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A machine vision system for classification of wheat and barley grain kernels

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Abstract

This study presents in detail a machine vision system that classifies objects into two classes. The procedure for the classification comprises two stages: a training stage and a testing stage. A feature vector, which is a sorted list of features that maximize the classification power, is computed in the training stage. Object classification was accomplished in the testing stage by means of discriminant analysis (DA) and K-nearest neighbors (K-NN) algorithms. The system was applied to the classification of wheat and barley grain kernels. Results obtained allow the researchers to conclude that in the classification of wheat and grain kernels with the presented system: (i) a high classification accuracy can be obtained; (ii) the employment of morphologic, color, and texture feature types together offers better accuracy than the employment of only one feature type; (iii) the extraction of the maximum radius, the green mean, and the *y* mean of the gray level co-occurrence matrix (GLCM) for 90° allows the highest classification accuracy; and (iv) the employment of more than three features increases the computational cost and may also reduce the classification accuracy.

Additional key words: cereal grains classification; color; digital image processing; features; morphology; texture; seed identification.

Resumen

Sistema de visión artificial para la clasificación de granos de trigo y cebada

Este estudio presenta en detalle un sistema de visión artificial que clasifica objetos en dos clases. El procedimiento por el que se realiza la clasificación se compone de dos etapas, una de entrenamiento y otra de prueba. En la etapa de entrenamiento se obtiene un vector de características, que es una lista ordenada de características que maximiza el poder de clasificación. En la etapa de prueba se lleva a cabo una clasificación basada en el análisis discriminante (AD) y en el algoritmo de los K vecinos más próximos. El sistema fue aplicado a la clasificación de granos de trigo y cebada. Los resultados obtenidos permiten concluir que en la clasificación de granos de trigo y cebada mediante el sistema presentado: (i) se puede obtener una precisión alta en la clasificación; (ii) el empleo de características morfológicas, de textura y de color de forma conjunta ofrece mejores resultados que el empleo de características de un sólo tipo; (iii) la extracción del radio máximo, el valor medio del componente verde y el valor *y* medio del nivel de gris de la matriz de co-ocurrencia GLCM orientada 90° ofrece los mejores resultados de clasificación; y (iv) el empleo de un número de características superior a tres incrementa el coste computacional y puede reducir la precisión en la clasificación.

Palabras clave adicionales:características; clasificación de granos de cereal; color; identificación de semillas; morfología; procesado digital de imágenes; textura.

Introduction

Machine vision is widely studied and used in many different fields as a result of the growth that new technologies have experienced in recent years and the extensive use of both digital images and digital video (Bebis *et al*., 2003). The field of agriculture is no exception; machine vision has been applied to different

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Abbreviations used: DA (discriminant analysis); FDR (Fisher discriminant ratio); GLCM (gray level co-occurrence matrix); GLN (gray level non-uniformity); GLRLM (gray level run length matrix); HGRE (high gray level run emphasis); K-NN (K-nearest neigbor); LGRE (low gray run emphasis); LRE (long run emphasis); RLN (run length non-uniformity); RP (run percentage); SRE (short run emphasis); SFS (sequential forward selection).

field tasks, such as guiding systems in sewing (Leemans and Destain, 2007) and agriculture-related tasks performed in laboratories, as in the case of the product inspection of vegetables (Marchant *et al*., 1990). This last kind of study includes works relating to cereal grain identification (Visen *et al*., 2002), and, in fact, machine vision is usually employed to detect weed seeds in cereal grains (Granitto *et al*., 2002).

Accurate identification of weed seeds in cereal grains should serve to prevent weeds developing in certain types of crops, thereby improving crop quality. For this reason, most of the studies focus on systems capable of identifying different grain types. These systems allow for the detection of weed seeds in commercial cereal grain lots (Churchill *et al*., 1993; Chtioui *et al*., 1996; Paliwal *et al*., 2003). There are several studies specific to the identification of wheat kernels, the most important ones being those by Zayas *et al*. (1989), Luo *et al*. (1999) and Majumdar and Jayas (2000a,b,c,d).

This article has two objectives: (i) to propose a machine vision system to classify objects between two possible types and (ii) to configure the proposed system for an optimal wheat and barley grain classification, and to obtain the classifying system accuracy for these two cereal grain types.

Material and methods

Material

A BenQ D E520 digital camera was used for image acquisition. The camera was stabilized using a Velbon DV-45 tripod, and a 20-watt desk lamp was employed for lighting the area to be photographed. The pictures were taken in total darkness. The kernels were placed on a white background, and a direct overhead beam from a desk lamp was cast on them, so as to avoid the formation of shadows. The camera was set on the tripod and angled to the kernels in the same fashion as the desk lamp. The distance between the camera lens and the seeds was 25 cm.

The LabVIEW development environment with the artificial image package IMAQ Vision 8.2.1 was employed to develop the software applications of this study. The software development and the performed tests were carried out on a Dell Inspiron 6400 laptop. This computer had a 1.83 GHz Intel Core 2 Duo processor, 2 GB of RAM memory and the Windows XP Media Center 2002 service pack 2 operating system.

Methods

Ten images of wheat grains and 10 images of barley grains were taken for the system training. Each one of these training images had around 60 grain samples. Ten images of wheat and barley grains were taken for the system testing. Each one of these testing images had around 60 grains, with approximately the same quantity of wheat and barley grains. The total number of wheat and barley kernels used in the testing system was 545. All the images were acquired in JPEG format, over the RGB space and with a 5-megapixel resolution (2,560 × 1,920 pixels). Figure 1 shows examples of training and testing images.

The methodology of this work was comprised of two stages: (i) the system training, where some parameters of the system were obtained; and (ii) the system testing, where the system performance was measured. The system training was accomplished according to the flow diagram of Figure 2. First, the image was converted to 256 gray levels. Next, an edge enhancement was accomplished by means of the mask presented in Table 1, where the x parameter was chosen as 9.8 after visual tests. Then, an automatic thresholding segmentation to separate the kernels from the background was performed. The necessary threshold value was obtained from the B histogram of the images by means of the next iterative process (Parker, 1993):

1. The number of pixels for each gray level was multiplied with the gray level value and summed.
2. The sum was divided by the total number of pixels to obtain the first threshold value, X_1.
3. The same procedure was performed for the two parts, *i.e.,* 0 to X_1 and $X_1 + 1$ to 255 (the number of gray level values in the image), to generate two more numbers, P_1 and P_2. The mean of P_1 and P_2 gave the second threshold value, X_2.
4. Now the procedure was performed for values from zero to X_2 and $X_2 + 1$ to 255, to generate P_3 and P_4. Taking the mean of P_3 and P_4 gave the new threshold, X_3.
5. This process was repeated until X_n was equal to X_{n+1}. This stabilized value of X was taken as the threshold for the image.

The images obtained after this thresholding were binary; the value of the pixels of kernels was 1 and the value of the pixels of the background was 0 (Fig. 3a). Then, various morphological operations were carried out to obtain the desired images. Initially, a dilation operation aimed at closing the contours of every kernel in the images was carried out. Next, a hole-filling algo-

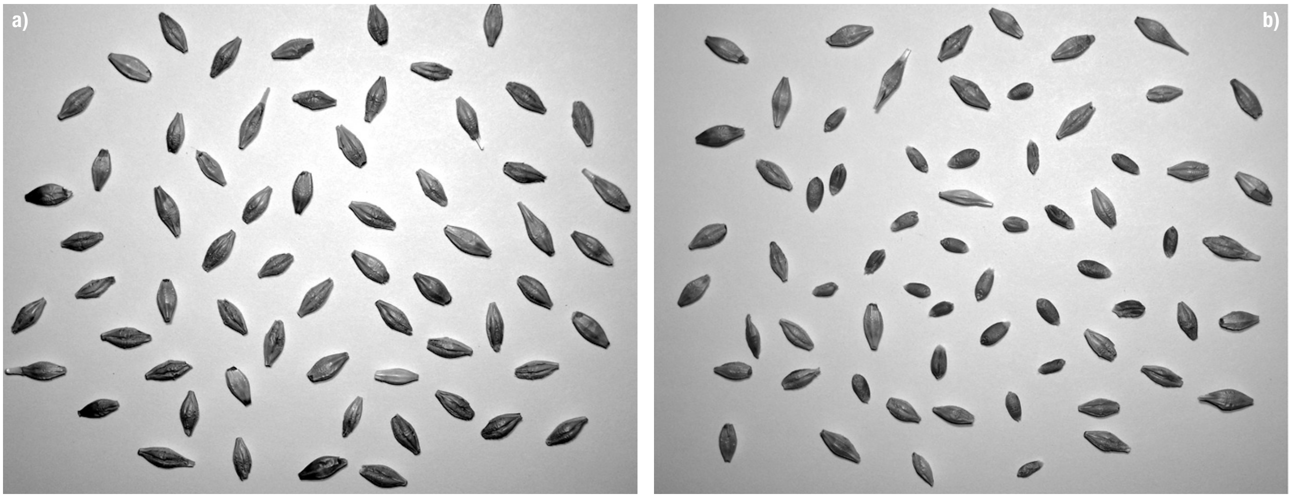

Figure 1. a) An image with barley grains that was taken to train the system. b) An image with barley and wheat grains that was taken to test the system.

rithm was applied, followed by an erosion operation with the same structural element. This last operation was done in order to recover the original shape of the kernels (Fig. 3b).

Each region of the processed images was labeled. The value of the center of mass and the original orientation values for each kernel were computed. Then, each region was rotated over the center of mass in order to make an appropriate measurement of dimensions during the feature extraction process. Since more computation time is needed when processing color images, prior to its rotation, each grain sample color image was

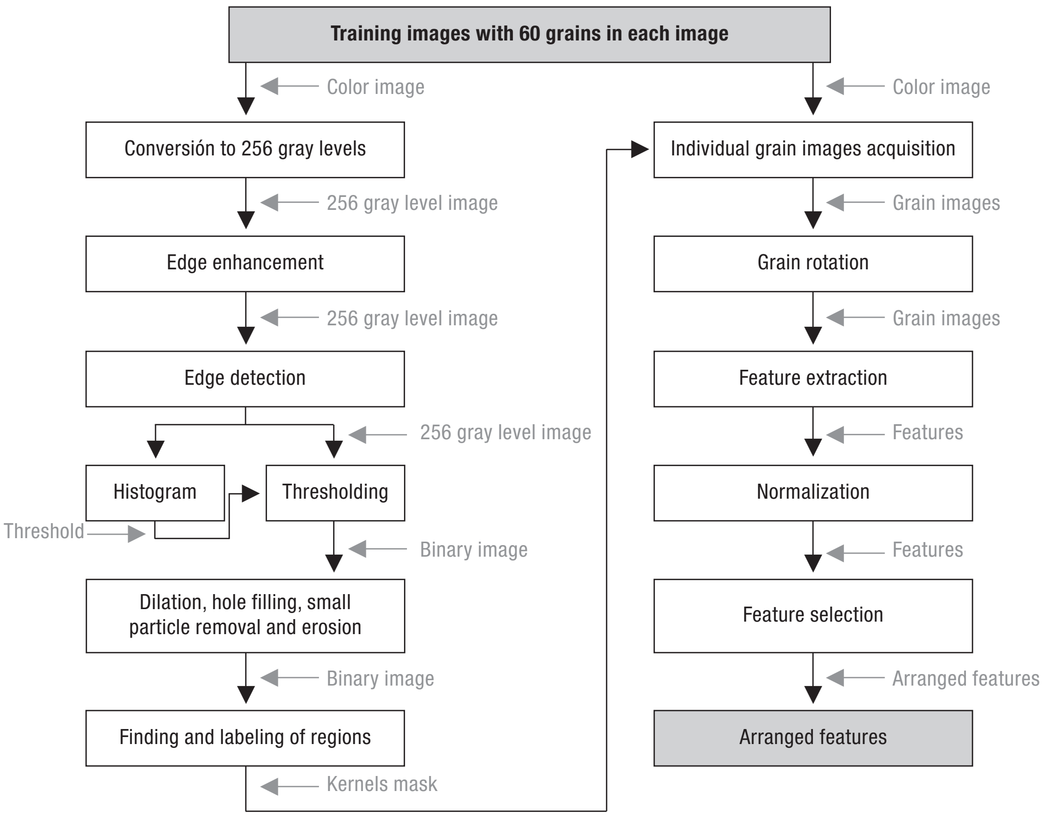

Figure 2. Flow diagram of the system training stage.

Table 1. Mask employed in the edge enhancements

–1	–1	–1
–1	×	–1
–1	–1	–1

transformed into a grayscale-based image with 256 gray levels. In later processes, either the grayscale rotated image or the original color unrotated image was used depending upon the later needs. Figure 4 shows two samples of individual cereal grain kernels before and after their rotations.

The next step was to extract 99 features from each cereal grain kernel, of which:

— 21 were morphological features: area, perimeter, thinness ratio, length, width, equivalent rectangle long side, equivalent rectangle short side, ratio equivalent rectangle sides, the seven Hu moments, rectangular aspect ratio, maximum radius, minimum radius, radius ratio, radius standard deviation and Haralick radius. Majumdar and Jayas (2000a) provided complete information about the meaning and computation of these morphological features.

— 6 were color features: the mean values and standard deviations for R, G and B components.

— 72 were texture features. Initially, the number of gray levels in the images was reduced from 256 to 32. Gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM) were calculated for different angles. Texture features were extracted using statistical methodology (Gonzalez and Woods, 2006). Majumdar and Jayas (2000c) provided complete information about the meaning and computation of these morphological features. In the end, 72 features were extracted. These were: i) mean of X, mean of Y, variance of X, variance of Y, uniformity or entropy, maximum probability, correlation homogeneity, cluster shade and cluster prominence of the GLCM for angles 0°, 90°, 45° and 135°; ii) short run emphasis (SRE), long run emphasis (LRE), gray level non-uniformity (GLN), run length non-uniformity (RLN), low gray level run emphasis (LGRE), run percentage (RP) and high gray level run emphasis (HGRE) of GLRLM for angles 0°, 90°, 45° and 135°.

The number of features extracted was too high for fast computation. Furthermore, some of these features were correlated and provided similar information, thus making the system inefficient. Therefore, it was necessary to make a classification of the features based on their contribution to the model, taking these correlations into account. For this purpose,

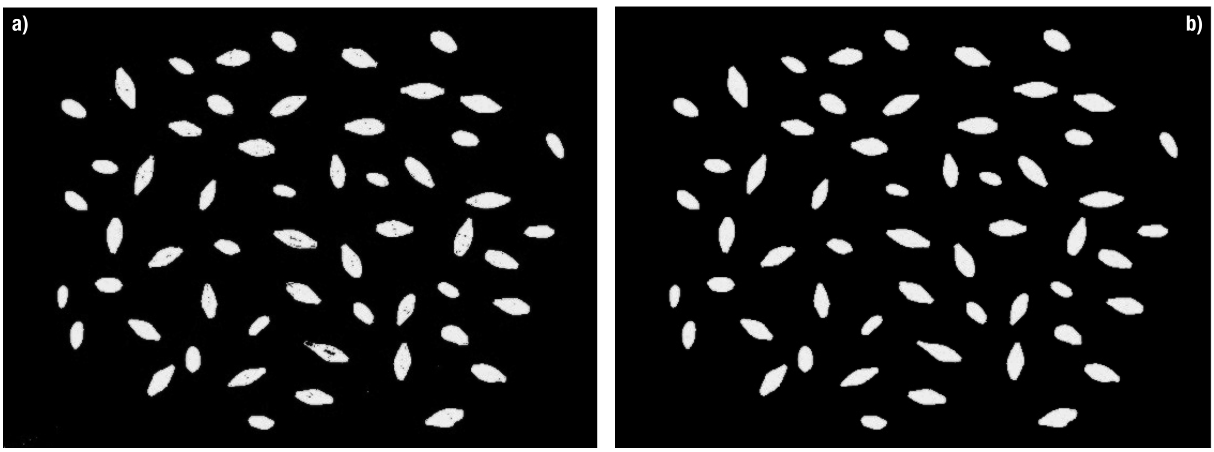

Figure 3. a) Binary image obtained after thresholding. b) Binary image obtained after some morphologic operations.

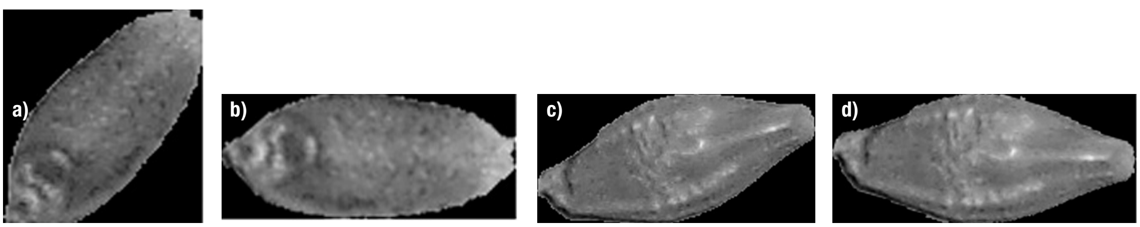

Figure 4. a) Wheat grain prior to its rotation. b) Rotated wheat grain. c) Barley grain prior to its rotation. d) Rotated barley grain.

initially, the feature values were normalized by means of Eq. [1]:

$$\widehat{x_{tk}} = \frac{x_k - E[x_k]}{\sigma_k} \qquad [1]$$

where $\widehat{x_{tk}}$ is a feature value normalized, x_k is a feature value, $E[x_k]$ is the mean value of a feature for all kernels, σ_k is the standard deviation of the values of a feature in all kernels, k is the feature index, and i is the kernel index. After applying Eq. [1], the features achieved a mean equal to zero and a mean error equal to one. Then, the features were arranged in a features vector, choosing as the first component of this vector the feature that had a larger Fisher discriminant ratio (FDR), which represents a measure of the contribution to the model of a feature and is computed by Eq. [2] (Theodoridis and Koutroumbas, 2006):

$$FDR_i = \sum_{i}^{M} \sum_{j \neq i}^{M} \frac{(\mu_i - \mu_j)^2}{\sigma^2{}_i + \sigma^2{}_j} \qquad [2]$$

where i is the feature index, M is the number of features, μ is the mean value of a feature, and σ is the standard deviation of the values of a feature. The next components of the features vector were selected by means of a sequential forward selection (SFS) algorithm, which employed a criterion function based on the scatter matrix (Theodoridis and Koutroumbas, 2006). This algorithm adds a new feature to the vector features, choosing the feature that offers a larger value in the criterion function. The criterion function chosen was based on the scatter matrix, which is defined by:

$$J_1 = \frac{trace\{S_m\}}{trace\{S_w\}} \qquad [3]$$

where trace is the sum of eigenvalues, S_m is the mixture scatter matrix, and S_w is the within-class scatter matrix. S_m (Eq. [4]) is the covariance matrix of the feature vector with respect to the global mean (Eq. [5]):

$$S_m = E[(\bar{x} - \bar{\mu}_0)\ (\bar{x} - \bar{\mu}_0)^T] \qquad [4]$$

$$\bar{\mu}_0 = \sum\nolimits_{i}^{M} p_i\ \bar{\mu}_i \qquad [5]$$

where p_i is the a priori probability of class ω_i, which is $p_i \cong n_i/N$ being the number of samples in class ω_i, out of a total of N samples, and $\bar{\mu}_i$ the vector of the mean of each class. The within-class scatter matrix S_w is defined by:

$$S_w = \sum\nolimits_{i=1}^{M} p_i\ S_i \qquad [6]$$

where S_i is the covariance matrix for class ω_i, given by:

$$S_i = E[(\bar{x} - \bar{\mu}_i)\ (\bar{x} - \bar{\mu}_i)^T] \qquad [4]$$

being $\bar{\mu}_i$ the vector of the mean of each class. This SFS procedure was repeated until the features vector contained all extracted features.

The system performance was evaluated in the system testing stage, which was accomplished according to the flow diagram of Figure 5. In this diagram, a new task appears, the classification task. It was accomplished in two ways: (i) by means of a discriminant analysis (DA) parametric classifier based on the normal distribution and (ii) by means of the non-parametric classifier K-nearest neighbor (K-NN).

The DA parametric classifier chosen was based on the normal distribution given by:

$$g_i(x) = log[p(\omega_i)] - \frac{1}{2}\ \bar{m}_i^T S_w^{-1}\ \bar{m}_i + \bar{x}^T\ S_w^{-1}\ \bar{m}_i \qquad [8]$$

where ω_i is the i possible class, S_W is the common group covariance matrix, $\bar{m}_i$ is a vector with the mean of the features of the class i, and $\bar{x}_i$ is a sample of the features vector to be assigned to a class. The measured features $\bar{x}$ are assigned to the class i in which is larger (Webb, 2002).

The non-parametric classifier K-NN assigns the sample of the features vector to the class represented more often by the K nearest samples of the features vector in the training stage (Duda *et al.*, 2001). Unlike parametric classifiers, this non-parametric classifier needs to maintain all training data.

Finally, the hold-out method was used to assess system performance (Theodoridis and Koutroumbas, 2006). According to this method, the samples were divided into two different data sets: the training data set that was used in the system training stage and the test data set that was used in the system test stage.

Results and discussion

The system training was performed with (i) only morphologic features, (ii) only color features, and (iii) morphologic, color, and texture features. Then, the results of the system training were the three vector features that optimize the wheat and barley classification with these feature types (Table 2).

The system testing was performed using (i) a DA parametric classifier based on normal distribution function and (ii) the nonparametric classifier based on K-NN. Both classifiers were tested with the three different feature vectors obtained in the system training. The system accuracy in the classification of wheat and barley grain kernels with both classifiers

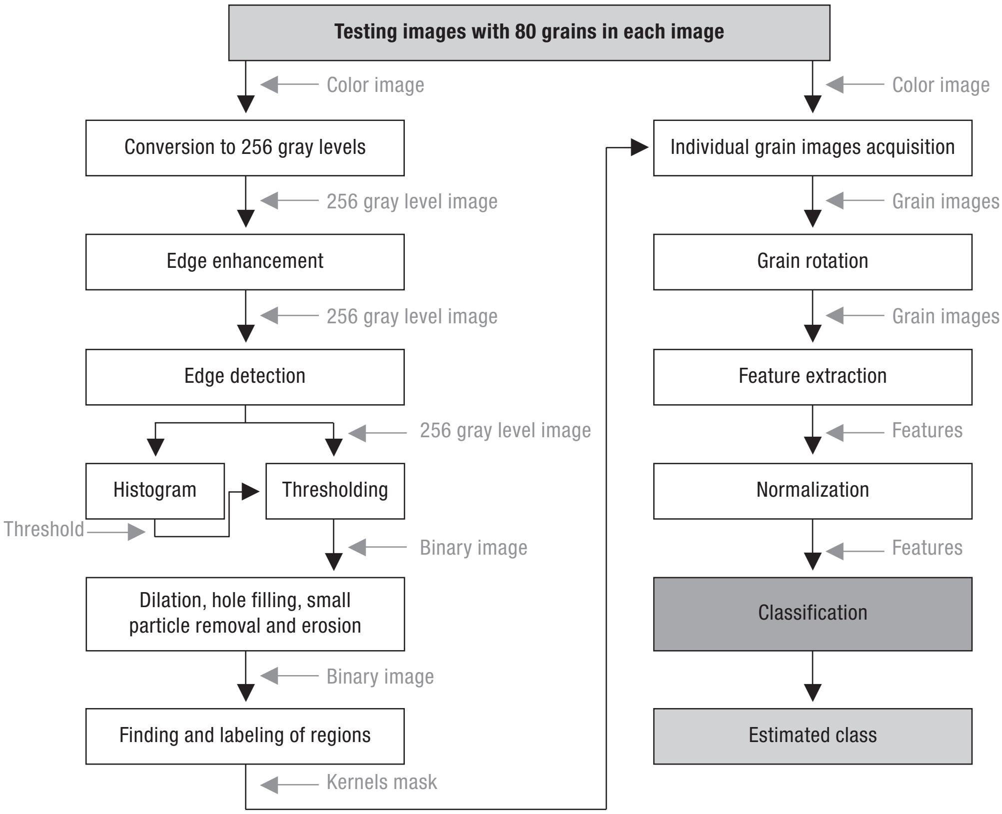

Figure 5. Flow diagram of the system testing stage.

Table 2. Feature vectors of the classification model taking into account: (i) only the morphologic features, (ii) only the texture features, and (iii) morphologic, color, and texture features. Only the first 20 features of each vector are presented

Ranking	Morphological features of individual kernels	Color features of individual kernels	Morphological texture and color features of individual kernels
1	Maximum radius	Green mean	Maximum radius (MF)
2	Haralick ratio	Red mean	Green mean (CF)
3	Minimum radius	Blue mean	*y* mean (GLCM 90°) (TF)
4	Equivalent rectangle short side	Standard deviation of green	SRE (GLCM 45°) (TF)
5	Width	Standard deviation of blue	Minimum ratio (MF)
6	Hu 1 moment	Standard deviation of red	Haralik ratio (MF)
7	Hu 2 moment		Equivalent rectangle short side (MF)
8	Length		Width (MF)
9	Hu 3 moment		HGRE (GLRLM 0°) (TF)
10	Rectangular aspect ratio		HGRE (GLRLM 90°) (TF)
11	Area		SRE (GLRLM 0°) (TF)
12	Equivalent rectangle ratio		Red mean (CF)
13	Perimeter		Standard deviation of radii (MF)
14	Hu 5 moment		LRE (GLCM 0°) (TF)
15	Hu 4 moment		RP (GLRLM 45°) (TF)
16	Hu 6 moment		Red standard deviation (CF)
17	Thinness ratio		Cluster prominence (GLCM 90°) (TF)
18	Standard deviation of radii		LGRE (GLRLM 0°) (TF)
19	Aspect ratio		Entropy (GLCM 90°) (TF)
20	Hu 7 moment		*y* variance (GLCM 45°)

Table 3. Classification accuracy results obtained regarding the number of features employed, for each feature type selected and for both classifiers employed. The first number in each cell represents the number of misclassified kernels from a total of 545 kernels, and the second number represents the classification correct percentage

Number of features	Discriminant analysis			K-nearest neighbor		
	MF[1]	CF[2]	AF[3]	MF[1]	CF[2]	AF[3]
1	10-98.17	90-83.49	10-98.17	4-99.27	94-82.75	4-99.27
2	10-98.17	36-93.39	4-99.27	8-98.53	42-92.29	2-99.63
3	6-98.90	1-99.82	0-100.0	8-98.53	9-98.34	1-99.82
4	6-98.90	1-99.82	0-100.0	3-99.45	10-98.17	1-99.82
5	4-99.27	93-82.94	0-100.0	3-99.45	236-56.70	2-99.63
10	5-99.08		0-100.0	4-99.27		4-99.27
15	3-99.45		0-100.0	4-99.27		4-99.27
20	3-99.45		0-100.0	6-98.90		4-99.27
25	3-99.45		0-100.0	6-98.90		4-99.27
30			1-99.82			4-99.27
35			1-99.82			4-99.27
40			75-86.35			5-99.08
45			88-83.35			5-99.08
50			118-78.34			5-99.08
55			106-80.55			4-99.27
60			124-77.25			2-99.63
65			123-75.42			3-99.44
70			125-77.06			3-99.44
75			122-77.61			3-99.44
80			105-80.67			4-99.27
85			94-82.75			6-98.90
90			88-83.85			9-98.35
95			88-83.85			9-98.35
99			88-83.85			9-98.35

[1] MF: group of morphological features. [2] CF: group of color features. [3] AF: group of morphologic, color and texture features.

was obtained (Table 3 and Fig. 6). Table 3 and Figure 6 show that (i) the combination of the morphologic, color, and texture features offers better classification accuracy than the extraction of features of only one type, (ii) the maximum radius, the green mean, and the *y* mean of the GLCM for 90° features offer the highest classification accuracy obtained, and (iii) a higher number of features sometimes does not improve the classification accuracy and sometimes worsens it.

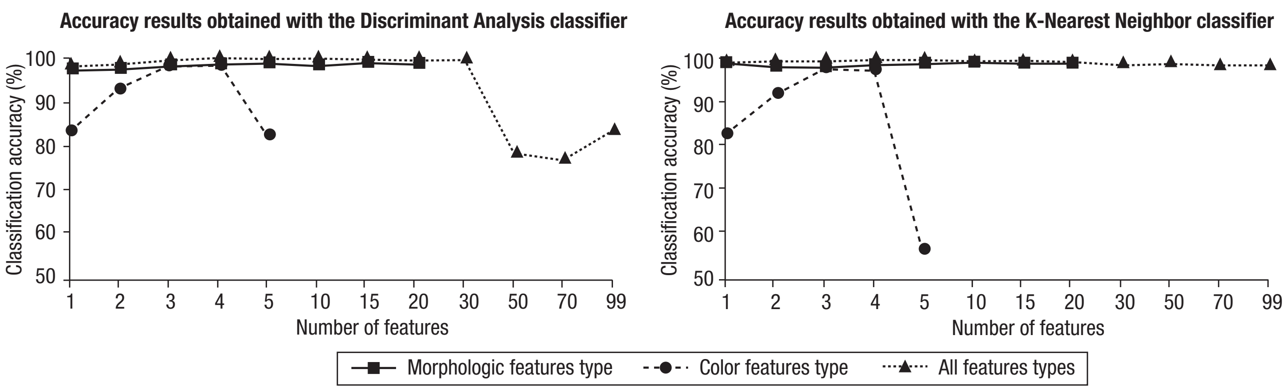

Figure 6. Classification accuracy results obtained in respect to the number of features employed, for each feature type selected and for both classifiers employed.

This study presents in detail a machine vision system to classify objects into two possible classes. The system was tested in the classification of wheat and barley grain kernels. The system extracts some characteristics of grain kernels and puts these characteristics into a DA or a K-NN classifier to estimate the kernel type.

The system presented better classification accuracies when a combination of the morphologic, color, and texture features were extracted than when only one feature type was employed. This concurs with the works of Majumdar and Jayas (2000d), Granitto *et al*. (2002), and Paliwal *et al*. (2003), where the importance of the use of different kinds of features in the identification of weed seeds was pointed out.

The best accuracy in the wheat and barley grain kernel classification performed with the proposed system was achieved extracting only three features from the grain kernels. Most classification scientific studies for the classification of similar appearance grain kernels employ a larger number of features (Wan *et al*., 2002; Chen *et al*., 2010). But, in concordance with our results, when the kernels to classify are dissimilar enough as happened in our study, only a small number of features are necessary to extract and process (Paliwal *et al*., 1999; Pearson *et al*., 2008).

In the reviewed literature, the employment of more than the optimum number of features either does not improve the classification accuracy (Majumdar and Jayas, 2000d; Choudhary *et al*., 2008, 2009), or it deteriorates the classifier's performance (Paliwal *et al*., 2003). These two behaviors, the non-improvement and the deterioration of the classification accuracy, are observed in the different graphs in the results section, where the classification accuracy with respect to the number of features was presented.

The system presented employs a feature classification process to obtain a feature vector that optimizes the classification accuracy. This feature selection is achieved by means of a SFS algorithm, which is a suboptimal selection algorithm (Theodoridis and Koutroumbas, 2006). The high number of features to arrange made obtaining the optimum feature vector computationally infeasible.

The features selection process in this study and in the research literature reviewed are only concerned with the classification accuracy. Since the feature extraction computational cost is different for each feature to be extracted, the different computational costs could be taken into account in future lines of research.

The system presented was tested classifying wheat and barley grain kernels. This classification could serve to detect the presence of barley seeds in lots of wheat seeds. The system presented could also serve to detect weed seed presence in lots of seed. For that, a training of the system with the seed type of the lots and with seeds of the weed type must be performed.

In conclusion, this article presents a machine vision system to classify objects between two possible classes. Results of the system in the classification of barley and wheat kernels suggest that accuracies higher than 99% can be achieved when morphologic, color, and texture features are extracted from the grain kernels. To obtain these accuracies, only three features are necessary to extract from the kernels: the maximum radius that is a morphological feature, the green mean that is a color feature, and the *y* mean of the GLCM for 90° that is a texture feature. The employment of a higher number of features increases the computational cost and may also reduce the classification accuracy.

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