MOMENT OF INERTIA BASED RADIAL CODING FEATURES OF INVARIANT CHARACTER RECOGNITION USING FUZZY MIN-MAX NEURAL NETWORKS

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Abstract:

This paper proposes a character recognition system that is invariant to translation, rotation and scale. The system has two main components feature extraction and recognition. The feature extraction is carried out using moment of inertia based radial coding features. The main advantage of this feature vector is that it doesn't require the normalization of character. These features also easy to understand and implement compared to other methods computer requirements are also negligible. The Fuzzy Min-Max neural network (FMNN) is used in the recognition phase. The nine dimensional feature vector consists of Normalized moment of inertia and eight radial coding features. The character recognition systems is tested on 26 uppercase typed and hand written English letters. This character recognition system is also tested on different fonts (Ariel Unicode, Ariel Narrow, Microsoft scan serif) and hand written characters of five different writers.

Key words: Character Recognition System, Fuzzy Min-Max Neural network, Invariant Character Recognition, Moment of Inertia, and Radial Coding Features.

I. Introduction

Character recognition is one of the most successful applications of pattern recognition. Automated character recognition is of vital importance in many industries such as banking and shipping. A variety of character recognition methods are available such as boundary-based analysis via Fourier descriptors [3], neural-networks models [4] and invariant moment's [5]. Boundary-based analysis using discrete Fourier transforms has been proposed for character recognition. Algorithms based on this kind of analysis are called Fourier descriptors and basically, invariance is obtained by normalizing the frequency representation of the character shape. Its major drawback is that it is unable to cope with large translations and rotations in the character. High-order networks have been utilized recently for invariant recognition.

In this type of model, one has to encode the properties of invariance in the values of the synaptic weights. The relations between pixels of the characters are used, and the invariance is directly constructed in the network. The number of combinations of possible relations between pixels increases in a nonlinear proportion to the number of input data. This is the main disadvantage of this approach. However, most of these methods are too computationally expensive or are not invariant under the three types of transformations: scaling, translation and rotation.

Invariant Character Recognition (ICR) that achieves excellent invariance under translation, rotation and scaling is proposed. The main contribution in this paper is the development and implementation of one new feature and use different character recognition algorithm for the improving character recognition performance.

II. Basic Block Diagram of Recognition System

Recognition can be defined as class assignment for input pattern that are not identical to the patterns used for training of

the classifier. Figure 1 shows the basic block diagram of recognition or classification system [2]. The recognition system consists of input transducer providing input pattern data to feature extractor. Inputs to the feature extractor are sets of data vectors; each such set of data vector consists of real numbers for given application. The converted data at the output of the transducer can be compressed while still maintaining same level of machine performance called as features. The feature space dimensionality is to be much smaller than dimensionality of pattern space. Classifier assigns a class to input pattern by using extracted features of feature extractor.

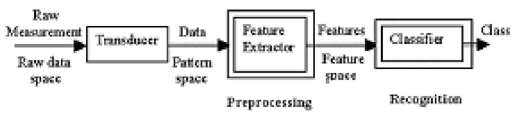


Figure 1 Basic block diagram of recognition system

PREPROCESSING

In invariant character recognition method, preprocessing is defined as the extraction of appropriate invariant features that are then used for recognition by a classification system. Feature can be defined as quantitative description of input character with in less dimension space and which is invariant under translation rotation and scale. The features play an important role in the recognition and classification system. Because the total information related to input character consists with in the extracted feature values. According to these feature values the high discriminate power of the classifier classifies the input character. The invariant features in this method are real numbers that are fed as vectors to the classification system.

The proposed invariant feature extraction takes reference from the centroid of the binary character. To find the centroid of two-dimensional object treat character as a very thin plate divide the object into small areas . For finding the centroid of object take the sum of the product of each area and the distance to an axis then divide by the total area of the object.

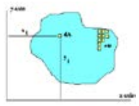


Figure.2 Centroid of the 2-D object

Centroid of character is calculated as follows:

For a given character the summation of product of each pixel x-coordinate and its gray value and divide the total number of character pixels in the character gives the x-coordinate of centroid.

Similarly y-coordinate of centroid can be calculated.

The centroid position is constant, even if the character is translated from its original position or rotates or scaled it. Taking reference as the centroid the Normalized moment of inertia radial coding features are found.

3.1 Normalized Moment of Inertia (NMI)

In general the moment of inertia quantifies the inertia of rotating object by considering its mass distribution. The moment of inertia is normally calculated by dividing the object into N-small pieces of mass m1, m2…..mN. Each pieces at a distance r1, r2…rN from the axis. The moment inertia of the object is where are the centroid co-ordinates. the image pixel co-ordinates of the character. 'N' is the total number of pixels in the character. By dividing moment of inertia by N 2 (we will name it IN) we get the Normalized moment of inertia. Due to the finite resolution of any digitized image, a rotated character may not conserve the number of pixels intact. So moment of inertia may vary but using normalized moment of inertia reduces this problem. The value of normalized moment of inertia invariant under translation rotation and scale invariant. The character 'A' and 'B' with different orientations showed in Figure 3, and results shown in Table 1

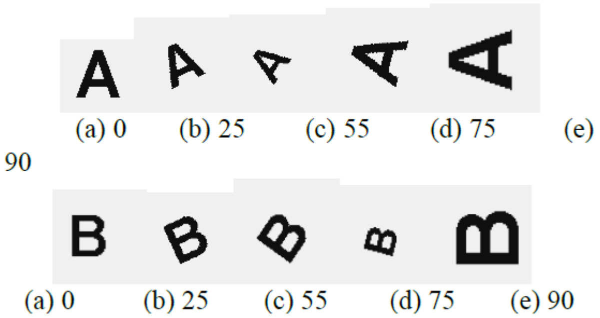


Figure.3 Testing images of letter ‘A’ and ‘B’ for different orientations

Table 1: NMI Features for Characters ‘A’ and ‘B’ for different orientations.

Cases

(a) (b) (c) (d) (e)

NMI A 0.2902 0.2933 0.2985 0.2940 0.2957

B 0.3061 027680.2819 0.2760 0.2838

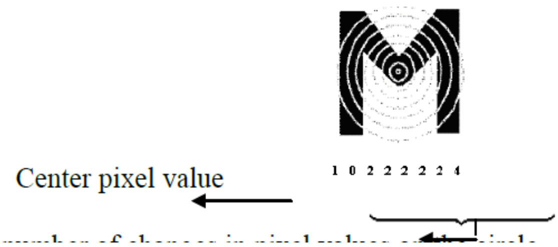
3.2 Radial Coding Features

The radial coding features are based on the fact that circle is the only geometrical shape that is naturally and perfectly invariant to rotation. In this we consider the number of intensity changes on two circular boundaries of some radius inside the character as it crosses it. This simple coding scheme extracts the topological characteristics of the character regardless of its position orientation and size. The methodology to obtain the radial coding features of a character can be summarized as follows:

1) Obtain the centroid of the character.

2) Generate K equidistant constant circles around the centroid. The spacing is equal to the distance between the centroid and furthest pixel of the object divided by K.

3) For each circular boundary, count the number of intensity changes (zero to one or one to zero) that occur in the image.



of changes in pixel values on the circle.

In the above parameters the first value is the centroid pixel value. The remaining values are number of changes in pixel values on the circle. Combining these normalized moment of inertia and radial coding features we develop a feature vector call as moment of inertia based radial coding features is input to the classification system.

IV. CHARACTER RECOGNITION SYSTEM

Proposed block diagram of character recognition system consists of two main blocks Preprocessing and Recognition shown in Figure 4. In preprocessing block we extract the Normalized moment of inertia and radial coding features of

Cases		(a)	(b)	(c)	(d)	(e)
NMI	A	0.2902	0.2933	0.2985	0.2940	0.2957
	B	0.3061	02768	0.2819	0.2760	0.2838

character. The radial coding method gives the number of intensity changes on the circular boundaries of some radius inside the character around the centroid develops eight features. Combining these features to develop a ten dimensional training feature vector in which nine attributes are features tenth one assigned as pattern class. For testing the characters the feature vector is of nine dimensions only except the class of character.

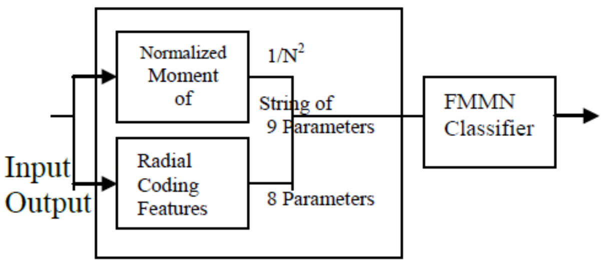


Figure 4 Block diagram of character recognition system.

The fuzzy min-max neural network (FMMN) proposed by Patrick Simpson [8] is a supervised learning neural network (NN) classifier that utilizes fuzzy sets as pattern classes. A fuzzy set hyperbox is an n-dimensional box defined by a min point and a max point with corresponding

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membership function. The min-max points are determined using the fuzzy min-max learning algorithm. An expansion-contraction process learns nonlinear class boundaries in a single pass through data and provides the ability to incorporate new and refine existing classes without retraining.

It is a three layer feed forward neural network shown in Figure 5. FA, FB, and FC represent these three layers respectively. FA layer consists of n processing nodes equal to the dimension of the input pattern. The number of nodes in FB layer is created during training, each FB node in this layer represents a hyperbox fuzzy set where FA to FB connections is the min-max points of hyper box and the FB transfer function is the hyper box membership function. The min points are stored in matrix V and max points are stored in matrix W. The connections are adjusted using learning algorithm. The FC layer consists of m nodes, each FC node represent a class.

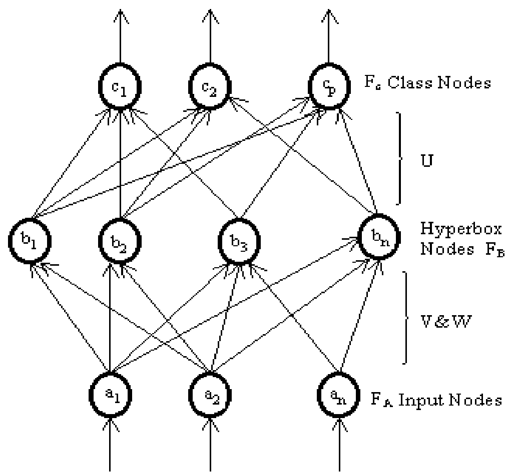

Figure.5 The Architecture of FMMN

The FMMN learning algorithm has four steps. They are initialization, hyperbox expansion, hyperbox overlap test and contraction. Initialization process is to create the first hyperbox with the first input pattern equal to the min-max points of the hyperbox. Hyperbox expansion processes test the expansion criteria of all ready created same class of max membership value hyperbox with presented input pattern. Overlap test allows the overlap between the hyperboxes from the same class and eliminates the overlap between the hyperboxes of different classes. Checks the overlap with the all dimensions of hyperbox and stores the minimum overlap dimension. In contraction process contract the overlapped hyperboxes along the minimum overlap dimension. The last three steps are repeated for all input patterns.

V. RESULTS

The character recognition system is tested using the 26 uppercase letters of the alphabet. Twelve different sizes and eight different orientations of each of 26 alphabets ninety-six experimental characters for each of the alphabet and in total 2496 experimental characters for all alphabets were generated. The largest character consists of 65x65 white pixels and smallest character consists of 15x15 white pixels. The Figure 6 shows few of the generated characters of letter E for different orientations and different sizes.

Learning Phase:

In order to obtain increased noise tolerance, during learning stage fifty percent of the randomly selected patterns from the total database used for learning. These patterns are called as training set including the class of character. Ten-dimension feature vector forms each training vector, in which first nine attributes are features and last one is its identifier. The first attribute is the normalized moment of inertia. The remaining eight features are number of changes of intensity pixel values, when the eight circles are intersected around the centroid of the character.

Recognition Phase:

Case	NMI	**CHARACTER ‘X’**
(a)	0.3381	1 0 3 4 4 4 4 4
(b)	0.3036	1 0 2 3 4 4 4 4
(c)	0.3146	1 0 2 4 4 4 4 3
(d)	0.3133	1 0 3 4 4 4 4 2
(e)	0.3356	1 0 3 4 4 4 4 4
(f)	0.3218	1 0 3 4 4 4 4 2
(g)	0.3384	1 0 3 4 4 4 4 4
(h)	0.3426	1 0 3 4 4 4 4 4

Each one of the 96 characters for all the 26 letters were used as the testing data set. During this recognition phase all the extracted features of testing data set except class were presented to the character recognition system and their classes were found out. The results were then compared with original class of the character presented.

It is important to mention that most of the characters are used to test the method present a certain degree of noise or deformation. The noise is intrinsically produced during the transformation of the letters to other sizes and orientations.

Table 2 demonstrates moment of inertia based radial coding features of character ‘X’ with different sizes and different orientations (0, 10, 25, 30.55, 75, 90, and 110).

One can observe that the moment of inertia based radial coding features for character ‘X’ almost constant (with marginal variations) even though size, position and rotation of the character are changed.

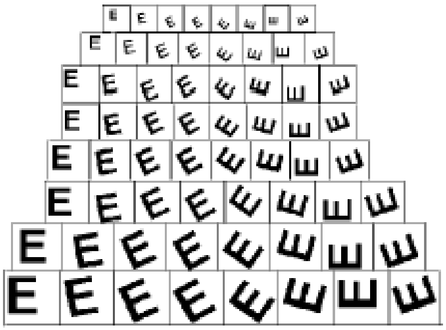

Figure 6: Testing images of letter ‘E’ for different orientations

Table 2: Moment of inertia based radial coding features for letter ‘X’ for different orientations and different sizes.

Figue 7: Testing character of letter ‘X’ for different orientations

These feature vectors can be used as input to the FMMN classification algorithm. The character recognition system is implemented on Pentium IV 1.4 GHz PC. The total database is used for the testing set of recognition purpose. The algorithm tested for this database moment of inertia based radial coding features. The percentage of recognition rate can be defined as

RECOGNITIONRATE

Initially, the FMMN algorithm is trained with different size of trained parameter (sensitivity parameter) equal to one.

Font type	%Recognition rate
Microsoft Scan serif	78.0
Ariel Unicode	82.0
Ariel Narrow	78.0

5.1 Results of single type of fonts

The results obtained with combination of moment of inertia and radial coding features shown in Table 3 and Table 4. The Table 3 shows the FMMN algorithm creates 404 hyperboxes and yields 100% recognition for training database. The table 4 shows the performance of FMMN algorithm with testing database and gives 98% recognition at which □ =0.03.

Table 3: Hyperboxes created and recognition rates obtained with the Training data set of moment inertia based radial coding Features

Hyperbox size	No.of created	%Recognition rate
0.05	280	97.5
0.04	331	97.9
0.03	404	98.0

Table 4: Hyperboxes created and recognition rates obtained with the Testing data set of moment inertia based radial coding Features

Hyperbox size	No.of created Hyperboxes	%Recognition rate
0.02	404	100

Table 5: Average percent recognition for each of the 26 letters

Letters	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
Percent Recogniti on	89	100	98	98	99	97	100	100	100	95	100	100	99

5.2 Results of different type of fonts

The character recognition system was also used test the different fonts (Arial Unicode, Arial Narrow, Microsoft scan Serif) of characters. The algorithm is trained with single font of database test with the different fonts. The Table 6 shows the percent recognition of different fonts. Mixed font of database prepared by taken a fifty percent of the data from each font of character. The algorithm is trained with mixed fonts

5.3 Results of handwritten characters

Character recognition system was also used to test for hand written characters of five different writers and seven different orientations (0, 10, 25, 30, 55, 75, and 90). The database prepare with these orientations for all five different writers. The fifty percent of the total database randomly selected used for training the classifier. The Table 8 shows the FMMN algorithm creates 270 hyperboxes and yields 100% recognition rate of training data set.

Table 8: Hyperboxes created and Recognition rates are obtained with the Training data set of moment of inertia based Radial Coding Features

Hyperbox size No.of created

Hyperboxes

%Recognition rate

0.02 270 100

The total prepared database of hand written characters used for testing the FMMN algorithm. Table 9 shows FMMN algorithm yields 85% recognition rate for testing data set at which

Table 9: Hyperboxes created and Recognition rates are obtained with the Testing data set of moment of inertia based Radial Coding Features

Hyperboxsize No. of created

Hyperboxes %Recognition rate

0.04 217 82.4

0.03 238 83.7

0.02 270 85.0

CONCLUSION

This work demonstrates a novel system to recognize the characters. The character recognition system is invariant to translation, rotation and scaling is reported to a very good recognition. This implemented recognition system based on FMMN classification algorithm is most robust and easy to implement. It is observed that the recall time of FMMN is small if the created hyperboxes are less. So choose the value of which will create less number of hyperboxes and recognize all the training patterns correctly.

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