APPLICATION OF UAV REMOTE SENSING FOR DETECTING PLASTIC CONTAMINANTS IN COTTON FIELDS

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Abstract

Plastic contamination of cotton is a serious problem for the U.S. cotton industry and abroad, and therefore it must be addressed to maintain quality of cotton fiber for its marketability and industry sustainability. Most plastic contamination comes from plastic wraps on round cotton modules, plastic mulch used in crops production, and plastic that blows onto cotton fields like shopping bags. The issue has become common enough that the USDA AMS cotton program began implementing a new extraneous matter code for plastic contamination in bales in 2018. Manual detection of plastic in cotton fields is tedious and labor-intensive. In this study, we conducted an experiment targeted at detecting plastic contamination from shopping bags in cotton fields using an Unmanned Aerial Vehicle (UAV). Two field tests were conducted at two locations (Weslaco, TX and College Station, TX) and two stages of the growing season (before and after defoliation) by manually tying plastic bags at randomized locations and three different heights (bottom, middle and top). A five-band multispectral camera was mounted on the UAV to collect aerial imagery, and an image processing algorithm was developed to detect presence and locations of plastic contaminants in cotton field. Mahalanobis distance supervised classification was used after extracting textural features for plastic bags. Initial results have shown that for pixel-based classification, plastic bags were detected with a maximum class accuracy of 64.17% before defoliation and 90.07% after defoliation. For bag-based accuracy, top bags were detected with a maximum accuracy of 66.67% before defoliation while top-white bags were detected with a maximum accuracy of 73.33% and bottom-brown bags were detected with the least accuracy of 13.33% post defoliation.

Introduction

Presence of any foreign material in cotton that can potentially affect quality of cotton fiber is called cotton contamination. Plastic is one such foreign material that is commonly found and has become a serious problem not only to the U.S. cotton industry but to the cotton industry worldwide. To preserve the former reputation of U.S. cotton as the cleanest lint in the world (Derek et.al., 2018), this issue needs to be addressed as soon as possible. Plastic contaminants like shopping bags and plastic mulch that get may be present in cotton fields during harvest as well as plastic wraps on round cotton modules pose serious concerns to U.S. cotton. Plastic contamination has become so common that the United States Department of Agriculture (USDA) Agricultural Marketing Service (AMS) has implemented new extraneous matter codes (71 and 72) for bales contaminated with plastic.

To remove plastic contaminants from raw cotton, either manual labor or some detection technology must be deployed. Detection becomes more challenging once these plastics break into small pieces due to mechanical processes at cotton gins. Byler et.al. (2013) showed that gin cleaning machinery fails to remove all plastic contamination. Hence, detecting and removing pieces prior to ginning, while they are still larger, and even prior to harvest is a better solution. To address this issue, we designed an experiment that uses an unmanned aerial vehicle (UAV) to remotely detect and locate plastic contaminants, particularly due to shopping bags in cotton fields. Hardin et.al. (2018) previously showed successful use of a UAV platform for detecting plastic trash in cotton fields, but their tests were limited in spatial resolution due to flying at higher altitudes and in spectral resolution due to the camera used. The current study was done as an expansion to their previous study. The specific objectives were to (a) detect plastic shopping bags in a cotton field by UAV remote sensing, (b) to consider the effect of vertical position of the bags relative to the top of the plants, and (c) to consider the effect of bag color.

Materials and Methods

We developed a semi-automated image processing algorithm that can detect and locate plastic shopping bags in cotton fields. Detection of plastic bags in cotton field becomes more challenging when bags are white, green or brown in color as cotton bolls and cotton plants appear spectrally similar. To address detection issues for spectrally similar objects, a texture-based classification approach was used. Ding et.al. (2009) showed that gray level co-occurrence matrix (GLCM) based texture features can be used to discriminate cotton contaminants efficiently. Haralick et.al. (1973) initially proposed fourteen statistical features from GLCM values for texture-based classification. However, Ding et al. (2009) preferred only three of them (correlation, entropy and contrast). We used seven of them (variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation) in an exploratory process. Yadav et. al. (2019) showed that supervised classification algorithms like Mahalanobis Distance classification, when used after extracting textural features, can yield better classification results. Another factor that can pose a challenge in detection is height of plastic bags attached to cotton plants. Hence, we tested variation in detection accuracy as a function of height on plants and color of bags.

Experimental Site

We conducted two experiments at two different locations: Weslaco in southern Texas, and College Station in central Texas. The test was conducted before defoliation in Weslaco on June 28, 2019, and after defoliation in College Station on October 24, 2019. A commercial cotton farm was chosen in Weslaco (figure 1, left), while the university research farm was used in College Station (figure 1, right). Regions within red box represent areas of test for which results are presented in this paper. Yellow boxes represent sections in which plastic bags were tied in some randomly generated order that is explained under “experimental design” section.

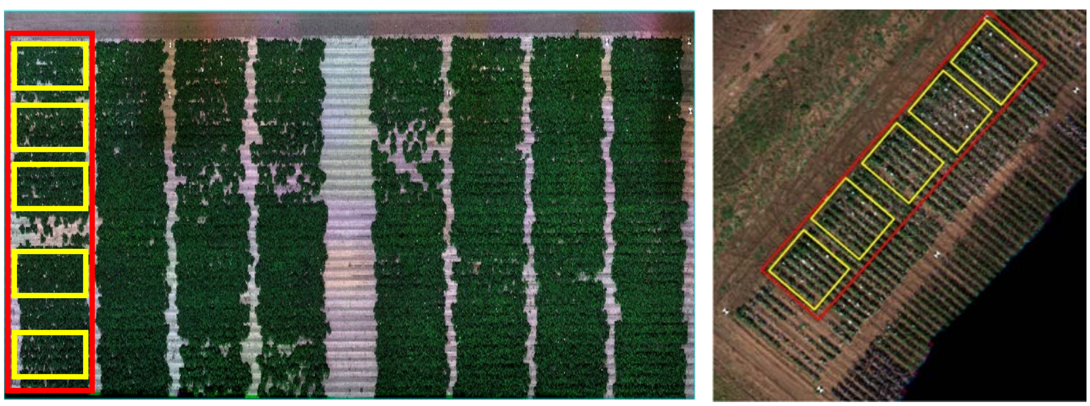
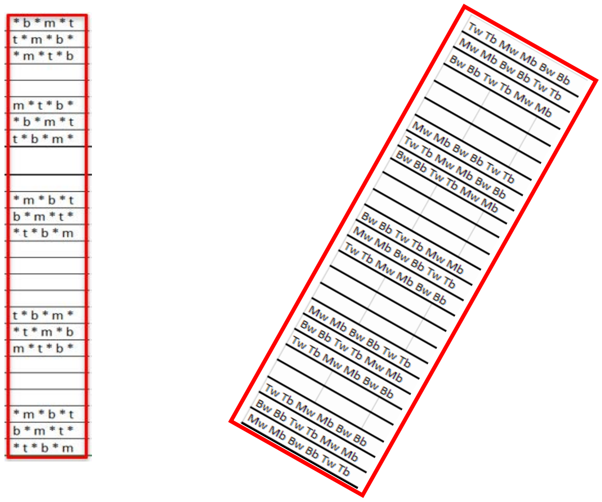


Figure 1. Test plot area for Weslaco, TX (left) and College Station, TX (right)

Experimental Design

Plastic bags of size 29 cm x 56 cm were purchased from a commercial grocery store and tied at three different heights on cotton plants (top, middle and bottom). Only white shopping bags were used in Weslaco while white and brown bags were used in College Station. The order in which the various heights and colors were placed (Figure 2: Weslaco at left, College Station at right) was randomly generated with Microsoft Excel software. A total of 45 white plastic bags were used in Weslaco and 90 bags in College Station



Height/Color Code	Height/Color
t	Top
m	Middle
b	Bottom
Tw	Top-White
Tb	Top-Brown
Mw	Middle-White
Mb	Middle-Brown
Bw	Bottom-White
Bb	Bottom-Brown

Figure 2. Plastic bags randomized order for Weslaco (left) and College Station (right)

Aerial Data Collection

A RedEdge multispectral camera (MicaSense, Seattle, WA) mounted on a DJI Matrice-100 quadcopter (DJI, Shenzhen, China) was used to collect aerial imagery at an altitude of 60 ft above ground level (AGL) providing 4.1 cm/pixel ground sampling distance (GSD). The RedEdge camera consists of 5 spectral bands with center wavelengths as shown in table 1.

Table 1. Center wavelength of each spectral band of MicaSense RedEdge sensor

Spectral band	Center Wavelength (nm)
Blue	475
Green	560
Red	668
RedEdge	717
NIR	840

Figure 3. DJI Matrice-100 (left) and Micasense RedEdge multispectral camera (right)

Image Processing Algorithm

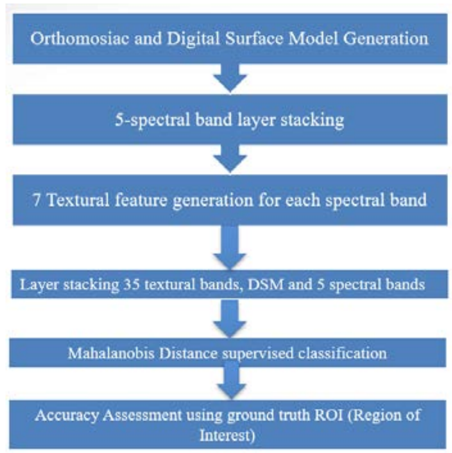


Figure 4. Image processing algorithm flowchart

Figure 4 is a flowchart representing the steps carried out to implement the image processing method. Once an orthomosaic and a digital surface model (DSM) were generated with Pix4DMapper Pro software, ENVI 5.5 (64-bit), ArcMap 10.6 and Python 3.5 software were used for post-processing the images. A 3x3 filter represents nine pixels of 4.1 cm each on ground which roughly translates into 10% of total bag area. This filter size was chosen because it gave detection resolution of 10% of plastic bag size. Texture classification on individual bands showed the maximum variance along 90^o. Hence, all five spectral bands were layer stacked, and then a 3x3 co-occurrence filter was used in the direction of 90^o to extract seven textural features for each band. The textural features from each spectral band were added to the layer stack along with the DSM layer in order to integrate an elevation feature. Then Mahalanobis distance supervised classification was used to obtain a final classified result. Classification aggregation was used as a post-classification method, and the aggregation parameter was 98 pixels, which roughly corresponded to the full size of a plastic bag. Finally, a confusion matrix was generated to obtain pixel-based classification accuracy. A ground truth RGB (Red, Green, Blue) image was used for this purpose. Morphological transformations (erosion and dilation) were implemented with OpenCV library in Python 3.5 to smoothen out pixels near object boundaries. A 5x5 kernel with an iteration of 1 was used for this process. Bag-based classification accuracy was obtained by matching GPS coordinates of detected regions of bags along with bags seen in the RGB image and the design layout as shown in figure 2.

Results and Discussion

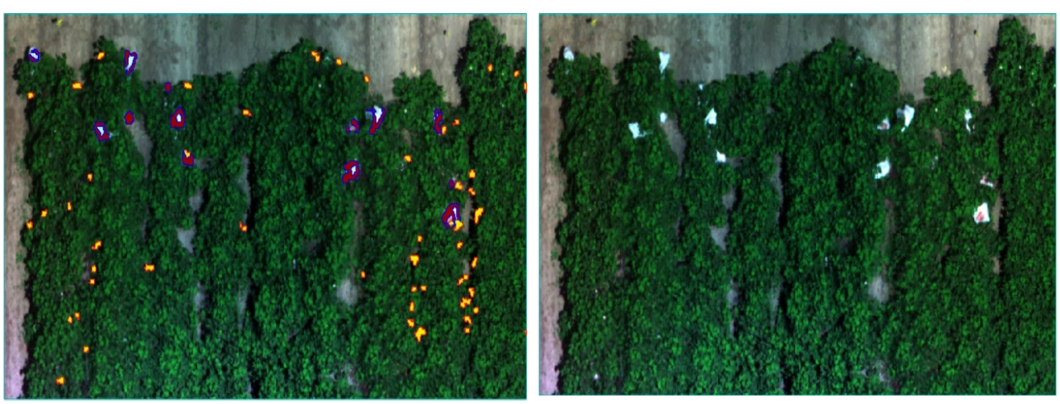


Figure 5. Detected plastic bags (left) and ground truth RGB image (right)

Figure 5 is a representation of the results in Weslaco. The left image shows detected areas of plastic bags marked by purple colored regions, whereas orange regions are detected regions of cotton bolls. The right image is the ground truth RGB image for the same section of field. Table 2 shows that white plastic bags were detected with a class accuracy of 64.17 % based on pixel-based classification. Table 3 shows that 10 out of 15 top bags were detected, resulting in an accuracy of 67%, while middle bags were detected with an accuracy of 60% and bottom bags were detected with an accuracy of 40%.

Table 2. Pixel-based classification accuracy for Weslaco

Class	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
	Percent	Percent	Pixels	Pixels
TX Soil	99.62	99.91	56580/56794	56580/56631
TX_CottonPlant	85.63	75.56	739/863	739/978
Tx_CottonBoll	55.75	20.90	223/400	223/1067
Tex_PlasticBag	**64.17**	86.79	1524/2375	1524/1756

Table 3. Bag-based classification accuracy for Weslaco

Weslaco-Test	Actual	Detected	Accuracy
Top	15	10	66.67
Middle	15	9	60.00
Bottom	15	6	40.00

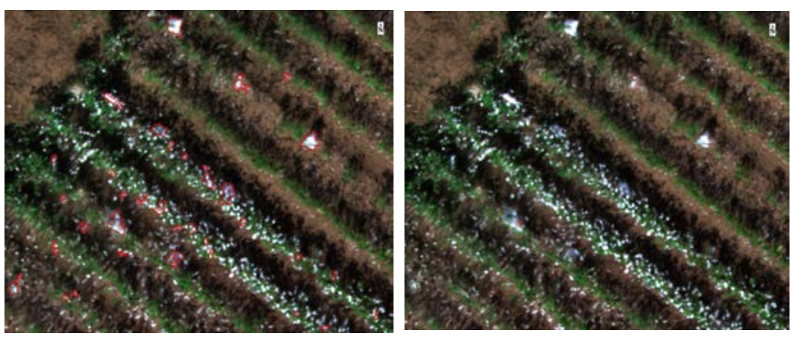


Figure 6. Detected plastic bags before morphological transformation (left) and ground truth RGB image (right)

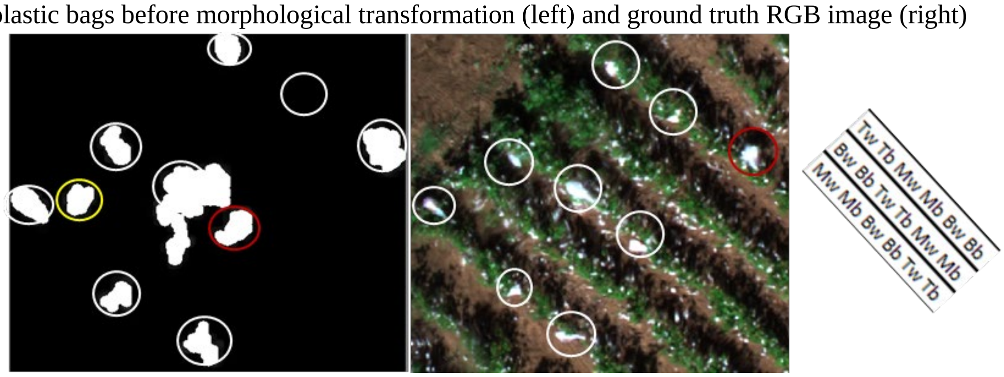


Figure 7. Detected plastic bags after morphological transformation (left) and ground truth RGB image (right)

Figures 6 and 7 are representations of the results in College Station. The left image in figure 6 shows detected plastic bags for a section of field. This is the result before morphological transformation was performed. The left image in figure 7 shows detected plastic bags after the morphological transformation was performed. White circles around objects represent detected while plastic bags, while brown circles around objects represent detected brown bags; yellow circles around objects represent mis-classified regions. A white circle around a black region represents no detection of a bag even when a bag was present, as seen on ground truth RGB image at right.

Table 4. Pixel-based classification accuracy for College Station

Class	Prod.acc (percent)	User acc. (percent)	Prod acc. (pixels)	User acc. (pixels)
Plastic_bags	90.07	100.00	1207/1340	1207/1207
Nobags	100.00	81.27	577/577	577/710

Table 4 shows that plastic bags were detected with a class accuracy of 90% when other remaining classes were combined together as a “Nobags” class. This outcome was unlike the test in Weslaco, in which remaining classes were not combined together. Since this College Station result is a binary classified result, morphological transformation could be implemented on the images unlike those from Weslaco. Table 5 shows that top-white bags were detected with a maximum accuracy of 73%, while bottom brown bags were detected with the least accuracy at 13%.

Table 5. Bag-based classification accuracy for College Station

TAMU-Farm-Test	Actual	Detected	Accuracy
Top(B)	15	9	60.00
Top(W)	15	11	73.33
Middle(B)	15	3	20.00
Middle(W)	15	8	53.33
Bottom(B)	15	2	13.33
Bottom(W)	15	4	26.67

Summary

The image processing algorithm developed was successful at detecting plastic bags in cotton fields with good detection accuracy in certain cases. Namely, white bags near the tops of defoliated cotton plants were detected roughly 9 times out of 10. Further field trails are required to test repeatability and performance accuracy of the methods and classification algorithm. The algorithm presented here is semi-automatic and still requires manual image annotation. The future goal is to make the detection algorithm fully automatic and detect plastic bags in near-real time by implementing a convolutional neural network (CNN). GPS coordinates of detected locations of plastics bags could be used by ground-based autonomous vehicles to collect the identified bags, thereby reducing the requirement for labor.

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