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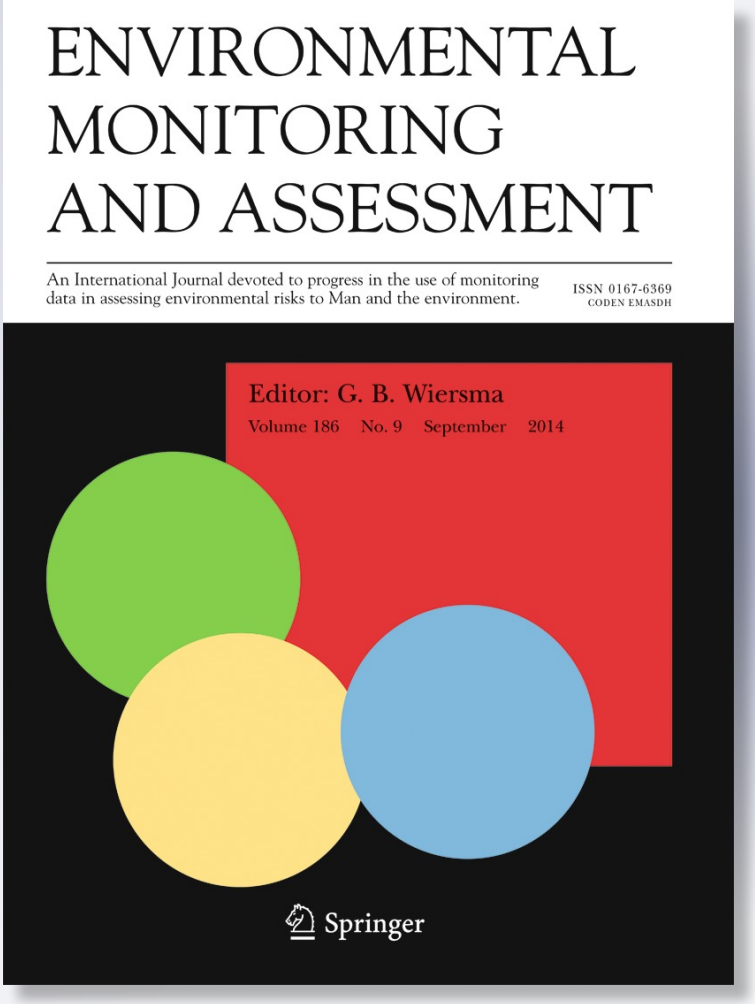

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Feature extraction using Hough transform for solid waste bin level detection and classification

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Abstract This paper deals with the solid waste image detection and classification to detect and classify the solid waste bin level. To do so, Hough transform techniques is used for feature extraction to identify the line detection based on image's gradient field. The feedforward neural network (FFNN) model is used to classify the level content of solid waste based on learning concept. Numbers of training have been performed using FFNN to learn and match the targets of the testing images to compute the sum squared error with the performance goal met. The images for each class are used as input samples for classification. Result from the neural network and the rules decision are used to build the receiver operating characteristic (ROC) graph. Decision graph shows the performance of the system waste system based on area under curve (AUC), WS-class reached 0.9875 for excellent result and WS-grade reached 0.8293 for good result. The system has been successfully designated with the motivation of solid waste bin monitoring system that can applied to a wide variety of local municipal authorities system.

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Keywords Image processing · Hough transform · Feature extraction · Solid waste bin monitoring system · MLP

Introduction

With the continued economic progress and rapid growth of cities and towns in developing countries, solid waste management remains a major challenge in urban areas worldwide (Latifah et al. 2009). The complexity of a similar urban context is a primary concern for local municipal authorities, particularly with regard to aspects related to collection, transportation, and processing of residential solid waste (World Bank 2005). Therefore, solid waste management and monitoring require immediate attention, especially in countries such as China, Japan, and Malaysia (Arebey et al. 2011). Statistics shows that the world population reached six billion in 2001, with 46 % of this residing in urban areas. In Malaysia, the population has continued to increase at a rate of 2.4 % per annum or about 600,000 per annum since 1994. With this rate of population growth, municipal solid waste generation also increases, and hence its management becomes a crucial issue (Latifah et al. 2009). Growth, municipal solid waste generation also increases; and hence, its management becomes a crucial issue (Latifah et al. 2009).

The Malaysian government is currently focusing its efforts on the development of methods to address the issue. In recent years, waste management services have made a concerted effort to use information technology to reduce waste management cost and to monitor solid

waste generation in residential areas. Intelligent systems can provide efficiently processed and personalized information to customers and waste management administrators to reduce costs and achieve efficiency (Belal and Morshed 2007; Abdoli 2009; Hannan et al. 2009; Arebey et al. 2011). Application of these principles can be facilitated by the use of image sensors, radio-frequency identification (RFID) and mobile technology such as general packet radio service (GPRS)/GSM and geographic information system (GIS). A number of municipalities in Malaysia have focused on the importance of new technologies in recycling industries.

The solid waste planning, monitoring, and management requires comprehensive, reliable data and information on solid waste (Latifah et al. 2009). In order to deal with this great demand on data management, advanced information technologies such as image sensor, GPRS, GPS, and GPS solution must be used (Arebey et al. 2011). Solid waste management companies have been focusing on high technologies to solve some of the problems related to solid waste database. For example, the data of the waste bins are taken by a camera that is installed on the truck and transmitted to the control station server. Thus, the system could realize whether the truck arrived to the bin location or not. This types of technologies used in the navigation system are matured, which ensures the system is practical, universal, and with perfect function (Hassan et al. 2000).

The usage of the advanced technologies can bring down the solid waste management costs and improve the management level. Developing a new method and system on the solid waste information, amount of solid waste production, bin physical status, and truck position can enhance the service efficiency. Feature extraction is the major task applied in solid waste level detection and classification (Rau and Chen 2003).

With the rise in awareness on environmental protection, sustainable development and improvement in living standards have made people to expect significant efforts from local authorities with regard to the safety and the effectiveness of waste management procedures. Although monitoring and optimization applications based on container sensors were presented in the past, these have been limited in terms of detection at the container content level. Previous applications did not also consider waste sampling and monitoring within landfills or automatic waste sorting plants (Rovetta et al. 2009). Therefore, this paper deals with solid waste feature extraction that uses Hough transform algorithm to identify the level of solid waste in bins. The extracted features are used to classify the waste level in the bin based on teaching and learning concepts with the use of a multilayer perceptron (MLP) classifier.

Solid waste scenario in Malaysia

In Malaysia, solid waste problem is one of the most controversial environmental issues due to inadequate management practices and indiscriminate dumping of wastes (Fadel 2006). Moreover, rapid development, growing population, and changes in consumption pattern directly resulted in the generation of enormous amount of waste. However, with Vision 2020, Malaysia would become a fully developed country. Therefore, a lot of improvements have to be done in solid waste monitoring and management.

The amount of solid waste generated in Malaysia is steadily increasing (JICA 2010). So far, less than 5 % of the waste is being recycled. Despite the massive amount and complexity of waste produced, the standards of waste management in Malaysia are still poor. However, the government is currently focusing on methods to approach the challenge. Table 1 shows the

Table 1 Total quantity of domestic waste generated daily (tons per day)

States	JICA study estimation: total quantity of waste in tons per day			
	2002	2004	2007	2010
Johor	2,154	2,636	3,071	3,579
Kedah	1,309	1,602	1,866	2,175
Kelantan	1,073	1,313	1,529	1,783
Melaka	504	617	719	838
Sembilan	891	848	988	1,149
Pahang	1,024	1,253	1,460	1,702
Perak	1,644	2,012	2,344	2,733
Perlis	165	202	236	275
Pinang	1,026	1,266	1,462	1,705
Selangor	3,293	4,031	4,695	5,473
Terengganu	733	898	1,038	1,219
Kuala Lumpur	1,088	1,332	1,551	1,808
Sarawak	1,674	2,058	2,387	2,783
Sabah	2,085	2,517	2,962	3,418
Total	18,494	22,638	26,419	30,794

total waste generation in Malaysia projected up to 2010 (JICA 2010). It is seen that due to the growing population and increasing consumption, the amount of solid waste generated in Malaysia went up from 18,494 t/day in 2002 to 26,419 t in 2007. Currently, over 30,000 t of waste is produced each day in Malaysia (JICA 2010). This resulted in an increase amount of the national average waste generated at 0.5–0.8 kg/person/day, but in the cities, the figures have escalated to 1.7 kg/person.

The availability of solid waste database in Malaysia is limited and most of these data are kept as hardcopies and not compiled or synthesized for further usage (Ping and Yang 2006). Today, there is no existing system dedicated by the government of Malaysia to standardize, compile, verify, store, manage, and update solid waste data using a single database system for future planning and management. Thus, a significant prediction tools is needed for the estimation of produced waste, routing optimization, and monitoring trucks and bins to support future planning.

A traditional solid waste management system involves the use of trucks, bins, and landfills. However, the scarcity of land near urban centers and the growing opposition from the public with regard to landfill disposal have led many communities to look for alternative waste disposal methods through an integrated solid waste management system (Johansson 2006). Many companies in Malaysia have focused on the use of remote sensing systems. For instance, Alam Flora uses a truck monitoring and tracking system that requires real-time truck location analysis to control solid waste collection and to improve truck use efficiency (Alam Flora 2009). Rafia and Masuda (2010) found that majority of households (54 %) were dissatisfied with the quality of current waste collection services, and 28 % were highly concerned about the environment. Households in Kuala Lumpur were also not receiving enough information on the benefits of waste separation and recycling. Therefore, concerted efforts to raise environmental consciousness through education and information dissemination on waste management are needed. Socioeconomic characteristics and the quality of waste collection services influence the willingness of individuals to pay for the use of effective waste management systems.

Methodology

In this section, solid waste database development, Hough transform for feature extraction and MLP based FFNN with Hough transform have been discussed. In this research, 250 samples of solid waste images of the bins are captured under various levels by using Logitech web camera to create a database of the waste bin monitoring system. The database images consists of four classes, the level of waste in the bin can be represented as empty, medium, full, and over flow, respectively. Figure 1 shows samples of database under different classes of waste level.

The bin was filled with different kind of waste started from cardboard, paper normal waste different colors of bags, and different situation being simulated during the database collection. The main objective of the paper was to provide quantitative data referring mainly to level of the bin that being collected in order to allow the implementation of organizational activities such as resource planning (number of bins and trucks needed in every zone). Moreover, the establishing of appropriate waste management policies, such as encouraging the overall reduction of MSW using data related to specific locations, may also be facilitated.

Hough transform

Hough transform (HT) is a global method for detecting edges by Paul Hough who patented the method in 1962, used for feature extraction algorithm to classify the level of waste bin (Hamarneh et al. 1999). Image analysis system, consists of extraction features from the image, measure the quantities information's and use it for classification or identification of the level of the waste bin. The distinct feature between images of varies level of solid waste inside the bin is used to monitor the level of bin using directional pattern. This directional pattern can be detected using directional filter, such as Hough transform. Line detection with varies angle and points are used to filter the solid waste images and the output are used as input to artificial neural network.

Hough transform is a general technique for identifying the location and orientations of certain types of features in digital image and used to isolates features of a particular shape within an image. Originally conceived to detect straight lines, the Hough transform was extend to other parametric models and finally generalized to any parametric shapes method for gradient detection in text image, based on an extension of the Hough transform and the modeling of lightness

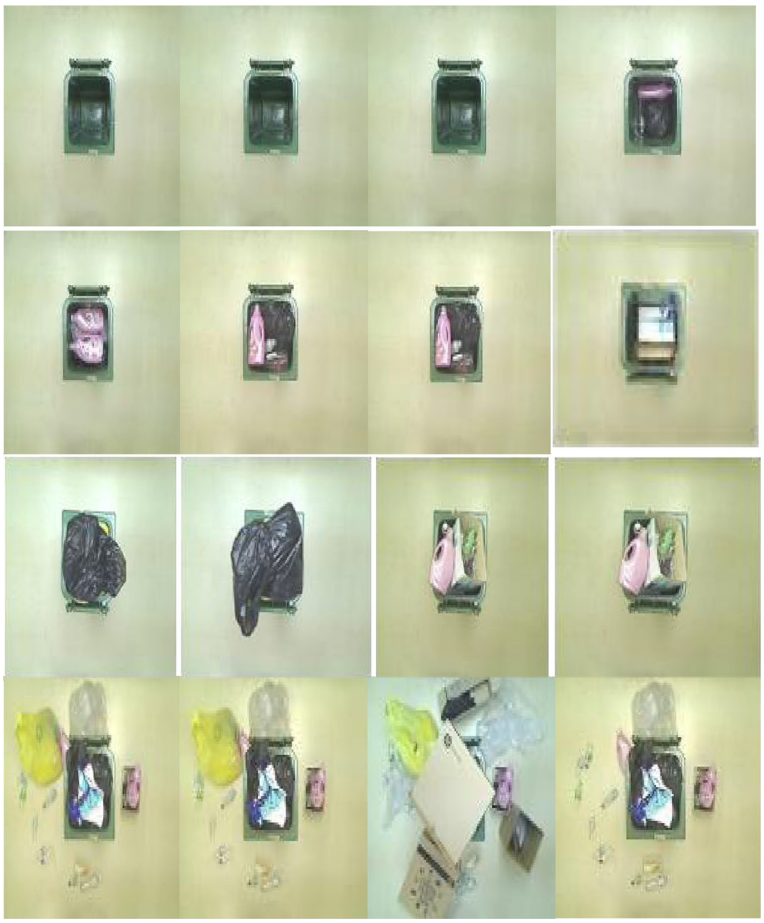


Fig. 1 Samples of database of the four classes of waste level

gradients as planes are apply in the combined spatial—feature space (Dimosthenis 2008; Lee et al. 2008).

Feature extraction using Hough transform

The Hough transform is an important image-processing technique which can be used to isolate features of a particular within an image. The transform between the Cartesian space and a parameter space is defined by the straight lines or other boundary formulation (Hamarneh et al. 1999; Shylaja et al. 2011). The purpose of this technique is to find imperfect instances of objects in a parameter space within a certain class of shapes by a histogram voting procedure. This voting procedure is carried out in parameter space, from which object candidates are obtained as local maxima in a so-called accumulator space that is explicitly constructed by algorithm for computing the Hough transform. The local maxima obtained from the accumulator array are used in training of back propagation neural network (Hamarneh et al. 1999).

Hough transform can be mathematically expressed for instances lines, circle, or ellipse. In this study, Hough transform for line detection based on image's gradient field (MathWork) are used. The Hough transform is designed to find lines in images, but it can be easily varied to find other shapes. In order to briefly describe the Hough transform and provide a rationale for this paper, Hough transform need to be explained first. The idea is simple expressed by McAndrew (2004). For example, (x, y) is a point in the binary image. In model $y=ax+b$, all the pairs of (a, b) are plotted into an accumulator array. The (a, b) array is the transform array. If $(x, y)=(1, 1)$, the equation relating a and b is $1=a.1+b$, and it can written as $b=-a+1$. Thus, the line $b=-a+1$, consists of all pairs of points relating to the single point (1, 1) as shown in Fig. 2.

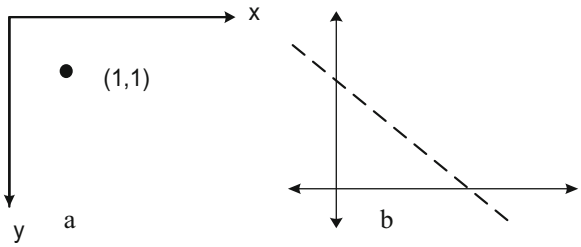


Fig. 2 A point in an image and its corresponding line in transform for **a** image and **b** transform

Each point in the image is mapped onto a line in the transform. The points in the transform corresponding to the greatest number of intersections correspond to the strongest line in the image. For example, if an image with five points such as (1, 0), (1, 1), (2, 1), (4, 1), and (3, 2), the corresponding points can be expressed as follows:

$(1, 0) \rightarrow b = -a$
$(1, 1) \rightarrow b = -a + 1$
$(2, 1) \rightarrow b = -2a + 1$
$(4, 1) \rightarrow b = -4a + 1$
$(3, 2) \rightarrow b = -3a + 2$

Each of these lines appears in the transform are shown in Fig. 3.

The dots in the transform indicate places where there are maximum intersections of lines: at each dot, three lines intersect. The coordinates of the dots are $(a, b)=(1, 0)$ and $(a, b)=(1, -1)$. These value correspond to the lines $y=1.x+0$ and $y=1.x+(-1)$ or $y=x$ and $y=x-1$ on the image is shown in Fig. 4a. These are indeed the strongest lines in the images in that they contain the greatest number of points. Implementation of the Hough transform cannot be expressed a vertical line in the form $y=mx+c$, because m represents the gradient and a vertical line has infinite gradient.

In general, any line can be described in terms of the two parameters rho (ρ) and theta (θ) as shown in Fig. 4b, in which ρ is the perpendicular distance from the line to origin, and θ is the angle of the line's perpendicular to the x-axis. In this parameterization, vertical lines are simply, $\theta=0$. However, if ρ is equal to negative values, then θ is restricted with the range of $-90° < \theta \leq 90°$. With this parameterization, it needs to be able to find the equation of the line. First, note that the point (p, q) is perpendicular to the line at $(p, q)=(\rho \cos \theta, \rho \sin \theta)$. Also note that the gradient of the perpendicular is $\tan \theta$. Now let (x, y) be any point on the line. The gradient of the line is as follows:

$$\frac{\text{rise}}{run} = \frac{y-q}{x-p} = \frac{y-p\sin\theta}{x-p\cos\theta} \tag{1}$$

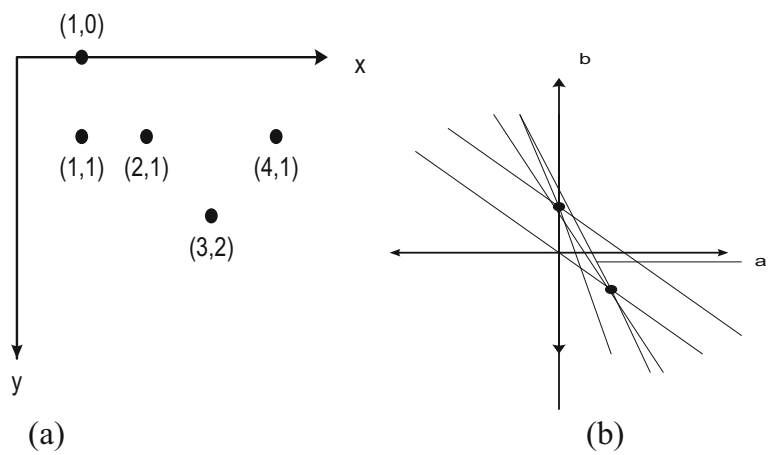
As the gradient of the line's perpendicular is $\tan \theta$, the gradient of the line itself must be

$$-\frac{1}{\tan\theta} = -\frac{\cos\theta}{\sin\theta} \tag{2}$$

Combining these two expressions for the gradient, it can be write as follows:

$$\frac{y-p\sin\theta}{x-p\cos\theta} = -\frac{\cos\theta}{\sin\theta} \tag{3}$$

Fig. 3 An image and its corresponding lines in the transform for **a** image and **b** transform



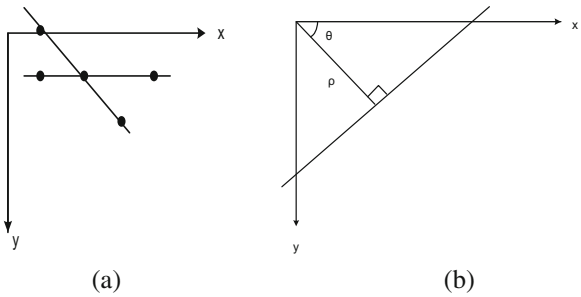


Fig. 4 **a** Lines found by the Hough transform. **b** A line with perpendicular and angular parameters

Modifying the Eq. (3), the required equation for the line can be written as follows:

$$x\cos\theta + y\sin\theta = \rho\left(\sin^2\theta + \cos^2\theta\right) = \rho \tag{4}$$

By choosing a discrete set of values of ρ and θ, the Hough transform can be implemented. For each pixel of (x, y), the image can be computed. For each value of θ, the result of the appropriate position is placed in the (ρ, θ) array. At the end, the values of (ρ, θ) with the highest values in the array correspond to strongest lines in the images as shown in Fig. 5.

To clarify the image shown in Fig. 5, the θ is discretized with only the values of −45°, 0°, 45°, and 90°. The all values of $x\cos\theta + y\sin\theta$ for each point and value are summarized in an accumulator array as shown in Table 2 (McAndrew 2004).

In practice, this array will vary and can be displayed as an image. From the sample given on the Table 3, the two equal, largest values occur at $(\rho, \theta)=(2, 0°)$ and $(\rho, \theta)=(3, 90°)$. The lines are then $x\cos 0 + y\sin 0 = 2$ or $x = 2$, and $x\cos 90 + y\sin 90 = 3$ or $y = 3$. These lines are shown in Fig. 6 (McAndrew 2004)

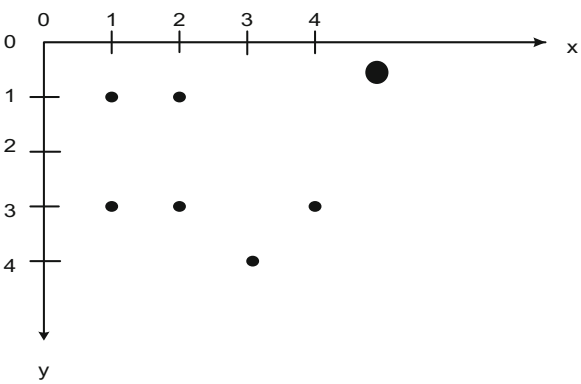


Fig. 5 Image of the line

Table 2 A sample accumulator array

Axis	Theta			
(x, y)	−45°	0°	45°	90°
(2, 0)	1.4	2	1.4	0
(1, 1)	0	1	1.4	1
(2, 1)	0.7	2	2.1	1
(1, 3)	−1.4	1	2.8	3
(2, 3)	−0.7	2	3.5	3
(4, 3)	0.7	4	4.9	3
(3, 4)	−0.7	3	4.9	4

MLP with Hough transform

The artificial neural network (ANN) is an adaptive or nonlinear system, which topology include the perceptron, multilayer perceptron (MLP), the radius basis function network (RBF), etc. The ANN system parameters are changed during training operation, and the system are deployed to solve the problem at the testing phase (Richard 2006). The MLP based on feedforward neural network (FFNN) used with Hough transform. In this network, the information moves in only forward direction from the input nodes, through the hidden and the output nodes.

This paper considered the network with hidden units to enlarge the space of hypotheses for the network representation. Figure 7 shows a network with four hidden units with a three layer network. At the output layer, the weight-update rule is identical by equation $W_j \rightarrow W_j + \alpha \times \mathrm{Err}_i \times g(\mathrm{in}) \times x_j$. Let Err_i be ith component of the error vector. Also, we can define a modified error $\Delta_i = \mathrm{Err}_i \times g(\mathrm{in}_i)$, so the weight-update rules are as follows:

$$W_{j,i} \leftarrow W_{j,i} + \alpha \times \alpha_j \times \Delta_i \tag{5}$$

To update the connections between the input units and the hidden units, a quantity analogous to the error term need to be defined for output nodes by doing the error back-propagation. Hidden node j is responsible for some fraction of the error Δ_i in each of the output nodes to which it connects. The Δ_i values are divided according to each output node and propagate back to provide the Δ_j values for hidden layer. The propagation rule for the Δ_j value can be defined as follows:

$$\Delta_j = g\left(\mathrm{in}_j\right)\sum W_{j,i} \tag{6}$$

Table 3 A samples of array possibility large values

Theta	Possibility large values, rho												
	−1.4	−0.7	0	0.7	1	1.4	2	2.1	2.8	3	3.5	4	4.9
−45°	1	2	1	2	0	1	0	0	0	0	0	0	0
0°	0	0	0	0	2	0	3	0	0	1	0	1	0
45°	0	0	0	0	0	2	0	1	1	0	1	0	2
90°	0	0	1	0	2	0	0	0	0	3	0	2	0

So, the weight-update rule for the weights between the input and the hidden layer is almost identical to the output layer.

$$W_{k,j} \leftarrow W_{k,j} + \alpha \times \alpha_k \times \Delta_j \tag{7}$$

Again, the back-propagation is as follows:

$$E = \frac{1}{2}\sum_i (y_i - \alpha_i)^2 \tag{8}$$

To obtain the gradient with the respect to a specific weight $W_{i,J}$ in the output layer, from the expanding and derivation, we can express as follows:

$$\frac{\partial E}{\partial W_{j,i}} = -\alpha_j \Delta_i \tag{9}$$

And, to obtain the gradient with the respect to a specific weight $W_{k,j}$ in the input layer, the derivation of the derivative operator propagates back through the network:

$$\frac{\partial E}{\partial W_{k,j}} = -\alpha_k \Delta_j \tag{10}$$

The ANN-MLP-based model has been explored to be used to monitor the level of solid waste. The development of ANN models based on waste level verification system can classify the level content of solid waste inside the bin.

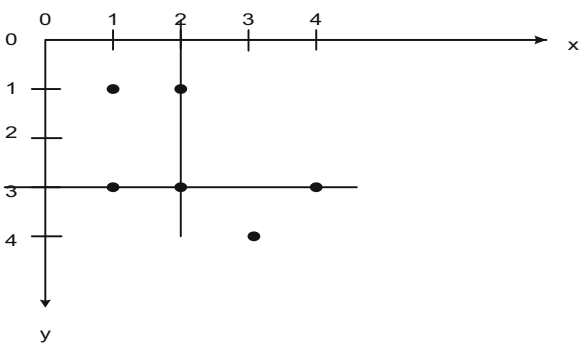


Fig. 6 Lines found by the Hough transform

Results and discussion

Feature extraction performance using Hough transforms

The feature extraction algorithm has been extensively obtained by Matlab programming for detecting lines based on gradient field of the image. Once the image preparation estimates the waste image boundaries, the normalization technique changes the range of pixel intensity values as shown in Fig. 8. In this way, the pixel intensities can be spread over the total range of intensity. The normalization process will result in replacing very dark pixels with lighter ones but the brightness relativity of the pixels will be kept. To control the sensitivities of line detection, the default value 0.08 is used where the value range from 0 to 1.

The physical meaning of this parameter is to control the system based on fuzzy logic. The less the value, the more features in the image will be considered as lines. Figure 6 shows result for feature extraction and normalization of the system in accumulator array sized 400.

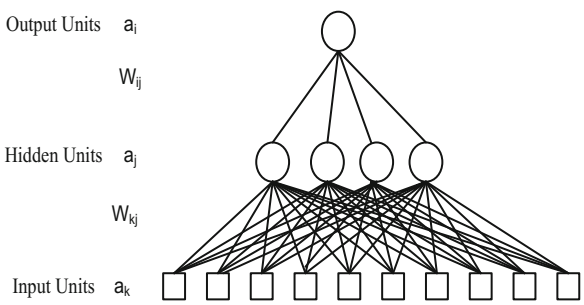


Fig. 7 A multilayer neural networks with one hidden layer and 10 inputs. Source: Russell and Norvig 2003

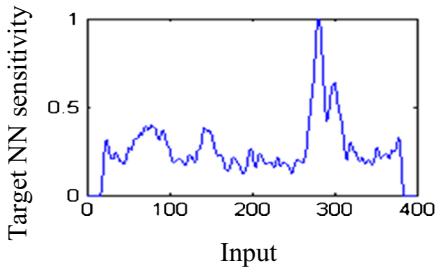


Fig. 8 The feature extraction and normalization

Figure 9 shows the result of the feature extraction using Hough transform for Fig. 9a shows the result of the detected lines which are marked with '0' in the accumulator array (vote histogram) done by Hough transform. Figure 9b, c shows the raw image with lines detected and lines segment detecteds and Fig. 9d shows the vote diagram in 3D. The results of Hough transform are store in a matrix N-by-2 in accumulator array (*accum*) in which *theta* is the horizontal dimension and *rho* is the vertical dimension. *Rho* is the perpendicular distance from the line to the origin of the image. The Hough transform generates a number of votes for a group of defined lines in the image. The parameter describes the line orientation and the segment's length.

Performance MLP classifications

The FFNN is used to improve the performance of the classification of waste bin images. Total of 250 images are used to train the system, 20 images from each class are used to test the FFNN classifier, and 30 images to train the FFNN classifier. After the training procedure, all the weights are saved into a test file. Neural networks learning process leads to compute the sum squared error function which will be used in the back propagation of errors step.

Figure 10 shows the result of training performance using FFNN where the performance goal was met at epoch 28257, MSE 0.000999994/0.001, Gradient 0.00239639/1e-010. Beginning with a data set in the classes which are known in the model building process, the algorithm will show the relationship between the values of the input target (predictors) and the value of the target by using the rules decision.

Table 4 shows the sample of building data model for the classification task which begins with the data set for class assignment. By using rule decision algorithm, rules are generated with the predictions and probabilities. If the rules of the class equal to 1, it is stated that waste should inside the bin; if rules of the class equal to −1, it is stated that the waste should be outside the bin. Referring to Table 4, which shows the binary

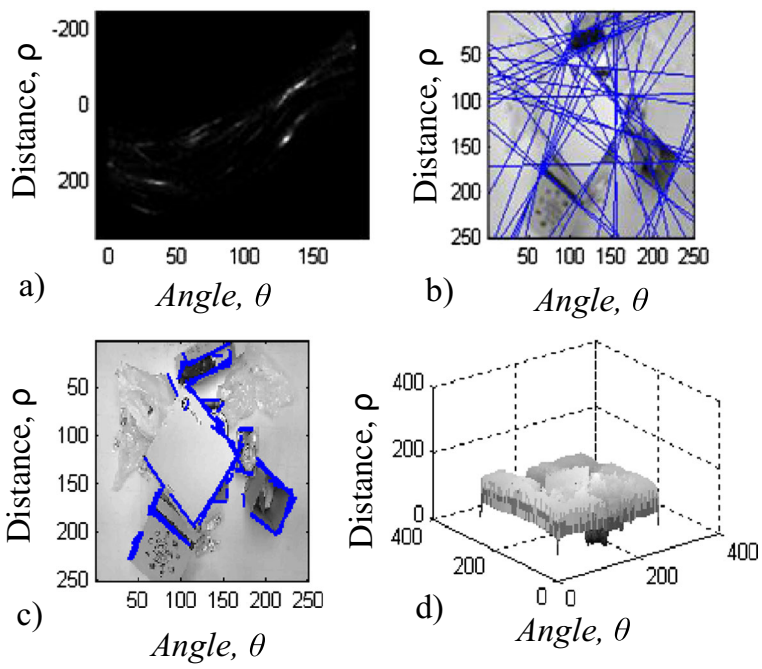


Fig. 9 The feature extraction using Hough transform. **a** The Hough transform result in accumulator array (vote histogram) **b** The raw image with lines detected. **c** The raw image with lines segment detected. **d** Vote histogram in 3D

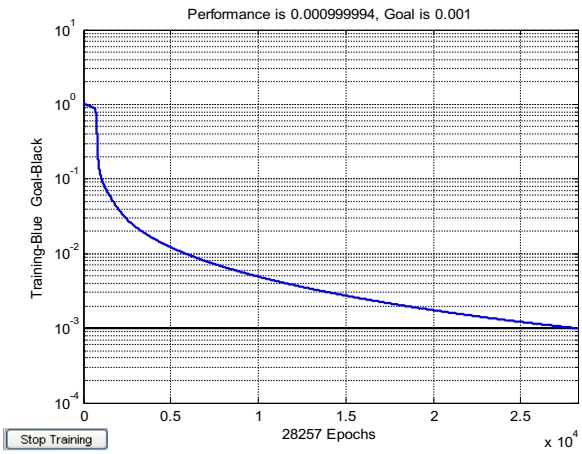


Fig. 10 Training performance using feedforward neural network

classification for the binary target 1 0, the output will classify the waste inside the bin (empty class). If the binary target 1 1, the output target will classify the waste inside the bin (medium class). If the binary target 1–1, the output target will classify the waste still inside the bin (full class). If the binary target −1 1, the output target will classify the waste outside the bin (flow class), and if the binary target −1 0, the output target will classify the waste outside the bin (overflow class).

The receiver operating characteristic (ROC) graph and the grade performance of the system are presented in order to evaluate the overall performance of the system. Figure 11 shows the result of level waste classification system using Hough gradient and artificial neural network algorithm. The classification discriminating ability of the model is determined by using the area under the curve (AUC). The curve is generated by calculating the sensitivity and specificity of increasing numbers of data. The larger the AUC, the higher the likelihood will be assigned for a higher probabilities of being positive than actual negative case. The AUC curve measuring is significantly necessary for data sets with unbalanced target distribution. The rough way to classify the accuracy of test is the traditional method: 0.90–1 for excellent, 0.80–0.90 for good, 0.70–0.80 for fair, 0.60–0.70 for poor, and 0.50–0.60 for fail. The graph includes three ROC curves representing WS class, WS-grade and baseline tests plotted on the same graph, the test accuracy relies on how well the test divides the group being tested into WS-class and WS-grade. Accuracy is determined by computing the AUC under the ROC curve. An area of 1 represents a perfect test; an area of 0.5 represents a worthless test. The AUC of WS-class/AUC reached 0.9875 or 98.75 % which is an excellent classification result for representing the level of the waste in or out the waste bin. The WS-grade/AUC reached 0.8293 or 82.93 % which is high classification result accuracy to determine the exact level of the waste in the bin. The proposed system got a promising performance in waste level classification in terms of and waste grading concept.

Table 4 Sample build data model for waste bin classification

Rules decision—target			Waste classification description
WS-class	WS-grade		
1	0	Waste inside the bin	Bin empty
1	1	Waste inside the bin	Bin medium
1	−1	Waste inside the bin	Bin full
−1	1	Waste outside the bin	Bin flow
−1	0	Waste outside the bin	Bin overflow

Accordingly, an intelligent solid waste bin and truck monitoring and management system is implemented in which camera and communication technology are mounted on the truck to capture information and images of the bin. When the truck comes in close contact to the bin, collection time, bin status images, bin and truck ID, waste content inside bins, and GPS data are collected in real time. All the data are then forwarded to the control center through the GPRS modem. An advanced image-processing technique is developed to facilitate the real-time detection, classification, and recognition of bin levels as well as waste truck route optimization. The performance of the developed system is therefore provides real-time information to the solid waste operator, for carry out appropriate action during solid waste monitoring and management. Thus, the developed system is enhancing waste collection efficiency, monitoring, and management process.

The result of the test showed that the developed system for solid waste bin level detection and classification is fully operational during the collection operation. All the bins were collected and represented on the map in the control center. The movement of the truck during the collection operation was successfully recorded during the whole collection operation. Figure 12 shows the received data on the map during the collection. The red line shows the route of the truck being monitored and the location of the bins.

In collection operation, all wastes collected by the appointed contractor are disposed to the landfill on a

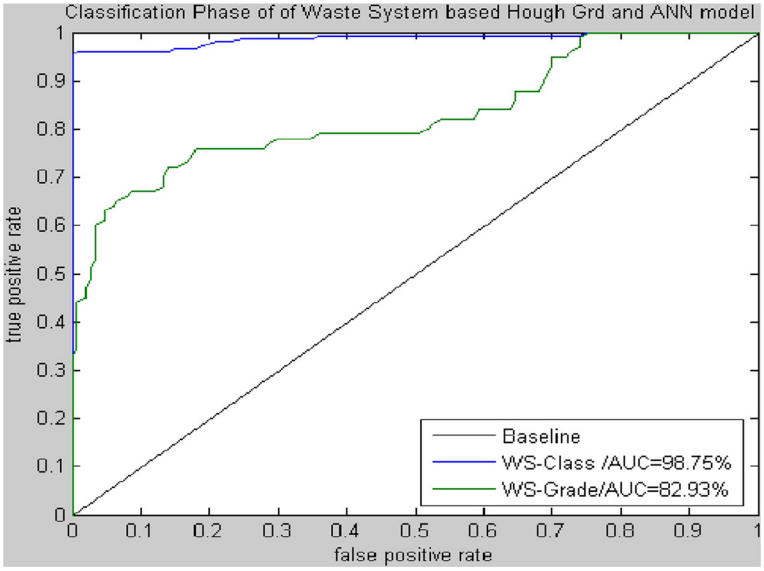


Fig. 11 Classification performance of waste system based on AUC

daily basis. Informal recycling activities are carried out by some cleaners and canteen operators. Domestic waste, wet canteen waste, food waste, and solid waste from identified collection bins are collected, transported, and disposed to an approved disposal site. Two types of trucks are used, namely, a compactor and an open tipper to collect wastes from designated bins. The collection trucks enter the perimeter daily to collect on assigned routes. Depending on the location and on the amount of waste generated, some trash bins are emptied daily, while some on alternative days. The truck is used for 10 h a day to collect and transport the waste to the land fill. A total of 160 bins distributed and must be collected three times a week.

Fig. 12 The monitored truck and the distributed bin on the digital map

Conclusion

Solid waste bin monitoring system was achieved based on the integration of image sensor using latest technologies such as GPRS and GIS. The performance of the system suggests a proper efficiency as a solution for waste management. The simulation result of the system shows the solid waste data information, amount of solid waste production, bin physical status, vehicles position, detection of potential hazard material, and solid waste content to support solid waste bin monitoring. Graphical image analysis in solid waste control center provides better organization planning in order to realize effective distribution, monitoring, safety, and prevention. The main intention of this work was to improve monitoring of waste bins therefore the local authorities can apply this system for a wide variety.

The system formed from three main parts; image acquisition, feature extractions, and classification. In this study, focusing on image-processing technique based on applying Hough transform for feature extraction and also neural network for waste classification and finally verification. The result of the system suggests a reliable and effective classification of captured images. Captured images will be sent via a wireless system and saved into the database. The system will resize the original images into 250×250 and will convert to gray-scale image and then normalize to a matrix with values from 0 to 1. Hough transform algorithm is used to transform the image and obtain the image gradient of

captured image as a Hough vector. In this study, the transformation result is good for classification of solid waste. The waste level classification accuracy was high and accurate. The decision graph shows the system performance based on AUC for WS-class and WS-grade which achieved 98.75 and 82.93 %, respectively. The result shows a successful waste bin classification system based on the level of the waste either the bin full, empty, or in between. The developed system was able to achieve high classification performance based on class and grade rules decision algorithm concept of the solid waste.

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