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APPLIED LINEAR DISCRIMINANT ANALYSIS AND ARTIFICIAL NEURAL NETWORK FOR SORTING DRIED FIGS BASED ON TEXTURE PROPERTIES

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Abstract. Dried figs are one of the horticultural products that require sorting in the post-harvest stage in order to be presented to the market. In Iran, figs are graded manually by professional workers or automatically by mechanical machines. This paper presents a new algorithm based on machine vision technology applicable to be installed in the fig sorting machines. In the presented methodology, image texture properties of figs are extracted by an image processing algorithm. Some features selected by stepwise linear discriminant analysis were introduced as the superior ones for discriminating different classes of dried figs. Among the ten features, discriminant analysis selected six. The selected texture features were fed to artificial neural networks in order to implement the classification process. The image processing assisted neural networks methodology showed promising result as the total sorting accuracy was 100%.

Key words: figs, sorting, texture properties, discriminant analysis, neural network

INTRODUCTION

Figs are fruits of *Ficus carica* L. a member of Moraceae family, originated in the Mediterranean and western Asian regions. Some varieties of edible fig in Iran are Izmir, General and Sanpedro. Iran is third largest producer and exporter of figs in the world. With respect to the cultivated area, after Portugal, Egypt, Turkey, Iran ranks the fourth in the world. With regard to the amount of production, after Egypt and Turkey, Iran possesses the third ranking in the world [FAO 2012]. Cultivation area of figs is 44 293.6 acres in Iran, which is cultured in both dry and water farming and total production is 57 057 tons [Anonymous 2010].

Figs are an excellent source of minerals, vitamins, and dietary fibers; they are free from fat and cholesterol and contain a high amount of amino acids. Figs are cultivated in tropical and semi-tropical areas. In addition, they contain a high amount of flavon-

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oids, polyphenols and anthocyanins, which are essential for human health and in the Mediterranean food diet [Slavin 2006; Solomon et al. 2006]. Phenolic acids and flavonoids of three kinds of Mediterranean fig were investigated by Veberic et al. [2008].

In today's competitive market, since consumers tend to use healthy and homogenous products, producers have to present their products, which are sorted according to physical characteristics like appearance, size, color and internal health. Sorting the fruit can increase uniformity in size and shape, reduce packaging and transportation costs and may provide an optimum packaging configuration [Tabatabaeefar et al. 2000].

It is very difficult to manually sort and separate products. Manual inspection involves labor intensive work and made decision can be very subjective depending on the mood and condition of the involved people. Furthermore, this manual procedure can be very time-consuming and inefficient, especially when dealing with high production volume.

In most early mechanical sorting machines, grading is done based on product size that is generally its diameter. However, these machines are not able to investigate and grade products based on appearance and internal properties. Moreover, these machines could cause mechanical damage to the products [Mc Rae 1985; Amiriparian et al. 2008].

Considering these mentioned reasons, the new methods like machine vision systems have been introduced for grading. The systems that are non-destructive and lack fatigue would be an invaluable tool for handling and quality monitoring. Nowadays, some research increasingly used for sorting fruits based on external [Chen et al. 2002; Blasco et al. 2003, 2008; Rocha et al. 2010] and internal properties in terms of external properties [Kondo et al. 2000].

In developing machine vision system for fruit inspection, shape is the best basis for inspection. Heinemann et al. [1996] and Noordam et al. [2000] have developed an automated machine vision for shape classification of potatoes. Blasco et al. [2009] developed a machine vision-based system for inspecting and sorting mandarin segments by extracting morphological features to rate in commercial categories. Their results showed that the machine could correctly classify by 93.2%.

Color is another property of products that is measured by machine vision and has been a great help in identifying objects for many years. The process of color classification involves extraction of useful information concerning spectral properties of the object surfaces and discovering the best match from a set of known descriptions or class models to implement the recognition task [Sahin 1997]. Color features have been extensively applied for apple quality evaluation, mainly in defect detection. For instance, color features of each pixel in images obtained in three components of RGB spaces could be successfully used to segment defects on 'Jonagold' apples [Leemans 1999, 2004]. To separate open-mouthed pistachio, Pearson and Toyofuku [2000] conducted a study and separated damaged, open-mouthed, and closed-mouthed pistachio using color characteristic with accuracy of 95%. Also, Nasirahmadi and Behroozi [2013] used machine vision for identifying bean varieties according to color features.

Texture is one of the most active topics in machine intelligence and pattern analysis since 1970 [Haralick et al. 1973; Kartikeyan and Sarkar 1991]. Image texture analysis is a more robust method than direct grey-level intensity measurement because texture is independent from tones of the images and image texture contains statistical information in spatial domain [Nasirahmadi and Behroozi-Khazaei 2013]. The grey-tone spatial-dependence matrix, or co-occurrence matrix (COM), which is statistical relationship of a pixel's intensity-to-intensity of its neighboring pixels, has been used for image texture analysis. Another way frequently used for texture analysis was based on statistical properties of histogram intensity.

Image texture analysis has been used for agricultural and food product quality and safety evaluation, particularly in grading and inspection [Park and Chen 2001]. COM texture analysis has been used for agricultural applications, such as plant canopy identification [Peres et al. 2011], bread texture analysis [Zayas 1993], determining spatiotemporal fracture behavior of crispy or crunchy food products [Dan et al. 2007] and classification of apples grades after dehydration with accuracy of 95% [Fernandez et al. 2005]. Statistical properties based on the intensity histogram are a frequently used approach for texture. Letal et al. [2003] obtained MRI of apple varieties during ripening and storage and analyzed them by texture analysis (TA) to determine the correlation between TA parameters and firmness, soluble solids content (SSC) and titratable acids. In another study, Ghazanfari et al. [1997] classified pistachios in four sorting classes. In this research, projected area and Fourier descriptor extracted based on the two-dimensional images and recognition features. Then, three classification methods and neural network were used for separating the pistachio. Zhao-Yan and Fang [2005] identified rice varieties using image processing techniques and neural networks. Kondo et al. [2000] was reported predicting oranges sugar content with correlation coefficient of 0.83 based on external properties.

Burks et al. [2000] was used near-infrared spectroscopy for measuring quality of figs. The figs classified to insect infested, rotten, sour and dirty defect categories. Correct classifications for these varieties ranged from 83 to 100%. Also, Souri et al. [2011] designed and fabricated a moisture-based fig sorter. Based on some physical properties of figs, which are affected by moisture content, coefficient of static friction and rolling resistance were introduced as key characteristics in fig sorting. Results showed that both belt slope arrangement and belt speed had a highly significant effect on sorting accuracy. The best sorting accuracy of about 80% was obtained at belt speed of 9.4 $m \cdot min^{-1}$ and belt slope arrangement of 8, 9, 10 degrees.

In the literature review, little information can be found about figs sorting. Figs need to be graded before being presented to the market. Considering disadvantages of traditional grading methods and mechanical machines, this study tried to present an algorithm based on machine vision in order to extract figs texture properties. The machine vision algorithm was also investigated for extracting texture properties; then, effective textures were selected using linear discriminant analysis and these selective features were fed to ANN to grade the figs to three classes.

MATERIALS AND METHODS

Samples and Image Acquisition Set up. In this study, the figs obtained from Neyriz and Estahban in Fars Province, Iran, were used. Most kinds of the figs in these closed cities included Izmir and Green varieties, which are late type, yellow-green and dried fruit. Biong opened-mouthed is considered an acceptable attribute for the market. Based on being open-mouthed, the figs were divided to the three classes: completely open-mouthed figs (first class), little open-mouthed figs (second class) and closed-mouthed figs (third class) (Fig. 1). In this study, 180 figs were randomly selected from the market and expert people graded the figs. Initial moisture content of the figs was about 20% (d.b).

Fig. 1. Three classes of figs
Rys. 1. Trzy klasy fig

The image acquisition system was composed of three parts of imaging, processing and information display unit. The imaging unit, which was responsible for recording images, included a camera and a lighting system. To take pictures, a 750 × 540 pixels resolution Samsung camera (SCC-101 PA) was used. Low-level vision processing tasks need good lighting in the work environment. Hence, good and uniform illumination from external light source is essential for machine vision applications [Kopparapu 2006]. In this research, a fluorescent lamp was used for lighting and a fiberglass sheet in front of it was utilized for producing homogenous lighting. The processing unit included three actions: transferring the camera signals to the computer, developing, and extracting the image characteristics. Transferring the information from the camera to the computer was done by capture card (ACEDVio, Canopus). Image development was done for removing noise and lighting non-homogeneity from the images. The main purpose of image processing was to extract features, which was done using science of image processing [Gonzalez and Woods 2007].

Image Processing Algorithm. Since mouth region of figs has different textures from region of surface figs (Fig. 1), classification of figs was done based on the investigated texture properties. The machine vision algorithm, which was developed in this research calculated texture parameters like energy, homogeneity, contrast and correlation, which were extracted from COM, and texture parameters, which were statistically extracted from intensity of histogram, included entropy, uniformity, third momentum, smoothness, average gray level and average contrast.

The images were provided in the RGB space. In the first step, to develop the image process algorithm, images were smoothed. The second stage of image processing was image segmentation, which is probably the most important stage in leading to high success of any image processing algorithm [Gonzalez and Woods 2007; Mallahi et al.

2010; Zhang et al. 2011]. For segmentation, histogram-based method was used. Selecting the correct threshold in this method influences success of segmentation [Bulanon et al. 2002]. Gray of R channel was used to determine the threshold level (Fig. 2). Threshold 0 was assigned to the background and the mouth region and threshold 1 was assigned to the surface region (Fig. 3 c).

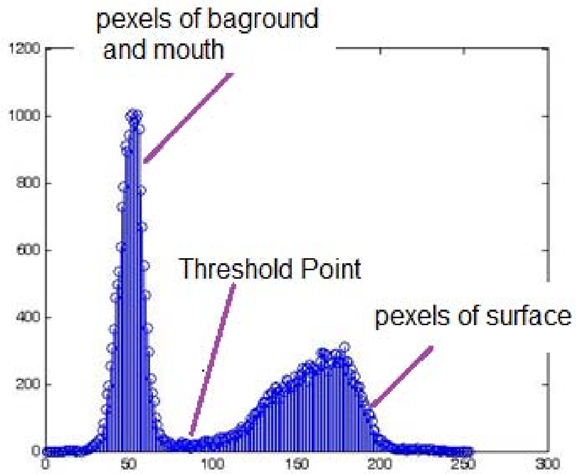

Fig. 2. Histogram of R
Rys. 2. Histogram R

The holes located in the figs' mouth region were filled. To extract texture parameters, binary image (Fig. 3 d) was used for masking on RGB image (Fig. 3 a) and then R channel of the RGB image was separated and used for extracting COM and statistical texture properties. For one image, different COMs can be formed for each angle of θ (θ = 0°, 45°, 90°, 135). Once COMs are formed, texture features can be computed [Shearer and Holmes 1990]. In this study, four COMs were extracted and texture parameters were calculated. Then, texture parameters extracted from these matrices were averaged. In addition, statistical texture properties were extracted from the intensity of the R channel histogram.

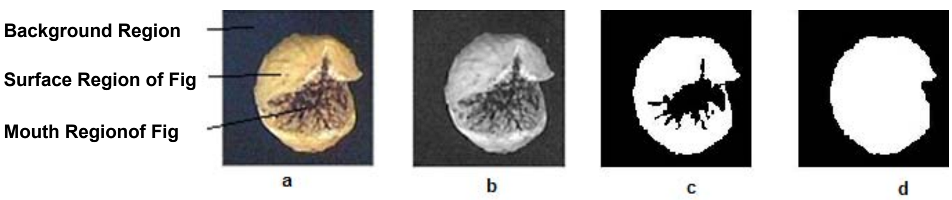

Fig. 3. a) RGB, b) Gary level of R, c) binary of R, d) filled binary image
Rys. 3. a) RGB, b) poziom R Gary'ego, c) R binarne, d) pełny obraz binarny

Linear Discriminant Analysis. Linear discriminant analysis is a supervised technique that can be used to obtain a classification model for group membership prediction. This method produces a set of discriminant functions based on linear combinations of independent variables with a priori knowledge about each sample group membership. In this work, LDA was used to obtain classification rules for making differentiation between fig samples according to textures properties. Prior probabilities were computed based on size of each group. A stepwise technique, using Wilk's lambda method with usual probabilities of F for a variable to be included (0.05) or removed (0.10) from the model, was applied for variable selection. This procedure used a combination of forward selection and backward elimination procedures, where, before selecting a new variable to be included, it is checked whether all the variables previously selected remained significant or not. Therefore, by using this approach, it was possible to identify the significant variables from among all the used texture parameters. Thus, discriminant analysis was performed to classify individual figs to three groups: first class, second class or third class. To verify which canonical discriminant functions were significant, Wilks' Lambda test was applied [Peres et al. 2011]. To avoid overoptimistic data modulation, a leaving-one-out cross-validation procedure was carried out for assessing the model performance.

Classification. Feed forward neural networks (NN) have been established as a general approximator for fitting nonlinear models from input-output data. Ability of NN to deal with complex problems, generalization of the result from known situation to unforeseen situation and ability to carry out classifications of elements of a given set make them one of the most useful techniques in pattern recognition and classification [Poggio and Girosi 1990]. In this study, neural networks helped to estimate posteriori probabilities of an input pattern to belong to each class.

In this research, neural network model inputs were the significant parameter selected by discriminate analysis method. Three neurons were used in the output layer. In ANN, if the output layer equaled [1 0 0] matrix, it meant the first class; if it equaled [0 1 0] matrix, it meant the second class and [0 0 1] referred to the third class. In this method, each fig belonged to a class, the neurons of which had the highest value in the output layer.

Since the neural network was trained in a supervised mode (desired classification class labels were known in advance), the input data patterns were divided to three disjointed data sets: the training set to properly train the network under the supervised mode, validity set that was for checking over fitting of the network learning procedure and the testing set to test generalization capabilities of the network after the training step. Thus, the figs were manually classified by a human expert in three classes in order to provide supervised learning to the neural network classifier. From the 180 images for three classes, 70% composed the training set, 15% was validation and the remaining 15% was used for testing purposes. All the training, validity and testing data sets were randomly selected and normalized. Once the data sets were separated to these groups, they were saved for all the subsequent networks. The Levenberg-Marquart backpropagation algorithm with mean square error (MSE) was used to train learning parameters of the NN model.

RESULTS AND DISCUSSION

Ten texture features were extracted from the images of figs. Table 1 lists descriptive statistics of the figs' texture features computed from the images. As can be seen in this table, means of features between the groups were close to each other. Therefore, it was difficult to develop a simple model, like a linear model, to predict figs' classes based on these texture features. Also, identifying effective features for classification was difficult and performance of a classification system chiefly depended on selecting an appropriate set of features which best described their associate classes. Thus in this study, the applied LDA was used for identifying effective parameters and then the ANN model was developed for classifying figs to three groups.

Table 1. Descriptive statistics (mean ± standard deviation) of texture features measured in this research
Tabela 1. Statystyki opisowe (średnia ± odchylenie standardowe) właściwości tekstury zmierzonych w prezentowanych badaniach

Extracted method Metoda uzyskania	Texture feature Właściwość	Class – Klasa		
		first (A)	second (B)	third (C)
COM	energy	0.84±0.03	0.85±0.02	0.86±0.03
	homogeneity	0.98±0.005	0.98±0.002	0.99±0.004
	contrast	0.10±0.02	0.78±0.01	0.074±0.01
	correlation	0.97±0.002	0.98±0.004	0.99±0.004
Statistical	average gray level	168.66±5.1	170.12±4.7	175.57±3.66
	average contrast	80.18±5.3	77.48±5.5	74.88±7.53
	smoothness	0.053±0.009	0.049±0.008	0.047±0.011
	third momentum	10.9±2.2	9.95±2.2	10.04±2.83
	uniformity	0.84±0.03	0.85±0.21	0.86±0.031
	entropy	0.92±0.20	0.83±0.13	0.76±0.17

Table 2. Effective texture features selected by discriminant analysis
Tabela 2. istotne właściwości tekstury wybrane za pomocą analizy dyskryminacyjnej

Step Krok	Entered parameter Parametr wejściowy	F statics	Wilks' lambda
1	contrast	32.81	0.659
2	smoothness	19.21	0.587
3	third momentum	16.73	0.422
4	entropy	15.06	0.385
5	uniformity	16.78	0.353
6	average contrast	15.32	0.325

F statistics and Wilks' lambda value are two criteria that are used to show significance of a feature in classification. Small F statistics and high values for Wilks' lambda cause a feature to be excluded or included in the discriminant functions. Stepwise discriminant analysis was able to diminish size of features from ten to six; i.e. to assign each class, six texture features were sufficient (tab. 2). These feature selections accelerated processing time and increased reliability of a classifier by eliminating redundant and irrelevant features. Discriminant functions can be used to define membership of each individual plant to the target groups. Canonical discriminant function coefficients are reported in Table 3. The LDA showed canonical correlation of 78.7% for the first function, which explained 90.7% of total variance. The second function explained only 9.3% of total variance, indicating that maximum possible classification of figs was explained by the first function. Wilks' Lambda multivariate statistic test indicated highly significant ($P < 0.00001$) difference between classes for the first function.

Table 3. Canonical discriminant function coefficients
Tabela 3. Współczyniki kanonicznej funkcji dyskryminacyjnej

Parameter	Function 1	Function 2
Contrast Kontrast	7.54	-2.83
Smoothness Gładkość	-28.49	22.54
Third momentum Trzeci moment	-50.58	33.63
Entropy Entropia	66.85	-31.65
Uniformity Jednorodność	13.55	53.79
Average contrast Średni kontrast	34.98	30.25
(Constant) (Stała)	-17.11	-54.03

The figs could be now classified by means of the discriminant function considering their distance to group's centroids. Group centroids were determined by discriminant analysis for each class. The results of classification using six selected texture features are shown in Table 4. Successful recognition rate was 73.4, 66.6 and 71.6% with original and 66.7, 58.3 and 66.8% with cross validation data for the first, second and third classes, respectively (tab. 4). Results of this table showed that LDA was not able to satisfactory distinguish the three studied classes for the original grouped cases.

To overcome these difficulties and trying to improve classification performance, an alternative multivariate technique was evaluated. Therefore, MLP-ANNs were used for figs' classification purposes using the six texture features selected by discriminant analysis. The neural networks, with four layers, were trained and selected using two different data subsets (training and verification sets, respectively) and afterwards validated using the experimental data which were not used in the two previous steps (validation set). Several neural networks trained based on the same datasets and the network that gave minimum mean-squared error of the verification subset was chosen (tab. 5).

Table 4. Classification results with LDA
Tabela 4. Wyniki sortowania przy użyciu LDA

	Class type Klasa	Predicted group membership Prognozowana przynależność grupowa				Accuracy (%) Dokładność (%)			
		A	B	C	total	A	B	C	total
Original Oryginał	first (A)	44	12	4	60	73.4	20	6.6	100
	second (B)	2	40	18	60	3.4	66.6	30	100
	third (C)	2	15	43	60	3.4	25	71.6	100
Cross-validation Atestacja krzyżowa	first (A)	40	13	7	60	66.7	21.7	11.6	100
	second (B)	6	35	19	60	10	58.3	31.7	100
	third (C)	4	16	40	60	6.7	26.6	66.8	100

Table 5. Artificial neural network results
Tabela 5. Wyniki sztucznej sieci neuronowej

Number of neurons Liczba neuronów		Mean square error (MSE) Średni błąd kwadratowy (MSE)		
first layer	second layer	train	validation	test
5	5	8.41E-4	2.26E-3	2.06E-3
10	5	6.95E-3	2.01E-2	1.71E-2
15	10	5.52E-6	1.97E-5	1.87E-5
20	10	1.04E-5	4.88E-5	5.88E-5
25	15	1.12E-5	5.5E-5	5.12E-5
30	15	3.23E-5	4.02E-5	3.92E-5

Finally, the selected MLP-ANN (6:15:10:3) was used to evaluate ability of this multivariate technique for figs' classification. The results obtained with the selected network presented in Table 6, which represent that this network was able to correctly classify figs with 100% accuracy for each class. These results, when compared with previously results obtained using LDA (tab. 4), showed that correct classification of figs' class was improved using MLP-ANN. Therefore, the machine vision and MLP-ANN model proposed in the present study along with the six applied texture features were reliable practical methods for classifying figs to three classes. Some researchers have been shown that using machine vision for measuring properties and neural network tool for classification has good capability for sorting, inspection and recognition [Arribas et al. 2011; Dubey et al. 2006; Ghazanfari et al. 1997].

Table 6. Classification results with ANN
Tabela 6. Wyniki sortowania przy użyciu ANN

	Class type Klasa	Predicted Group Membership Prognozowana przynależność grupowa				Accuracy (%) Dokładność (%)			
		A	B	C	total	A	B	C	total
Training Uczenie	first (A)	40	0	0	40	100	0	0	100
	second (B)	0	40	0	40	0	100	0	100
	third (C)	0	0	40	40	0	0	100	100
Verification Weryfikacja	first (A)	10	0	0	10	100	0	0	100
	second (B)	0	10	0	10	0	100	0	100
	third (C)	0	0	10	10	0	0	100	100
Validation Atestacja	first (A)	10	0	0	10	100	0	0	100
	second (B)	0	10	0	10	0	100	0	100
	third (C)	0	0	10	10	0	0	100	100

In the six feature selected for classification, there was only one feature (contrast) from COM. For calculating this feature, it's necessary COMs in four angles ($\theta = 0°$, 45°, 90°, 135) were calculated and averaged. Therefore, it was time-consuming. For increasing speed of image processing algorithm, this feature eliminated and classification was done by ANN with five features (only statistical features). The classification with these features had 96% accuracy and time-consuming by algorithm reduced about 30%.

CONCLUSIONS

In this paper, vision machine was used for extracting texture features and LDA and ANN were presented in order to sort figs based on texture properties. LDA selected six features for classifying figs with 66.7, 58.3 and 66.8% accuracy for the first, second and third classes with cross validation data, respectively. Then, neural networks were trained by the selected properties in order to classify figs to the three classes. The obtained results demonstrated that ANN was able to classify three classes with high accuracy (100%). These results showed that correct classification of figs using ANN was better than LDA.

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ZASTOSOWANIE LINIOWEJ ANALIZY DYSKRYMINACYJNEJ I SZTUCZNEJ SIECI NEURONOWEJ DO SORTOWANIA SUSZONYCH FIG W OPARCIU O WŁAŚCIWOŚCI TEKSTURY

Streszczenie. Suszone figi są jednym z produktów rolniczych, które wymagają sortowania na etapie po zbiorze ze względu na potrzeby rynku. W Iranie figi są sortowane ręcznie przez wyspecjalizowanych pracowników lub automatycznie przez urządzenia mechaniczne. Niniejsza praca prezentuje nowy algorytm oparty na maszynowej technice wizyjnej zainstalowanej w urządzeniu sortującym figi. W prezentowanej metodyce właściwości tekstury fig uzyskiwane są przy wykorzystaniu algorytmu obróbki obrazu. Niektóre właściwości wybrane za pomocą krokowej liniowej analizy dyskryminacyjnej zostały wprowadzone jako nadrzędne dla rozróżnienia klas suszonych fig. Spośród dziesięciu właściwości, analiza dyskryminacyjna wybrała sześć. Te wybrane właściwości tekstury wprowadzono do sztucznej sieci neuronowej w celu zaimplementowania procesu sortowania fig. Metodyka sieci neuronowych z wykorzystaniem obróbki obrazu wykazała, że wyniki są obiecujące ponieważ ogólna dokładność sortowania fig wyniosła 100%.

Słowa kluczowe: figi, sortowanie, właściwości tekstury, analiza dyskryminacyjna, sieć neuronowa