A Novel Algorithm for Translation, Rotation and Scale Invariant Character Recognition

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***Abstract*—This paper presents a novel algorithm, called Radial Sector Coding (RSC), for Translation, Rotation and Scale invariant character recognition. Translation invariance is obtained using Center of Mass (CoM). Scaling invariance is achieved by normalizing the features of characters. To obtain most challenging rotation invariance, RSC searches a rotation invariant Line of Reference (LoR) by exploiting the symmetry property for symmetric characters and Axis of Reference (AoR) for non-symmetric characters. RSC uses the LoR to generate invariant topological features for different characters. The topological features are then used as inputs for a multilayer feed-forward artificial neural network (ANN). We test the proposed approach on two widely used English fonts Arial and Tahoma and got 98.6% recognition performance on average.**

I. Introduction

Optical character recognition is one of the most explored and successful area of computer vision. But Invariant Character Recognition (ICR), which is the recognition of characters independent of translation, rotation and scaling is still a hard problem in computer vision. There have been much works in ICR over the years. Most ICR algorithms used some kind of invariant moments.

In 1962 Hu [1] proposed translation, rotation and scale invariant moment for character recognition. Geometric moments [2]–[4] are also used for ICR. However, these moment based approaches are not orthogonal resulting in redundancy, and they are also computationally expensive. Orthogonal moments, such as Zernike [5], Pseudo-Zernike and Orthogonal Fourier-Mellin moments [6], are better for ICR [7] as they have very low redundancy. But they are even more computationally expensive than non-orthogonal moments. FARES *et al.* [8] used a projection based ring detector for recognizing rotated characters. Choi and Kim [9] proposed an algorithm for rotation invariant template matching based on combination of projection method and Zernike moment. But projection based methods are also inefficient in terms of data redundancy. Boundary based methods [10]–[14] in combination with other methods are also used for ICR. Boundary based methods work much well on rigid natural object recognition but it is not very good for character recognition as it cannot capture the internal topological information of characters. There are some ICR algorithms which extracted topological invariant features successfully. Torres-Mndez *et al.* [15] proposed radial coding and differential radial coding for extracting invariant features. SAFER proposed by Monirul Islam *et al.* [16] was a two stage algorithm for ICR which used a novel approach for extracting invariant features and used artificial neural network for classification. Both radial coding and SAFER used multiple concentric circles for feature extraction. Because of finite image resolution this method is erroneous for small circles. So both inner circles and circles at small characters generate erroneous features. Neural networks are extensively used in OCR and ICR as classifier and also as combination of feature extractor and classifier. Madaline structures for translation-invariant recognition [17], the self-organized recognition [18], and high-order neural networks [19]–[21] are examples of ICR neural-based methods. Yuceer and Oflazer [22], Fukushim [23], Hussain and Kabuka [24], Khotan-zad and Lu [25] also focused on invariant character recognition.

This paper proposes a new algorithm, called Radial Sector Coding (RSC) which extracts invariant topological features for translation, rotation and scale invariant character recognition. RSC emphasizes on both simplicity and generalization ability of the classification system. RSC is different from previous works on ICR in a number of ways. First, RSC uses simple method to extract topological features which is not computationally expensive like Cartesian, Zernike and other moment based methods.

Second, RSC do not sample the whole character for extracting features like Projection methods [8], [9]. So RSC do not have data redundancy like projection methods.

Third, unlike Boundary based methods [10]–[14] which consider the outer boundary only, RSC considers inside of the characters also for feature extraction. So RSC provides more topological information than boundary methods.

Fourth, Radial Coding [15] and SAFER [16] used multiple concentric circles and so small circles at inner side or in case of small characters create problems. In RSC we used single enclosing circle and its radii. So problems due to small circles are eliminated. Radii for being straight lines require less computation than circles also.

Fifth, we introduced the concept of Double Reverse Mirror Symmetry which is a feature of N, S and Z. Though in our current work we do not use this feature but in future both extension of RSC algorithm or other algorithms can exploit this feature.

Rest of the paper is organized as follows. In section II we describe the details of the RSC algorithm. Section III describes the classifier shortly. Section IV presents details of experimental results and analysis of result and the algorithm as a whole. Finally, section V gives the concluding remarks.

II. RSC

RSC uses a simple and new method to extract invariant topological features. At first, we have found Center of Mass (CoM) which locates the character within the image independent of translation. CoM is also a rotation invariant feature. Scaling invariance is easily obtained by normalization of features. The most challenging part was achieving rotation invariance. We achieved it by finding Axis of Reference which is a rotation invariant feature for all characters. Then we found Line of Reference from Axis of Reference which is considered as 0° line for feature generation and thus we generated Translation, Rotation and Scale invariant features. Major steps of RSC are given below which are further explained in later sections.

1) Find the Center of Mass (CoM) which locates the character independent of translation within the image.
2) Find the pixel of character having largest distance from the Center of Mass. This is the radius of enclosing circle centered at CoM for the character. Single enclosing circle is used as circle is the perfect rotation invariant shape. Inner circles are not used like [15], [16] for feature extraction as small circles result in erroneous data due to finite resolution of image.
3) Draw n radii at equal angular distance to divide the circle into n sectors. Because of using radii which are straight lines, problems of circles are avoided and straight line is also computationally less expensive than circle.
4) Find the cut-points for each radius. Cut-point is the pixel of intensity change in the character image with respect to radii.
5) Calculate distances of all cut-points from Center of Mass on each radius and calculate maximum cut-point distance and average distance of all cut-points for each radius.
6) Find Axis of Reference (AoR). AoR is a diameter of enclosing circle which is a rotation invariant feature for all characters. Details of finding AoR are explained in later section.
7) Find Line of Reference (LoR). Axis of Reference can be considered as a straight line containing two line segments joined at Center of Mass. LoR is one of the two line segments selected by maximum cut-point distance.
8) Consider Line of Reference as 0° line and generate feature vector of size $n/2$ considering the radii clockwise. Elements of feature vector are average of all cut-point distances for each radius.

The RSC algorithm described above is simple and effective for extracting topological features and the experimental results show that it achieves high recognition rate. Details of the steps of RSC algorithm is given in the following sections.

A. Center of Mass

Center of Mass (CoM) is a translation and rotation invariant feature for the character. If (C_x, C_y) is the CoM then it can be calculated in following way

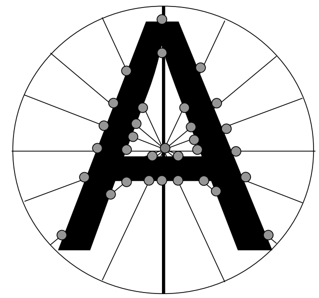

Fig. 1. Cut-points of A. Thicker line is the Axis of Reference of A

$$C_x = \frac{m_{10}}{m_{00}} \quad \text{and} \quad C_y = \frac{m_{01}}{m_{00}} \tag{1}$$

where, m_{pq} is the discrete Cartesian Moment of order $(p+q)$ and is defined as

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y) \tag{2}$$

here, $f(x,y)$ is the pixel value of the image at location (x,y).

B. Cut-point

Cut-point is the pixel of intensity change i.e. changes from white to black or from black to white with respect to a reference line. In RSC we have drawn n radii of character enclosing circle. For each radius we find cut-points of the character with the radius. Fig. 1 shows the cut-points of A.

C. Axis of Reference

Axis of Reference (AoR) is the straight line through the Center of Mass which is the axis of symmetry for symmetric characters and a rotation invariant feature for all characters.

We can determine the axis of symmetry of a symmetric character by comparing the maximum or average distance of cut-points for each pair of lines having equal angular distance from line of symmetry. For a symmetric character they will be nearly equal. So the summation of the absolute difference of the maximum or average cut-point distance of all pair of lines will be very low.

Now we can find the axis of symmetry by exploiting this fact. As we do not know the actual axis of symmetry we can consider each axis as a potential axis of symmetry and then we can calculate the sum of absolute difference of all pair of lines. One of them will have minimum sum and the line considered as an axis of symmetry for that case is the actual axis of symmetry.

Moreover, the axis found in this way for a nonsymmetrical character is invariant under rotation. So in this method we get axis of symmetry for symmetrical characters and a rotation invariant line for all characters. So we call it Axis of Reference rather than axis of symmetry.

We are using maximum distance instead of average distance. Rotation introduces boundary noise. In case of average distance more than one value is used which is found to be less

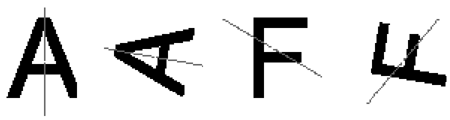

Fig. 2. Axis of Reference of Symmetrical character A and Non-symmetrical character F.

Fig. 3. Line of Reference of Symmetrical character A and Non-symmetrical character F.

robust practically compared to the maximum distance in case of which we are using one value. Thicker line in Fig. 1 is the Axis of Reference of A.

Now the Axis of Reference can be defined mathematically in following way-

Let d_i denotes maximum cut-point distance along each radius and initial sampling starting at 0° is

$$d_0, d_1, d_2, \ldots, d_n \qquad \text{(n is odd)} \tag{3}$$

Now there exists an ordering

$$d_i, d_{i+1}, \ldots, d_n, d_1, \ldots, d_{i-1} \tag{4}$$

where

$$\sum_{k=i+1}^{i+\frac{n-1}{2}} |d_k - d_{(k+\frac{n+1}{2})\%(n+1)}| \tag{5}$$

is minimum with respect to all other orderings.

Now let the points for d_i and $d_{i+\frac{n+1}{2}}$ are (x_i, y_i) and $(x_{i+\frac{n+1}{2}}, y_{i+\frac{n+1}{2}})$ respectively. Then the line connecting (x_i, y_i) and $(x_{i+\frac{n+1}{2}}, y_{i+\frac{n+1}{2}})$ is the Axis of Reference which passes through Center of Mass.

For example, let $d_0, d_1, d_2, \ldots, d_n$ is represented by 0 1 2 . . . n. For n = 35, consider the following case-
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 **18** 19 20 21 22 23 24 25 26 24 28 29 30 31 32 33 34 35
Now line connecting points of (0, 18) will be AoR if

$$\sum_{k=1}^{17} |d_k - d_{(k+18)\%36}| = \\ |d_1 - d_{19}| + |d_2 - d_{20}| + \ldots + |d_{17} - d_{35}| \tag{6}$$

is minimum with respect to all other orderings.

Similarly consider the following case-
7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 **25** 26 27 28 29 30 31 32 33 34 35 0 1 2 3 4 5 6
Now line connecting points of (7, 25) will be AoR if

$$\sum_{k=8}^{24} |d_k - d_{(k+18)\%36}| = \\ |d_8 - d_{26}| + |d_9 - d_{27}| + \ldots + |d_{24} - d_6| \tag{7}$$

is minimum with respect to all other orderings. Fig. 2 shows Axis of Reference for both symmetrical and nonsymmetrical characters.

D. Line of Reference

Let the boundary points of AoR are (x_i, y_i), $(x_{i+\frac{n+1}{2}}, y_{i+\frac{n+1}{2}})$ and the CoM is (C_x, C_y). AoR can be considered as two joining lines, one of which is the line connecting (C_x, C_y), (x_i, y_i) and other is the line connecting (C_x, C_y), $(x_{i+\frac{n+1}{2}}, y_{i+\frac{n+1}{2}})$. Now Line of Reference is defined as following:

Line of Reference is the line connecting (C_x, C_y), (x_i, y_i) if this line has maximum cut-point distance than the line connecting (C_x, C_y), $(x_{i+\frac{n+1}{2}}, y_{i+\frac{n+1}{2}})$. Otherwise, line connecting (C_x, C_y), $(x_{i+\frac{n+1}{2}}, y_{i+\frac{n+1}{2}})$ is the Line of Reference.

Fig. 3 shows Line of Reference for both symmetrical and non-symmetrical characters.

E. Feature Vector

We are using feature vector of size 18. After finding the Line of Reference it is considered as 0° line. Then average distance of cut-points on 18 radii drawn at equal angular distance staring from Line of Reference is calculated. The average distance is divided by the radius value to normalize for scale invariance. These 18 values consist of the feature vector. This feature vector captures the information of topological structure of the character.

III. Classifier

Multilayer feed-forward artificial neural network (ANN) is used as classifier. ANN has good noise tolerance and generalization capability. Rotation of the character introduces boundary noise and so noise in the feature is unavoidable. ANN is much robust to noise tolerance. High generalization capability is also desired in a character recognition system. This goal is also achieved using ANN.

IV. Experimental Results and Analysis

A. Data Set

We used 26 uppercase English characters for performance evaluation of RSC. Different rotated and scaled versions of Arial and Tahoma fonts for each character were used. We used two sets of characters. One set for training of artificial neural network and other set is used for performance test.

B. Experimental Setup

We used Matlab (Version 7.1.0.246 R14 Service Pack3) for feature generation and experimental evaluation. We used three layer feed-forward artificial neural network. Feature vector size at RSC is 18. So the input layer has 18 neurons. As we consider uppercase English characters the output layer is of size 26. We experimented with different architecture of the network. Among them 18-100-26 performed best.

Sigmoid function is used at the output layer of ANN which gives values between 0 and 1 and this range of value is desired for the classification of character. Hyperbolic tangent function is used in other layers of the ANN in RSC. It gives value

TABLE I

RECOGNITION RATE FOR ARIAL FONT. 40X40 PIXEL 0° TO 90° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TRAINING. 40X40 PIXEL 0° TO 350° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TESTING. TOTAL NUMBER OF TRAINING CHARACTERS IS 26X10 = 260. TOTAL NUMBER OF TEST CHARACTERS IS 26X36 = 936

Character	Accuracy	Character	Accuracy
A	100	N	100
B	100	O	100
C	100	P	100
D	100	Q	100
E	100	R	100
F	94.44444	S	100
G	91.66667	T	100
H	100	U	100
I	100	V	100
J	100	W	100
K	97.22222	X	100
L	100	Y	100
M	100	Z	100
Average			99.35897

TABLE II

RECOGNITION RATE FOR ARIAL FONT. 40X40 PIXEL 0° TO 135° ROTATED CHARACTERS AT 15° GAP ARE USED FOR TRAINING. 40X40 PIXEL 0° TO 355° ROTATED CHARACTERS AT 5° GAP ARE USED FOR TESTING. TOTAL NUMBER OF TRAINING CHARACTERS IS 26X10 = 260. TOTAL NUMBER OF TEST CHARACTERS IS 26X72 = 1872

Character	Accuracy	Character	Accuracy
A	98.61111	N	100
B	100	O	100
C	100	P	100
D	100	Q	97.22222
E	100	R	100
F	88.88889	S	100
G	98.61111	T	100
H	100	U	98.61111
I	100	V	100
J	100	W	97.22222
K	94.44444	X	97.22222
L	100	Y	97.22222
M	100	Z	100
Average			98.77137

between -1 and 1 and it is desired for the input and hidden layers as the synaptic weights may be negative.

In the training phase of the network learning goal was set to 0.0001 and learning rate was set to 0.2. Back-propagation algorithm with momentum and adaptive learning rate was used.

C. Experimental Results

Our experiments result in 98.6% recognition rate on average. Table I to Table VI show the recognition rate for different experimental setup. Table VII shows the average recognition rate for all characters considering Table I to Table VI and overall accuracy of RSC.

D. Analysis

In this section different aspects of RSC algorithm is analyzed.

1) Correlation of Features: Fig. 4 shows the features of 0° to 90° rotated A. From the graph it is clear that RSC generated highly correlated features under different rotation of characters.

TABLE III

RECOGNITION RATE FOR ARIAL FONT. 50X50 PIXEL 0° TO 90° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TRAINING. 50X50 PIXEL 0° TO 350° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TESTING. TOTAL NUMBER OF TRAINING CHARACTERS IS 26X10 = 260. TOTAL NUMBER OF TEST CHARACTERS IS 26X36 = 936

Character	Accuracy	Character	Accuracy
A	100	N	100
B	91.66667	O	100
C	100	P	100
D	100	Q	97.22222
E	100	R	100
F	97.22222	S	97.22222
G	100	T	100
H	100	U	100
I	100	V	100
J	100	W	100
K	100	X	100
L	100	Y	100
M	100	Z	83.33333
Average			98.71795

TABLE IV

RECOGNITION RATE FOR ARIAL FONT. 30X30 PIXEL 0° TO 90° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TRAINING. 30X30 PIXEL 0° TO 350° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TESTING. TOTAL NUMBER OF TRAINING CHARACTERS IS 26X10 = 260. TOTAL NUMBER OF TEST CHARACTERS IS 26X36 = 936

Character	Accuracy	Character	Accuracy
A	100	N	100
B	100	O	100
C	94.44444	P	100
D	100	Q	97.22222
E	100	R	100
F	100	S	83.33333
G	88.88889	T	100
H	97.22222	U	100
I	97.22222	V	100
J	100	W	100
K	97.22222	X	97.22222
L	94.44444	Y	100
M	100	Z	100
Average			97.97009

TABLE V

RECOGNITION RATE FOR ARIAL FONT. 40X40 PIXEL 0° TO 90° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TRAINING. 50X50 PIXEL 0° TO 350° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TESTING. TOTAL NO OF TRAINING CHARACTERS IS 26X10 = 260. TOTAL NUMBER OF TEST CHARACTERS IS 26X36 = 936

Character	Accuracy	Character	Accuracy
A	100	N	100
B	100	O	100
C	100	P	100
D	100	Q	100
E	100	R	100
F	100	S	100
G	100	T	100
H	97.22222	U	100
I	97.22222	V	100
J	100	W	100
K	100	X	100
L	100	Y	100
M	100	Z	100
Average			99.78632

2) Discrimination Capability for Similar Characters: In uppercase English characters there are some similar characters like C, O; O, Q. Some characters like A, V; N, Z; M, W are also similar when rotation is considered. RSC generates quite

TABLE VI
RECOGNITION RATE FOR TAHOMA FONT. 40X40 PIXEL 0° TO 90° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TRAINING. 50X50 PIXEL 0° TO 350° ROTATED CHARACTERS AT 10° GAP ARE USED FOR TESTING. TOTAL NUMBER OF TRAINING CHARACTERS IS 26X10 = 260. TOTAL NUMBER OF TEST CHARACTERS IS 26X36 = 936

Character	Accuracy	Character	Accuracy
A	100	N	100
B	55.55556	O	100
C	100	P	100
D	100	Q	100
E	100	R	91.66667
F	91.66667	S	100
G	100	T	100
H	100	U	97.22222
I	100	V	100
J	100	W	88.88889
K	100	X	97.22222
L	100	Y	100
M	100	Z	100
Average			97.00855

TABLE VII
AVERAGE RECOGNITION RATE FOR ALL CHARACTERS CONSIDERING TABLE I TO VI

Character	Accuracy	Character	Accuracy
A	99.76852	N	100
B	91.2037	O	100
C	100	P	100
D	100	Q	98.61111
E	100	R	98.61111
F	95.37037	S	96.75926
G	96.52778	T	100
H	99.07407	U	99.30556
I	99.07407	V	100
J	100	W	97.68519
K	98.14815	X	98.61111
L	99.07407	Y	99.53704
M	100	Z	97.22222
Average			98.60221

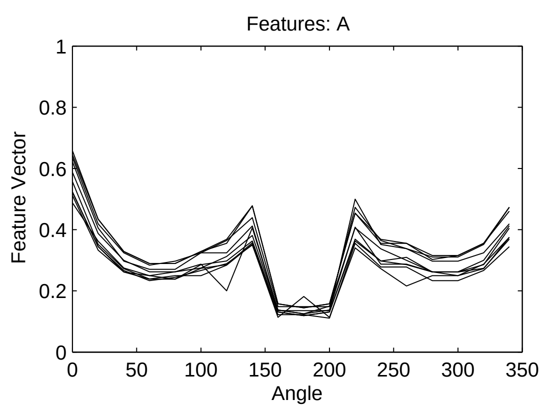

Fig. 4. Features of 0° to 90° rotated A.

distinct features to successfully classify them separately. This is because of considering whole area of the character enclosing circle for feature extraction. Fig. 5 compares the features of A and V.

3) Double Mirror Symmetry: H and I have two Axis of Symmetry. Any one of them is selected by RSC and hence we get two different LoR. So we get two sets of correlated feature. In our current work of RSC we do not use this double

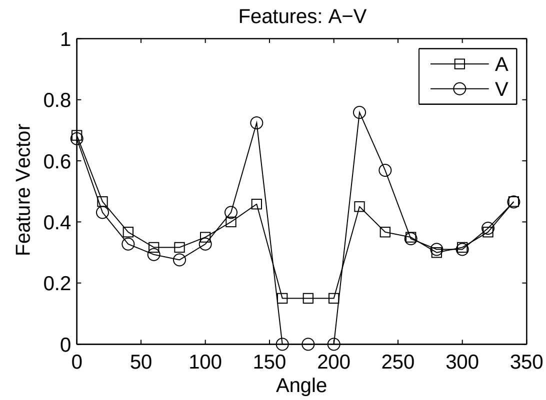

Fig. 5. Feature vector of 0° A and V.

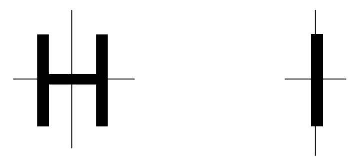

Fig. 6. Double Mirror Symmetry of H and I.

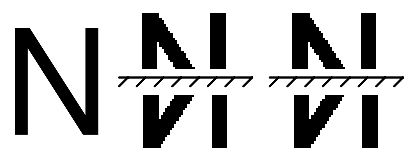

Fig. 7. Horizontal reverse mirror symmetry of N. Mirror reflection is shown at middle. Reverse of mirror reflection is shown at right.

symmetry property. In future, this property can be exploited to make RSC more robust as single set of correlated feature is better than two set of correlated features for classifier. But currently, we are not facing much problems as we have two set of correlated features for both training and testing. Fig. 6 shows the double axis of symmetry for H and I.

4) Double Reverse Mirror Symmetry: N, S and Z are not mirror symmetric but they are also symmetric if we reverse the mirror reflected part. So we call them Reverse Mirror Symmetric. Moreover they have two reverse mirror symmetric axis. So it is also natural to get two different Axis of Reference and hence two different LoR for them. So two set of correlated features are obtained. Again, classifier is not facing much problems as we have 2 set of correlated features for both training and testing. This property can also be exploited in future to make RSC even more robust. Fig. 7 and Fig. 8 show two reverse mirror symmetry of N. S and Z are also similar to N.

5) Inherent Difficulties: Some inherent difficulties for ICR are described in this section.

a) Finite Resolution: Character images have finite resolution. Beyond that sampling cannot be done. So the feature extraction process is limited by the resolution of the character image. Finite resolution creates more problems in case of low resolution images. The extracted features are poor from

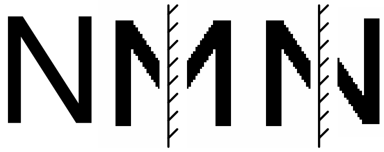

Fig. 8. Vertical reverse mirror symmetry of N. Mirror reflection is shown at middle. Reverse of mirror reflection is shown at right.

such images and as a result low performance is shown by the algorithm.

b) Round up error: The digital Image has discrete pixels and values. So any measure which has to mapped to image must be rounded up. In RSC, Center of Mass is used. If the calculated Center of Mass has fractional value then it is rounded up to map with the image pixel. Again, lines are used for sampling in the character image. Most of the times points of the line were fractional and it is rounded up to match the image pixel. These rounding of values introduce noise in the feature extraction which is unavoidable.

c) Boundary distortion: Rotation of character image introduces boundary noise which is unavoidable. This noise effects the feature extraction and different rotated version of same character has slight deviation in extracted features due to boundary noise.

V. Conclusion

In this paper we proposed a simple and inexpensive invariant topological feature extraction method for ICR. Different existing algorithms for ICR used different kinds of data set to evaluate their algorithms. Direct comparison of RSC with other existing algorithms is not possible unless we re-implement and test them under similar data set. However, we tested RSC over large and different kinds of data sets. Experimental results show that our algorithm achieves high recognition rate compared to existing expensive moment based algorithms and other algorithms. In our current implementation we used basic feed-forward ANN. Without using sophisticated classifier we achieve high recognition rate which proves the efficiency of our proposed RSC algorithm.

RSC is easy to implement and can be extended for multi-level images easily. In our current version of RSC algorithm we did not used double mirror symmetry and double reverse mirror symmetry property. But in future the double mirror symmetry and double reverse mirror symmetry property can be utilized. Also, performance of the algorithm may be increased by using more sophisticated classifier.

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