Handwritten Character Recognition Based on Moment Features Derived From Image Partition

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Abstract

In this work we present a novel approach to handwritten character recognition which is based on the intuitive way in which characters are written as one or a few continuous lines. Therefore we calculate the zeroth, first and second radial moment as a function of the angle. In practice this is done by dividing the character in 32 angular sections. The three obtained curves can be used for pattern recognition using statistical analysis. The method has been evaluated using the NIST handwritten character data set. At first, a simple chi-square test gave a result of 80.81% recognition rate at zero rejection rate for digits. Using a back-propagation algorithm the recognition rate obtained was 87.54% also at zero rejection rate. Showing that the features are sufficient to discriminate the characters.

1 Introduction

The recognition of handwriting characters still pose an interesting challenge in the field of pattern recognition. Its importance ranges from the innumerable relevant application connected to the interaction between humans and machines. And with the automation of several different tasks such as the letter sorting in post-offices. Several methods had been studied in the past years, using statistical or structural approaches. Here we concentrate our effort on the moment-base approach to the problem of recognition of segmented handwriting characters.

Moment-base method is a widely studied field in pattern recognition. It has been used for several different problems such as image analysis [1], shape discrimination [2], image reconstruction [3], and character recognition [4], [5]. In this work we try to exploit typical features of the handwriting characters namely that they are usually written as a continuous trace. Viewing from the center of mass, which makes the recognition translation invariant, the character can be seen as a continuous line of which the distance and the width varies with the angle. If we consider a trace through the character for a given angle it is clear that the distribution of density (black pixels) can be characterized by a few normalized moments (mass, distance and standard deviation). Plotting the respective moments as a function of angle we obtain a fingerprint of the character which we believe can be a good base for recognition provided that the proper statistics is used. Inasmuch, using the chi-square test and a back-propagation algorithm we showed that the normalized radial moments in function of the angular partition provide a good feature set for handwriting characters.

2 Feature Extraction

A fundamental process in any recognition system is the feature extraction. The objective here is to capture the essential characteristic of the patterns. A simple and straightforward approach is to use the actual raster image. Alternatively, one can extract certain attributes that is sufficient to characterize the image while leaving out the unimportant features. In this way, we reduce the amount of data that needs to be handled and also the amount of time needed by the system. Robustness and practical constraint are very
important and must be taken into consideration. Our approach is to divide the image in several angular partitions in respect to the center of mass of each image and measure the normalized radial moments of each section. In this way, we characterize an image by the first three moments in function of angular sections.

2.1 Angular Partition

A binary image of a segmented handwritten character is divided into angular partitions according to the center of mass of the image. The number of partitions can vary from a single partition; this will be the case of measuring the moments of the whole image, to partitioning the image completely by lines. Both extremes, using the normalized radial moments, showed not to be good neither to characterize the image nor to yield an acceptable recognition rate. An intermediate number of partitions was then used and showed to be sufficient for these purposes.

Using the Bresenham’s line algorithm we divided the image in 32 partition, as shown in figure 1. Then we calculated the normalized radial moments for each section. Dividing the image with other number of partition is possible and yields result as good as 32 partitions. However an optimal number of partition must exist and is problem dependable.

\[
m(p) = \frac{1}{M} \sum_{r \in P} r_i^0
\]

\[
r(p) = \frac{1}{R} \sum_{r \in P} r_i^1
\]

\[
\sigma^2(p) = \frac{1}{S} \sum_{r \in P} (r_i - \bar{r}_p)^2
\]

Where the summation goes over the black pixels of the partition and \( r \) is the distance of the pixel to the center of mass. The normalizing factor \( M, R \) and \( S \) are given for each moment by the summation over the whole image.

We then plot the respective moments as a function of angular rotation (clockwise). Repeating the procedure for all characters of that type in the training set we obtain the average of the moments and the standard deviation. Figure 2 shows the plot of these measurements for digit 3 using 32 angular partitions. This procedure is now repeated for all different types of character. In the present work we limit ourselves to the handwritten digits of the NIST HSC special database 3 [6].

3 Classification

The objective of any classifier is to assign to an unknown pattern a correct pattern class. There are several different approaches for this problem, however the performance of a classifier depends on the nature of the problem. Furthermore, the speed (either in the learning or in the test phase) and the rate of correct recognition are essential aspects in the choice of a classifier. Two methods were used for the classification task. At first a simple statistical approach using the chi-square test and secondly a neural network approach using a back-propagation algorithm.

For the recognition of a new character, we performed the same radial moment analysis. The test set used was also taken from the same NIST database but different from the learning set.

3.1 Chi-Square

The chi-square test is a simple and straightforward method to implement. It came as a natural choice for a statistical classifier since it measure if two sets of data are drawn from the same or different distribution functions.

The average moment curves obtained by the image partitions (figure 2) from several different characters of the same type are used as a learning set. We calculate the radial moments of an unknown character
then perform the chi-square test for all average moment curves, which represents the known characters. The test character is then classified according to the known character which gives the minimum $\chi^2$. The chi-square statistic is given by:

$$\chi^2 = \sum_{i=1}^{p} \left( \frac{M_i - \mu_i}{\sigma_i} \right)^2$$  \hspace{1cm} (1)

Where $M_i$ represents a test data and $\mu_i$ and $\sigma_i$ are obtained by the learning data set. The summation goes over all the partitions. Table 1 shows the numbers of learning set, the numbers of test set and the recognition rate using the chi-square test. An overall result of 80.81% of recognition rate at zero rejection rate shows that the radial moments are sufficient to discriminate the character. A clear advantage of this method is the speed in both the learning and the recognition process.

![Figure 3: Topology of the back-propagation network.](image)

Table 1: Results for the chi-square test.

| Character | Learning Set | Test Set | Correct | %    |
|-----------|--------------|----------|---------|------|
| 0         | 561          | 112      | 82      | 73.21% |
| 1         | 597          | 123      | 109     | 88.62% |
| 2         | 513          | 110      | 96      | 87.27% |
| 3         | 541          | 119      | 103     | 87.27% |
| 4         | 508          | 100      | 96      | 96.00% |
| 5         | 455          | 98       | 62      | 63.27% |
| 6         | 517          | 103      | 96      | 93.20% |
| 7         | 559          | 108      | 98      | 90.74% |
| 8         | 516          | 111      | 69      | 62.16% |
| 9         | 514          | 105      | 67      | 63.26% |
| Overall   |              |          |         | 80.81% |

3.2 Back-Propagation

Neural networks have been widely used in pattern recognition and several other fields [8], [9], [10]. Here we used a back-propagation algorithm with one hidden layer. The back-propagation algorithm is a feed-forward neural networks that consist in an interactive minimization of a cost function, by making weight connection adjustments according to the error between the computed and the desired output values. The cost function (error function) is defined as the mean square sum of differences between the output values of the network and the desired target values. Figure 3 shows the topology of the back-propagation network used.

The input layer of neural network was feed with the 96 feature taken from the moment description as shown in section 2.2. The network is fully-connected that is all the units in one layer is connected to all the units in the following layer. The hidden layer consisted of 32 units and the output layer of 10 units, each representing the 10 diferents classes of the classified digits.

One very important aspect of the network is convergence. The back-propagation is not guaranteed to find the global error minimum during training but only the local error minimum. This can cause oscillations in the weight changes during training. Keeping this problem in mind, we stopped the training process when the total error in the training test was less then 3%. We used 700 image for each character for the training process, therefore an epoch consisted of 7000 images. Table 2 shows the results of this system, one can see that this approach has a good overall recognition rate, furthermore an increase in the numbers of images in the training set and slight changes in the topology of the network can be done to improve the recognition rate.

| Character | Test Set | Correct | %    |
|-----------|----------|---------|------|
| 0         | 112      | 107     | 95.53% |
| 1         | 123      | 109     | 88.61% |
| 2         | 110      | 93      | 84.54% |
| 3         | 119      | 102     | 85.71% |
| 4         | 100      | 87      | 87.00% |
| 5         | 98       | 67      | 67.35% |
| 6         | 103      | 98      | 93.20% |
| 7         | 108      | 106     | 98.15% |
| 8         | 111      | 91      | 81.98% |
| 9         | 105      | 98      | 93.33% |
| Overall   |          |         | 87.54% |

Table 2: Results for the back-propagation algorithm.

4 Summary and Conclusions

We presented a novel method to the problem of segmented handwritten character recognition. It is based
on dividing the image in angular partitions in respect to the center of mass and calculating three order radial moment for each partition. The method yields representative features for the handwritten character set, since the recognition rate obtained using two different classifier were quite satisfactory. Thus it proves to be a promising technique to be used in equivalent problems in pattern recognition. Nevertheless, several improvements are still possible and under investigation. As for example the use of robust statistical methods and of other classifier systems. Furthermore, different architectures for neural network classifiers can be used to improve the recognition rate.

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