VISUAL SORTING OF RECYCLABLE GOODS USING A SUPPORT VECTOR MACHINE

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Abstract

Mounting environmental concerns and changing attitudes have led to recycling programs to divert waste from entering landfill sites. This trend has led municipalities to explore improved methods and tools such as machine vision for sorting and managing the growing volume of recyclable materials. This paper describes an approach to visual sorting using image intensity data and a support vector machine applied to the unique problem of sorting polycoat containers from plastic bottles. The approach is rotation, translation and scale invariant since it uses features derived from image histograms. We also demonstrate that the approach is robust to the size, shape, varied labeling and deformation of the recycled material. An experiment is performed to verify the approach using separate test and training data. Despite the use of a modest number of training images, the system achieves a classification accuracy of over 96% using images obtained from a single grey-scale camera.

1. INTRODUCTION

The need for high speed sorting systems has become increasingly important for the recycling industry and for municipalities. In Canada during the year 2006, 7.75 megatons of recyclable material were processed by material recovery facilities (MRF), an increase of 9.2% from 2004 [1]. Municipalities offset recycling costs by selling sorted recovered materials back to manufacturers; where the selling price correlates to the purity of the material. Some of these materials can be readily separated using mechanical systems such as metal cans which can be extracted from the material stream using magnets. Other materials are better suited for visual sorting, and many facilities still rely on some manual sorting. Although visual sorting technology for recycling has begun to appear, it remains a difficult engineering problem. The sorting challenges will only increase as many municipalities move towards single-stream recycling.

Traditional machine vision approaches to feature extraction from images of recyclable products often employ geometric descriptors of the object under observation [2–4]. These geometric descriptors can be used to discriminate between objects of different size and shape. Unfortunately, the variation in shape of objects of the same class can be very large. Furthermore, when objects are randomly deformed in shape prior to recycling, geometric measurements become increasingly varied.

This paper explores the unique issue of separating polycoat containers from plastic bottles. This is a difficult problem because labeling and printing causes significant in-class variation. Further, the recycling material can be in a variety of conditions - anywhere from almost pristine to crushed and distorted. However, we hypothesize that the presence or absence of the specular component of the object appearance is the dominant factor in the overall histograms shape. This is because the plastic bottles will be highly specular compared to the polycoat containers. This specularity is somewhat invariant to the condition of the container or bottle. We proposed a feature space based on image histograms, which we hypothesized would have less within-class variation in addition to being rotation, translation and scale invariant. We can then classify the resulting histograms with a linear decision boundary. Given the fact that a reasonable number of training examples are readily available for this application, it is advantageous to use an approach which learns the optimal decision boundary from the training examples. As a result, we opted to employ a linear support vector machine (SVM) for classification.

Herein, we will show that the general shape of the histogram of a wide variety of polycoat containers and bottles can be accurately classified using a linear decision boundary using a modest number of training examples. The images are segmented a-priori using a simple segmentation approach based on edge detection. Our approach achieved a high degree of accuracy with 48 training examples of each class on a test set of 160 previously unseen examples.

2. PREVIOUS WORK AND OUR APPROACH

Overall, there appears to be few papers dealing with the area of visual sorting of recyclable objects. The work that has been done has relied on the use of image features such as shape [2, 3, 5], texture [5], or using an image histogram [6].

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Classification of objects has used techniques such as neural networks [2, 3] or linear discriminate analysis (LDA) [6].

In [6] the authors used a histogram of a region of interest to sort PET (Polyethylene terephthalate) and non-PET bottles which are classified using LDA. In this paper we propose using a histogram of an entire object to sort polycoat and plastic bottles. Our approach makes no attempt to find regions of interest in the image. Instead, we begin using grayscale images that are segmented from the background with a bounding box around the entire object and then classifying the object using a support vector machine (SVM). The SVM has been shown to give good overall classification and generalization performance over a wide variety of applications.

Fig. 1. Plastic bottles piled in bales at the Hamilton, Ontario Material Recovery Facility

For a linear SVM, a labeled set of an l dimensional feature vector (formed from the frequency in each of l histogram bins) and its corresponding class membership $\{\mathbf{x}_i, y_i\}$ is constructed for all i images in the training dataset. The class of feature $\mathbf{c}_i$ is defined by $y_i = \{1, -1\}$ and corresponds to plastic and polycoat bottles respectively. The training data follows $y_i(\mathbf{x}_i\mathbf{w} + b) - 1 \geq 0 \quad \forall i$. The points for which the above equality holds lie on the hyperplanes $\mathbf{x}_i\mathbf{w} + b = 1$ and $\mathbf{x}_i\mathbf{w}+b = -1$. The SVM classifier uses the hyperplane which provides the maximum margin solution. This hyperplane is found by maximizing the Lagrangian dual representation for the margin [7]:

$$L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j \left(\mathbf{x}_i{}^T \mathbf{x}_j + \frac{1}{C} \delta_{ij} \right).$$

where α are the Lagrangian multipliers, C is the slack parameter, and δ_{ij} is the Kronecker δ defined to be 1 if $i = j$ and 0 otherwise.

A summary of the approach proposed in this paper is shown in Figure 2. The pre-processing stage consisted of segmenting, filtering, taking the image histogram, and dividing the images into training and test sets. Segmenting the images was accomplished by first subtracting the static background from the image followed by edge detection using a Canny edge detector. This facilitated the cropping of a simple rectangular sub-image around the respective container. Image noise was reduced using a median filter. An image histogram was used to capture the appearance of the container which had the added benefit of providing features which were rotation, translation and scale invariant. The histogram of the segmented image was then supplied as input to an SVM built using the LIBSVM library [8]. Figures 3 and 4 show the resulting 256 bin histograms of a typical polycoat container and plastic bottles respectively.

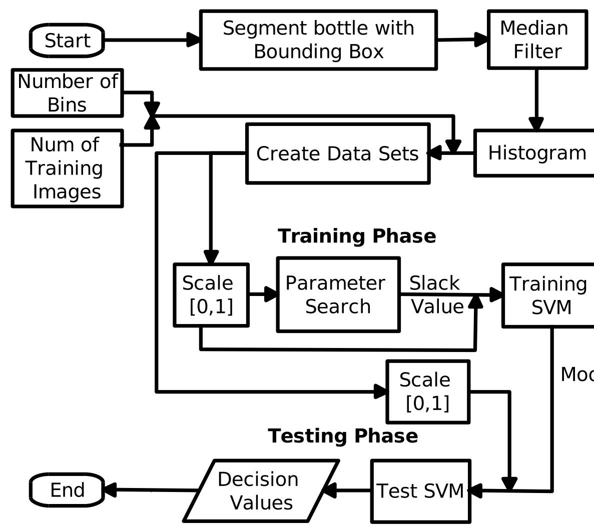

Fig. 2. Experiment Algorithm Outline

3. EXPERIMENTAL SETUP

A classification experiment was performed to validate the algorithm using sample images of polycoat containers (such as TetraPaks ®) and plastic bottles made of PET. Each container was imaged individually under similar lighting conditions with a black background. A monochrome 640x480 firewire camera was used to capture images.

An initial experiment was performed to determine an appropriate number of training images and the number of histogram bins. To do this we selected 200 sets of training and test images for each of 18 different training set sizes and for varying bin sizes. The images were randomly assigned to test and training sets with a constant ratio of polycoat containers to plastic bottles. We used these parameters in a subsequent experiment which was then run 100,000 times.

Figures 4 and 3 shows typical containers from each class. Note that all training operations consisted of scaling the data sets [9] and determining the optimal C value via leave-one-out cross validation.

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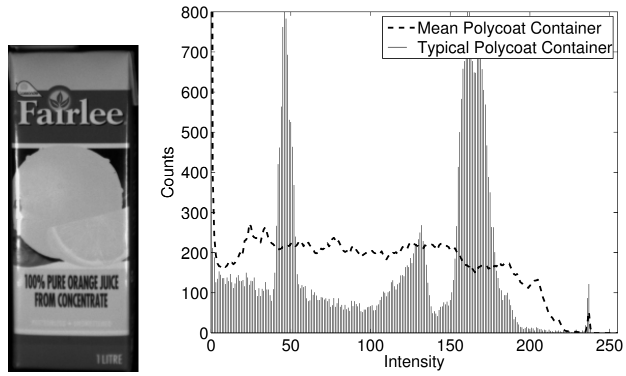
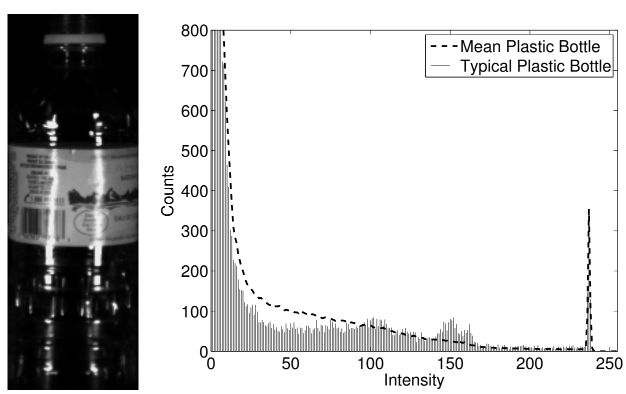
Accuracy	96.57%
True Positive Rate	98.12%
False Positive Rate	6.31%
False Negative Rate	1.88%
True Negative Rate	93.69%

Table 1. Mean and Standard Deviation of the Recognition Rate over 100,000 sets of 48 randomly selected training images and 160 randomly selected test images.



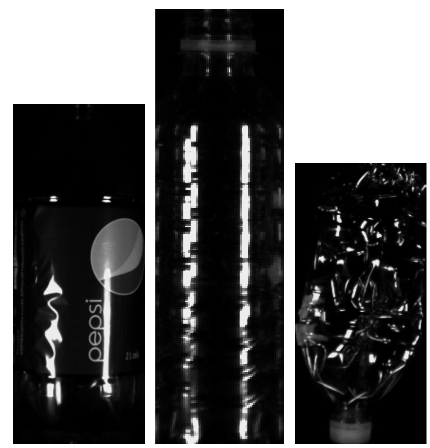
(a) Image with bounding box (b) Image histogram and average histogram

Fig. 3. Typical Polycoat Container image and resulting histogram



(a) Image with bounding box (b) Image histogram and average histogram

Fig. 4. Typical plastic bottle image and resulting histogram



(a) Sample Plastic Bottle images

(b) Sample Polycoat Container Images

Fig. 5. Sample Images

4. EXPERIMENTAL RESULTS AND DISCUSSION

The results of the initial experiment to determine the number of training images and bin size is shown in Figure 6. From the figure, we found that a small bin size of 16 was sufficient and the accuracy did not improve beyond 48 training images. The results of the subsequent experiment using the number of training images and bin size determined in the initial experiment are shown in Table 1. This experiment is the result of 100,000 runs with a bin size of 16 using randomly selected groups of training and test images of size 48 and 160 respectively. We found a mean classification accuracy of 96.57%, a true positive rate of 98.12% and a false positive rate of 6.31%. This translated to an average of 2 plastic bottles and 4 polycoat containers being misclassified. Over all SVM models tested in our 100,000 run experiment, the mean number of support vectors was 26.67% of the number of training images with a standard deviation of 12.75%. The fact that we only

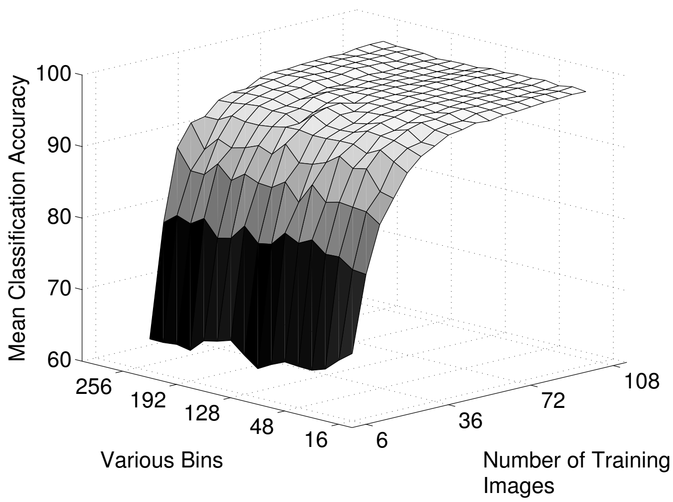


Fig. 6. Mean classification accuracy for various vector and training sizes

need small number of bins, a small number of training images and a modest number of support vectors to produce high classification accuracy indicates that our hypothesis about using a linear SVM is reasonable and that the SVM generalizes well for this application.

5. CONCLUSION

This paper has demonstrated an approach to sort recycled polycoat and PET materials using intensity images. Image histograms were used as input to an SVM to perform the classification. The approach is rotation, translation and scale invariant and was tested on polycoat and PET containers of various sizes, shapes and conditions. Further, we perform minimal image pre-processing and all parameters (the decision boundary and the slack parameter) were learned from a small number of training images. We achieved the correct classification of approximately 93.7% of polycoat containers and 98.1% of plastic bottles. Despite the straightforward nature of our approach, we have shown that it is a robust and effective way to sort polycoat and PET containers.

6. FUTURE WORK

The above work could be expanded to include the sorting of different material types with differing reflectance properties. Additionally, further investigation could be performed of the effect of crushing or distorting materials on the reflectance properties. This approach would be effective for visually sorting other materials in a single-stream recycling facility where other mechanical sorting techniques are not practical.

7. REFERENCES

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