RESEARCH ARTICLE OPEN ACCESS

Comparison of Distance Transform Based Features

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ABSTRACT
The distance transform based features are widely used in pattern recognition applications. A distance transform assigns to each background pixel in a binary image a value equal to its distance to the nearest foreground pixel according to a defined metric. Among these metrics the Chessboard, Euclidean, Chamfer and City-block are popular. The role of a feature extraction method is quite important in pattern recognition applications. Before applying a feature, it is essential to judge its performance on the given applications. In this research work, a study on the performance of above mentioned distance transform based features is made. We have conducted experiments with 500 hand-printed characters/class and the study has been performed on 43 classes. The classifiers used are *k*-NN, MLP, SVM and PNN.

Keywords – Characters, Devanagari, Distance Transform, Hand-printed, Recognition

I. INTRODUCTION

A recognition system works in various stages such as scanning, preprocessing, feature extraction, classification and post processing. In a typical pattern recognition problems the feature extraction phase plays an important role as some essential properties of the images are extracted in this phase that is important for taking a classification decision. If we look at the hand-printed character images which are contributed by different writers having varying writing styles. There is a lot of variability in the hand-printed images within each class that is not easy to handle. The properties used to segregate the characters must possess small intra-class variability and large inter-class separation capability.

The distance transform (DT) is a technique in which the distance relationships among the pixels of an image are used to obtain a feature map. It converts a binary image into a gray level distance map (DM). The DT algorithm proposed by Rosenfeld et al[1] is earliest. The DT based features have been used by Smith et al [3], Koύacs et al [4] and Oh et al[5] for handwritten recognition and Negi et al [78] for machine-printed Telugu character recognition. In [4], the L_1 norm is used as distance metric to compute DT of a binary image where distance map is computed from a 32×32 image and subsequently it is sub-sampled to 8×8. In [3], Hamming distance, pixel distance and pen-stroke are used as a distance measure. In [5] its performance is compared with other features on English capital letters, English numerals and Hangul characters and Manhattan distance metric is used for this purpose. In this case distance map is computed from 16×16 binary image giving 256 features.

Selecting a best technique for a particular application is a daunting task. One has to exhaustively study the literature, implement them and observe their performance. Obviously this is a big task. As far as feature extraction stage is concerned, Govindan et al[9] classified the various features in three categories i.e. statistical, structural and global transforms and series expansion. Each category has its pros and cons in terms of computational speed, computational complicacy and accuracy. The distance transform based features are statistical features.

The paper is arranged as follows: Section II covers Distance Transform, Section III covers Feature Extraction, Section IV covers Experimental Results, Section V covers Discussion and Conclusion.

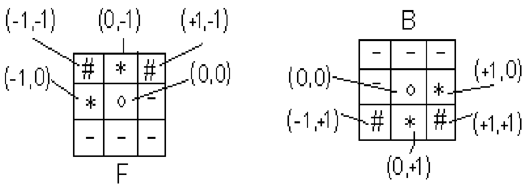
II. DISTANCE TRANSFORM

The A distance transform assigns to each white pixel (background) of a binary image a value equal to its distance to the nearest black pixels (foreground) according to a defined metric. A new image, which has same size as that of an original image, is created using distance transform and this image is called as distance map (DM). In DM each background pixel has some value whereas each foreground pixel has 0 value. The distance map of 30×30 binary image (Fig. 2) computed using Chessboard distance as a metric is given in Fig. 3. Borgefors[2] presented the Chamfer distance algorithm(CDA) that efficiently and accurately calculates the DT of 2 dimensional images[5,6]. It works in two passes. Initially the distance map as well as the character image is padded with two extra rows (one each on top and bottom) and two extra columns (one each on left and right). These extra pixels are treated as background pixels in a given image. The distance map is initialized as:

$$DM(x,y)=\begin{cases}0 & \textit{if} \quad I(x,y)=1 \quad i.e. \quad black \\ v & Otherwise\end{cases} \qquad (1)$$

Where v is infinite or we may choose a sufficiently large value.

Pass 1: In this pass distance map is scanned in forward direction, *i.e.*, top to bottom and left to right. Minimum distance for each position of the distance map is computed using a 3×3 forward mask F which is given in Figure 1(*a*).



a) *b)*

Fig. 1 : *a*) Forward mask *F* ; *b*) Backward mask *B*.

For a given location (*x*,*y*) of distance map (DM), the minimum distance is computed as:

$$DM(x,y)=\min\begin{cases}DM(x-1,y-1)+F(-1,-1),\\ DM(x,y-1)+F(0,-1),\\ DM(x+1,y-1)+F(+1,-1),\\ DM(x-1,y)+F(-1,0),\\ DM(x,y)+F(0,0)\end{cases} \qquad (2)$$

Pass 2: In this pass distance map is scanned in backward direction. Minimum distance for each position of the distance map is computed using a 3×3 backward mask *B* which is given in Fig. 1(*b*). For a given location (*x*,*y*) of distance map (*DM)*, the minimum distance is computed as:

$$DM(x,y)=\min\begin{cases}DM(x+1,y)+B(+1,0),\\ DM(x+1,y+1)+B(+1,+1),\\ DM(x,y+1)+B(0,+1),\\ DM(x-1,y+1)+B(-1,+1),\\ DM(x,y)+B(0,0)\end{cases} \qquad (3)$$

The values of '#' and '*' in both masks depend upon the type of distance metric used. The value of *'o'* is zero in both masks and \`–\` represents a point that is not to be used in computation. The various 3×3 masks used during forward and backward scanning depends upon the type of distance metric used and some of these masks are given in Table 1.

TABLE 1: Some Metric Distances and Their Corresponding Forward and Backward Masks.

Distance Metric	Forward Scan			Backward Scan		
Chamfer Distance	4	3	4	-	-	-
	3	o	-	-	o	3
	-	-	-	4	3	4
Euclidean Distance	$\sqrt{2}$	1	$\sqrt{2}$	-	-	-
	1	o	-	-	o	1
	-	-	-	$\sqrt{2}$	1	$\sqrt{2}$
Chessboard Distance	1	1	1	-	-	-
	1	o	-	-	o	1
	-	-	-	1	1	1
City-block Distance	-	1	-	-	-	-
	1	o	-	-	o	1
	-	-	-	-	1	-

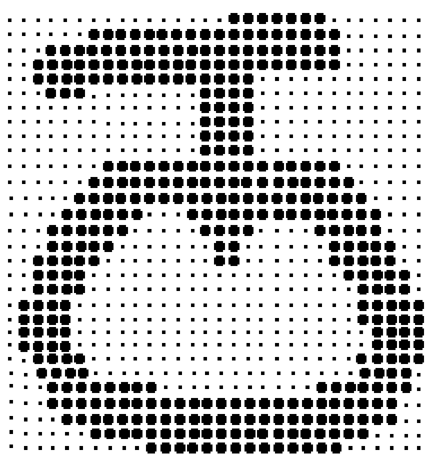


Fig. 2: A normalized binary character image.

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32222111111111100000001123456
221111000000000000000000123456
211000000000000000000000123456
210000000000000000000000123456
210000000000000000111111123456
211000111111111000012222223456
221111122222210000123333333455
322222222333321000012333333445
333332222222210000122222223344
443322111111110000111111122334
433221100000000000000000112233
332211000000000000000000011223
322110000000000000000000001123
321100000001110000000000000122
221000000112110000111100000112
211000000112221100112211000012
210000001122322100122221000011
210000112233321111233211000001
110000122334322222223322110001
100001123344333333333322100000
100001223444444444444332100000
100001223444444555444432110000
100001123333333444443333211000
110000122222223333333222210000
210000111111222222222211110001
211000000000111111111110000001
221000000000000000000000000011
321100000000000000000000000012
322111000000000000000000001112
332221111100000000000000111222
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Fig. 3: Distance map of normalized binary character image computed using Chessboard distance.

Complexity: 1). To compute distance map, the two passes through the image are required. In each pass at each pixel, a window of 4 valid locations is convolved with image to get four distances. This requires 4 addition operations as the value of $F(0,0)$ and $B(0,0)$, in (*1*) and (*2*), respectively, is 0 and the addition operations, $DM\ (x, y) + B(0,0)$ or $DM\ (x, y) + F(0,0)$, are not required to perform. To find minimum distance out of these five distances, 5 comparison operations are needed. So, in each pass at each pixel, 9 arithmetic and logical operations are required to find *DM* of an image. Ultimately, we have to pass through the image twice with some arithmetic and logic operations at each pixel. The time complexity for doing so is $O(T1) = O(2\times N\times M) \sim O(N\times M)$.

2). To extract feature vector, the *DT* map is divided into $X\times Y$ regions. In all $X\times Y$ regions, the number of addition operations required is $N\times M$ and number of division operations performed is $X\times Y$. It means at each pixel, only some arithmetic operations are performed. The complexity is linearly proportional to the number of pixels in each image i.e. $O(T2) = O(N\times M)$.

The total time complexity for computing DM and extracting feature vector from DM is as:

$$\begin{aligned} O(T) &= O(T1) + O(T2) \\ &= O(N\times M) + O(N\times M) \\ &\sim O(N\times M) \end{aligned}$$

III. FEATURE EXTRACTION

To The distance transform (DT) can be computed using various distance metrics. We have computed DT with four methods given in Table 1, *i.e.*, Euclidean, Chessboard, Chamfer and City-block and compared their recognition performance with each other. The character bitmap size taken is 30×30. In each case the image is convolved with 3×3 windows given in Table 1 and distance map (DM) is computed using (2-3). The distance map is divided into 10×10 regions. The average minimum distance in each region is computed. The feature vector is normalized by dividing each feature component with maximum value of average minimum distance obtained out of all the features for a given image.

Distance Type (Feature Name)	Classifier	Recognition Rate (%)				
		A	B	C	D	Average
Euclidean 10×10 (DT(E)-100)	*k*-NN	79.1	71.8	72.7	75.6	74.8
	PNN	78.1	72.1	73.6	74.1	74.5
	MLP	85.8	79.7	80.6	84.2	82.6
	SVM	91.0	85.8	85.9	89.6	88.1
Chessboard 10×10 (DT(Che)-100)	*k*-NN,	79.0	72.1	72.6	75.6	74.8
	PNN	79.3	72.5	72.7	75.3	75.5
	MLP	86.3	79.9	80.5	84.6	82.8
	SVM	90.8	85.4	84.7	89.3	87.5
Chamfer 10×10 (DT(Cha)-100)	k-NN,	79.3	72.0	72.8	75.7	74.9
	PNN	80.2	73.2	73.7	75.4	75.6
	MLP	87.1	80.0	80.2	85.9	83.3
	SVM	90.8	85.8	86.1	89.7	88.1
City-block 10×10 (DT(CB)-100)	*k*-NN	78.6	71.4	72.1	75.0	74.3
	PNN	77.8	71.7	73.3	73.8	74.2
	MLP	85.4	79.3	80.3	83.9	82.2
	SVM	90.5	85.3	85.1	88.8	87.4

Table 2: Experimental results with Euclidean, Chessboard Chamfer distances and City-block.

IV. EXPERIMENTAL RESULTS

Our database consists of more than 600 characters per class, the characters of each class are numbered. For our experiments we have used 600 characters per class (alphabet character). In order to cross validate the results we have partitioned our database in four subsets: A, B, C and D. The size of each subset is equal. In each trial, 75% data is used for training and 25% data is used for testing, *i.e*. one subset is used to test and three subsets are used to train the classifier. The experiments are also conducted by partitioning the distance map into 4×4, 6×6 and 8×8 regions, but the recognition rates recoded are low as compared to the recognition rates for 10×10 given in Table 2.

V. Discussion and Conclusion

The following can be concluded from the results:

1). The results of Table 2 clearly predict the superiority of Chamfer and Euclidean distances over Chessboard.

2). Performance of Chamfer and Euclidean is neck to neck in case of SVM whereas Chamfer is more than Euclidean on PNN, *k*-NN and MLP.

3). Performance of Chessboard and city-block is neck to neck in case of SVM whereas Chessboard is more than city-block on PNN, *k*-NN and MLP.

4) The City-block is performing least as compared to other classifiers on all classifiers.

5) The *k*-NN and PNN are performing neck to neck.

The better recognition rates in these two cases are due to the fact that the values of constants '*' and '#' taken in forward and backward windows, in both these cases, are different as compared to Chessboard where these values are same. The maximum recognition rate achieved with SVM classifier is 88.1 % and with MLP classifier is 83.3%. Both Chamfer and Euclidean distance metric give same results with SVM. However, their results with MLP are different. If we want to use MLP then Chamfer distance is better as compared to Euclidean distance.

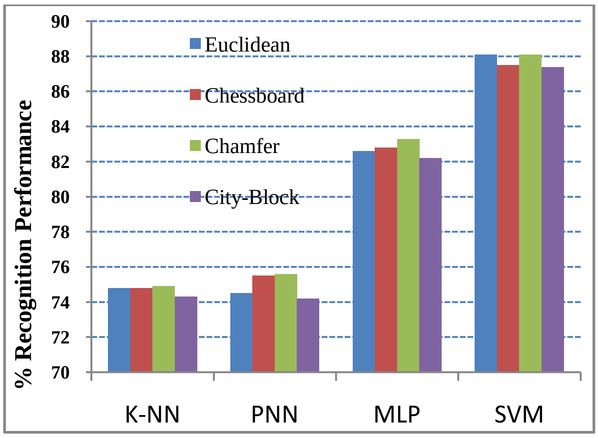

Fig. 4: Recognition performance of various distance metrics.

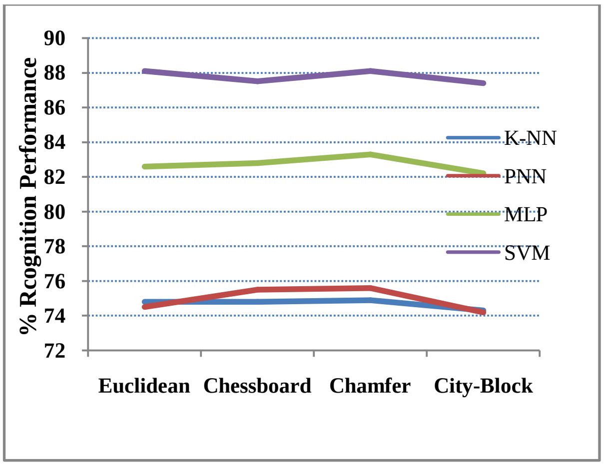

Fig. 5: Recognition performance of various classifiers.

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