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HOUGH AND BINARY PATTERN BASED DESCRIPTOR FOR 2D SHAPES

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Abstract- In this paper, we propose Hough and Binary Pattern based shape descriptor for 2D shapes. The Hough Transform estimates the parameters of a shape from its boundary and region points and is robust to noise. It is capable of capturing the region information. The Euclidean Distance metric is used for the feature matching. We have also proposed decision level fusion of Hough and Binary Pattern approach for enhancing the accuracy of representation and classification of 2d shapes. The Binary Pattern is a local descriptor capturing the local information by considering 8 neighbors of every shape pixel. The Earth Movers Distance (EMD) distance is used as the metric for feature matching. The decision level fusion of Hough and BBP descriptor gives better classification accuracy which has been demonstrated experimentally on the publicly available shape databases namely, Kimia-99 and Kimia-216 and MPEG-7 data sets. The Precision-Recall graph has been drawn for MPEG-7 dataset presenting the retrieval accuracy. The experimental results demonstrate the success of the proposed approach.
Keywords– Hough Transform, Binary Pattern, Euclidean distance, Earth Movers Distance, Combined classifier, Decision fusion, Shape Representation, Shape Classification, Shape descriptor.

1. INTRODUCTION

Recognition of objects is very significant task in modern intelligent systems. The growing demands of object recognition in industrial inspection system, optical character recognition systems, medical imaging, defense and bio-metrics motivated researchers to develop sophisticated algorithms for the object recognition. In order to have an efficient and accurate recognition system, a powerful representation scheme is very essential. There are several representation schemes available in the state of art literature. Out of which, the shape of 2D objects forms a more dominant representation scheme and also provides a powerful semantic clue for feature matching compared to color or texture. In most of the applications, the image analysis can be reduced to the analysis of shapes, hence shape based approaches receiving increased attention from researchers. There are many algorithms exists in the literature for the shape representation which are broadly classified as contour based [3] [7] [18] and region based [4] [6] [11] [17] methods. There are approaches which combine both contour and region based methods and also more than one feature vectors [2] [5] in order to enhance the accuracy of the representation and classification. In this paper we have used decision level fusion of Hough and Binary Pattern based features.
The rest of the paper is organized as follows. Proposed approach is explained in section II. Experimental results are presented in section III. Conclusion is presented in section IV.

2. PROPOSED ALGORITHM

In our work, we propose Hough transform and Binary pattern for representing 2D shapes. The following section presents in detail the proposed approach. Firstly, the Hough Transformation features of the shape are calculated. The Euclidean distance measure is used to compare the Hough features. Then we have integrated Hough Transformation with the Binary Pattern based features, where EMD metric is employed to find out the distance between Binary Pattern based features of every two shapes. The decision level fusion of distance matrices gives rise to an accurate combined classifier model.

2.1 Hough Transform based feature extraction –

The Hough Transform method was introduced by P.V.C. Hough in 1962, in the form of a patent [13]. It was first used to find lines in images by Duda in 1972 [14]. The process of finding Hough Transformation of the image is given below. The parameter space is divided into cells (ρ_i, Θ_j), known as accumulator cells with (ρ max; ρ min) and (Θmax; Θmin) being the expected ranges of $\rho\Theta$ plane. Initially All the cells are initialized to zero. For every (x, y) the following steps are performed. Let Θ= every subdivision on the Θ-axis. The ρ value is computed as follows $\rho = xk\cos\Theta + yk\sin\Theta$. The ρ value is rounded off to the nearest allotted value on the ρ-axis. The accumulator cell (ρ_i, Θ_j) is incremented by 1 and the corresponding value for ρ is computed. This is the value for the accumulator cell (ρ_i, Θ_j).

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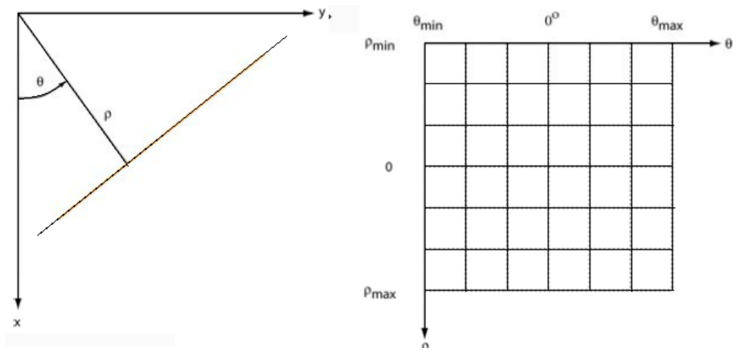

Figure 1. (a)Normal representation of a line (b)Subdivision of the ρΘ plane into cells

We have pre-processed the shape dataset as follows. Firstly, the shapes are aligned to the horizontal axis to avoid the problems related to the rotation. Secondly, the shapes are resized to a predefined dimension 200x100. A rectangular bounding box is fitted to the shape to eliminate irrelevant pixels. The Hough transform is applied and the coefficients of the Hough transformed image are taken as a feature vector. The feature vector is stored in the knowledge base. Repeat the above process for every shape in the training set forming the Hough knowledge base. The Figure 2 shows the Hough transformed image for the given shapes.

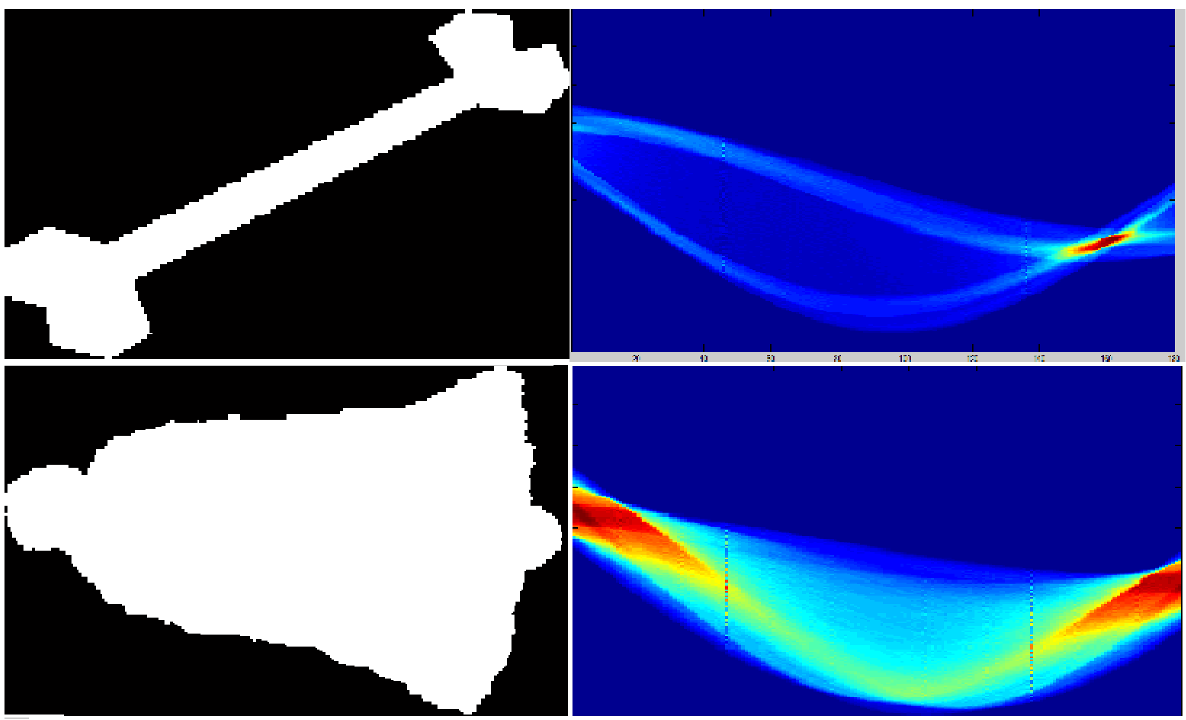

Figure 2. Shapes and their corresponding Hough transformed images.

In order to obtain Binary Pattern for the shape, we carry out the following process. Every shape pixel is assigned a decimal value based on the neighboring pixels. In this process 8 neighbors are considered. The binary values of the 8 neighbors are traversed in a clockwise direction forming a binary stream. The decimal equivalent of this is dependent on the position of traversal and is rotation variant. Hence we performed series of shift operation and a minimal decimal equivalent of the binary series is taken for the further processing. This minimal decimal equivalent of the binary stream represents the new value for the pixel under consideration. After performing this decimal computation process for all the pixels, we get an image with all the pixels having decimal values. Now, we convert this image into 10 bin histogram, forming the feature vector. . The process of computing the new value for the central pixel is explained in detail in our paper [17]. Repeat the above process for every shape in the training set and the feature vectors are stored in the knowledge base.

2.2 Decision level fusion and Classification –

In the above feature extraction method gives us 2 set of features i.e. Hough based and Binary Pattern based features. These features are combined using decision level fusion method. The Hough based feature vectors are compared using Euclidean distance metric. The Binary Pattern feature vectors are compared using Earth Movers Distance Metric. The distance matrices obtained using decision level fusion resulting in resultant matrix as follows.

$DR = D_H + \beta D_B$ ----------- (1)

Where D_H is the decision matrix corresponding to Hough features, D_B is the decision matrix corresponding Binary Pattern based features and β is the parameter whose value deduced experimentally.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments have been conducted on publicly available shape datasets namely Kimia-99, Kimia-216 and MPEG-7 Datasets. The Kimia-99 dataset contains 99 shapes with 9 classes and 11 samples. The Table-1 presents top-N retrievals for the Kimia-99 dataset. We have also presented a comparative analysis with few well known algorithms from the literature.

Table 1. Top 10 closest matching shapes on Kimia's 99 dataset – A comparison

Approach	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	Total
SC [15]	97	91	88	85	84	77	75	66	56	37	756
CPDH+EMD (Eucl) [18]	96	94	94	87	88	82	80	70	62	55	808
CPDH+EMD (shift) [18]	98	94	95	92	90	88	85	84	71	52	849
Proposed Hough	**99**	**98**	**95**	**95**	**88**	**80**	**84**	**84**	**71**	**63**	**857**
Gen Model [19]	99	97	99	98	96	96	94	83	75	48	885
Learned manifold [5]	99	99	98	98	98	96	95	89	80	65	917
Proposed Hough+BBP	**99**	**99**	**99**	**96**	**95**	**93**	**93**	**87**	**84**	**76**	**921**

The Kimia-216 dataset contains 216 shapes with 18 classes and 12 samples. The Table-2 presents the retrieval results in terms of top-N retrieval for Kimia-216 dataset, in comparison with other well known approaches in the literature.

Table 2. Top 11 closest matching shapes on Kimia's 216 dataset – A comparison

Approach	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	Total
SC [15]	214	209	205	197	191	178	161	144	131	101	78	1809
CPDH+EMD(Eucl)[18]	214	215	209	204	200	193	187	180	168	146	114	2030
CPDH+EMD(shift)[18]	215	215	213	205	203	204	190	180	168	154	123	2070
Proposed Hough	**211**	**209**	**208**	**200**	**197**	**196**	**185**	**169**	**173**	**147**	**135**	**2030**
Proposed Hough+BBP	**215**	**215**	**211**	**207**	**205**	**204**	**203**	**194**	**185**	**184**	**157**	**2180**

The MPEG-7 dataset contains 1400 shapes with 70 classes and 20 samples. We have also presented retrieval accuracy interms of Bull's eye score for MPEG-7 dataset, in comparison with other well known approaches. The Figure 3 presents the Precision-Recall graph of IDSC approach and the proposed approach. We can notice proposed approach exhibits better accuracy compared to IDSC.

Table 3. Retrieval rate (Bull's eye Score) on MPEG-7 dataset - A comparative Analysis

Approach	MPEG-7
Proposed Hough+BBP	**88.64**
Learned manifold [5]	88.52
Two Strategies [1]	88.39
Aspect shape context [4]	88.30
Hierarchical Parts [10]	88.30
Shape tree [12]	87.70
TAR+Shape complexity global [8]	87.23
TAR+Shape complexity [9]	87.13
SC+DP [16]	86.80
HPM [3]	86.35
Symbolic representation [7]	85.92

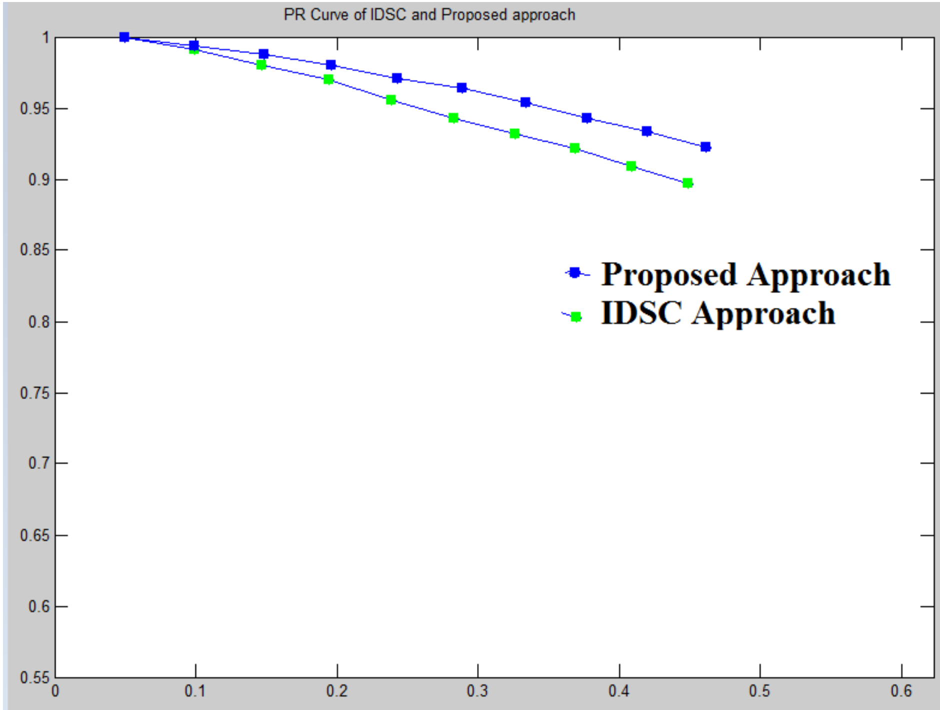

Figure 3. Precision-Recall graph on MPEG-7 dataset.

The performance of the proposed approach interms of Bull’s eye score for various standard shape datasets is shown in Table-8.

Table 4. Bull's Eye Score on MPEG-7, Kimia-216, Kimia-99 datasets.

Approach	MPEG-7	KIMIA-216	KIMIA-99
Proposed Hough	77.11	93.60	95.96
Proposed Hough+BBP	88.64	95.14	98.62

4. CONCLUSION

In this work, we have designed a shape descriptor based on Hough Transform and Binary Pattern. The Hough transform is capable of capturing the region information and is insensitive to boundary noise. The Binary Pattern captures local information of the shape, which is invariant to rotation and shift of the object. The decision level fusion of these two works well and gives better classification accuracy. The Experimental results of proposed approach on standard shape databases namely MPEG-7, Kimia-216 and Kimia-99 datasets exhibit the success of the proposed approach.

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