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AUTOMATED DAMAGE DETECTION IN PEANUT GRADE SAMPLES

by

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SUMMARY:

Peanut kernels from grade samples were sorted into damaged and undamaged categories based on their optical characteristics using two chroma meters, a machine vision system, and a spectrophotometer. The spectrophotometer outperformed the other sensors by correctly classifying 100% of the undamaged kernels and 94.5% of the damaged kernels.

KEYWORDS:

Inspection, Grading, Peanuts, Spectral reflectance, Machine vision

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AUTOMATED DAMAGE DETECTION IN PEANUT GRADE SAMPLES

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INTRODUCTION

Quality evaluations are made on samples of all peanuts marketed in the U.S. These evaluations include measuring the amount of moisture, foreign material, damaged kernels, and kernels of different size categories in small samples representing larger lots. Most measurements such as kernel size and moisture content are made objectively using machines developed to determine specific quality factors. However, damaged kernels are evaluated subjectively using trained inspectors.

Kernel damage may occur any time in the production, marketing, storage, or manufacturing process. Damage may be caused by insects, fungal growth, improper curing, or freeze damage. Most types of damage will usually result in poor quality factors that are reflected in poor flavor or toxic residues produced by fungal growth. Inspectors are trained to identify kernel discolorations, which indicate damage, on 500 g or 1000 g samples and are provided with color charts and pictures to help in this identification. If a discoloration indicating damage is identified, then a judgement must be made to determine if the kernel is over 25% discolored (FSIS, 1988). Because of the burden placed on individual inspectors and the inherent variability induced by human decisions, the peanut industry has requested that an objective means of determining damage be developed.

Peanuts are inspected at two points, once when the farmer markets his crop, and again when the sheller markets shelled kernels from his shelling plant. The percentage and type of damage detected indicate the quality of the peanuts and is reflected in the price received by the farmer or sheller. The presence and quantity of certain types of damage can result in penalties to farmers of 1 to 75% of the value of the peanuts. Sheller losses occur when remilling is required to remove damaged kernels if the damage percentage is above 1%. From a quality standpoint, the correct identification of certain types of fungal damage is critical since

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fungal damage is an indication of the presence of aflatoxin, a carcinogen, in peanuts. Other types of damage may not adversely affect flavor quality but affect appearance. Therefore, if peanuts are to be ground, no penalty should be assessed on good quality discolored kernels. The present system, however, penalizes for discolorations that do not affect quality. If the kernels are to be used whole, the discolored kernels will need to be removed for appearance purposes. Thus, depending on the end use, there is considerable potential to classify kernels into damage categories. To insure accurate determination of quality and value, accurate identification of kernel damage is critical.

LITERATURE REVIEW

Man can distinguish several million colors, however, man's ability to use the same criteria to determine the color of an object all day and every day is poor. In addition, two observers may differ in their opinion of what is, for example, dark brownish-grey. Thus, a means of removing human bias from the color determination process is needed. Several manufacturers, such as Hunter[2] and Minolta, market meters to simulate the color response of the human eye. These meters use sensors filtered to measure the three primary colors, thus enabling determination of tristimulus values. These tristimulus values can be translated into three-dimensional sets of color coordinates which indicate color perceived by the eye. The three dimensions correspond to intensity and chromaticity coordinates. Hue and saturation are the components of chromaticity. Any of the coordinates can be used to distinguish between two objects and are an estimate of the objects hue, saturation, and intensity. Hue indicates what color, such as red, dominates the object. Saturation indicates how much of the color is there, such as vivid red. Intensity indicates how bright the color is, such as light red.

Three common sets of color space coordinates are L*a*b*, L*C*H°, and Yxy. L*a*b* uses cartesian coordinates to indicate perceived color. L* is the intensity factor, a* and b* are chromaticity coordinates. L*C*H° is similar to L*a*b* but uses cylindrical coordinates. L* is again the intensity factor, C* is saturation, and H° is the hue angle. Yxy is also similar to L*a*b* but equal distances in the chromaticity diagram do not represent equal differences in perceived color and thus less closely represents human sensitivity to color. Y is the intensity factor while x and y are chromaticity coordinates (Minolta, 1988).

Color machine vision systems have been used experimentally to determine the color of agricultural commodities. Machine vision systems have the advantage of extracting not only color information but also shape information. Wigger et al. (1988) classified fungal-damaged soybeans with about 98% accuracy using a color machine vision system. Intensity and ratios of red to blue, red to green, and green to blue were used to classify kernels instead of hue, saturation, and intensity values. The first derivative of pixel values was used to aid in correct classification. Shyy and Misra (1989) used similar procedures to classify damaged soybeans with about 85% accuracy. Miller and Delwiche (1988) graded peaches by color using red, green, and blue inputs. They normalized luminance to remove illumination effects and reduced the red, green, and blue inputs to two-dimensional chromaticity coordinates. Peaches were correctly classified with 65% accuracy and with a correlation coefficient of 0.90. Indirect diffuse lighting was used.

Color filters on black and white cameras allow color information to be obtained without the expense of a color system. Gunasekaran et al. (1988) used a red filter (610 nm) on a black and white machine vision system to classify fungal-damaged soybeans and corn. The corn was classified correctly 84% of the time and soybeans 80% of the time. Front lighting and a black background provided the best illumination configuration.

Sanders and Pearson (1982) showed that the current criteria for determining peanut kernel damage should be reevaluated. They showed that only slight differences in objective quality determination occurred between undamaged peanuts and peanuts having purple discolorations. Thus a more precise damage detection system that can classify damage into discoloration categories may be warranted.

PROCEDURES

Four sensors were used to determine damage in peanuts kernels: (1) intensity measurement only; (2) non-contact hue, saturation and intensity measurement; (3) contact hue, saturation and intensity measurement; and (4) measurement of the relative reflectance over the visible spectrum.

Damage detection by intensity measurement

Intensity, measured by levels of grey, was measured using a black and white machine vision system. A Dage Newvicon MTI-65 tube camera viewed objects for an Imaging Technologies, Inc. Model 151 imaging system. The camera lens was placed 11.4 cm above the viewing area. The system had 512 vertical by 512 horizontal pixel resolution. The system was controlled and data collected with a Compaq Model 40 portable 20 MHz computer with an 80386 processor. A Moritex MHF 150L fiber optic ring light attached to the camera lens provided illumination. A 120 PVC black friction belt was used as a background when viewing freeze damaged kernels whereas a Dorner #1 hard top accumulator white belt was used as a background for viewing other damaged kernels.

A grey scale threshold was selected by observing damaged and undamaged kernels with the machine vision system and choosing a grey level that gave minimum misclassification errors. The percentage of the discoloration on the projected area of the darkest side of each kernel was recorded. If 50% of the side of the kernel being viewed was discolored, then the kernel was considered to have at least 25% total discoloration and was classified as damaged. Individual kernels were placed into the viewing area by hand.

Damage detection by contact color measurement

A Minolta Chroma Meter CR-200 with an 8 mm diameter measuring area was used to determine damage characteristics. A built in pulsed xenon arc lamp illuminated the kernel. L*a*b*, L*C*H°, and Yxy color space coordinates were collected on a computer for later analysis. CIE standard illuminant C was used to calibrate the meter.

Kernels were individually placed on a glass specimen plate directly over the viewing area. The specimen plate insured that all kernels were the same distance from the viewing area. Initial tests showed that viewing through the plate did not adversely affect meter readings. The 8 mm viewing area enabled only about one half of the kernel to be viewed.

Color space coordinate thresholds resulting in minimum misclassification of undamaged and damaged kernels were selected. The CR-200 cannot determine the amount of surface area discolored, only the color space coordinates of the viewing area. Thus, only the color, not amount, of kernel discolored was determined.

Damage detection by non-contact color measurement

A Minolta Chroma Meter CS-100 with a viewing area of about 10 mm was used for non-contact measurement. A close-up lens was used to achieve the 10 mm viewing area. As with the CR-200 meter, only a portion of the kernel was viewed. The color coordinates described above were collected on a computer. The meter was attached to a stand so that the meter lens was about 15 cm from the kernel. An 80 cm by 130 cm Graphic Technology, Inc. viewing station with a D7500 light source provided uniform consistent illumination. CIE standard illuminant D_{65} was used to calibrate the meter. All ambient lighting was excluded during testing.

Color space coordinate thresholds resulting in minimum misclassification of undamaged and damaged kernels were selected. The CS-100 cannot determine the amount of surface area discolored, only the color space coordinates of the viewing area. Thus, only the color, not amount, of kernels discolored was determined.

Damage detection by spectral reflectance

An X-Rite 968 reflection spectrophotometer measured kernel spectral reflectance from 400 nm to 700 nm in 10 nm intervals. The spectrophotometer had a 0° illumination angle, 45° viewing angle, and an 8 mm target window. The target window was placed over the darkest discoloration on the kernels. Kernels were individually placed by hand into the viewing area. All data was collected and stored on a computer. CIE illuminant C was used to calibrate the meter.

As with the chroma meters, the amount of surface discolored could not be determined. Thus, only spectral information was collected. Spectral curve thresholds were selected that resulted in minimum misclassification of undamaged and damaged kernels.

Sample Description

The Federal State Inspection Service (FSIS) provided samples for evaluating the four sensors. The FSIS establishes the guidelines for determining damage and trains inspectors to identify damage in grade samples. Approximately one hundred kernels from each of five peanut categories were supplied by FSIS. These five categories were: obviously damaged redskins, questionably damaged, questionably undamaged, obviously undamaged, and freeze damaged peanut kernels. The skins were removed (blanched) from the freeze damaged kernels for comparison with undamaged blanched kernels. An additional 500 damaged kernels were used for further testing of the spectrophotometer.

The average of the top and bottom viewing for each kernel was used for the chroma meter tests while the side of the kernel showing the most discoloration was analyzed for the machine vision and spectrophotometer tests. The same kernels were used for comparing the four sensors.

RESULTS AND DISCUSSION

Sensor performance can be evaluated by calculating the percentage of good kernels classified as damaged kernels or by calculating the percentage of damaged kernels classified as good kernels. The former scenario, good kernels erroneously classified as damaged kernels, results in financial losses because of excess damage penalties assessed to the farmer selling peanuts out of the field. Misclassified good kernels will also result in financial losses to the sheller because of the costs associated with remilling to remove excess damage. Undamaged kernels may be worth up to 5 times the value of damaged kernels, thus, aside from penalties or remilling losses, misclassification can result in significant financial losses for those kernels that were misclassified.

The second scenario, damaged kernels erroneously classified as good kernels, results in poor quality peanuts reaching the consumer since they were not detected in the grading process. Although financial losses may not be immediate, the impact can be significant if domestic consumers and export markets are not pleased with the quality of peanuts in their raw or manufactured products. Both scenarios are important, however the second scenario was used as a more significant factor in evaluating the sensors since guaranteeing quality peanuts is the primary goal of the U.S. peanut industry.

Difficulty arises when evaluating an objective system to replace a subjective system in which correct decisions cannot be consistently made. For example, the effectiveness of an objective system developed to determine if something is black or white can be easily evaluated. However, evaluating the effectiveness of an objective system to determine whether a subjectively classified object is dark brownish grey or dark brownish green cannot be clearly evaluated since the subjective decision used to compare the objective decision to may initially have been wrong. This problem of classification and system evaluation applies to developing and evaluating a system to classify questionably undamaged or questionably damaged kernels since the initial subjective classification of those kernels may be wrong.

For reasons cited above, the category of questionably undamaged and questionably damaged peanuts supplied by FSIS were treated as damaged peanuts since there was some doubt as to their quality by the inspectors. Thus, the sensors were evaluated to determine how accurately and consistently obviously undamaged redskin and blanched kernels could be separated from all other categories.

Machine Vision Results

All freeze damaged kernels were correctly classified with the machine vision system. However, misclassifications of 31% to 68% of the other damage categories occurred when using the optimum threshold value (Table 1). A damaged kernel was considered one that had more than 25% of the kernel surface discolored as in FSIS requirements. An increase in the percent discoloration was seen as the degree of damage increased (Table 2) however, differences in grey level intensities were not prominent enough to distinguish between many undamaged and damaged kernels.

Although the machine vision system misclassified 34.8% of the damaged kernels, this system has the added dimension of measuring the percent of the kernel discolored. Thus, a color system that measures the percentage of surface area discolored in addition to the degree of discoloration may significantly increase the accuracy of this approach.

Chroma Meter Results

Both the CS-100 and CR-200 showed similar results. This similarity was expected since the meters are of similar technology, the only differences being the illumination and viewing methods. The CR-200 was easier to use because the built-in light source enabled more control over lighting conditions. The three color spaces, L*a*b*, L*C*H°, and Yxy showed similar results which can be expected since the three color spaces are mathematical transformations of each other. Only the color space coordinates showing the most significant differences between damage categories are reported.

Misclassification of damaged kernels by the CR-200 ranged from 1% for freeze damage to 16% for the questionably undamaged kernels when using the optimum threshold values (Table 1). An average of 8.3% of the damaged kernels and 4% of the undamaged kernels were misclassified. Slightly more damaged kernels were misclassified with the CS-100 with 0% freeze damaged but 47% of the questionably undamaged kernels counted as good kernels. Overall averages for the CS-100 were 17% damaged and 2.5% undamaged kernels misclassified. Both chroma meters classified freeze damage with almost no errors, however, classification errors for other damage categories and for undamaged peanuts were considered excessive.

The measure of luminance, L* or Y, with the CR-200 and CS-100 showed little promise for detecting differences between any damage categories, except for freeze damage as noted above. This indicates that although the hue and saturation of damaged kernels may be different, the intensity of the colors is similar. This is supported by the poor performance of the machine vision results where only intensity was measured. A general decrease in a*, C*, and x values was seen as the degree of damage increased. A slight increase in b*, H°, and y values from obviously undamaged to obviously damaged kernels was seen, but much overlap between these classifications existed. Table 2 shows the means and standard deviations for three of the color space coordinates that showed the greatest differences when using the CR-200.

Spectrophotometer results

The spectral curves for undamaged redskin and undamaged blanched kernels were plotted and key features describing their shape identified. This was done by measuring the minimum and maximum spectral reflectance ranges and slopes at critical locations where sharp changes in the shape of the curve occurred. Tables 3 and 4 show the ranges and slopes used to characterize these curves. With these limits set, damaged kernels were compared to the undamaged kernel parameters. In the comparison, if the spectral curve describing a kernel fell outside of the undamaged kernel limits at any of the prescribed points, the kernel was considered damaged. Figures 1 and 2 show the limits characterizing the undamaged blanched and undamaged redskin peanuts along with plots of several damaged kernels. With limits set as described, only 5.5% of the damaged kernels were misclassified and no undamaged kernels were misclassified (Table 1).

In addition to the above method of comparison, the Kolmogorov-Smirnov statistical test was used to compare curves as an alternative method of detecting if two kernels were different (Steel and Torrie, 1980). However, the test was too conservative since it only compared distributions, not line slopes or where minimums and maximums occurred. It was found that slopes and locations of minimums and maximums were critical for correct classification of kernels.

Conclusions

Classification of undamaged and damaged peanut kernels using a black and white machine vision system, two colorimeters, and a spectrophotometer showed the potential to replace the present subjective damage classification system with an objective one. Specific results were: (1) All sensors classified freeze damaged kernels with 99-100% accuracy; (2) the spectrophotometer correctly classified more of the other types of kernels than did the other sensors. The contact colorimeter, non-contact colorimeter, machine vision system, and spectrophotometer misclassified 8.3, 17, 34.8, and 5.5%, respectively, of the damaged kernels and correctly classified 96, 97.5, 100, and 100%, respectively, of the undamaged kernels.

Future Work

Future work will consider the use of a black and white camera with filters passing only the wavelengths specified using the spectrophotometer. In addition, a black and white camera tied to an image analysis system would permit for the calculation of the amount of the surface area discolored. This should aid in more precisely assessing the degree of damage. In addition, a method for three dimensional viewing needs to be incorporated into the system.

Certain types of damaged kernels were noted to have characteristic spectral curves. Thus, it should be possible to classify damaged kernels as to the type of discolorations. For example, kernels may be classified into categories of damaged caused by insects, freezing, curing, fungal invasion, or others. If an excessive amount of certain damage types is detected, then specific actions can be taken to remove these damaged kernels, thus insuring peanut quality.

In summary, the spectrophotometer showed considerable potential for detecting damaged peanut kernels. The information collected here should lay the foundation for developing an automated objective system for determining kernel damage.

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Table 1. Percentage of kernels classified as undamaged kernels when using a CR-200 or CS-100 chroma meter, a black and white machine vision system, or a spectrophotometer.

Damage Category	CR-200	CS-100	Machine vision	Spectro-photometer
Undamaged Redskins	92%	98%	100%	100%
Undamaged Blanched	100%	97%	100%	100%
Questionably Undamaged	16%	47%	68%	7%
Questionably Damaged	7%	12%	31%	12%
Damaged	9%	9%	40%	3%
Freeze Damaged (Blanched)	1%	0%	0%	0%
Percent good kernels classified correctly	96%	97.5%	100%	100%
Percent damaged kernels classified incorrectly	8.3%	17%	34.8%	5.5%
Redskin Threshold[1]	a*=7	a*=11	grey level=15	
Blanched Threshold[1]	L*=66.2	L*=75.7	grey level=103	

[1]a* and L* values are color coordinate thresholds resulting in the most significant differences between damaged and undamaged kernels. Spectrophotometer thresholds are given in Tables 3 and 4.

Table 2. Selected color space coordinate values obtained from the Minolta CR-200 colorimeter and a machine vision system for damaged and undamaged peanut kernels.

Damage Category	Color Space Coordinates L*	a*	H°	Percent Discoloration[1]
Undamaged Redskins				
Mean	55.1	8.5	65.6	0.2
Std. Deviation	2.2	1.2	3.9	0.2
Undamaged (Blanched)				
Mean	73.1	-2.9	99.2	0
Std. Deviation	1.8	0.4	1.1	0
Questionable Undamaged				
Mean	49.1	5.0	68.8	12.2
Std. Deviation	6.8	2.6	12.7	8.4
Questionably Damaged				
Mean	52.2	3.3	75.3	21.7
Std. Deviation	8.3	2.9	13.2	13.4
Damaged				
Mean	50.4	2.9	77.7	26.8
Std. Deviation	7.6	3.1	10.7	22.1
Freeze Damaged (Blanched)				
Mean	59.4	-0.5	91.9	100.0
Std. Deviation	4.4	2.1	6.3	0

[1]Values obtained from the machine vision system.

Table 3. Minimum and maximum spectral reflectance values at specified points used to characterize undamaged redskin and undamaged blanched kernels.

Wavelength (nm)	Min	Max
Redskins		
400	3.56	16.93
550	9.87	32.53
580	13.45	37.90
630	26.54	59.38
700	40.73	70.00
Blanched		
400	9.60	22.10
440	21.67	40.94
590	41.95	64.17
640	43.13	67.17
670	45.81	72.64
700	45.74	74.37

Table 4. Minimum and maximum slopes of spectral reflectance values used to characterize undamaged redskin and undamaged blanched kernels.

Wave length (nm) range	Min. Slope	Max. Slope
Redskins		
400-550	0.04	0.11
550-580	0.11	0.21
580-630	0.22	0.49
630-700	0.09	0.28
Blanched		
400-440	0.28	0.54
440-590	0.10	0.20
590-640	-0.01	0.07
640-670	0.09	0.23
670-700	-0.01	0.08

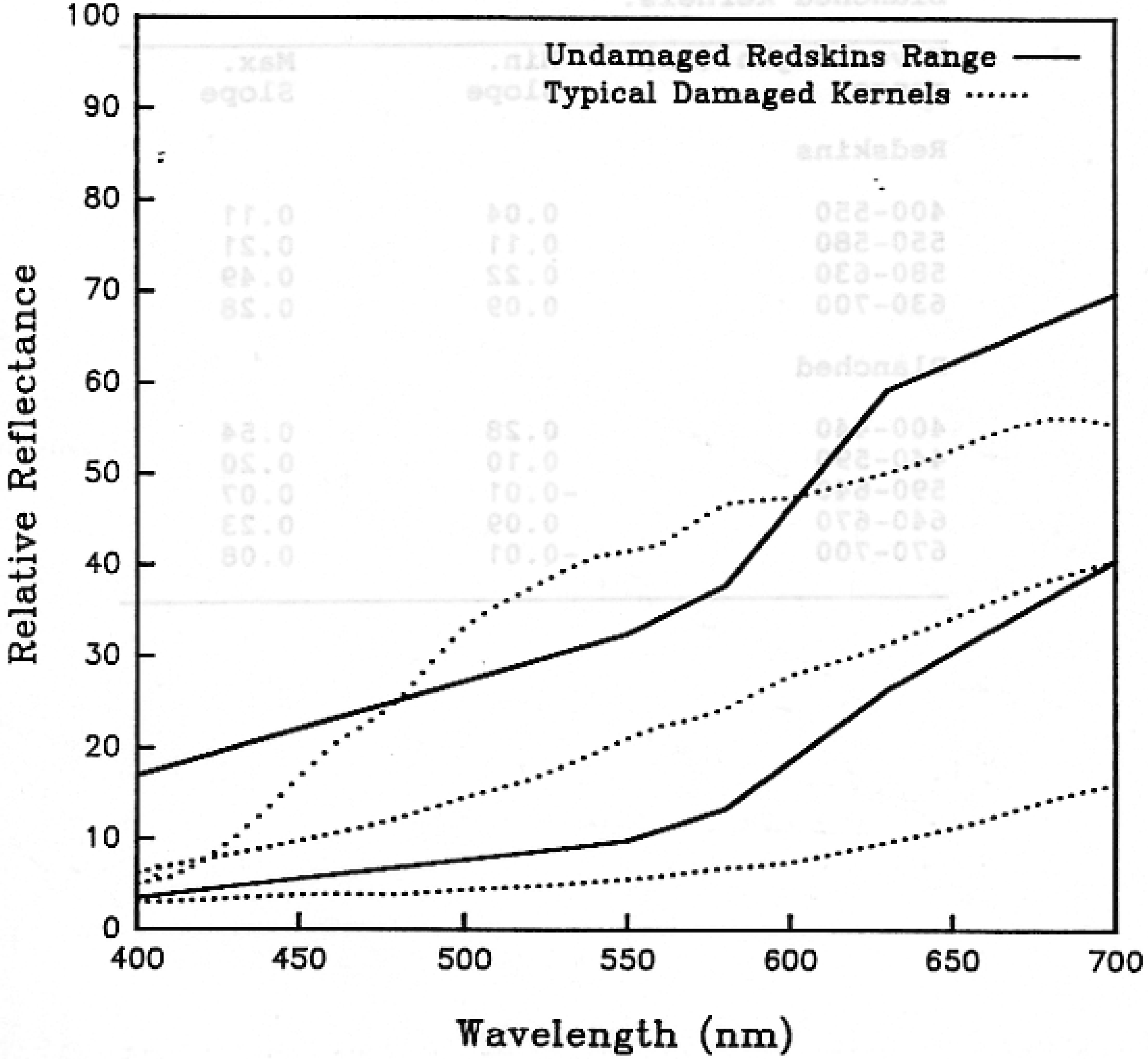

Figure 1 Minimum and maximum undamaged redskin spectral curve limits. Damaged kernels spectral curves were compared to the line slopes and ranges at 400, 550, 580, 630, and 700 nm.

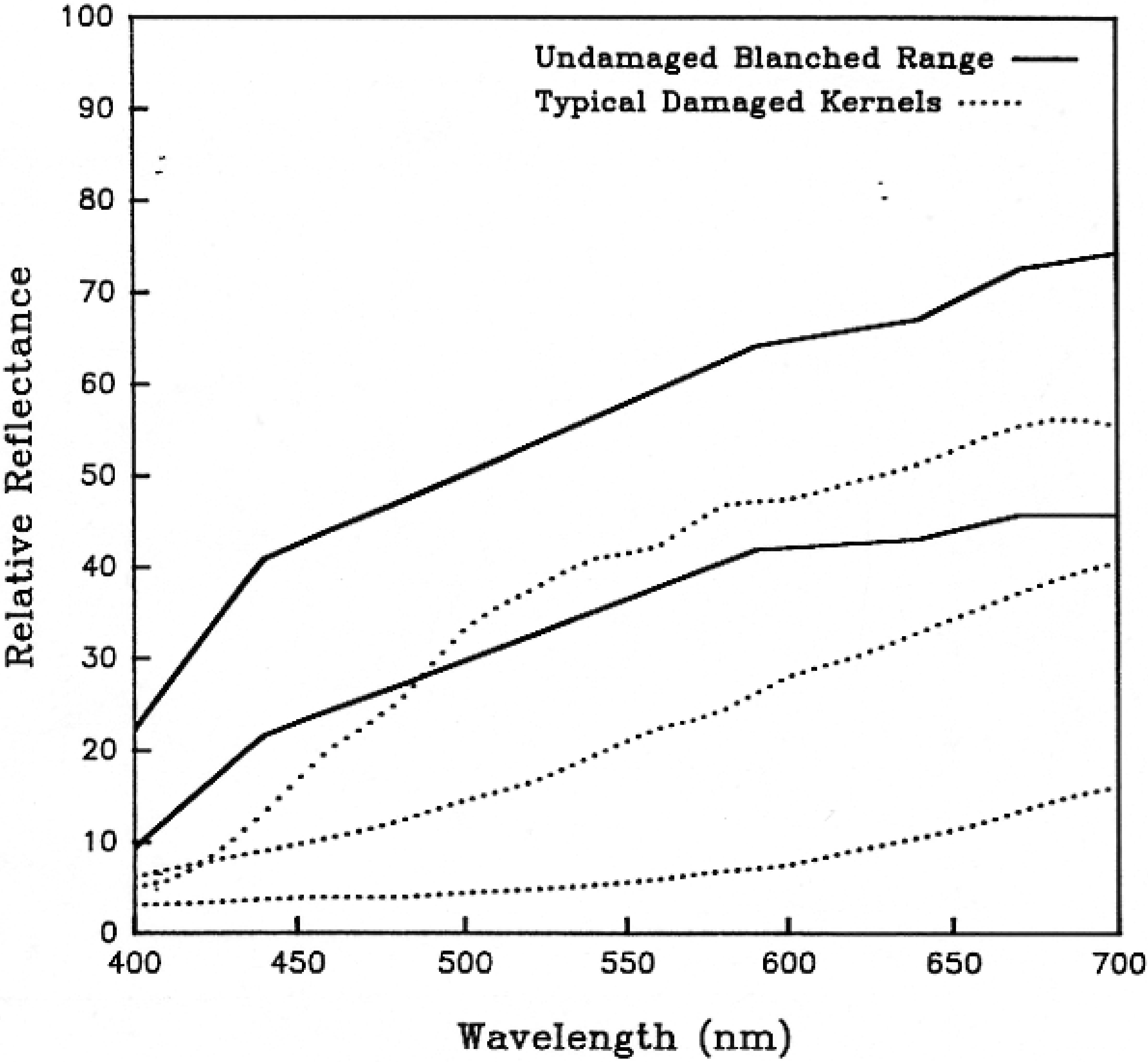

Figure 2 Minimum and maximum undamaged blanched spectral curve limits. Damaged kernels spectral curves were compared to the line slopes and ranges at 400, 440, 590, 640, 670, and 700 nm.