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Solid waste bin detection and classification using Dynamic Time Warping and MLP classifier

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ABSTRACT

The increasing requirement for Solid Waste Management (SWM) has become a significant challenge for municipal authorities. A number of integrated systems and methods have introduced to overcome this challenge. Many researchers have aimed to develop an ideal SWM system, including approaches involving software-based routing, Geographic Information Systems (GIS), Radio-frequency Identification (RFID), or sensor intelligent bins. Image processing solutions for the Solid Waste (SW) collection have also been developed; however, during capturing the bin image, it is challenging to position the camera for getting a bin area centralized image. As yet, there is no ideal system which can correctly estimate the amount of SW. This paper briefly discusses an efficient image processing solution to overcome these problems. Dynamic Time Warping (DTW) was used for detecting and cropping the bin area and Gabor wavelet (GW) was introduced for feature extraction of the waste bin image. Image features were used to train the classifier. A Multi-Layer Perceptron (MLP) classifier was used to classify the waste bin level and estimate the amount of waste inside the bin. The area under the Receiver Operating Characteristic (ROC) curves was used to statistically evaluate classifier performance. The results of this developed system are comparable to previous image processing based system. The system demonstration using DTW with GW for feature extraction and an MLP classifier led to promising results with respect to the accuracy of waste level estimation (98.50%). The application can be used to optimize the routing of waste collection based on the estimated bin level.

1. Introduction

SWM and monitoring is a critical issue for the metropolitan authorities of developed and developing countries (Guerrero et al., 2013). It is a challenge for the municipal authorities due to the rapidly increasing amount of waste generated. The statistics show that, the amount of SW generation has been increasing sharply since the beginning of the last decade (Guerrero et al., 2013). The burden has posed heavily on municipal yearly budget, 20–50 present of the municipal yearly budget is needed for SWM (Noor et al., 2013).

This time most of the researchers are focusing on the green environment and environmentally friendly SWM system (Budzianowski, 2012). SW collection is the most important part in SWM. A study has shown the different routing and scheduling policy's effectiveness using concurrent data of collection location and bin from the recycling system station in Malmoe, Sweden (Johansson, 2006). Johansson has summarized that the collection process has been improved by the equipping bins with level sensors.

An improved waste collection system has introduced in Sweden by using wireless communication devices and level sensors and a stripe of IR LEDs fitted recycling bins to estimate the waste inside the bin. Real time bin status is sent to the operator when more than two sensors are obstructed (Pascoe and Connell, 2003). This system is not economic for waste collection system, where thousands of waste bins are situated in a small city area. Capacitive level sensor has been developed by Reverter et al. (2003), which is manufactured by cheap metallic adhesive tape and simply can be attached with waste bin. It has been used to bin level detection but they do not work well for volume measurement due to the humidity sensitivity of capacitive sensor and are not suited for other types of material (Patrícia et al., 2010). An optical sensor for bin level detection has been also proposed by Patrícia et al. (2010), but scheduled cleaning needs to be provided.

There are some methods for bin level identification; several types of sensors embedded with the waste bin, manual data collection by man and webcam with image processing are mostly common used methods (Rada et al., 2013; Faccio et al., 2011). Researches have carried out for waste level detection focusing

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latest image processing technique instead of various level sensors (Vicentini et al., 2009). An automated waste collection system has been developed by Politecnico di Milano, they have estimated bin level using distance sensor integrated with image processing technique (Rovetta et al., 2009). A robust system of SWM can maximize the efficiency of waste collection and create an opportunity of a sustainable environment.

Zhu et al. (2009) 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 new image of the bin's contents is compared to the previous image to determine the amount new waste disposed in the bin.

An application of advanced computer image processing techniques integrated with communication technologies has been examined for solving the problem of solid waste collection and automated bin level detection (Rovetta et al., 2009). a method of bin level detection has been implemented using a GW filter GLCM and BGLAM 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 (Arebey et al., 2012). 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.

The prime problems of the existing image processing systems for SWM have summarized:

- No real-time image processing method that integrates advanced methods for waste amount estimation.
- Camera positioning problem in image processing based solid waste bin level estimation system.

This paper proposes GW transform with DTW system that can overcome these problems. The system is trained and tested with MLP classifier to classify bin level. The bin is classified based on the developed decision algorithm. The proposed automated SW bin level detection system is robust to analyze the waste bin features and estimates the amount of waste level. The proposed approach can be used for SW level identification and classification for municipalities. Accordingly, the implemented approach can be used by SWM companies, for their SW detection and classification and to optimize their collection, monitoring and management policies.

2. Waste scenario in Malaysia

According to the department of statistics Malaysia, the population growth rate has continued of 2.4% per year since 1994 (Dept. of Stat. Malaysia, 2012). With this high rate of population growth, generation of municipal SW has been increased and therefore its management turns into a critical issue. A study found that near to 54% of households were dissatisfied with the current quality of waste collection services and 28% were concerned about the environment (Rafia and Masuda, 2010). Now Malaysian government has given attention on developing new SWM methods addressing these issues. Waste bins, waste collection trucks, municipal's labors and landfills are involved in the typical waste collection system. The inadequacy of suitable land in urban areas and public awareness are growing opposition to landfill dumping have led to many municipalities to look for alternative dumping methods like integrated SWM system (Johansson, 2006; Pek and Jamal, 2011).

Many companies have focused on the use of wireless sensing systems (Rovetta et al., 2009). In Malaysia, Alam Flora, a private SWM company, have used a real-time monitoring and tracking system that monitor collection truck location and waste collection to improve collection efficiency (Alam Flora, 2009). In Kuala Lumpur, households are not receiving sufficient information on the benefits of waste recycling and separation. Japan International Corporation Agency (JICA) report in 2012 has shown the Malaysian waste generation amount in each state since 2004–2012 (JICA, 2012) in Fig. 1. The given statistics clear the fact that the overall waste generation amount has increased rapidly due to the growing number of people with higher consumption rate (JICA, 2012; MHLG, 2011).

3. Bin image capturing and detection technique

Various image processing techniques and algorithms have been developed for image feature extraction since the image processing technique has been introduced. Those techniques or algorithms have been developed considering the various problems like Marr-Hildreth edge detector and the Canny edge detector has developed for edge detection, Gray Level Difference Matrix (GLDM) for texture analysis, Gray Level Difference Matrix (GLCM) for feature extraction (Nadernejad, 2008; Roberti et al., 2013).

Artificial intelligence, like neural network embedded with image processing techniques has made a very efficient system for texture analysis and correctly image classification. Texture analysis is widely used in biomedical engineering, pattern recognition, object detection, road sign detection of intelligent vehicles, unmanned aerial vehicles like drones, documents processing like Optical Character Recognition (OCR), medical image analysis (Phinyomark et al., 2012). The level classifications of the bin during the waste collection operation enhance the efficiency of the waste collection and overall SWM process.

In waste collection system, automatic waste level detection is a big challenge and it is mostly related to level recognition (Hannan et al., 2012). The positioning of the bin and the camera is quite a big challenge. To get the bin centralized in the image needs special training to the camera operator. The camera operator always takes care about the bin position at the time of capturing bin image because without centralized bin image the system sometimes failed to find the bin. The article has developed a reliable solution that can detect the position of the bin in the image using DTW and then estimating the level of the waste inside the bin. The image processing technique for bin level detection system consists of some phases such as image capturing, database, image pre-processing, bin detection by DTW, feature extraction and classification; it has shown in Fig. 2.

3.1. Bin image database

The main goal is to create a database with different bin level images. The database keeps on record all the different bin level's images and updates it with a certain time interval. The images have been captured by Logitech HD Pro Webcam C910. The camera has been attached to the collection truck and several distances from the waste bin have been tested to capture the best view of the bin area, the best distance has selected between the camera and the bin is around 1 m. The bin image has been captured at four different levels (low, medium, full, and flow). All the images in the database are saved as JPG format. Fig. 3 shows a certain number of samples in the different waste levels waste bin of the database system.

3.2. Image pre-processing

All the images need to be pre-processed before the feature extraction stage. It makes the feature extraction process easier

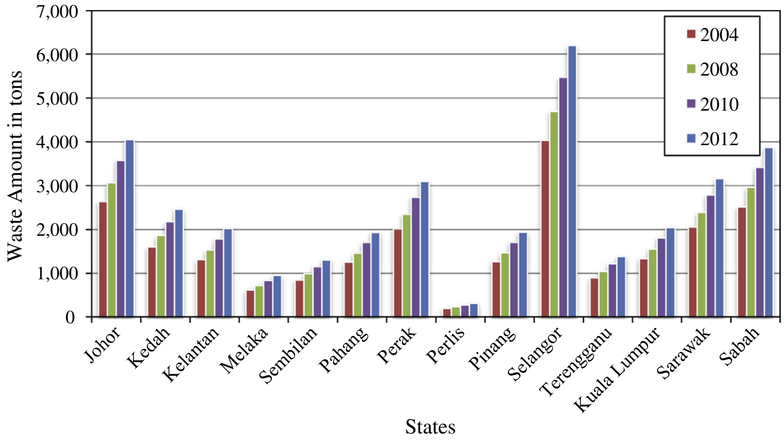

Fig. 1. JICA study 2004–2012: Waste generation in 14 states of Malaysia (tons/day).

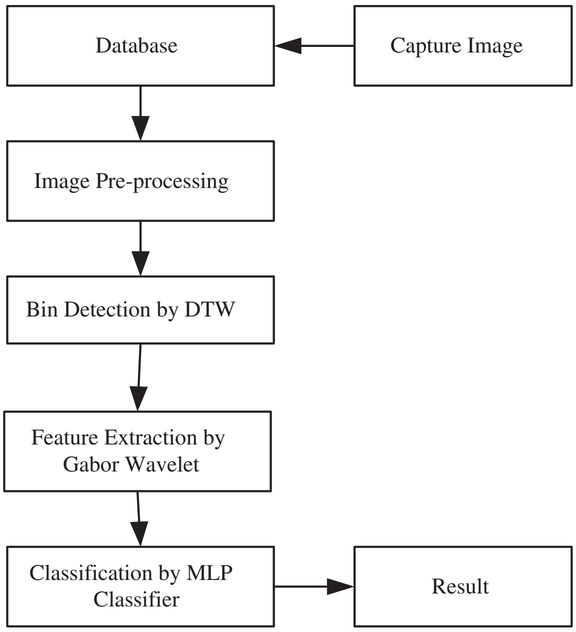

Fig. 2. Bin image detection, feature extraction and classification system block diagram.

and gives better results than unprocessed raw images. Sunlight, weather conditions, surrounding environment on the images can result in improper level detection. The pre-processing phase has the following steps:

- The images of the bin and the collected database have taken under different uncontrolled external illuminations and weather conditions to enhance the quality of database collection.
- Color conversion, the true color RGB image has converted to a grayscale format for image analysis. An integer value between 0 and 255 characterize the brightness of image pixel of a grayscale image.
- Image resizing, the original image of 800 × 600 pixels has resized to a smaller size of 300 × 300 to reduce the computational complexity and to save storage memory.

3.3. Dynamic Time Warping (DTW) for bin detection

To classify the bin, the first important task is to find the bin from the captured images. This part is mostly related to object detection. There are many methods to find an object from an image like background subtraction method, Gabor Co-occurrence Similarity (GCS), Color Co-occurrence Matrix (CCM), DTW (Zou et al., 2013). DTW has chosen instead of GCS and CCM to find the bin from the image as there are lots of color variations of waste materials.

It is a technique of distance measurement between two “1 dimensional time series” data that measures the similarities between them (Adwan and Arof, 2012). DTW is commonly applied technique for time-dependent series optimum alignment between two time series. This technique warped the nonlinearly series with another nonlinear series efficiently (Niels, 2004). In addition for data querying (Palazón-González and Marzal, 2012), DTW is commonly applied to robotics vision, gesture recognition, manufacturing industries, speech processing system and drugs (Jeong et al., 2011). The time series is a universal form of data presentation in the field of virtual data computational area (Yu et al., 2011; Tabib et al., 2013). The Euclidean distance measure is a very simple distance measuring technique of time domain series some cases it's like will suffice. Sometime two time sequences have similar shapes, although the shapes cannot arrange up in *X*-axis, shown in Fig. 4. In those cases, the time axis of both series have warped and averaging them to achieve an enhanced alignment (Jeong et al., 2011).

3.4. DTW theorem

DTW algorithm has grossed its acceptance by being very efficient to detect pattern similarity. It minimizes the distortion and shifting effects by permitting elastic transformation of time series (Assecondi et al., 2009).

Suppose P and T are two time series; where, n and m are the respective length, so

$$P = p_1,\ p_2,\ \ldots p_i,\ \ldots p_n \quad (1)$$

$$T = t_1,\ t_2,\ \ldots t_i,\ \ldots t_n \quad (2)$$

A matrix n-by-m creates to align two time sequences in DTW algorithm. Where, the distance $d(p_i,t_j)$ between p_i and t_j of the (ith,jth) matrix element and $d(p_i,t_j) = (p_i - t_j)^2$ is the Euclidean distance. The matrix element (i,j) corresponds to the alignment between the points p_i, and t_j is illustrated in Fig. 5. The mapping between P and T adjoin by a warping path W. The kth element of W is defined as $w_k = (i,j)_k$;

Fig. 3. Bin database samples at different levels (flow, full, medium, and low).

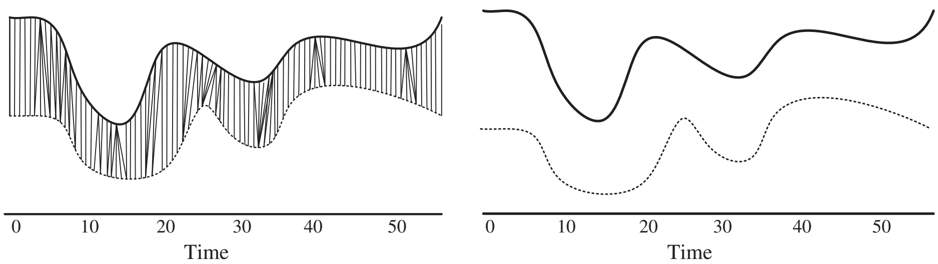

Fig. 4. Time series data present the *Y* axis position of a human signature of two separate days and an alignment of two nonlinear series by DTW.

where

$$W = w_1,\ w_2, \ldots w_k, \ldots,\ w_k \quad \max(m \cdot n) \leqslant K < m + n - 1 \tag{3}$$

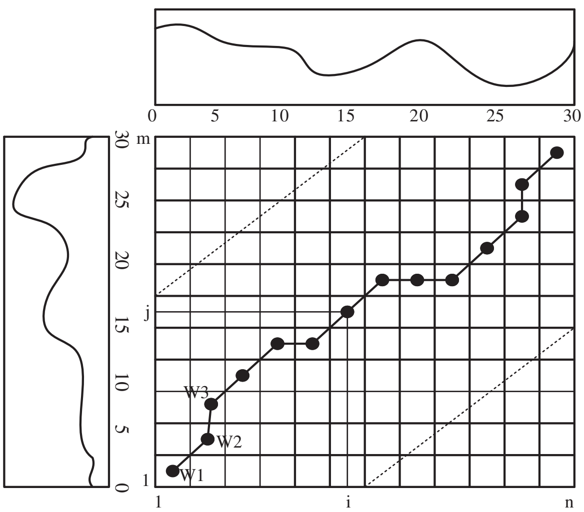

Fig. 5. Warping path of two single dimensional time spaced shapes.

The constraints of the warping path are as follows:

- *Starting and Ending conditions:* $w_1 = (1,1)$ and $w_k = (m,n)$, the opposite diagonal cells are the starting and ending of the warping path.
- *Continuousness:* The neighboring cells of the warping path allow by following conditions, If, $w_k = (a,b)$ then $w_{k-1} = (a',b')$ here $a–a' \leqslant 1$ and $b–b' \leqslant 1$.
- *Monotonicity:* The cells of warping path W is monotonically in time spaced as $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a–a' \geqslant 0$ and $b–b' \geqslant 0$.

There are several warping paths that fulfill the above conditions but we are interested/fascinated to the path which minimizes the cost of warping (Zhou and Wong, 2011):

$$DTW(P,\ C) = \min\left\{\sqrt{\sum_{k=1}^{K} w_k / K}\right\} \tag{4}$$

There are various warping path lengths and the denominator K is used for normalizing path length. Dynamic programming can be used to find the path very efficiently in order to evaluate the cumulative distance $\upsilon(i,j)$ as the current cell distance $d(i,j)$ and the minimum of the cumulative distances of the neighboring elements:

$$\upsilon(i,\ j) = d(P_i,\ T_j) + \min\{\upsilon(i-1,\ j-1),\ \upsilon(i-1,\ j),\ \upsilon(i,\ j-1)\} \tag{5}$$

3.5. Projection computation

The projection computation is an important part of object detection from an image. Correctly bin detection depends on the image projection computation and projection matching with template's projection. The computational algorithm has shown in Fig. 6. The algorithm simultaneously calculates the vertical and horizontal projection. The overall projection of the image constructs by placing the vertical and horizontal projection side by side. The horizontal projection is constructed by taking the sum of pixels of each row and divided by the number of columns. The pixel values plotted in the time domain for projection construction. The vertical projection gets from the sum of pixels of each column and divided by the number of rows.

The projection computational process is simplified by skipping 20 rows and 20 columns for each iteration. In iteration, it takes different image sections of same frame size, in Fig. 7. As the middle of the bin is darker than the all around edges so vertical and horizontal projections are individually like "U" and when two projections have placed on side by side the projection of the bin becomes like "W". The bin image's projection is compared with the template projection and the least warping path is considered to get the maximum matching. If the boundary conditions are fulfilled then the bin crops from the image and save it for feature extraction by GW transform.

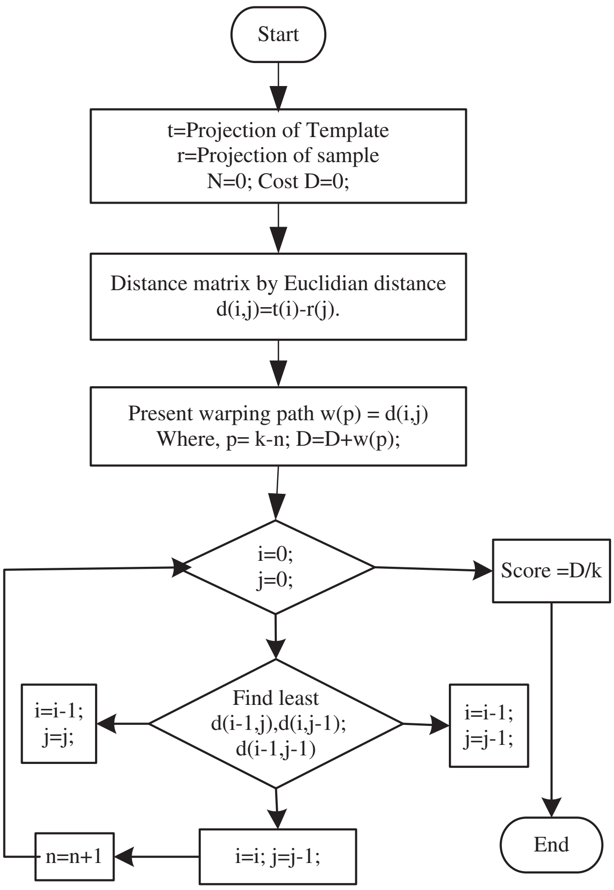

Fig. 6. Flow chart for bin detection using test image.

4. Feature extraction and classification

There are different features like statistical features, structural feature, projection profile, curvature features, and directional features (Chang et al., 2011). The features are extracted considering the problem and application area. Image features applications are wide like intelligent vehicle, biomedical and Geo-sciences. A quality classification may lead by a good and relevant feature extraction. In this paper, the statistical features using the GW feature extraction method has been proposed.

4.1. GW filter for feature extraction

In image processing, GW was initiated because of its computational attributes and biological relevance. GW has been exercised for feature extraction due to its frequency domain and optimal localization properties. The GW exhibit desirable characteristics of spatial locality and orientation selectivity, and are optimally localized in the space and frequency domains.

If an image is $I(x,y)$, its discrete convolution gives GW transform as follows (Lades, 1993):

$$G_{\mu\cdot\upsilon}(x,\ y) = \sum_U \sum_V I(x-U,\ y-V)\psi^*_{\mu\cdot\upsilon}(U,\ V) \tag{6}$$

here, filter mask variables are U and V, and complex conjugate $\chi^*_{\mu\cdot\upsilon}$ that is generated from mother wavelet's $\psi_{\mu\cdot\upsilon}$ rotation and dilation. Eq. (7) defines a general function of 2D GW in frequency domain and space,

$$\psi_{x\cdot y} = 1/(2\pi\sigma^2)exp[-1/2(x^2+y^2)/\sigma^2)]exp(j2\pi\omega x) \tag{7}$$

$$x_r = x\cos\theta + y\sin\theta \tag{8}$$

$$y_r = -y\sin\theta + x\cos\theta \tag{9}$$

here, the modulated sinusoidal wave frequency is f and the orientation of the elliptical Gaussian's major axis is θ. The Fourier transforms of Eq. (7) (2D GW) is as follows (Soares et al., 2006).

$$\psi_{\mu\cdot\upsilon}(x,\ y) = \frac{\|k_{\mu\cdot\upsilon}\|^2}{\sigma^2} e^{\left(-\frac{\|k_{\mu\cdot\upsilon}\|^2\|z\|^2}{2\sigma^2}\right)} \left[e^{ik_{\mu\cdot\upsilon z}} - e^{\frac{-\sigma^2}{2}}\right] \tag{10}$$

Here, $\|\cdot\|$ symbolizes the norm operator, υ and μ are scale and orientation of Gabor kernels (x,y). The wave vector is defined as follows:

$$K_{\mu\cdot\upsilon} = k_\upsilon e^{i\phi_\mu} \tag{11}$$

Here, $K_v = K_{max}/F^v$ and $\phi_\mu = \pi\mu/8$. In frequency domain kernels spacing factor is F and the maximum frequency is K_{max} (Lades, 1993).

All the kernels in Eq. (10) are looking alike since they have created from one filter. It is the rotation and scaling of the mother wavelet via the wave vector $K_{\mu\cdot\upsilon}$. In the Eq. (10), in the third parenthesis have two terms, first terms defines the oscillatory value and second term recompense the DC value. The DC term effect becomes insignificant to the large value of the parameter σ which is the proportion of wavelength and Gaussian window width (Soares et al., 2006).

The Gabor filters parameters have been specified considering the frequency levels and mask size. The waste images enhancing are performed by GW filter is a convolution process of filters' coefficient matrix and the image. The computational cost influenced by the filtering performance and mask size (Ishak et al., 2009). The enhancement process is suffered for larger mask size (Zhao et al., 2012). The size of window changes with the sinusoid frequency and when the value of k is changed from 1 to 4, the Gaussian

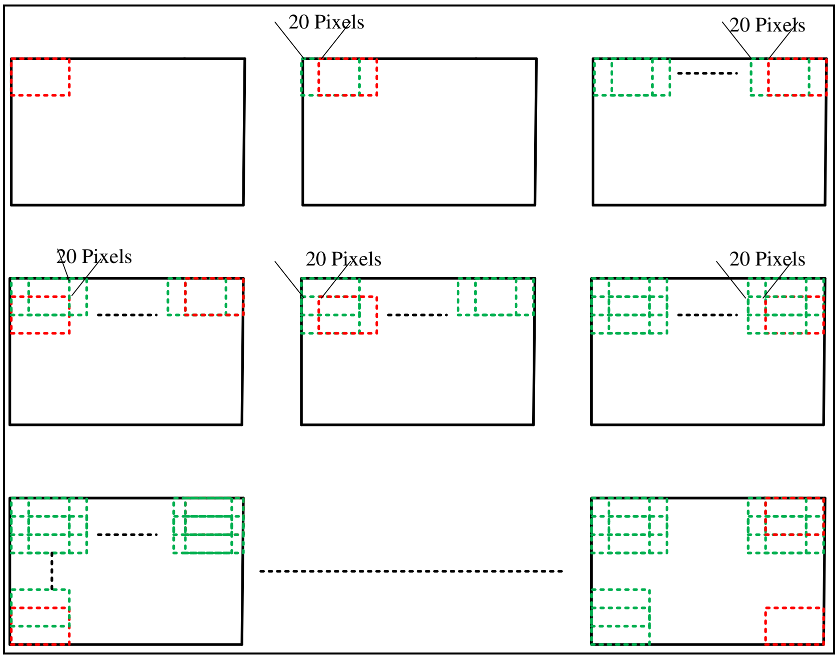

Fig. 7. Image segmentation, red is new and green is old segments from previous iterations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

window size increases with the reduced sinusoid frequency (Bashyal and Venayagamoorthy, 2008).

In GW, the demonstration of an image is a convolution of Gabor kernels with the image. Where, an image gray level intensity distribution is $I_{(x,y)}$, explained above, the Eq. (6) defines the convolution of the image I with Gabor kernel $\psi_{(\mu \cdot \upsilon)}$. The value of each $G_{\mu \cdot \upsilon}(x,y)$ can be derived by using the convolution theorem thru the Fast Fourier Transform (FFT). The Eq. (12) computes the final output.

$$\text{output} = \sqrt{R_{ave}^2 + I_{ave}^2} \tag{12}$$

where R_{ave} is the result of real filter mask convolution with the image and I_{ave} is the result of the imaginary filter mask convolution with the image.

4.2. MLP classifier

MLP is a classification technique based on a feed forward algorithm. The classifier is consists of a set of neurons that arranged in multiple layers and connected with neighboring layer by weights (Roberti et al., 2013). The first layer is input and the last layer is output layer. A layer between the input and output layers is called the hidden layer (Lin et al., 2008; Zheng et al., 2011). The perceptron concludes a pair of output values from a series of numerous inputs and the information moves to forward direction from the input layers to output nodes through the hidden layers (Zanaty et al., 2012). Input features vector and target vector sets are used to train the network to set internal relations between input and output nodes to organize the data into corresponding pattern classes (Li et al., 2010). After a complete training the network tends to able rational answers when presented with unseen inputs. The weight has updated at the output layer by below equation (Yilmaz and Kaynar, 2011):

$$W_{j,i} + \alpha \times E_{rri} \times g'(in) \times x_j \rightarrow W_j \tag{13}$$

There have multiple output units, where E_{rri} be ith component of the error vector and modified error $\Delta_i = E_{rri} \times g'(in_i)$, so that the updated weight by Eq. (14).

$$W_{j,i} + \alpha \times \alpha_j \times \Delta_i \rightarrow W_{j,i} \tag{14}$$

A quantity analogous error term is needed to update the connections between the hidden units and input values. The Δ_i values are divided according to each of the output nodule and are propagated back to providing the Δ_i values for hidden layer. The decision rules for the classifier have shown in Table 1.

The classification network is framed with three-layer and the output range are preferred bipolar values 0 and 1. The neural nodes generate various output sets depend the input; those sets classify the bin classes. The classifier is trained with two third of database images and the rest of them are used for testing the system. The number of input neural nodes are 8, corresponding to the four sets. The number of output neural nodes are 2, the output sets, i.e., (1,0), (1,1), (1,−1) and (−1,0) correspond to the four bin level images. The network training function is an adaptive learning rate and momentum based gradient descending function. The performance of the classifier network is determined by ROC curve analysis. The decision making cost and benefit study is also related to ROC curve analysis. If the area under the ROC curves become higher, less computational time is required for proper decision thus the decision cost is low and vice versa.

5. Results and discussion

The image features extracted by GW transform and MLP classifier has applied for classification. The training and testing performance assessment has done by the ROC curve analysis. This

Table 1
Sets of the MLP output value for corresponding bin level.

Rules of decision	Bin classification
0, 1	Bin empty
1, 1	Bin medium
1, −1	Bin full
−1, 0	Bin flow

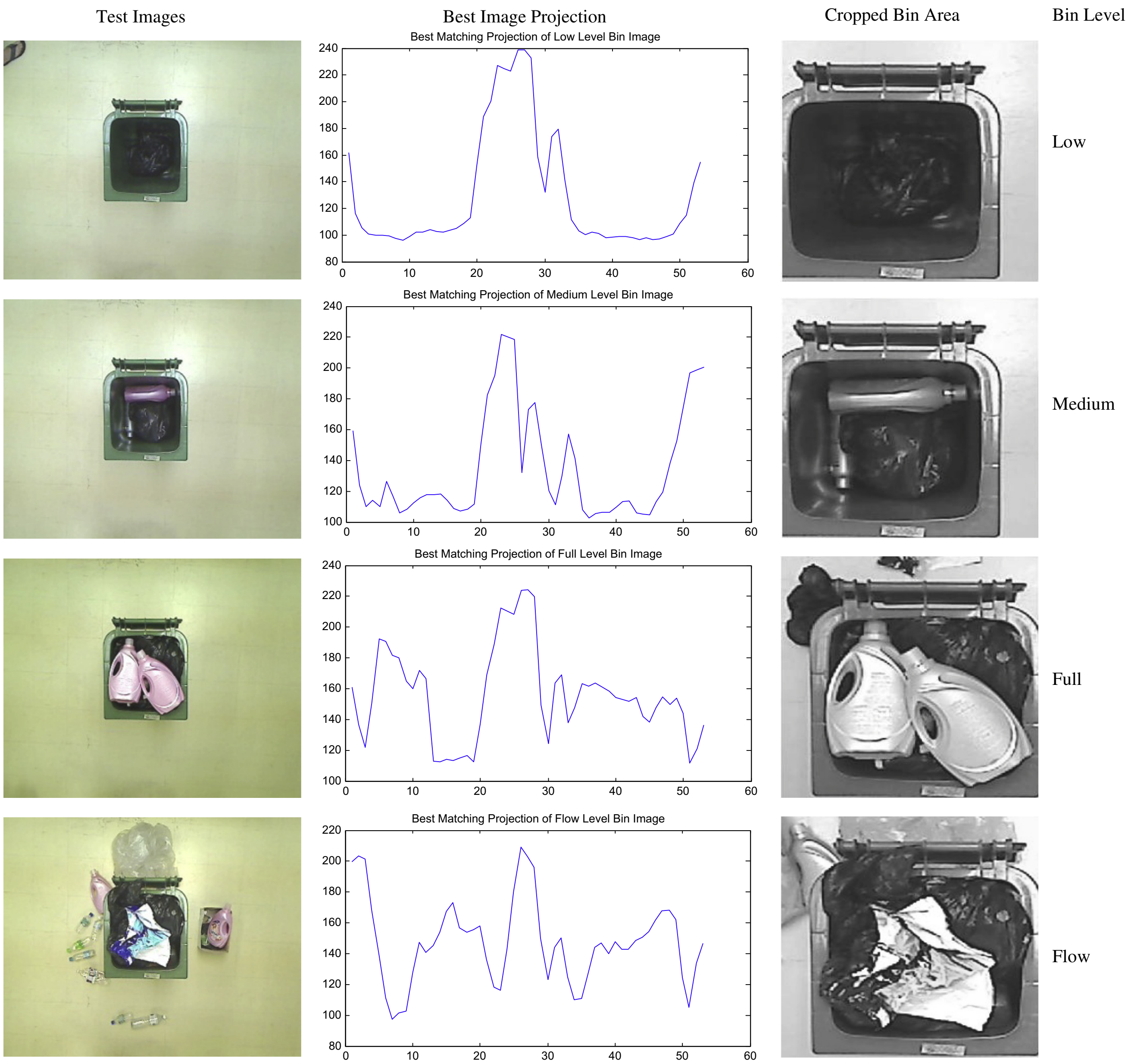

Fig. 8. Best matched projection of test images and cropped bin area.

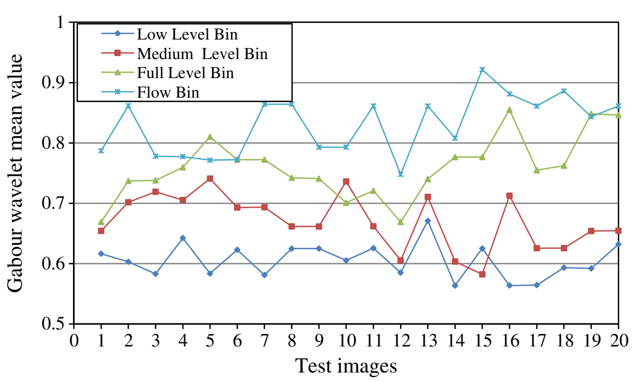

Fig. 9. Features characteristics curve for GW transform.

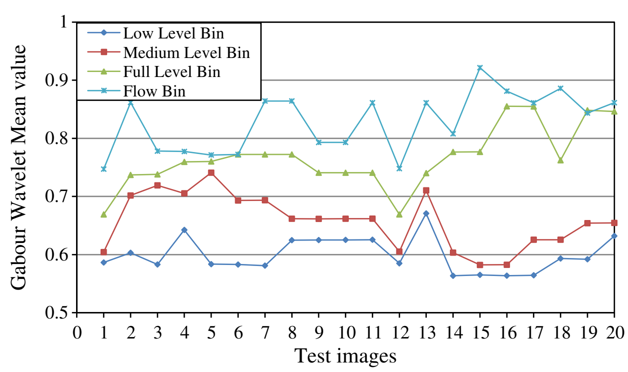

Fig. 10. Features characteristics curve for GW transform with DTW.

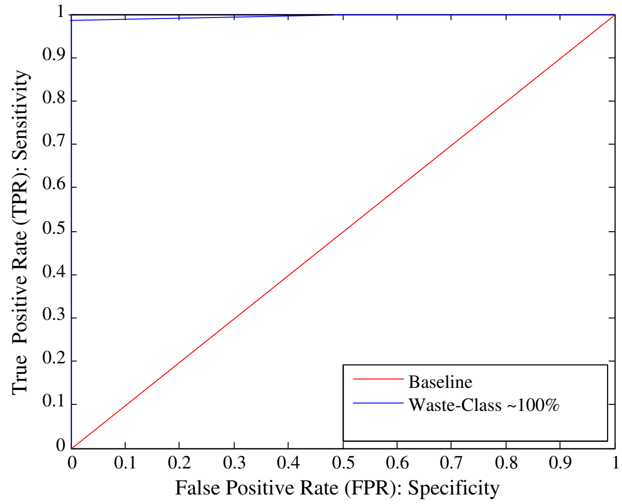

Fig. 11. System training performance based on area under ROC curve.

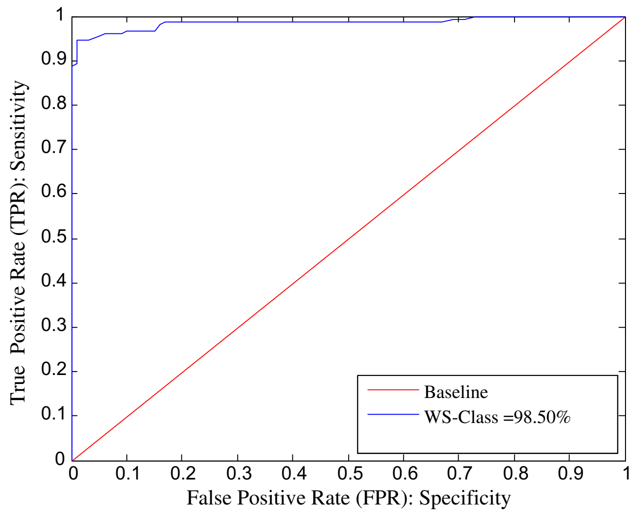

Fig. 12. System performance for test images based on area under ROC curve.

image feature extraction and classification system would offer a solution to SWM companies with waste amount estimation.

5.1. Image preprocessing and bin detection

All the raw images are converted to a smaller dimension, 300 × 300 pixels, to save the storage space and computational complexity reduction. To get a better result and to avoid the environmental effect only the waste bin area has been considered. The bin area is detected from the image by using DTW. It calculates the maximum similarities between two patterns of one dimension in time domain. DTW calculates the projection as a pattern of the bin. The projection of the bin is 'W' shaped, as the middle of the bin is darker than the edges so the each horizontal or vertical projection is like a "U" shaped and two projection side by side made it "W" shaped. If the projection of the bin matches with the bin template projection then the boundary of the bin calculates as per boundary condition. Finally the bin area is detected and cropped from the image for feature extraction. The best projection matching graph for the test image is displayed and the cropped bin area is shown in Fig. 8.

5.2. Bin feature extraction

Image feature extraction is a prime step for any classification. The cropped bins from the images are used for feature extraction by GW transformation. The GW features has been used for bin classification. The GW features of different class's bin images are plotted. The classification performance for various image sets, like low, medium, full, depend upon how the features graphs are separated from each other and there is no overlapping between them. The GW feature extraction performance has been tested by a set of bin images without bin area cropping in Fig. 9. The GW feature vectors are saved to a new file before to train the classifier. It gives a wrong classification in the overlapping region. The next graph shows the features graph of GW for a crop bin area using DTW in Fig. 10.

The graph shows a very minimal overlapping region among the features, so after cropping bin area applying DTW, the performance becomes better and there are a few chances of wrong classification. The GW features vectors are used to train the MLP classifier.

5.3. Classification performance

The classifier is trained with three fourth numbers of database images and the rest of the database images are used for testing and performance evaluation. The performance of the system has been evaluated considering the ROC graph. In this experiment, a three-layer feed-forward network trained with Back Propagation (BP). The system was trained with 180 bin images. The images were pre-processed with the feature extractor. The GW output is used as the input of the classifier and two output vectors of the classifier represent the various bin classes (low, medium, full, flow). The ROC curves for the training are shown in Fig. 11 illustrating the relationship between True Positive Rate (TPR) and False Positive Rate (FPR). The area under the ROC curve is a training accuracy measuring parameter. The higher area under the ROC curve measures the greater likely hood and higher probabilities of being positive for actual positive case than the actual negative case. In this work, the training performance by measure of the area under the ROC curve is about 99.50%. Therefore, the result of the training procedure is satisfactory. The classification accuracy measure is guided by the generalized point system: excellent (A) for 90–100, good (B) for 80–90, fair (C) for 70–80, poor (D) for 60–70 and fail (F) for 50–60. The performance curve measures the 99.50% classification accuracy that is validating the classification system.

The classifier has been tested with the four sets of the bin images, which are randomly selected and different from those used for training. Already it has explained that the system has been trained with three-fourth of the images of the database and tested with the rest of the images. In this demonstration, a bin level is successfully classified. Fig. 12 illustrates the performance of the classification algorithm through the ROC curve analysis. In this experiment, the classification testing performance is observed 98.50% by considering area under the ROC curve, which is very acceptable. However, the efficiency of classification can be better by compelling more images into the classifier training phase. Furthermore, more study of methods and techniques should be considered to improve the method of classification.

The comparison with similar image processing based classification system has summarized in Table 2 of validate the result of GW with DTW and MLP classification system all the results have considered and compared with nearly similar image processing based systems results. The Gray Level Aure Matrix (GLAM) and GLCM methods have considered for comparison. The classification sensitivity (TPR), specificity (FPR) and area under the ROC curve for training and testing have taken account for comparison. The

Table 2
Performance indices comparison with other methods of classification.

Results	GLAM (%)	GLCM (%)	Proposed system (%)
Sensitivity	96.50	95.50	98.00
Specificity	96.00	96.50	98.50
ROC for training	99.00	99.50	~100
ROC for testing	97.50	96.00	98.50

similar systems have been demonstrated and compared for same test image sets and same computer configuration. 45 Sample images of each class have been selected for training and 15 sample images for testing phase.

The proposed method has been tested on the 15 sample images, which are different from those used in the training procedure. 45 Sample images in the database were used for training. An application of GLAM for solid waste level estimation system developed by Hannan et al. (2012) and waste bin level estimation system demonstration by Arebey et al. (2012) using GLCM gave very good classification accuracy within 95.5–97.50%. Previous system gave more than 99.00% training accuracy. It observed that the performance of the proposed system has improved to 98.50% for testing and about 99.50% for training. There was a significant impact of DTW to improve the performance. DTW detects the bin from the sample images and cropped it for feature extraction. In our experiments, a bin level is successfully detected by both the class and the grade. In this work, the results are quite satisfactory. However, the angle of view is responsible for mis-classification due images could not be snapped directly to the center or the bin. The efficiency of grade classification can be improved by taking more data into the training stage, which helps the MLP classifier to identify most of the cases.

6. Conclusion

SW Bin level estimation system has been successfully designated by using a webcam as image capturing device integrated with latest image processing techniques. In this paper, image processing technique has focused for object detection and feature extraction using DTW and GW respectively and an MLP network for waste level classification. The system composed of four main stages: image capturing, bin detection, feature extraction and classification. The classification performances have investigated and compared to other system. The efficiency of the proposed technique was justified by demonstrating a good number of sample images. The developed system can be estimated the quantity and quality of waste in the bin. In order to deal with great demand for SW monitoring and management, this accurate information of waste features and estimates the amount of waste level can be used for optimizing the entire waste management process. However, under the same concept, the same techniques should be applicable with larger sizes of bins. The system is efficient and able to meet field application requirements. Consequently, this classification system can be a promising solution for bin level detection.

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