A MACHINE VISION BASED SYSTEM FOR AUTOMATIC DISCRIMINATION OF BEAN SEEDS

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INTRODUCTION

Machine vision techniques are being employed with satisfactory results in different agricultural and agro-industrial tasks like fruit or embryos sorting (Bellon *et al.*, 1992a; Moltó and Harrell, 1993), detection of blemishes, plant propagation, robotic harvesting of fruits, selective weed control, etc. Particularly, attempts to apply these techniques to bean cultivation and post-harvest processing are currently in progress, as examples we may mention the work of McMillan and Schwartz (1993) in quantification of bean rust leaf damage or Palomares *et al.* (1993) in classifying bean seeds.

Our previous work demonstrated the feasibility of classifying six different bean cultivars by means of image analysis using a general purpose, commercial system. Results were satisfactory but manual calibration outperformed the artificial system.

The present report describes a machine vision based system more specifically designed to discriminate bean seeds, capable of differentiating between 6 cultivars with more than 90% accuracy. This system could help the genetists to characterize the cultivars and the industrials to determine the homogeneity of seed samples.

MATERIALS AND METHODS

Six hundred seeds (100 for each of the cultivars studied), representative of the most economically interesting varieties in our country: Long White (BL), White Kidney (RI), Palmeña (PA), Round White (BR), Pinta (PI) and Navy (NAV) were imaged using a commercial image analyzer with a monochrome CCD camera and artificial lighting provided by three conventional incandescent lamps.

50 images of each cultivar were randomly selected to create a training set of 300 images and the rest were assigned to a testing set. Figure 1 shows examples of binarized images from each of the analyzed cultivars.

Image segmentation was performed automatically by the analyzer using the so called "white top hat" algorithm, which consists of a relative regional thresholding of the grey level image acquired by the camera, giving a binary image. This last image was then transferred to a PC in which the developed software calculated ten features, described in Table 1, related to objects size and shape. Data collected from the six hundred objects were statistically treated by a Linear Discriminant Analysis program. Features calculated from the training set were used to build a classifier while those of the test set were employed to estimate the performance of the system.

Table 1.- Set of features used in the analysis

NAME	DESCRIPTION
SURFACE	Area contained within perimeter
PERIMETER	Length of the perimeter
LENGTH	Object length
WIDTH	Object width
CM_X	
CM_Y	Central inertia moments
CM_{XY}	
BOX_FILL	AREA / (LENGTH*WIDTH)
ROUGHNESS	$PERIMETER^2/(4*\pi*AREA)$
RAD_VAR	$(1/32)\Sigma(r_i - AVE\_RAD)^2$

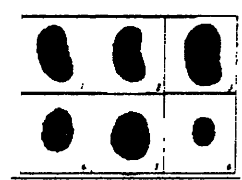

Figure 1.-Binarized images of seeds: 1) Long White 2) White Kidney 3) Palmeña 4)Round White 5) Pinta 6) Navy

RESULTS AND DISCUSSION

Due to the fact that cultivars PI and PA are colored, while the four others are white, a decision algorithm was built assuming that the system was able to perceive this difference in color. This could have been easily implemented in a more modern image analyzer but it was impossible to achieve with the current hardware. Therefore, two groups of discriminant functions were deducted, one for white seeds and the other for colored seeds.

Table 2 summarizes the results of the application of these discriminant functions over the independent test set, which is an estimate of the expected performance of the classification system. There was a 100% accuracy in the discrimination between the two pigmented cultivars. Canonical analysis indicated that "surface", "width", "box filling", "length", "perimeter" and "roughness" features had the highest discriminant power, separating small, rounded objects from larger, thinner ones.

Table 2.-Classification results over the test set

REAL CLASS	PREDICTED CLASSIFICATION					
	PALMEÑA	PINTA	NAVY	LONG W.	ROUND W.	KIDNEY W.
PALMEÑA (PA)	100%	0%				
PINTA (PI)	0%	100%				
NAVY (NAV)			100%	0%	0%	0%
LONG W. (BL)			2%	92%	0%	6%
ROUND W. (BR)			0%	0%	100%	0%
KIDNEY W. (RI)			0%	6%	0%	94%

In the white cultivars, 100% of the NAV and BR, and more than 90% of BL and RI varieties were properly classified. Moreover, the results showed that misclassification occurred only between classes BL and RI, which coincides with human perception. In this case, size features like "width" and "length" made a first selection while shape features as "box filling" completed the differentiation.

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