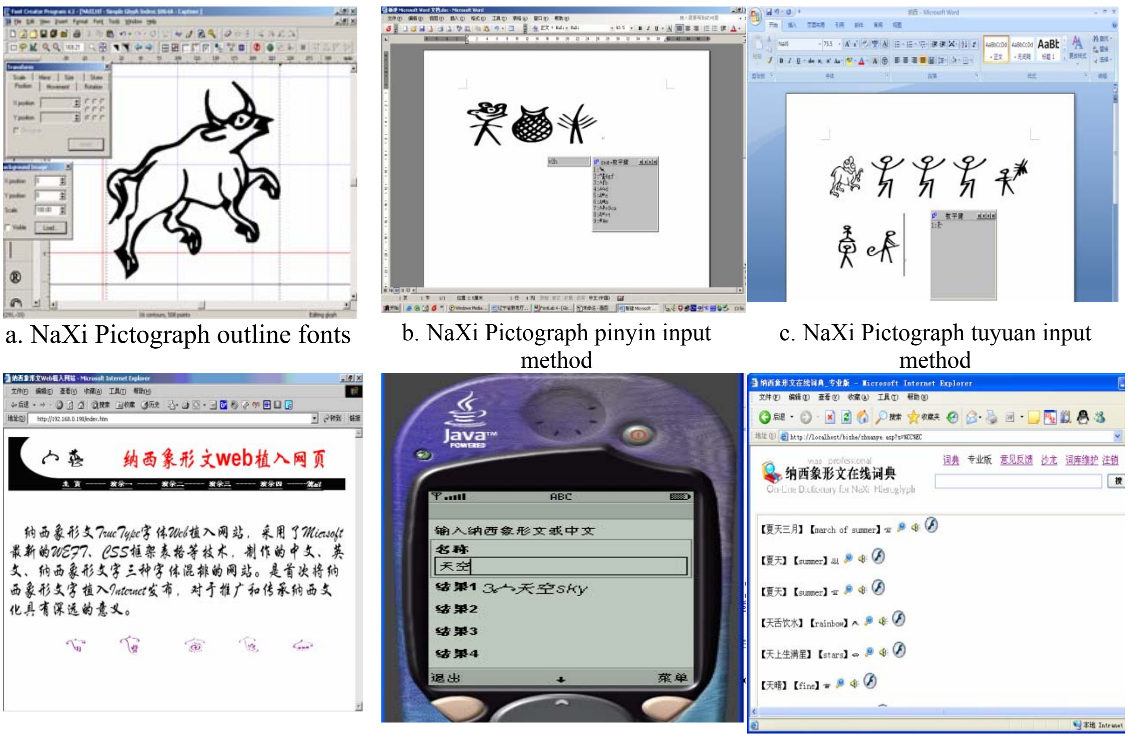
*1).Large quantities of categories.* NaXi pictograph consists of 2010 common characters, and its recognition belongs to the pattern recognition with large number of categories. It is to say that NaXi pictograph recognition belongs to the pattern recognition with oversized categories. The larger is the number of categories, the harder is the task of classification and recognition. So, the large number of characters are one of the major reasons resulting that the recognition task is very hard.

*2).Complicated structure.* NaXi pictograph is a character with intensity structure. It is an independent pictograph character in the shape, and each character has some primitives which are specifically distributed. NaXi pictograph written by different people has the same topology. The basic primitive is the most basic component element, and the most basic primitive is only one component element, such as “ ”. The most primitive has dozens of component elements, such as “ ”. The number of primitives is varied, which explains the complication degree of NaXi pictograph characters’ structures. The different permutation and combination of primitives forms NaXi pictograph characters with different implication and extremely complicated structures. Since NaXi pictograph character is not alphabetized and are different from spelling words, its structure is the most complex compared with the other national scripts in the world. NaXi pictograph is a kind of graphic character. Most Naxi can just recognize and read it, and only few of people can write it.

*3). A large amount of similar characters.* There are some tiny differences between NaXi pictograph characters. For example, there is only a different primitive among “ ”, “ ”, and “ ”. Because and are very similar with each other, the recognition task is very difficult. Therefore, as long as the suitable features are chosen, we can carry out the task of efficient character recognition. Even if the characters are recognized manually, we will make mistakes easily without the context information. Recognition algorithm and system should judge these tiny differences, otherwise mistakes will be taken.

### *B. Previous Work onPreprocessing of Naxi Pictographs*

Since 2001, the author of this article has made the research about computer information processing technologies of NaXi Pictograph, and developed NaXi




a. NaXi Pictograph outline fonts b. NaXi Pictograph pinyin input method c. NaXi Pictograph tuyuan input method

d. NaXi Pictograph WEFT e. NaXi Pictograph Mobile Phone Dictionary f. Naxi Pictograph Online Dictionary

Figure 1. NaXi Pictograph information processing

Pictograph outline fonts, NaXi Pictograph pinyin input method, NaXi Pictograph tuyuan input method, NaXi Pictograph WEFT, NaXi Pictograph Mobile Phone Dictionary and Naxi Pictograph Online Dictionary, etc [9-11]. Parts of early results about NaXi Pictograph information processing are shown in figure 1.

## III. PRETREATMENT OF NAXI CHARACTER RECOGNITION

The pretreatment of Naxi character recognition generally includes binary processing, line and word segmentation, smoothing, noise reduction, normalization and thinning images(or extracting contour). Requirements for pretreatment are different for different recognition methods. For example, in structure recognition method, the requirements for word normalization and pretreatment can be simple, and even unnecessary. In some methods, requirements of pretreatment for thinning images can be high. But some methods just demand contour extraction and contours are used as sources of features in Naxi pictograph characters.

OSTU method is applied to binary processing of NaXi pictograph. It is argued through experiments that this method is more suitable for binary processing of NaXi pictograph. We have done special researches on segmentation of lines and columns for NaXi pictograph. Experiments show that window detection method that we have put forward is more advisable for segmentation of NaXi pictograph, and the precision of segmentation is more than 93%[12]. The pretreatment of NaXi is introduced in literature[13]. In literature[14], wavelet technology is applied to noise reduction and contours extraction in pretreatment of NaXi pictograph recognition. The results are very good.

## IV. THE FEATURE EXTRACTION METHOD OF NAXI PICTOGRAPH

### *A..Coarse grid features*

Coarse grid is a local features, and belongs to the statistical feature, which reflects the distribution of the overall shape. We can use coarse grid to divide the character into M×M grids, and count the number of pixels in each grid. In stage of recognition, statistical features in grids can be combined into the statistical features for characters, which will be used to achieve the task of character recognition. Each pixel in the grid can reflect features of characters. Feature extraction method of Naxi pictograph based on coarse grid is shown as follows:

- Obtain the external borders of final image after pretreatment.
- Divide framed image into 8 × 8 grids, as shown in Figure 2.
- Take statistics at the percentage of black pixels within each grid.
- Line 8 × 8 statistical black pixels, and a 64-dimensional feature vector of character grid will be gotten.

This method is relatively simple and easy to implement. But the anti-interference ability of stroke position is poor. In literature[15], it is improved. Its idea is that the center of recognized character image is found firstly, then character image is shifted to the template center, and finally coarse grid feature of characters is extracted.

(1) The location of the image

After sample tibetan character is pretreated, a M*M lattice image is obtained which is denoted as $g(x, y)$.

$$g(i,\ j) = \begin{cases} 0, & \text{white} \\ 1, & \text{black} \end{cases} \qquad (1)$$

The location of the character image is shown as follows:

Step1. Search the character image starting at the first column, from top to bottom. When the number of columns is satisfied with the conditions $g(x-1, y) = 0$, $g(x, y) = 1$ and $g(x, y+1) = 1 (x > 0)$ or $g(0, y) = 1$ and $g(0, y+1) = 1$, the number of column y will be written down, and it is used as character boundary in character image, which is denoted as $A_{\min}$ .

Step 2. Search the character image starting at the last column, from bottom to top. When the number of columns is satisfied with the conditions $g(x-1, y) = 0$, $g(x, y) = 1$ and $g(x, y-1) = 1(x > 0)$ or $g(0, y) = 1$ and $g(0, y-1) = 1$, the number of column y will be written down, and it is used as character boundary in character image, which is denoted as $A_{\max}$.

Step 3. Search the character image starting at the first row, from left to right. When the number of rows is satisfied with the conditions $g(x, y-1) = 0,$ $g(x, y) = 1$ and $g(x+1, y) = 1(y > 0)$ or $g(x, 0) = 1$ and $g(x+1, 0) = 1$, the number of row x will be written down, and it is used as character boundary in character image, which is denoted as $B_{\min}$.

Step 4. Search the character image starting at the last row, from left to right. When the number of rows is satisfied with the conditions $g(x, y-1) = 0,$ $g(x, y) = 1$ and $g(x-1, y) = 1(y > 0)$ or $g(x, 0) = 1$ and $g(x-1, 0) = 1$ , the number of row x will be written down, and it is used as character boundary in character image, which is denoted as $B_{\max}$.

Step 5.Computing the character center (p, q):

$$p = \frac{A_{\max} + A_{\min}}{2}, \quad q = \frac{B_{\max} + B_{\min}}{2} \qquad (2)$$

(2)The shift of image

The image is shifted according to formula (3).

$$x' = x - p_x, y' = y - q_y \qquad (3)$$

Here $p_x = p - x_0$, $q_y = q - y_0$, and $(x_0, y_0)$ is the center of the standard template, which is called as the center of the grid.

(3)Feature extraction of coarse grid

Based on the method of coarse grid, feature vectors are extracted from the processed Naxi character image.

### *B. The Feature of Permeability Number*

In a M*M lattice of NaXi pictograph, the character is scanned in different directions. Based on the number of

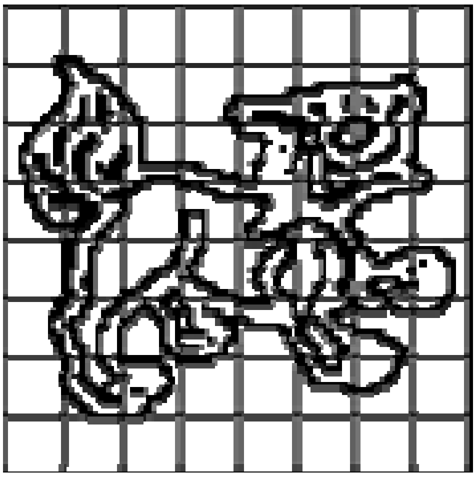


Figure 2. Coarse grid features of Naxi Pictograph

computers and contours crossing, feature function H of permeability number is defined. Here, we select horizontal and vertical directions, and n (n = 16) features are selected in each direction, from which a 2n-dimensional feature vector H is obtained.

$$H = (h_{11}, h_{12}, \cdots, h_{1n}, h_{21}, h_{22}, \cdots, h_{2n}) \qquad n = 1, 2, \cdots, 16 \tag{4}$$

Suppose that the horizontal and vertical coordinates of the character are normalized into $1 \sim p$ . Let $p_n = p / n$ . Suppose that $p_n$ is each initial value for function H. $h_n$ in H is shown as follows:

$$h_n = n \Big/ p * \sum_{t=1}^{p_n} h(k + p_s - 1) \qquad s = 1,2 \qquad t = 1,2,\cdots,n \tag{5}$$

It is permeability number feature of Naxi pictograph.

### C. Invariant moment

In character recognition of Naxi pictograph, we select invariant moment, that is widely used in image retrieval and image recognition. Because some moment of the image area is unchangeable for shift, rotation, scaling and other geometric operations, the method of moment representation is very important in object classification and recognition.[16]

For the two-dimensional continuous function $f(x, y)$, moment with order $(j + k)$ is defined in formula (6).

$$m_{jk} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x^j y^k f(x, y) d_x d_y \qquad j, k = 0,1,2,\cdots \tag{6}$$

Since j and k are all non-negative integers, an infinite set of moments is obtained. Moreover, function $f(x, y)$ can be determined based on this set. For function $f(x, y)$, the set $\{m_{jk}\}$ is unique. Function $f(x, y)$ has this particular moment set.

In order to describe the shape of the object, we assume that the function value of target object is 1, and the function value of the background is 0 in $f(x, y)$. This means that the function only reflects the shape of the object and ignores its details in gray level.

Parameter $j + k$ is called as moment order. Zero-order moments is the area of the object, which is defined in formula (7).

$$m_{00} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) d_x d_y \tag{7}$$

When the condition j=1, k=0 is satisfied, $m_{10}$ is the sum of horizontal coordinates x of all points in object for binary image. Similarly, $m_{01}$ is the sum of vertical coordinates y of all points in object. Let

$$\overline{x} = \frac{m_{10}}{m_{00}} \qquad \overline{y} = \frac{m_{01}}{m_{00}}$$

$(\overline{x}, \overline{y})$ is the coordinate of an object centroid in a binary image.

Central moment is defined as:

$$\mu_{jk} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} (x - \overline{x})^j (y - \overline{y})^k f(x, y) d_x d_y \tag{8}$$

If the $f(x, y)$ is digital image, the above formula is shown as follows:

$$\mu_{jk} = \sum_x \sum_y (x - \overline{x})^j (y - \overline{y})^k f(x, y)$$

Normalized central moment is defined in formula (9).

$$\mu_{jk} = \frac{\mu_{jk}}{(\mu_{00})^\gamma}, \gamma = \left(\frac{j+k}{2} + 1\right) \tag{9}$$

Based on normalized central moment, 7 kinds of invariant moments can be gotten, which are insensitive to shift, scaling, mirror and rotation. They are defined as follows:

$$\beta_1 = \mu_{20} + \mu_{02} \tag{10}$$

$$\beta_2 = (\mu_{20} + \mu_{02})^2 + 4\mu_{11} \tag{11}$$

$$\beta_3 = (\mu_{30} + \mu_{12})^2 + (3\mu_{21} - \mu_{03})^2 \tag{12}$$

$$\beta_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2 \tag{13}$$

$$\begin{aligned} \beta_5 = {} & (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03}) \\ & \left[(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2\right] + \\ & (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03}) \\ & \left[3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2\right] \end{aligned} \tag{14}$$

$$\begin{aligned} \beta_6 = {} & (\mu_{20} - \mu_{02}) \\ & \left[(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2\right] \\ & + 4\mu_{11}^2 (\mu_{30} + \mu_{21})(\mu_{21} + \mu_{03}) \end{aligned} \tag{15}$$

$$\begin{aligned} \beta_7 = {} & (3\mu_{12} - \mu_{30})(\mu_{30} + \mu_{12}) \\ & \left[(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2\right] + \\ & (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03}) \\ & \left[3(\mu_{30} + \mu_{12})^2 - (\mu_{21} - \mu_{03})^2\right] \end{aligned} \tag{16}$$

Figure 3. Contour extraction of Naxi pictograph.
a. Normalized character. b. Character after binary processing. c. Character after contour extraction

*D. Directional element feature*

Directional element feature is widely used in Chinese and English handwritten recognition, which is a grid direction feature after the contour is decomposed[17-18]. As an effective feature, directional element is widely used in various types of Chinese character recognition, and its effect is good. This is because that the Chinese character is composed of a dozen of different strokes, and the basic units constituting strokes are horizontal line, top-down vertical line, left-downward slope line and short pausing stroke. Chinese characters can be determined uniquely by the type, quantity and relative position in space, of these basic units. Directional element feature is a good description for the number of 4 basic units including horizontal line, top-down vertical line, left-downward slope line and short pausing stroke, and how these 4 basic units are located in different positions of a Chinese character in the space. This will provide the composition information of this Chinese character comprehensively, accurately, and stablely.

Naxi character is a kind of pictograph, and it does not have a variety of radicals and strokes in Chinese character. However, every primitive and every basic unite in Naxi pictograph characters should have a specific structure, and this structure can be reflected in three aspects of level, local and detail. Directional element feature is an effective means for describing these structural features.The implementation of standard direction clues includes three parts:

Step1. Contour extraction. After preprocessing, contours will be extracted. If a white pixel adjoins a black pixel in upward, downward, left, and right directions, the black pixel is on contour. The feature vector is extracted from the pixels of contour. The feature vector also can be extracted from a skeleton of character image[19]. However, by examining the properties of handwritten characters, it is shown that there are a lot of characters that have certain degree of blur. So, when a skeleton method is used in handwritten character recognition, important information of blurred parts will be lost. Even in the case that a big part of character is mangled, strokes on the outside can be measured according to feature vectors extracted from the contour. An example of contour is shown in Figure. 3.

Step2. Dot Orientation. In dot-orientation, four types of line elements, vertical, horizontal and two oblique lines slanted at $\pm 45^o$, are assigned to each black pixel. For a center black pixel in a 3x3 mask, two cases are considerable: One type of line element is assigned (see Figure. 4a to Figure. 4d); or if three black pixels are connected as in Figure. 4e to Figure. 4I, two types of line elements are assigned. For example, in the case of Figure. 4f, a $45^o$ line element and a vertical line element are assigned simultaneously.

Here, eight-neighbors are used to determine the direction of a black pixel. An example of oriented-dot image is shown in Figure. 5.

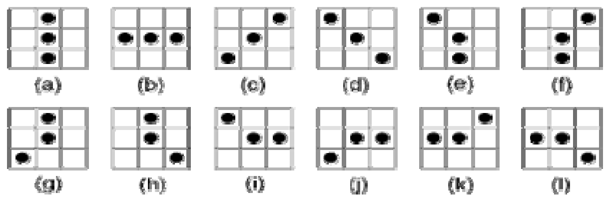



Figure 4. Types of connections of black pixels.

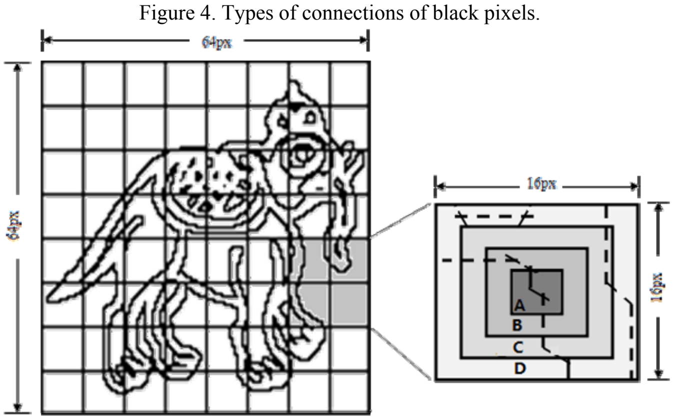



Figure 5 . An example of oriented-dot image

Vector construction

Step3. Directional element feature is assigned to each black pixel in contour. Divide image into 7×7 subregions with 16 × 16 pixels, and each subregion is overlapped with its adjacent subregions. Then each sub-region is divided into 4 nested blocks which are denoted as A, B, C and D, whose sizes are 16×16, 12×12, 8×8, and 4×4 respectively, as showed in figure. 6.

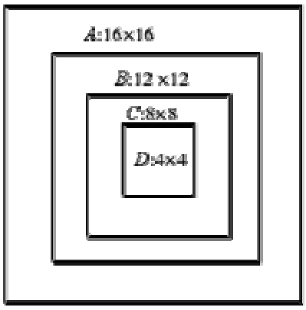



Figure 6. Division of subregion

For each subregion, a 4-dimensional vector $X = (x_1, x_2, x_3, x_4)^T$ is defined, where x1, x2, x3, and x4 represent respectively the numbers of directional elements in four direction including $0^0$, $90^0$, $45^0$, and $135^0$. In order to avoid the impact of changing character image position, weights are assigned to each block. So, for a subregion with 16×16 pixels, we can get the formula (17).

$$\begin{aligned} X_j &= x_j^A + x_j^B + x_j^C + x_j^D \\ &= 4x_j^D + 3\left(x_j^C - x_j^D\right) + \\ &\quad 2\left(x_j^B - x_j^C\right) + \left(x_j^A - x_j^B\right) \\ j &= 1,2,3,4 \end{aligned} \tag{17}$$

Here, $x_j^A, x_j^B, x_j^C, x_j^D$ represent the numbers of directional elements respectively in some direction in block A, block B, block C, and block D. In this way, a 4-dimensional feature vector can be gotten from each subregion. From each character image, a 7×7×4=196 dimensional feature vector will be obtained, which is called as the feature vector of directional elements.

## V. Rough Classification

Distance is the simplest pattern recognition question, and it is also an important research contents in recognition classification. In this paper, the effects on feature classification of NaXi pictograph characters are merely compared. Therefore, we use some simple and common distances.

If a character image is defined as a m*n data matrix X, which is viewed as m 1*n row vectors x1, x2, ..., xm, the various distances between vector xs and xt are defined as follows:

Euclidean distance

$$d_{st}^2 = (x_s - x_t)(x_s - x_t)' \tag{18}$$

Notice that the Euclidean distance is a special case of the Minkowski metric, where p = 2.

Standardized Euclidean distance

$$d_{st}^2 = (x_s - x_t)V^{-1}(x_s - x_t)' \tag{19}$$

V is the n*n diagonal matrix whose jth diagonal element is $S(j)^2$,, and S is the vector of standard deviations.

Minkowski metric

$$d_{st} = \sqrt[p]{\sum_{j=1}^{n} \left|x_{sj} - x_{tj}\right|^p} \tag{20}$$

Notice that for the special case of p = 1, the Minkowski metric becomes the city block metric, for the special case of p = 2, the Minkowski metric becomes the Euclidean distance, and for the special case of p = ∞, the Minkowski metric becomes the Chebychev distance.

Chebychev distance

$$d_{st} = \max_j \left\{\left|x_{sj} - x_{tj}\right|\right\} \tag{21}$$

Notice that the Chebychev distance is a special case of the Minkowski metric, where p = ∞.

City distance

$$d_{st} = 1 - \frac{x_s x_t'}{\sqrt{(x_s x_s')(x_t x_t')}} \tag{22}$$

Correlation distance

$$d_{st} = 1 - \frac{(x_s - \overline{x_s})(x_t - \overline{x_t})'}{\sqrt{(x_s - \overline{x_s})(x_s - \overline{x_s})'}\sqrt{(x_t - \overline{x_t})(x_t - \overline{x_t})'}}$$

$$\text{where } \overline{x_s} = \frac{1}{n}\sum_j x_{sj} \text{ and } \overline{x_t} = \frac{1}{n}\sum_j x_{tj} . \tag{23}$$

## VI. Experiment

### A. Data

In order to verify the validity of the method in this paper, we construct sample database of NaXi pictograph. An automatic generation program is developed. In figure 7, we can use this tool to extract images of Naxi pictograph character directly from the sample database. 100 images of different sizes are extracted for each character. After pretreatment, these pictures are normalized into 64x64 size. The sample recognition database consists of 210,000 NaXi pictograph characters.

### B. Experimental results

In order to verify the effects of four characters on NaXi pictograph recognition, we preprocess and extract respectively contours of 210000 pictures in the sample database. Then they are divided into two parts. 20% of these pictures are used as training sample set, and 80% of these pictures are used as testing sample set. We use permeability number, coarse grid, invariant moment, directional element to extract features from image contours, and build four basic sample database. We use Euclidean distance and four features to test training sample set and testing sample set of Naxi pictograph, and training precision and testing precision are shown in table 1. At the same time, we utilize Seuclidean distance, Minkowski distance, Correlation distance, Cityblock distance, and Chebychev distance to test four features,

Figure 7. Sample database of NaXi pictograph characters.

and the training precision and testing precision are shown from table 2 to table 6.

We find that the performance of coarse grid is best, after the six groups of experimental data are analyzed. Its training precision achieves 99% and testing precision achieves 99% under six kinds of distances. That is because that our sample database is ideal sample database. But grid feature is a really efficient feature for recognizing NaXi pictograph characters.

Directional element feature is the variety of grid feature. Its training precision and testing precision almost approach 98% under six kinds of distances, and its effect is good. Because of testing samples in high quality, the intensity robustness of directional element can not be displayed. The robustness of directional element will be obviously displayed if we build the sample database which has noises or is in low quality in the future.

The classification effects of invariant moment feature are very bad under six kinds of distances, therefore, it is not suitable for character recognition of NaXi pictograph. The effect of permeability number feature is not very good under six kinds of distances, and its training precision and testing precision only approach 90% under cityblock distance. So it can be used as coarse classification feature for NaXi pictograph recognition.

## VII CONCLUSION

In this paper, the characteristics of NaXi pictograph are analyzed further. Four kinds of features and six kinds of

Table I. Classification results of Euclidean distance

| | permeability number | coarse grid | invariant moment | directional element |
|---|---|---|---|---|
| training accuracy | 71.91 | 99.821 | 35.032 | 97.3791 |
| testing accuracy | 80.528 | 99.956 | 32.039 | 96.3149 |

TableII. Classification results of standard Euclidean distance

| | permeability number | coarse grid | invariant moment | directional element |
|---|---|---|---|---|
| training accuracy | 0.0472 | 99.9558 | 61.9929 | 99.0124 |
| testing accuracy | 0.0472 | 99.8084 | 58.0712 | 98.3115 |

Table III. Classification results of Minkowski distance

| | permeability number | coarse grid | invariant moment | directional element |
|---|---|---|---|---|
| training accuracy | 64.036 | 99.956 | 32.63 | 97.41863 |
| testing accuracy | 73.007 | 99.718 | 29.952 | 97.70519 |

TableIV. Classification results of Correlation distance

| | permeability number | coarse grid | invariant moment | directional element |
|---|---|---|---|---|
| training accuracy | 65.504127 | 99.949882 | 25.507075 | 99.610849 |
| testing accuracy | 75.228479 | 99.84375 | 25.657429 | 99.120725 |

TableV Classification results of Cityblock distance

| | permeability number | coarse grid | invariant moment | directional element |
|---|---|---|---|---|
| training accuracy | 81.1822 | 99.944 | 40.6604 | 97.4941 |
| testing accuracy | 89.0293 | 99.8231 | 36.1955 | 96.4549 |

Table VI . Classification results of Chebychev distance

| | permeability number | coarse grid | invariant moment | directional element |
|---|---|---|---|---|
| training accuracy | 56.878538 | 99.607311 | 31.346698 | 97.233491 |
| testing accuracy | 66.586085 | 98.060142 | 31.929245 | 97.691038 |

distances are applied to feature extraction of NaXi pictograph recognition. Experimental results show that directional element feature and grid feature are more suitable for character recognition of NaXi pictograph. We use ideal samples because the experimental condition is limited. We will collect some noisy script samples to build sample database in low quality for comparing the features of NaXi pictograph recognition. At the same time, elastic grid, fourier descriptor, fractal feature and some other features will be introduced into NaXi pictograph recognition.

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**Hai Guo** received the M.Sc. degree in pattern recognition and intelligent system from the Kunming University of Science and Technology, China, in 2004. He has been teaching at Dalian Nationalities University since graduation. For many years, he has done research in image processing, pattern recognition. He has published more than 30 papers.

**Jing-ying Zhao** received the M.Sc. degree in computer application from the Changchun University of Science and Technology, China, in 2003. She has been teaching at Dalian Nationalities University since 2003. For many years, she has done research in image processing, pattern recognition. She has published more than 20 paper.