A Morphological-based Approach for Plastic Bottle Shape Classification

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In order to utilize or to extract the shape information of objects in an image for recognition, classification or retrieval, a method for representing shape is needed. In this paper, work on representing plastic bottle shape using morphological based approach for automated classification is reported. Morphological operations are used to describe the structure or form of an image. There are three primary morphological functions: erosion, dilation, and hit-or-miss. By using the two-dimensional description of plastic bottle silhouettes, we perform edge detection of the object silhouette followed by the erosion process. The morphological operation involves defining a set of flat and linear structuring elements and specifying the angle at 1° apart to obtain the maximum number of elements of 180° degrees. This is followed by a normalization procedure in which we divide the sum pixel value after erosion by the sum pixel of the whole silhouette. The normalized values are grouped into histograms of 9 bins and these histogram bins are sorted in decreasing order. The 9 sorted histogram bin of sum pixel value (9SHbSPV) obtained forms a set of feature set and is then used as inputs to train a neural network for plastic bottle shape classification. The extracted 9SHbSPV feature set was further analyzed and a reduced version was produced. Both feature sets were tested on their uniqueness to represent the shape. Results obtained showed that the proposed feature extraction method can be applied to discriminate plastic bottles according to shape as either slim or broad bottles efficiently.

1. Introduction

Automated plastic bottle sorting systems almost always employ a detection system or a combination of detection systems to identify the types of plastic recyclable. In shape based sorting activities, which involve massive amount of plastic bottles, the shapes of the bottles can vary enormously. In view of that, a study has been proposed to determine the viability of using computer vision for automated classification of plastic bottles based on shape features. Previously, plastic sorting or classification has been based on the type of material used (3).

Therefore, in this work we will address the issue of automated plastic bottle sorting based on shape by focusing on the effort to extract best feature vectors to represent the shapes of plastic bottles using the morphological based approach (MBA). As an initial effort, the work reported in this paper will focus only on recognizing two simple classes of plastic bottle shapes namely slim and broad bottles.

This paper has been structured accordingly. The next section briefly reports related previous work done by others followed by the methodology section. Subsequently, the results and discussion section is presented and followed by the conclusion.

2. Past Work

A common task in computer vision is to recognize and classify the input images accordingly. To do this, most computer vision systems start with the extraction of edges as primitives of pictures (Marr's primal sketch). Alessandra and Loris (1) suggested that the edge-based structural features be employed in their work in order to capture the luminance information carried by the edge map of an image. Specifically, they utilized the edge direction histogram (EDH) to characterize the structural and texture information of each block, similar to that of Jain and Vailaya (4). The Canny edge detector Canny (2) was used to extract the edges in an image. In the experiments, Jain and Vailaya (4) used a total of 37 bins to represent the edge direction histogram in which 36 bins represented the count of edge points of each block with edge directions quantized at 10° intervals, and the last bin represents the count of the number of pixels that do not contribute to an edge.

Wang and Zhang (10) extracted edge-based structural features and color moment features. These two sources of information are incorporated into a recognition system so as to provide complimentary information for robust image orientation detection. Support vector machines (SVMs) based classifiers were utilized for recognition. In Zhang et al. (11) the author proposed an automated method based on the boosting algorithm to estimate image orientation. A more recent work is by Neetanain et al.,(8) in which they presented a novel method for edge and corner detection in images. The approach involved extracting edges of the input image using morphological operator and then sending it for Chain Encoding. In this work, they have proposed a new morphological edge detector which returns a one pixel thick m-connected binary boundary image. All the shape representation techniques described above adopted the feature based approach which has proven to be effective in their target applications. As such, we have adopted the feature based approach to represent the shape of plastic bottles using MBA and produced a set of feature vectors for representing the 2D bottle
silhouette known as 9SHbSPV, short for 9 sorted histogram bin of sum pixel value.

3. Methodology

There are many types of bottle shapes available and classifying bottles according to shape can be a very complex and difficult task. For that reason, this work will only focus on categorizing the bottles as general as possible by classifying them in two different classes namely the slim and broad bottle classes. This will lead us to focus only on the 2-categorical pattern recognition task. In describing the image classification system, we distinguished between three different operations of preprocessing, feature extraction and classification. The proposed MBA algorithm for plastic bottle shape classification system is given as below:

**Morphological based approach algorithm****

START

- Preprocessing
  - for 1: total image
    - resizing 256 by 356 pixels
    - RGB to Binary image conversion
    - getting image’s silhouette
    - compute sum-pixel value of the image’s silhouette: A
    - getting image’s edge
- Defining structuring element
  - $SE = \text{strel}(\text{line}',LEN,DEG)$ – flat and linear structuring element.
- Apply morphological operation – erosion process on image’s edge
  - compute sum-pixel value after erosion for every $0^\circ$ to $180^\circ$
  - change to 9 histogram bin – every $(0^\circ$ to $36^\circ)$:B
  - normalization: divide B/A
  - save data
*/repeat loop for all image*/
  - end
  - generate 9 feature vectors for every image

STOP

3.1 Pre-processing

To obtain the 9SHbSPV set of feature vectors, an image has to go through the pre-processing stage. The image pre-processor module performs the following operations: image filtering, thresholding and edge detection process. Image filtering will filter all the noise due to lighting and also perform background subtraction. Thresholding is a non-linear operation that converts a gray-scale image into a binary image where the two levels are assigned to pixels that are below or above the specified threshold value. Upon obtaining the plastic bottle silhouette, the edges of the silhouette need to be computed.

3.2 Feature Extraction

Mathematical morphology provides an approach to the processing of digital images that is based on the spatial structure of objects in a scene (9). Mathematical morphology examines a geometrical structure of an image using structuring elements. Structuring element consists of patterns specified as the coordinates of a number of discrete points relative to some origin. Normally Cartesian coordinates are used and so a convenient way of representing the element is as a small image on a rectangular grid. The two basic morphological operators are erosion and dilation. These morphological operators may be applied to both binary and grayscale images. Erosion of a binary image on a rectangular grid. The two basic morphological operators are erosion and dilation. These morphological operators may be applied to both binary and grayscale images.

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3.3 Neural Network Classifier

Back-propagation classifier is one of the most common neural network structures. It is simple and effective, and as such, has found home in wide applications (5). Back-propagation starts as a network of nodes arranged in three layers: the input, hidden and output layers. The input and output layers serve as nodes to buffer input and output for the model and the hidden layer serves to provide a means for input relations to be represented in the output. Prior to running the data through the network, the weights for the nodes are set randomly. This will set an effect of making the
network much like a newborn’s brain, developed but without knowledge (6). Weights modification is done according to the gradient of the error curve, which points in the direction to the local minimum near the instance. At this stage, all the extracted 9SHbSPV from the processed images are used as input to the back-propagation neural network (BPNN model to perform the learning process. This BPNN model has to be trained so that the network can classify the plastic bottles images as either slim or broad. All necessary parameters are set before the network was trained.

4. Results and Discussion

A total collection of 100 images of plastic bottle constitutes the database to generate the input images. All these images are divided into two groups, slim and broad. In this work, the extracted morphological based feature vectors are the 9SHbSPV which were derived from the generated sum-pixel value after the erosion process. Figure 1 below displays the step-by-step results obtained from the pre-processing and morphological implementation for the two categories of plastic bottle shape.

As mentioned previously, the extracted feature vectors are used as input and fed to the neural network for the purpose of classifying plastic bottles based on shape. In this work, we have trained our neural classifier, specifically the back propagation multilayer perceptron (BP-MLP), using two sets of data. The first data set comprises of the extracted 9SHbSPV feature set where as the second data set is actually the reduced version of the extracted 9SHbSPV feature set. The reduced version only has two feature vectors which are $\sum Y_i$ and $Y_i/\sum Y_i$. Once trained, the BP-MLP classifier was tested for its classification ability that is to distinguish between the slim and broad plastic bottle shape classes. During training, the BP-MLP classifier was trained to recognize the slim bottle feature pattern as ‘-1’ and the broad bottle feature pattern as ‘+1’.

During the testing, an input image is loaded onto the system, pre-processed, its features extracted and fed to the BP-MLP classifier. If the input image belongs to the Slim class and the classifier output yields a negative class vector, then the test image is considered as being correctly classified as Slim class. Otherwise, the classification is considered incorrect.

<table>
<thead>
<tr>
<th>Slim Bottle</th>
<th>Broad Bottle</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="Image1" alt="Image" /></td>
<td><img src="Image2" alt="Image" /></td>
</tr>
</tbody>
</table>

Table 1: Result of NN Classification using full data set of 9SHbSPV

<table>
<thead>
<tr>
<th>Type of Plastic Bottle Shape</th>
<th>No. of Bottles</th>
<th>Classification rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slim</td>
<td>50</td>
<td>86%</td>
</tr>
<tr>
<td>Broad</td>
<td>50</td>
<td>82%</td>
</tr>
</tbody>
</table>

Table 2: Result of NN Classification using reduced data set of 9SHbSPV

<table>
<thead>
<tr>
<th>Type of Plastic Bottle Shape</th>
<th>No. of Bottles</th>
<th>Classification rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slim</td>
<td>50</td>
<td>96%</td>
</tr>
<tr>
<td>Broad</td>
<td>50</td>
<td>90%</td>
</tr>
</tbody>
</table>
Table 1 and 2 tabulate the classification results of the BP-MLP classifier using the two different data sets. It can be seen that the classification results obtained using the reduced set is better compared to when using the full set version. Accordingly the following results have been obtained. Our BP-MLP network trained with the reduced version of the extracted feature set was able to classify the plastic bottles according to shape with more than 90% accuracy outperforming the BP-MLP network trained with the full data set.

5. Conclusion

This paper has presented a novel feature extraction (FE) method to represent shape of plastic bottles which is robust in the sense that it is invariant to rotation. The FE method has been based on the MBA approach which produces the so-called 9SHbSPV feature set. Seeing the redundancy in this feature set, the need to eliminate the redundant features became more apparent. As such, a reduced version was derived simply by computing the $\Sigma Yi$ and $Y/\Sigma Yi$ values. The reduced version was proven to be more effective and it can be concluded that the reduced feature set compactly represents the shape of the plastic bottle. This work is still in its infancy and further work involving more recent and advance algorithms are required to enhance the results.

References