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Improving Isolated Digit Recognition using a Combination of Multiple Features

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***Abstract*— This paper investigates the combination of different statistical and structural features for recognition of isolated handwritten digits, a classical pattern recognition problem. The objective of this study is to improve the recognition rates by combining different representations of non-normalized handwritten digits. These features include some global statistics, moments, profile and projection based features and features computed from the contour and skeleton of the digits. Some of these features are extracted from the complete image of digit while others are extracted from different regions of the image by first applying a uniform grid sampling to the image. Classification is carried out using one-against-all SVM. The experiments conducted on the CVL Single Digit Database realized high recognition rates which are comparable to state-of-the-art methods on this subject.**

Keywords—Isolated handwritten digits; feature combination, Support Vector Machine.

I. INTRODUCTION

Handwriting recognition has been the premier research problem of the document analysis and recognition community for over three decades now. The sub problems in handwriting recognition mainly include line, word or character level segmentation, recognition of isolated characters, words, or complete lines/paragraphs and recognition of numerical strings and isolated digits. Among these different modalities of handwriting recognition, this research focuses on recognition of isolated digits, a classical pattern recognition problem that offers a wide range of applications. Unlike alphabet, the ten glyphs of the most commonly used Western Arabic numerals are shared by many scripts and languages around the world making them globally acceptable. The main challenges in handwritten digit recognition arise from variations in size, shape, slant, and most importantly, the differences in the writing styles of individuals.

With the recent advancements in image analysis and pattern classification, sophisticated digit recognition systems have been proposed which aim to enhance the overall recognition performance by improving the feature extraction or/and classification techniques used. Some of the studies aim to improve the classification performance by using a combination of multiple classifiers while others aim to combine multiple features and select the most pertinent and optimum set of features for this problem.

In this paper, we are interested in enhancing the feature extraction step for isolated digit recognition used for avoiding digit normalization. The idea is to find a combination of multiple features which improves the overall recognition rates by minimizing the intra-class variability and maximizing inter-class variability [4, 13, 23], the most desirable requirement of any pattern recognition system.

Over the years, various handwritten isolated digit recognition systems reporting high recognition rates have been proposed. Most of these systems have been evaluated on the widely used MNIST database. Recently, the handwritten digit recognition competition [19] held in conjunction with ICDAR 2013 also provided a platform for comparison of state-of-the-art digit recognition techniques under the same experimental conditions.

Among significant contributions to digit recognition, authors in [31] present a comprehensive comparison of different classification algorithms on the recognition task. Heutte et al. [15] proposed a combination of seven different features to feed a linear discrimination based classifier. Dong et al. [12] extracted a set of gradient features while Teow and Loe [16] computed linearly separable features from the MNIST database and applied triowise linear support vector machine with soft voting for classification. Belongie et al. [27] developed a novel similarity measure by finding the correspondences between points in two shapes and estimating an aligning transform. The proposed matching technique achieved high recognition rates when applied to digit recognition.

In another notable contribution, Lauer et al. [7] proposed a trainable feature extractor based on LeNet5 neural network architecture. Classification carried out using Support Vector

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Machine realized promising recognition rates. A comprehensive survey on handwritten digit recognition on CENPARMI, CEDAR, MNIST databases can be found in [34].

The objective of our study is to find a combination of features which achieves high recognition rates on non-normalized isolated handwritten digits. We have considered global and local, structural and statistical features [4] [13] [24] in our work. The features that we consider in our study include Hu's moment invariants, skew angle, Zernike moments, profile and project based features, background and foreground features and Ridgelet transform. The proposed approach aims to combine these different features to best represent the digits.

This paper is organized as follows. In the next section we discuss the features used in our study. Section III presents the classification mechanism while Section IV details the experiments conducted along with a discussion on the results achieved. Finally, we conclude the paper with a discussion on future perspectives on the subject.

II. FEATURE EXTRACTION

Feature extraction aims to express input data using a numerical representation or a set of symbols (coding) to select the best set of features (feature vector) for a particular problem, digit recognition in our case. [4, 8, 9, 13, 15]. Features are generally categorized into global or local and statistical or structural features. Statistical features represent pattern classes by statistical measures while structural features use formal structures for data representation. Commonly used statistical features include moments, descriptors and geometrical measurements etc. Examples of structural features include bends, end points, intersections, loops and measures of concavity etc. [28]. Structural properties can sometimes also be expressed using statistical measures. Each of these types of features can be extracted globally from the objects (digits, characters, words or paragraphs) under study or locally from small regions of these objects. However, each feature is more suited to one type or the other giving rise to global and local features.

In the following sections, we provide an overview of the features used in our study.

A. Global features

Global features are computed from the image of the digit as a whole. The global features we compute include the following.

i) ***Density***: the number of black pixels in an image divided by its size.

ii) ***Center of gravity***: two coordinates to represent the center of gravity of the digit image.

iii) ***2nd order Geometrical moments***:a statistical measure of the allocation of pixels around the center of gravity

iv) ***Number of transitions***: number of transitions from white to black (or vice versa) in the four principal directions.

B. Hu's Moment Invariants

Hu proposed the application of moment invariants to image analysis and object representation problems in [20, 21]. Since then, they have been effectively applied to a large number of shape matching and similar problems. Hu's seven moments are invariant with respect to position, scale and orientation. These moments capture information on image area, centroid and its orientation.

C. Skew

The skew or orientation of the digit is calculated using Radon transform of the image [1, 22]. Radon transform of the image is the sum of radon transform of each pixel in the image. The radon function takes parallel beam projections of the image from different angles and the skew angle is determined based on the maximum value of radon function which is used as a feature.

D. Zernike moments

Zernike moments [5] have been widely employed in a wide variety of pattern recognition problems and we use them in our study for characterizing the digits. For efficient computation of Zernike moments, we implemented the method in [5] which is based on recurrence relations for fast computation of radial polynomials of Zernike moments. In our implementation, we compute up to fourth order Zernike moments.

E. Projections

Horizontal and vertical projections are determined by counting the total number of text pixels in each row/column of the image. These values are normalized by the width/height of the image. The mean and variance of these projections are used as features in our study.

F. Profile Features

Left and right profiles are computed by considering for each image row, the distance between the first text pixel and the left (right) boundary of the digit image. Like projections, the profiles are normalized to the interval [0 1] and the mean and variance of these profiles are employed as features.

G. Background features

The background feature vector is based on the concavity information. These features are aimed at capturing the topological and geometrical properties of the digits. Each concavity feature is the number of white pixels belonging to a specific concavity configuration [24]. The label for each white pixel is chosen based on Freeman code with four directions. Each direction is explored until a black pixel or the extremity of the digit is met.

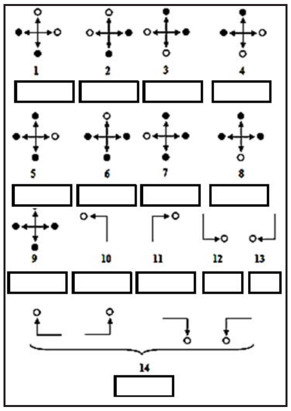

Figure 1. Different configurations of concavity

In addition to the nine standard concavity configurations, we also consider five additional configurations to more accurately model the loops in digits. These configurations are illustrated in Figure 1 and produce a 14 dimensional feature vector which is normalized between 0 and 1. Figure 2 shows concavity labels of the background pixel for a sample of digit '9'.

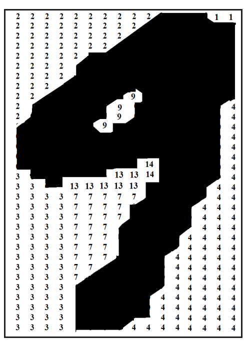

Figure 2. Concavity labels for digit '9'

H. Foreground features

The foreground features are computed from two different representations of digit, contour and skeleton. Each of these types of features is discussed in the following.

Contour Based Features: These features are aimed at capturing the dominant orientations in the shape of the digit and are computed from the contour of the (digit) image. The contour is detected using morphological operations [17, 18, 24, 28] and is represented by Freeman chain codes traversing the pixels in clockwise direction. This generates a string of codes in the interval [1 8] for the contour of a digit. The normalized histogram of these codes is then computed and is used as feature to characterize the digit (Figure 3).

This histogram of contour chain codes is effective in capturing the dominant stroke directions (horizontal, vertical or diagonal). However, these features are very sensitive to noise and also fail to capture the structure and topology of the digit.

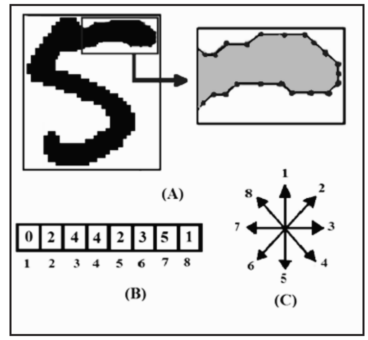

Figure 3. Contour detection: (A) Contour of the upper region, (B) Feature vector, and (C) 8-Freeman directions

Skeleton Based Features: These features are computed from the skeleton of the image of the digit. The skeleton of the image is computed [2, 8] and is searched for end points, crossings and (horizontal and vertical) directional points. Figure 4 illustrates some examples of each type of points (labeled as 1, 2, 3 and 4 respectively) in a digit. The normalized histogram of the occurrence of these points in a digit is used as a feature.

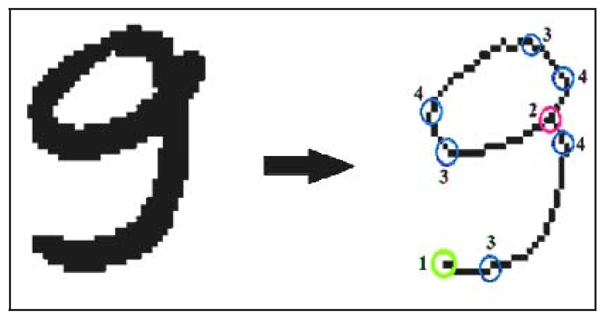

Figure 4. Features extracted from the skeleton

These skeleton based features compute the structural information of the digit but like contour based features; these features are also sensitive to noise in the image.

I. Ridgelet Transform

The Ridgelet transform defined by Candès and Donoho [6] has been effectively employed for pattern recognition [32]. The Ridgelet transform combines the Radon and wavelet transforms. Radon transform has the ability to detect lines in the image while the wavelet transform allows detecting line singularities along the Radon slices.

Ridgelet transform has been successfully applied to a number of problems including image compression, image transform coding, character recognition, watermarking, texture based image retrieval and biometric identification.

The Ridgelet transform is based on the Radon transform which is computed on several angular directions. Radon coefficients correspond to projections representing the shadow of the shape at each angle [6]. Consequently, significant linear features in any direction are expressed by high magnitudes. Thus, in order to characterize linear singularities, the one-dimensional wavelet transform is applied on Radon slices to yield the Ridgelet coefficients. Hence, along the Radon axis projection, the Ridgelet is constant while in the direction orthogonal to these ridges it is a wavelet [26].

For an image $I(p_1, p_2)$, the Ridgelet transform can be computed by first calculating the Radon transform as defined in [32].

$$T_{rad}(\theta,r) = \iint I(p_1,p_2)\delta(p_1\cos(\theta)+p_2\sin(\theta)-r)dp_1dp_2 \quad (1)$$

Where δ, θ and r are Dirac distribution, angular and radial variables, respectively.

The 1-D wavelet transform is then applied on each Radon slice in order to obtain the Ridgelet coefficients $T_{rad}(\theta,r)$. The sum of the normalized values of the coefficients is used as feature.

A summary of the features used in our study along with the dimensionality of each is summarized in Table I. Seven of these features (*f2, f3, f4, f5, f6, f7, f9*) are extracted directly from the image of the digit while three features (*f1, f8* and *f10*) are extracted from different regions of the image by applying the uniform grid method discussed in the following.

TABLE I. SUMMARY OF FEATURES

Feature	Description	Dimension
f1	Global features	8
f2	Hu's Moment Invariants	7
f3	Skew Angle	1
f4	Zernike Moments	50
f5	Projection Histograms	4
f6	Profile based features	4
f7	Background features	14
f8	Histogram of contour chain code	8
f9	Skeleton based features	4
f10	Ridgelet transform	1

Uniform grid sampling [10] is applied to the image of the digit which allows extracting features from different regions of the image separately. A uniform grid creates rectangular regions for sampling where each region is of the same size and has the same shape. For a given image of size H x L, the position of horizontal and vertical grid lines for sampling is determined as follows.

$$p_i = \left[i \times \frac{k}{n} \right] \qquad i = 1, 2, \ldots, n-1 \qquad (2)$$

Where p is the vector of line positions, n is the number of horizontal or vertical regions, and k is the width or the height of the image. Figure 5 illustrates an example of a digit split into a 2x2 grid. Once the image is divided into different regions, features are extracted from each region separately. This allows a different level of granularity and features extracted from similar regions of the digit can be compared with one another allowing more effective matching.

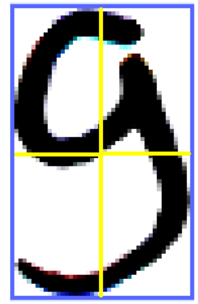

Figure 5. Example of splitting a digit using a uniform grid (2x2).

III. RECOGNITION

The proposed recognition engine is based on SVM multi-class approach using the one-against-all implementation [3, 30]. The features discussed in the previous section are extracted from the training data set (to be discussed in the next section) and are fed to the SVM. Two important parameters required for training the SVM include the regularization parameter (C) and the Radial Basis Function (RBF) kernel parameter (σ). These values of these parameters are empirically determined on a validation set and are fixed to C=159 and σ = 11.

The next section presents the experimental setup and the corresponding results.

IV. EXPERIMENTAL RESULTS

The proposed methodology was evaluated on the CVL Single Digit database [19]. The database comprises 7,000 digits for training, a validation set of equal size, and an evaluation set consisting of 21,780 digits. These samples are contributed by different writers with varying writing styles. Prior to feature extraction, we binarize all images using the KittlerMet binarization method [33]. The features are directly extracted from the binary images of digits without any size normalization.

TABLE II. RECOGNITION RESULTS ON INDIVIDUAL FEATURES.

Feature	Precision (%)	Recall (%)
f1	**93.81**	**93.80**
f2	17.13	20.02
f3	14.78	15.80
f4	**78.62**	**77.22**
f5	39.36	39.26
f6	53.15	49.07
f7	**85.05**	**84.78**
f8	20.40	20.52
f9	18.51	19.62
f10	25.61	23.27

The performance of the system is quantified by computing the precision and recall. We first present the results of individual features summarized in Table II. It can be seen that while the performance of these features varies significantly, the global features (*f1*) extracted from the four regions of the digit image outperform all other features reporting precision and recall of approximately 94%. Zernike moments (*f4*) and background features (*f7*) also realize acceptable recognition rates while the performance of rest of the features is not very impressive when evaluated individually.

Table III summarizes the performance of some of the feature combinations that we have tested. Almost all the combinations report high recognition rates whereas the highest recognition rate (recall and precision of 96.62%) is achieved when combining all the features (*f1-f10*)

TABLE III. RECOGNITION RESULTS ON FEATURE COMBINATIONS.

Features combinations	Precision (%)	Recall (%)
f1, f2, f3, f4, f5	94.86	94.88
f6, f7, f8, f9, f10	95.69	95.70
f1,f4,f7	96.16	96.18
f2, f3, f5, f6, f8, f9, f10	82.58	82.64
f1,f4,f7,f8,f9	96.18	96.23
f1, f2, f3, f4,f7, f8, f9	96.19	96.25
f1, f2, f3, f4,f7, f8, f9,f10	96.30	96.31
f1, f2,f3,f4,f5,f7,f8,f9,f10	96.61	96.62
f1-f10	**96.62**	**96.62**

We also carry out a series of experiments to compute the precision and recall for each of the digits (0-9) separately. The recognition results for each digit are summarized in Table IV. It can be observed from the results in Table IV that in general, the precision and recall values are more or less consistent across different classes. Relatively low recall is achieved on some digits (7, 8 and 9). Furthermore, it should be noted that some pairs like ('0','8'), ('2','7') and ('3','8') offer relatively less inter class variations making their recognition more challenging.

TABLE IV. RECOGNITION RATES ON INDIVIDUAL DIGITS

Class	Precision (%)	Recall (%)
0	97.77	98.67
1	96.16	98.76
2	97.49	98.16
3	95.85	95.36
4	95.59	97.61
5	96.74	96.74
6	97.80	98.12
7	96.88	95.50
8	96.79	95.41
9	95.10	91.87
Average	**96.62**	**96.62**

We also compare the performance of the proposed combination of features with state-of-the-art digit recognition systems submitted to the Digit Recognition Competition held in conjunction with ICDAR 2013. The database (CVL) and evaluation protocol considered in our study is the same as that of the aforementioned competition. This comparison is summarized in Table V where the precision of other systems has been reproduced from [19].

TABLE V. COMPARISON OF PROPOSED METHOD WITH STATE-OF-THE-ART METHODS [19]

Rank	Method	Precision (%)	Normalized Digits
1	Salzburg II	97.74	Yes
2	Salzburg I	96.72	Yes
3	**Our method**	**96.62**	**No**
4	Orand	95.44	Yes
5	Jadavpur	94.75	No
6	Paris Sud	94.24	Yes
7	François Rabelais	91.66	Yes
8	Hannover	89.58	Yes
9	Tébessa II	78.43	Yes
10	Tébessa I	77.53	No

It can be seen from Table V that the proposed method realizes better performances than most of the systems submitted to the competition. Two systems (Salzburg II and Salzburg I) report slightly better recognition rates with precisions of 97.74% and 96.72% respectively. It should however be noted that our method does not require any size normalization and the features are directly extracted from binarized images of isolated digits. The combination of multiple features in our case reduces the confusion between digit classes and consequently results in high values of precision and recall.

V. CONCLUSIONS AND FUTURE WORKS

The objective of this study was to find a representation of isolated handwritten digits that allows their effective recognition. We proposed a combination of ten features, seven are computed from the complete image of digit while three are computed by first applying uniform grid sampling to the image. This combination of features was investigated using SVM as classifier. The experiments conducted on a standard database of isolated digits without any normalization of images realized high recognition rates comparable with the state-of-the-art methods proposed on this problem.

The initial results obtained by the proposed combination of features are very encouraging. Our further study on this subject will include investigation of other features as well as a combination of different classifiers to further improve the recognition rates. A feature selection mechanism to identify the most appropriate subset of features for this problem would also be interesting to explore.

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