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In-air handwritten Chinese character recognition with locality-sensitive sparse representation toward optimized prototype classifier

Xiwen Qu[a], Weiqiang Wang[a,*], Ke Lu[a], Jianshe Zhou[b]

[a] School of Computer and Control Engineering, University of Chinese Academy of Sciences, Beijing, China
[b] Capital Normal University, Beijing, China

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ABSTRACT

Locality-sensitive sparse representation based classification has been shown to be effective for in-air handwritten Chinese character recognition (IAHCCR). In this paper, we present a locality-sensitive sparse representation toward optimized prototype classifier (LSROPC) for IAHCCR. In the proposed LSROPC, the learned dictionary can not only preserve local data structures, but also require the reconstruction of a pattern to get as close as possible to the prototype optimized by the minimum classification error (MCE) approach. So the LSROPC can help improve the classification accuracy effectively. The experiments are carried out on the datasets of traditional handwritten Chinese characters and in-air handwritten Chinese characters and the datasets designed for face recognition. The experimental results demonstrate the effectiveness of the proposed method.

1. Introduction

Impressive achievements have been made in the area of online handwritten Chinese character recognition (OHCCR) using touch devices as input [1–4]. In recent years, the 3D in-air character handwriting, as a new human-machine interaction way, has attracted attention from many researchers [5–13]. Compared with the traditional touch-device online handwriting, the in-air handwriting suffers less space constraints and has no pen-lift information, so the generated character has its unique characteristics, e.g., a character is always finished in one stroke, the structure of in-air handwritten characters is more complex in intra-class, the distinction between strokes in a character is very poor and the fluctuation of stroke is more evident. The difference between touch-device based handwritten characters with imaginary strokes [3,14] and in-air handwritten characters can be intuitively seen from some examples in Fig. 1.

In order to recognize in-air handwritten character effectively, many efforts have been made. Previous studies have shown the superiorities of 8-directional feature [14,15] and modified quadratic discriminant functions (MQDF) in recognizing handwritten Chinese character based on touch-devices [1,4,16,17]. In fact, the 8-directional feature and the MQDF classifier are also demonstrated to be effective in-air handwritten Chinese character recognition (IAHCCR) [5]. Additionally, a few other classifiers based on the 8-directional feature are also investigated to recognize in-air handwritten Chinese characters (IAHCC) [6,18,19]. In [6], Jin et al. propose classification-based segmentation strategy to recognize visual gesture character string. The method proposed in [18] introduces the adaptive discriminative locality alignment (ADLA) approach to discriminate similar characters and the recognition accuracy is effectively improved compared with the nearest prototype classifier (NPC) [20]. For further improving the recognition rate, the learning vector quantization (LVQ) [21] is exploited to obtain discriminative prototypes in [19]. In [15,16], the simple classifier NPC is utilized. Considering the in-air writing trajectory looks like a function curve, the high-order derivative information is extracted as a complement, since the 8-directional feature can only describe the first derivative and location for each point on the writing trajectory. At present, many methods based on the framework of sparse representation based classification (SRC) have been developed for a variety of specific applications [22–29]. In [28], a locality-constrained max-margin sparse coding framework is devised, which jointly considers reconstruction loss and hinge loss simultaneously and has been proved to be suitable for face recognition. In [29], Yu et al. propose a discriminative multi-scale sparse coding model and

* Corresponding author.
E-mail addresses: queiwen13b@mails.ucas.ac.cn (X. Qu), wqwang@ucas.ac.cn (W. Wang), luk@ucas.ac.cn (K. Lu), zhoujianshe@cnu.edu.cn (J. Zhou).

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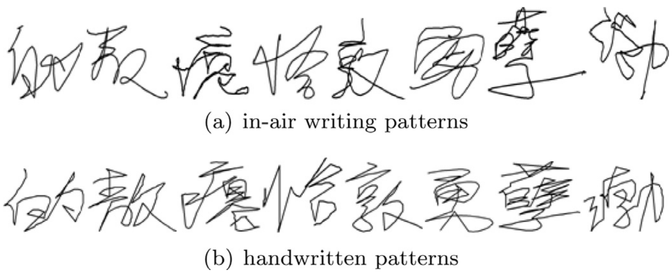

(a) in-air writing patterns

(b) handwritten patterns

Fig. 1. Examples for Chinese characters “碌脛”,“掳陆”,“卤帽”,“脟隆”,“露脂”,“脱胞”,“脛玫”,“虏鲁”.

can effectively deal with face recognition with occlusion. Locality-sensitive sparse representation based classifier (LSRC) [22] learns dictionary considering the locality-sensitive information and can learn dictionary for each class, so it is very suitable for recognition tasks with a large number of classes. LSRC has shown a good recognition accuracy in IAHCCR and it needs much less model storage cost than the MQDF classifier [5].

However, the LSRC ignores the global structure of data and lacks discriminative ability. In real applications, both global and local structures are important due to the complex distribution of data. In this paper, we propose locality-sensitive sparse representation toward optimized prototype classifier (LSROPC) for IAHCCR. The motivation of LSROPC is to preserve the merits of the LSRC and meanwhile improve the discriminative ability of the LSRC. In order to preserve the global structure and improve the classification accuracy, each pattern reconstruction of a class in the LSROPC can get as close as possible to the prototype of this class which is obtained by the minimum classification error (MCE) approach [30]. In MCE, a loss function based on discriminant functions is defined, and the empirical loss is minimized on a training pattern set by gradient descent to optimize the prototypes of all classes. So we can improve the discriminative ability of LSROPC by setting data reconstruction of a class as close as to the prototype of this class.

The rest of this paper is organized as follows. Section 2 briefly introduces the approaches of preprocessing and feature extraction. Section 3 gives an overview of the LSRC algorithm. Section 4 introduces the proposed method at length. The experimental results are reported in Section 5. We conclude this paper in Section 6.

2. Preprocessing and feature extraction

A character recognition system generally consists of three major steps: preprocessing, feature extraction and classification. In this section we briefly introduce the preprocessing methods and the details of feature extraction for IAHCCR in our system.

The wide variability of writing styles, the varied structure in intra-class and the confusion between similar characters always result in the reduction of recognition accuracy. The primary purpose of the preprocessing is to decrease the differences in intra-class so as to improve the recognition accuracy in IAHCCR [5,14,31,32]. The preprocessing for online character patterns include noise elimination, data reduction, and shape normalization, *etc*. The preprocessing steps in our system are summarized as follows. (1) The input trajectory of an in-air handwritten Chinese character is first mapped to an image coordinates with the fixed size of 64 by 64 pixels by linear normalization (LN) [15,33]. (2) We connect each pair of adjacent points on the trajectory of input pattern to form a line by the bresenham algorithm [34]. (3) Nonlinear shape normalization (NSN) [15] approach based on dot density equalization is used to alleviate the shape deformation of in-air handwritten Chinese characters. Then the repeated points generated by the NSN are removed. (4) The breakpoints on the trajectory of input pattern

Fig. 2. Examples of preprocessing for Chinese characters “陆拢”,“脢篓”,“脉路”,“脛冒”,. From left to right: input, LN, NSN, resampling and smoothing.

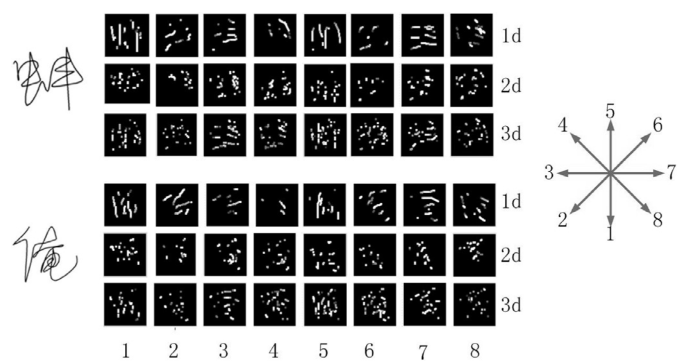

Fig. 3. Examples of directional pattern images.

resulted by the above steps are connected again using the bresenham algorithm. (5) The generated trajectory is resampled to form a sequence of equidistance points. The resampling interval is two pixels in our system. (6) To make the generated trajectory look smooth, the coordinates of each point (except two endpoints) on the trajectory are replaced by an average of the current point and two neighboring points. Finally the duplicate points on the trajectory are detected and removed. Fig. 2 shows some examples of preprocessing through the above steps.

After preprocessing, we extract features to represent the writing trajectory. In our system, the high-order directional feature [5] is applied for IAHCCR, since it considers the unique characteristic of in-air handwritten Chinese character. An in-air handwritten Chinese character is always finished in one stroke and looks like a function curve in a two dimensional plane, so we can obtain the infinite approximation representation of it by its Taylor expansion. Concretely, we exploit the slope, the rate of direction change and the change rate of the rate of direction change for each trajectory point as the description in the similar way with the 8-directional feature. The stroke direction of each point is decomposed into 8 directions and then the directional pattern images are generated. The directional pattern images of two characters “掳枚” and “掳鲁” are shown in Fig. 3, where the first column is the original characters, the eight directional pattern images are indexed by 1 to 8, and the 1st, 2nd and 3rd orders of directional pattern images are denoted by 1d, 2d, 3d. After that, each directional pattern image is blurred by a Gaussian filter and uniformly divided into 8 by 8 grids. Thus, the dimension of the extracted feature vector is $2 \times 8 \times 8 \times 8 = 1024$. Since the high-order directional feature has been shown to be very suitable for IAHCCR but not for HCCR, we adopt the 8-directional feature in the following experiments related to traditional HCCR.