

CONTENT-BASED IMAGE RETRIEVAL SYSTEM FOR SOLID WASTE BIN LEVEL CLASSIFICATION AND RECOGNITION

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ABSTRACT

This paper presents an automated bin level detection system using Gabor wavelets and gray level co-occurrence matrices (GLCM) a based on content-based image retrieval (CBIR). Parameters such as Euclidean, Bhattacharyya, Chisq, Cosine, and EMD distances were used to evaluate the CBIR system. The database consists of different bin images and is divided into five classes (low, medium, full, flow and overflow) with two bin sizes (120 L and 240 L). The features are extracted from both query images, and all the images in the database, the output of the query and the database images are compared using similarity distances. The result shows that the EMD similarity distance performs better than other distances in retrieving the top 20 images that are close to the query image. The performance of the automated bin level detection system using Gabor wavelets and GLCM with the CBIR system had high identification accuracy. The combination of the two techniques proved to be efficient and robust. Based on the results, this method has the potential to be used in solid waste bin level identification to provide a robust solution for solid waste bin level detection, monitoring and management.

Keywords: Solid waste monitoring and management; Gabor wavelet; GLCM; CBIR; EMD.

1. INTRODUCTION

With the advance of communication technology and image processing techniques and an increase in public interest, waste management has been drawing the attention of people beyond the traditional research community [1]. The amount of waste thrown in bins by residents has a great impact on

the environment, thus pushing many cities around the globe to look for solutions that will handle and enhance the collection process [2]. There are few researchers who have studied the detection of bin level and waste estimation. The detection of liquids inside tanks has been studied, but it was found to be incompatible with bin level detection [3]. The issue of solid waste is related to a variety of types of waste thrown inside bins as well as to the environmental situation of the bin.

There are few past research projects utilizing the image processing technique to estimate the bin level. Advanced image processing techniques have never been applied in waste collection operation and bin level detection. Zhu et al [4] developed an intelligent bin that can send a signal once it is full. Camera and ultrasonic distance sensors are mounted on top of the bin, so every time the bin opened and closed, the camera snaps a picture. The image and sensor measurements are sent to the control station via a general packet radio system (GPRS) connection. The image processing technique used by Zhu et al [4] is based on motion detection. The new image of the bin's contents is compared to the previous image to determine the amount new waste disposed in the bin. Subtracting the two images from each other is a weak and simple technique in image processing application. Moreover, if the bin is dirty, the camera produces low quality images and estimates the level of the bin incorrectly [5]. In addition, sensors, a GPS, a camera, and a GPRS modem are required to detect the bin level, making the system expensive and complex [6]. Furthermore, the system is not paired with radio frequency identification (RFID) system in the collection process, making the collection inefficient. The trucks, bins, and bin levels must be monitored to improve the efficiency of waste collection; the whole solid

waste management process can be improved if the efficiency of waste collection is maximized. An application of advanced computer image processing techniques integrated with communication technologies such as RFID, GPS, GPRS, and geographic information system (GIS) with a camera has been examined for solving the problem of solid waste collection and automated bin level detection[7] An innovative method of bin level detection has been implemented using a Gabor wavelet filter and GLCM as a feature extractor with artificial neural network (ANN) and K-nearest neighbor (KNN) as classifiers to provide a robust solution for solid waste automated bin level detection, collection and management [2]. However, unsatisfactory training samples for the ANN and KNN could lead to wrong bin level identification during the collection operation [8, 9]. Additionally, the training must be repeated from time to time to cope with an increasing number of bin images in the database, which makes the system quite complicated. Ideally, the identification of the exact level of the bin during the collection should be efficient and give the correct level of the collection in real time.

2. PROPOSED SYSTEM

This paper proposes a content-based image retrieval (CBIR) system that can overcome these limitations. The collection of waste involves many bin type and sizes, the proposed CBIR system considered 120 L and 240 L bins, Ultimately, we need to collect sufficient a database for bins with different filling levels and bin sizes. The prototype implementation of this approach can be used for solid waste identification and classification for municipalities. Accordingly, the implemented approach can be used by

SWM companies, for their solid waste detection and classification and to optimize their collection, monitoring and management policies.

Based on the literature, the information on solid waste collection, and the detailed theoretical framework, this research integrates multiple advanced technologies to develop an intelligent solid waste bin management system to monitor the trucks and check the status and level of the bin during the collection operation, as shown in Figure1.

RFID tags are mounted on the 120 L and 240 L bins to the gather the serial number of the bins. RFID provides resistance to environmental influences, as radio frequency waves are not absorbed by moisture and are more water-resistant. An RFID reader and camera are mounted in each truck to capture the serial number of the truck and bin and an image of the bin, which are forwarded to the control center via the GSM/GPRS network. When the truck approaches the bin, the RFID reader communicates with the RFID tag to capture the tag's ID and other information about the bin. The driver then takes the best position to take the first image before collection. The captured image is sent to the server, and the server acknowledges that the image was uploaded. The image is then uploaded onto the server along with the bin ID. After the collection process, the camera captures the second image and repeats the entire process with second image. All real-time information, such as tag ID, collection time, and GPS data, are forwarded to the server through the GPRS modem with the availability of the GPRS network. The monitoring interface on the control center presents a digital map of bin statuses and truck positions. All these data from the bins are stored in the database and are presented on the digital map. All the bins are represented on the map with gray color. Once a bin is collected, it blinks to show the

collection progress to the operator in the control center. Three different image processing techniques are applied to the received images to estimate the level of bins during the collection operation.

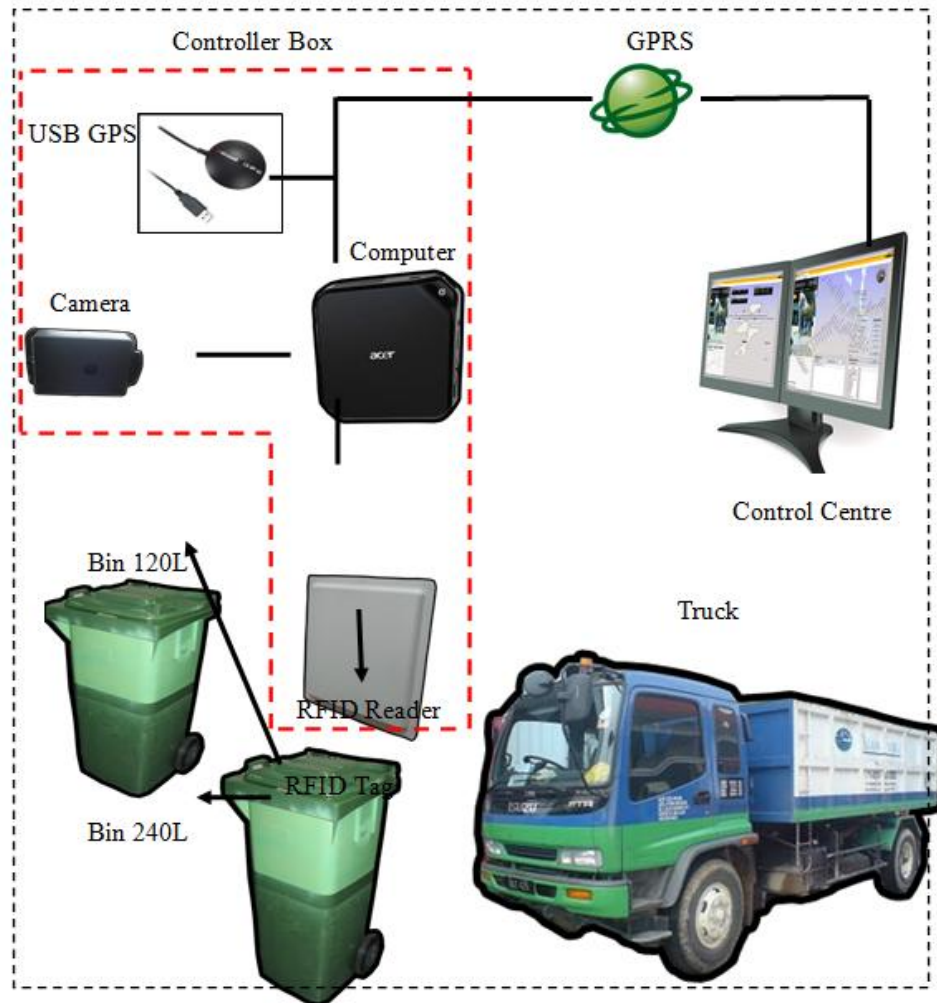


Fig.1 Architecture of solid waste monitoring and management system.

Hence, the selected hardware and the developed algorithm allow automatic truck and bin monitoring as well as tracking for waste collection operation under any environmental condition. The next section discusses the tools and

techniques that can detect the level of the bin during the collection operation. Several advanced image processing techniques were applied to the bin images to identify the level of the bin. The next section provides an introduction to the image processing techniques used as feature extractors, which capture the contents of the bin images, and the CBIR technique associated with the image processing techniques, which identify the level of the bin.

3. FEATURE EXTRACTION

The first step in bin level detection is usually building a robust image database. The texture features are compared with images in the database using the CBIR system to classify the new images. This paper is focused on improving the performance of the applied method by analyzing different distances.

A Gabor wavelet filter has been applied to various image recognition problems for feature extraction due to its optimal localization properties in both the spatial and frequency domains [10]. The Gabor wavelets were introduced to image analysis due to their biological relevance and computational properties. Feature extraction using a Gabor wavelet filter is explained in the following section.

Gray level co-occurrence matrices (GLCM) provide a second-order method for generating texture features [11]. GLCM calculates the relationship between the conditional joint probabilities of all pairwise combinations of gray levels in the image given two parameters: displacement (d) and orientation (q).

4. CONTENT-BASED IMAGE RETRIEVAL (CBIR)

The method proposed to identify the bin level for different size bins is Content-Based Image Retrieval (CBIR). CBIR searches databases for specific images that are similar to a given query. The proposed CBIR system aims to investigate the use of image retrieval with an extracted texture from the image of the bin to detect the bin level. The distance metric can be termed as a similarity measure, which is the key component in the CBIR system. If x and y is the query image and image in the database, respectively, then the distance metrics used to measure the similarity are defined as follows.

4.1 Euclidean Distance

The Euclidean distance is a measurement technique often used for comparing the feature vectors representing two images. The technique provides a measure of how similar a collection of values are between two templates.

$$D_{Euclid}(x, y) = \sqrt{\sum_{i=1}^d (x_i - y_i)^2} \quad (1)$$

where d is the dimension of the feature vector, x_j is the j -th component of the sample feature vector, and y_j is the j -th component of the template feature vector [12].

4.2 Bhattacharyya Distance

Used as a class similarity measure for class classification, the Bhattacharyya distance (D_b) between the query image x and target image y in the database is given by:

$$D_{Batt}(x, y) = \frac{1}{8} (M_x - M_y)^T \left[\frac{C_x + C_y}{2} \right]^{-1} (M_x - M_y) + \frac{1}{2} \ln \frac{\left| \frac{M_x + M_y}{2} \right|}{\sqrt{|C_x| |C_y|}} \quad (2)$$

where M_x and M_y are the mean vectors, and C_x and C_y are the covariance matrices of query image x and target image y , respectively [13].

4.3 Chi-Squared Distance (Chisq)

The chi-squared statistic determines the distance between the query image and the images in the database. The chi-squared distance is useful when comparing extracted features in one dimension [14]. This distance between two vectors is defined as

$$D_{Chisq}(x, y) = \frac{1}{2} \sum_{i=1}^d \frac{(x_i - y_i)^2}{(x_i + y_i)} \quad (3)$$

4.4 Cosine Distance

The similarity between two vectors is measured by the cosine of the angle between them, which shows whether two vectors are pointing in roughly the same direction. Applying cosine distance often compares images in the

CBIR system, and the value is derived using the Euclidean dot product formula [15]:

$$D_{Cos}(x, y) = \frac{\sum_{i=1}^d x_i y_i}{\sqrt{\sum_{i=1}^d x_i^2 \sum_{i=1}^d y_i^2}} \quad (4)$$

4.5 Earth Mover's Distance (EMD)

The EMD computes the distance between two distributions, which are represented by signatures. The signatures are sets of weighted user-defined features of any type and number of dimensions that capture the distributions. In particular, for the one-dimensional case where the cost is the Euclidean distance and the signatures have equal total weights, [16] showed that the EMD can be directly calculated by

$$EMD(x, y) = \sum_{i=1}^{m+n-1} \text{abs}(\text{cdf}(x) - \text{cdf}(y)) \quad (5)$$

5. RESULT AND DISCUSSION

In this section, the adopted method to evaluate the performance of the CBIR system for bin level detection retrieval is presented. To assess the accuracy of the proposed feature extraction techniques, intensive tests were conducted among 1250 bin images with different levels and two bin sizes (120 L and 240 L). The tested images were compared with other bin images in the database. The average retrieval rate is used to evaluate the performance of the retrieval system. The average retrieval rate for the query image is measured by counting the number of images from the same category, which

are found in the top N matches (N is the number of most retrieved images). N is considered as 1, 3, 5, 8, 10, 15, and 20. The results of the distances were compared to obtain the best retrieval accuracy. Details of the performance evaluation setup and other issues are discussed below.

5.1 The Gabor Wavelet Filter With The CBIR System

To compare the retrieval accuracy of the Gabor technique at different distances, tests were conducted among 1250 bin images. Table 1 shows the retrieval rate with several similarity distances. The EMD distance performed well with all the top matches and outperformed all other similarity distances. The EMD distance improved the performance of the CBIR system and performed well with all bin images at different levels. The EMD distance with Gabor filter is capable of obtaining 100% average retrieval rate from the top 1 to top 10 matches and 90% average retrieval rate from the top 15 matches. The average retrieval rate obtained by the EMD distance is noticeably high compared with the rest of the similarity distances.

TABLE 1. RETRIEVAL RATE ON THE IMAGES OF THE BIN DATABASE USING GABOR WAVELET WITH DIFFERENT DISTANCE METRICS (1, 3, 5, 8, 10, 15, 20 ARE THE TOP 'N' RETRIEVED IMAGES)

Method	Number of top matches						
	1	3	5	8	10	15	20
Bhattacharyya	100	100	100	62.5	50	33	30
Euclidean	100	100	100	100	100	66.7	50
Cosine	100	100	100	87.5	80	73	55
Chisq	100	100	100	87.5	70	66.7	50
EMD	100	100	100	100	100	90	60

Fig. 2(a) and Fig. 3(b) shows the performance of each distance based on the average retrieval rate and the F1 measure, respectively. Selected Gabor parameters for the retrieval system with the EMD distance are better than those for the other distances. The superiority of the EMD distance can also be observed with the Euclidean distance based on the F1 measure. The performance of the Euclidean distance is similar to the EMD distance until the top 10 matches. The superiority of the EMD distance is significant at the top 15. Only a 66.7% retrieval rate is achieved by the Euclidean distance, whereas a 90% retrieval rate is achieved by the EMD distance.

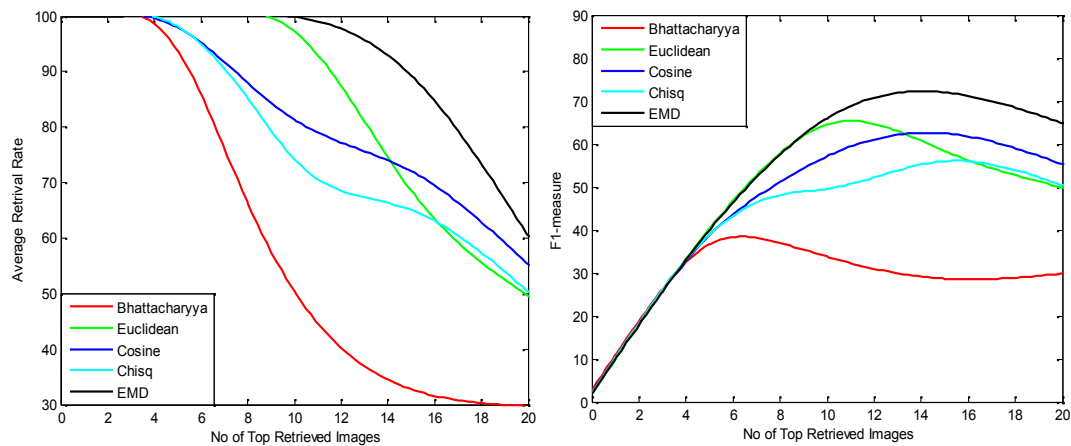


Fig. 2 (a) Comparative average retrieval rates with Gabor retrieval system (b) F1-measure with number of top retrieved images with the Gabor retrieval system.

A sample image from the database was tested and used as a query image with the EMD distance. The results of the retrieved images with the 20 top matches are shown in Fig. 2. In all cases, the images in the database of the system correctly match the query image. The accuracy of the system decreases as the top number of image retrieved, N , increases. As seen in Fig. 3, the dissimilarity distance between the query image and the first image is

0, and it increased with an increasing N value. The top N results are validated by all distances to increase the confidence of the CBIR system results with the selected distance.



Fig. 3 Top 20 retrieved images with using Gabor wavelet in retrieval system, the top left image is the query image

5.2 GLCM With The CBIR System

The five similarity distances are also used with the GLCM technique to measure and compare the average retrieval rate. The results show that the EMD distance is superior. The correct average retrieval rate was 100% for the top 5 matches among all distances except the Bhattacharyya distance. Above the top 5 matches, the performance of the EMD distance reached

70%, with the top 10 matches outperforming the other distances. The average retrieval rate was compared, and the results are detailed in Table 2. The EMD distance had the best performance, followed by the Chisq and the Euclidean distances.

TABLE 2. RETRIEVAL RATE ON THE IMAGES OF THE BIN DATABASE USING GLCM TECHNIQUE WITH DIFFERENT DISTANCE METRICS (1, 3, 5, 8, 10, 15, 20 ARE THE TOP 'N' RETRIEVED IMAGES)

Method	Number of top matches						
	1	3	5	8	10	15	20
Bhattacharyya	100	100	60	62.5	62.5	40	30
Euclidean	100	100	100	70	60	40	35
Cosine	100	100	100	75	70	46.7	35
Chisq	100	100	100	75	60	46.7	35
EMD	100	100	100	87.5	70	60	45

The plots of the average retrieval rate and the F1 measure with the number of most retrieved images are shown in Fig. 4(a) and Fig. 5(b). The performances of the systems averaged all the top matches with similarity. Five plots are shown in the figures for the CBIR system, revealing the performance of the five similarity distances. The plots indicate that the EMD distance significantly outperforms all other distances.

A sample image from the database is tested and used as a query image with the EMD distance. The results of the retrieved images with top 20 matches are shown in Fig. 5.

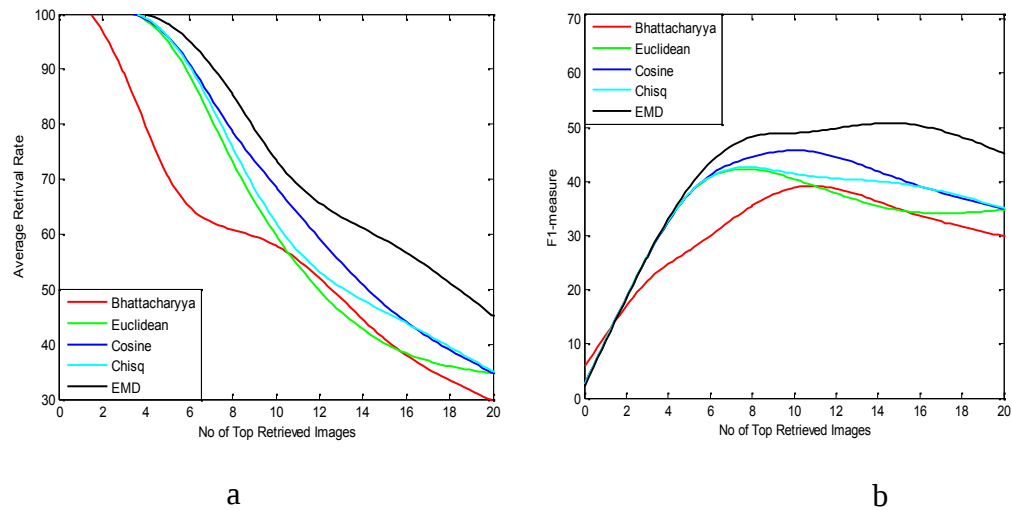


Fig. 4 (a) Comparative average retrieval rates with GLCM retrieval system(b) F1-measure with number of top retrieved images with GLCM retrieval system



Fig. 5. Top 20 retrieved images with using GLCM in the retrieval system, the top left image is the query image

A full description of the CBIR system used in the bin level detection system was presented. Various feature extraction techniques were performed with different similarity distances. The search algorithm for a given query image

and the retrieval of the best-ranked images were presented as well. The CBIR system relied on the texture features of the bin and its surrounding area, which is usually a structure that has a significant role in bin level detection. The CBIR system retrieved the top-ranked images along with the stored level of the database. The CBIR system was also validated by different similarity distances with each feature extraction technique. In the bin level detection system, the EMD distance achieved high accuracy among all N values. The EMD distance had better performance than the other distances. Similarly, the test showed that the top 10 images were correctly retrieved by the Gabor extraction techniques, while the EMD distance was very efficient and could be used in a bin level identification system. Unlike other feature extraction techniques, GLCM did not perform well in the CBIR system because the number of extracted features is less than that of the Gabor wavelet.

6. CONCLUSIONS

The objective of this paper is to detect and classify solid waste bin levels using various image processing techniques with a CBIR system. The performance of the developed system in solid waste collection was promising, as important information was identified, collected, and automatically recorded upon collection of the bins. Bin level detection during the collection was accurately carried out by most of the proposed image processing techniques. Different image processing techniques were used to identify the bin levels through different classification methods. Gabor wavelets, and GLCM were used as feature extraction techniques with the CBIR system. Different similarity distances were used to test and validate the efficiency of the CBIR system. The EMD distance outperform

the other similarity distances and was found to be the most suitable similarity distance for use with Gabor wavelet, and GLCM techniques. The accuracy reached up to 87.5%. The overall feedback received from the waste management dealers and managers was very positive. According to the materials manager, the proposed system was very efficient and can potentially save a significant amount of labor hours that would be used for manual recording of the collection operation.

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