ELSEVIER

Journal of Food Engineering 61 (2004) 101–107

JOURNAL OF FOOD ENGINEERING

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Comparison of three algorithms in the classification of table olives by means of computer vision

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Received 19 April 2002; accepted 14 May 2003

Abstract

The classification of table olive in different quality categories is performed depending on the defects in the surface of the fruits. However, the characteristics of every category are not defined. Then, it is necessary to apply learning algorithms that allow the extraction of quality information from batches previously classified by expert workers. In this research, a colorimetric characterisation of the more common defects has been carried out. An image analysis system has been used to segment the parameter set with the information from the olives quality. Three different algorithms have been applied to classify the olives in four quality categories. The results show that a neural network with a hidden layer is able to classify the olives with an accuracy of over 90%, while partial least squares discriminant and Mahalanobis distance are over 70%.

Keywords: Olives; Classification; Machine vision; Quality; Neural network

1. Introduction

The table olive is a food product which is usually consumed as an aperitif or in salads which has a wide market in the Mediterranean countries. Therefore, its presentation is essential, and also it is essential to have an homogeneous appearance dealing with size, colour and, above all, in the absence of defects. Traditionally, the people who are in charge of separating the olives into categories are the expert workers, placed on both sides of the processing line where they separate the olives which present defects.

Monochromatic cameras were used in the first attempts to automate the grading process of fruits and vegetables (Nimesh & Delwiche, 1994). Davenel, Guizard, Labatarre, and Sevilla (1988) designed a system for automatic detection of surface defects on golden delicious apples for automatic grading in four grades with a capability of five fruits per second.

In small fruits as olives, classification is based on the visual characteristics such as the colour of the olive skin or the presence of defects. Okamura, Delwiche, and Thompson (1993) used machine vision to allow the mechanisation of the selecting process of the olives by means of using charge-coupled device (CCD) colour cameras and capture cards.

One of the techniques most used for the classification process of images is discriminant analysis. Tao, Heinemann, Varghese, Morrow, and Sommer (1995) used linear discriminant analysis in a grading system to classify fruits in different classes, while Steinmetz, Roger, Molto, and Blasco (1999) used nonlinear discriminant analysis for the classification of peach.

Yang (1993) used 3 layered 9-6-3 neural networks for the classification of apple with a classification accuracy of 96.6%. Nagata and Cao (1998) developed a grading system for fruit and vegetables using neural network technologies, obtaining a high level of accuracy for strawberry and green pepper (94–98% and 89%, respectively).

In this study, olives have been characterised identifying the most common defects and its colorimetric properties (Díaz, Faus, Blasco, Blasco, & Moltó, 2000). Then, a capture and colour images processing system was used to extract the information from each olive. Afterwards, a grading system which is able to learn from

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doi:10.1016/S0260-8774(03)00191-2

the characteristic parameters of the olives previously classified by experts, was used to determine to which category each olive was more likely to belong. Finally, three different learning and classification algorithms have been applied to extracted parameters, comparing and analysing the grading results.

2. Materials and methods

2.1. Vegetable material

The table olives used in this paper belong to the "Manzanilla" variety (Olea europea pomiformis). The green olives used in this work are picked before the ripening cycle, before their colour changes and when the size of the product is adequate. At this moment the colour of the olives is yellowish-green. The collected olives are treated in lye and finally immersed in brine, where lactic fermentation takes place (Sanchez, Rejano, Duran, de Castro, & Montaño, 1990). When the fermentation process taking place in big hoppers has finished, the next step is the classification of the table olives according to their quality (Karaoulanis & Bamnidou, 1995). The brine olives are taken from the hoppers to the processing line, where after separating them according to their size, they are classified into different classes. Manufactures normally classify olives in two classes, suitable and unsuitable to be consumed. Nevertheless, in some occasions the producers use three or even four classes. The fourth class is unsuitable to be consumed and it is made up of excessively dark olives or olives containing a large amount of defects. The third class presents clearly noticeable defects, although it is suitable for consumption, it usually goes to different markets from table olives. The main difference between the first and the second class is the total absence of defects, however depending on the season and on the goal market, these two classes can be joined together. Olives of the four different classes are shown in Fig. 1.

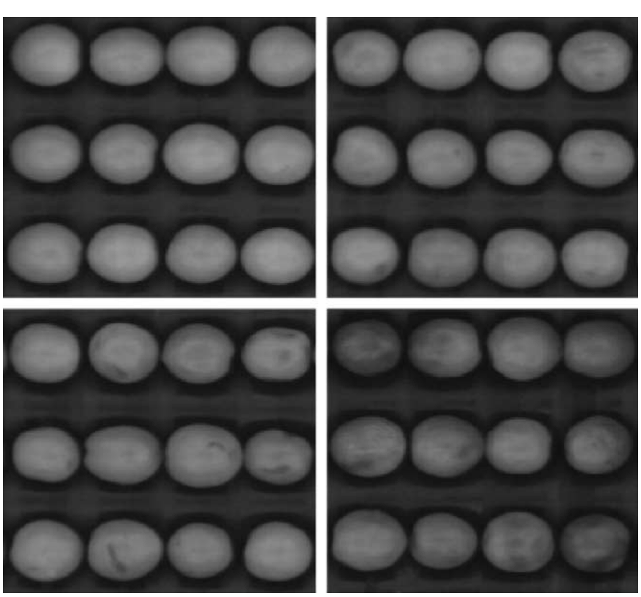

Fig. 1. Olives of the first, second, third and fourth classes respectively.

In order to carry out this task, experts separated the olives, previously measured according to their size, into four classes and they were packed in brine for their conservation until processing. The final set of olives consisted in 400 samples of which approximately half were used for training and half to validate.

The main types of defects for this variety are stain, hail, scratches, lifted skin, pitting, split, excessively dark colour and soft texture. Of these defects, the lifted skin and the soft texture cannot be easily noticed because they do not present a colour change. The other defects have colour changes in the affected area.

2.2. Colorimetric analysis

The colorimetric analysis has been carried out by means of a Miniscan Hunter Lab spectrocolorimeter MS/S-4000S with a D65 illuminant and a 10° observation angle (Díaz et al., 2000). The average colour of the defects were measured by cutting a certain number of olive pieces until filling the 80 mm circular box used for the reflection measurement.

In some cases there is a noticeable relation between defect and class, as for instance, the abnormal colour which is related to the fourth class. This class consists of olives too fermented with dark colour in the whole skin and green olives with big stains of a dark colour. In Table 1, it can be appreciated the abnormal colour is related with low values of R and G co-ordinates. However, the split and broken olives are also assigned to the fourth class, but in this case, the values of the three co-ordinates (R, G and B) are the highest. Due to the absence of the external skin, in the image appears the inner part of the fruit, which is of a lighter colour.

The most common defects in class 2 and 3 are the stains, scratches and hail-affected. Depending on the defect size, the olive is assigned to a class or to the other.

Table 1
RGB co-ordinates of the analysed defects in olives

Blemish	R	G	B
Pitting	20.09	13.89	6.82
Scratches	17.04	11.39	5.78
Wrinkles	18.68	12.54	6.53
Abnormal colour	12.78	10.47	6.90
Lifted skin	20.40	13.72	5.81
Stains	19.04	12.77	6.24
Hail-affected	18.15	12.53	6.31
Split	24.95	17.02	7.19

2.3. Description of the machine vision system

The measuring system designed for the tests based in a transport system, a lighting chamber and an image processing system. The moving belt has cylindrical rollers with grooves on which the olives are placed, as shown in Fig. 2. The rollers turned on their own axis in such a way that three images of each row of olives were captured, thus analysing practically the whole surface area. The selection and disposition of the illumination system is essential, since the olives are in brine, and its sparkle can mask the colorimetric information about the defects. In order to minimise this effect it was decided to place high frequency fluorescent tubes around the pitch area and to cover it with a cubic structure made of a translucent polymeric film which facilitates the light scattering with different angles on the samples.

The equipment used to capture the images consists of a PC, a XC-003 Sony colour 3-CCD camera and a Matrox Meteor capture card. A photocell synchronises the capture of the camera with the rollers movement. Every image captured has a resolution of 768×576 pixels, containing 6 rows with 11 olives.

The processing of an image starts with the transfer of the image to the specific buffers of the RAM memory of the PC, where the image analysis process is applied. After that, it is performed the segmentation towatermark determine if each pixel belongs to bottom, skin or defect. This process requires previous training to generate a Bayesian classification model. After that, the preprocessing takes place to filter the segmented image in order to eliminate noise in the edge detection stage. The next step is the shape recognition, where an algorithm determines the position of the olive shape in the image. After that, the area and the average colour of each type of skin and defect are calculated. In Fig. 3 is shown the flow chart of the image analysis process.

The parameters obtained from each olive in each image are the pixel number of lighter skin (Skin 1), of darker skin or olive profile (Skin 2), of light defect (Stain 1), of dark defect as a bite (Stain 2) and of unusual dark colour (Stain 3). Taking three images of each olive, a total number of 15 parameters can be obtained. In Fig. 4 is shown a picture after the image processing of a set of olives.

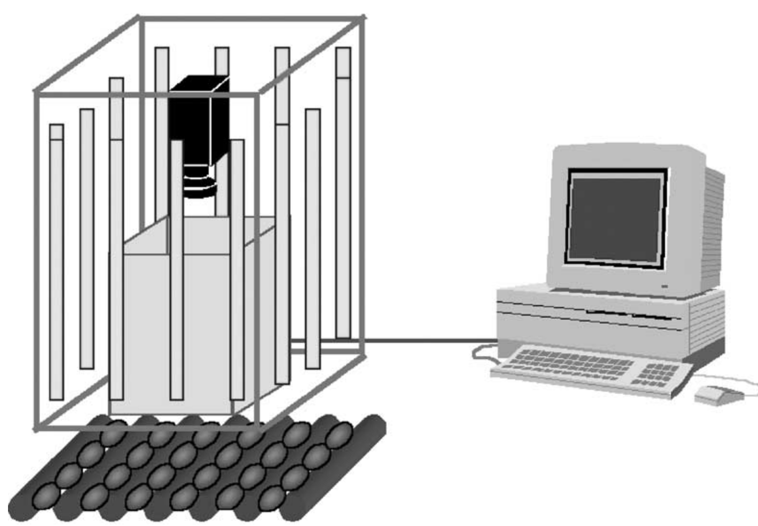

Fig. 2. Scheme of the prototype used to acquire the images of olives.

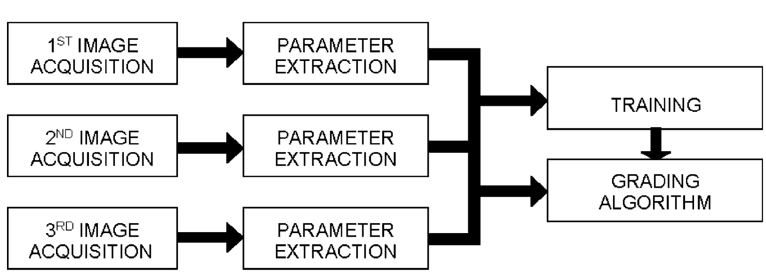

Fig. 3. Flow chart of the olive sorting process.

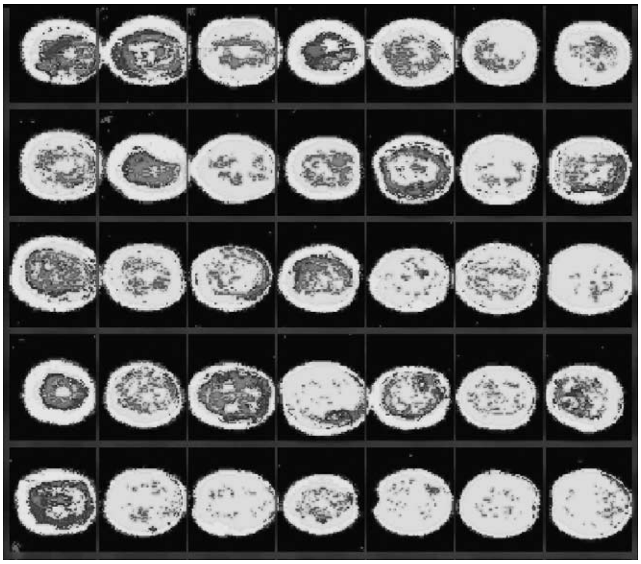

Fig. 4. In this image after the segmentation process can be appreciated that the bottom in black colour, the lighter skin in green and the dark skin in cyan. Stains appear in blue, red and dark green.

In this research, a set of 400 olives (Picus & Peleg, 2000) were used for the adaptive sorting based on observations of human assessment of fruit quality. After having drawn out the parameters, the influence of each parameter on each class of olive was studied. The averages of the parameters on each type are represented in Fig. 5. It can be appreciated that Skin 1 parameter has enormous influence on the first and second class, and less influence on the third and fourth, that is, the influence is proportional to the quality of the olives. Instead, Skin 2 parameter has an important influence on the third class but less influence on the second and fourth classes. This makes sense because this parameter tries to collect the colorimetric information of the dark skin in the olive profile, which coincides with the colour coordinates of some typical defects of the second and third type. Stain 1, Stain 2 and Stain 3 parameters have an important influence on the fourth class, and Stain 2 has more influence on the second and Stain 3 on the third.

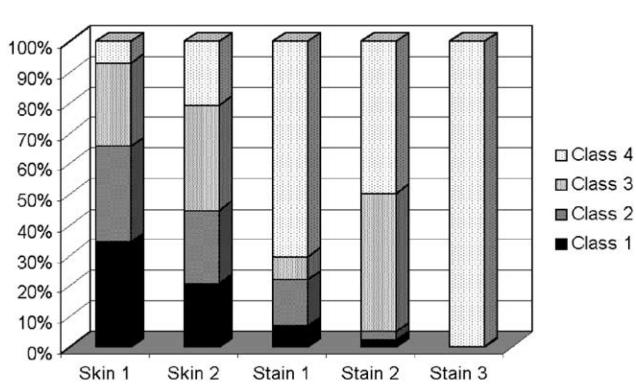

Fig. 5. Influence of the parameters resulting from the segmentation in the different four classes of olives.

2.4. Description of the grading algorithms used

In order to carry out the classification, a system was developed to learn from the olives preclassified by professional people. In this way it is possible to draw the knowledge of the expert to train the system to reproduce the classification process. Three algorithms have been tested to carry out the learning and the subsequent classification. The classical Bayesian discriminant analysis, the PLS multivariant discriminant analysis and neural networks based on backpropagation algorithm with a hidden layer. From the population available half of it was used to train or to measure the three types of algorithms and the other half to validate the results.

The Bayesian discriminant analysis (Chtioui, Bertrand, Dattee, & Devaux, 1996) is one of the classical techniques most widely used in the classification of vegetable products by means of machine vision. In this case, the Mahalanobis distance version to the $1-k$ nearest neighbours was used, which is a simplification of the Bayesian classificator, due to the assumption that the covariance matrices of each class are equal. The function that calculates the distance from a new vector to the centroid of every class is

$$d_M(X,i) = (X - m_i)^{\mathrm{T}} \cdot C_i^{-1} \cdot (X - m_i)$$

where i is the class, X is the array of characteristics of each olive: $X_N = [X_1 \cdots X_N]$, m_i is the mean array of the characteristics of the i class and C_i is the covariance matrix of the i class.

In order to obtain the average vectors of each class and the covariance matrix, it is necessary to carry out a previous training of the system to characterise the recogniser. Previously, a normalisation has been carried out by adding the results of the three views of each parameter and dividing by the total area.

The statistical projection methods, such as the principal component analysis (PCA) and partial least squares (PLS) techniques extract the most important information from the original data to be expressed in a system with less variables, called principal components.

These methods are called projection methods because they project the data into a new principal component system. The PLS prediction method has the advantage that, in comparison to other classical methods, it does not require complex mathematical operations which involve a huge computational task, because it does not require carrying out operations such as the matrix inversion.

Besides, these methods are able to calculate data with a certain level of noise, because these methods only extract the relevant information.

The PLS discriminant technique (PLS-DA), which is a variant of the PLS, has been used due to the fact that this method allows the classification of the samples into specific categories or classes previously introduced or not.

The artificial neural networks have as its main advantage that its flexible structure, although complex, allows its adaptation to the conditions of a classification problem with a certain accuracy. With a suitable structure of the neural network and an optimum training process, a classification system adapted can be obtained to classify olives.

The artificial neural network used is a multilayer network of three layers; an input layer, a hidden layer and an output layer. The input layer is made up of 15 neurons, one for each parameter. The hidden layer is also made up of 15 neurons, connected to all the input neurons and output neurons. And finally, there are 4 neurons in the output layer, one for each olive category.

The learning function used in order to train the neural network is the resilient back-propagation (Rprop). This function is a learning adaptive local process which performs a supervised batch learning in multilayer perceptrons (Riedmiller & Braun, 1993). The basic principle of the Rprop is to eliminate the harmful influence of the size of the partial error derivate on the weight step. For this reason, the sign of the derivate is only taken into account to indicate the direction of the weight update.

In this way, the neural network is able to adapt its structure in order to minimize the error function between the target outputs and the network outputs in a fast and, at the same time, a safe way.

3. Results and discussion

In order to analyse the results, the validation samples were separated into four different batches corresponding to the four available categories. In that way, it is possible to analyse the failures made on each batch and to see which class they are assigned, because it is acceptable that a second class olive is classified in the first category, but it must be avoid that a fourth class olive goes to the first class.

In Tables 2–4, the four batches of olives are indicated in the rows which correspond to the four categories, previously classified by experts. The columns indicate the number of olives that each technique has assigned to each category. Finally, the last column shows the success percentage which each technique has obtained in comparison to the previous classification performed by the expert.

The results of the application of the Mahalanobis algorithm are shown in Table 2. It works quite well to detect olive of the worst class, but first and second classes appears mixed.

Table 2
Classification results with the Mahalanobis algorithm

Class	First	Second	Third	Fourth	% Success
Batch first	35	14	0	1	70
Batch second	23	20	2	1	43
Batch third	3	0	39	7	80
Batch fourth	0	1	6	44	86

Table 3
Classification results with PLS discriminant

Class	First	Second	Third	Fourth	% Success
Batch first	43	6	1	0	86
Batch second	26	17	0	0	40
Batch third	5	0	43	0	90
Batch fourth	0	1	14	37	71

Table 4
Classification results with neural network with a hidden layer

Class	First	Second	Third	Fourth	% Success
Batch first	45	0	0	0	100
Batch second	3	41	0	1	91
Batch third	0	0	45	0	100
Batch fourth	0	0	3	42	93

After the PLS discriminant analysis of the training samples, the three principal components obtained show 80% of the data variability. This technique allows the representation of the scores to analyse the relationship among the samples (see Fig. 6). All the parameters extracted from the olive images were used as variables of the model, and were previously centred and scaled. The results of the classification using the PLS discriminant algorithm are shown in Table 3.

Before training the neural network, it is necessary to select the activation functions of the neurons and the characteristic parameters of the algorithm. The activation function selected is the typical "logistic" function. The parameters of the learning function are the initial update-value (Δ_0), the limit for the maximum step (Δ_{max}) and a parameter related to the weight-decay to improve the error output (α). The following values have been given to these parameters: $\Delta_0 = 0.2$, $\Delta_{max} = 10$ and $\alpha = 4$. The neural network application results are shown in Table 4.

By analysing these results in detail, it can be explained that the principal deviations have been to the adjacent classes, what in the case of the olives which are sent from the first to the second class, or vice versa, it cannot be even considered as an error, because this separation is not usually made in the sector industries,

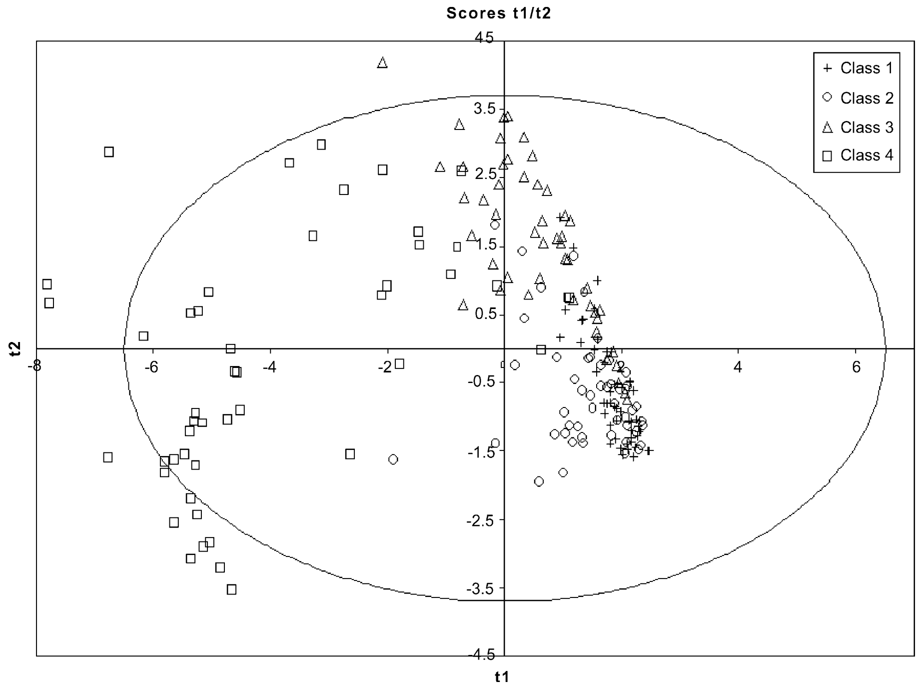

Fig. 6. Plot of the scores of the first and second principal components. Scores of first and second classes are overlapped, while third and fourth classes are more separated.

that habitually consider these categories as a unique class.

The Mahalanobis distance algorithm achieves good classification percentages for the first, third, and fourth categories. Nevertheless, for the second a quite reasonable result is achieved, although it can be appreciated that 50% of batch 2 was wrongly assigned to the first. The most relevant failure is the assignation of 6% of third category olives to the first class.

PLS discriminant improves the classification results of the first and third categories, although some samples from the fourth class were classified to the third. Furthermore, the overlapping between the first two classes is repeated, specially when classifying the samples of the second class, because in this case 60% of the second class olives was classify to the first category.

Finally, neural networks improve the results gotten with the previous techniques. An explanation to these better results amongst Mahalanobis distance could be that the covariance matrix were not equal. The olives of first and third are classified perfectly, while second and fourth has a failure rate of 8.9% and 6.7% respectively. With this algorithm, first and second classes appears clearly separated, disappearing the overlapping present in the other algorithms. The only remarkable failure is that a second class olive which is assigned to the fourth category.

The results can be improved if the image resolution is increased or even if the number of olives per image is decreased. The first proposed option will cause a rise in the final price of the system for possible users, whereas the second option would involve a reduction in the production capacity.

4. Conclusions

1. Table olives classification is problematic due to the small size of the defects. It is necessary to increase the resolution of the CCD camera or to decrease the number of olives per image, but these solutions involve a rise in the price of the system or a reduction in the productivity.
2. Olives of best quality, first and second categories, are quite overlapped, but producers usually join them in a single category.
3. It is important to avoid the classification of first category olives in the fourth class, because olives of the best quality are rejected. On the other hand, consumers should not find a bad olive in a high quality product. Therefore, an olive of the fourth category should not be sent to the first class.
4. Neural network based on resilient back-propagation is the algorithm with the best results in discriminating the forth classes.
5. One additional advantage of the proposed learning system for grading table olives is the possibility of using different models to adapt to the variations of each harvest.

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