ISSN (Online) 2394-6849



International Journal of Engineering Research in Electronics and Communication Engineering (IJERECE) Vol 3, Issue 10, October 2016

A Real Time Fruit Grading Technique Based on Machine Vision and Image Processing

 ^[1] Chandra Sekhar Nandi, ^[2] Bipan Tudu, ^[3] Chiranjib Koley
 ^[1] Applied Electronics and Instrumentation Engineering Department, University Institute of Technology, the University of Burdwan, Burdwan, India,
 ^[2] Instrumentation and Electronics Engineering Department, Jadavpur University, Salt Lake Campus, Kolkata, India.
 ^[3] Electrical Engineering Department, National Institute of Technology, Durgapur, India.
 ^[1] csnandi@uit.buruniv.ac.in, ^[2] bipantudu@gmail.com, ^[3] chiranjib@ieee.org

Abstract: -- In agricultural and food industry the proper grading of fruits is important to increase the profitability. In this paper, a scheme for real time mango (Mangifera Indica L.) grading technique according to their maturity level and quality attributes like size, shape, weight, surface defect has been proposed. The proposed scheme works on intelligent machine vision based techniques for grading of mangoes in four different categories, which are determined on the basis of market value. In this system video image is captured by a CCD camera placed on the top of a conveyer belt carrying mangoes, thereafter several image processing techniques are applied to collect features which are sensitive to the maturity level and quality level. For maturity prediction Support Vector Machine (SVM) based classifier has been employed and for estimation of quality from the quality attributes, Multi Attribute Decision Making (MADM) system have been adopted. Finally fuzzy incremental learning algorithm has been used for grading based on maturity and quality. The performance accuracy achieved using this proposed system for grading of mango fruit is nearly 90%. Moreover, the repeatability of the proposed system is found to be 100%.

Index Terms:- Grading, RFE-SVM, MADM, fuzzy incremental learning

I. INTRODUCTION

Automated fruit gradation plays an important role to increase the value of produces. Currently, the agriculture and food industry has a better improvement, particularly in terms of grading of fruits, but the process is needed to be upgraded. Grading of the fruit products is vital to improve the profitability. The demand for fresh mango is now increased in both local and foreign market and the quality of the mangoes presented to the market has a major influence on their price. The distributors demand batches of homogeneous quality and maturity, while the intrinsic of these agricultural products varies widely, from one variety to another variety even from one garden to another, and in time. The grading is thus an essential step; however it is a tedious job and it is difficult for the graders to maintain constant vigilance. If this task could be performed by real time machine vision, the result would be more objective; it would also save labour and enhance output. So, high quality fruits can be exported to other countries and generates a good income.

In general, the gradation indices of fruits are maturity, size, shape, weight and surface defects, etc. With the progress in machine vision technology, the gradation technique based on machine vision has developed. Machine vision based gradation technology is real-time. nondestructive, and can detect multi-index simultaneously. Machine Vision is now becoming an objective, rapid and non-contact quality evaluation tool for the food industry [1]. The application of machine vision in agriculture has increased considerably in recent years. There are many fields in which computer vision is involved, including terrestrial and aerial mapping of natural resources, crop monitoring [2], quality control in food and agriculture [3-5]. automatic guidance, non-destructive inspection of product properties, safety and quality control, process automation, medical diagnostics, aerial surveillance and very recently in the field of automated sorting and grading of agricultural and food products.

Machine vision systems have been also developed for agricultural grading applications such as direct color mapping system to evaluate the quality of tomatoes and dates [6], apples quality estimator using machine vision [7], automated strawberry grading based on image processing [8] and sorting of sweet tamarind [9]. Development of jatropha curcas color grading system for ripeness evaluation using RGB color space because of its basic synthesis property and direct application in the image display [10].



Recently authors [11] applied Least Square Support Vector Machine (LS-SVM), to classify mango according to the degree of browning in mango skin and [12] presented the bio-inspired multi-modality sensing system for classification and quality assessment of Harumanis mango using charge coupled device (CCD) camera and Infrared (IR) camera. Authors used fuzzy logic for automatic mango fruit grading [13] and machine vision based maturity prediction system for sorting of harvested mangoes is discussed details in [14].

The present work is the extension version of previous work [14] with an objective to develop an upgraded machine vision based system for real time grading of harvested mangoes based on maturity level and quality level considering the quality attributes like size, shape, weight and surface defects. The method is discussed in Section II. Theory of Multi Attribute Decision Making (MADM) and the theory of Fuzzy discussed in the Section III and Section IV, respectively. The result and discussions is discussed in Section V. We summarize our work and conclude this paper along with the future scope of the research in Section VI.

II. METHOD

Present section discuss about the mango samples collection and different preprocessing techniques in brief and also the details methodology adopted in the work for automated real time gradation of harvested mangoes.

2.1 Material and Preprocessing

For the experimental works five different varieties of harvested mangoes locally termed as "Kumrapali" (KU), "Amrapali" (AM), "Sori" (SO), "Langra" (LA) and "Himsagar" (HI) were collected from different places of West Bengal, India. Each mango was used to pass through a conveyer belt to capture the video image of the mango and was presented to the experts for recording of human experts score.

Details of image capturing method, experimental procedure, color calibration of camera and all the preprocessing issues, like still frames extraction, filtering, edge detection, background elimination, alignment of mango image and their calculation is discussed details in previous work [15] using different image processing method.

2.2 Manual Fruit Grading Process

In general, mango grading is done by using the human experts. Human experts grade the mangoes using hands, noses and eyes which cause lack of objectivity, efficiency and accuracy. Table I shows how the standard applies to commercial varieties of mangoes to be supplied fresh to the consumers [16], for all classes, subjected to the special provisions for each class and the tolerances allowed. In relation to the evolution of the change of surface color, size, shape, and weight may vary according to variety of mango. The appropriate degree of maturity corresponding to the varietal characteristics is also required to withstand transport and handling, and to arrive in satisfactory condition at the place of destination.

2.3 Automated fruit grading process

The automated grading process can be divided into two groups, one is maturity estimation and second one is estimation of quality. In our previous work [14], the maturity of these varieties of mangoes, have been successfully estimated with the help of optimum set of features extracted from the mango images using of Support Vector Machine (SVM) based Recursive Feature Elimination (RFE) technique.

In the previous work, for classification of mangoes into four different maturity levels, an ensemble binary classification model has been applied. The details of the process and the extracted features can be found in [14].

In this work, a MADM system has been employed for estimation of mango quality from the attributes like shape, size, weight, and surface defects. Finally a Fuzzy incremental learning algorithm has been applied to combine the decisions of SVM and MADM on maturity and quality estimation respectively, for final gradation of mangoes into the four different categories. The different steps of complete grading process are shown in Fig.1.

Table IStandard for gradation of commercial varieties of
mangoes



Grade	Attributes concerning gradation						
G1 (Very Good)	Mangoes in this class must be matured, superior quality and must be characteristic of the variety. They must be big size, good shape and weight and free of defects, with the exception of very slight superficial defects.						
G2 (Good)	Mangoes in this class must be matured and good quality. They must be characteristic of the variety. They have medium size and weight, slight defects in shape and skin.						
G3 (Medi -um)	This class includes mangoes which are semimature and satisfy the minimum quality requirements. The following defects, however, may be allowed, provided the mangoes retain their essential characteristics as regards the quality: defects in shape and skin. They have light weight and small size.						
G4 (Poor)	Premature or overmature mangoes having large skin and shape defects, with small size and weight are in this class. Generally such mangoes are not supplied to the consumer, but may be used for industrial processing.						

The following section presents the details of features extraction process for estimation of quality, followed by brief theory of MADM and Fuzzy.

2.3.1 Features Extraction for Quality Attributes. 2.3.1.1 Size Calculation

Size is an important quality attributes for mango grading. If the camera resolution and the distance of the object from camera are known then size of mango can be directly obtained from the mango image. The maximum major axis (L_{max}), maximum minor axis (W_{max}) and the total number of pixels hence size is already calculated and discussed in previous work [17].

2.1.1.1 Determination of Surface Defects

Surface defects is the another quality attribute used by the farmer or customer. It may occur due to rubbing or sunburn, suberized stains and resin exudation. It degrades the quality of the fruit. The number of defect pixels are calculated where from the percentage of defect area is determined and shown in our previous work [17].

2.1.1.1 Shape Measurement

Shape is also a quality attributes used for mango grading. Presently, there are many methods available for analyzing shape of an object which includes, authors [18], [19] investigated the use of Fourier Descriptors (FD) for object shape recognition and distinguishing star fruits [20]

using computer vision. In this work we used line length method for shape analysis of different categories of mango. Before implementing this method, several image preprocessing operations like image binaries, back ground elimination, contour detection, image alignment (apex at the top), and filtration were performed on the mango image.



Fig.1. Flow diagram of proposed real time machine vision based mango grading process.

In this paper the mango shape feature parameters is obtained by extracting line sequences from the contour of the mango image and normalizing the length of these line sequences to eliminate the influence of the mango size for a particular variety.



Fig.2. Extraction of shape characteristics of the AM variety mango

The different preprocessing steps of the mango images before extracting the line length are already discussed in our previous study [15]. Then the contour



curve of mango image is used to obtain the Lmax and Wmax as discussed in our previous study [17]. The line 11, i.e. Lmax, in the longitudinal axis direction of the mango and line d_1 , i.e., width of the mango at middle in the transverse axis direction. The mango image is divided evenly using nine lines in horizontal direction $(l_1, l_2, l_3, \ldots, l_9)$ and nine lines in the vertical direction $(d_1, d_2, d_3, \ldots, d_9)$, respectively, and 18 lines are obtained as shown in Fig.2. where the distance between two vertical line is $W_{max}/10$ and the distance between the two horizontal line is $L_{max}/10$. So the l_1 and d_1 are passing through the center of the mango image. After obtaining the 18 lines, they are normalized as:

$$\mathbf{x}_{i1} = \mathbf{I}_2 / \mathbf{I}_1, \ \mathbf{x}_{i2} = \mathbf{I}_3 / \mathbf{I}_1, \dots, \mathbf{x}_{i8} = \mathbf{I}_9 / \mathbf{I}_1$$

$$\mathbf{x}_{i9} = d_2/d_1, \, \mathbf{x}_{i10} = d_3/d_1, \, \dots, \, \mathbf{x}_{i16} = d_9/d_1$$

The $x_{i1}, x_{i2}, \ldots, x_{i16}$ are standardizing the shape feature parameters of ith variety of mangoes. The line length of each mango is also calculated and the bigger the differences in the line lengths are, the more different they are in terms of shape.

2.1.1.1 Weight Measurement

Exact weight measurement using machine vision is very tough. We determined the weight by measuring the volume of mango. The alignment of the acquired mango images are made vertically in such a way that the apex will be at the top. The Cylinder approximation analysis method is used in this project to estimate the volume of mango as shown in Fig.3.



Fig.3. Dimension measurement of AM variety mango

The height, h and radius, r was extracted from the acquired mango images. This cylinder method was applied reconsidering the mango's cylinder section.

The volume is defined based on the cylinder volume formula, where the width, W and length, L is obtained from the mango sample measured:

$$V = \prod r^2 h$$

$$r = W/2$$
$$h = L/2$$

Where, V = estimated volume, r = radius and h = height Based on this calculated volume the weight of mango is estimated.

III THEORY OF MADM SYSTEM

A Multi Attribute Decision Making (MADM) method specified how attribute information is to be process in order to arrive at a choice. It can be assigned different weights to different attributes of the object according to different standards to achieve the simplification of the multi-attribute problems. The *i*th alternatives score can be determined with the magnitude of the index P_i (i = 1,2,...,m):

$$P_i = \sum_{j=1}^{n} w_j (m_{ij})_{normal}$$

where, w_j is the weight of the attribution j, $(m_{ij})_{normal}$ represents the normalized value of m_{ij} of the attribution j of alternatives i, n is the number of indices, in our system it is 4. Considering the sum of all weights equals to 1 i.e. $w_1 + w_2 + w_3 + w_4 = 1$. And P_i is the overall or composite score of the alternative A_i .

Theory of Fuzzy

Fuzzy Inference System (FIS) based on Takagi-Sugeno model [21] shown in Fig.4, where the antecedents are fuzzy and the consequent is crisp. The two inputs of FIS, maturity level and quality level are first fuzyfied into a fuzzy set. The fuzzy model proposed by Wang and Mendel [22], [23] is widely used for generating rules using inputoutput data [24], [25].

We have two data points that corresponds to normalized value of maturity level and quality level. The membership function used for the two inputs and output are shown in Fig. 5. The set of input-output data pairs is given as follows:

$$(x_1^{(i)}, x_2^{(i)}; g^{(i)}).$$

Here $x_1^{(i)}$ and $x_2^{(i)}$ are the normalized values of inputs, and $g^{(i)}$ is the output of i^{th} mango sample. Here we generate a set of fuzzy rules from the above data and use these fuzzy rules to determine a mapping $f:(x_1, x_2) \to g$.





Fig.5. Membership function used for: (a) maturity level and grade output and (b) quality level.

Rules obtained from each pair of input-output data as

$$R_{i} = IF x_{1}^{(i)} \text{ is } r_{a}(\mu_{r_{a}}^{(i)}) \text{ and } x_{2}^{(i)} \text{ is } r_{b}(\mu_{r_{b}}^{(i)})$$
$$THEN \ g^{(i)} \text{ is } r_{c}(\mu_{r_{c}}^{(i)})$$

Where R_i is the *i*th rule, r_a and r_b are the fuzzy sets representing different regions of the input space, r_c is the fuzzy set representing the region in the output space, and $\mu^{(i)}$'s are the corresponding membership values. The maximum number of rules that can be generated for this system is 5×4=20. In each rule, there are two atomic clauses in the antecedent part.

In this paper, the fuzzy classification rules have been generated by applying the WM method [22], [23] using an incremental-learning approach. In this method the classifier can incrementally acquire new data without forgetting the previous knowledge. Centroid defuzzification method is used to determine the output grade g for given input x_1 and x_2 .

IV RESULT AND DISCUSSIONS

The obtained results are grouped into two subsections, first section presented the obtained results for prediction of maturity using RFE-SVM and estimation of quality using MADM, with the help of the four attributes. The second section presents the final results on grading of mangoes into four different grades with the help of fuzzy incremental learning algorithm.

Mango Maturity Evaluation

The mango color features are extracted in RGB color model to implement the mango color gradation. Total 1350 mangoes of five different varieties were collected for the test in three batches with one week interval in between batches. In each batch for each of the variety 90 numbers of mango were collected, with average of 30 mangoes from each garden. Recursive Feature Elimination (RFE) technique in combination with Support Vector Machine (SVM) based classifier has been employed to identify the most relevant features among the initially chosen 27 number of features. Finally the optimum set of reduced number of features used for classification of the mangoes into four different classes according to maturity level. For classification an ensemble of 7 binary SVM classifiers has been combined in Error Correcting Output Code (ECOC), and the minimum hamming distance based rule has been applied in decision making phase. The average performance accuracy of the proposed system and the experts are compared and discussed details in our previous study [14].

Quality Evaluation

The quality evaluation depends on the proper estimation of the four attributes i.e. size, shape, and weight and surface defects. In the previous work [17], it has been observed that the size estimation error remains within the limit of ± 3 % and it has also been observed that the errors in determination of surface defects remain within the limit of 10%.

Shape Gradation Test

Shape analysis using direct thresholding method can not be used for recognizing such standardized shape feature parameters (i.e. $x_{i1}, x_{i2}, \ldots, x_{i16}$), because of the difficulty in establishing effective shape threshold. Support Vector Machine based statistical approach is used here to recognize the shape feature parameters for determining the shape of the mangoes. In order to make the shape gradation adapt various kinds of mango, and have a faster processing speed to meet the real-time requirement, the automated



mango grading system is implemented using this method to determine the shape.

100 mangoes of each variety were used to analyze and distinguish to validate the gradation effect of the automated mango grading system. The results show that there were 91% mangoes graded correctly. Experimentally it is seen that this normalized shape feature parameters are deviated from one variety to another variety. So the vendor must select the mango variety before grading for better classification performance.

Weight Gradation Test

The scatter plot for estimating the volume for AM variety mango is shown in Fig.6. The estimation of actual weight for the mangoes shows high correlation, with R^2 equals to 0.9202.



Fig.6. Scatter plot of actual weight and estimated volume of AM variety

The high prediction accuracy obtained shows that this simple formula is adequate to predict fruits weight and volume (measured volume using the cylinder method). The correlation formula derived based on the collected data is determined as W=1.0445V - 56.9079 where W is estimated weight in grams and V is estimated volume.

Experimentally it is noticed that the density of the mango slightly varies from one variety to another variety and also with its maturity level. Therefore in this system a correction factor is determined on the basis mango variety (selected by the vendor) and its maturity level (predicted before weight estimation). After the estimation of quality attributes finally the automated mango grading system is designed to evaluate quality by these four indices simultaneously. Normally, the index conflicts with one another during multi indices grading. For example, some mangoes have large sizes but their surface is defective so as to have an influence when they are placed together. To solve these problems, Multi Attribute Decision Making (MADM) theory is adopted in this system. It can assign different weights to different quality attributes of the mango according to different standards to achieve the simplification of the multi-attribute problems.

In this quality evaluation system, j = 1, 2, 3, 4 expresses the size, shape, weight and surface defects considering the sum of all weights equals to 1 i.e. $w_1 + w_2 + w_3 + w_4 = 1$. P_i is the overall or composite score of the alternative A_i . The P_i value shown in Table II indicates the quality level. The alternative with the highest value of P_i indicates the best quality. As all the attributes are consider in normalized domain, it can be applicable for all varieties. Final selection of w_1 , w_2 , w_3 and w_4 are by the knowledge of experts and vendors. Vendor can also change these weights manually according to the market demands considering different variety of mangoes also.

Table II Decision table in MADM methods

Altem atixes (A _i)	Size w1= 0.25	Shape w2= 0.15	Weight w3= 0.25	Surface Quality w4=0.35	Composite Score (P _i)
Alt 1	0.9	0.9	0.85	0.9	0.86
Alt 2	0.5	0.7	0.5	0.8	0.63
Alt 3	0.7	0.65	0.65	0.8	0.71
Alt N	0.85	0.8	0.85	0.7	0.79

Grading of mangoes based on Quality and Maturity

Fuzzy incremental learning algorithm is used for grading of mango considering maturity and quality level are two inputs. Maximum 20 number of rules can be generated by the input-output data. 100 mangoes each of five different varieties were used to test. The whole automated mango grading system was conducted and the performance accuracy of the proposed system is shown in Table III.

Table III Performance analysis of proposed system

Variety	Performance Accuracy				
(Local Name)	G1	G2	G3	G4	
KU	90.4	88.7	89.4	89.4	
AM	90.1	89.1	88.2	89.4	
SO	89.7	89.1	88.3	89.5	
LA	90.5	88.6	88.8	89.7	
HI	89.4	90.0	89.1	90.0	

The results showed that all the varieties are fitted together well and enable to achieve the mango gradation action. However, it should be noted that the experts gradation is also subject to error, so that 100% agreement cannot be expected. However, when the same samples are v alidated by executing the proposed system, the repeatability is found to be again 100%. The present study, thus, confirms that the proposed system estimates mango quality with considerable accuracy using machine vision exhibiting at the same time an effective human visual perception. In fact, the results of this study are quite promising and precise.

V. CONCLUSIONS AND FUTURE WORK

Proposed grading system classify the mangoes into four grades based on experts perception. The multi-attribute decision making theory was introduced for quality evaluation. It can assign different weights to different attributes of the object according to different standards to achieve the simplification of the multi-attribute problems. According to the grading require, the grading index and the weight of attribution were entered to realize the multiattributes for classification of mango. Results show that the mango classification algorithm is designed viable and accurate. Mango size error is less than 3%, the color grading accuracy rate is 95%, accuracy for measurement of shape is 91% and weight is 92% and the accuracy rate for measurement of surface defect is over 90%. The average time to grade one mango is no more than 0.4 sec.

We observed problems in detecting the firmness from this vision based measurement. An impact sensor may be used for firmness detection. The limitation of this proposed system is that the motion of the mangoes interferes with accurate assessment of shape, although it is seen that the motion has little effect on determining the size. Though in case of mango grading by the proposed system chances is very less to appear calyx and stem of mango in the top. If happen the calyx and stem ends will be considered as defects by the current system. It can be detected using a correlation pattern recognition technique.

REFERENCES

[1] D.W Sun, "Computer Vision: An objective, rapid and non-contact quality evaluation tool for the food industry", J. of Food Eng., vol. 61, 2003, pp.1-2.

[2] G.Q. Jiang, C. J. Zhao, and Y. S. Si, "A machine vision based crop rows detection for agricultural robots", IEEE Int. Conf. on Wavelet Analysis and Pattern Recognition (ICWAPR), Qingdao, 11-14 July 2010, pp. 114 – 118.

[3] K.K.Patel, A. Kar, S. N. Jha and M. A. Khan, "Machine Vision sysrem: A tool for quality inspection of food and agricultural products", J. of Food Sci. and Technol. 2012 April 49(2), pp. 123-141.

[4] C. McCarthy, "Practical Application of Machine Vision in Australian Agricultural Research at NCEA", IEEE RAS TC on Agricultural Robotics and Automation Webinar, March 28, 2014, Brisbane, Australia.

[5] L. Wang, X. Tian, A. Li, and H. Li, "Machine Vision Applications in Agricultural Food Logistics", IEEE Sixth Int. Conf. on Business Intelligence and Financial Engg. (BIFE), 14-16 Nov. 2013 pp.125 - 129

[6] D. J. Lee, J. K. Archibald, and Guangming Xiong. "Rapid color grading for fruit quality evaluation using direct color mapping," IEEE Trans. Autom. Sci. Eng., vol. 8(2), 2011, pp. 292–302.

[7] A. P. S. Chauhan and A. P. Singh, "Intelligent Estimator for Assessing Apple Fruit Quality", Int. J. of Comp. Appl. vol. 60,no.5, Dec. 2012.

[8] X. Liming and Z. Yancho, "Automated Straberry grading System Based on Image Processing", Comp. and Elec. In Agri., 71S (2010), S32-S39.

[9] B. Jarimopas and N Jaisin. "An experimental Machine Vision system for sorting sweet Tamarind," J. of Food Eng., vol. 89(3), 2008, pp. 291–297.

[10] Z. Effendi, R. Ramli, J.A. Ghani, and Z. Yaakob, "Development of Jatropha Curcas color grading system for ripeness evaluation", European J. of Scientific Research, vol.30 no.4 (2009), pp.662-669.

[11] H. Zheng and H. Lu, "A least-squares support vector machine (LS-SVM) based on fractal analysis and CIELab parameters for the detection of browning degree on



mango (Mangifera indica L.),"J. Comp. and Electr. Agri., vol.83, 2012, pp.47-51.

[12] F.S.A Saad, A.Y.M. Shakaff, A. Zakaria, M.Z Abdullah, and A.H. Adom, "Bio-inspired Vision Fusion for Quality Assessment of Harumanis Mangoes," Int. conf. on Intelligent Systems, Modelling and Simulation (ISMS), 8-10 Feb. 2012 pp.317-324,

[13] Y. K.Teoh, S. A. Hasan and S. Sauddin,"Automated Mango Fruit Grading System Using Fuzzy Logic", J. Agri. Sci. Vol. 6 No. 1, 2014.

[14] C. S. Nandi, B. Tudu, and C. Koley, "A Machine Vision Based Maturity Prediction System for Sorting of Harvested Mangoes", IEEE Trans. Inst. and Meas., Vol. 63, No 7, July 2014, pp.1722-1731.

[15] C. S. Nandi, B. Tudu, and C. Koley "An automated machine vision based system for fruit sorting and grading," IEEE 6th Int. Conf. on Sensing Tech. (ICST), Dec, 2012, pp.195-200.

[16] Codex Standard For Mango (CODEX STAN 184-1993), pp.1-4.

[17] C. S. Nandi, B. Tudu, and C. Koley, "A Computer Vision Based Mango Fruit Grading System", Int. Conf. on Innov. Engg. Tech., ICIET, Bangkok, Dec. 28-29, 2014, pp. 1-5.

[18] C.T. Zahn, and R.Z. Rookies, "Fourier descriptors for closed curves." IEEE Trans. of Compu., 1972, C(21), pp. 269-281.

[19] Sun D. W, "Computer vision technology for food quality evaluation", Academic Press, April, 2011.

[20] M.Z. Abdullah, J. Mohamad-Saleh, A.S. Fathinal-Syahir, B.M.N. Mohd-Azemi, "Discrimination and classification of fresh-cut star fruits (Averrhoa carambola L.) using automated machine vision system", J. of Food Engg., vol. 76, Issue 4, Oct.2006, pp.506-523

[21] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its application to modeling and control," IEEE Trans. Syst., Man, Cybern., vol. SMC-15, no.1, 1985, pp.116-132.

[22] L-X Wang and J. M. Mendel, "Generating fuzzy rules by learning from examples," IEEE Trans. Syst., Man, Cybern., vol.22, no. 6, Nov/Dec 1992, pp. 1414-1428.

[23] L-X Wang, "The WM method completed: SA flexible fuzzy systems approaches to data mining," IEEE Trans. Fuzzy Syst., vol.11, no. 6, Dec 2003, pp. 768-782.

[24] G. Tsekouras, H. Sarimveis, and G. Bafas, "A simple algorithm for training fuzzy systems using inputoutput data," Adv. Eng. Softw., vol. 34, no. 5, May 2003, pp.247-259.

[25] B.Tudu, A. Metla, B. Das, N. Bhattacharyya, A. Jana, D. Ghosh, and R. Bandyopadhyay, "Towards Versatile Electronic Nose Pattern Classifier for Black Tea Quality Evaluation: An Incremental Fuzzy Approach", IEEE Trans. on Instru. and Meas. vol. 58, no. 9, Sept 2009, pp.3069-3078.