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Training of an on-line handwritten Japanese character recognizer by artificial patterns

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ABSTRACT

This paper presents effects of a large amount of training patterns artificially generated to train an on-line handwritten Japanese character recognizer, which is based on the Markov Random Field model. In general, the more training patterns, the higher the recognition accuracy. In reality, however, the existing pattern samples are not enough, especially for languages with large sets of characters, for which a higher number of parameters needs to be adjusted. We use six types of linear distortion models and combine them among themselves and with a non-linear distortion model to generate a large amount of artificial patterns. These models are based on several geometry transform models, which are considered to simulate distortions in real handwriting. We apply these models to the TUAT Nakayosi database and expand its volume by up to 300 times while evaluating the notable effect of the TUAT Kuchibue database for improving recognition accuracy. The effect is analyzed for subgroups in the character set and a significant effect is observed for *Kanji*, ideographic characters of Chinese origin. This paper also considers the order of linear and non-linear distortion models and the strategy to select patterns in the original database from patterns close to character class models to those away from them or vice versa. For this consideration, we merge the Nakayosi and Kuchibue databases. We take 100 patterns existed in the merged database to form the testing set, while the remaining samples to form the training set. For the order, linear then non-linear distortions produce higher recognition accuracy. For the strategy, selecting patterns away from character class models to those close to them produce higher accuracy.

1. Introduction

Research on on-line handwritten Japanese character recognition has pursued recognition accuracy high enough to be accepted by users of real applications (Plamondon and Srihari, 2000; Liu et al., 2004). To deal with the problem that character patterns are often distorted, there are four main methods. One is to decrease distortion by non-linear normalization (Yamada et al., 1984; Tsukumo and Tanaka, 1988; Liu et al., 2003) or try to remove distortion by reverse distortion in a normalization step (Wakahara and Odaka, 1996; Satoh et al., 1999). The second is to improve discriminant functions such as MQDF for off-line recognition (Kimura et al., 1987), HMM (Jaeger et al., 2001) or MRF for on-line recognition (Zhu and Nakagawa, 2011). The third is to select or extract stable features (Liu and Zhou, 2006). The fourth is to train classifiers by an increased amount of training patterns (Smith et al., 1994). To collect training patterns is very costly, however, so that artificial pattern generation has been used (Ha and Bunke, 1997; Mori et al., 2000; Leung et al., 1985; Leung and Leung, 2009).

This paper focuses on artificial pattern generation. In general, the more training patterns are employed, the higher the recognition accuracy is achieved. In reality, however, the existing pattern samples are not enough, especially for languages with large sets of characters, for which a higher number of parameters need to be adjusted. Thus, we consider artificial pattern generation. Several works have been proposed to transform character patterns in accordance with some models and produce artificial patterns. Ha and Bunke (1997) used the concept of perturbation due to writing habits and instruments for off-line handwritten numeral recognition, where they proposed six types of linear distortion models to reverse an input image back to its standard form to solve the problem of patterns variation. Mori et al. (2000) proposed a character pattern generation method based on point correspondence between patterns. Leung et al. (1985) and Leung and Leung (2009) generated a huge number of training samples artificially in accordance with a non-linear distortion model for off-line handwritten Chinese characters recognition, which demonstrates that applying distorted sample generation is effective in addition to regularization of class covariance matrices and feature dimension reduction, when the dimension of the feature vector is high while the number of training samples is not sufficient. Velek et al. (2002) proposed a method to generate brush-written off-line patterns from on-line

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patterns. Postal address recognition had problems reading characters written with a traditional brush for new year cards, since the amount of training patterns was limited for such patterns.

In this paper, we consider on-line pattern generation for on-line handwritten Japanese character recognition. We propose six types of linear distortion models (LDMs) as proposed by Ha and Bunke (1997) and use them to generate a great deal of artificial patterns, with which we train a handwritten Japanese character recognizer. Then, we combine LDMs with non-linear distortion model (NLDM) proposed by Leung et al. (1985) and Leung and Leung (2009) to obtain combined distortion models (CDMs) and generate artificial patterns again to train the above recognizer.

Here it is worth noting that the basic LDMs proposed by Ha and Bunke (1997) were applied in preprocessing to reverse an input image back to its standard form; they were applied to just numerical patterns; and they were employed in recognition stage so that additional recognition time was incurred. On the other hand, we employed them for pattern generation so that the recognition time is not affected. Moreover, Leung et al. (1985) and Leung and Leung (2009) proposed the non-linear distortion model for off-line Chinese character recognition while we combined them with LDMs for on-line recognition.

This paper is an extension to the conference papers (Chen et al., 2010, 2011), which reported the increase of recognition rate by employing the proposed method to generate artificial patterns for training. This paper shows them in more detail and considers effects of selecting the combination sequence for CDMs and original pattern selection strategy. There are two combination sequences: LDMs then NLDM and NLDM then LDMs. Moreover, there are two original pattern selection strategies: selecting patterns in the original database, from patterns close to character class models to those away from them and vice versa. These two combination sequences and two original pattern selection strategies are combined pairwisely. For this consideration, we merge the Nakayosi and Kuchibue databases, and take 100 patterns in the merged database to form the testing set, while the remaining samples to form the training set. Moreover, we also attempt to find a generating method with relatively less real patterns employed while increasing recognition accuracy efficiently. The detailed performance evaluations and discussions will be presented that show the effectiveness of the proposed method.

The rest of this paper is organized as follows: Section 2 describes basic ideas of our proposed method. Section 3 briefly describes databases, pattern transformation. Section 4 introduces our recognition classifier that we used. Section 5 details 12 LDMs, NLDM, and CDMs and experimental results for increasing their recognition accuracy. Section 6 presents experiments on the two combination sequences and two original pattern selection strategies. Section 7 describes the results and analysis. Section 6 draws our concluding remarks.

2. Basic ideas

Our approach to generating artificial patterns is based on the observation of how people write and deform character patterns. First, people try to write characters beautifully in accordance with the rules of calligraphy. As far as calligraphy is concerned, characters should be written by following several types of distortion, different with printed type. Fig. 1(a) shows calligraphy styles corresponding to printed types. Samples of shear along the X-direction and Y-direction and shrink toward four directions are shown.

In real handwriting, some people fail to write characters neatly because of their habits as shown Fig. 1(c). Distortions include not only shear and shrink shown in Fig. 1(c) but also perspective. Its models are similar to the shrink models, but they are different in keeping the balance between left and right, or up and down as shown in Fig. 2(a), so that the center of a character pattern is shifted toward the narrowing direction in perspective models while it remains in shrink models. In fact, we often face these distortions in daily life. These distortions can be modeled by the shear model, shrink models, perspective models, and their combinations.

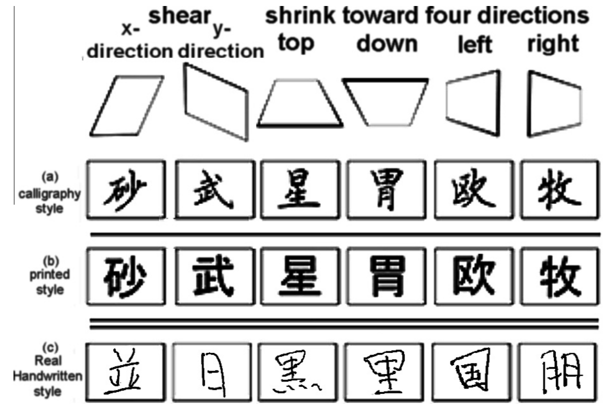

Fig. 1. Handwriting styles based on calligraphy (a), printed (b) and real handwritten styles (c).

Not just these, however, since some people deform the balance between radicals as shown in Fig. 2(b), which is different from the perspective distortion, since shrunk radicals, keep either their height or width. Specifically, people deform patterns non-linearly, which is why non-linear normalization works. Moreover, configuration of the writer's arm, hand, pen, and paper may produce rotated patterns as shown in Fig. 2(c). This type of distortion is modeled by rotation.

Patterns generated from these models are expected to simulate real handwritten samples. In the following sections we will detail the distortion models.

3. Database, and pattern transformation

3.1. Databases

An on-line handwritten character pattern is composed of a sequence of strokes and each stroke is composed of a time-sequence of coordinates sampled from a tablet or touch sensitive device. TUAT HANDS Nakayosi and Kuchibue databases of on-line handwritten Japanese characters patterns (Nakagawa and Matsumoto, 2004) are applied in this experiment. The Kuchibue database contains the patterns of 120 writers: 11,962 patterns per writer covering 3356 categories. Excluding the JIS level-2 Kanji characters, there are 11,951 patterns for 3345 JIS level-1 categories (including 2965 Kanji characters and 380 non-Kanji symbols), which are frequently used in recognition experiments. The Nakayosi database contains the samples of 163 writers, 10403 patterns covering 4438 classes adding frequently used JIS level-2 categories per writer (Nakagawa and Matsumoto, 2004; Jaeger and Nakagawa, 2001).

3.2. Pattern transformation

LDM proposed by Ha and Bunke (1997) and NLDM proposed by Leung et al. (1985) and Leung and Leung (2009) have been applied to transform off-line patterns where each black pixel is moved according to the LDM or NLDM. We can also apply them to transform our on-line patterns. Fig. 3(a) shows an example for pattern transformation. An original on-line pattern has a sequence of coordinates $\{(x_1,y_1), (x_2,y_2), \ldots, (x_i,y_i), \ldots, (x_p,y_p)\}$. We apply LDM, NLDM or CDM to move each coordinate (x_i,y_i) to a new coordinate (x_i^1, y_i^1)