Performance Improvement of Dot-Matrix Character Recognition by Variation Model based Learning

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Abstract. This paper describes an effective learning technique for optical dot-matrix characters recognition. Automatic reading system for dot-matrix character is promising for reduction of cost and labor required for quality control of products. Although dot-matrix characters are constructed by specific dot patterns, variation of character appearance due to three-dimensional rotation of printing surface, bleeding of ink and missing parts of character is not negligible. The appearance variation causes degradation of recognition accuracy. The authors propose a technique improving accuracy and robustness of dot-matrix character recognition against such variation, using variation model based learning. The variation model based learning generates training samples containing four types of appearance variation and trains a Modified Quadratic Discriminant Function (MQDF) classifier using generated samples. The effectiveness of the proposed learning technique is empirically evaluated with a dataset which contains 38 classes (2030 character samples) captured from actual products by standard digital cameras. The recognition accuracy has been improved from 78.37% to 98.52% by introducing the variation model based learning.

1 Introduction

Dot-matrix characters are widely used for clarifying important information of a product such as consumption or appreciation expiration dates. The dot-matrix characters must be printed directly on the products in order to make both consumers and producers being able to read information about the products. Automatic reading system for the dot-matrix characters is promising for reduction of cost and labor required for quality control of products.

Fig.1 shows examples of actual camera-captured dot-matrix characters. As implied by the figure, recognition of dot-matrix characters contains several types of difference from standard character recognition. Since a dot-matrix character is constructed by multiple dots which are observed as multiple separated connected components in recognition process, a preprocessing which connects these dots is required to handle a character as one connected component. Although dot-matrix characters are constructed by specific dot patterns, variation of character appearance due to three-dimensional rotation of printing surface, diffusing or squeeze out of ink and lack of dots in a printing pattern is not negligible.

For accurate recognition of these dot-matrix characters, several attempts have been proposed [1–5]. These methods are mainly divided into two groups, i.e. preprocessing-based and training-based methods. The preprocessing-based methods employ several ad hoc preprocessing techniques such as blob-connection, slant and rotation correction to restrict appearance variations of captured dot-matrix characters[3, 5, 4]. However, dot-matrix characters used in actual production scene contain a large amount of variation in matrix font patterns, dot size, printing quality and degradation. Construction of an universal preprocessing technique is quite difficult. Training-based methods employ classification models which are trained to capture possible appearance variation of dot-matrix characters. Artificial neural networks were employed as classifiers in literatures[1, 2].

It is also known that there are many undocumented dot-matrix recognition products for factory automation. Many of them simplify the recognition task by restriction of appearance variation of character using controlled environment for character image capturing. And it is also relatively easy to recognize controlled dot-matrix characters using actual training dataset consists of the same capturing environment. If an universal recognition technique which is applicable uncontrolled or less-controlled environment, it should have certain amount of contributions for industrial scene.

In this paper, the authors propose a technique improving accuracy and robustness of dot-matrix character recognition against such variation, using variation model based learning. The variation model based learning generates training samples containing four types of appearance variation and trains a Modified Quadratic Discriminant Function (MQDF) classifier using generated samples. The effectiveness of the proposed learning technique is empirically evaluated with a dataset which contains 38 classes (2030 character samples) captured from actual products.

The paper is organized as follows. In Section 2, generation models for training dataset is described. Classification process on this research is shown in section 3. section 4 provides information about evaluation experiments and results. Finally, conclusions of the paper is given by section 5.

2 Variation model based learning

Training dataset which correctly reflect a model of data generation is necessary for a classifier obtaining high recognition performance. Since obtaining a priori generation model is generally difficult, an approach where the generation model is estimated from given or sampled training data is employed. Although the size of training data does not guarantee the accuracy of estimated model, it is expected that a large size of training data contributes improving statistical accuracy of the model.

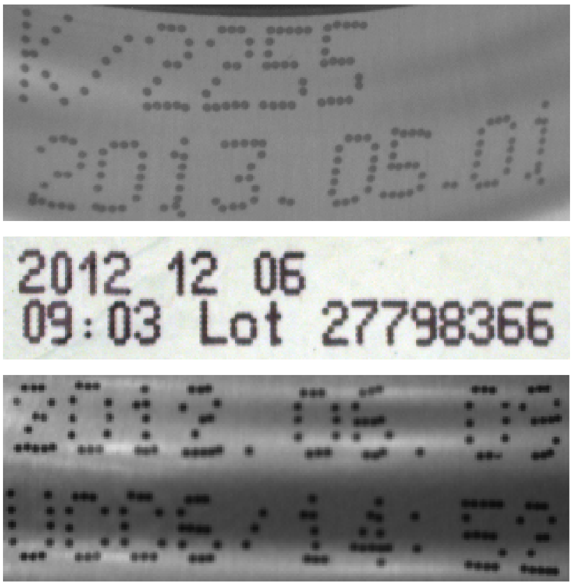


Fig. 1. Examples of actual camera-captured dot-matrix characters

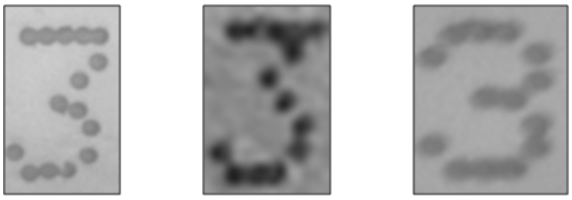


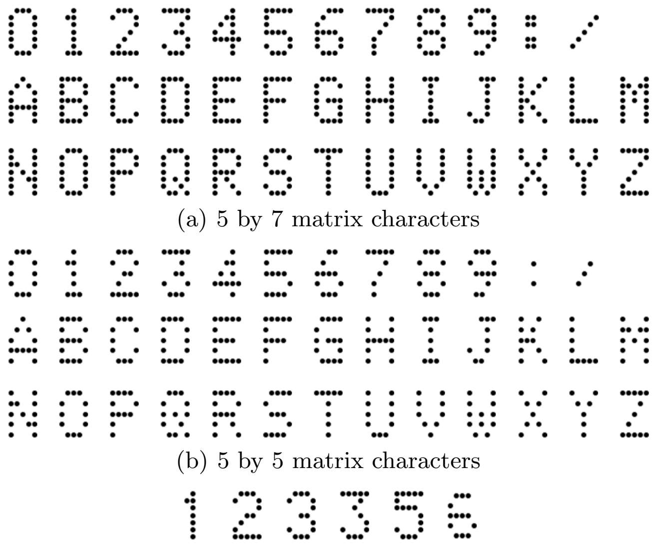
Fig. 2. Variation of actual dot-matrix font face

Small size of training data sometimes cause insufficient accuracy of estimated model. The generative learning, which artificially generates training dataset from assumptions or a priori knowledge of data generation process, has been proposed as a promising solution for similar situation[6].

The variation model based learning proposed in this paper also generates large scale training data containing four possible appearance variations of dot-matrix characters to recognize. In this section, we describe data generation process for these appearance variations.

2.1 Multiple dot-matrix font faces

Fig.2 shows examples of actual dot-matrix characters in the same class. As shown in the figure, multiple dot-matrix font faces are employed even they are same characters. The proposed method employs two types matrices, i.e. 5 by 7 and 5



(a) 5 by 7 matrix characters

(b) 5 by 5 matrix characters

(c) extra dot-matrix font face

Fig. 3. Generated multiple dot-matrix font face

by 5 which are widely used by actual products. Fig.3 (a) and (b) shows generated 5 by 7 and 5 by 5 standard dot-matrix characters, respectively.

Some character class consists of multiple font face to improve readability by human. For instance, '3' contains multiple font face as shown by Fig.2. To correctly recognize these characters, the proposed method also generate extra font faces addition in the standard characters. Specifically, one extra font face is added for each of '1', '2', '5' and '6', and two are added for '3'. Fig.3 (c) shows actual extra font faces.

2.2 Three dimensional rotation

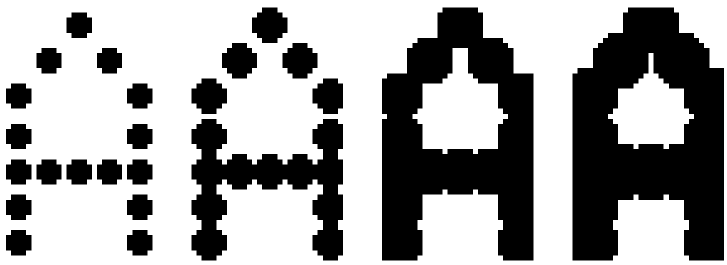
A major problem of camera-based character recognition is three-dimensional rotation of captured characters. Occurred situation in dot-matrix character recognition is that characters printed on rounded surface easily change their appearance by spacial relationship between the camera and the product. To handle these appearance variation, the proposed method generates rotated dot-matrix characters and add them to the training dataset. Fig.4 illustrates generation process of three dimensional rotation characters.

2.3 Size of dots

Dots constructing characters are easily diffused in printing. Diffusing dots also causes large appearance variation. To handle such variation, the proposed method generates the training dot-matrix characters with multiple diameter d. Fig.5 shows examples of dot-matrix character 'A' generated with different d.

(a) three dimensional rotation (b) x-axis rotation (c) y-axis rotation (d) z-axis rotation

Fig. 4. Generation of variation model by three dimensional rotation



(a) d=5 (b) d=7 (c) d=9 (d) d=11

Fig. 5. Appearance variation by difference of diameter of dots

2.4 Missing dots

The dots constructing characters sometimes disappear due to printing error or capturing environment. When even one dot disappears, the dot-matrix character changes significantly in appearance. To recognize characters containing missing dots, the method generates characters of which one dot is deleted as shown by Fig.6. Additionally, deleting one dot from a character results ambiguous appearance between two different character class. These ambiguous characters are excluded from training dataset. Fig.7 shows examples of excluded dot-matrix patterns.

3 Classification

3.1 Gradient feature extraction

In this research, the gradient feature vector [7] are used for classification. The gradient feature vector is composed of directional histogram of gradient of the input character image. In this section, we summarize the gradient feature extraction. The gradient feature extraction is performed as in the following steps:

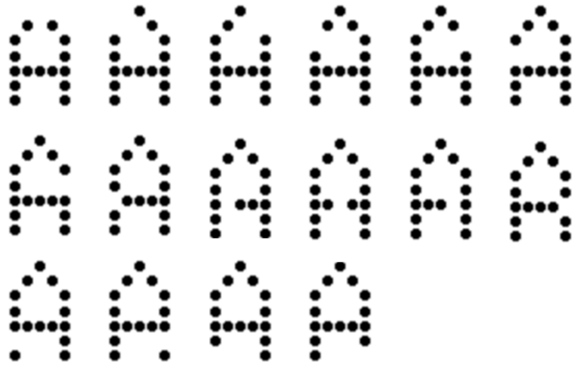


Fig. 6. Examples of generated character of which one constructing dot is deleted

Step 1: A 2×2 mean filtering is applied 4 times on the input image.

Step 2: The gray-scale image obtained in Step 1 is normalized so that the mean gray scale values lie in the range of -1 to +1, with a mean value of 0.

Step 3: Roberts filter is applied to the image to obtain gradient image. The direction of the gradient is initially quantized into $4D$ directions and the strength of the gradient is accumulated for each of the quantized direction. The strength and the direction of the gradient are defined by (1) and (2) respectively.

$$f(x, y) = \sqrt{(\Delta u)^2 + (\Delta v)^2}, \tag{1}$$

$$\theta(x, y) = \tan^{-1} \frac{\Delta v}{\Delta u}, \tag{2}$$

$$\Delta u = g(x + 1, y + 1) - g(x, y),$$

$$\Delta v = g(x + 1, y) - g(x, y + 1).$$

Step 4: The enclosing rectangular of the input character is divided into $2m - 1$ square blocks in height and width respectively and the histogram of $(2m - 1)^2 \times 4D$ dimension is extracted.

Step 5: Directional histogram of $(2m - 1) \times (2m - 1)$ blocks and $4D$ directions are down sampled into $m \times m$ blocks and D directions using Gaussian filters, and the histogram of $m^2 \times D$ dimension is obtained.

In this research, m and D are set as 6 and 8, respectively, so we obtained $6^2 \times 8 = 288$ dimensional original feature vector.

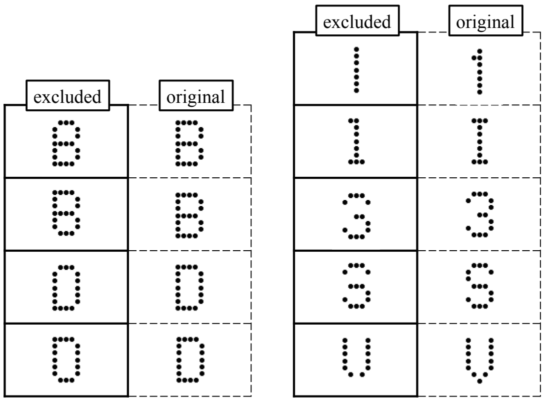


Fig. 7. Excluded dot-matrix characters due to ambiguous appearance

3.2 MQDF classfier

The MQDF [8] classifier was employed. The MQDF is expressed by:

$$\begin{aligned} g(X) = (N + N_0 + n - 1)\ln[1 + \frac{1}{N_0\sigma^2}[||X - M||^2 \\ - \sum_{i=1}^{k} \frac{\lambda_i}{\lambda_i + \frac{N_0}{N}\sigma^2}\left\{\Phi_i^T(X - M)\right\}^2]] \\ + \sum_{i=1}^{k} \ln\left(\lambda_i + \frac{N_0}{N}\sigma^2\right) - 2\ln P(\omega), \end{aligned} \tag{3}$$

where, X denotes a n-dimensional gradient feature vector of input dot-matrix character, M is mean vector of training samples, λ_i and Φ_i are i-th eigenvalue and corresponding eigenvector of covariance matrix of training samples, respectively. k is a parameter which denotes the number of eigenvectors used for classification. N and $P(\omega)$ denote the number of training data and a priori probability of class ω. σ^2 is variance assuming spherical a priori distribution of X and determined by mean of all eigenvalues in all classes.

The parameter k which denotes the number of eigenvector used for classification is determined by prior experiment with verification dataset, i.e. a sub-set of experimental dataset. N_0 is defined by:

$$N_0 = \frac{\alpha}{1 - \alpha}N, \tag{4}$$

where, the parameter $\alpha \quad (0 < \alpha < 1)$ is also determined by prior experiment.

4 Experiments and results

To confirm the effectiveness of the proposed variation model based learning, we conducted evaluation experiments.

4.1 Evaluation dataset

The evaluation dataset employed in this research consists of 2030 dot-matrix character images of 38 character classes. Each character image is captured from actual industrial, medical and food products by digital cameras and extracted and binarized manually. As shown in Fig.1, the evaluation dataset contains appearance variations due to distortion, blur, multiple font-face and three-dimensional rotation. Since the character classes '0 (numeral)' and 'O (alphabetical)' have same appearance, they are handled as a same character class.

4.2 Experimental results

Fig. 8 shows recognition performances by combinations of training data generation methods. (a) to (d) in the table below bar chart denote:

(a) multiple dot-matrix font face,
(b) three dimensional rotation,
(c) multiple size of dots,
(d) missing dots,

respectively. Circles in the table mean that a corresponding variation model is employed for data generation.

The original recognition accuracy of 78.37% was improved by introducing generated training data and the highest recognition accuracy of 98.52% has been obtained when all of four variation models were employed for training data generation. This results imply that training data generation reflecting appearance variation is effective for performance improvement even when no actual captured character images are available in the training dataset.

Failure recognition samples are shown in Fig.9. Since significant degradation of characters were not included in the training dataset, the MQDF classifier could not handle these degraded characters.

5 Conclusions

In this paper, the authors propose a technique improving accuracy and robustness of dot-matrix character recognition against such variation, using variation model based learning. The variation model based learning generates training samples containing four type of appearance variation and trains a MQDF classifier using generated samples. The effectiveness of the proposed training data generation was confirmed by the experiments using actual camera-captured dot-matrix characters. The MQDF classifier trained generated dataset, which did not

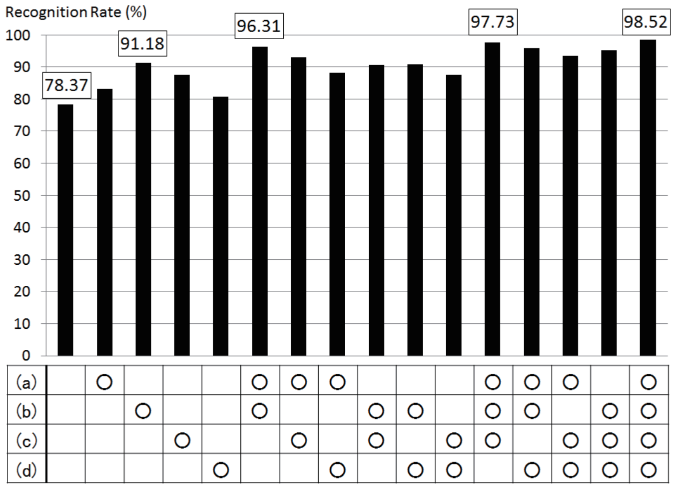


Fig. 8. Improvement of recognition performance by variation model based learning

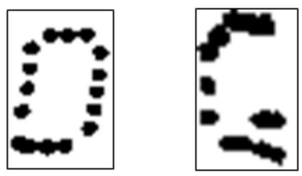


Fig. 9. Examples of failure character recognition due to significant degradation of dot-matrix patterns

contain any actual captured data, successfully recognize dot-matrix characters against appearance variations happened in usual industrial scene.

Future study topics include (1) further performance improvement by optimization of data generation conditions, (2) integration of the proposed recognition method and a dot-matrix character detection method and (3) introducing failure printing detection.

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