EVALUATION AND IMPLEMENTATION OF A MACHINE VISION SYSTEM TO CATEGORIZE EXTRANEOUS MATTER IN COTTON

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Abstract

The Cotton Trash Identification System (CTIS) developed at the Southwestern Cotton Ginning Research Laboratory was evaluated for identification and categorization of extraneous matter (EM) in cotton. The system's categorization of trash objects in cotton images was evaluated against Agricultural Marketing Service classer EM calls. AMS classers were tasked in assigning extraneous matter calls (bark/grass) in images acquired by various High Volume Instruments (HVI). Soft computing techniques were used to identify EM in the acquired cotton images and categorize them into bark/grass, stick, leaf, and pepper trash categories. Classer EM calls in the HVI images are compared with CTIS bark/grass and stick categorization. Images were acquired from different HVI systems on both the upper and lower camera head, and human classer's identified the EM by marking the objects on the acquired images. CTIS categorization of EM, were later compared to the Classer assigned EM calls. The main objective of this research is to use CTIS as an effective tool to aid classers in the identification of EM in cotton and, eventually, aid in the development of EM standards for cotton classification.

Introduction

The USDA-Agricultural Marketing Service (AMS) has developed standardized procedures for measuring physical attributes of raw cotton related to the quality of cotton (AMS, 2001). Cotton classification, based on these physical attributes, is used to determine the price of cotton on the world market. All cotton produced under the commodity loan program in the United States is classed by the AMS cotton classing office under these procedures. AMS cotton classification currently consists of determinations of fiber length, length uniformity, strength, micronaire, color, preparation, leaf, and extraneous matter.

Extraneous matter (EM) is any substance in cotton other than fiber or leaf. Examples of EM are bark, grass, spindle twist, seedcoat fragments (scf), dust, and oil. The kind and an indication of the amount (light or heavy) of EM are noted by the classer on the classification document (AMS, 2001). There are a wide variety of factors that influence the type and quantities of EM: the cotton growing region of the United States, the growing season (typically grass can be expected during rainy seasons), equipment maintenance (the presence of oil due to poor maintenance of harvesting or gin machinery), and cotton variety (upland or pima, hairy or smooth leaf). Ginning can have an impact on the type and quantity of EM left in the cotton through the selection of the seed cotton cleaning equipment, the amount of lint cleaning performed, and the type of ginning (saw ginning or roller ginning).

Fiber length, length uniformity, strength, and micronaire are inherent fiber properties. These attributes along with color are measured using High Volume Instrument (HVI) machines. These HVI measurements have been accepted by the cotton industry for quality purposes. However, human classers determine the presence of EM by the visual inspection of the cotton sample during classification along with the leaf grade and preparation.

The USDA-ARS Southwestern Cotton Ginning Research Laboratory (SWCGRL) developed the Cotton Trash Identification System (CTIS); a machine vision-based system that identifies trash objects commonly found in ginned cotton. CTIS categorizes the trash objects into bark/grass, stick, leaf, and pepper categories (Siddaiah et al., 2000 and 2002). In a previous study by Siddaiah et al. (2009), an EPSON® perfection 3170 photo scanner was used to acquire cotton images. The scanner acquired images were large area cotton images [181 cm^2 (28 in^2)], which were significantly larger than HVI images, and CTIS was used to analyze the images and categorize trash objects as EM (bark/stick) and leaf/pepper. Results indicated the system's EM identification was comparable to that of the human classer.

As the HVI is the standard means by which cotton quality is measured, AMS and ARS researchers agreed that CTIS should be evaluated using HVI images and implemented on HVI machines for further analyses. The goal of this research effort was to evaluate CTIS categorization of bark/grass in HVI images of cotton samples and compare its efficacy in predicting classer assigned EM calls on the same HVI images.

Materials and Methods

Cotton Trash Identification System

The Cotton Trash Identification System (CTIS) developed at the Southwestern Cotton Ginning Research Laboratory (SWCGRL), is a Microsoft Windows based system for the acquisition and processing of cotton images. The system processes images, acquired with a scanner or camera, of cotton samples and counts, measures, and categorizes the trash objects in the cotton samples into bark/grass, stick, leaf, and pepper categories. In this study, cotton images acquired on various HVI systems were analyzed to evaluate CTIS performance and compare them to the human classer identification of EM. The HVI systems images are the same images that are currently used in the measurement of percent trash, and use an area of 58 cm^2 (9 in^2) in the imaging window for trash analysis.

AMS HVI Images

In order to evaluate the CTIS performance on images acquired by HVI systems, AMS provided both the acquired cotton images on various HVI systems, as well as images in which the human classer had identified the EM. Figure 1 illustrates a typical HVI cotton image with the EM identified by the classer (circled in red).

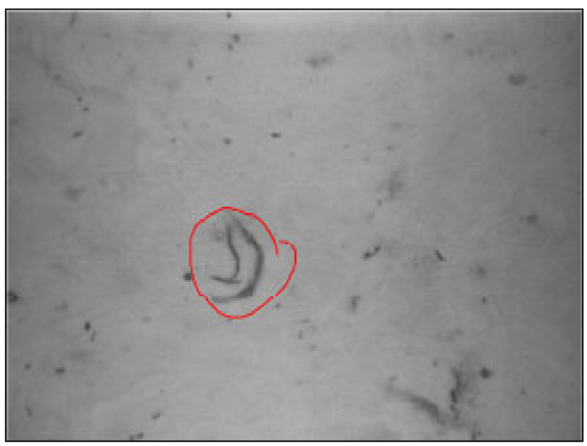

Figure 1. HVI image with classer identified extraneous matter.

The scanner images used in the previous study by Siddaiah et al. (2009) were color images and the entropy thresholding technique used to create segmented binary images where the trash pixels were separated from the lint background performed well. The segmentation technique used is an automatic thresholding technique and the threshold level is unique for each cotton image. The images acquired by the HVI were gray scale images and the entropy thresholding technique created large shadows on the left and the right edges in some images. Figure 2 shows the segmented binary image of an HVI image and illustrates the shadows on the edges of the images.

There are two reasons that may explain the occurrence of the shadows in the segmented binary images: a) the pixel intensity levels in the HVI images are lower than those in the typical scanner acquired images, and b) the HVI images tend to be darker on the edges in comparison to the middle, possibly due to lighting issues.

Figures 3 and 4 illustrates the white reference tile acquired with the scanner and the HVI system, respectively. As evident from the two images as well as Table 1, the pixel intensity level is significant lower (and hence darker) for the HVI white reference tile, in comparion to the scanner acquired white reference tile image. Typically, the pixel intensity level for a white reference tile should be closer to 255 (theoritically).

Figure 2. Segmented binary image.

Figure 3. White reference tile – Scanner image.

Figure 4. White reference tile – HVI image.

Table 1. White reference tile image statistics

White reference tile	Pixel intensity level			
	Min	Max	Mean	Std Dev
Scanner	129	247	238.23	2.11
HVI	93	197	142.18	16.95

Figures 5 and 6 illustrate the pixel distribution for select columns across the 640 x 480 scanner and HVI white reference tile images: two columns near the left edge (columns 0 and 25) of the image, two columns near the center (columns 294 and 344), and two columns near the right edge (columns 614 and 639) of the image. As seen in Figure 5, the pixel levels among columns and the pixel levels across the rows are fairly uniform and near 255 in the scanner based white tile image (figure 3). On the other hand, in the HVI white tile image (figure 4), the pixels levels tend to be lower in the columns closer to the edges of the image and the pixel levels are less uniform across the the rows, as illustrated by the curvature of the distribution.

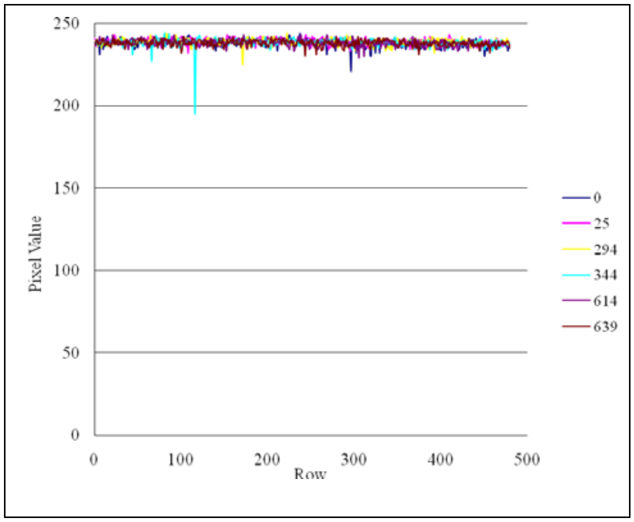

Figure 5. Pixel distribution – Scanner image.

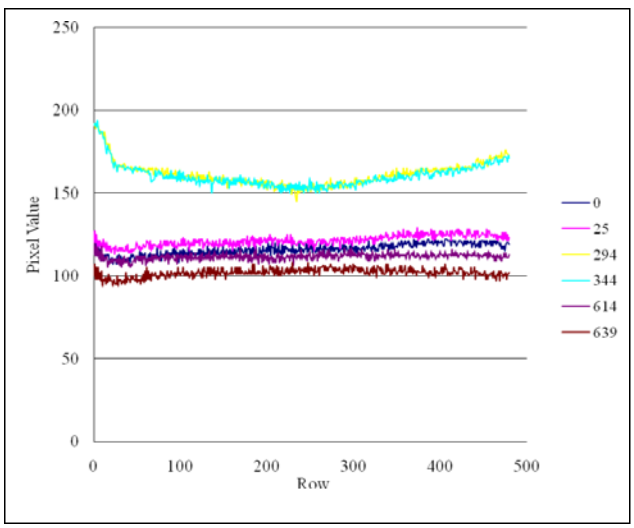

Figure 6. Pixel distribution – HVI image.

<u>Flat-Field Correction</u>

In order to correct the image for defects due to non-uniform lighting, Flat-field correction was performed on the HVI images.

Flat-field correction (Lieberman, and Patil, 1997) is a process wherein the intensity of a pixel located in an area of lower illumination is increased and the intensity of a pixel in an area of higher illumination is decreased. The intensity level of each pixel is multiplied by the ratio of the average intensity of the reference tile image (white tile) to the intensity of the respective reference pixel. If $I_{x,\,y}$, represents the intensity level of a pixel at the location x, y, then the intensity of a flat-field corrected image is represented by

$$I_{x,y}^{(\text{out})} = I_{x,y}^{(\text{in})} \frac{I^{(\text{tile\_avg})}}{I_{x,y}^{(\text{tile})}} \quad \text{Where,}$$

$I_{x,y}$ = intensity at position x, y

out = output image pixels

in = input image pixels

tile = reference image pixels

tile_avg = average gray level for the reference tile.

Figure 7 illustrates the raw cotton image acquired by the HVI system and Figure 8 corresponds to the flat-field corrected image. It is evident that flat-field correction corrects for the non-uniform illumination defects in the HVI cotton images. The column pixel levels along the rows are more uniformly distributed after flat-field correction. The spikes along the columns represent the trash pixels located in the given column. Figure 9 shows the segmented binary image where the trash pixels were separated from the lint background after flat-field correction of the HVI image. As seen, the shadows that were evident on the left and right edges of segmented binary image of the raw HVI image (figure 2) were eliminated after flat-field correction, illustrating the effectiveness of the technique.

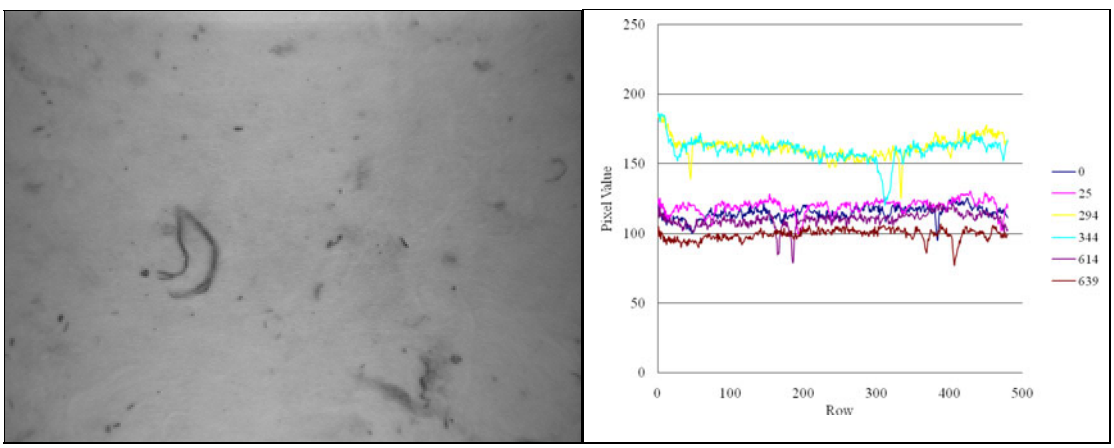

Figure 7. Cotton HVI raw image and pixel distribution.

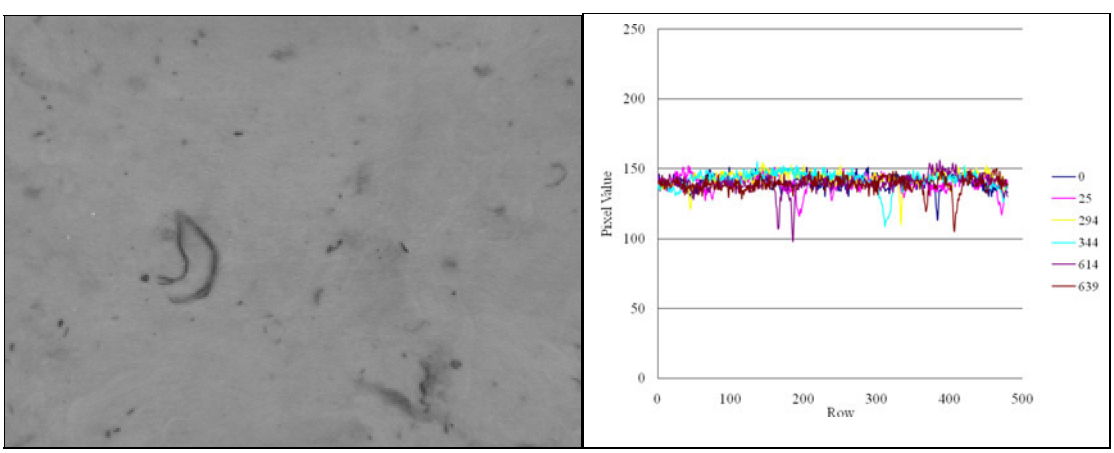

Figure 8. Flat-field corrected HVI image and pixel distribution.

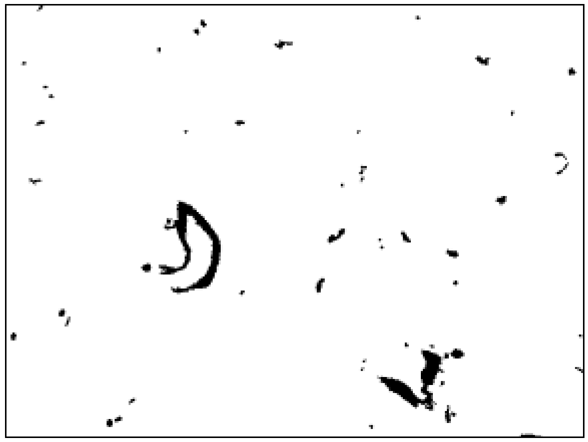

Figure 9. Segmented binary image after flat-field corection.

AMS Classing Data

To evaluate CTIS performance in identifying EM, comparisons were made between AMS classer EM call for the HVI images and CTIS EM categorization. Images were acquired by AMS classing officers at the USDA-AMS, Cotton & Tobacco Program, Standardization & Engineering Branch, Memphis, TN. Images (called faces) were acquired on different HVI systems. On some systems, images from both the upper and lower color head were acquired. The presence of EM in each of the faces was indicated by encircling the objects in red on the HVI digital image illustrated in Figure 1. The acquired images were analyzed with CTIS at the SWCGRL to generate the trash identification summary reports. The trash objects were categorized into EM (bark/stick) and leaf (leaf/pepper) categories.

Results and Discussion

Figure 10 illustrates a CTIS trash identified image along with the AMS classer identification. The boundaries of the CTIS identified EM objects are colored red and are assigned a number in the trash identified image which corresponds to the object number generated by the analysis software, while the boundaries of the leaf objects are colored green. For example, trash object 35 was the 35th object identified by CTIS in the image and was also identified and circled by the classer as EM. CTIS identified object 59 as EM, as well. Based on the shape descriptor of the object, the CTIS neural network categorized the object as EM. In general, CTIS identifies more objects as EM than the human classer. The entropy thresholding technique previously used by CTIS on scanner acquired images was effective in identifying the trash pixels from the lint background and identifying EM (Siddaiah et al., 2009). However, the performance of the entropy thresholding technique on HVI images was less satisfactory.

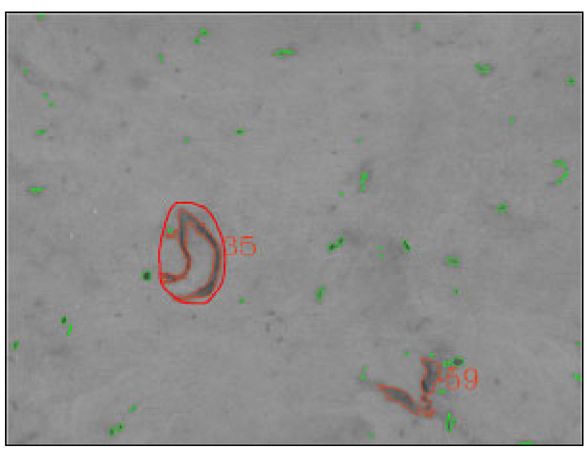

Figure 10. CTIS and classer identfication of extraneous matter.

As illustrated in Figure 11, the technique did not identify many trash pixels that were obviously trash and, as such, missed, mis-identified, or partially identified some of the EM objects in the cotton sample (object 1). In some instances, a single EM object was identified as more than one object resulting in the categorization as more than one EM. For example, CTIS identified objects 22 and 35 as two separate EM trash objects, while the human classer has identified as a single EM object.

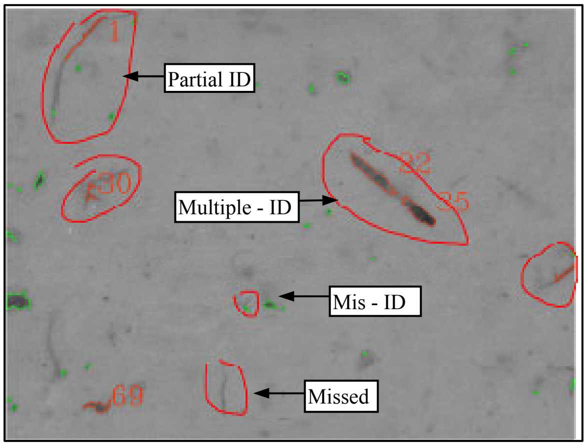

Figure 11. Illustration of trash objects CTIS missed, mis-identified, partially identified, and identified as more than one object.

Figure 12 shows a comparison between CTIS and classer EM calls for 52 images acquired on a single HVI system (917U) and processed with CTIS using the entropy thresholding technique. These images are from the upper color head and consisted of 13 samples (4 reps or images each). It is evident that in a majority of images, CTIS assigned more EM calls than the human classer. Certain objects maybe mis-categorized as bark/grass objects. Also, unlike the classer, CTIS will classify an object as EM if the shape descriptors indicate so, no matter how small. While in reality, the categorization as bark/grass may be meaningless due to the objects very small size. Often buried trash and shadows in the cotton images are identified as trash objects and are then categorized as bark/grass based on their shape descriptors by the CTIS algorithm. Thus, the three main issues that may cause CTIS to categorize a much high number of objects as EM in HVI images can be summarized as:

1. Poor segmentation due to non-uniform lighting.
2. Artifacts of buried trash segmentation resulting in mis-identification.
3. Very small objects identified as EM that the classer might ignore as insignificant due to its size or assign as leaf.

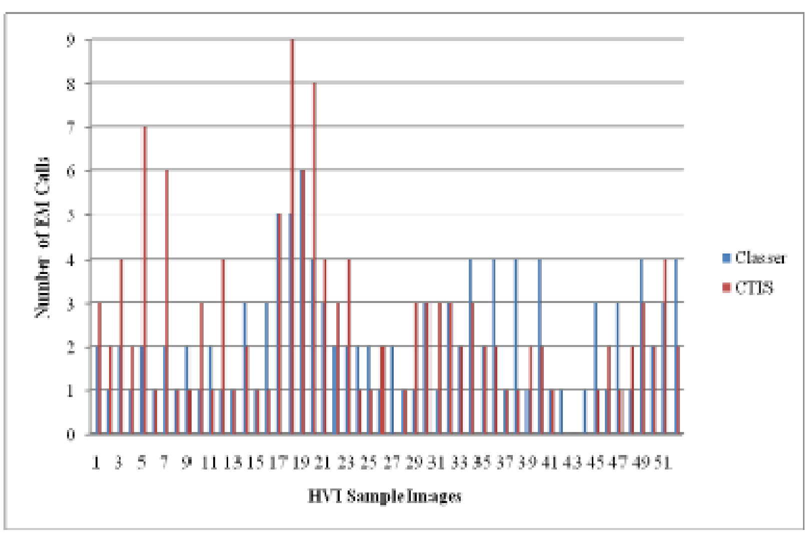

Figure 12. CTIS vs Classer EM calls on HVI images (917U).

In order to obtain better segmentation of the HVI cotton images, different thresholding techniques were evaluated. Figures 13 and 14 show segmented images with the OTSU (Otsu Nobuyuki, 1979) and the Simple Image Statistics (SIS) thresholding techniques. Both the OTSU and the SIS thresholding techniques typically identified more trash objects than the human classer identifies. Both these techniques were sensitive in identifying buried trash objects as well (note object 160 in figure 13 and object 156 in figure 14). These methods also had fewer missed, mis-identified, and partially identified EM objects. Hence, the number of EM identified by CTIS using the methods was higher than those identified using the entropy technique and by the human classer.

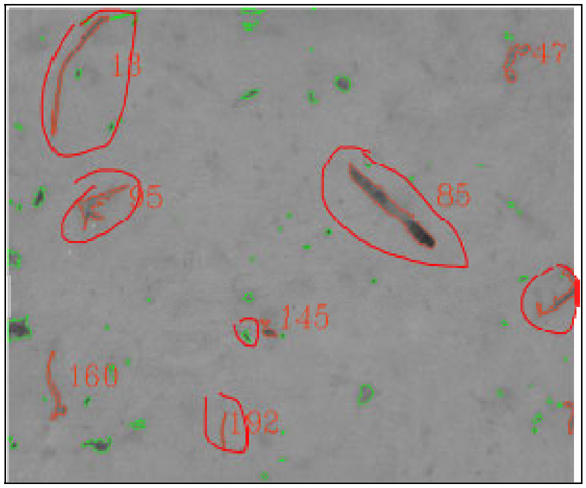

Figure 13. CTIS trash identification image using the OTSU thresholding method.

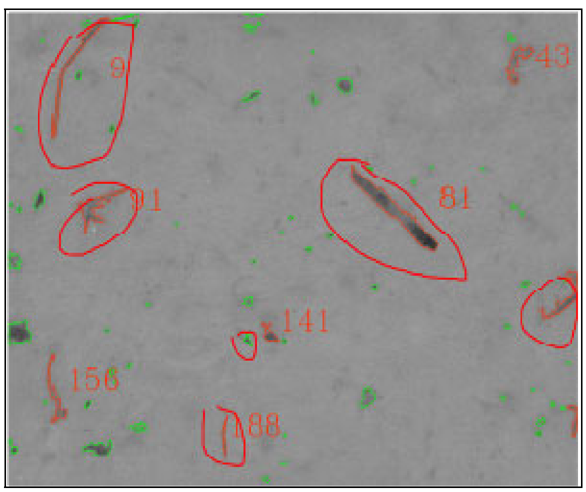

Figure 14. CTIS trash identification image using the SIS thresholding method.

Table 2 shows a comparison of CTIS trash categorization using the three thresholding techniques and the classer for the two HVI sample images (Figures 10 & 11) discussed above. Note that the OTSU and SIS methods categorized not only more EM objects, but also more total trash.

Table 2. Trash categorization for the sample images in Figure 10 & 11

	Fig. 10 Sample				Fig. 11 Sample			
Segmentation	Entropy	OTSU	SIS	Classer	Entropy	OTSU	SIS	Classer
Extraneous Matter	2	6	6	5	6	9	9	6
Leaf Count	52	75	75	NA	30	65	64	NA
Total Count	54	81	81	NA	36	74	73	NA
% Trash	1.37	2.92	2.91	NA	0.74	2.14	2.11	NA

When human classers assign EM calls to cotton samples, there is little information with regards to decision making process. There is need for additional input about other attributes (such as total trash, number of EM objects, size, distribution, etc.) that the human classer considers when assigning classer calls to cotton samples. Towards this end, further testing of a larger set of HVI images is required and planned. Based on the human classer identification of EM objects, it is hypothesized that some kind of baseline or decision matrix can be established to modify the CTIS algorithms and further fine tune CTIS EM categorization to gain better agreement with the classer. Also, better thresholding techniques and additional shape descriptors for the CTIS neural network classifier may result from further study to help mitigate the high number of EM calls assigned by CTIS.

Summary

HVI images of cotton samples with EM were analyzed with the Cotton Trash Identification System to evaluate its performance in identifying bark/grass trash found in cotton. The preliminary results show that CTIS agreed fairly well with the classer in the identification of bark/grass in cotton samples. In all samples where the classer identified objects as bark or grass, CTIS also categorized the objects as bark/grass in the samples, but usually more objects were identified. The system was sensitive in identifying smaller trash objects as well as buried trash, resulting in overestimating the EM calls in comparison to the human classer. Additional analyses are required with input from AMS classers with regards to the decision making process in terms of numbers, size, and distribution of trash and EM when assigning EM calls. This information will be used to modify CTIS algorithms and may lead to better thresholding techniques and additional shape descriptors for the CTIS neural network to increase the system's accuracy in predicting classer EM calls. In the future, CTIS, as a machine-vision-based independent EM-classification system, may aid the classer in assigning EM calls for classification of cotton by alerting the classer to certain levels of EM, high and low, or by aiding in the development of EM standards for calibration of machine grading systems.

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