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Fish Shape Recognition –An Approach using Histogram, Edge Detection and Hough Transform

Doyel Basu
School of Education Technology
Jadavpur University
Kolkata,India

Joydeep Mukherjee
School of Education Technology
Jadavpur University
Kolkata,India

ABSTRACT
This paper studies recognition of fish shapes using histogram, edge detection and hough transform[4]. The shapes are varied through scaling and rotation. The study of the recognition rate by using histogram, edge detection and hough transform is done separately. Then they are combined to get hybrid feature vectors for improving recognition rate.

General Terms
Fish Shape recognition

Keywords
Histogram, Edge Detection, Hough Transform.

1. INTRODUCTION
The number of digital images is growing rapidly, a consequence of the intense use of digital cameras, multimedia services etc. Imagery is being generated and maintained for a large variety of applications including art galleries, architectural and engineering design, geographic information systems, weather forecasting, medical diagnostics and law enforcement. Besides, in many areas, the use of image analysis has increased. In this situation, the ability to classify images is essential in order to manage and organize the collection of images on a database. Image search engines are generally based on textual metadata (e.g. file name, author, file size, creating date).

In contrast, content-based image recognition (CBIR) systems filter images based on their color, texture, shape or other features, providing better indexing and giving more accurate results. When an image is searched on the Internet, through search engines like Google and Yahoo, often, it is not possible to get the results of the expected image. In content-based image database systems, intrinsic properties of the query images are extracted in feature vectors which are indexed or compared to dataset images during query processing to find similar images from the database. Image classification is related to various areas.

This paper proposes a methodology to identify and recognize images in a CBIR scenario using histogram, edge detection and hough transform. The organization of the paper is as follows: section 2 provides an overview of the previous works, section 3 outlines the proposed approach, section 4 details the experimentations done and results obtained, section 5 brings up the overall conclusions and future scopes.

2. RELATED WORK

The Hough transform was introduced in a U.S. patent in 1962 [4], and was initially used to locate particle tracks in bubble chamber imagery. It was brought to the attention of the computer vision community by Rosenfeld [10]. Breuel [11] described a line detection technique related to the Hough transform that searches hierarchical subdivisions of the parameter space using a bounded error model and thus avoids some of the problems of the accumulator method. In this technique, the parameter space is divided into cells that are tested to determine whether they can contain a line that passes within the bounded localization error of a specified number of pixels. If the cell cannot be ruled out, the cell is divided and the procedure is repeated recursively. This continues until the cells become sufficiently small, at which point they are considered to be lines satisfying the output criterion. Shapiro and Iannino [20] have given a geometric construction of the region in the parameter space that a point in the image maps to for line detection under a bounded error assumption. This information was applied to the determination of the appropriate size for cells in the accumulator method of peak detection. Shapiro [24] further considered a Hough transform variation where the edge points are mapped into all of the curves in the parameter space that satisfy the error model for the edge point. We argue that this is the correct direction to take in propagating discretization and localization error in the Hough transform.

The main advantage of the histogram is that it can be determined very quickly. The color histogram approach is an attractive method for object recognition, because of its simplicity, speed and robustness. However, its reliance on object color and (to a lesser degree) light source intensity make it inappropriate for many recognition problems. The focus of our work has been to develop a similar technique using local descriptions of an object's shape provided by a vector of linear receptive fields [24].

A further advantage in image processing is, that it can be calculated incrementally (which is useful e.g. for the calculation of histograms in overlapping windows) [23].

3. PROPOSED METHODOLOGY

The present paper proposes a scheme for automated detection of 2 classes of fish shapes. Each class is represented by 40 images with transformed variations (rotated and scaled).There are some training and testing sets in each class. First, we calculate the class mean for training set of each class. Then for each samples, in each class of testing set, calculate the distance between the sample and the training set class mean. Now find the minimum distance among each sample of each class with each class mean and thus increase the count for each class having minimum distance .Then find the accuracy for each class and finally compute the combined accuracy.

The features are grouped into three categories: (1) Histogram (2) Edge detection and (3) Hough transform. For each group, the similarity measure is used i.e. Euclidean distance.

3.1 Histogram

Histogram is a graphical representation of the distribution of data. It is an estimate of the probability distribution of a continuous variable [25].

In mathematics a histogram is a function ***mi*** that counts the number of observations that falls in each of the category (bins). Thus, if ***n*** is the total number of observations and ***k*** is the total number of bins, the histogram ***mi*** meets the following conditions:

$$n = \Sigma\,(mi) \quad \text{when } i=1 \text{ to } k$$

In our proposed approach image histogram feature is extracted by applying this formulae. So the histogram value matrix holds only values between zero and ones.

3.2 Edge Detection

Shape of an image describes more or less each and every object presented in an image. Edge extracted from an image tells us about the full content of an image. It is a primary tool in image processing, particularly in the areas of feature detection and feature extraction, which aim at identifying points in an image at which the image brightness changes sharply or, more formally, has discontinuities.

There are various techniques of edge detection available i.e. Prewitt method, Sobel method, Robert method etc. But in our proposed system Canny's method is used. It is proposed by John Canny. He derived optimal smoothing filter algorithm by giving criteria of detection, localization and minimizing multiple responses to a single edge. He used a filter that is well approximated by first-order derivatives of Gaussians. Though it is an old approach, but it is still hard to find an edge detection technique better than this.

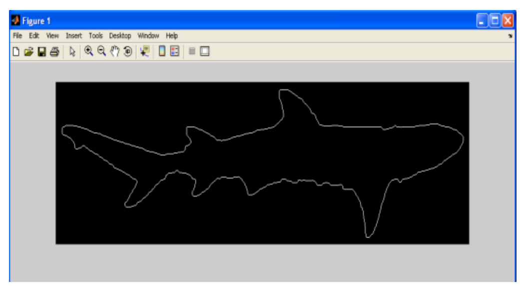
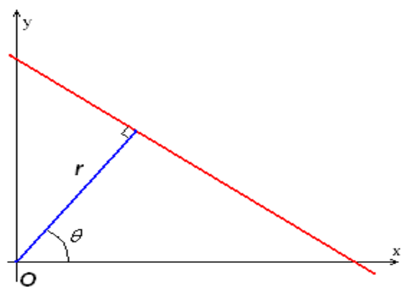


Fig 1: Edge detection by Canny method

3.3 Hough Transform

The Hough transform is a method that can be used to find features of any shape in an image. It is generally used for finding straight lines or circles. The computational complexity of the method grows rapidly with more complex shapes.

In the image space, the straight line can be described as $y = mx + b$ where the parameter m is the slope of the line, and b is the intercept (y-intercept). This is called the slope-intercept model of a straight line. In the Hough transform, a main idea is to consider the characteristics of the straight line not as discrete image points (x_1, y_1), (x_2, y_2), etc., but instead, in terms of its parameters according to the slope-intercept model, i.e., the slope parameter m and the intercept parameter b. In general, the straight line $y = mx + b$ can be represented as a point (b, m) in the parameter space. However, vertical lines pose a problem. They are more naturally described as $x = a$ and would give rise to unbounded values of the slope parameter m. Thus, for computational reasons, Duda and Hart proposed the use of a different pair of parameters, denoted r and θ (*theta*), for the lines in the Hough transform. These two values, taken in conjunction, define a polar coordinate.



The parameter r represents the algebraic distance between the line and the origin, while θ is the angle of the vector orthogonal to the line and pointing toward the half upper plane. If the line is located above the origin, θ is simply the angle of the vector from the origin to this closest point. Using this parameterization, the equation of the line can be written as

$$y = \left(-\frac{\cos\theta}{\sin\theta}\right)x + \left(\frac{r}{\sin\theta}\right)$$

which can be rearranged to $r = x\cos\theta + y\sin\theta$.It is therefore possible to associate with each line of the image a pair (r,θ) which is unique if $\theta \in [0, \pi)$ and $r \in \mathbf{R}$,or if $\theta \in [0, 2\pi)$ and $r \geq 0$. The (r,θ) plane is sometimes referred to as *Hough space* for the set of straight lines in two dimensions.

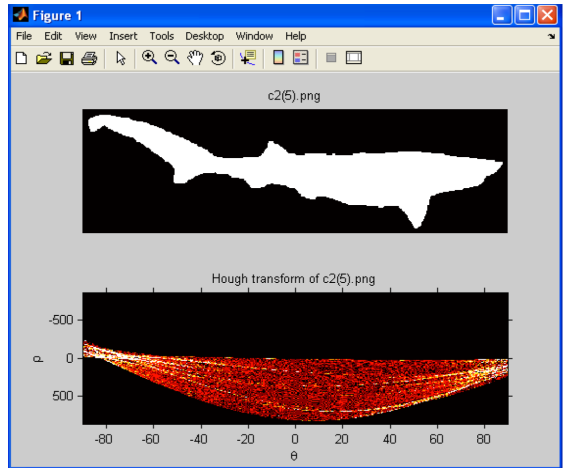


Fig 2: Hough Transform of an image

4. EXPERIMENTAL RESULTS

Experimentations are performed by using 80 fish images taken from the Shape CN dataset [16]. The dataset is divided into 2 classes of 40 samples each, out of which 12 sample is used for training the system and the remaining 28 samples are used for testing. All images are saved in PNG format .

The test samples are either a scaled or rotated version of the training sample. For each class, the first 12 test samples are derived by scaling the training sample by 20%, 40%, 60%, 80% and the remaining 16 test samples are derived by rotating the training sample by 7 degrees, 35 degrees, 132 degrees, 201 degrees and 298 degrees. Fig. 3 depicts the training images of 2 classes.

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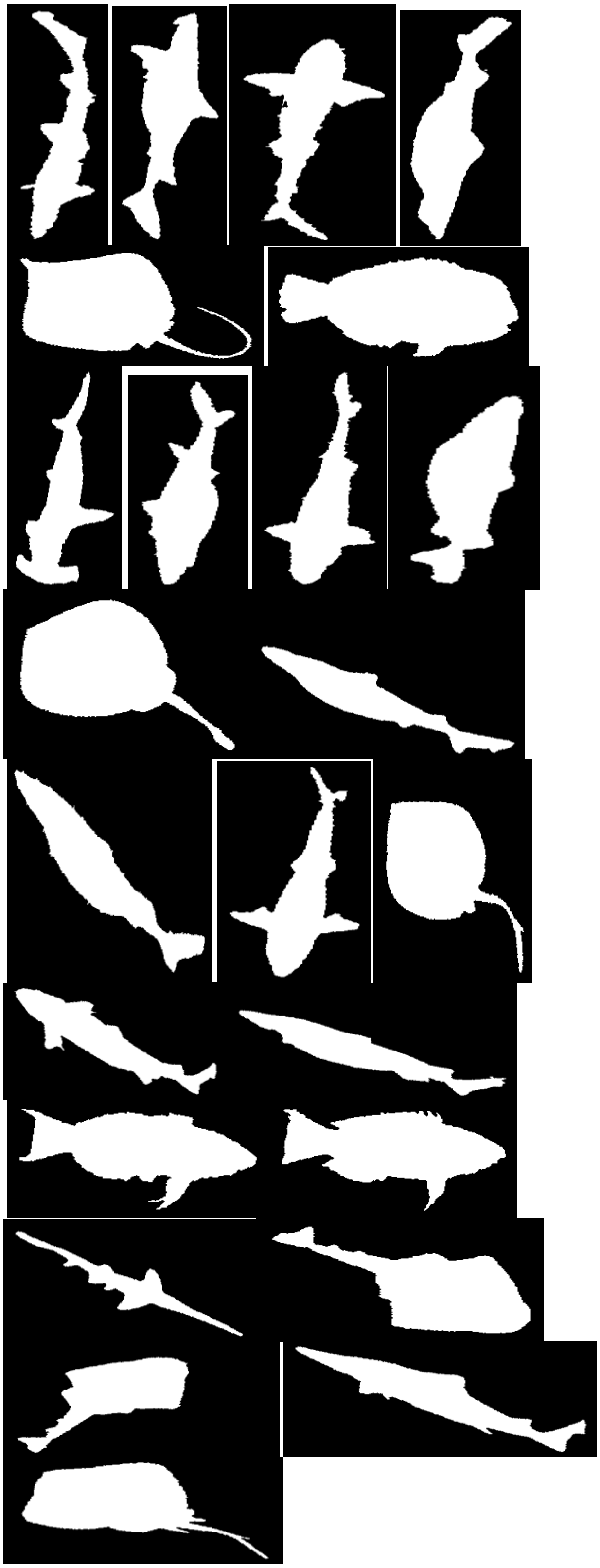


Fig 3: Training Images for 2 classes

Accuracy Table:

Table 1. Accuracy table for different features

	Accuracy Percentage		
	Only Histogram	**Only Edge**	**Only Hough Transform**
Class1	55.53	57.14	67.86
Class2	60.75	96.43	90.43
Overall Accuracy	58.14	76.79	79.14

Table 2. Recognition rate using combined features

Features Used	**Overall recognition rate (%) achieved**
Histogram+ Edge+ Hough transform Approach	83.93

To provide a visual representation of the variation of these feature values over the classes, Fig. 4 & Fig.5 depicts classification plots of Training set and Testing set for two classes namely class-1, class-2.

Fig.4. Plot of Feature Values of Training Set

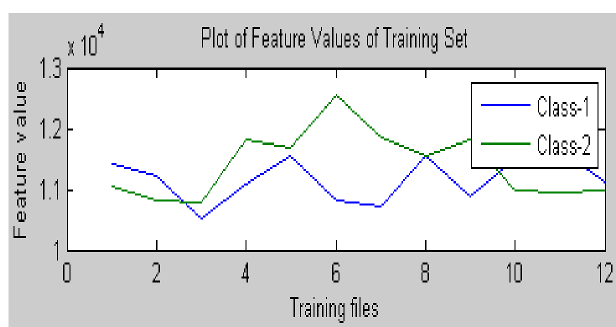


Fig.5. Plot of Feature Values of Testing Set

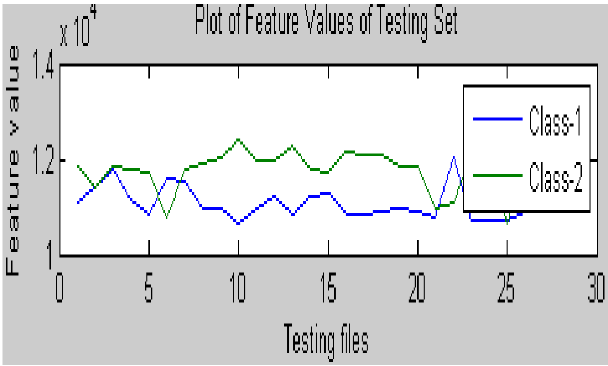
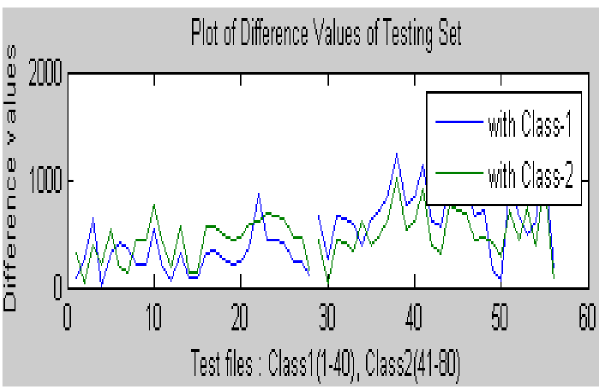


Fig.6. Plot of Difference Values of Testing Set



5. CONCLUSIONS & FUTURE SCOPES

In this paper, transformation and scaling of the original image are taken into account. Experiments show that Hough tranform gives the highest accuracy value. Combining histogram and edge detection with Hough transform produces an improvement upon of these features individually. The different feature extraction methods used in this paper are experimented with binary images. Though, transformation and scaling are considered, but noise is not applied on the query image.

Future work, can involve segmentation and other feature extraction methods and can involve Fourier descriptors .

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