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ORIGINAL RESEARCH PAPER

AN APPLE GRADING SYSTEM ACCORDING TO EUROPEAN FRUIT QUALITY STANDARDS USING GABOR FILTER AND ARTIFICIAL NEURAL NETWORKS

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Abstract: With the advent of applications of machine learning methods in food engineering in recent decades, several intelligent methods have been introduced in fruit grading technology. In this study, an apple grading system is presented using image's textural features extraction and artificial intelligence. The objective of this study was to simplify the use of Gabor filter in classification of two varieties of apple fruits (*Golden Delicious* and *Red Delicious*) in four categories according to the European fruit quality standards. Using this filter, neural network classifier was trained for four category grading of the fruits. Two textural parameters were extracted from each obtained image: mean and variance of energy values of obtained image representing image's luminous intensity and contrast, respectively. Experimental results indicated that the training of extracted features of about 350 fruits enabled the network to classify the test samples with appropriate accuracy. Compared to the state-of-the-art, the proposed grading categories ('*Extra*', '*Type 1*', '*Type 2*' and '*Rejected*' classes) achieved acceptable recognition rates of about 89 % and 92 % overall accuracy for *Golden Delicious* and *Red Delicious* varieties, respectively. These experimental results show the appropriate application of proposed method in fast grading of apple fruits. Furthermore, proposed feature extraction and network training methods can be used efficiently in online applications.

Keywords: *apple, food engineering, fruit grading technology, fruit quality standard, image Gabor features, image processing*

INTRODUCTION

Although there are hundreds of published research studies on the grading techniques of agricultural products as a post-harvest processing, just few of them have offered simple and accurate methods to grade products having different levels of quality. Nowadays, machine vision and real time image processing have become important techniques in food industry systems [1, 2]. In recent years, researchers used different techniques like X-ray imaging [3], hyperspectral imaging [4], spectral reflectance based methods [5, 6] and image features extraction [7] to grade apple fruits.

In [8], researchers presented an image processing system with digital CCD camera to grade apple fruits using a quadratic discriminant classifier and an artificial neural network for classification, and achieved about 75 % classification accuracy.

In a research, a system containing color camera is proposed to grade apple fruits into three quality categories by thresholding and reported 86 % classification accuracy [9]. However, the use of color threshold-based methods in visual automatic grading of agricultural products is not an appropriate technique in industrial applications due to the differences in light conditions.

The authors of [10] extracted statistical, textural and shape features from each segmented apple fruit sample and utilized linear discriminant, nearest neighbor, fuzzy nearest neighbor, support vector machine and adaboost as classification methods.

In [11], authors developed an automatic adjustable algorithm for segmentation of color images to grade and sort apple fruits using support vector machine and Otsu's thresholding method. They reported that their method provided a robust performance for sorting and grading apples in a multi-channel color space.

In a study, an industrial automated inspection of apple quality is introduced involving computer recognition of apples quality based on geometric and statistical features derived from apple images [12].

Quality grading of apple fruit by machine vision is a burdensome task due to the variance of the problem. Thus, the search for a robust, generic and accurate grading system that works for all apple varieties while respecting all norms of standards is still in progress [13].

One of the most conventional standards for apple fruit grading is the one defined by the Commission of the European Communities [14]. According to the European standards, apple fruits should be graded into four categories based on their external quality including '*Extra*' with no defects, '*Type 1*' with small skin defects, '*Type 2*' belonging to fruits with more serious defects and finally, *'Rejected'* for fruits which do not reach the minimum requirements [14]. Color and shape specifications are not considered in this grading system which allows image's texture based machine visions to achieve better performances since these methods are scale invariant.

An important technique of image processing is image's textural feature analysis. Texture is one of the common indicators used for indexing the images especially in agricultural applications [15 – 17]. It is often used as an area descriptor in image analysis and computer vision. To represent texture of the images digitally, it is necessary to make measurements on each pixel taking into account its neighborhood and combine these measures into a vector. A Gabor filter is a linear filter that is used for image textural extraction and defined by a Gaussian filter and sinusoidal oriented [18].

The Gabor filters are considered as space-frequency filters. Spatial-frequency representations preserve both global and local information [19]. Thus, they are well suited for quasi-periodic signals. Indeed, the textures are quasi-periodic signals that have frequency localized energy and allow us to characterize the texture at different scales [20]. Therefore, image properties such as smoothness, coarseness and regularity can be measured by textural features.
The main objective of this study was therefore to introduce a simple apple grading system which extracts several features from the skin and classifies apples into corresponding quality categories by a syntactical classifier. Classification is performed into four quality grades according to the European standards: '*Extra*', '*Type 1*', '*Type 2*' and '*Rejected*' classes.

MATERIALS AND METHODS

Theoretical background of Gabor filters

For a given image $I(X, Y)$ with the dimensions of P × Q, discrete Gabor transform $G(X, Y)$ is given by [20]:

$$G_{m,n}(X,Y) = \sum_{s}\sum_{t} I(X-Y, Y-t)\Psi^{*}{}_{m,n}(s,t) \qquad (1)$$

where:
s, t: represent the length and the height (size) of the mask filter,
I: shows the function of the grey-level of the pixel,
m = 0, 1 ... M-1 and n = 0, 1 ..., N-1: indicate the number of the scale and orientation of the filter, respectively,
$\Psi^{*}_{m,n}$: is the complex conjugate of $\Psi_{m,n}$ which can be obtained as follows:

$$\Psi_{m,n}(X,Y) = \frac{1}{2\pi}\sigma_x\sigma_y \exp[-\frac{1}{2}(\frac{x^2}{\sigma_x{}^2} + \frac{y^2}{\sigma_y{}^2})]\exp(j2\pi W_X) \qquad (2)$$

where:
σ_x and σ_y: are variances along the axis X and Y, respectively,
W_X is the modulation frequency. Finally, variance values along the axis X and Y can be calculated as follows:

$$\sigma_{X,mn} = \frac{\left(\left(\frac{U_h}{U_l}\right)+1\right)\sqrt{I_n}}{2\pi\left(\frac{U_h}{U_l}\right)^{\frac{m}{M-1}}\left(\left(\frac{U_h}{U_l}\right)^{\frac{1}{M-1}}-1\right)U_l} \qquad (3)$$

$$\sigma_{Y,mn} = \frac{1}{2\pi}\tan\left(\frac{\pi}{2N}\right)\sqrt{\left(\frac{U_h^2}{2I_n}\right)-\left(\frac{1}{2\pi}\sigma_{X,mn}\right)^2} \qquad (4)$$

where: $\sigma_{X,mn}$ and $\sigma_{Y,mn}$ are variances along the axis X and Y, respectively [20]. The terms m, M, and I are introduced above while U_h and U_l are constant parameters and their values are considered approximately 0.4 and 0.05, respectively. N is an arbitrary integer number.

Design of the image acquisition system

A machine vision-based apple inspection system should first perform precise segmentation of defective skin and then achieve correct grading of apples into corresponding quality categories. In Figure 1, an illustration of the destructed image acquisition system for two varieties of apple fruits (*Golden Delicious* and *Red Delicious*) is presented. This module consisted of a shielded 150 mm-width belt conveyor which was driven by an electromotor with rotational speed of 24 RPM to transfer the fruit samples along a CCD color camera (NEXT, 1/3" Sony chip, China with CCTV 8.1-100.5 mm lenz) and a 100-LEDs array lightening unit (not shown in the figure).

Since the symptoms of fruits' defects can be only visible on just a particular view of the fruit in most cases, one-view inspection methods certainly will not lead to an acceptable grading accuracy. Therefore, the conveyor and image acquisition system were designed in a way that the fruit could roll over the conveyor belt and several images can be triggered from each fruit.

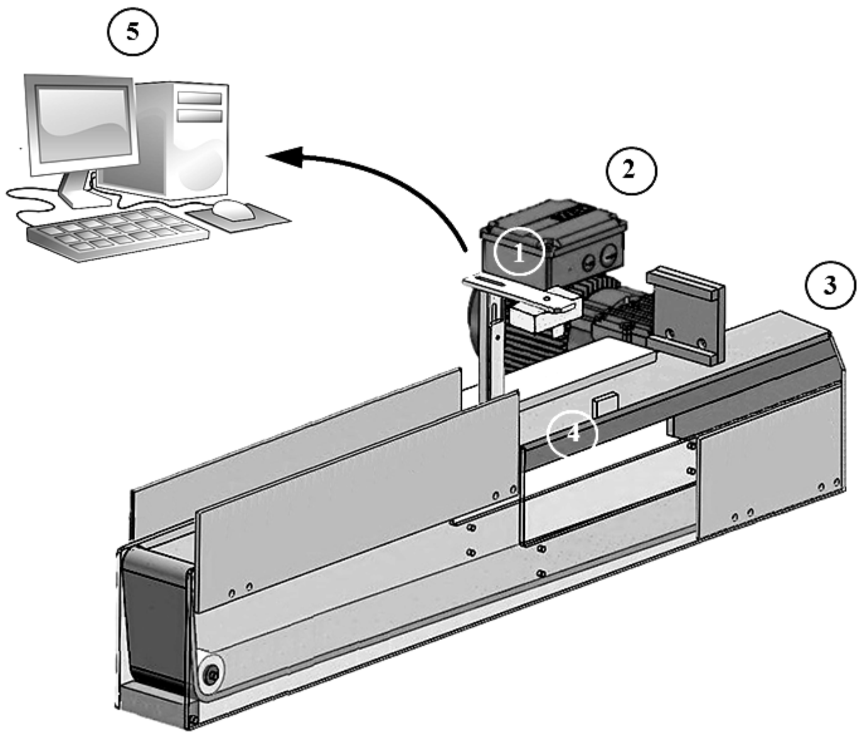

***Figure 1**. Illustration of the image acquisition system used in this study: (1) CCD camera, (2) electromotor, (3) conveyor belt, (4) infrared sensor, (5) computer*

Since there were possibilities to obtain some images including two or more apple fruits, it was necessary to assign a determining index to each fruit. Therefore, an infrared sensor (TCRT5000, VISHAY, Taiwan) was embedded on the conveyor for real-time passage detection of each sample along the image acquisition module. Obtained images were transferred online to a computer via a USB cable for feature extraction and image textural analysis.

Image textural features extraction

A Gabor filtering unit was designed to characterize textures of the obtained images from image accusation unit. Each filter was then applied to the original image, and procedure created a single feature vector (based on statistical calculations) [19]. This process is represented by the flowchart shown in Figure 2.

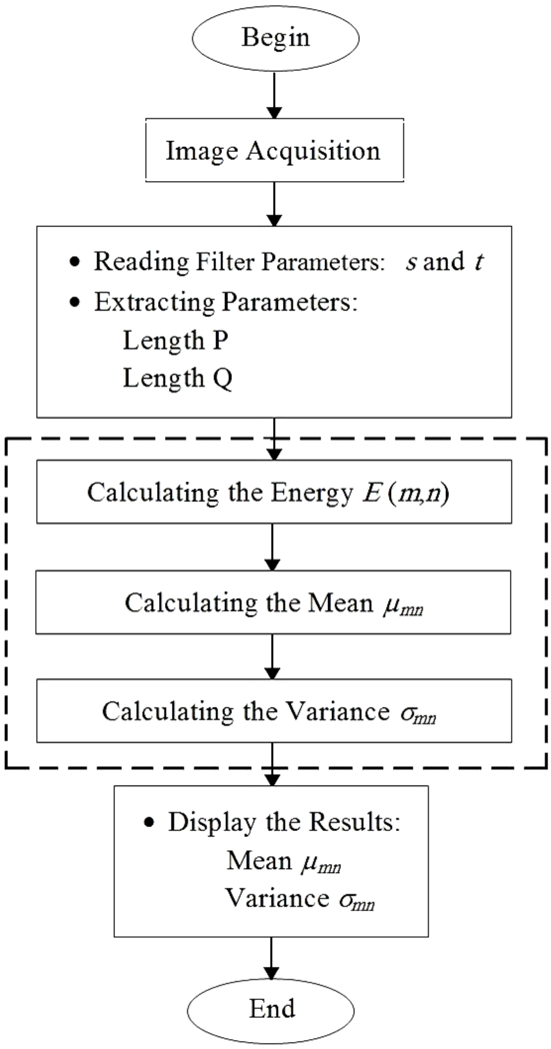

Figure 2. *Sequential algorithm of Gabor filters to extract the characteristics of image textures*

The main image textural feature corresponding to the use of Gabor filter was energy. The energy belongs to the sum of the grey-levels of all primary elements (pixels). It is a numerical value represented by the level of grey-scale brightness. After applying Gabor filters on the image with different orientations and scales, a set of variables (energy magnitudes) was obtained in the form of $E(m,n)$:

$$E(m,n) = \sum_{X}\sum_{Y} G_{m,n}(X,Y) \tag{5}$$

where:
m = 0, 1 ... M-1 and n = 0, 1 ..., N-1: indicate the number of the scale and orientation of the filter, respectively. The E quantities represented the energy content at different scales and orientations of the image [20]. Two parameters of the Gabor transform were utilized to represent the texture of homogeneous regions of the images: mean $\mu_{m,n}$ characterizing the luminous intensity of the image and average grey-level of the primitive elements (pixels) variance, and σ_{mn} which characterizes the image contrast. These parameters were calculated from energy values as follows:

$$\mu_{m,n} = \frac{E(m,n)}{PQ} \tag{6}$$

$$\sigma_{m,n} = \sqrt{\frac{(E(m,n)-\mu_{m,n})^2}{PQ}} \tag{7}$$

A matrix F (texture representation) was created using the values of mean and variance (equation 8).

$$F = \begin{vmatrix} \mu_{00} & \sigma_{00} \\ \mu_{01} & \sigma_{01} \\ : & : \\ : & : \\ \mu_{mn} & \sigma_{mn} \end{vmatrix} \tag{8}$$

Design of the artificial neural network

In order to classify fruits into quality categories, the following syntactical classifier was used. The extracted features (mean and variance of energy values) were considered as input layer nodes in a three-layer artificial neural network and different quality categories of sample fruits as output layer nodes. According to the European fruit grading standards [14], four different quality categories including '*Extra*', '*Type 1*', '*Type 2*' and '*Rejected*' classes were chosen for appropriate grading of two conventional varieties of apple fruits.

The network was trained with Levenberg-Marquardt back-propagation algorithm. Therefore, the ANN architecture was considered as a 2-*n*-4 network which represents variable nodes in the hidden layer to investigate the effect of network architecture on the accuracy of grading process. The choice of the hidden layer size is one of the most important considerations for the ANN design and this area of study is still under intensive research with no conclusive solutions available yet [21].

The exact analysis of this issue was quite difficult due to the complexity of the network mapping and the nondeterministic nature of the many successfully completed training procedures. In this work, the number of neurons in the hidden layer is determined by the trial and error approach. Furthermore, along with other researches, the number of train samples was chosen approximately 60 % of the whole dataset which these train data were used to modify the parameters (weights) of the neurons in the hidden layer. The process of cross validation was also used to monitor capability of the neural network to build generalized outputs. Lastly, testing data was used to validate the quality of proposed ANN model. Stop criteria and weight reset were used in order to cope with under fitting/over fitting problems.

Experimental setup for evaluation of the proposed system

Extracted features of 350, 50, and 159 images of apple fruits obtained from image acquisition module were used to train, cross validate, and test the proposed grading method, respectively. Characteristics of the two varieties datasets are presented in Table 1.

Table 1. *Characteristics of the two varieties datasets*

Data type	Golden Delicious	Red Delicious
Number of images	261	298
'Extra' fruits [%]	63.32	69.84
'Type 1' fruits [%]	16.43	12.60
'Type 2' fruits [%]	5.20	3.71
'Rejected' fruits [%]	15.15	13.85

In comparison, healthy fruits which were represented by the category title '*Extra*' encompassed the major samples in the studied dataset. The initial grading of the fruits to obtain the label of each fruit (from no 1 to 4) was carried out subjectively using human operators. The main fruit defects which affected the decision of operators about their quality were bruises, wounds (impacts, birds), scab, russet, fungal attack, bitter pit, scar tissue, frost damage, and insect attack.

RESULTS AND DISCUSSION

Table 2 shows some examples of the training data. As it can be seen in this table, mean and variance of energy values are represented for the displayed sample images. As expected, by several investigations, it was cleared out that it is not possible to perform a regression model to predict output variable (the category of fruits' quality). In total, when the regression and statistical methods cannot model the high-dimension datasets, black-box methods such as artificial neural networks and other artificial intelligence methods seem to be useful to create a model with proper prediction accuracy [22].
The performance of proposed artificial network in the prediction accuracy of samples' category is presented in Table 3 for train, cross validation, and test data for different network architectures. According to this table, the highest accuracy value for ANN was achieved in the 2-12-4 ANN architecture for both studied apple varieties, while the lowest accuracy was obtained from the 2-2-4 case. During the training process, it was found that the increase of the number of neurons in the hidden layer was not directly

related to the increase of the accuracy. Results showed that the highest accuracy was achieved 89.3 % and 92.3 % for *Golden Delicious* and *Red Delicious* varieties, respectively at the testing phase. No further increase of the accuracy was achieved even if the number of iteration was increased. Therefore, 2-12-4 architecture network was selected as the optimum model to predict grading categories of apple samples. The accuracies at the testing phase were higher than those of the training phase, meaning that the network had good generalization ability [21].

Table 2. *Examples of the training data set (values are normalized between 0 and 1)*

Fruit image	**Input of the network**		**Output**
	Mean	**Variance**	**Fruit Grading**
	0.43	0.11	*'Extra'*
	0.22	0.05	*'Type 1'*
	0.27	0.23	*'Type 2'*
	0.26	0.31	*'Rejected'*
	0.28	0.29	*'Rejected'*

Table 3. *Accuracy of proposed network in the prediction of output variable [%]*

Network architecture	Golden Delicious			Red Delicious		
	Train	Cross Validation	Test	Train	Cross Validation	Test
2-2-4	74.9	71.3	71.5	71.8	70.9	65.5
2-4-4	75.8	73.0	69.7	72.5	71.3	70.4
2-6-4	77.4	73.1	71.6	75.8	75.0	72.6
2-8-4	83.4	81.9	76.6	81.9	76.2	77.5
2-10-4	88.4	86.7	84.4	89.8	85.0	84.9
2-12-4	90.3	88.3	89.3	93.0	94.2	92.3
2-14-4	89.5	90.4	88.7	90.4	92.9	89.5
2-16-4	87.9	86.0	86.9	85.0	90.4	88.9
2-18-4	88.3	84.9	83.9	88.5`	84.3	82.9
2-20-4	85.9	83.8	81.5	82.0	83.9	80.6

To investigate the performance of proposed network for different apple grading categories, the confusion matrix of the selected artificial neural network (the one with 2-12-4 architecture) in grading of apple fruits are represented in Tables 4 and 5 for *Golden Delicious* and *Red Delicious* varieties, respectively.

Table 4. *Confusion matrix of the selected artificial neural network in grading of Golden Delicious apples [%]*

True categories	Predicted categories			
	'Extra'	**'Type 1'**	**'Type 2'**	**'Reject'**
'Extra'	91.1	2.1	3.2	3.6
'Type 1'	6.5	89.2	2.9	1.4
'Type 2'	4.3	1.0	88.3	6.4
'Reject'	9.5	4.4	3.6	82.5

Table 5. *Confusion matrix of the selected artificial neural network in grading of Red Delicious apples [%]*

True categories	Predicted categories			
	'Extra'	**'Type 1'**	**'Type 2'**	**'Reject'**
'Extra'	93.6	2.6	0.9	2.9
'Type 1'	3.6	91.9	1.4	3.1
'Type 2'	5.1	1.3	92.2	1.4
'Reject'	7.2	4.4	2.5	85.9

As an example to illustrate how to interpret the data shown in these two tables, it can be said that from 100 % of '*Extra*' type *Golden Delicious* apple fruits, 91.1 %, 2.1 %, 3.2 %, and 3.6 % of them were recognized as '*Extra*', '*Type 1*', '*Type 2*', and '*Reject*' categories using the proposed neural network. These tables showed that the fruits were more likely graded as '*Extra*' in comparison with other categories. This phenomenon can be explained considering that there are some defects which can just be monitored from a particular view of the fruit. On the other hand, these tables showed that the fruits in category '*Extra*' were somehow better graded than those belonging to other classes for both studied varieties. This result was along with other researches [8, 11].

The analysis of the classification errors for the *Red Delicious* apples showed several origins including the presence of lots of blobs or bruise on poorly graded apples, especially when the bruise was located in the fruit blush area. The subjective investigation of misgraded apple fruits showed that recent bruises had higher effects on the decrease of grading accuracy in comparison with old bruises. Similar results have been obtained by Leemans *et al.* [8] for *Jonagold* apple variety. The reason here can be assumed the changes of image textural features of bruises during a time period. In contrast, for *Golden Delicious* apples, the recognition errors came mainly from the bruises and it was reported that blobs were not poorly grading agents. One of the most important aspects in this study is the correctly grading of the images presenting calyx of the fruits.

In the method described in this study, a simple two features extraction method has been used for grading purpose, contrary to the complex ones proposed earlier [8, 11]. This can lead to enhance the acceleration of the procedure making it possible to use proposed method in online applications.

CONCLUSIONS

In this paper, an automatic grading technique is introduced for *Golden Delicious* and *Red Delicious* apples using machine vision. In the proposed system, the way of image textural features extraction (energy and mean of variance) in a pixel-wise manner and then, the way of assigning quality categories to the corresponding fruits using artificial neural network classifier had resulted appropriate grading accuracy of two conventional apple varieties. Experimental results obtained from performance evaluation of the proposed four-categories grading method achieved acceptable recognition rates of about 89 % and 92 % overall accuracy for *Golden Delicious* and *Red Delicious* varieties, respectively. The proposed method with relatively small number of extracted features for apple grading system has enabled us to perform a fast and accurate extraction of characteristics of image textures using Gabor filter.

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