Solid Waste Bin Classification using Gabor Wavelet Transform

Arivienanand Rajamanikam, Mahmud Iwan Solihin

***Abstract:** Solid waste dumping has become an issue and a threat towards health and it is continuing to deteriorate with time. It is known that solid waste (SW) accumulation will rise drastically over time and epidemiological effects will soon rise from unplanned or unscheduled solid waste dumping. With Solid Waste Management (SWM) at its optimum performance, this problem can be mitigated. There are several reasons for a system to fail but one is focussed to engineer a solution towards waste treatment. Solid waste segregation takes longer to process compared to treating it on a weekly schedule. By utilising machine vision and machine learning technologies, solid waste bin classification can be done norm as a pathway towards efficient waste segregation. In this paper Gabor wavelet transformation (GWT) is used for classifying solid waste images by convoluting an image with Gabor wavelet kernels with different scales and orientation. The features are extracted from the image training database to model a supervised Artificial Neural Network (ANN) with the actual bin level grades. The computational speed or efficiency of the GWT is increased by using Genetic algorithm (GA) where a total of 48 out 80 features are used sufficiently, whereby less wavelets are used in the process thus increasing the performance to a maximum of 47.52%. The mean squared error before and after optimisation gave a difference of 91.9% in improvement with GA. The proposed method proved that with GWT and GA, SW is gradable with random waste images and it has proven to be optimum from analysis*

***Keywords:** Gabor wavelet transformation (GWT), Solid Waste Management (SWM, solid waste (SW), Artificial Neural Network (ANN)*

I. INTRODUCTION

Solid waste management (SWM) is a pressing issue in most developing countries. With higher economic development, municipal solid waste (MSW) will increase as well and practically half the world occupants are living in urban areas [1]. Around 1.3 billion tons of MSW are produced in a year and it is expected to rise to 2.2 billion tons per year in 2025 and Malaysia alone has produced 7 million tons of MSW in 2010 [1, 2]. The average increase in MSW alone is approximately three percent, which is identical to other known developing countries. Solid waste (SW) can be either municipal or non-municipal which includes SW from construction sites and demolition sites [2].

If SWM is not considered there are consequences to be faced in the future with respect to economic development, health, environmental and many more. There are epidemiological effects that can be caused from such an environment which has been considered hazardous as assessed by UNEP [3] and it has been suggested that an integrated system can eliminate or mitigate such problems. A study was conducted by surveying the people of Bangkok, Thailand on methods and current methods of MSW management [3] and the survey results suggested that by implementing technology into SWM, the system is optimised to profit by reducing the financial burden for collection, transportation, treatment and disposal.

Low cost recycling technologies are still in use and an update is required with low cost technologies that are sustainable. Data acquisition is necessary for statistic wise as it can be used for future waste controls and it is considered mandatory. It is necessary to understand the variety of bin sizes available besides household bins which are relatively small compared to the bins in the factory that handles SW. In terms of conducting the process of segregating SW it is difficult to comply with such activity because of the health consequences [4]. There are also SW that are not separated but it is directly routed for waste disposal without any treatment. Lack of awareness on SWM makes it vulnerable towards illegal dumping site which can lead to dangerous diseases from respiratory issues to skin diseases. Therefore it is important to have an optimised management system that can properly collect and segregate waste for better use in treatment plants. In the industry it is crucial to identify the bin level as fast as possible in the most unpredictable environmental conditions. With the latest advancement in data acquisition technology, optimised waste management is achievable.

Unresolved SWM does pose a threat to a large society and its mitigation procedures are not fully resolved and optimised. Traditionally the bins are collected from residential areas, shop lots, commercial areas and industrial areas [5]. Theses wastes are commonly collected by a truck but it is known that Malaysia is limited in data management, which is part of SWM, where the local authorities or contractors are responsible. Due to lack of cooperation between these individuals, the public is motivated in burning solid waste (Open burning) which affects the community from inside and outside the burning zone in terms of health due to its toxic fumes being released into the environment. Waste incineration is highly beneficial in the power industry since it has the capacity to generate 5 MW of electrical power and this advantage should be embraced by the power industry, thus instilling motivation within the industry to collect SW [1].

Therefore, a resolved and optimised SWM starts from an engineering aspect of designing a solution through available

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technologies. Segregation plays a crucial engineering task or problem in the industry since it was proven to consume more time compared to treating SW. There are physical sensors that can be used in capturing the appropriate information from a solid waste bin [6] .Level sensors such as a capacitive sensor were used for detecting the level of waste but the sensor can be affected by humidity and an optical sensor can also be used, but it requires regular maintenance. These physical sensors can deteriorate with time, some of them are not accurate due to environmental effects on the sensor. In present there are multiple options on sensing technologies in identifying bin levels but the problem lies more in data acquisition [7] and imaging technologies has proven itself to be versatile in the roughest environment. Therefore, a low cost camera is used to capture the image of SW materials.

Abundant of research has been done in investigating the most appropriate feature extraction algorithm required to classify a bin. Hough transform was used by utilising the line gradient properties within the image thus being able to identify geometrical significance in the image itself [8]. Hough transformation was used in investigating geometrical features which is then used in classifying the amount of waste in the bin. Besides the use of Hough transform, Gabor Wavelets were used as well to investigate the spatial frequency of the image [6] This will provide different spatial frequency analysis for different bin levels, which made it possible to train a neural network to classify SW images since they are highly distinctive.

The main problem in current solid waste classification are the lack of mathematical parameters for image processing and classification, program execution by using GWT has low computational efficiency, vertical positioning of a camera and the lack of estimation on the amount of waste which is affected by the discrepancy in bin levels. In this paper, GWT is done by convoluting Gabor wavelets discreetly with the pre-processed images. By using evolutionary computation (Based on the theory of evolution), genetic algorithm (GA) is used to optimise the convolution process which in result provides better computational speed and efficiency where it uses less wavelets to convolute with an image, thus extracting less features by simultaneously not compromising the accuracy and precision of classifying or grading SW images. Artificial Neural Network (ANN) is used to classify images to its appropriate grade of waste volume. The main objectives of this paper are to develop a framework for GWT feature extraction, use artificial intelligence to develop a classification and optimisation model, evaluate the system based on the grade of waste volume.

II. METHODOLOGY

First the image is captured from a camera, pre-processed by changing the resolution size of the image and lastly uploading it to a secured database. The image is then pre-processed again in MATLAB for converting the file format from colour to grayscale and from unsigned integer to double precision. These conversions are done because each pixel in the Gabor wavelet kernel is complex, therefore it is suitable to have a double precision image. The image will be sharpen with high boost filtering to increase the edge's intensity [9 sundarmutrh]. The GWT settings are as follows. Total number of scales and orientations are 5 and 8 respectively where fh=0.25, fl=0.1, $\sigma_x = \sigma_y = 5$ and the kernel size is set to 39x39. There will be a total of 40 kernel windows. GWT is then used for obtaining the output and there will 40 output images after convolution. Features will be extracted based on the computation made with in the algorithm.

These features will be used in NN training and optimisation. The NN training is done based on the optimisation results and GA depends on the NN training algorithm for building the system. The classification NN architecture consist of 3 hidden layers, 1 input layer and 1 output layer as previously mentioned. The binary encoding for each waste grade are shown in table I. A hyperbolic tangent sigmoid activation function is used since bipolar values of 0 and 1 are the expected outputs. The classifier is trained with 90% of the images in the database. The performance of the NN is evaluated from a performance curve, where smaller performance values gives the best NN outcome. Genetic algorithm will then use the initial NN training algorithm for optimising the number of wavelets to be used in GWT. GA uses at least a population size of 50 with uniform crossover and mutation process. Crossover fraction and mutation rates are set to 0.66 and 0.005 respectively. From the optimisation results, NN training will be done again with less features to compare the computational efficiency between a classifier with 40 features and with less than 40 features.

Table. 1 Binary Encoding For Grading Bin Levels

Y1	Y2	Output
0	0	-
0	1	Low
1	0	Medium
1	1	High

III. RESULT AND DISCUSSION

In this paper a total 95 images are used in NN training. An extra of 39 images will be used calculating the classification error between 2 different classification functions where 1 of them is optimised by GA The images extracted by GWT and ANN classifier has applied for classification. The performance assessments are done using a NN performance curve. Fig. 1 shows the outcome from GWT after convoluting a solid waste image (magnitude).

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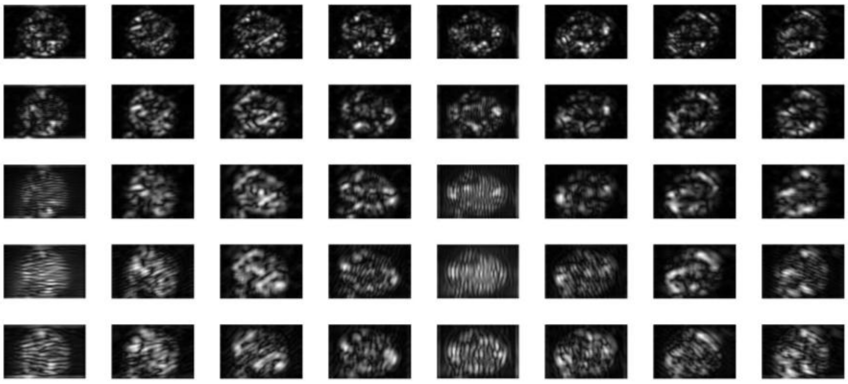

Fig. 1 GWT output magnitude

The NN training with 40 features is done first to a classification function. The most suitable training function in this NN training is Leveberg-Marquardt. The performance curve for this training is shown in Fig. 2. By using the first NN training algorithm, GA is able to produce an optimised solution in maximising the classification performance. Fig. 4 shows the best individual 24 out of 40 Gabor wavelets are to be used in classification and fig. 3 shows which wavelet is to be used for training the NN with a smaller input vector. The best fitness averaged at $1.18\text{x}10^{-5}$, with a mean fitness of 0.0540. NN training was executed once more to obtain the optimised classification function, Bayesian Regularisation was used as the training function and the performance curve is shown in fig. 4. After redeveloping the classification function, both optimised and non-optimised classifier are compared to evaluate the computational efficiency of the program, measuring the time of response and mean the squared error (mse).

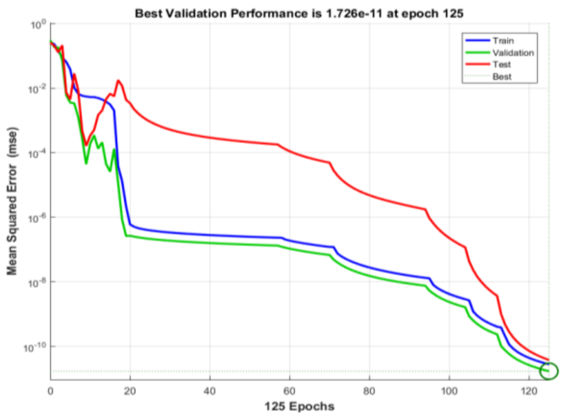

Fig. 2 NN performance curve

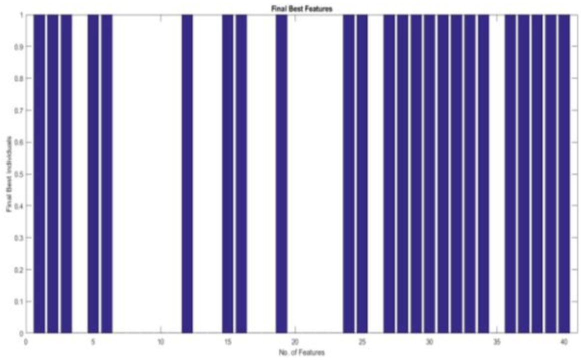

Fig. 3 Best Individual or Chromosome

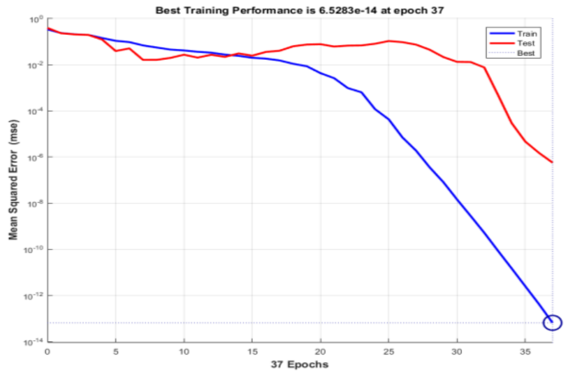

Fig. 4 Optimised NN performance plot

Fig.5 shows the time taken for each image to be processed and it can be seen clearly that the optimised function reduces the processing time significantly and images were classified in less than 2 s (imain.m uses 40 features and imainoptm.m uses 24 features). Fig. 6 shows the increase in performance for each image classified withthe best, lowest and average increment in performance of 47.52%, 31.65% and 39.16% respectively. The second set of images are used in evaluating the mse. These images are randomly captured compared to the first set. The difference in mse between the classifier functions is calculated to be 91.9% which proved that by using GA, the precision and accuracy of classifying images are not compromised with the reduction in feature vector.

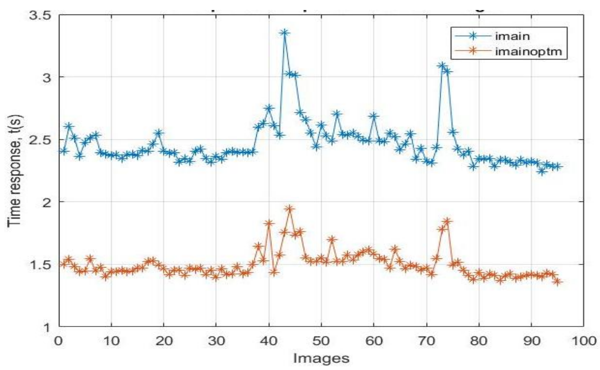

Fig. 5 Time response comparison between images using NN images

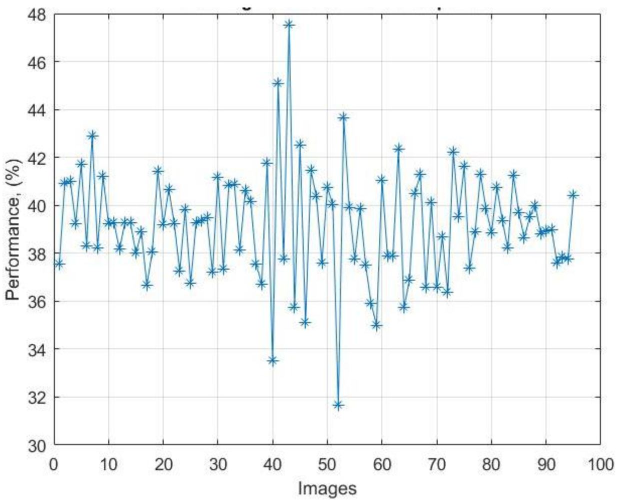

Fig. 6 Percentage increase in performance using NN images

IV. CONCLUSION

In this paper, the concept of machine learning and machine vision has been used in classifying solid waste images from a bin. The focus was made on the Gabor wavelet generator where its purpose was to create wavelets of different scales, orientation, sizes and frequencies. GWT focuses on convoluting a SW image with the generated wavelets, therefore being able to extract features from the convoluted image. The process of classifying a solid waste image is composed of five processes, image capturing, image pre-processing, GWT, multiple feature extraction and intelligent classification. In this paper, a supervised Artificial Neural Network was developed to classify each SW image and Genetic algorithm was devised to optimise the computational efficiency of GWT. The images had to be captured in a controlled environment for image preservation. The approach of using GWT was reasonably valid for identifying bin level and the features from the image were able to be extracted. Using mean and standard deviation as feature extraction data types, it has proven to be useful as input data for the NN classification function and the images were successfully classified. 48 out of 80 image features were used by using GA optimisation. This in result reduced the number of neurons in the NN model used in the final application.

The performance has been significantly increased after optimisation was done. The highest increase in performance was computed to be 47.52%. The difference in mean squared error with and without GA gave a difference of 91.9%. The approach of using GWT is reasonably valid for identifying bin level. Using mean and standard deviation as feature data type has proven to be useful as input data for the NN classification function. The limitation of this study is the environmental settings of capturing images because the surrounding can be either too dark or too bright and this can cause the image to be misclassified, in return the input features can be unreliable, therefore supervised NN training is important in mitigating this issue.

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