ONE DIMENSIONAL REPRESENTATION OF TWO DIMENSIONAL INFORMATION FOR HMM BASED HANDWRITING RECOGNITION

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Abstract: In this study, we introduce a set of one-dimensional features to represent two dimensional shape information for HMM (Hidden Markov Model) based handwritten optical character recognition problem. The proposed feature set embeds two-dimensional information into an observation sequence of one-dimensional string, selected from a code-book. It provides a consistent normalization among distinct classes of shapes, which is very convenient for HMM based shape recognition schemes. The normalization parameters, which maximize the recognition rate, are dynamically estimated in the training stage of HMM. The proposed character recognition system is tested on handwritten data of the NIST database and a local database. The experimental results indicate very high recognition rates.

Keywords: Isolated character recognition, handwriting, normalization, Hidden Markov Model, directional skeletons.

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1. Introduction

Hidden Markov Model (HMM) is a very powerful tool for modeling and recognition problems of one-dimensional signals. However, the extension of the HMM into two-dimensional image analysis applications are not as successful as the one-dimensional case. This is basically because of the requirement of large number of parameters to large amount of training data. On the other hand, the use of the one-dimensional HMM in the two-dimensional problems requires embedding the two dimensional information in the one-dimensional representation, where the major limitation is the difficulty of expressing the two dimensional neighborhood relation in the observation sequences. Therefore, the power of the Markovian property is not effectively reflected in the neighborhood relations, if the one-dimensional representations of two dimensional image grid is used.

Optical character recognition of handwriting is an attractive field of the shape recognition problems, which is intensively studied in the last decade and yet has still a long way to achieve the final goal of fluent machine reading. Among many others, one of the most popular systems of character recognition is the HMM based recognizer. There are many studies, which employ hundreds of features on various types of HMM, for solving the handwritten character recognition problem. However, none of the representations are sufficient to express full characteristics of handwriting, A good source of references in recent developments in hand-written character recognition by HMM can be found in Mohamed (1996), Kornai (1995), Chen (1995), Atici (1997), Kundu (1998), and Knerr (1998).

In this study, we introduce a one-dimensional representation of the image grid, which is very convenient for HMM based handwriting recognition. The proposed method extracts a set of directional skeletons of the binarized character shapes by scanning the image grid in various directions and extracting the skeletons of the digital image in each direction. Then, each extracted directional skeleton is appended one after the other. Finally, the coordinates of the skeleton pixels are coded by the assigned code of the regions where the sparse skeleton pixels lie.

A critical point of the HMM recognizers is the relationship between the dimension of the feature space and the HMM topology. Selection of the HMM topology is mostly done by trial and error, gradually increasing the number of states and nonzero state transitions until the highest recognition rates are achieved during the experiments (Connel (1996)). It is well known that the number of states and the non-zero state transitions of each pattern class proportionally increase as the size of the observation sequence and the code-book get larger. Therefore, finding the optimal topology, which covers all the patterns of varying length of the observation sequence is not easy. This fact brings the character normalization problem for HMM recognizers. On the other hand, character normalization may be hazardous, since it may cause important information loss in the data. A normalization method, which preserves between class variances while keeping within class variances small, is highly desirable. The normalization parameters should be optimal in the sense that the HMM recognition rates are maximum.

In this study, a normalization process is developed to reduce the character size variations. This process provides a meaningful comparison platform for observation probabilities of HMM. The normalization parameters are estimated during the training stage. The proposed normalization and coding scheme, effectively, embeds the two-dimensional information into a one-dimensional string representation. Experiments are performed on a local database and the NIST database. It is observed that, the character representation proposed in this study is insensitive to noise. High recognition rates are achieved, even for considerable variations in writing styles and sizes.

The paper is organized s follows: Section 2 describes the normalization and the feature extraction methods proposed in this study. Section 3 presents the HMM training and recognition, which handles the parameter estimation for HMM models and that of normalization. Section 5 tests the proposed method on the recognition of the number digits and isolated characters. Finally, section 6 compares the proposed method to the available methods in the literature and gives the concluding remarks.

2. Normalization and Character Representation

The normalization process, proposed in this study, is not only for making the recognition system size invariant, but also, for obtaining equal length of observation sequences for the characters of different size. This enables us to find an optimal HMM topology, which is valid for all the pattern classes. The fixed size observation sequences, fed to an optimal HMM topology, grant the highest recognition rates, provided that the normalization process does not introduce distortion on the information to be retained from the feature space. Normalization process also, enables us making the recognition probabilities of the characters comparable.

In their original form, the character images have different sizes and are not tightly cut to the characters contained within them. In order to reduce these inconsistencies, the minimum bounding box for each character is obtained and the character images are normalized to a fixed size window. For this purpose, horizontal and vertical size normalization is applied. Then, each fixed size window is further divided into various regions in different directions.

There are three major parameters of the normalization process: The first one is the size of the window, which requires the estimation of the length and the width. The second parameter is the number of scanning directions. Each window is scanned in various directions. The number of directions depends on the window size. For relatively small size, the horizontal and vertical directions are sufficient to reach the satisfactory recognition rates. As the size of the window is increased, two diagonal directions or more are to be included into the scanning procedure. The third parameter is the number of regions in each scanning direction. The scan lines in all directions are divided into equal regions. Each region is coded by the powers of 2. Figure 1 indicates the coded regions when there are four scanning directions. The number of the regions also, depends on the size of the window. Small windows are divided into two regions. As the size of the window grows, more regions are required to represent each character.

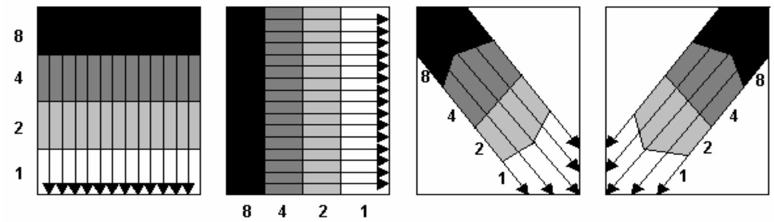


Figure 1: Codes of the regions when there are four scanning directions

Selection of the normalization parameters is of critical importance, since they have an immediate effect on the recognition rates. Initially, all of the normalization parameters are taken as variables. These parameters are, then, estimated in the training stage of the HMM together with the model parameters, as it is explained in the next section. Once, the size of the normalized window and the corresponding scanning directions and regions are estimated, it is fixed for all of the characters in the recognition stage. As a second step, the normalized gray scale characters are binarized for feature extraction. The binarization process uses the optimal thresholding algorithm proposed by Trier (1995). Figure 2, indicates two sample characters ("*e*" and "*l*") and their normalization with various window parameters. This figure illustrates the effect of the window size selection to the character representation. The third box for each letter indicates the optimal window size which is the smallest size preserving the shape information

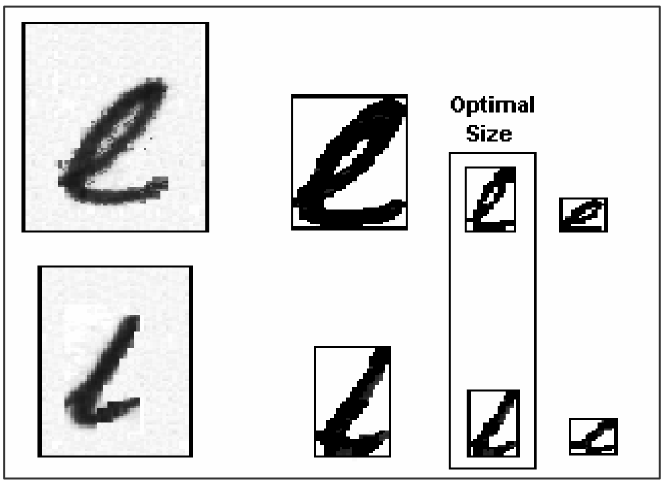


Figure 2: Normalization of Characters "*e*" and "*l*" with different parameters.

For character representation, in each scan line, the medians of the black runs are identified. The code of the region, wherein the median of that run is located, represents that particular run. Each scan line is, then, represented by the sum of the codes of the regions where the medians of the runs are located (Figure 3). This procedure is implemented by the following algorithm:

Character Representation

1. Construct and reset a bit stream which contains N bits, where N is the number of regions

   $bitstream\ [i] = 0,\ 0 \leq i \leq N\text{-}1$.

2. Load the bits, which corresponds to the medians of the runs.
3. Find the value of this stream as the representation of that scan line as

   $$\sum_{i=0}^{N-1} bitstream\ [i] * 2^{i}$$

A character is represented by a concatenated integer string of each scanning direction. This yields an observation sequence of length T. For the example of Figure 3, the summation of the codes generates integers between 0 and 15 (8+4+2+1) and T= 12+12+6+6 (12 values for columns and 12 values for rows, 6 values for each diagonal, as depicted in Figure 3).

The size of the normalized window and the number of the regions of the scan lines are selected in such a way that there exists, at most, one run in each region.

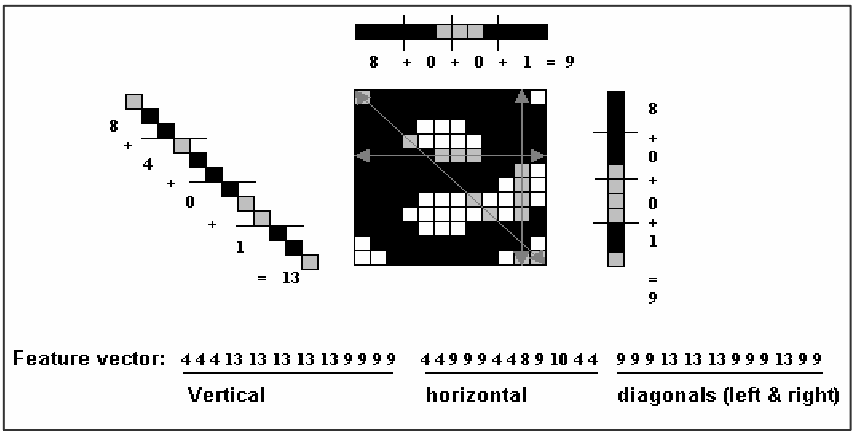


Figure 3: Feature Extraction Process for character "e"

In the above feature extraction method, the median in each scanning direction represents a sparse skeleton of the character obtained in a specific direction. It is well known that a skeleton of a character preserves almost all the shape information of a character. On the other hand, the directional skeletons, defined in this study, are more convenient than the classical skeletons for representing the shape information of the characters in HMM based recognition schemas: First of all, concatonated directional skeletons preserves almost all the skeletal information of the characters. It is possible to obtain curse to fine representation of the complicated skeletons, by increasing the number of scanning directions. More importantly, in the proposed directional skeleton representation there are no cross points and branch points as in the classical skeletons. These qualitative features form inconvinient representation for HMM recognizers. In the directional skeletons there are no such points (see Figure 4).

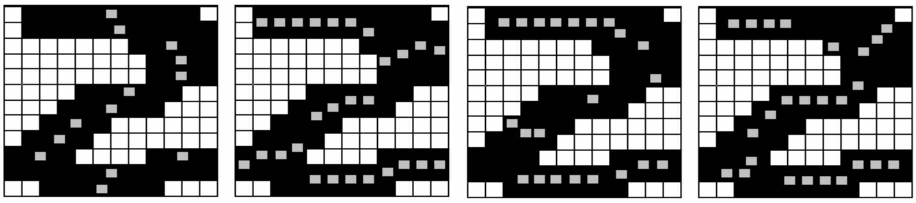


Figure 4. Directional Skeletons obtained from vertical, horizontal, left and right diagonal scanning

3. The HMM Training and Recognition

In this study, the discrete density left-to right HMM is used as the recognizer. The discrete HMM for each character can be represented by $\lambda_l = \{\Delta_l, \Theta_l, S, T\}$, where $\Delta_l = \{\delta_{ij}\}$ is state transition probability matrix for transition from state i to state j, $\Theta_l = \{\theta_i(k)\}$ is the observation probability matrix of observing the code k in i^{th} state for $1 \leq i \leq S$, $1 \leq j \leq S$, $i \leq j$, S is the number of states in the model, T is the length of observation sequence, $k \in V$ and $V = \{0, \ldots\ldots, M\}$ is the set of codes obtained in the feature set (Juang (1990)). Number of the distinct code symbols M and the length of the observation sequence, T varies with the normalization parameters. For the example of Figure 3, when there are four scanning directions and four regions for each scanning direction, M=15, and T=36.

A training set is formed to estimate the model parameters, Δ_l, Θ_l and the three normalization parameters, namely, the size of the normalized window, the number of scanning directions and the number of regions. For this purpose, a normalization tree is formed with the nodes in the first level representing varying sizes of the window. The nodes in the second level represent varying numbers of scanning directions for each window size and the third level represents the number of regions for each number of scanning directions. Then, the problem is to find the optimum path from the root to the leaf, which maximizes the recognition rate. In other word, for each path, Δ and Θ parameters of HMM model for every character class is estimated via the Baum-Welch method (Juang (1990)). Then, the characters in the training set are recognized via forward-backward algorithm. The path, which gives the maximum recognition rate for the training set, is taken as the optimum path. During this process, the number of states of the HMM model is increased proportionally with the size of the normalized window, from S=10 to S=45. The normalization parameters, are fixed for the recognition stage.

In the recognition stage, the probability of observing the unknown character by every HMM is calculated. Then, the observed string $O = \{o_1, \ldots, o_T\}$ is labeled with the class which maximizes the probability $P(O/\lambda_l)$.

4. Performance Evaluation

The experiments are performed in UNIX environment under C programming language. The proposed scheme is tested on two categories of data:

1. Handwritten digit recognition,
2. Handwritten character recognition.

For handwritten digit recognition, two sets of data are tested. First, NIST (National Institute of Standards and Technology) Special Database 19- Hand Printed Forms and Characters, is used. This database contains 3699 scanned pages of binary images of handwritten sample forms. There are total of 814 255 segmented handprinted digits and letters extracted from those forms. The segmented characters occupy 128x128-pixel raster and are labeled by one of 62 classes corresponding to 0-9 A-Z and a-z. In this database, the characters have been manually checked and it is observed that there is about 0.1% misclassified characters. Then, the experiments are repeated on a machine segmented connected digit strings, generated by the students of our department. There are total of 2000 4-digit numbers, which yields 2000x4=8000 numerals, in our local database. The segmentation algorithm, used for the isolation of the numerals, is presented in Arica (1998). Due to the automatic segmentation, these numerals may carry some ligatures or some portions close to the end points of the characters may be missing, depending on the location of the segmentation boundaries.

As it is mentioned in the previous section, the normalization parameters of the feature space are estimated in the training stage of the HMM. This is the worst case situation. An intelligent selection of the training data could definitely increase the recognition rates reported in this study (see: figure 5).

In the training stage, the HMM models are estimated for each entry of the normalization tree. Then, the corresponding recognition rates in the training data are calculated. The normalization parameters, which correspond to the maximum recognition rate, are fixed in the recognition stage.

- *The window size:* The smallest window size is taken 10x10 and increased to 30x60. Increments are also applied to the length to width ratios of the windows. At each window width, the length-to-width ratio is increased gradually from 1 to 2. During the experiments it is observed that the optimal recognition rate depends on the window size as well as length to width ratio. The optimal window size (total number of pixels) depends on the size of the writing. The bigger the characters of the data set, the larger the optimal window size. On the other hand, the optimal length-to-width ratio depends on the deviation o the character's ascending and descending parts from the main body.
- *The number of the scanning direction:* In our experiments we take vertical and horizontal scanning directions, first. Then, we add the left and right diagonals. In our local database, the recognition rates

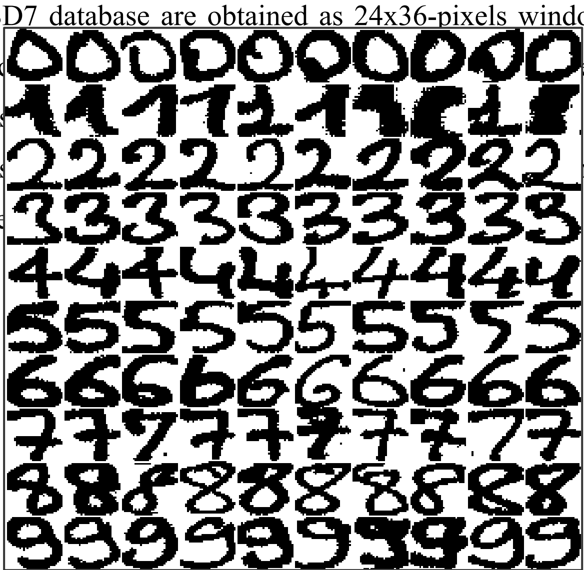
are around 90% by using only two scanning directions. However, the recognition rates for the two scanning directions are around 80% for the NIST database. This result indicates that, for clearly written characters, two directions are sufficient. But, higher number of scanning directions is required as the number of the writers is increased and as the data set gets larger. On the other hand, for four scanning directions, the local database and the NIST database recognition results are above 95%. Increasing the number of the scanning directions to 6, 8 and 10 yields slight improvements in the recognition rates. However, considering the extra complexity added to the system, we do not report the experiments for higher numbers of scanning directions.

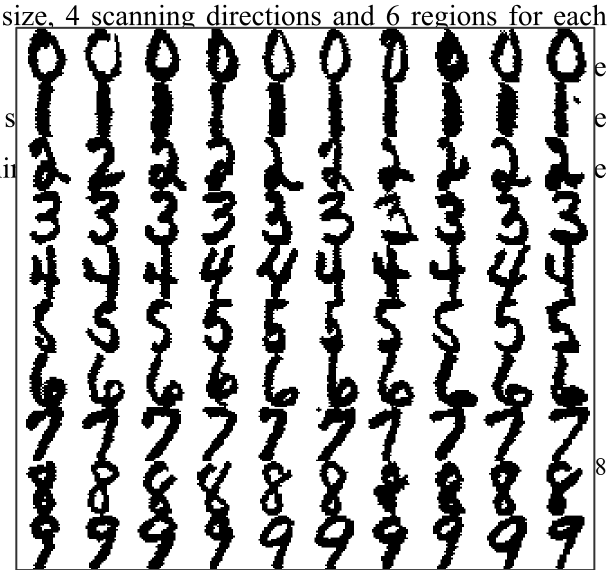
- *Number of regions at each scanning directions:* The experiments are performed for n= 4,5,6,7 regions for each scanning directions. It is observed that for our local database n=4 regions are sufficient to obtain a recognition rate above 95%. However, the recognition rate of the NIST database increase proportionally for n=4,5,6. It is observed that for n > 7 the improvements in the recognition rates are insignificant.

- *HMM topology*: Left-to- right Bakis model has nonzero state transition probabilities, $a_{i,i+k} \neq 0$, for $0 \leq k \leq 3$. The smallest number of state is taken as 15 for 10x10-window. The ratio of the window width to number of the states is kept constant as 1.5 during the experiments. This ratio is determined in another set of experiments in the training state. Therefore, the maximum number of states is 45 for the maximum window width of 30.

4.1 Tests on the Handwritten Digit Recognition

Handwritten digit recognition is tested on NIST SD3 and SD7 databases. 100 samples from each digit class are used for the estimation of the normalization parameters. Table 1 and figure: 6 indicates the HMM recognition rates for 4, 5 and 6 regions in SD3. Note that the recognition rates reach to a local optimum for each optimal window length. The increasing trend of the recognition rates continues as we increase the window width. However, the improvement of the recognition becomes insignificant as the window width gets larger than 30 pixels. Similar trends are observed when the scanning directions and the regions exceed the values presented in the tables. The optimal normalization parameters for NIST SD7 database are obtained as 24x36-pixels window size, 4 scanning directions and 6 regions for each

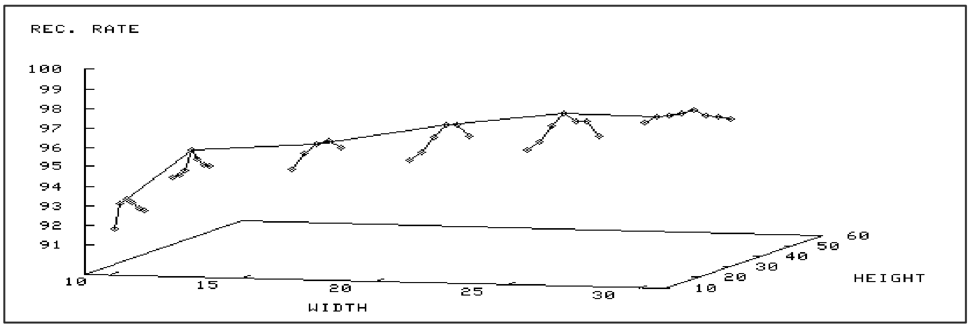




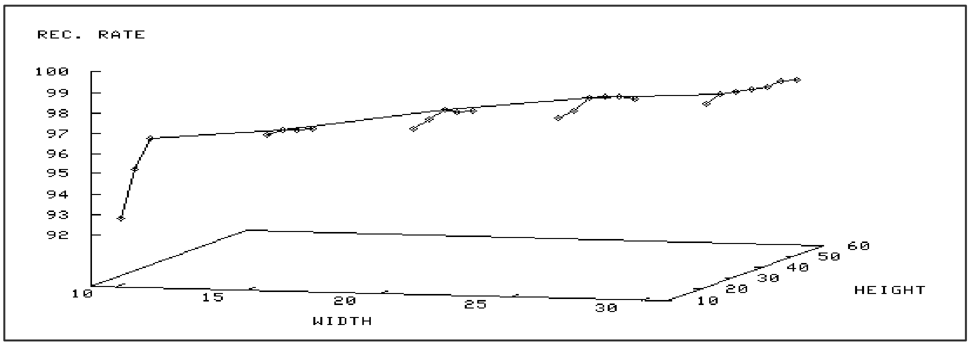
(a) **(b)**

Figure 5. Samples from (a) Local and (b) NIST SD 3 Digit Database

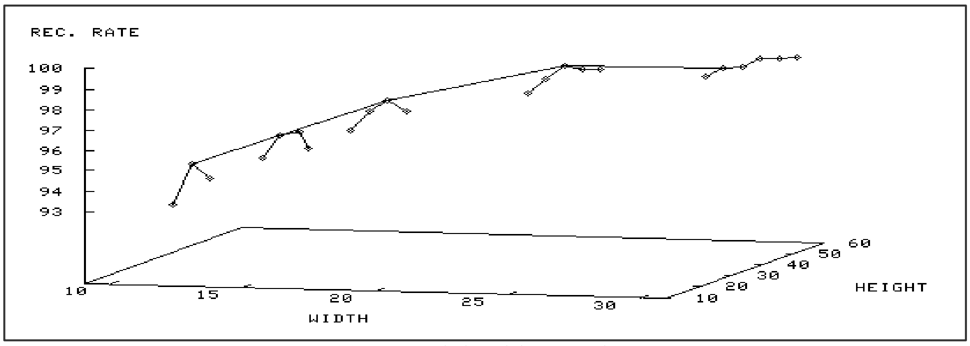
NIST SD7 has more variations in the writing (collected from the students). Note that the optimal normalization parameters are the same as that of SD3. However, the maximum recognition rate of 97.9% is slightly lower then the NIST SD 3 rates (99.3%) for 100 samples in the training set. It is possible to obtain a maximum recognition rate above 99% in NIST SD 7 database by increasing the size of the training data and increasing the optimal window size. HMM parameters are estimated using 500 samples in the training stage. Then, in the recognition stage, the remaining data is recognized with a rate of 97.9%.



(a) SD3 Digit with 4 Regions.



(b) SD3 Digit with 5 Regions.



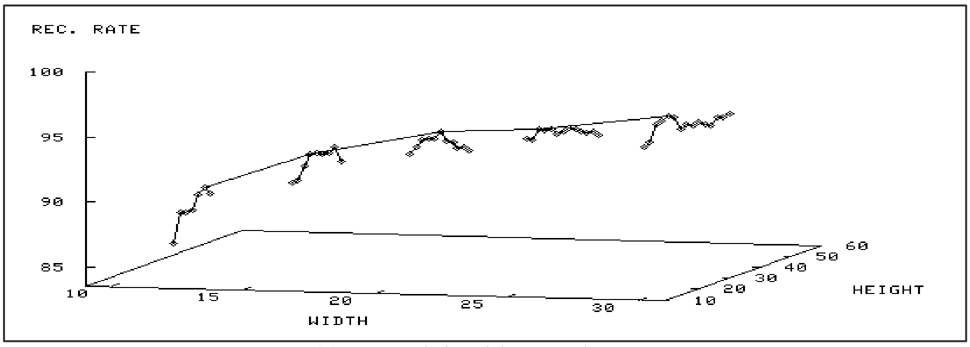
(c) SD3 Digit with 6 Regions.

Figure 6.NIST SD 3 Digit Training Results

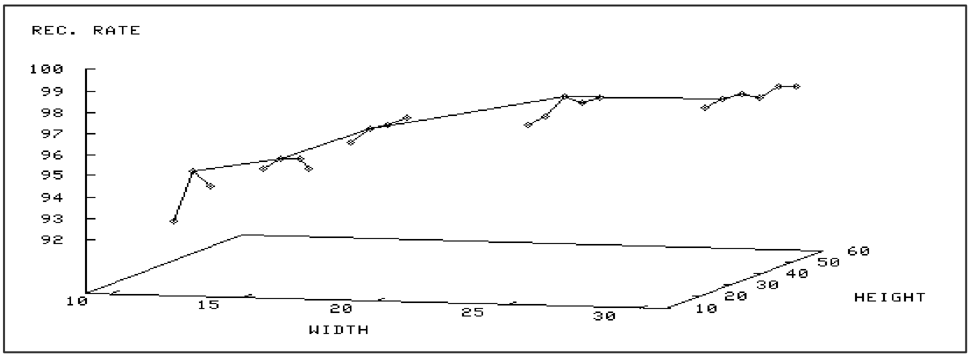
Table:1 Maximum Recognition Rates in NIST SD 3 Digit Training

Number of	Window Size	Length to Width Ratio	Recognition Rate

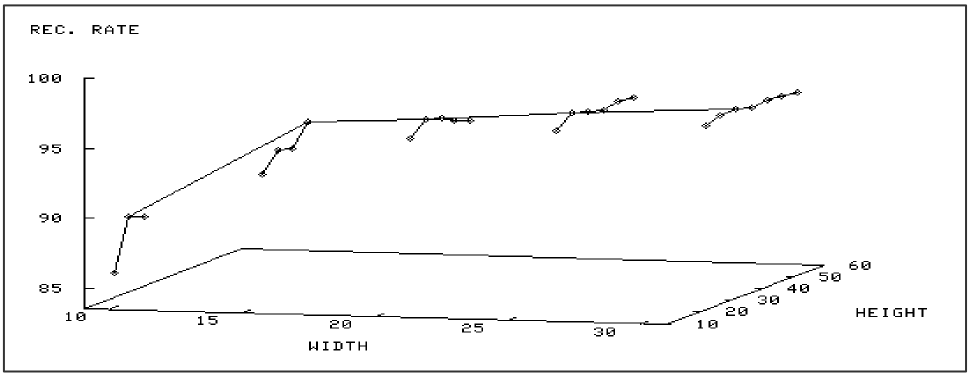
Regions			
4	10x14	1.4	93.1
4	12x18	1.5	95.5
4	16x24	1.5	95.6
4	24x36	1.5	96.8
4	28x32	1.15	97.0
5	10x20	2.0	96.2
5	15x20	1.33	96.8
5	20x30	1.5	97.4
5	25x35	1.4	97.9
5	30x35	1.17	98.2
6	12x18	1.5	94.9
6	15x21	1.4	96.3
6	18x30	1.6	97.6
6	24x36	1.5	99.2
6	30x36	1.2	99.3



(a) SD7 Digit with 4 Regions.



(b) SD7 Digit with 5 Regions.



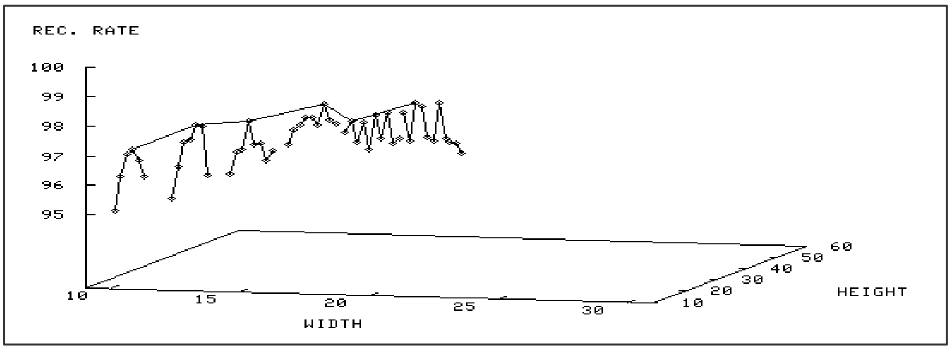
(c) SD7 Digit with 6 Regions.

Figure 7.NIST SD 7 Digit Training Results

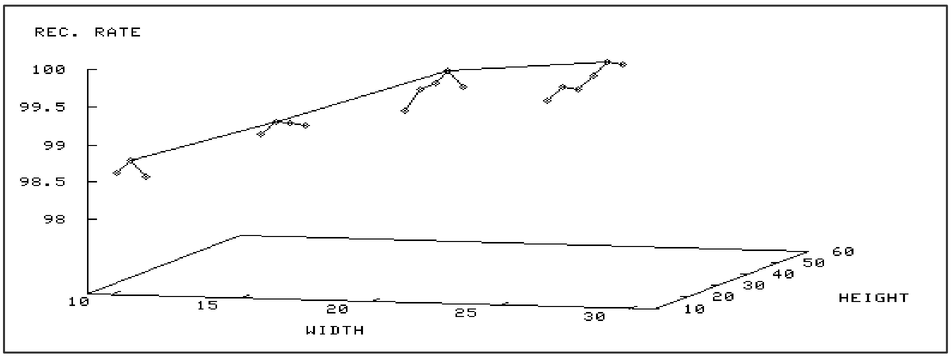
Table:2 Maximum Recognition Rates in NIST SD 7 Digit Training

Number of Regions	Window Size	Length to Width Ratio	Recognition Rate
4	12x22	1.83	90.1
4	16x22	1.38	93.0
4	20x30	1.5	94.5
4	24x28	1.18	94.8
4	28x36	1.28	95.4
5	10x15	1.5	89.6
5	15x30	2.0	95.5
5	20x25	1.25	96.3
5	25x30	1.2	96.6
5	30x35	1.17	96.3
6	12x18	1.5	94.8
6	15x21	1.4	95.4
6	18x24	1.33	96.7
6	24x36	1.5	97.8
6	30x36	1.2	97.9

Our local database employs 5 regions in each of the 4 scanning directions with 20x35-pixel window size for optimal normalization parameters. 100 samples are used for the estimation of the normalization parameters. Then, 100 more samples are added for the estimation of the HMM parameters, for each class. The remaining samples are recognized with a rate above 98%, in the recognition stage. Increasing the number of regions in each scanning direction to 6 gives 99% recognition rate.



(a) Local Digit with 4 segment



(a) Local Digit with 5 segment

Figure 8.Local Database Digit Training Results

Table 3. Maximum Recognition Rates in Local Database Digit Training

Number of Regions	Window Size	Length to Width Ratio	Recognition Rate
4	10x16	1.6	97.0
4	12x20	1.68	97.7

4	14x20	1.47	97.9
4	16x28	1.75	98.2
4	18x20	1.12	98.0
4	20x24	1.2	98.5
5	10x15	1.5	98.7
5	15x20	1.33	99.3
5	20x35	1.75	99.7
5	25x45	1.8	99.7

Table 4. Handwritten Digit Recognition Test Results

Database	Samples for HMM training	Samples for recognition	Window Size	No. of Regions	Rec. Result
NIST SD3	200	218 000	24x36	6	95.6
NIST SD7	500	50 000	24x36	6	95.0
NIST SD19	200	118 000	24x36	6	95.4
Local	200	6 000	20x35	5	98.8

4.2 Tests on the Handwritten character recognition

Although the nature of the problem of the character recognition is the same as that of the number digit recognition, the tests on both cases require data specific care. The major distinction between the number digit recognition and the character recognition is the ascending and the descending portions of the characters, These portions do not exists in the number digits. The existence of the ascending and the descending portions of the characters affect firstly, the length-to width ratio of the normalized window. In fact the optimal length-to-width ratio is obtained around 2.0 for the character database, whereas the optimal ratio for number digits is around 1.2. Secondly, The ascending and descending portions of the characters form a relatively more uneven pixel distribution in the normalized window compared to the distribution of the number digits. This implies the requirement of higher number of regions in each scanning direction.

The NIST SD19 has a smaller number of characters compared to the number digits. Since the number of classes for character recognition is much more then the digit classes, we are restricted to use 100 samples for each class in the training stage. These samples are used to estimate both the model parameters and the normalization parameters. The recognition rates for all the NIST databases are obtained around 87%. Increasing the size of the training data gives higher recognition rates.

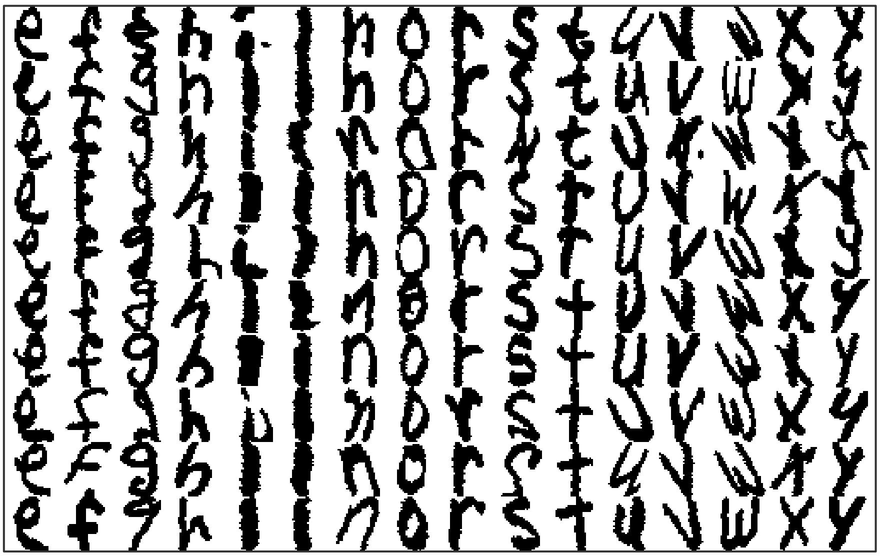


Figure 9. Samples from NIST SD 7 Lower Character Database

Table 5. Maximum Recognition Rates in SD7 Character Training

Number of Regions	Window Size	Length to Width Ratio	Recognition Rate
6	12x24	2	93.4
6	15x27	1.8	94.2
6	18x30	1.7	96.0
6	21x39	1.87	96.4
6	24x45	1.88	96.7
6	30x51	1.7	97.4
7	14x28	2.0	94.5
7	21x35	1.66	96.8
7	28x56	2.0	97.9

Table 6. Handwritten Character Recognition Test Results

Database	Samples for HMM training	Samples for recognition	Window Size	No. of Regions	Rec. Result
NIST SD3	100	40 000	28x56	7	87.3
NIST SD7	100	10 000	28x56	7	86.2
NIST SD19	100	20 000	28x56	7	87.1

5 Conclusion

Although the theory of the Hidden Markov Model is well established and there are successful applications in one-dimensional problems, the implementation of HMM in the image analysis applications involves a large number of restrictive condition and assumption. In this study, we focused on the OCR field as an application domain and attack two major problems of HMM based recognition schemes. First, a one-dimensional representation of two-dimensional shape information is proposed. Then, the estimation of the parameters of this representation is embedded in the HMM training stage. This approach yields the "best" set of normalization parameters which keeps the HMM recognition maximum.

It is not easy to compare the results obtained from the proposed method to the reported results in the literature, because of different test platforms and data sizes. A quick scan in the literature indicates a diverse variation in the recognition rates. For handwritten digit recognition, the rates vary between 85%-98% (Amin 1998, Jain 1998). For handwritten character recognition the reports give as low as 75% as a successful rate (Plamondon 1993). All of the methods have their own superiorities and weaknesses depending on the quality of the writing and the size of the training and recognition data.

We choose two recent studies for comparing our results in NIST database. As a first comparison platform, the best 10 results reported on the NIST database is used. These results are obtained on an OCR competition in the NIST conference (Wilkinson 1992). The tests are performed on NIST SD7 for isolated digit recognition with unlimited competition time and training data size. The best 10 methods give recognition rates between 95.9% and 96.8%. The results are obtained by using huge training sets (more than 50 000 samples) gathered from inside of NIST database as well as from the outside sources. Considering the robustness of our approach and 100 times less data used for the training sets, our results are more appropriate for many applications . Note also that there is no effort spent to construct an appropriate training data in our experiments.

Secondly, our results are compared to the results of the study presented by Connel (1996), which is accomplished in Almaden Research center of IBM. In Connel (1996) sets of 1000 and 2000 images were used during the training stage of HMM. On the other hand, only 100-200 samples were selected from the NIST database as test data, in our tests. Additionally, the authors do not report which special data set is used. Their method which uses single state HMM obtains 88.2% recognition rate, whereas the method which uses multi-state HMM obtains 79.1% recognition rate, both for a training set of 1000 samples per class. On the other hand, our result gives 87-96% recognition rate on various NIST databases by using only 200 samples per class for training.

The above discussion indicates that the proposed representation and normalization methods increase the success rates of HMM based recognizers a great deal, on Optical Character Recognition applications. .

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