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Rotation and Scale Invariant Automated Logo Recognition System using Moment Invariants and Hough Transform

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Abstract: ***This paper proposes an automated system for rotation and scale invariant logo recognition system based on black and white logo images. Logo images are recognized using two shape features namely Moment Invariants and Hough Transform. For Moment Invariant Method the first two central normalized moments out of Hu's seven invariant moments are used In case of Hough Transform, first Standard Hough Transform (SHT) is performed. The Hough Transform matrix (H) along with array of theta and rho values over which H is generated is computed. Then six large singular values are calculated from this three parameters and they are added together to form the specified Hough Transform Feature. The data set consists of about 1700 black and white logo images where there are 100 different classes in which each class has got rotation, scaling and composite variations of each image, which are classified using Manhattan and Euclidian Distances. The user also has the flexibility of applying any arbitrary angle of rotation and scaling factor over the logo image and then correctly recognizing the logo, thus making this approach a rotation and scale invariant one. The proposed approach is highly scalable and robust providing better accuracy results than other techniques.***

Keywords: Logo Recognition, Moment Invariants, Hough Transform, Rotation and Scale Invariant

1. Introduction

A Logo is basically a graphic mark or symbol commonly used by commercial enterprises, organizations to promote public recognition of their organizations. Logos can be either purely graphical (only symbol), purely textual (only name of the organization) or textual-graphical (combination of both). Logos and their design are protected by copyright via various intellectual property rights thus making a logo always unique to an organization and thus provides a good recognition rate. Currently, the main applications of a logo Recognition System is in various security and detective agencies where they can track or identify an organization by recognizing the logo which may be present in any of the items they come across in their investigations. In case of sports, a logo is an important way to recognize a team's history and intimidate opponents. The challenges in a Logo Recognition System include building a reliable data model to represent the asymmetric logo shapes and finding ways of comparing the models with accuracy and in real time. Other challenges include rotation and scale variations that changes the original orientations of the image. This paper proposes an automated system for rotation and scale invariant black and white logo recognition based on various shape features. The organization of the paper is as follows: section 2 provides an overview of related work, section 3 provides an outline on the proposed approach with discussions on overview, feature extraction and classification schemes, section 4 provides details of the dataset and experimentation results obtained and section 5 provides overall conclusion and future scope for research.

2. Related Works

Many methodologies have been proposed for logo recognition. Most of the proposed approaches are based on shape features which represent the shape of the logo. Sometimes, also color features are taken into consideration for improving recognition accuracies. One of the earliest works [1] used negative shape features for Logo Recognition. They used global shape descriptors like eccentricity, circularity, rectangularity and local shape descriptors like horizontal gaps per total area and vertical gaps per total area. The concept Of Hough transform has been described for image processing applications in [2]. In [3] the authors used Fourier Transform and information entropy for E-goods Logo Recognition. They used Correlation ratio threshold and entropy difference ratio threshold for matching. Various methods were used to compare their effectiveness in Logo Recognition in [4] such as Log-Polar Transform, Fourier-Mellin Transform and Gradient Location-Orientation Histogram. In [5] the authors use Harris Corner Detector for localization of interest regions and then uses color Histogram. Comparison of various local shape descriptors have been done on [6]. Scale Invariant Feature Transform (SIFT) was used to detect the interest regions and approximate nearest neighbor is used for efficient matching in [7]. The authors in [8] used Speeded Up Robust Feature (SURF) for Logo Recognition. Authors in [9] used Angular Radial Transform (ART) to classify logo images. In [10], various methods such as radialTchebichef moments, Zernike Moments, Legendre Moments were used.

3. Proposed Approach

This paper proposes an automated system for rotation and scale invariant Logo Recognition based on shape features like Moment Invariants and Hough Transform. Finally Euclidian Distance is used as the classifier.

3.1 Moment Invariants

M-K Hu [11] proposed 7 moment features to describe shape that are invariant to rotation, scaling and translation. For an image the moment of a pixel P(x,y) at a location (x,y) is defined as the product of pixel values and its coordinate distances i.e. m=x.y.P(x,y). The moment of an entire image is the summation of moments of all the pixels. The moment of order (p,q) of an image I(x,y) is given by

$m_{pq}= \sum_x \sum_y [x^p y^q I(x,y)]$ (1)

Based on the values of p,q the following moments are defined

$m_{00} =\sum_x \sum_y [x^0y^0I(x,y)]= \sum_x \sum_y [I(x,y)]$
$m_{10} =\sum_x \sum_y [x^1y^0I(x,y)]= \sum_x \sum_y [xI(x,y)]$
$m_{01} =\sum_x \sum_y [x^0y^1I(x,y)]= \sum_x \sum_y [y(x,y)]$
$m_{11} =\sum_x \sum_y [x^1y^1I(x,y)]= \sum_x \sum_y [xyI(x,y)]$
$m_{20} =\sum_x \sum_y [x^2y^0I(x,y)]= \sum_x \sum_y [x^2I(x,y)]$ (2)
$m_{02} =\sum_x \sum_y [x^0y^0I(x,y)]= \sum_x \sum_y [y^2I(x,y)]$
$m_{21} =\sum_x \sum_y [x^0y^0I(x,y)]= \sum_x \sum_y [x^2yI(x,y)]$
$m_{12} =\sum_x \sum_y [x^0y^0I(x,y)]= \sum_x \sum_y [xy^2I(x,y)]$
$m_{30} =\sum_x \sum_y [x^0y^0I(x,y)]= \sum_x \sum_y [x^3I(x,y)]$
$m_{03} =\sum_x \sum_y [x^0y^0I(x,y)]= \sum_x \sum_y [y^3I(x,y)]$

The first 3 moments invariant to rotation are described as follows:

$\varphi_1 = m_{20} + m_{02}$
$\varphi_2 = (m_{20} - m_{02})^2 + (2m_{11})^2$(3)
$\varphi 3 = (m_{30} - m_{12})^2 + (3m_{21} - m_{03})^2$

To make the moments invariant to translation, the image is shifted such that its centroid coincides with the origin of the coordinate system. The centroid of image in terms of moments is given by:

$$x_c = \frac{m10}{m00} \qquad (4)$$
$$y_c = \frac{m01}{m00}$$

The central moments are defined as follows:

$$\mu_{pq} = \sum_x \sum_y [(x-x_c)^p (y-y_c)^q \, I(x,y)] \qquad (5)$$

To compute Hu moments using central moments the m terms in (2) are replaced by μ terms such that $\mu_{00} = m_{00}$.

To make the moments invariant to scaling, the moments are normalized by dividing by a power of μ_{00}. The normalized central moments are defined as follows:

$$\delta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\omega}} \text{ where } \omega = 1 + \frac{p+q}{2} \qquad (6)$$

The normalized central moments are defined by substituting the m terms in equation (4) by δ terms. The first and second central normalized invariant moments of an image I are therefore defined as:

$$M1\ (I) = \delta 20 + \delta 02 \qquad (7)$$
$$M2\ (I) = (\delta 20 - \delta 02)\ \hat{}2 + (2\delta 11)\ \hat{}2$$

3.2 Hough Transform

Paul Hough [12] proposed Hough Transform as method to recognize complex patterns. Later, Duda and Hart [13] modified it and proposed generalized Hough Transform for identification of lines within an image. Finally Ballard [14] popularized Hough Transform to detect arbitrary shapes. Originally Hough Transform was used to detect lines which used the parametric representation of a line:

$$\rho = x\cos\theta + y\sin\theta \qquad (8)$$

The variable ρ (rho) is the distance from origin to the line along a vector perpendicular to this line and θ (theta) is the angle between x axis and this vector.

3.3 Feature Vector and Classification

For each logo image, the first and second order invariant moments, M_1 and M_2 are calculated. Then Hough Transform is applied on the logo image and as a result three different matrices the Hough Matrix (H), Rho matrix and Theta matrix are obtained. Since, all of them are large sparse matrices, only six highest singular values of each of them are taken and added together to form the feature for Hough Transform, HT. The final feature vector E is a three element vector comprising of M_1, M_2 and HT.

$$E = [M_1 M_2\ HT] \qquad (9)$$

Finally the feature vector of the input test image is compared with the feature vectors of the test images and the distance is computed using Euclidian Distance Classifier and is classified correctly to the class for which the Euclidian distance is minimum.

3.4 Discrimination between Known and Unknown Logo Images

First before processing any logo image and calculating feature values, a check is done to determine whether it is a logo image within the dataset or is an unknown logo image. The check is done by comparing the minimum distance of the input test image with a certain threshold value. The threshold value is fixed by calculating the maximum of all the minimum distances of all 1700 test images in the dataset which is obtained by rotating, scaling and both each of the 100 classes of logo. If the minimum distance of the input test image exceeds the threshold value, then it does not belong to the dataset. If its value is less than threshold value, then it belongs to the dataset and is processed further for feature calculation.

4. Experimentations and Results

For experimentation, UMD-Logos [15] dataset is used. The UMD-Logos dataset consists of 100 different classes of black and white images, each class consisting of nine different rotation variations of 9°, 15°, 30°, 45° ,60°, 90°, 120°,150° and 180°, five different scaling variations with scaling factors 0.5, 0.75, 0.9, 1.25, 2, and three composite transformations with rotation by 30° followed by scaling factor 0.5, rotation by 60 followed by scaling 0.7 and

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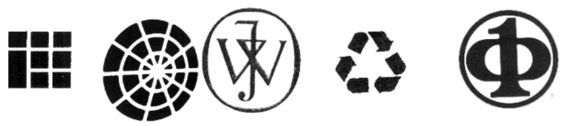
rotation 120 followed by scaling factor 1.2.

Total no. of rotated images = 900
Total no. of scaled images = 500
Total no. of scaled and rotated images = 300
Total no. of images = 1700

Apart from this the user has the provision of rotating and scaling the input image by arbitrary value and then classifying the transformed image thus making infinite variations possible for each class of logo images. The images are in BMP Format. All different variations of images are shown in Fig. 1.

1 6 8 10 17



23 28 32 35 40

42 49 54 61 69

75 82 89 98 100

Figure 1: Sample of Logo images with Class Number

Rotation Rotation Rotation Rotation Rotation by 9° by 15° by 30° by 45° by 60°

Rotation RotationRotationRotation by 90° by 120° by 150° by 180°

Scaling ScalingScalingScalingScaling by 0.5 by 0.75 by 0.9by 1.25by 2.0

Rotation 30, Rotation 60, Rotation 90, scaling 0.5 scaling 0.7 scaling 1.2

Figure 2: Variations of Logo images

From each class of the dataset, the first four images are sequentially read as training images and the feature vector are computed. For comparing among various features, the individual features are normalized by multiplying with some factors. Feature Values of 5 different classes are mentioned below in Table 1.

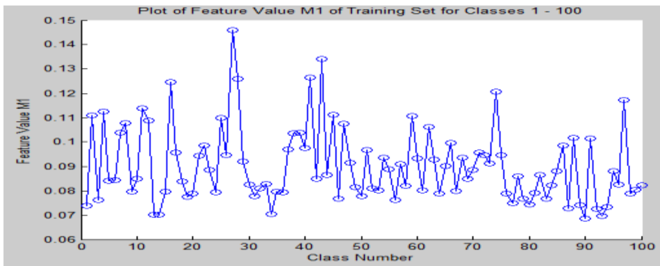
$M1n = M1 \times 10^{2}$

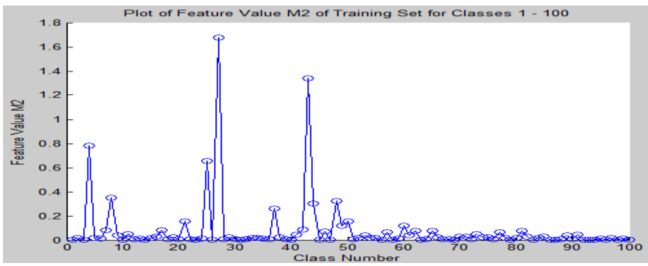
$M2n = M2 \times 10^{6}$

$HTn = HT \times 10^{-5}$

Table 1: Feature Values of Training Set Samples

Class	Sample no.	M1n	M2n	HTn
1	1	0.0742	2.68×10^{-3}	0.1424
	2	0.0739	2.42×10^{-3}	0.1427
	3	0.0740	2.68×10^{-3}	0.1426
	4	0.0739	2.46×10^{-3}	0.1429
51	1	0.1063	0.0179	0.1982
	2	0.1090	0.0113	0.2054
	3	0.1066	0.0081	0.2039
	4	0.1096	0.0054	0.2038
75	1	0.0947	0.0300	0.2914
	2	0.0947	0.0262	0.2982
	3	0.0947	0.0224	0.2811
	4	0.0947	0.0263	0.2969
100	1	0.0821	1.16×10^{-3}	0.2963
	2	0.0822	1.28×10^{-3}	0.2968
	3	0.0821	1.11×10^{-3}	0.2969
	4	0.0822	1.16×10^{-3}	0.2975





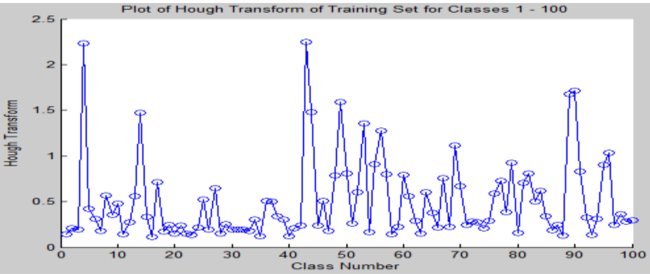


Figure 3: Variation of Feature Value M1, M2, HT of Training Set in 2D Space for Classes 1 - 100

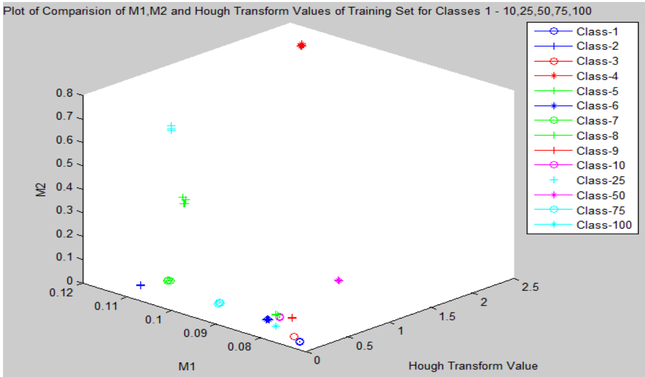
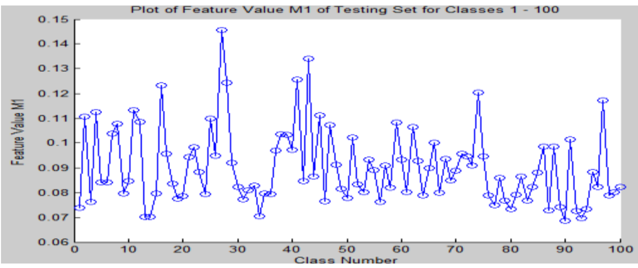
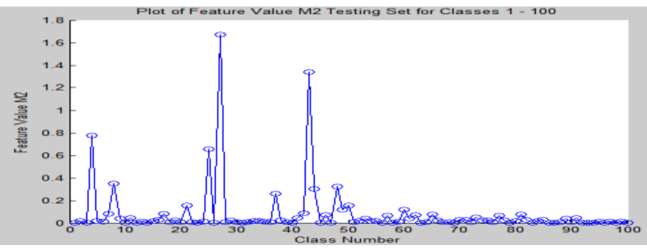


Figure 4: Variationof Feature Value M1-M2-HTof Training Set in 3D Space

Table 2: Feature Values of Testing Set Samples

Class	Sample no.	M1n	M2n	HTn
1	5	0.0739	2.34×10^{-3}	0.1427
	6	0.0738	2.44×10^{-3}	0.1428
	7	0.0739	2.56×10^{-3}	0.1426
	8	0.0739	2.46×10^{-3}	0.1428
51	5	0.1070	0.0157	0.2038
	6	0.1088	0.0096	0.2056
	7	0.1066	0.0078	0.3187
	8	0.1088	0.0096	0.2059
75	5	0.0947	0.0301	0.2934
	6	0.0947	0.0263	0.2976
	7	0.0947	0.0225	0.2810
	8	0.0946	0.0263	0.2974
100	5	0.0821	0.95×10^{-3}	0.2972
	6	0.0821	0.94×10^{-3}	0.2962
	7	0.0821	0.99×10^{-3}	0.2968
	8	0.0821	1.06×10^{-3}	0.2967





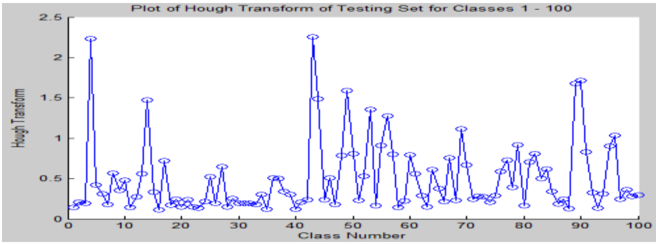


Figure 5: Variation of Feature Value M1, M2, and HT of Testing Set in 2D Space for classes 1 – 100

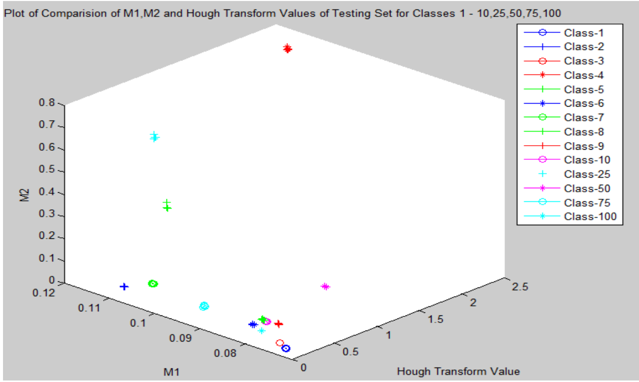


Figure 6: Variation of Feature Value M1-M2-HT of Testing Set in 3D Space

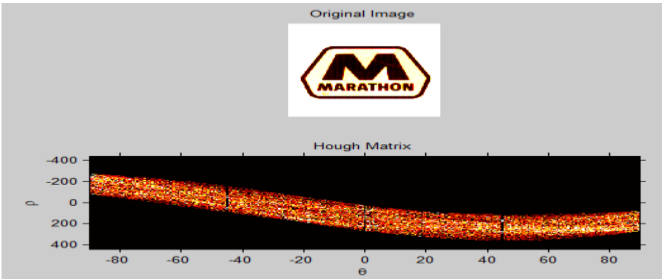
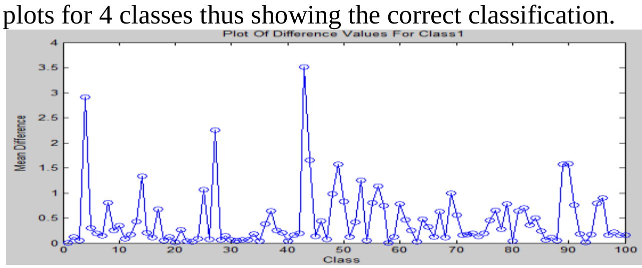
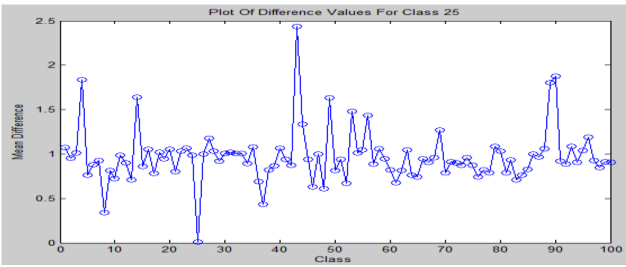


Figure 7: Original Image and its Hough Transform

After computing the feature vectors, the difference between train and test samples are calculated using Euclidian distance Classifier and test sample is classified to the class with minimum difference plots. Figure 8 shows the difference plots for 4 classes thus showing the correct classification.





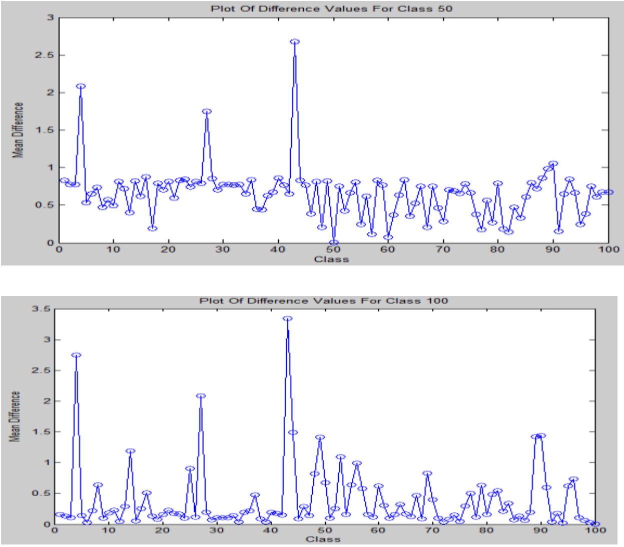


Figure 8: Difference Plots for Classes 1, 25, 50, 100

4.1Discrimination between Known and Unknown Logo Images

Fig. 9 below displays the plot to discriminate between known logo images within the dataset and unknown logo images by comparing with a threshold value. For experimental purposes, 10 unknown logo images have been compared with 10 known logo images of the dataset using a threshold value. The threshold value is calculated as discussed earlier by taking the maximum of all the minimum distances of all 1700 test images in the dataset. In this case the threshold computed is 0.0150. The 10 images with minimum distance greater than threshold value is classified as unknown classes, whereas 10 images having minimum distance less than the threshold is termed as known classes.

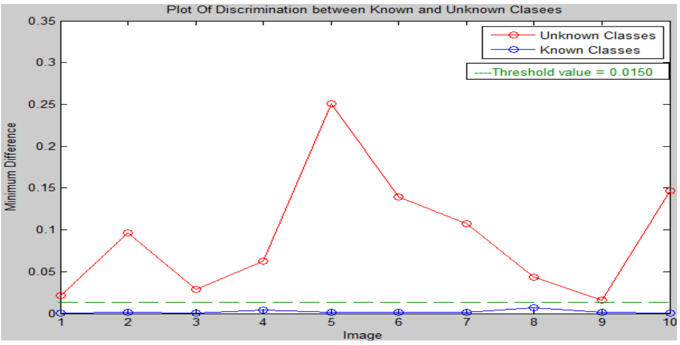


Figure 9: Plot of Discrimination between Known and Unknown Logo Images using threshold

Accuracy:
For UMD-Logos Dataset with rotation variations, by rotating, scaling the original image consisting a total of 1700 images, recognition accuracy using combination of various features is shown in Table 3.

The highest recorded accuracy is by using the features M1, M2 and HT as a vector which is 98.94%. Other than this predefined variations, the user can apply arbitrary rotation and scaling variations on any image from dataset and then can classify the images.

Table 3: Recognition Accuracy obtained from various methods

Features	M1	HT	M1 M2	M1 HT	M1 M2 HT
% Accuracy	64.2	78.4	87.2	95.75	98.94

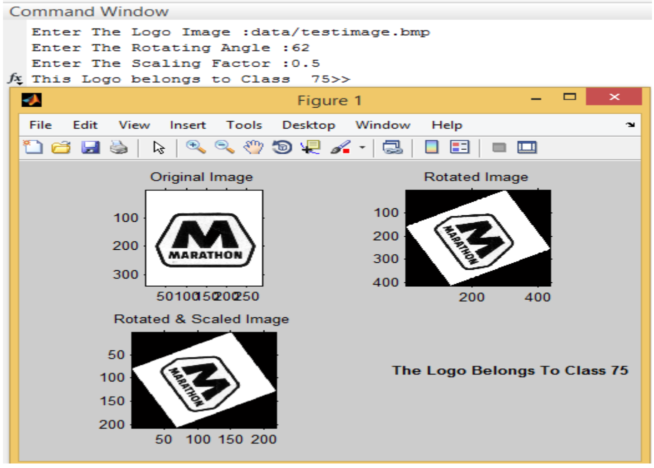


Figure 10: Experimentation Results using arbitrary variations input by User

5. Analysis

Automated recognition of logo images have been done using combination of various methods. Hough Transform gives a better result than individual Moment invariant M1 but M1 and M2 used as a vector gives better result than individual M1 or HT. But the proposed approach using M1 M2 HT as a vector gives the best result. To put the above results in perspective with the state of art, the following table shows comparison of the proposed approach with that of [4]. In both approaches, the transformation applied to original logos images are of 5 types, namely scaling by 0.5, 0.75 and rotation by 15°, 30°, and 45°. After applying his transformations the results obtained for the two methods are explained in details in Table 4:

Table 4: Comparison between recognition accuracy of approaches used in [4] and proposed approach

Different Approach	No. of Classes	Total No. of images	Processing Time	Combined Recognition Accuracy % (Using all 5 transformations)
FMT in [4]	46	230	3.92 min	84.84
LPT in [4]	46	230	9.73 min	86.83
Moment Invariant in [4]	46	230	9.30 min	90.27
Proposed Approach	100	500	3.40 min	99

5.1 Comparison of methods in [4] and proposed approach

From the above table it can be inferred that the proposed approach outperforms all the methods mentioned in approach [4] both in terms of recognition accuracy and processing time and also in terms of database size. Also another constraint of [4] is that their images needs to be resized to 256 × 256 before extracting features.

Further Log Polar Transform (LPT) and Fourier Mellin Transform (FMT) suffer loss of information due to conversion into log polar form, as Cartesian coordinates cannot be mapped one-to-one into log-polar coordinate space. Therefore average of the surrounding pixels is used in mapping in log polar space, which results in loss of information. Also LPT and FMT has low recognition rates as they are affected by interpolation artifacts while rotating the images. The proposed approach solves all the above problems showing good results for both rotation and scaling.
In [9] Angular radial transform(ART) is used to classify logos using transformations with rotation of 9°, 30, 60°, 90° and 180° and scaling factors of 0.5, 0.7, 0.9 separately. Following tables 5 and 6 show in details the comparison between two methods.

Table 5: Comparison between recognition accuracy of approaches under different rotation angles

Rotation Angle	*ART System[9]*	*Proposed Approach*
9°	99.0476	100
30°	73.3333	99
60°	61.9048	95
90°	66.6667	100
180°	92.3810	100
Average	78.6667	99.8

Table 6: Comparison between recognition accuracy of approaches under different scaling factors

Scaling Factor	*ART System[9]*	*Proposed Approach*
0.5	53.3333	99
0.75	78.0952	99
0.9	95.2381	100
Average	75.5555	99.33

5.2 Comparison of Methods in [9] and Proposed Approach

The major drawback of ART is that for segmented planar objects from real images, one have to take into account unspecified rotations. As the basis functions are symmetrical in the angular direction, the invariance is inherent for planar rotations. Unspecified rotations induce a real deformation of the original shape due to the perspective projection into the image plan. More precisely ART is not invariant to all rotations, but in case of proposed approach, user can apply any rotations of his choice and still correctly recognize the logo.

It therefore can be said that the accuracies reported in the current paper are comparable to the best results reported in extant literature and the proposed approach clearly outperforms the other approaches in case of rotation and scaling thus proving the robustness of the proposed system.

In [10] various methods, like Zernike Moments (ZM), Legendre Moments (LM), RadialTchebichef Moments (RTM) have been used for logo recognition using rotation and scaling transformations. Various rotation transformations such as 30°, 60°, 90°, 120° and 150° and composite transformations such as scaling & rotation are performed. The comparison of the above method and proposed approach is shown in the table 7 and 8.

Table 7: Comparison between recognition accuracy of approaches under different rotation angles

Rotation Angle	ZM method used in [10]	LM method used in [10]	RTM method used in [10]	Proposed Approach
30°	20	30	90	99
60°	20	28	72	95
90°	98	6	100	100
120°	20	20	74	97
150°	20	26	80	100
Average Rate	21.2	22	83.2	98.2

Table 8: Comparison between recognition accuracy of approaches under different rotation and scaling

Rotation Angles & Scaling Factor	LM method used in [10]	ZM method used in [10]	RTM method used in [10]	Proposed Approach
Rotation 30°, Scaling 0.5	30	20	38	99
Rotation 60°, Scaling 0.75	28	20	36	100
Rotation 90°, Scaling 1.25	6	98	52	100
Average Rate	21.33	34	42	99.67

5.3 Comparison of Methods in [10] and Proposed Approach

The main disadvantages of Zernike moments are that the image coordinate space must be transformed to the domain where the orthogonal polynomial is defined. The continuous integrals in Zernike moments must be approximated by discrete summations. This approximation not only leads to numerical errors in the computed moments, but also severely affects the analytical properties such as rotational invariance. Computational complexity of the radial Zernike polynomial increases as the order becomes large. Comparing the results in the above 3 methods it can be clearly stated the proposed approach clearly outperforms the other approaches in case of rotation and scaling thus proving the robustness of the proposed system.

5.4 Overall Comparison of other methods with Proposed Approach (PA)

Table 9: Comparison Of Various Approaches with rotation and scaling transformations

	RTM	ZM	LM	ART	FMT	LPT	PA
% Acc	53.75	59.7	63	76.6	84.8	86.8	98.94

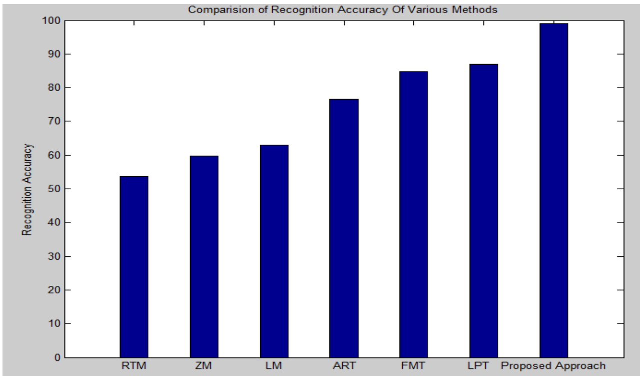


Figure 10: Comparison Plot of Recognition Accuracy of Various Methods

6. Conclusions and Future Scopes

This paper proposes an automated system for rotation and scale invariant logo recognition. This system uses 1st and 2nd Order Invariant Moments along with Hough transform for recognizing logo images of the UMD-Logos Dataset. The accuracy of the proposed approach is comparable to those reported in contemporary works. One of the salient features of the system is the high scalability, flexibility and robustness allowing the user to apply arbitrary variations in rotation and scaling. Future work would involve research in the following directions: (1) applying non-uniform scaling and other transformations to distort the image and then recognize it, (2) using various texture features other than shape and color features to recognize distorted images with a good recognition accuracy, and (3) using other dataset or other logo images to increase the scalability of the proposed approach.

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