HANDWRITTEN CHARACTER RECOGNITION USING SOME (ANTI)-DIAGONAL STRUCTURAL FEATURES

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ABSTRACT. In this paper, we present a methodology for off-line handwritten character recognition. The proposed methodology relies on a new feature extraction technique based on structural characteristics, histograms and profiles. As novelty, we propose the extraction of new eight histograms and four profiles from the 32×32 matrices that represent the characters, creating 256-dimension feature vectors. These feature vectors are then employed in a classification step that uses a k-means algorithm. We performed experiments using the NIST database to evaluate our proposal. Namely, the recognition system was trained using 1000 samples and 64 classes for each symbol and was tested on 500 samples for each symbol. We obtain promising accuracy results that vary from 81.74% to 93.75%, depending on the difficulty of the character category, showing better accuracy results than other methods from the state of the art also based on structural characteristics.

1. INTRODUCTION

Character recognition, popularly referred as optical character recognition (OCR), has been one of the interesting, fascinating and challenging fields of research in pattern recognition, artificial intelligence and machine vision in the last years [14, 9]. Researchers have already paid many efforts in designing handwritten character recognition systems because of its important applications, such as bank checking process, reading postal codes and reading different forms [3, 4, 15]. For the recognition of English handwritten characters, various methods have been proposed in [10, 14, 15, 17]. One can find information about recent trends and tools in OCR in [17].

In general, an isolated character recognition procedure consists of two steps:

(i) feature extraction, where each character is represented as a feature vector;
(ii) classification of the vectors into a number of classes corresponding to each letter.

The selection of a feature extraction method is important for achieving a high recognition performance. A feature extraction algorithm must be robust enough so that for a variety of instances of the same symbol, similar feature sets are generated, thereby making the subsequent classification task less difficult [7]. In [8] Govindan and Shivaprasad distinguished two categories of features: the structural and the statistical features, while Arica and Yarman-Vural [2] mentioned additional, global transformations, feature extraction model. In [5] Bunke and Sanfeliu mentioned that the structural approach is closer to the human way of recognition. The structural features are based on topological and geometrical properties of the character, such as maxima and minima, reference lines, ascenders, descenders, cusps above
and below a threshold, cross points, branch points, strokes and their directions, inflection between two points, horizontal curves at top or bottom, etc.

There are many works in OCR using structural feature extraction models. Ol-
szewski [16] designed a structural recognition approach for extracting morphological features and performing classification without relying on domain knowledge. This system employs a statistical classification technique on structural features as a nat-
ural solution. Lee and Gomes [13] used the structural features for handwritten numeral recognition such as number of central, left and right cavities, location of each central cavity, the crossing sequences, the number of intersections with the principal and secondary axes and the pixel distribution. Chan and Yeung [6] proposed a syntactic (structural) approach for the analysis of on-line handwritten mathematical expressions. Amin [1] used seven types of structural features such as number of sub words, number of peaks of each word, number of loops of each peak, number and position of complimentary characters, the height and width of each peak for recognition of printed Arabic text. Rocha and Pavlidis [18] gave a method for the recognition of multi-font printed characters using the following structural features: convex arcs and strokes, singular points and their relationships. Kavallieratou, Fakotakis and Kokkinakis [12] proposed an integrated analysis sys-

tem for unconstrained handwriting, where the handwritten character recognition technique was developed as the last module of the system (see also [11]). They used a structural approach, extracting a 280-dimensional feature vector for each char-
acter, consisting of the horizontal, vertical and radial histograms and the out-in and in-out radial profiles, and used $k$-means algorithm for the classification. Yang, Lijia and Chen [20], in order to solve the polluted English character recognition problem with interference of external noise, presented an approach based on ex-
tracting combined structural and statistical features, and using a BP network for the classification.

In this paper we propose a new algorithm for isolated English handwritten char-
acter recognition based on some structural features, using eight new histograms and four new profiles. Thus we extract a 256-dimensional integral vector for each character and then employ the $k$-means clustering algorithm for the classification step. we compare our results to those given in [11], as the methods for feature extraction and classification are the most similar to ours. Our illustrative tables show that we reduce the dimension of the feature vectors and improve the accuracy of recognition.

The proposed technique, which is described in detail in Section 2 is fast and simple. The experimental results, illustrated in Section 3 are quite promising, and in the nearest future will be used in a mobile (iOS) application developed by the second author.

2. Proposed algorithm

2.1. Preliminaries. A handwritten character recognition system usually requires a preprocessing phase before the feature extraction and classification steps [10]. The main goal of this preprocessing phase is to obtain isolated characters and represent them conveniently for the following steps. In most cases, this includes a segmentation stage and a binarization stage to get the isolated characters in the form of $m \times n$ binary matrices. These matrices are then generally normalized by
reducing the size and removing the redundant information from the image without losing any important information.

Then, the feature extraction is applied over these matrices. This step can be considered as the heart of the system, as the feature selection is usually the most important factor to achieve high accuracies in the recognition process. After the normalization of the character images, the objective of the feature extraction is to represent the isolated characters as unique feature vectors. The key is to maximize the recognition rate using as few features as possible.

Finally, the classification stage is the main decision-making stage of the system, and it uses the feature vectors to identify the text segment according to preset rules. In this stage, the basic task is to design a decision rule that is easy to compute and that maximizes the certainty of the misclassification relative to the power of the feature extraction scheme employed.

2.2. **Preprocessing.** For the experimental evaluation, we plan to use NIST database [19], which contains $128 \times 128$ BMP files for isolated handwritten English characters. Thus, before extracting the features, the preprocessing step must binarize and then normalize each original image data file to obtain a $32 \times 32$ matrix with entries in $\{0, 1\}$, such that 0s stand for white pixels while 1s for black pixels.

2.3. **Features extraction.** As we have already mentioned, in this paper we focus on structural characteristics for feature extraction. Instead of the well-known horizontal and vertical histograms, we introduce new horizontal left and right histograms and vertical upper and lower histograms. We also employ new orthodiagonal and orthoantidiagonal histograms and profiles. All these features are used for the first time in the optical character recognition research. We will study if these new features improve the accuracy of the handwritten character recognition algorithm in comparison with [11].

Now, we give the formal definition of these features. We need a map

$$f : [32] \times [32] \rightarrow \{0, 1\}$$

defined as follows: $f(l, m)$ is the value of the element in the $l$-th row and $m$-th column of the character matrix, and $[32] = \{1, \ldots, 32\}$.

The horizontal left and right histograms, $H_{hl}$ and $H_{hr}$, of the character matrix are the number of black pixels in the even rows of the left half of the matrix and the odd rows of the right half of the matrix, respectively (i.e., 32 features):

$$H_{hl}(n) = \sum_{m=1}^{16} f(2n, m) \quad \text{for all } 1 \leq n \leq 16,$$

and

$$H_{hr}(n) = \sum_{m=16}^{32} f(2n - 1, m) \quad \text{for all } 1 \leq n \leq 16.$$

The vertical upper and lower histograms, $H_{vu}$ and $H_{vl}$, of the character matrix are the number of black pixels in the even columns of the upper half of the matrix and the odd columns of the lower half of the matrix, respectively (i.e., 32 features):

$$H_{vu}(n) = \sum_{m=1}^{16} f(m, 2n) \quad \text{for all } 1 \leq n \leq 16,$$

and

$$H_{vl}(n) = \sum_{m=1}^{32} f(2n, m - 1) \quad \text{for all } 1 \leq n \leq 16.$$
and

$$H_{ud}(n) = \sum_{k \geq 0} f(2n - 1 - k, 2n - 1 + k) \quad \text{for all } 1 \leq n \leq 16,$$

Besides above-given histograms, we introduce several other new histograms. We start with the upper and lower diagonal histograms, $H_{ud}$ and $H_{ld}$, given by the number of black pixels according to the odd and even orthogonal lines to the diagonal of the character matrix in the upper and lower triangles, respectively (i.e., 32 features in total):

$$H_{ud}(n) = \sum_{k \geq 0, \frac{2n}{2} \leq j \leq 16} f(2n - 1 - k, 2n - 1 + k) \quad \text{for all } 1 \leq n \leq 16,$$

and

$$H_{ld}(n) = \sum_{k \geq 0, \frac{2n}{2} \leq j \leq 16} f(2n + k, 2n - k) \quad \text{for all } 1 \leq n \leq 16.$$

Symmetrically, the upper and lower antidiagonal histograms, $H_{uad}$ and $H_{lad}$, are defined as the number of black pixels according to the even and odd orthogonal lines to the antidiagonal of character matrix in upper and lower triangles, respectively (i.e., again 32 features in total):

$$H_{uad}(n) = \sum_{k \geq 0, \frac{33}{32} \leq j \leq 16} f(2n - k, 33 - 2n - k) \quad \text{for all } 1 \leq n \leq 16,$$

and

$$H_{lad}(n) = \sum_{k \geq 0, \frac{34}{32} \leq j \leq 16} f(2n - k, 34 - 2n + k) \quad \text{for all } 1 \leq n \leq 16.$$

Additionally, we introduce the out-in and in-out diagonal and antidiagonal profiles for each normalised character. Namely, out-in upper diagonal profile $P_{oiud}$ and out-in lower diagonal profile $P_{oiid}$ are defined at the index $1 \leq n \leq 16$ as the position of the first black pixel found in the $(2n-1)$-th orthogonal line to the diagonal of the character matrix, starting from the periphery in the upper triangle going down; and the $2n$-th orthogonal line to the diagonal of the character matrix, starting in lower triangle going up, respectively (i.e., 32 features in total):

$$P_{oiud}(n) = \begin{cases} I & \sum_{k \geq 0, \frac{2n}{2} \leq j \leq 16} f(2n - 1 - k, 2n - 1 + k) = 0 \\ \sum_{k \geq 0, \frac{2n}{2} \leq j \leq 16} f(2n - 1 - I, 2n - 1 + I) = 1 \end{cases}$$

for all $1 \leq n \leq 16$, and

$$P_{oiid}(n) = \begin{cases} J & \sum_{k \geq 0, \frac{2n}{2} \leq j \leq 16} f(2n + k, 2n - k) = 0 \\ \sum_{k \geq 0, \frac{2n}{2} \leq j \leq 16} f(2n + J, 2n - J) = 1 \end{cases}$$

for all $1 \leq n \leq 16$. 
Symmetrically, we introduce the out-in upper antidiagonal profile $P_{\text{ouad}}$ and the out-in lower antidiagonal profile $P_{\text{oilad}}$, which are defined at the index $1 \leq n \leq 16$ as the position of the first black pixel found in the $2n$-th orthogonal line to the antidiagonal of the character matrix, starting from the periphery in upper triangle going down; and the $(2n-1)$-th orthogonal line to the antidiagonal of the character matrix, starting in lower triangle going up, respectively (i.e., 32 features in total):

$$P_{\text{ouad}}(n) = \begin{cases} I & \sum_{k \geq I+1}^{2n-k \geq 1} f(2n-k, 33-2n-k) = 0 \\ 2n-k \geq 1 & f(2n-I, 33-2n-I) = 1 \end{cases}$$

for all $1 \leq n \leq 16$, and

$$P_{\text{oilad}}(n) = \begin{cases} J & \sum_{k \geq J+1}^{2n-k \geq 1} f(2n-1+k, 34-2n+k) = 0 \\ 2n-1+k \leq 32 & f(2n-1+J, 34-2n+J) = 1 \end{cases}$$

for all $1 \leq n \leq 16$.

Moreover, the in-out upper diagonal profile $P_{\text{inoud}}$ and the in-out lower diagonal profile $P_{\text{inold}}$ are defined at the index $1 \leq n \leq 16$ as the position of the first black pixel found in the $(2n-1)$-th and in the $2n$-th orthogonal lines to the diagonal of character matrix starting from the diagonal going to the periphery in the upper and lower triangles, respectively (i.e., 32 features in total):

$$P_{\text{inoud}}(n) = \begin{cases} I & \sum_{k \geq 0}^{2n-1-k \geq 1} f(2n-1-k, 2n-1+k) = 0 \\ 2n-1+k \leq 32 & f(2n-1-I, 2n-1+I) = 1 \end{cases}$$

for all $1 \leq n \leq 16$, and

$$P_{\text{inold}}(n) = \begin{cases} J & \sum_{k \geq 0}^{2n+k \leq 32} f(2n+k, 2n-k) = 0 \\ 2n+k \leq 32 & f(2n+J, 2n-J) = 1 \end{cases}$$

for all $1 \leq n \leq 16$.

Symmetrically, we introduce the in-out upper antidiagonal profile $P_{\text{inouad}}$ and the in-out lower antidiagonal profile $P_{\text{inoilad}}$, which are defined at the index $1 \leq n \leq 16$ as the position of the first black pixel found in the $2n$-th and in the $(2n-1)$-th orthogonal lines to the antidiagonal of the character matrix, starting from the antidiagonal going to the periphery in upper and lower triangles, respectively (i.e., 32 features in total):
Table 1. Training set from NIST database

| NIST database      | Partition | Handwriting Sample Forms |
|--------------------|-----------|--------------------------|
| Digits             | HSF₀      | F0000…F0999              |
| Uppercase characters | HSF₀, HSF₁ | F0000…F0999              |
| Lowercase characters | HSF₀, HSF₁ | F0000…F0999              |

Table 2. Test set from NIST database

| NIST database      | Partition | Handwriting Sample Forms |
|--------------------|-----------|--------------------------|
| Digits             | HSF₀      | F0100…F1499              |
| Uppercase characters | HSF₃      | F1000…F1499              |
| Lowercase characters | HSF₃      | F1000…F1499              |

Table 3. Results of Algorithm [11]

|                  | 1st Choice | 2nd Choice | 3rd Choice |
|------------------|------------|------------|------------|
| Digits           | 92.48%     | 96.02%     | 97.60%     |
| Uppercase characters | 87.08%     | 92.95%     | 95.26%     |
| Lowercase characters | 79.71%     | 88.62%     | 92.12%     |

Table 4. Results of our Algorithm

|                  | 1st Choice | 2nd Choice | 3rd Choice |
|------------------|------------|------------|------------|
| Digits           | 93.75%     | 97.02%     | 97.90%     |
| Uppercase characters | 88.58%     | 94.09%     | 95.79%     |
| Lowercase characters | 81.74%     | 90.13%     | 92.89%     |

\[
P_{\text{isolad}}(n) = \begin{cases} 
I & \sum_{k \geq 0} f(2n - k, 33 - 2n - k) = 0 \\
& \sum_{2n-k \geq 1} f(2n - I, 33 - 2n - I) = 1 
\end{cases}
\]

for all \(1 \leq n \leq 16\), and

\[
P_{\text{isolad}}(n) = \begin{cases} 
J & \sum_{k > 0} f(2n - 1 + k, 34 - 2n + k) = 0 \\
& \sum_{2n-1+k \leq 32} f(2n - 1 + J, 34 - 2n + J) = 1 
\end{cases}
\]

for all \(1 \leq n \leq 16\).

2.4. Classification. In the previous step, a 256-dimensional feature vector have been extracted from each isolated handwritten character image. These feature vectors are then used in the classification step, where we use the \(k\)-means clustering algorithm to train and create a classification model.
3. Experimental evaluation

In order to evaluate our technique, we performed experiments using the NIST database of handwritten English characters [19]. The experiments were held for each one of the following categories separately: digits, uppercase characters and lowercase characters.

In more detail, using programs written in Python, our recognition algorithm was trained and tested in comparison with the algorithm given in [11] on about 1000 samples and 64 classes and on 500 samples for each isolated handwritten character from NIST database, respectively. Namely, Table 1 and Table 2 show the exact input data for our experiments.

Thus, the training and the test set of our experiments were completely disjoint, which means that the writers used in testing were completely different from the ones used for training.

We show the accuracy rate obtained by [11] for each character category in Table 3, whereas Table 4 shows the accuracy of our method. Since the output of the proposed character recognizer could be further improved by using lexicons, the recognition accuracy when the second and the third choices are taken into account is also given. These results show that our technique outperforms the algorithm in [11] for all categories, in some cases by a margin of more than 2 percentage points.

4. Conclusion

In this paper, we present a technique for English handwritten character recognition. The proposed technique is focused on the extraction of the features that best describe a handwritten character introducing eight new histograms and four new profiles. These features form a reliable representation of a handwritten character and will be applied, as future work, to characters from other languages, e.g. Georgian characters. Due to the nature of our method, it is possible to reduce the current number of features, 256 in this paper, according to the needs of the application where the technique will be used.

The described approach has been tested on the NIST database with recognition accuracy varying from 81.74% to 93.75% depending on the difficulty of the character category, outperforming previous attempts of using just structural features.

The results are promising and usable in some sort of applications. In the nearest future they will be implemented in a mobile (iOS) application.

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