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Image Processing Techniques to Recognize and Classify Bottle Articles

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ABSTRACT
Solid object recognition and classification has been an area of interest with the increasing environmental and economic concerns. Our work mainly concentrates on identification of bottles and classifying the same into one of several categories, like glass, metal, polystyrene, and low density polyethylene (LDPE). Using a combination of several standard image processing techniques like Principle Component Analysis (PCA), Hough Transforms (HT) and Rod Touch Analysis (RTA) we deduce an algorithm called the Bottle Recognition and Classification (BRC) to efficiently recognize and classify the bottles to various classes with good degree of speed and accuracy.

Keywords
solid object detection; object recognition; image processing; principle component analysis; hough transforms

1. INTRODUCTION
Solid object recognition and classification has been an area of Solid object recognition and classification has been an area of interest in the field of Image Processing [5]. Many researches have taken place for recognition and classification of solid articles, and here is an attempt to recognize bottles articles and classify them into one of several classes like glass, metal, polystyrene, and low density polyethylene (LDPE) bottles.

There are many standard object recognition algorithms [2] available to facilitate solid object detection and classification. Considering the merits and demerits of some of these algorithms, we have come up with an efficient algorithm called as the Bottle Detection and Recognition (BDR) to accomplish bottle recognition and classification.
For any object detection approach, an input image will be of varying sizes, textures and orientations. Hence, in order to identify bottles among them accurately and to classify them to respective classes is a challenging task. In order to efficiently recognize and classify any given input of varying characteristics, we pass the input image through a sequence of stages as follows.

- Pre-processing of the input image.
- Recognizing if the image is a bottle or not.
- If the image is a bottle, classifying them to respective classes.

In general, when we take a snapshot of an image for object recognition, the image will be usually out of place with different orientation and overlapping. So to input a consistent image to BRC, we first pre-process the image. This increases the detection and classification rate. After pre-processing, we produce the pre-processed image to BRC. BRC mainly consists of Hough Transforms (HT), Principle Component Analysis (PCA) and Rod Touch Analysis (RTA).

We performed our implementation in Matlab R2011. In general we observe that the algorithms provide accurate classification for single isolated images, but performance gradually decreases with increasing clutter.

The rest of the paper is organized as follows. Section 2 elaborates on the adopted mechanism to implement BRC algorithm. Section 3 discusses on implementation of the proposed algorithm. Section 4 discusses on the results and accuracy and efficiency of the proposed model. We conclude with Section 5.

2. PROPOSED MECHANISM
As an initial step of bottle recognition, we first pre-process the image. The sequence of steps in pre-processing the image is described in Algorithm 1.
The algorithm explains the preprocessing steps that need to be followed before producing the image to BRC algorithm. First we normalize the given input image since each image obtained will be of different types and dimensions. To bring about the standardization, we convert the image to standard 640 × 480 dimension and store them as a jpeg image to maintain consistency. Then we sharpen the given image by applying Laplacian filter mask [4] as shown in the algorithm and produce the output of this step as the input to BRC.
Algorithm 1: Preprocessing Image (input_image)

begin

1. Convert the image under consideration to a standard jpeg image;
2. Resize the given image for the dimension 640 x 480;
3. Apply Laplacian Filter to sharpen the scaled image. The Laplacian transformation is obtained by applying convolution with the following 2D filter kernel :
   a. $$\begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$
4. Produce this as the input to BRC

Recognition of bottle articles is implemented in two stages. First we apply Hough Transforms (HT) on the given image. Then we tried to recognize using standard Principle Component Analysis (PCA). Once we successfully identify the bottles, we then move on to classify them to various classes of bottles. Each of the mechanism has its sets of advantages and demerits.

The generic flow of our mechanism is shown in the algorithmic representation below.
Algorithm 2: BRC (preprocessed _image)

begin

1. Apply Hough Transform to recognize the preprocessed _image based on geometry;

2. Produce the output of Hough Transform to Principle Component Analysis to increase the accuracy of the recognized image;

3. Once a bottle is recognized, apply rod-touch analysis to classify the image into various clusters of bottles;

4. Output the king of bottle under consideration

The first step of BRC is applying of Hough Transforms on the pre-processed image.

A. *Hough Transforms*

This phase aims to recognize the presence of bottles. The procedure is based on identification of an image based on shape of the object. The Hough Transform is a feature-extraction technique which can be used to detect simple shapes. This is a method for estimating the parameters of a shape from its boundary points. This is more efficient than some other techniques, because the orientation of the object does not pose a problem in this case. The Hough Transform considers points along the edge of the shapes 0, draws lines of angles from -90 to +90 degrees, uses the Line equation shown in (Fig.1)[SPECIFY the equation here], to find the inclination and length of the perpendicular to those lines from the origin, and then computes a table of values of angles (θ) and lengths (r) for each point [1].

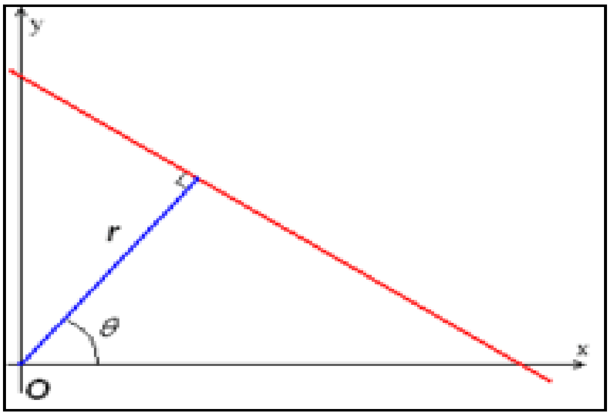

Figure 1

Using this, the transform then plots a graph of r vs. θ values, to produce a graph called as the Hough space graph [6] as shown in Figure 2.

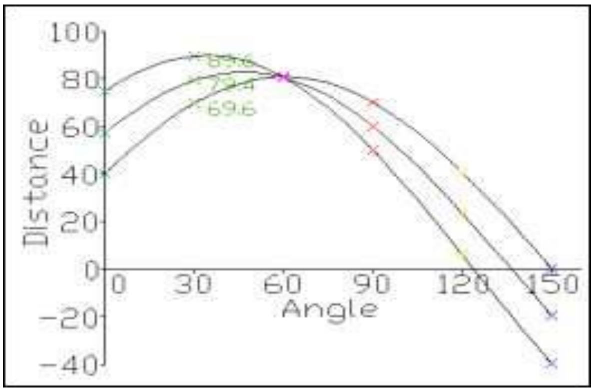

Figure 2

We then extract the frequency information from the Hough space graph, and use it to differentiate between the bottles and cups. We see that there is a variation in the Hough graphs for bottles and other type of articles.

B. *Principle Component Analysis*

Once the image has been recognized as bottle by the shape analysis through Hough transforms, we further strengthen the detection by producing this image as an input to Principle Component Analysis.

Principal component analysis (PCA) is a multivariate technique that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables [2]. Its goal is to extract the important information from the table, to represent it as a set of new orthogonal variables called principal components, and to display the pattern of similarity of the observations and of the variables as points in maps.

There are many interesting applications of Principle Component Analysis and the latest and most significant being in the field of Face Recognition. We propose a model for bottle recognition using principle component analysis.

We start off with matrix representation of the detected image from HT.

1. We represent them as an array of one dimensional vector in step (1).
2. We calculate the mean of each vector in step (2).
3. In step (3), we subtract the pixel value from the mean and make an array *A* of such values
4. We observe an important fact here that we calculate $C=AA^T$ and not A^TA. This is mainly for the dimensionality reduction. We then compute the Eigen values and Eigen vectors for *C.* We finally preserve only K largest Eigen values and check the distance of these vectors from the vectors of bottle images in the database. If it's found to be less than the threshold, then we declare it to be a misclassified image, else, it is confirmed to be recognized as bottle

The below algorithm explains the various stages of bottle recognition through PCA.

Algorithm 3: PCA(Pre-processed_image)

begin

1. Represent the pre-processed image as an N array of 1-D vectors;
2. Calculate the mean $\tilde{x}_i = \frac{1}{N} \times \sum_{i=1}^{m} x_i$;
3. Calculate $\delta_i = x_i - \bar{x}$;
4. Form a matrix $A = [\tilde{x_1}, \tilde{x_2}, \ldots, \tilde{x_N}]$;
5. Compute the covariance matrix $C = AA^T$;
6. Compute the Eigen vectors $C : \lambda_1 > \lambda_2 > \ldots > \lambda_N$;
7. Compute the Eigen vectors $C : u_1, y_2, \ldots, u_N$;
8. Keep only the K-largest Eigen values and test them against the stored database of plastics and non-plastics;

C. *Rod Touch Analysis*

Classification accuracy can be improved using multiple types of sensors. We have attempted to use audible noise spectra for our analysis.

In this section, we attempted to differentiate bottles belonging to various categories. The distinguishing criterion in this case is the sound emitted when the sample is struck with another object. Since different classes emit different sounds when struck, we chose to use this as a means to distinguish between the two clusters.

First of all, the samples were collected, and struck with a rod (a metal rod in this case). The sound was recorded using a microphone built into the computer, and this was then processed in MATLAB. Each sample was struck repeatedly (4-5 times at different points) with a metal rod with similar force, at the same distance from the microphone. The audio files were in 44Kbps wav format. The signal was then loaded onto MATLAB and the Audio Processing Toolbox was used for the next stage.

- *Audio Processing:* First of all, the recorded sounds in the wav files were loaded onto MATLAB, and an algorithm was written to automate the process of extracting individual samples from the series of hits. This was done by detecting the peaks of the signals by using a threshold, then using Standard Deviations to detect the points [3] where the signal amplitude falls after a peak.

- Using this index, the peak positions were calculated, and the signal trimmed for 0.5 seconds around the peak (This was done to limit the length of the waveform for the individual strikes). Then, each of the trimmed sequences were loaded onto an array, and then processed.

- The next step involved finding the Fourier Transform of each of the signal sequences. MATLAB's built-in FFT function was used in this case to get the frequency profiles of the samples. Different FFT samples were taken for different bottle samples, and their frequency profiles were compared for effective classification.

3. IMPLEMENTATION

The types of bottles that we considered for experimentation include glass bottles, metallic bottles, polystyrene plastic bottles and low density polyethylene (LDPE).

For the implementation of bottle detection using HT, we maintained ideal conditions by taking all the images from a distance of 1 meter from the digital camera with a black background for the image. The database was built with this kind of a set up.

For the implementation of PCA, we collected 500 bottle images and 500 non bottle images. We tested these 500 images individually, and then we simulated a clutter environment and tried to check the efficiency of our algorithm in case of sparse clutters and dense clutters [Quantify].

For the detection of individual classes of bottles, we used the same dataset as that of PCA, and using a metal rod we captured the sound in laptop microphones. Later the sound waves was normalized and subjected to analysis. The following section gives the results of the bottle images that are being tested for HT, PCA and RTA.

4. RESULTS AND OBSERVATIONS

The following section contains the results of our experiments

D. Hough Transforms

Firstly we tested the pre-processed image by applying Hough transforms. We observed the following.

Figure 3 shows the original input image. . Figure 5 shows the processed image of the original image Figure 4 shows the Hough space graph of that input image. Finally figure 6 shows the Hough intensity plot for the input image.

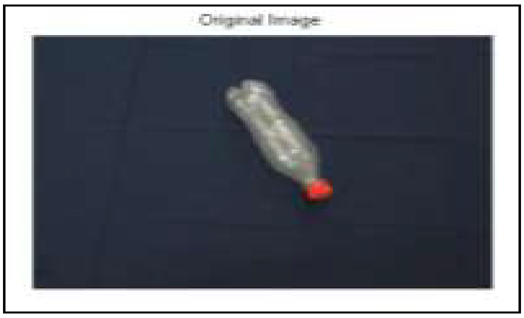

Figure 3

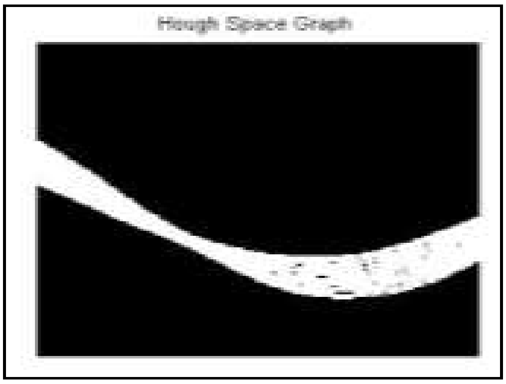

Figure 4

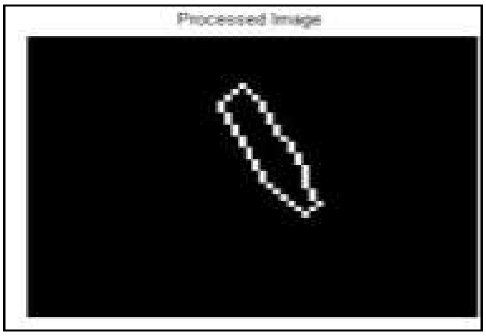

Figure 5

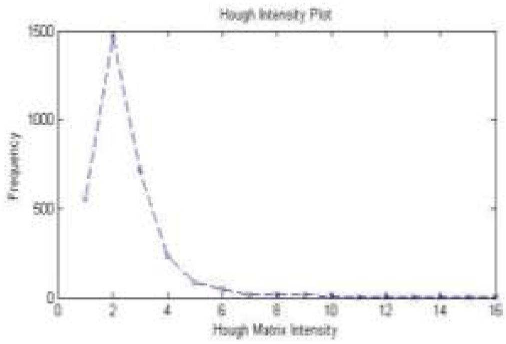

Figure 6

When we applied Hough transforms against the non bottle articles such as cups, we got a different frequency threshold justifying our recognition methodology as shown in figures 7, 8, 9 and 10.

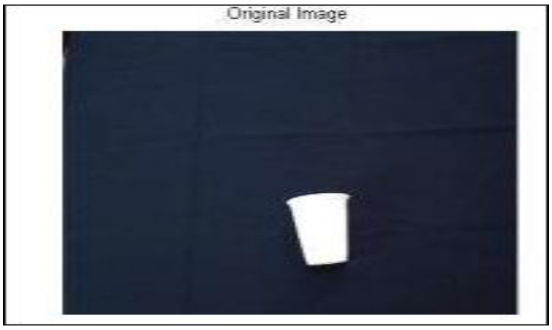

Figure 7

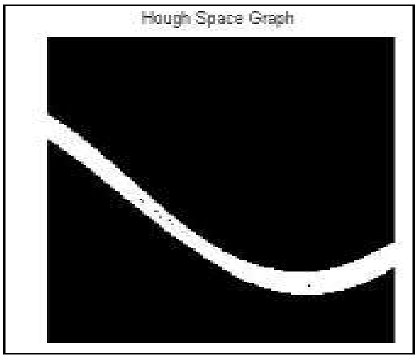

Figure 8

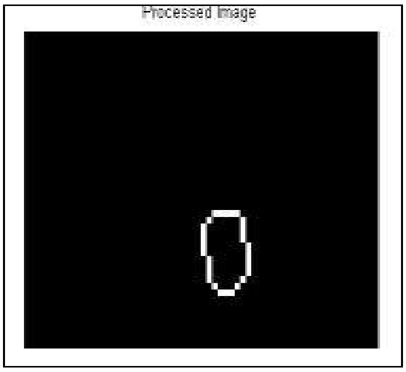

Figure 9

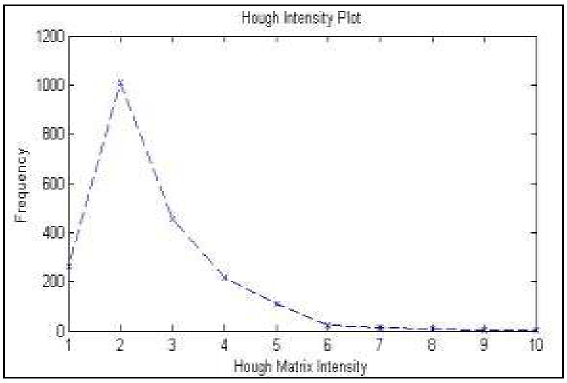

Figure 10

After testing the algorithm on 500 samples including both bottles and non-bottles, with variations in shapes, colors, transparencies and orientations, the results were obtained. The algorithm classified the samples correctly, with 95% accuracy. This included a couple of crumpled bottles and cups.

However, in a bigger collection of samples (850 bottles and 850 non-bottles), there were a few misclassifications. This indicates an accuracy of 90% in this case.

E. Principle Component Analysis

Once we recognize an image as bottle through Hough Transforms, we increase the detection efficiency by producing the output of the Hough transform as an input to PCA. We observe the following results on application of PCA.

We first store the *k* largest Eigen vectors of all the types of expected bottles in the training dataset. Then we check if the *k* largest Eigen vectors of the testing image matches with that of the image in the training dataset. If so, it declares the object in the testing image as bottle. Else it gives a message saying, the object in the image was misclassified as bottle in HT analysis.

This is being shown in the below figures where the *k* largest Eigen vectors of testing image and the image in the training dataset matched.

Figure 11

Figure 11 shows a sample test image that is being tested against the image in the training dataset. One thing that needs to be observed is that the testing image produced to PCA is nothing but the output of HT. The equivalent image of the bottle in the training dataset is given in the Figure 12 below.

Figure 12

F. Rod Touch Analysis

Once we confirm that the detected image is bottle, we further try to classify them to various classes by subjecting them to rod touch analysis.

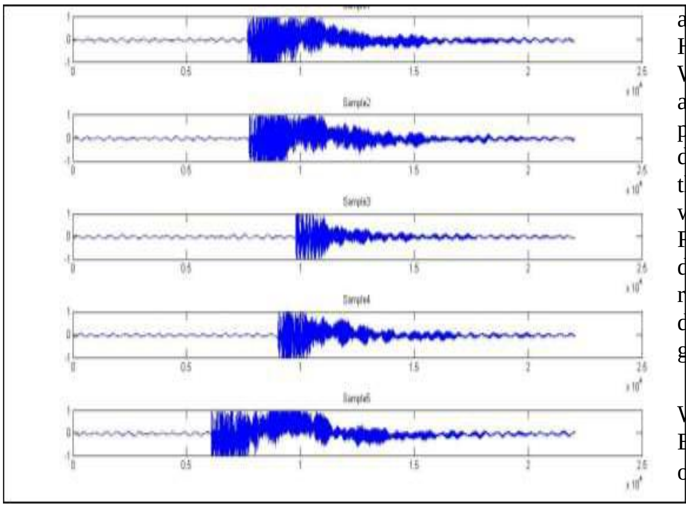

Figure 13

The trimmed waveforms of the first few samples of the sound extracted is being shown in Figure 13. We then go on to compare the FFT's of glass and non-glass bottles. This is being shown in figure 14.

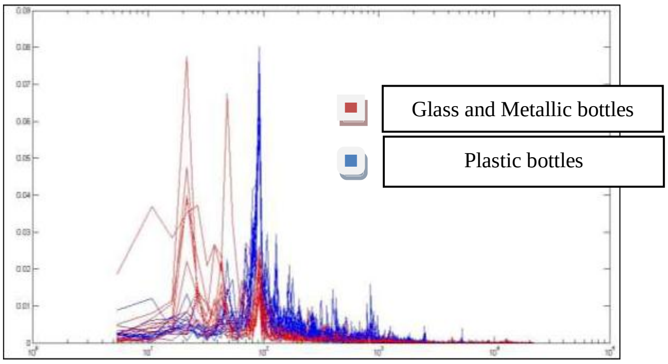

Figure 14

In the figure, red represents the FFT for glass and metallic bottles and green represents the FFT of polystyrene plastic bottles and low density polyethylene bottles. As we can see, the range of FFT values for these types are bottles are different, which enables us to classify among the 4 classes. When we performed the peak analysis, we obtained the different peaks for these four clusters as shown in figure 15.

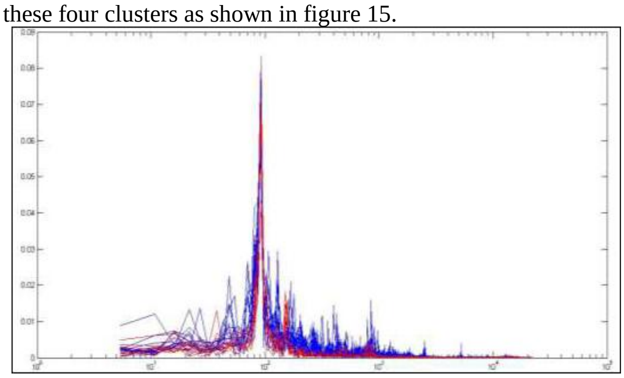

FIGURE 15

5. CONCLUSION

We were able to achieve good efficiency in recognition and classification of glass articles by deploying BRC algorithm. We adopted a hybrid approach to implement the BRC algorithm. However, there were some limitations in implementing BRC. While using Hough Transforms, image processing thresholds and limits were calibrated for the photographic conditions in place. Variation in lighting, resolution, background, camera distance would necessitate recalibration. The classification thresholds were decided upon for the given set of samples. A wider set of samples would require more calibration. In case of RTA, we observed that while there is a potential possibility to differentiate among various classes of bottles, the difference in range is low which might lead to misclassified bottles for deformed bottles. However, for normal bottles, BRC works with good accuracy as shown in results.

6. ACKNOWLEDGMENT

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