Design and Recognition of Human-Readable and Machine-Readable Patterns

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Abstract

In this paper, design and recognition of human-readable and machine-readable patterns are investigated. Specifically speaking, we design character images printed with a horizontal stripe pattern, called a cross ratio pattern. The cross ratio derived from the cross ratio pattern represents the class information of the character. Since the cross ratio is invariant to projective distortion, the class information is extracted correctly regardless of camera angle. The character image itself is human-readable and therefore the character image with the cross ratio pattern is not only human-readable and but also machine-readable and can be used as a medium for human-machine communication.

1. Introduction

Camera-based character recognition [1] is a promising way for acquiring various textual information from real scenes. Several hurdles, however, should be cleared for practical and accurate camera-based character recognition. For example, the character images often undergo geometric distortions, such as projective distortion.

The aim of this paper is to realize accurate camera-based character recognition by embedding class information into each character image. Specifically, each character image is printed with a horizontal stripe pattern, called a *cross ratio pattern*. The cross ratio derived from the cross ratio pattern represents the class information of the character. Since the cross ratio is invariant to the projective distortion [2], the class information will be correctly extracted even from character images captured from an arbitrary camera angle.

In Section 2, we describe how a cross ratio is embedded into a character image for providing the class information of the character. The extraction of the embedded cross ratio from the character image is also discussed in this section.

When the variations of the cross ratios are fewer than character classes, the same cross ratio is assigned to several different character classes. In this case, we cannot determine the character class uniquely from the extracted cross ratio. Thus, in Section 3, we use a shape similarity between reference and input character images as well as the cross ratio for the unique determination. In Section 4, we point out that the assignment of the cross ratios to the character classes affects the recognition performance attained by the combination of the cross ratio.

In Section 5, we evaluate the proposed technique quantitatively through recognition experiments. In Section 6, the proposed technique is compared to other strategies where class information is provided in different manners. Finally, we present our conclusions and future works in Section 7.

2. Embedment of cross ratio pattern to character image

2.1. Cross ratio pattern

In the proposed technique, a horizontal stripe pattern, called a *cross ratio pattern*, is embedded to each character image. Figure 1(a) shows a character image "K" printed with a cross ratio pattern. Characters of a certain class is printed with the same cross ratio pattern. The cross ratio pattern is comprised of five horizontal stripes. The first and the last stripes are guides which have a fixed width and define the beginning and the end of the cross ratio pattern, respectively. The remaining three stripes have variable widths, l_1, l_2, and l_3.

Instead of using l_1, l_2, or l_3 directly, we use the following numerical value r, called the *cross ratio*, for representing class information:

$$r = \frac{(l_1 + l_2)(l_2 + l_3)}{l_2(l_1 + l_2 + l_3)}. \quad (1)$$

It is well-known that the cross ratio is invariant to projective distortions. Thus, by using the cross ratio, we can extract the class information correctly regardless of camera angle.

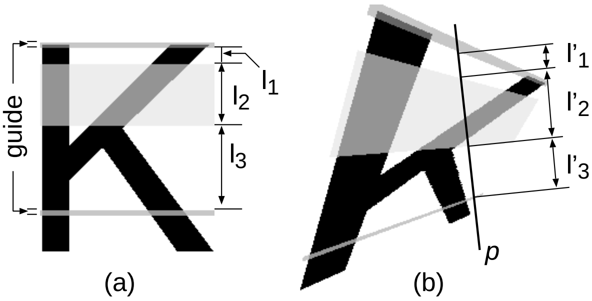

Figure 1: (a) A character image "K" where a cross ratio pattern is embedded. (b) Projective distortion. Note that a high-contrast cross ratio pattern is intentionally used here for visual emphasis.

Since character classes are discrete, the cross ratio r is discretized into K levels, r_k $(k = 1, 2, \ldots, K)$, and assigned to $|\boldsymbol{C}|$ classes, where $\boldsymbol{C}$ is the set of character classes. The detail of the assignment will be discussed in Section 4.

2.2. Extraction of cross ratio

The cross ratio r_k can be extracted from a character image printed with a cross ratio pattern by the following procedure:

Step 1: Draw a line p which crosses two guides (Fig. 1(b)).

Step 2: Measure the widths of the three stripes on p (l'_1, l'_2, and l'_3 of Fig. 1(b)).

Step 3: Using l'_1, l'_2, and l'_3 instead of l_1, l_2, and l_3, obtain r_k according to (1).

The value r_k obtained by this procedure is theoretically invariant to projective distortions. This means that we can extract the same cross ratio r_k regardless of camera angle. In addition, the value r_k is also invariant to the position and the slope of the line p.

The accuracy of the extracted cross ratio may be degraded due to insufficient camera resolution. In order to avoid this degradation, we use the following robust estimation strategy: (i) we draw the line p on the character image P times changing its position and slope randomly, (ii) obtain P cross ratio values, (iii) quantize each of those values into one of r_k, and (iv) choose the most frequent r_k as the cross ratio embedded.

2.3. Design of cross ratio patterns

The K cross ratios, $r_1, \ldots, r_k, \ldots, r_K$, are prepared by changing the proportion of l_2 and l_3. Specifically, assuming $L = l_1 + l_2 + l_3$ and l_1 are constant, r_k is determined by (1) with the following l_2 and l_3:

$$\begin{cases} l_2 &= \dfrac{(L - l_1 - 2\epsilon)(k-1)}{K-1} + \epsilon, \\ l_3 &= L - l_1 - l_2, \end{cases} \tag{2}$$

where ϵ is a positive constant specifying the minimum of l_2 and l_3.

The above strategy is based on a simple linear quantization and may be weak against errors on the stripe widths l_1, l_2, and l_3 due to the insufficient camera resolution. In fact, larger k becomes, closer r_k and r_{k+1} become. Thus, a small error on the stripe widths may confuse those close cross ratios. Future work should focus on a more sophisticated strategy to avoid the confusion as possible.

3. Recognition by cross ratio and shape similarity

In most cases, we cannot expect one-to-one assignment of K cross ratios to $|\boldsymbol{C}|$ classes. Specifically, $|\boldsymbol{C}|$ is often large (e.g., $|\boldsymbol{C}| > 1000$ for Chinese characters) whereas K is bounded by $L - l_1 - 2\epsilon$ ($\sim$ character height in pixel) according to (2). Thus, the same cross ratio r_k will be assigned to several classes $\boldsymbol{C}_k \subset \boldsymbol{C}$, where $\boldsymbol{C}_1, \ldots, \boldsymbol{C}_k, \ldots, \boldsymbol{C}_K$ are disjoint subsets of $\boldsymbol{C}$, and therefore the class c of an input character image cannot be determined by the extracted cross ratio r_k. In other words, there are $|\boldsymbol{C}_k|$ candidates of the correct class when r_k is extracted.

For choosing the most reliable class from the $|\boldsymbol{C}_k|$ candidates, we employ some shape similarity between two character images. Assuming that a reference character pattern (i.e., a template) is prepared for each class, the complete recognition procedure based on a combination of the cross ratio and the shape similarity is as follows:

Step 1: Extract the embedded cross ratio r_k from an input character image by the procedure of Section 2.2.

Step 2: For each class in $\boldsymbol{C}_k$, calculate the shape similarity between the reference character image of the class and the input character image.

Step 3: Choose the class with the highest shape similarity.

Note that this procedure totally relies on the extracted cross ratio r_k. If a wrong r_k is extracted, the correct class is never chosen by the procedure. Fortunately, the cross ratio r_k can be extracted with high accuracy (around 99%, as shown in Section 5.2), thus good performance is expected.

4. Assignment of cross ratios to classes

The assignment of K cross ratios to $|\boldsymbol{C}|$ classes, that is, the partition of $\boldsymbol{C}$ into the disjoint subsets $\{\boldsymbol{C}_k\}$, is crucial for better performance of the proposed technique. The

Figure 2: Character images printed with different cross ratio patterns (i.e., $K = 26$).

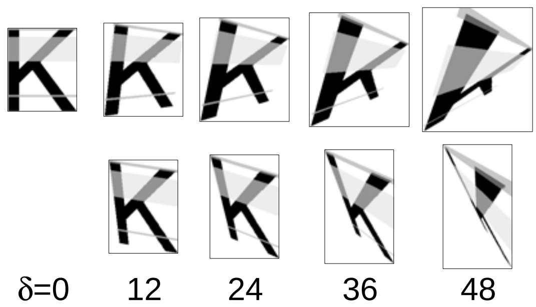

Figure 3: Test patterns.

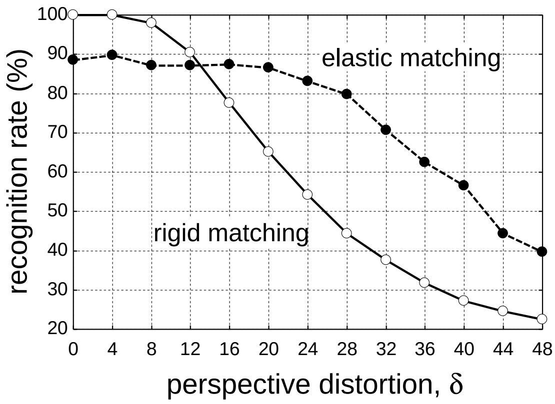

Figure 4: Recognition rates attained by using shape similarity alone.

recognition procedure of Section 3 provides correct recognition result if (i) the cross ratio r_k is correctly extracted and (ii) the correct class has the highest shape similarity in $\boldsymbol{C}_k$. Thus, for better recognition performance by satisfying the latter condition (ii), the subset $\boldsymbol{C}_k$ should be comprised of classes which are "less easy to confuse" for the shape similarity, as shown in the following example.

Assume that "H" and "N" are confusing classes (that is, "H" is often misrecognized as "N" by the shape similarity) and "H" and "N" are assigned to the same subset $\boldsymbol{C}_k$. In this case, we will suffer from the misrecognition between "H" and "N", even though their cross ratios are correctly extracted. Clearly, this is because they cannot be distinguished by their cross ratios. In contrast, if these two classes are assigned to different subsets, they can be distinguished by their cross ratios and therefore correct recognition results will be provided. As shown by this example, the assignment $\{\boldsymbol{C}_k\}$ should be optimized with a criterion that confusing classes are assigned to different subsets. In the experiment of Section 5, the assignment was optimized by the strategy of [6], where the so-called confusion matrix of the shape similarity is used to identify its confusing classes.

5. Simulation experiment

5.1. Experimental setup

5.1.1 Original character images

The 26 capital English letter images from the font-set called "Arial" were used as original character images. After embedding cross ratio patterns into them (according to the scheme of the following sections), those images are used as not only reference patterns but also the source patterns for synthesizing test patterns. Their heights were around 200 pixels. On the other hand, their widths were not the same; the maximum, the minimum, and the mean of widths were 251 (of "W"), 52 (of "I"), and 170, respectively.

5.1.2 Design of cross ratio patterns

According to the procedure of Section 2.3, $K (\leq 26 = |\boldsymbol{C}|)$ cross ratio patterns, $r_1, \ldots, r_k, \ldots, r_K$, were designed. Figure 2 shows the original character images printed with $K = 26$ different cross ratio patterns. The width of the guide was 5 pixels. The widths L, l_1, and ϵ, were fixed at 150, 15, and 15 pixels, respectively. The assignment of K

Table 1: Confusion matrix by using the shape similarity by elastic matching.

		recognition result																									
		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
input	A	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	B	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	C	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	D	14	0	0	241	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	E	0	26	0	0	230	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	F	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	G	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	H	0	0	0	0	0	0	0	250	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0
	I	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	J	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	K	0	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	L	0	0	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	M	0	0	0	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0	0	0	0	0	0
	N	0	0	0	0	0	0	0	182	0	0	0	0	64	10	0	0	0	0	0	0	0	0	0	0	0	0
	O	0	0	0	42	0	0	0	0	0	0	0	0	0	0	214	0	0	0	0	0	0	0	0	0	0	0
	P	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	252	0	0	0	0	0	0	0	0	0	0
	Q	0	0	0	6	0	0	0	0	0	0	0	0	0	0	24	0	226	0	0	0	0	0	0	0	0	0
	R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	0	0
	S	0	4	0	0	0	0	58	0	0	0	0	0	0	0	0	0	0	0	194	0	0	0	0	0	0	0
	T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0
	U	0	0	0	0	0	0	0	0	0	0	0	0	113	0	0	0	0	0	0	0	140	3	0	0	0	0
	V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	81	175	0	0	0	0
	W	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256	0	0	0
	X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256	0	0
	Y	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	51	0	0	203	0
	Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256

cross ratios to 26 classes, that is, the specification of $\boldsymbol{C}_k$ was done by the two strategies described in Section 5.1.5.

5.1.3 Test patterns

Test patterns were synthesized by applying projective distortions on the original character images with the cross ratio patterns. The projective distortion was simulated by displacing four corners of a character image for $\pm\delta$ pixels ($\delta = 0, 4, 8, \ldots, 48$) in their x and y directions. Thus, for each value of δ, 256 test patterns were created from a single original character image. Figure 3 shows several test patterns synthesized from the same character image of the class "K". This figure reveals that there are heavily distorted patterns in the test patterns.

5.1.4 Shape similarity

As noted in Section 3, the proposed technique can employ any shape similarity (or the score given by any conventional recognizer) between a reference pattern (i.e., an original character pattern) and an input pattern. In the experiment, the following two matching techniques are employed to evaluate the shape similarity.

- Rigid matching $\cdots$ This is a technique to obtain a similarity score by simple superimposing.
- Elastic matching$\cdots$ This is a technique to obtain a similarity score after fitting the reference pattern to the input pattern nonlinearly [7]. The elastic matching technique employed here possesses enough flexibility for compensating projective distortions.

Note that both techniques used simple gray-level as their pixel feature.

Figure 4 shows recognition accuracy attained by the shape similarities by the above two matching techniques. The rigid matching was very sensitive to projective distortions and its recognition accuracy decrease drastically according to the increase of δ. On the other hand, the elastic matching is rather robust to the projective distortions; its recognition accuracy does not decrease for $\delta \leq 28$. For more heavy distortions, however, its accuracy decreases like the rigid matching.

Table 1 is the confusion matrix by the shape similarity of the elastic matching for $256\times$ 26 test data of $\delta = 4$. Most of "N" were misrecognized as "H" or "M" with the shape similarity alone because their shapes become similar after

Table 2: Naive and optimal assignments of cross ratios to 26 classes. Note that the assignment is optimized for elastic matching.

class		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
$K=4$	naive	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2
	opt.	1	1	1	1	2	3	3	2	1	2	1	2	3	4	4	2	2	4	1	4	2	1	1	4	3	2
$K=12$	naive	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2
	opt.	1	2	3	4	5	6	7	5	4	8	2	9	6	10	11	8	9	10	1	11	12	3	4	11	7	12
$K=20$	naive	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	1	2	3	4	5	6
	opt.	1	2	3	4	5	6	7	8	9	10	11	12	6	13	14	15	16	17	18	14	19	3	9	20	7	19

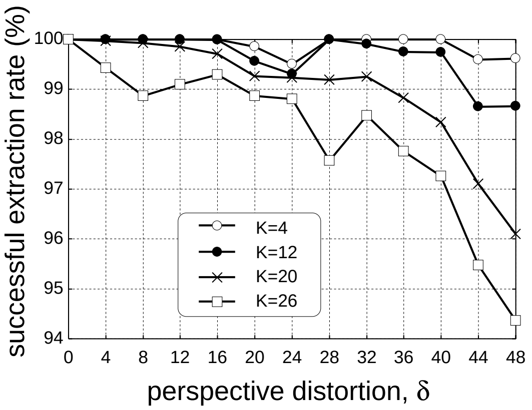

Figure 5: Extraction accuracy of cross ratios.

nonlinear fitting of the elastic matching.

5.1.5 Assignment of cross ratios to classes

The following two strategies were used for assigning cross ratios to classes.

- Naive assignment $\cdots$ K cross ratios are assigned to $|\boldsymbol{C}|$ classes by a simple numerical order.
- Optimal assignment $\cdots$ According to the discussion of Section 4, the assignment was optimized by the algorithm proposed in [6].

Table 2 shows the naive assignment and the optimal assignment for the elastic matching at $K = 4$, 12, and 20. As shown in this table, the same cross ratio is assigned to the classes "C" and "V", by the optimal assignment at any K. This fact means that "C" and "V" are not confusing classes for the elastic matching.

5.2. Extraction accuracy of cross ratios

Figure 5 shows the extraction accuracy of the cross ratios as a function of δ. This graph indicates that the cross ratios can be extracted very accurately even under heavy distortions. By comparing Figures 5 and 4, it is shown that this accuracy is often 10 (or more) times higher than the recognition rates by shape-similarities. Thus, the cross ratio is more reliable information than the shape similarities for camera-based character recognition.

The graph at $K = 26$ in Fig. 5 shows the recognition rate attained by using the cross ratio alone and that a recognition rate exceeds 98% without using any character shape information if $\delta \leq 24$.

Extraction failures are mainly due to slight errors (such as $\pm$ 1 pixel) of l'_1, l'_2, l'_3 by insufficient resolution. In fact, at $K = 26$, 85% of extraction failures are "near-misses" that r_k was detected as $r_{k\pm1}$. More serious failures that r_k was detected as $r_{k\pm\Delta}$ $(\Delta \geq 2)$ are 10%. The remaining 5% are the failures that the guide was not detected.

5.3. Recognition accuracy by using cross ratio and shape similarity

Figures 6 and 7 are the recognition rates attained by using the extracted cross ratios and the shape similarity according to the procedure of Section 3. As shape similarities, the rigid matching score and the elastic matching score were used in Fig. 6 and 7, respectively. In both cases, $K \in \{4, 12, 20, 26\}$ cross ratios were assigned to $|\boldsymbol{C}| = 26$ classes according to the naive assignment. (See Table 2, for the naive assignment at $K = 4, 12$, and 20.)

Those two figures firstly indicate that recognition rates are drastically improved from the rates of Fig. 4, that is, the rates attained by the shape similarities. At $\delta = 4$, for example, the recognition rate attained by the shape similarity by the elastic matching was 89.8% and improved to 97.4%, 99.1%, and 99.97% with $K = 4$, 12, and 20 cross ratios, respectively.

This improvement is achieved by removing the ambiguity in the shape similarity using the extracted cross ratio. For example, as indicated by the column "H" of the confusion matrix of Table 1, there are two correct classes candidates, "N" and "H", for an input character recognized as "H" by the elastic matching score. Fortunately, if its cross ratio is extracted correctly, the correct class is chosen from the candidates. This is because as shown in Table 2, different cross ratios are assigned to classes "N" and "H" by the

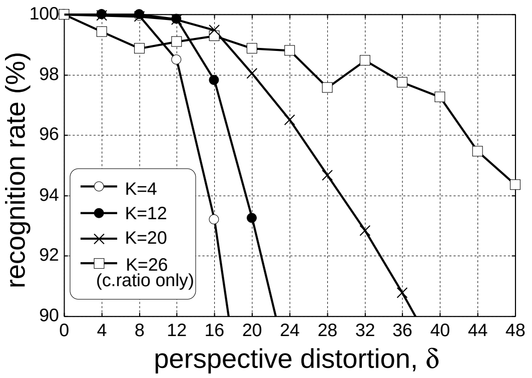

Figure 6: Recognition rate by *rigid* matching and cross ratio. The naive assignment was used here.

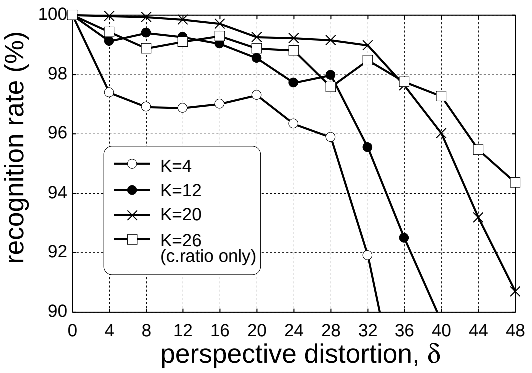

Figure 7: Recognition rate by *elastic* matching and cross ratio. The naive assignment was used here.

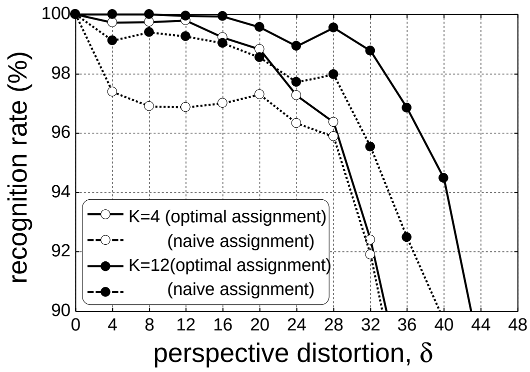

Figure 8: Naive assignment versus optimal assignment. The latter can attain higher rates under the same number of cross ratios, K.

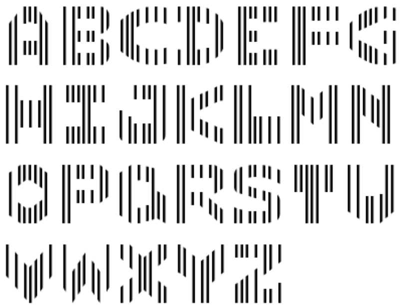

Figure 9: MICR font called C.M.C.7.

naive assignment (for any K), and therefore the true class of the input character can be determined by the extracted cross ratio.

On the other hand, Figures 6 and 7 also show the usefulness of the shape similarities. In fact, when $\delta \leq 16$, the recognition rate attained by $K = 20$ exceeds that attained by $K = 26$ (where the recognition is done by only the extracted cross ratio). This is because, if many cross ratios are used (e.g., $K = 26$), their extraction accuracy is slightly degraded as shown in Fig. 5. Thus, it will be a reasonable strategy to (i) use as many cross ratios as possible under the condition that those cross ratios can be extracted near-perfectly and then (ii) remove the remaining ambiguity by a shape similarity.

5.4. Naive assignment versus optimal assignment

Figure 8 shows the recognition accuracies with two different assignment strategies, i.e., the naive assignment and the optimal assignment of Section 5.1.5. The shape similarity by the elastic matching was used here.

This result shows that the optimal assignment outperforms the naive assignment for any δ and K. This superiority comes from the fact that the optimal assignment can remove the ambiguity in confusing classes effectively. At $\delta = 4$, for example, the same cross ratio is assigned to "M" and "U" by the naive assignment as shown in Table 2, although "M" and "U" are confusing classes as shown in Table 1. On the other hand, different cross ratios are assigned to "M" and "U" by the optimal assignment since a confusion matrix used for the optimization confesses that "M" and "U" are confusing classes. It is noteworthy that optimally assigned 4 cross ratios outperform naively assigned 12 cross ratios for $\delta \leq 20$.

6. Relation to other techniques

6.1. OCR/MICR fonts and DataGlyph

The proposed technique is closely related to so-called "OCR fonts" and "MICR (magnetic ink character recognition) fonts", which were proposed in the dawn of OCR/MICR research [3]. In those fonts, class information is embedded into their shapes. Figure 9 shows the MICR font called C.M.C.7, where each character is comprised of six vertical lines with class-dependent intervals. DataGlyph [4, 5] is a more recent font where some data is embedded as a fine hatching pattern.

Those conventional fonts are not designed to be robust against perspective distortions. For example, the interval of the vertical lines of the C.M.C.7 font will vary according to perspective distortions. Thus, for camera-based recognition, some dewarping process, which itself is not a trivial task in general, should be performed on those fonts in advance.

6.2. Barcode and watermark

Barcodes are also related to the proposed technique. If a barcode represents a text, we can read the text by a barcode scanner with very high accuracy. Recently, two-dimensional barcodes, such as QR code, have been developed as pictorial codes having larger data capacities. Among them, the QR code is promising because it can be read under perspective distortion.

The barcodes have the following drawbacks when they are used for representing some text data:

- Barcodes are machine-readable and not human-readable. Thus, users cannot know in advance what a barcode represents.
- Barcodes cannot allow "partial reading" that a user tries to read only a part of an entire text.
- Barcodes are printed separately from character images. Thus, barcodes should be "conspicuous" enough to show their existence. This means that barcodes will spoil the design of documents. The longer texts becomes, the larger, i.e., the more unsightly, a barcode becomes.

Watermark is invisible or near-invisible data representation and often embedded into the background of a document. Watermark also has the first and the second drawbacks of the barcodes because generally it is encoded end embedded by a special manner (i.e., not human-readable) and has no explicit correspondence to individual characters (i.e., not partially readable). On the other hand, watermark may avoid the third drawback of the barcodes, i.e., unsightliness, because of its invisibility; however, this fact leads a conflicting situation. If a watermark is perfectly concealed on a document to avoid the unsightliness, a user cannot detect it and thus cannot extract an embedded text from the watermark. Hence, if a watermark is used, a "visible mark" that indicates the location of the watermark is necessary.

7. Conclusion and future work

For camera-based character recognition as easy and accurate as bar-code reading, the embedment of class information into each character image is investigated. The class information is represented as a horizontal stripe pattern, called a cross ratio pattern, and the character image is printed with the pattern. Since cross ratio is invariant to projective distortion, the same class information can be extracted from character images captured at an arbitrary camera angle. Experimental results showed that (i) the cross ratio can be extracted from distorted character images with very high accuracy and (ii) the cross ratio can enhance the recognition performance of conventional matching-based recognizers.

Future work will focus on the following points:

- Experiments using character images captured by a camera.
- Improvement of the design of the cross ratio patterns. It is also possible to use some distortion invariant other than cross ratio.
- Improvement of shape similarity. If the confusion matrix by the shape similarity can be sparse, the number of cross ratios can be saved.
- Embedment of data other than class information. For example, copyright information to character strings can be embedded by cross ratio patterns.

Pattern recognition research has a long history of the struggle to recognize image patterns having high human-readability and low machine-readability. Handwritten character recognition is a typical example. In upcoming ubiquitous computing age, image patterns are often exposed to computers via cameras and therefore often to be acquired/recognized by computers. Thus, it will become more important to use image patterns having not only high human-readability but also high machine-readability as a medium for human-machine communication. The proposed character image with the cross ratio pattern can be a promising candidate as the medium.

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