Bin Level Detection Using Gray Level Co-occurrence Matrix in Solid Waste Collection

Maher Arebey, M A Hannan, Hassan Basri and R A Begum

Abstract—**This paper presents the image processing technique gray level co-occurance matrix (GLCM) in solid waste bin level detection and classification. Advanced communication technologies are integrated with GLCM to improve the waste collection operation. The GLCM parameters such as displacement (d) and quantization (G) are investigated to determine the best parameters values of the bin images. The optimum classification accuracy of the system is obtained by investigating the values of d and G. In this paper, the parameters values with selected texture features are used to form the GLCM database. The most appropriate features collected from the GLCM are then used as inputs to the multi-layer perception (MLP) and K-nearest neighbor (KNN) for bin image classification and grading. The results demonstrated that the KNN classifier at KNN=3, d=1 and maximum G values performs better than that of using MLP with same database. Based on the results, this new method has the potential to be used in solid waste bin level classification and grading to provide a robust solution for solid waste bin level detection, collection, monitoring and management.**

Index Terms— **Solid waste monitoring and management · GLCM· MLP·KNN· classification and grading·**

I. Introduction

SSolid waste management (SWM) is an important environmental health service, and is an integral part of basic urban services [1]. From the earliest primitive human society there have been attempts to safely collect and dispose the solid waste. It is consider as one of the basic services that are currently receiving wide attention in many developing countries [2].The challenges of the SWM sector are continuing to grow with the growing of urbanization. Urbanization has become a worldwide trend, and is particularly rapid in the developing world [3].

Manuscript submitted July 15, 2011.

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A traditional solid waste management system consists of trucks, bin and landfill. Due to the growing issue of landfill disposal from the, many researches are investigating waste diversion through an integrated solid waste management system [4]. The solid waste planner, monitor and management require comprehensive, reliable data and information on solid waste [5]. However, the solid waste database in Malaysia is limited to manage the data by individual local authorities or waste contractors [6]. In order to deal with this great demand on data management, advanced information technologies such as RFID, GPRS, GPS and GPS solution must be utilized [7].
The collection process can be improved, if there is a system that can monitor the truck and bin in real time. The sufficient information about the bin can allow the operator to reallocate the bins position depends on their situation and bin level status and can be optimized the truck schedules. The waste that is being discarded around the bin destroy the view of big cities, bin being overflowed all the time in some places is a serious problem and need close monitoring. These are the reasons for motivation to develop real time system for classifying the bin status and detect it level for monitoring and management. There is few researchers studied the detection level of the bin. The level for liquids waste tanks has been studied in many researches but it is not applicable for bin level detection [5]. The issue of solid waste is related to variety of the waste that has been thrown inside the bin and the environmental situation of the bin [8]

Solid waste collection is the most important part in solid waste management system. In Sweden, 3300 recycling bins equipped with level sensors and wireless communication equipment and fitted with a line of infrared LEDs to estimate the level inside the container. It sends an alarm signal when three of the four sensors are obstructed and a different one for the four LEDs giving the operator real time information on the status of each bin [9]. Reference [5] has studied the effectiveness of different scheduling and routing policies utilizing the bin real-time data from recycling station system in Malmoe, Sweden. It concluded that the bins equipped with level sensors improved the collection process, dynamic scheduling and routing policies based on the bin information which is less operation cost, shorts distance, and reduced the collection time comparing to the static collection with fixed routes.

Reference [10] proposed capacitive sensor to determine the moisture content of the bin for combustion in a furnace and analyzes possible cross sensitivities of the sensor principle. Reference [11] developed a point-level capacitive sensor for the bin which is built from low-cost adhesive metallic tape and can be easily tailored to any bin. The sensor has been applied to detect the bin when it's full with cardboard. The capacitive sensors are so sensitive to humidity that they cannot work well for volume measurement and not suited for other type of material [12].

ISBN: 978-988-19252-4-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

Accordingly, Reference [12] proposed an optical sensor for assessing the bin level detection can work with some amount of contamination but scheduled cleaning need to be provided.

Few researches so far utilized the image processing technique to estimate the bin level. Politecnico di Milano and Shanghai Jiao Tong University developed automated bin collection and proposed set of sensors mounted onto the bin. The bin level was calculated on the basis of the interaction of image processing and a digital distance sensor [13]. The software used for the image processing is based on the motion detection methodology. The idea is to compare the last image of bin's content with the previous one, the two received images subtracted from each other in order to obtain the image of the differences and to examine only the newest garbage thrown into the bin [14]. Subtracting two images from each other is a simple method in image processing techniques and has a lot of drawbacks. For example, if the new image effected by some factors, it is hard to be estimated and also contamination of the bin that affect the image quality. For these reasons new methods must be developed to achieve high efficiency.

The main problems of the existing solid waste collection and bin level detection system are as follows [15]–[17].

- There is no system that can be used to estimate the bin level with different kind of materials being thrown in the bin.
- Lack of the proper system for monitoring, tracking the trucks and trash bin that have been collected in real time.
- There is no system utilized advanced image processing technique to estimate the amount of solid waste inside the bin and the surrounding area.

However, with the existing system, it is hard to get all the facilities on time. Solid waste monitoring and management need accurate information to make good decision. To stimulate all these facilities, an effective and robust system is needed.

II. System Details

The method of the proposed system is developed using communication technologies such as radio frequency identification (RFID), geographical information system(GIS) and general packet radio system (GPRS) interfaced with low cost camera for solution of existing problems and streamline solid waste monitoring and management efficiencies. In this system, there is a great deal of process intelligence to ensure the system capability and also justify its validity. This is not only in time-related factors such as time spent to, from and at locations, but more importantly, the accurate tracking of a solid waste bin's serial number and location. The main goal involved in improving the overall efficiency is to estimate the waste level from bin. RFID tag is attached to each bin in order to monitor and track the bin during the collection process. Low cost camera attached to the truck in order to get bin images. Once the truck enters within the bin area, the camera takes images before and after the bin collection, to estimate the waste level in the bin and its surrounding area. The system is developed to be as compact, robust, energetically efficient and reliable as possible. Data from the truck network are recorded and forwarded to a control server through GPS GPRS system. The control server monitors the information and optimizes truck routes and bins location according to the waste estimation.

The proposed system is based on web-access architecture of a network of distributed bin and trucks. Three main layers of the proposed system are as RFID system and camera, the geographical information storage and the database management system and the control station for controlling the information access for making decision. The main role of the proposed system to acquire data in real time from the truck and the camera to provide solid waste status of the bin and the truck position System operation

RFID tag is mounted on 120 L bin, in order to the gather the serial number of the bin. RFID provides resistance to environmental influences such as radio frequency wavelength is not absorbed by moisture and more water-resistant. RFID reader and camera are mounted in the truck to capture the serial number of the truck and bin as well as image of the bin and forwarded to the control sever via GPRS network. When the truck comes closer to the bin RFID reader communicates with the RFID tag to capture the tags ID and other information about the bin and sends it to the control server to ensure proper collection and management of waste. When the control server received the serial number, the system would receive the first image and compared it with the reference images that stored in GLCM database. After the collection process is done, the camera captures the second image. In this way, the actual level of the bin and its surrounding area can be estimated with high precision. The camera interfaced with RFID reader and placed on the top of the truck, can provide the shape and the area of the objects. Regarding the camera, a low resolution RGB camera mounted on top of the truck in position that can cover 3 m2 around the bin. However, in this paper, we have focused on GLCM features extractor for solid waste bin level detection and classification using MLP and KNN.

III. GLCM Approach

The GLCM is a feature extraction method, which deals with the RGB images that have been received in the server to solve the problems of bin level detection and classification. The first step in bin level detection is usually building a robust image database. The texture features, training and testing the output of GLCM using artificial neural network MLP and KNN algorithm to classify the new images. This paper is focused on improving the performance of the applied method by optimizing the GLCM.

A. Image Database

The image database represents all the bin images at different levels such as low, medium, full, flow and overflow. The purpose of taking the bin images at different levels was to make the training and testing of database more robust and to test by the MLP and KNN classifiers. A low cost camera was used as explained in the previous section to obtain the bin images under various levels. The database has been changed from time to time as new images are added.

B. GLCM texture features

The GLCM provide a second-order method for generating texture features to calculate the relationship between the conditional joint probabilities of all pairs of combinations of grey levels in the image parameters such as displacement, d and orientation, θ [18]. The GLCM can be calculated as symmetric or non-symmetric matrices. The symmetric of the GLCM is often defined a pair of grey levels (*i,j*) oriented at $\theta=0^0$ and also be considered as being oriented at $\theta=180^0$. So, the entries would be made at (*i,j*) and (*j,i*) and each GLCM is dimensioned to the number of quantized grey levels, *G* [19].

Various texture features can be generated by applying GLCM statistics. However, before texture features can be calculated, the measures required that each GLCM matrix contain not a count rather a probability. The probability density function normalizes the GLCM by the number of outcome occurs, divided by the total number of possible outcomes. The probability measure can be defined as:

$$\mathrm{P}_r(x) = C_{ij}\,(d,\theta) \qquad (1)$$

where (C_{ij}) the co-occurrence probability between grey levels *i* and *j* is defined as:

$$C_{ij} = \frac{P_{ij}}{\sum_{i,j=1}^{G} P_{ij}} \qquad (2)$$

where P_{ij} represents the number of occurrences of grey levels *i* and *j* within the given *d* and θ and *G* is the quantized number of grey levels.

Reference [18] proposed 14 statistical features extracted from GLCM to estimate the similarity between them. Some of these features must be selected to reduce the computational cost. Reference [20] stated that the most appropriate features to be represented with GLCM are entropy, contrast, correlation and homogeneity. The following equations defined the co-occurrence probability of the features as;

$$\mu_i = \sum \mathrm{i}\,\mathrm{C}_{\mathrm{ij}} \qquad (3)$$

$$\mu_j = \sum j\, C_{ij} \qquad (4)$$

$$\sigma_i^2 = \sum C_{ij}\,(1-\mu_i)^2 \qquad (5)$$

$$\sigma_j^2 = \sum C_{ij}\,\left(1-\mu_j\right)^2 \qquad (6)$$

where μ is mean and σ is standard deviations for the rows and columns of the matrix.

The features are as following:

(1) Entropy:

$$ENT = \sum C_{ij}\, \log C_{ij}^2 \qquad (7)$$

(2) Contrast:

$$CON = \sum C_{ij}(i-j)^2 \qquad (8)$$

(3) Correlation:

$$COR = \sum \frac{(1-\mu_i)\left(1-\mu_j\right) C_{ij}}{\sigma_i\,\sigma_j} \qquad (9)$$

(4) Homogeneity:

$$HOM = \sum \frac{1}{1+(i-j)^2}\, C_{ij} \qquad (10)$$

There are many important factors such as quantization levels, *G*, displacement value, *d* and orientation value, θ need to be consider for designing the GLCM. In this paper, the role of *G* and *d* are tested, while θ is not discussed since it is accepted by many researchers that 0^0, 45^0, 90^0, 135^0 provide more accurate classifications.

Quantization, *G:* The number of gray levels consider as a crucial factor in the computation of GLCM. The decision that we have to make is to choose value of *G* to represent the textures successfully. In this paper, different values of *G* have been investigated to get the best classification result.

Displacement, *d:* Displacement, *d* is the second crucial parameter for the computation of GLCM. Applying a large value of *d* to the image would produce GLCM features that do not capture all the information in the image.

Orientation, θ: The orientation is the third parameter for GLCM computation, however, which was consider less important comparing to other GLCM parameters. In this study, we set the values of θ to 0^0, 45^0, 90^0 and 135^0 in all the cases.

Thus, based on the concepts explained above, the following research questions are raised.

- Choosing the suitable features that can represent the texture feature.
- Selecting the suitable parameters *d* and *G* that can give the best classification and grading result.
- Classification accuracy of the choosing features with different classifier.

By giving the answer the above questions, we can a preferred set of parameters to be selected for consistent automated bin collection and improve the classification accuracy by choosing the best value of *G* and *d* and strong classifier.

IV. CLASSIFICATION

In the classification stage, we used two methods to classify the bin images based on the level. The methods that were used in this paper are Multilayer Layer Perception (MLP) and K-nearest neighbor algorithm (KNN).

A. Training Setup

In this experiment, we have tested the selected statistical GLCM features with different G values. The database has been created and contains features such as contrast, entropy, homogeneity and correlation). These features were investigated by many researchers for different applications and we were able to utilize these features in bin level detection.

The type of MLP used in this study is [10 5 2] as input, hidden and output layers. The network is formulated as a three-layer hyperbolic tangent sigmoid transfer function network since the output range is perfect for learning the output bipolar values, i.e. 0 and 1. The input layer of neural nodes is 10 corresponding to the five sets. The output layer of neural nodes is 2. The output values of the five sets of bin level images are [1 0], [1 1], [1-1], [-1 0] and [-1 1], in which the first two numbers 1 and -1 representing the class of the bin either waste inside or outside the bin. On the other hand, second three numbers 0, 1 and -1, represents the grade of the waste varies from low to full in the inside bin and flow or overflow of the outside bin. Testing the neural network confirmed that the number of neural nodes in the hidden layers is 5. The training function of the BP neural network is a gradient descending function based on a momentum and an adaptive learning rate connected to the weights and the threshold values of the learning algorithm.

For KNN, the values of K used in this study were 3, 5, and 7. The three values of K were investigated using Euclidean distance to measure the distance between the query image and the training dataset. The database is divided into 5 classes of bin images such as class1, class2, class 3, class4 and class5 represented the five levels of the bin low, medium, full, flow and overflow, respectively.

V. Experimental Results

The parameters are investigated to guide to chosen GLCM parameters that has formed GLCM texture extractor. The parameters are analyzed and evaluated individually to investigate the effect of each feature.

A. Parameter Analysis

Five sample sets from all the five levels were selected to do the experiment. Four *d* values were tested from 1 to 4 and four *G* values 8, 16, 32, 64 were used to measure the effect of those parameters on the suitability of various features and seperability of the five sets. 4 features such as contrast, entropy, homogeneity and correlation are derived from co-occurrence matrices to calculate the original bin images. All the 4 features were used to create the co-occurrence matrices and the feature vectors were clearly affected by the *d* values. Fig. 1 to Fig 4 show the features output in the five sets for *d* values from 1 to 4 and *G*=8. The computational cost is reduced for setting small value of *G* and adequate distinguishable information is captured to be the input to the classifier. By analyzing the curves, it is clear that *d*=1 is the most suitable GLCM parameter for calculating co-occurrence matrices task. It is also clear that the all five sets of figures are well separated from the figure set 1 at *d*=1. *G* value affects the amount of computation needed to create co-occurrence matrices as well as classification accuracy. Generally, a larger *G* will be able to pick up more details but noise will be increased. For real-time application consideration, the *G* value must be minimized.

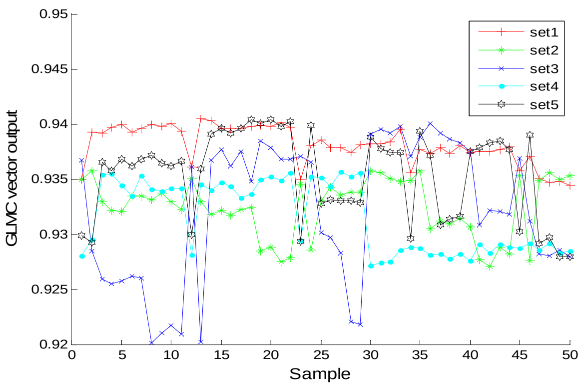

Fig. 1. The output features for d=1 and G=8.

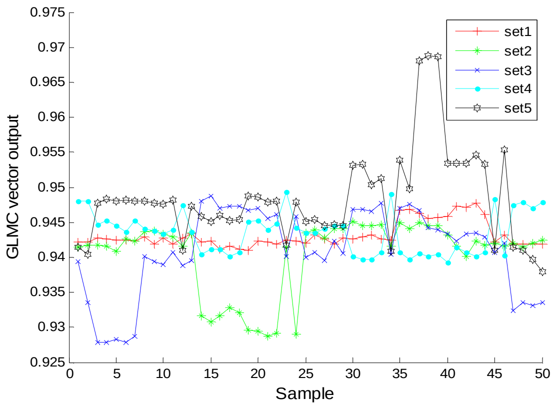

Fig. 2. The output features for d=2 and G=8.

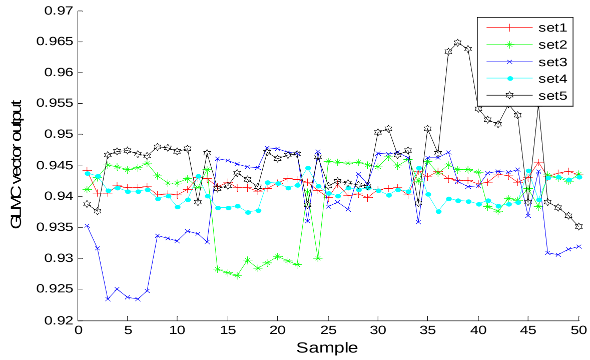

Fig. 3. The output features for d=3 and G=8.

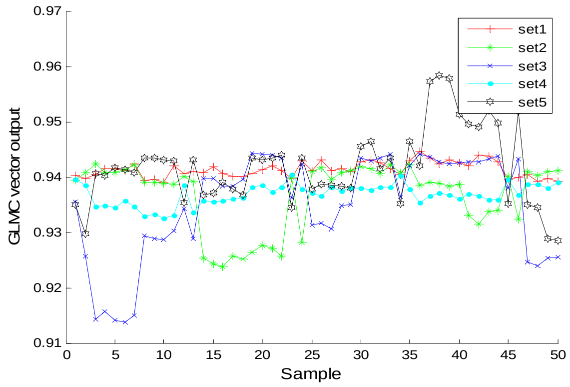

Fig. 4. The output features for d=4 and G=8.

This paper deals with the experiments to get better features for the bin level and its surrounding area detection as well as to get better classification result. Thus, results from the parameter analysis, it can be concluded that the desirable values of *d* =1 and *G*= 8, 16, 32, 64 are the most suitable parameters values to be applied with GLCM.

VI. Evaluation of Parameters and Features Selection

To evaluate the parameters selection in the parameters analysis section, MLP was employed to evaluate all *d* and *G* values that have been analyzed. To reduce the number of combinations analyzed at once, each *d* and *G* value was initially analyzed separately for 4 features. The classification result in Table I shows that the classification accuracy for *d*=1 is best with all *G* values. It is seen that at *d*=1, the average classification rate was more than 91% and average grading rate was 80% at all *G* values. It is noticed from the table that the classification accuracy decreased as the *d* value increased which justify our analysis to be choosing *d*=1 with all *G* values for the best classification and grading. The classification result is considered to give the best set of parameters to be represented with GLCM.

TABLE I
Classification (C) and Grading (G) Accuracy (%) of MLP with Various Values of D and G.

G	d=1		d=2		d=3		d=4	
	C	G	C	G	C	G	C	G
8	85.9	77.3	83.9	74.5	82.8	73.9	81.9	73.5
16	90.4	77.3	88.8	76.2	89.9	74.7	88.7	74.2
32	93.3	87.0	91.8	83.8	92.8	80.6	90.2	76.9

ISBN: 978-988-19252-4-4
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

64	97	81.0	93.5	80.9	95.0	80.7	97	78.0

Table II and Table III shows the classification and grading performance selected features were evaluated with both MLP and KNN classifiers. The results demonstrated that the KNN classifier performs better than that of using MLP with same database. For instance, by employing G=16, 32, the classification and grading accuracy of the KNN at K=3 were 99.50%, 97.50%, 99.50% and 97.77%, respectively. Both, the classification and grading overcome the MLP performances which were 93.38%, 87.03%, 97.00% and 81.03%, respectively.

TABLE II
CLASSIFICATION (C) AND GRADING (G) ACCURACY (%) OF MLP WITH VARIOUS VALUES OF D AND G.

4 features	***d*=1; *θ*=0⁰,45⁰, 90⁰,135⁰**	
	C	**G**
G=8	85.94%	77.30%
G=16	90.48%	77.30%
G=32	93.38%	87.03%
G=64	97.00%	81.03%

TABLE III
CLASSIFICATION (C) AND GRADING (G) ACCURACY (%) OF KNN WITH VARIOUS VALUES OF D AND G.

KNN	***d*=1; *G*=8**		***d*=1; *G*=16**		***d*=1; *G*=32**		***d*=1; *G*=64**	
	C	**G**	**C**	**G**	**C**	**G**	**C**	**G**
3	91.9	93.1	98.5	94.8	99.5	97.5	99.5	97.7
5	95.5	92.3	99	97.4	98.5	99.0	95.4	92.6
7	96.4	88.8	97.6	98	95.4	98.1	97.6	99

Fig. 5 shows ROC graph with the best MLP classification and grading results were 93.38% and 87.03% obtained at *d*=1 and *G*=32. The variation of the result shows how the values of *G* are important factor in GLCM technique and can affect the classifier performance accuracy.

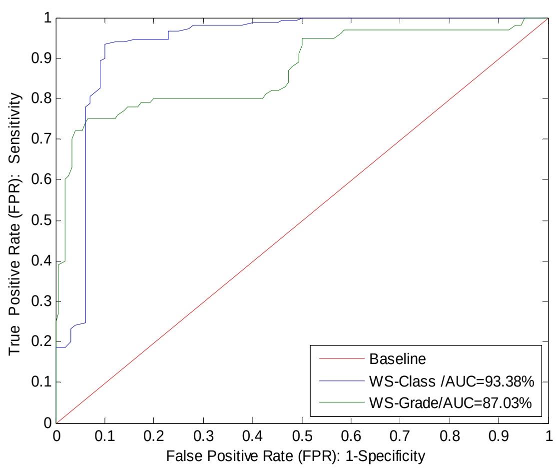

Fig. 5. MLP classification and grading with 4 selected features at d=1 and G=32.

Fig. 6 shows the ROC graph with the best KNN classification and grading results were 99.50% and 97.67% obtained at KNN=3 for d=1 and G=32. The training dataset of the KNN consists of only 5 classes of bin level images of the training samples. The testing data is classified by the training labels of the KNN training datasets nearest to the testing image. The best classification result has been obtained with value of d=1 at KNN=3. The KNN classification and grading result shows that the values of KNN, d and G affected the classifier performance accuracy, the KNN classifier proved to be better than MLP classifier in both classification and grading.

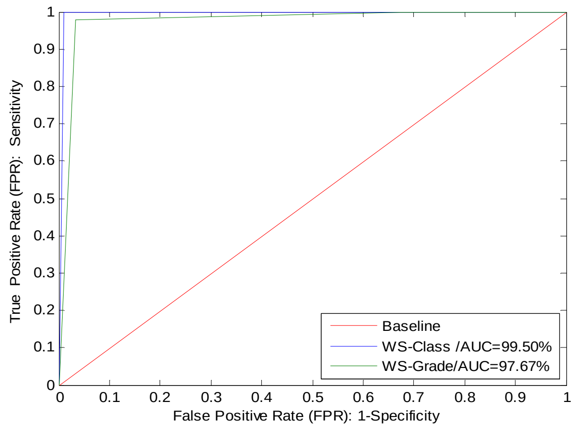

Fig. 6. KNN=3 4 features d=1 G=32

Fig. 7 provides the comparison between the total data i.e. five classes of training and testing datasets and tested KNN decision. The classes of the bin are marked with different colors, the training data marked with dots (•) and the testing data marked with circle (○). The tested data is classified by using KNN at different values. The samples that are correctly classified grouped with the training samples, most of the circle symbols lay inside or near to the dot symbols which shows high classification accuracy. It is identified that if the dot comes inside the circle, the sample is well classified. However, if the dot does not locate inside the circle, the sample is misclassified. It is seen that first 30 samples from each class are classified 100%, however, the misclassified samples appeared in the last 20 sample from each class.

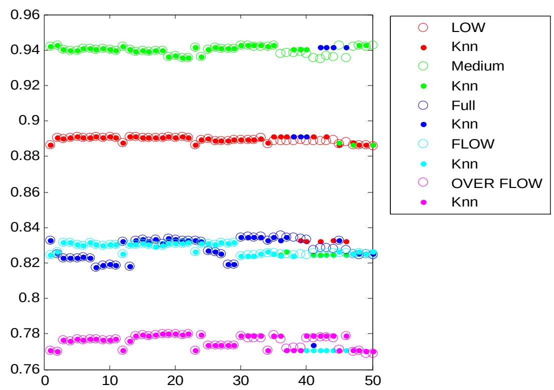

Fig. 7. Classification accuracy between the original data and trained data by KNN.

VII. CONCLUSION AND DISCUSSION

The objective of paper is to detect and classify the solid waste bin level i.e. low, medium, full, flow and overflow by GLCM parameters on the performance of co-occurrence matrix texture measures using MLP and KNN classifier. The performance of MLP and KNN is significantly affected by the GLCM parameters.

Value of *d=1* is selected and the rest of the values were eliminated due to the poor seperability between the 5 sets and classification. The lower *G* values were eliminated in the real application due to reduction of the bin image information and the worst classification results in all the databases. The best classification and grading results obtained from MLP confirmed that *d*=1 and maximum *G* values are best displacement and quantization, respectively. Similarly, the best classification results obtained from KNN confirmed that at KNN=3, *d*=1 is best displacement.

The classification and grading results shows that using the KNN classifier outperforms than that of MLP. The KNN classification and grading performance at KNN=3, *d*=1 and maximum values of *G* beats all values of G of the MLP classifier. Thus, it can be concluded that at *d*=1 and higher values of *G* may even lead to higher detection and classification accuracy of solid waste bin level.

Acknowledgment

The authors are acknowledged this work for the financial support under the grant ukm-pts-003-2009.

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