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Global feature for online character recognition

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ABSTRACT

This paper focuses on the importance of global features for online character recognition. Global features represent the relationship between two temporally distant points in a handwriting pattern. For example, it can be defined as the relative vector of two *xy*-coordinate features of two temporally separated points. Most existing online character recognition methods do not utilize global features, since their non-Markovian property prevents the use of the traditional recognition methodologies, such as dynamic time warping and hidden Markov models. However, we can understand the importance of, for example, the relationship between the starting and the ending points by attempting to discriminate “0” and “6”. This relationship cannot be represented by local features defined at individual points but by global features. Since $O(N^2)$ global features can be extracted from a handwriting pattern with N points, selecting those that are truly discriminative is very important. In this paper, AdaBoost is employed for feature selection. Experiments prove that many global features are discriminative and the combined use of local and global features can improve the recognition accuracy.

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1. Introduction

In recent years, interest in online character recognition has increased because of the rapid adoption of smartphones and tablet PCs. Online character recognition is a better method than software keyboards for such small devices. An online character recognition method is needed that offers better recognition performance and is more robust against the variation in input environment.

In the long history of handwritten character recognition, feature extraction has been one of the most important topics. Any handwritten character is comprised of one or more strokes and thus has a peculiar structure unlike those of visual objects. Feature extraction as the representation of character strokes is, therefore, an important stage and affects the classification accuracy.

In this paper we tackle the unsolved problem of feature extraction; that is, how important are *global features* of character strokes for character recognition?[1] Prior to introducing the idea of global features, let us start with an explanation of *local features*. Since a character stroke is the trajectory (of a pen), its local features are defined as sequences of local parts of the trajectory. The most basic local feature is *xy*-coordinates at each point on the stroke (that is, the position of the pen-tip at each time step). Another popular local feature is the local direction feature (Tappert et al., 1990; Bahlmann, 2006), which is derived as the relative vector of two adjacent points. Moreover, dynamic features that consider handwriting movements such as the velocity e.g. (Plamondon et al., 1993) or other biomechanics e.g. (Plamondon and Guerfali, 1998) have been proposed (Bezine et al., 2003; Kherallah et al., 2008). These methods use Beta modeling and elliptical trajectory modeling to analyze handwriting, and use the parameters defined in each modeling method as features for online digit recognition. Therefore, they can be regarded as not only local features but also medium-sized shape descriptions.

In contrast, the global features examined in this paper capture the global structure of character strokes. The most basic definition of a global feature is a numerical representation of the relationship between two temporally separated points. An example is the positional relationship between the two end-points of “0”.

We define a global feature as the relative vector between arbitrary point pairs on the stroke. In spite of its simple definition, global features have high potential to represent various key characteristics of character strokes. In the above example of “0”, its starting and ending points are spatially close to each other. This closeness is represented directly by the global feature between those points, an ability not offered by local features.

Most online character recognition methods have used only local features such as the *xy*-coordinate feature and the local direction feature to represent character strokes. This might be derived from

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[1] This paper extends (Mori et al., 2012) with an improved algorithm for feature selection, additional empirical results, and an in-depth analysis of the performance of global features compared to local features.

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the fact that online character recognition methods are often based on dynamic time warping (DTW) or hidden Markov models (HMM) using sequences of local features. Both of them require that the problem have the Markovian property. Unfortunately, the use of global features clearly violates this Markovian constraint because they deal with the relationship between distant points. Consequently, to the best of the authors' knowledge, global features have not fully been investigated and thus the superiority of global features over local features has not been confirmed.

The main contributions of this paper can be summarized as follows: first, we prove that global features are often more discriminative than local features. This is proved through an experiment on automatic feature selection using the AdaBoost-based machine learning framework. In the experiment, an online numeral dataset is utilized for training a classifier. We also observe the global features that are selected and show that the global features that link separated points are certainly important for character shape description. Second, through a recognition experiment on a test dataset, we prove that the use of global features yields better recognition accuracy.

We examine the performance of global features for the online character recognition task throughout this paper. An important note is that if global features are useful in the online classification task, they will also be useful in the offline classification task. In fact, nowadays, offline recognition methods can employ techniques created for online recognition. For example, in Mori et al. (1992), offline recognition is performed by extracting local online features of strokes by image processing. More dramatically, it is possible to use some stroke recovery method to convert an offline pattern into an online pattern.

The rest of this paper is organized as follows: Section 2 reviews related works in feature extraction. Section 3 explains the global feature approach. Experiments and results are reported and discussed in Section 4. Section 5 derives conclusions and future works.

2. Related Work

Most online character recognition methods use local features, such as *xy*-coordinate features and local direction features, as noted in Section 1. Those local features are sequential and thus traditional Markovian methodologies such as DTW and HMM can be applied. However, this fact does not prove that the handwriting process is purely Markovian. While writing a character pattern, we are usually watching not only the pen-tip but also the stroke shape of the written part. This process is totally non-Markovian and helpful in avoiding confusion between "0" and "6".

In spite of the expected merit of global features, only a few trials have been made on utilizing them in the online character recognition task. One study examined the relative stroke position feature (Shin et al., 1999; Ota et al., 2007). This feature represents inter-stroke relationship and thus does not represent the stroke shape. Another trial is the star feature (Mandalapu and Krishna, 2007) which is based on an eight-directional representation (i.e., a quantized representation) of the entire character stroke; it can be seen as a online version of the classical Sonde method (Johnson, 1956) for offline character recognition.

The trial by Izadi and Suen (Izadi and Suen, 2009) is the work closest to our study. They proposed a feature, called relational context, that computes the relative pairwise distances and angles between arbitrary point pairs. Their trial, however, was merely a preliminary evaluation of the usefulness of global features. They used online patterns, each of which was re-sampled to just 6 points, and all ${}_6C_2$ pairs were used for extracting ${}_6C_2$ global features. As shown by the feature selection experiment in Section 4, our method has no need to use all such pairs in extracting useful global features. In other words, we reveal that each character class has its own important global structure; this important fact is not examined in Izadi and Suen (2009).

In offline handwritten character recognition (OCR), we can find features representing the relationship *spatially* distant points, i.e., pixels. One classical example is the so-called crossing features (Johnson, 1956; Glucksman, 1967), which describe the relationship between a target pixel and spatially distant strokes. Features that extract relative angle and relative position from spatially adjacent strokes have also been proposed (Mori et al., 1998).

3. Global features

We denote a handwriting pattern as the sequence, $p_1, \ldots, p_n, \ldots, p_N$, where p_n is the *xy*-coordinate feature of the *n*th trajectory point. We assume that the number of trajectory points, N, is fixed for all patterns by using some resampling procedure. The coordinate feature, p_n, is considered as a local feature. Another local feature candidate is the local direction feature, which is defined as $p_n - p_{n-1}$. The experiments in Section 4 uses them as typical local features.

The global feature used in this paper is simply defined as the relative vector between two temporally separated points n, n', that is, $p_n - p_{n'}$. Fig. 1 shows the global features $p_n - p_{n'}$ from n to $n' \in \{1, \ldots, N\}$. It should be noted that the global features include the local direction features as a special case. Hereafter, we assume that $n > n'$ for choosing one of the two reciprocal features, $p_n - p_{n'}$ and $p_{n'} - p_n$. Thus, for a handwriting pattern with N trajectory points, there are ${}_NC_2$ possible global features.

Fig. 2 (a) shows an example where the global feature $p_N - p_n$ is discriminative for two classes, "2" and "3". It is also shown that the other global feature, $p_n - p_1$, is almost the same in both classes and thus less discriminative; however, global features between more distant points, say $p_N - p_1$, become more discriminative and thus we can expect a set of global features to yield correct discrimination between "2" and "3". Fig. 2 (b) shows the global feature $p_N - p_1$ of "0". We can easily expect that this global feature can well discriminate "0" from "6".

As indicated by Fig. 2 (a), different global features have different discriminative power. In other words, we do not need to use all of the ${}_NC_2$ global features. This observation suggests the necessity of some appropriate feature selection procedure. Section 4 adopts AdaBoost for feature selection (Freund and Schapire, 1997); AdaBoost has been utilized as not only a machine-learning method for training a classifier but also as a feature selection method. Thus, by using AdaBoost, we can select the global features that offer better classification and obtain a strong classifier for online character recognition.

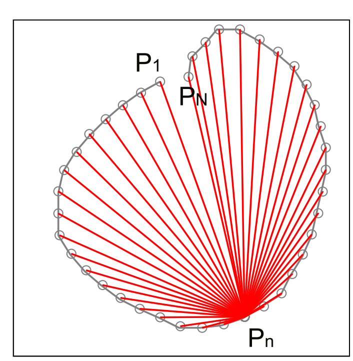

Fig. 1. Global feature extraction.

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