Computer-Assisted Color Classification of Peanut Pods[1]

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ABSTRACT

Mesocarp color classification in the Hull Scrape Maturity Method is the most important step in determining peanut maturity and optimum harvest date. This research involved the development of an image acquisition system and a software procedure for color classification. Images of peanut pods that had been sorted manually into color classes and subclasses were used in computer training. After training with sorted color classes, the computer-assisted procedure correctly identified and classified the peanut pods, with a 99% precision for the same sample in different alignment, and with a 95% precision for different size samples taken from the same population. Pod size measurement with a resolution of 0.1 mm was also performed using image processing techniques.

Key Words: *Arachis hypogaea* L., image processing, peanut maturity.

The production of peanuts in the United States had an annual farm value of more than one billion dollars during 1988-1998 (USDA-NASS, 1999). Cultural practices, environment, harvest timing, and harvesting methods all influence peanut production (Henning *et al.*, 1982).

The Pod Maturity Profile (also called the Hull-Scrape Method) developed by Williams and Drexler (1981) is based on the color change of the middle layer (mesocarp) of the peanut hull as the pod matures. Pods are classified into color classes (white, yellow, orange A, orange B, brown, and black) (Sanders *et al.*, 1990; Sanders and Bett, 1995) according to the mesocarp color found on the dorsal surface at the attachment point of the basal seed, and into subclasses as a function of overall color of the pod. In this method, peanut samples are placed on a Peanut Profile Board (Baldwin and Beasley, 1990) according to color class, and subsequently the optimum harvest date is determined. The method is limited in that it is based on manual classification and is subject to variability due to lighting conditions, fatigue, inherent differences among human sorters, and requires trained personnel. These problems can be overcome by a computer-assisted classification system that uses machine vision and image analysis of the peanut pods. The computer-based system is insensitive to ambient lighting variations and is consistent, fast, and relatively inexpensive. It offers a method for measuring different parameters of the pods, such as width and length and various spectral parameters.

Human vision cannot differentiate between more than about 30 levels of gray in a black and white image (Russ, 1999), while a computer can distinguish between 256 or more levels of gray, depending on hardware capabilities. For computer color analysis, the visible spectrum can be roughly separated into three different regions, corresponding to red, green, and blue (RGB) regions. All other colors can be expressed as combinations of RGB values (van der Heijden, 1994; Jahne, 1997; Russ, 1999). McConnell and Blau (1994) used machine vision to classify muffin color according to the degree of cooking. In their classification they used the minimum description analysis method. Other researchers also studied the use of machine vision in the food industry (Domenico and Gary, 1994; Jones and Griner, 1994; Lake, 1994; Ling and Ruzhitsky, 1994; White and Sellers, 1994).

The purpose of this research was to develop and test a computer-based system for mesocarp color classification and size analysis of peanut pods. The system is based on the current pod maturity profile harvest date estimation method that uses manual classification of peanut pods in mesocarp color classes and subclasses.

Materials and Methods

An image acquisition board (pod holder) was built from residential home sheathing insulation from the Dow Chemical Company (Midland, MI), which was glued to a $^3/_4$-in. plywood sheet to provide rigidity and strength.

Two professional image processing cameras, a $^3/_4$-in. Color CCD JVC Model TK-870U (JVC USA, Wayne, NJ) and a $^1/_2$-in. Hitachi KP-D50 (I-CUBE, Crofton, MD), were used with a Truevision TARGA+ image acquisition card (Truevision, Indianapolis, IN) to digitize images for storage on a 486 Intel PC. The JVC camera was equipped with a zoom lens, Model JVC HZ-C611AF(U), and the Hitachi camera was equipped with a custom lens (Mills and Stoltzman, 1988) with a focal point of 8.5 mm.

A Sony VAIO Digital Studio desktop computer, Model PVC-E302DS, with Windows 98 operating system (Microsoft Corp., Redmond, WA); Adobe Photoshop 5.5 image processing software (Adobe Systems Inc., Salinas, CA) upgraded with Image Processing ToolKit (Reindeer Games Inc., Gainesville, FL); and a 486 Intel PC with Windows 95 and MS-DOS operating systems (Microsoft Corp., Redmond, WA) equipped with TARGA+ (Truevision, Indianapolis, IN) video acquisition and output card and Way-2C (Wayland Research Inc., Cohasset, MA) color pattern recognition system were used as image processing tools. Statistical data analysis was performed with Microsoft Office 97 (Microsoft Corp., Redmond, WA) software package.

Experimental Procedure. Two cultivars of peanuts (*Arachis hypogaea* L.) were used in this study: NC 9, a virginia type, and Georgia Green, a runner type. NC 9 peanut plants were hand dug at the North Carolina Dept. of

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Agric., Peanut Belt Res. Sta. (Lewiston-Woodville, NC) and transported to the USDA, ARS, Market Quality and Handling Res. Unit storage facility at North Carolina State Univ., Raleigh, NC. After 2 d, all pods were handpicked from the plants and placed in wire baskets for maturity class processing. Fresh Georgia Green pods (110 kg) from a single field at the USDA, ARS, Nat. Peanut Res. Lab. in Dawson, GA were shipped to North Carolina State Univ. and placed in refrigerated storage. Random samples were taken from the refrigerated storage at different intervals as needed.

A wet pod impact blaster (Pearman Engineering Co., Chula, GA) with a slurry of abrasive glass beads (Cataphote Inc., Jackson, MI) was used for exocarp removal (Williams and Monroe, 1986). The terms used in this paper for pod anatomy are those defined by Williams and Drexler (1981).

Based on the color at the attachment point of the basal seed, pods were sorted manually into color classes (yellow, orange A, orange B, brown, and black) and black subclasses (Sanders *et al.,* 1990; Sanders and Bett, 1995). The white color class was excluded from the analysis because the hulls of pods in this color class were soft and easily destroyed during the blasting process. Manual color classification was performed by trained and highly experienced personnel.

The color of the pod ventral surface was used for classification of the black color subclasses. Color transition between classes is the slowest on the ventral surface (Fig. 1A) (Williams and Drexler, 1981). The dorsal (top row) and ventral views (bottom row) of the six subclasses of the black color class are presented in Figure 1B. Color of the ventral surface changes from orange to brown to black in subclass (immature to mature) (VI to I). Therefore, in order to classify black color subclasses, both dorsal and ventral images of each set of pods are required.

About 300 pods were used in preliminary studies to determine the feasibility of the project and to develop the image acquisition stand and the software procedure. More than 3000 pods were used in this study for training the color recognition software.

The image acquisition board (Fig. 1C) was constructed to hold a maximum of 50 pods (10 x 5) with dimensions of 44 x 32 cm. Images of dorsal and ventral surfaces were acquired alternatively by manually spinning the pods between acquisitions without changing their relative positions on the board.

The final image acquisition system, constructed to meet optimum illumination criteria (Gennert and Wittels, 1994), included a Hitachi KP-D50 camera with custom lenses (8.5 mm), light bulbs, light diffuser, and board. All system components were enclosed in a black plywood box (47.6 x 36.2 x 99.1 cm) to eliminate any interference of outside light.

The image processing procedure consisted of three steps — background removal, size measurement, and color analysis (Boldor, 2000). Background removal and pod size measurements were performed using Adobe Photoshop Version 5.5 (Adobe Systems, Inc., Salinas, CA) upgraded with Image Processing ToolKit (Reindeer Games Inc., Gainesville, FL). Pod size measurements were performed only on pods in black and brown color classes.

Color Classification. Color classification was performed for all images using the Way-2C Color Pattern Recognition System (Wayland Res. Inc, Cohasset, MA). Way-2C uses a minimum description analysis method to recognize and

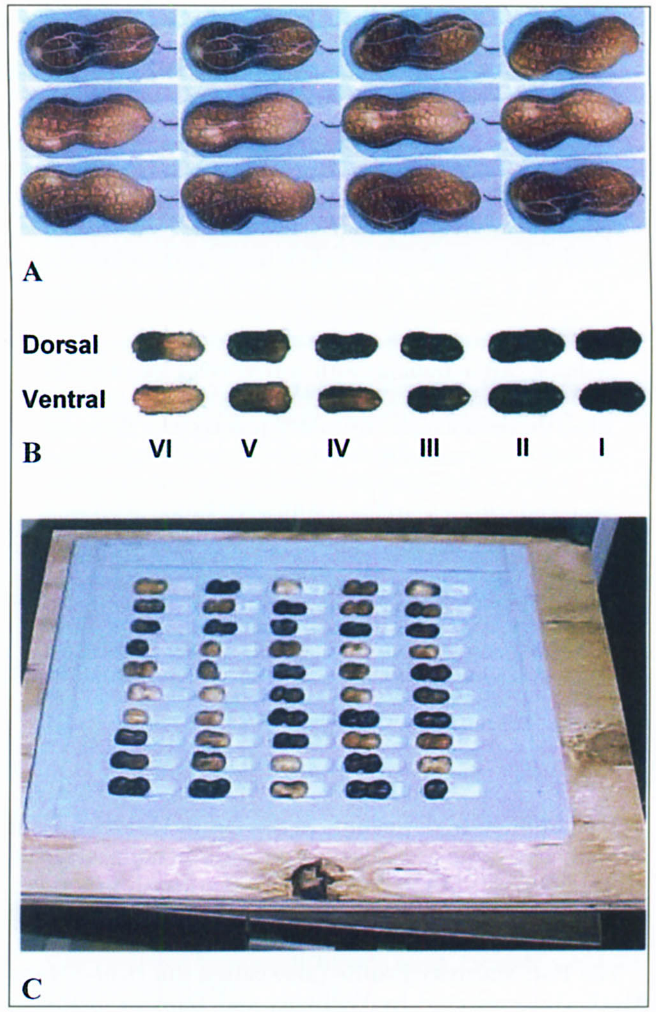

Fig. 1. A. Color transition in different views of a peanut pod, starting with the dorsal view (top left) and rotated around its longitudinal axis in increments of 30°. B. The six subclasses of the black color class, with the most mature at the right. C. Pod arrangement on the image acquisition board.

classify objects based on their color. Images of manually sorted pods were used in software training for color class recognition. For each color class, or subclass, a reference was created and saved during training. Square regions from each pod, corresponding to the most advanced color at the attachment point of the basal seed, were used in color class training. References were used to classify pods in different images. Two kinds of images were used for classification. The first type consisted of images of the same pods used in training in different arrangements on the board. The second type used images of pods that were not previously manually sorted. A proper alignment of pods in rows and columns equally distributed and oriented with respect to the camera was very important, so that the computer could read the regions with the most advanced color on the pods (regions of interest). Proper positioning of pods on the board was important so that the system could determine the most advanced color in the region of interest. The computer-classified pods were labeled with colored squares corresponding to each color class, and then the images were saved. Along with the images, a text file containing the number of pods in each color class also was saved.

In this study, the image processing steps, even though automated, were not performed online. The system can be setup in such a manner that the classification into color classes and subclasses is performed as soon as the board is inserted in the box and the image is acquired.

Black Color Subclasses. For training and classification of the black color subclasses, rectangular regions that enclosed the overall ventral surface of the pods were used. References for each black color subclass were created using manually classified pods, and those references were used to classify pods in other images.

Data Analysis. Results obtained from the color classification were analyzed using Microsoft Excel (Microsoft Corp., Redmond, WA). Two kinds of comparisons were made, one using correlation and one using a goodness-of-fit test. Manual classification was compared with computer-assisted classification for accuracy and two or more computer classifications of the same pods in different arrangements or different sample sizes taken from the same population were compared to estimate system precision.

Results and Discussion

Classification into Color Classes. The distributions obtained from automated classifications of two NC 9 peanut samples, 340 pods and 227 pods, are compared in Figures 2 and 3. The correlation coefficients for classification of color classes of NC 9 peanuts are much higher between two automated classifications than between manual and automatic classification (Table 1). Correlation coefficients, while not validating any statistical hypothesis, show a general trend on how closely related are two sets of data. The results of the chi-square test for classification of NC 9 peanuts in color classes (Table 2) indicate that expected and actual values are not statistically different (P = 0.05). All P-values of the chi-square test for two different automated classifications are greater than 0.05 (highlighted), validating the hypothesis that the two distributions were statistically equal. Therefore, the computer-assisted classification can identify the color classes as they are used now in the hull scrape method.

For Georgia Green peanuts, four samples of different sizes (200, 350, 500, and 524 pods) randomly selected from the same population were compared. The automated classification in color classes is illustrated in Figure 4. The correlation coefficients and values of the chi-square tests for Georgia Green peanuts are displayed in Tables 3, 4, and 5.

The correlation coefficients for samples of different sizes from the same population are above 94% with the exception of the 524 pods sample, which has correlation coefficients with the other samples between 84 and 90%

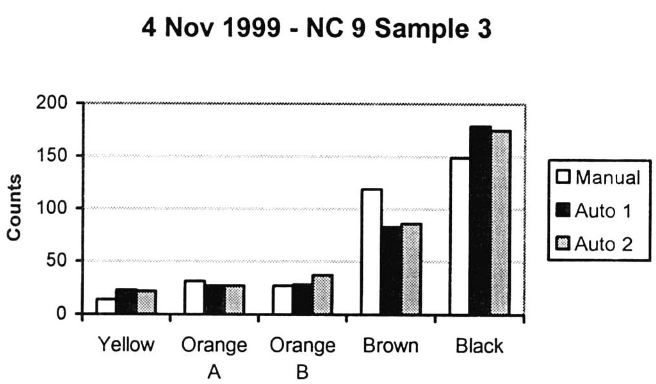

Fig. 2. Comparison of manual and computer-assisted classification in color classes of a 340-pod NC 9 sample.

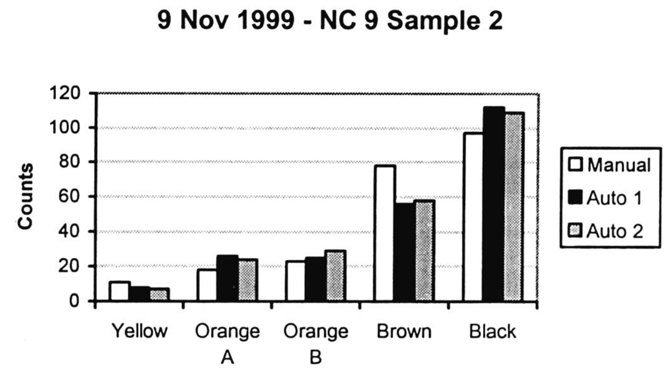

Fig. 3. Comparison of manual and computer-assisted classification in color classes of a 227-pod NC 9 sample.

Table 1. Correlation coefficients for manual and automated classification in color classes of NC 9 peanut pod samples.

		18 Oct. 99			27 Oct. 99			4 Nov. 99			9 Nov. 99		
		Sample			Sample			Sample			Sample		
		1	2	3	1	2	3	1	2	3	1	2	3
		No. pods			No. pods			No. pods			No. pods		
Classification		200	200	97	233	289	222	309	325	340	237	227	300
Manual 1	Auto 1	0.886	0.823	0.788	0.988	0.783	0.786	0.989	0.972	0.933	0.859	0.940	-
	Auto 2	0.970	0.893	0.801	0.925	0.578	0.843	0.984	0.966	0.940	0.804	0.950	-
	Auto 3	0.899	0.791	0.756	0.908	0.728	0.749	-	-	-	-	-	-
Auto 1	Auto 2	0.963	0.977	0.992	0.964	0.918	0.963	0.997	0.999	0.998	0.985	0.998	0.993
	Auto 3	0.993	0.999	0.992	0.948	0.987	0.944	-	-	-	-	-	-
Auto 2	Auto 3	0.977	0.969	0.993	0.997	0.890	0.981	-	-	-	-	-	-

Table 2. Chi-square test results (P-values) for manual and automated classification of NC 9 peanuts in color classes.

Values		18 Oct. 99			27 Oct. 99		
		Sample			Sample		
Exp.	Actual	1	2	3	1	2	3
Man. 1	Man. 2	N/A	N/A	0.380	N/A	N/A	N/A
Man. 1	Auto 1	N/A	N/A	0.110	N/A	N/A	N/A
Man. 1	Auto 2	N/A	N/A	0.154	N/A	N/A	N/A
Man. 1	Auto 3	N/A	N/A	0.069	N/A	N/A	N/A
Man. 2	Auto 1	0.038	0.023	0.259	0.849	0.017	0.004
Man. 2	Auto 2	0.412	0.095	0.540	0.186	0.001	0.068
Man. 2	Auto 3	0.097	0.004	0.237	0.090	0.005	0.009
Auto 1	Auto 2	0.488	0.713	0.987	0.585	0.278	0.354
Auto 1	Auto 3	0.914	0.967	0.979	0.344	0.968	0.176
Auto 2	Auto 3	0.792	0.528	0.950	0.990	0.178	0.767
		4 Nov. 99			9 Nov. 99		
		Sample			Sample		
		1	2	3	1	2	3
Man.	Auto 1	0.040	0.032	0.001	0.006	0.011	N/A
Man.	Auto 2	0.001	0.008	0.001	0.001	0.020	N/A
Auto 1	Auto 2	0.410	0.99	0.536	0.720	0.899	0.081

N/A = Not available.

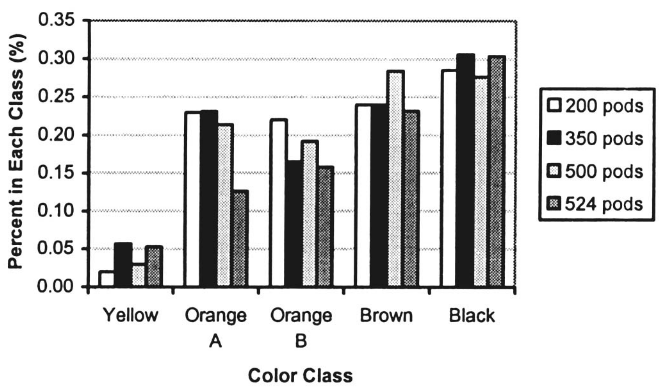

Fig. 4. Automated color classification of four samples from the same population of Georgia Green peanuts.

(Table 3). The correlation coefficients between manual and automated classification, as shown in Table 4, are below 90%, while the correlation coefficients between the automated classifications are above 94% for all Georgia Green peanut samples. Also, the P-value of the chi-square test (Table 5) is below the 0.05 cut-off limit when manual and automated classification are compared (not highlighted), while between different automated classifications the P-value is well above the cutoff limit of 0.05 (highlighted). The smaller correlation coefficients and P-values of the chi-square test for Georgia Green peanuts were most likely because a much smaller number of pods was used to train the color recognition software (420 Georgia Green; 2000 NC 9).

Errors in automated classifications occurred only when single seed pods were misaligned on the board because

Table 3. Correlation coefficients for four samples of different sizes from the same population of Georgia Green type peanuts.

Sample size	200	350	500	524
200	1.000			
350	0.943	1.000		
500	0.963	0.945	1.000	
524	0.838	0.891	0.878	1.000

Table 4. Correlation coefficients for manual and automated classification in color classes of Georgia Green peanuts for three different samples and for the same sample in different arrangements.

Manual	Auto	Sample 1	Sample 2	Sample 3
		0.892	0.849	0.787

	Manual 1	Manual 2	Auto 1	Auto 2	Auto 3
Manual 1	1.000				
Manual 2	0.839	1.000			
Auto 1	0.181	0.608	1.000		
Auto 2	0.117	0.592	0.989	1.000	
Auto 3	0.081	0.579	0.950	0.980	1.000

Table 5. Chi-square test results (P-values) for manual and automated classification of Georgia Green peanuts in color classes.

Expected values	Actual values	Sample 3
Manual 1	Manual 2	**0.147**
Manual 1	Auto 1	0.000
Manual 1	Auto 2	0.000
Manual 1	Auto 3	0.000
Manual 2	Auto 1	0.008
Manual 2	Auto 2	0.001
Manual 2	Auto 3	0.004
Auto 1	Auto 2	**0.480**
Auto 1	Auto 3	**0.697**
Auto 2	Auto 3	**0.946**

of shorter pod length, and the region on the pod (the attachment point of the basal seed) used for classification was misaligned. Also, in the case of very small pods, generally those that were in immature color classes (yellow and orange A), the region used in automated color classification was too large, and misclassification was more frequent. Other differences between manual and automated classification might have occurred because of human error in classifying various color classes.

Classification in Black Color Subclasses. Harvest day prediction in the Hull Scrape Maturity Method is generally based on the black color class. The classification of black pods into six subclasses is very important to the accuracy of harvest date prediction. Black subclasses from the most immature to the most mature have been numbered VI, V, IV, III, II, and I.

Peanut pods were first classified in color classes based on dorsal surface color. Only those pods identified as belonging to the black color class were subsequently classified into subclasses. In classification of black subclasses, pods are arranged in columns on the board according to manual classification from the most mature to the most immature subclass. An empty slot was placed between subclasses. A comparison between manual and computer-assisted classification of NC 9 peanut pods in black subclasses is illustrated in Figure 5.

The correlation coefficients and P-values of the chi-square tests (Tables 6 and 7) are greater when comparing two automated classifications than when comparing a manual classification with an automated classification. For chi-square tests, all P-values of the automated classifications were above the cutoff limit of 0.05, meaning that the two distributions were statistically equal.

Pod Size Distribution. Distribution of pod and sizes in black and brown color classes as determined by automated classification for NC 9 peanuts is illustrated in Figure 6. Pod sizes in the two color classes had a normal distribution, similar to the distribution obtained by other researchers (Davidson *et al.*, 1978; Williams *et al.*, 1987).

Table 6. Correlation coefficients for manual and automated classification in black subclasses.

		18 Oct. 99			27 Oct. 99			4 Nov. 99			9 Nov. 99		
		Sample			Sample			Sample			Sample		
		1	2	3	1	2	3	1	2	3	1	2	3
		No. pods			No. pods			No. pods			No. pods		
Classification		200	200	97	233	289	222	309	325	340	237	227	300
Manual 1	Auto 1	0.715	0.870	0.637	0.166	0.362	--	0.638	0.620	0.582	0.829	0.468	--
	Auto 2	0.764	0.843	0.581	--	0.562	0.528	--	0.444	0.211	0.928	0.485	--
	Auto 3	0.880	0.892	0.666	--	0.132	0.399	--	--	--	--	--	--
Auto 1	Auto 2	0.911	0.991	0.925	--	0.824	--	--	0.684	0.865	0.969	0.950	
	Auto 3	0.864	0.956	0.982	--	0.916	--	--	--	--	--	--	--
Auto 2	Auto 3	0.868	0.957	0.952	--	0.843	0.727	--	--	--	--	--	--

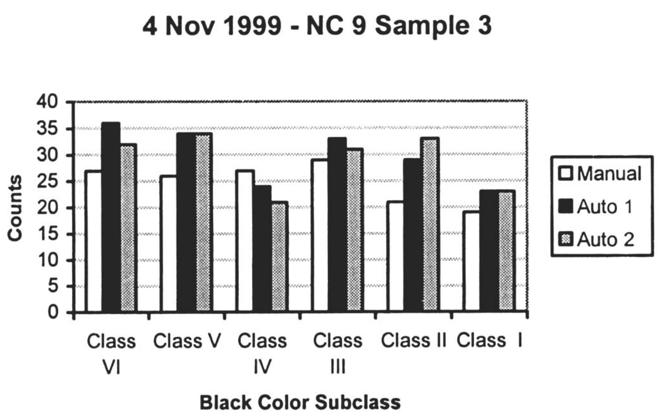

Fig. 5. Comparison of manual and computer-assisted classification in black color subclasses of a 340-pod NC 9 sample.

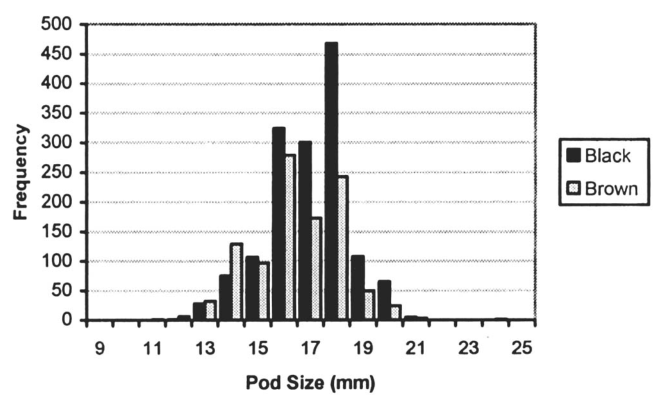

Fig. 6. Pod size distribution in black and brown color classes.

Table 7. Chi-square test results (P-values) for manual and automated classification of NC 9 peanuts in black color subclasses.

Values		18 Oct. 99			27 Oct. 99		
		Sample			Sample		
Exp.	Actual	1	2	3	1	2	3
Man. 1	Man. 2	N/A	N/A	0.150	N/A	N/A	N/A
Man. 1	Auto 1	N/A	N/A	0.400	N/A	N/A	N/A
Man. 1	Auto 2	N/A	N/A	0.465	N/A	N/A	N/A
Man. 1	Auto 3	N/A	N/A	0.513	N/A	N/A	N/A
Man. 2	Auto 1	0.677	0.143	0.368	0.001	0.000	N/A
Man. 2	Auto 2	0.056	0.173	0.779	N/A	0.000	0.001
Man. 2	Auto 3	0.631	0.171	0.472	N/A	0.000	0.000
Auto 1	Auto 2	0.526	0.946	0.549	N/A	0.126	N/A
Auto 1	Auto 3	0.192	0.535	0.607	N/A	0.179	N/A
Auto 2	Auto 3	0.147	0.402	0.883	N/A	0.082	0.254
		4 Nov. 99			9 Nov. 99		
		Sample			Sample		
		1	2	3	1	2	3
Man.	Auto 1	0.071	0.090	0.069	0.016	0.000	N/A
Man.	Auto 2	N/A	0.010	0.028	0.132	0.000	N/A
Auto 1	Auto 2	N/A	0.079	0.914	0.699	0.835	N/A

N/A = Not available.

Summary

A methodology for color and size classification of peanut pods using machine vision and image analysis was designed. The general concept of the hull scrape method is conserved and the same number of pods (200) are used in the process. The ability to classify correctly pods based on their colors provides a valuable alternative to the present system based on manual classification, transforming the task of predicting optimum harvest date into an easy and rapid process. Furthermore, once images of peanut pods are acquired, the automated classification can be performed off-site at a central location by transferring the images via the Internet. This presents an opportunity to create a regional database of overall crop maturity. A database of pod and approximate seed size distributions will provide an estimate of the maturity-based quality and of shelling out-turn of a particular region. Another advantage of this system is that the images may be stored for further analysis of color classes in different ways, based on different color parameters. The system can be implemented easily at peanut buying points and county agent offices, where the manual classification is currently performed. Image acquisition does not require any special training. With future developments of other image acquisition devices, such as digital cameras and web cameras with image quality increase and price reductions, the image-processing camera and the video acquisition card can be eliminated from the hardware setup, making image acquisition accessible at the individual computer level.

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