COTTON FOREIGN MATTER DETECTION USING HYPERSPECTRAL TRANSMITTANCE IMAGING

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Abstract

Cotton plays an important role in the U.S. national economy. This commodity can be contaminated by various foreign matter (FM) during harvesting and processing, leading to potential damage to textile products. Current sensing methods can only detect the presence of foreign matter on the surface of cotton, but cannot detect and classify foreign matter that is mixed with and embedded inside the cotton. This research focused on the detection and classification of common foreign matter hidden within the cotton lint by hyperspectral transmittance imaging in the spectral range from 950-1650 nm. Three cultivars of cotton and 10 common types of foreign matter were collected from the field and the foreign matter were sandwiched by two thin cotton lint webs. The transmittance imaging platform was designed and optimized for the best performance of the transmittance mode. After acquiring images of cotton and foreign matter mixture, minimum noise fraction (MNF) rotation was utilized to obtain component images to assist visual detection and mean spectra extraction from a total of 141 bands. Linear discriminant analysis (LDA) and support vector machine (SVM) were performed for classification at the spectral and pixel level, respectively. Over 90% of the accurate classification rate was achieved for the spectral data and about 95% for the pixel classification. The preliminary results demonstrated that it was feasible to detect certain types of foreign matter that was buried within cotton using hyperspectral transmittance imaging.

Introduction

Foreign matter (FM) could affect the quality, appearance, and price paid for textile products, as well as the performance of ginning (Himmelsbach et al., 2006). In cotton industry, ginning is a very significant process to separate cotton fiber from seed and clean cotton lint. Ginners must balance the effect of trash removal and fiber damage depending on accurate identification of foreign matter (Anthony and Mayfield, 1995). Since the ginning procedures and cotton quality assessment were affected directly by the content of FM, it is important to classify cotton FM to improve cotton grading and provide information for processing of cotton (Fortier et al., 2011).

Recently, many studies have been conducted for the identification of cotton foreign matter. Color imaging based method was widely used, due to its relatively ease of use, high speed, and spatial information (Huang and Xu, 2002; Bel et al., 2012). For instance, the high volume instrument (HVI) employs color imaging to obtain trash percent area and trash particle count. Although HVI provides a relative measurement of cotton trash, it cannot give detailed information about the type of cotton trash (Foulk et al., 2006), because color camera can hardly classify foreign matter with similar color.

Spectroscopy could improve the classification performance by providing more spectral information. Fourier transform near-infrared (FT-NIR) spectroscopy was investigated to distinguish individual types of cotton trash from the fiber and achieved over 98% identification accuracy of cotton trash (Fortier et al., 2011; Fortier et al., 2012). Most foreign matter from machine harvesting, such as stem, bract, hull and seed, are composed of lignin or protein, while cotton lint is mainly composed of cellulose (Himmelsbach et al., 2006). Lignin, protein, and cellulose are made of molecular bonds such as CH_3, OH and NH that have absorption bands in the NIR spectral range (Wakelyn et al., 2006). The spectral range from 780~1800nm was optimal for distinguishing these foreign fibers, such as polypropylene and polyethylene materials, hairs and feathers (Yang et al., 2009). However, spectroscopy cannot provide spatial information for image classification of FM with cotton.

Hyperspectral imaging can provide not only spatial information in the form of an image at a certain wavelength, but the spectral information of any pixels on the image. With both spatial and spectral information, the hyperspectral imaging technique has become an emerging analytical tool for quality detection(Lu and Chen, 1999) . A hyperspectral imaging system was developed to detect cotton lint foreign matter. The results showed that this system is effective to recognize and classify FM on the lint surface with the correct classification result of over 90% (Jiang and Li, 2015b; Jiang and Li, 2015a). For foreign matter hidden within the cotton, one study investigated the detection at the depth of 1~6 mm in cotton using hyperspectral imaging based on reflectance mode (Guo et al., 2012). The results indicated that the detection was affected by the depth of the cotton lint. At the depths of 3~4mm and 5~6mm, the spectra of foreign matter were not clearly differentiated from the cotton.

Transmission characteristics of foreign matter are different from cotton lint due to decreasing level of the light energy after transmission. Using multispectral CCD camera with optical transmittance mode to detect foreign matter could manage the issue of difficulties in inner foreign matter detection (Jia and Ding, 2005). For the foreign matter that were buried in deeper depth in cotton, Jia and Ding utilized transmittance for their research on the detection of foreign matter buried in about 10mm depth in cotton. The detection ratio was 91% for cotton tread, bristles and nylon wire. Their experiment showed that transmittance could be an effective method to detect a wide range of foreign matter below the surface (Jia and Liu, 2008). However, classification of cotton foreign matter using hyperspectral transmittance imaging has not been reported.

Overall, the goal of this study was to explore the feasibility of hyperspectral imaging system using transmittance mode to detect and classify common types of foreign matter that were hidden inside the cotton lint at the spectral range of 950~1650nm. The specific objectives of this study were to: (1) extract and compare the pure spectra of FM with the mixed spectra of FM and cotton; (2) classify cotton FM at the spectral and imaging domain.

Materials and Methods

Cotton Lint and FM samples

The lint from three cotton cultivars and ten types of foreign matter (Figure 1) were collected from the field during 2014 harvest season on the Tifton Campus of the University of Georgia Tifton Campus. The three cotton cultivars were Stoneville (ST) 6448, PhytoGen (PHY) 499, and Delta Pine (DP) 1252. The botanical FM included stem, seed coat, seed, hull, bract, bark and green leaf, which were manually selected from the seed cotton and ginned cotton rash. The Non-botanical FM contained twine, paper, plastic package, which were mixed with the lint during machine harvesting and packaging process.

When foreign matter were hidden inside the cotton layers, it was difficult to find them by human naked eyes, so the size of the FM was purposely prepared larger than typical FM found in lint. Stem, bark and twine were clipped to about 10mm in length and hull, bract, green leaf, paper and plastic package were cut into square shape with about 10×10mm. Seed coat and seed were kept their original size and shape.

To obtain the pure spectra of each type of FM and the spectra of the FM when they are mixed with lint, there were two methods to prepare samples. To extract pure spectra of the FM, four replicates of nine types of FM were prepared except plastic package, because the camera was saturated with the light passing through the thin plastic package directly. A black paper mask (240×200 mm) with four very small rectangular holes (1~1.5×5mm) was made to hold the foreign matter, with FM fully covering the holes. For lint with FM inside, 30 replicates of FM and 60 replicates of thin lint web (10~12×12~14cm in shape, 6~10mm in thickness, 0.5~0.8g in weight) were made by hand. To avoid the effect of other unknown FM and cotton unevenness, the lint webs were cleaned and disentangled manually. For mixed samples, ten types of FM were sandwiched between two lint webs.

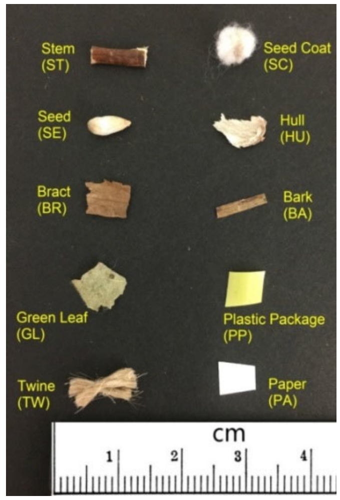


Figure 1. Ten types of foreign matter

Hyperspectral Transmittance Imaging System

A shortwave infrared (SWIR) hyperspectral imaging system based on liquid crystal tunable filter (LCTF) developed by the Bio-sensing and Instrumentation Lab at the University of Georgia was utilized to acquire images of FM and cotton using transmittance mode (Figure 2). The system consisted of a hyperspectral imaging subsystem (HIS), an illumination unit and an objective table. The HIS was integrated by a LCTF (LNIR 20-HC-20, Cambridge Research &Instrumentation, Cambridge, MA, USA), an indium gallium arsenide (InGaAs) SWIR camera (SU320KTS-1.7RT, Goodrich, Sensors Unlimited, Inc., Princeton, NJ, USA) combined with an near infrared lens (SOLO 50, Goodrich, Sensors Unlimited, Inc., Princeton, NJ, USA) (Wang et al., 2012b). The imaging procedure was controlled by an in-house built LabVIEW program using a computer (Intel® Pentium® D Processor, 4 GB DDR3, Windows 7) via the Camera Link (Wang et al., 2012a). To provide a wide spectrum illumination, a halogen floodlight (Portfolio® 50W T4, L G Sourcing, Inc., NC, USA) was supplied by adjustable direct current (DC). To obtain transmittance images, the sample was held by a floated borosilicate glass plate (BOROFLOAT® 33, thickness = 2.00 mm, Home Tech SCHOTT North America, Inc., Louisville, KY, USA) of the objective table above the halogen light. The glass plate has over 90% transmission in near infrared spectral range. To make the cotton lint web uniform for acquiring better quality images, the sample was pressed by the same type of glass plate and four wood blocks were placed in four corners to increase cotton uniformity. The weight of each glass plate was 200 g and for the weight of each wood block was 100 g. The total weight on top of the sample was 600 g. The FM with the black mask were clamped with the two glass plates to ensure the same condition of illumination as the mixed samples.

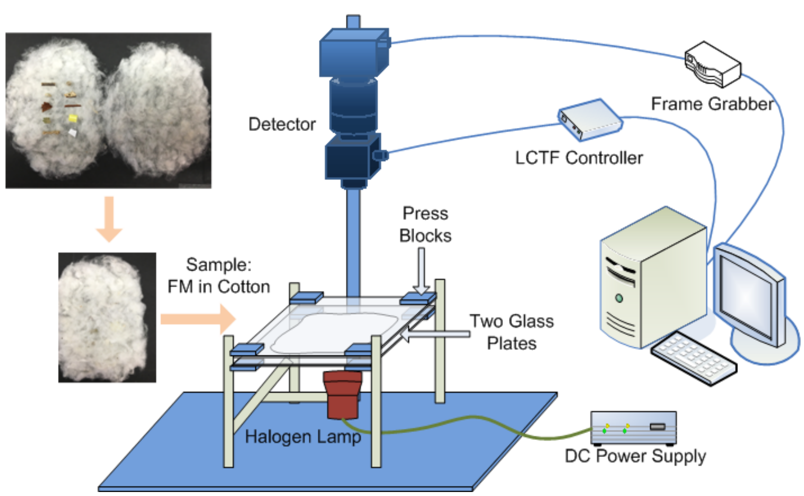


Figure 2. Hyperspectral transmittance imaging system

All samples were scanned from the spectral range of 950 to 1650 nm with a 5 nm spectral interval. The samples were kept in an enclosed chamber to avoid interference from the ambient light. The light was powered under the condition of 24W and 12V. The distance from the lens of the camera to the button glass surface was 875 mm. Figure 3 shows the principles of hyperspectral imaging. After scanning a sample, a three-dimensional (x, y, λ) image cube was constructed with both spatial (320×256 pixels) and spectral data (141 wavelength bands). The spatial information of x and y can form an image at a certain wavelength and a pixel in the 3D image cube represents a spectrum.

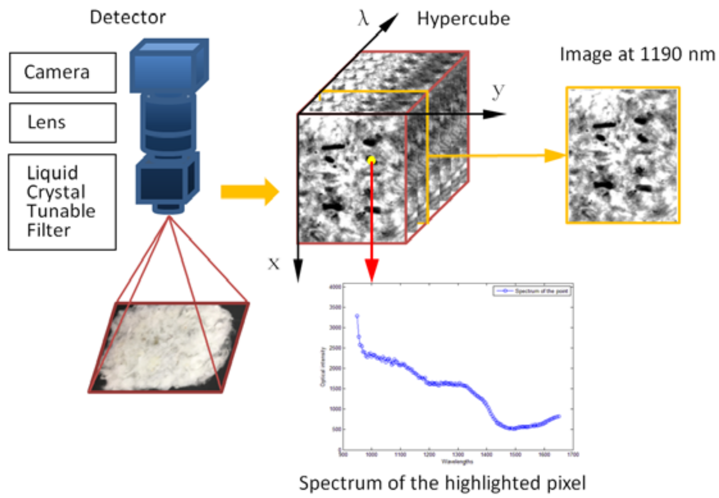


Figure 3. The principles of hyperspectral imaging

The acquired transmittance images were calibrated using flat field correction algorithm (Equation 1) implemented in Interactive Dynamic Language (IDL4.7, Exelis Visual Information Solutions, Boulder, CO, USA) (Wang et al., 2012c). The bright images were acquired by replacing the sample with polytetrafluoroethylene (PTFE) Teflon (Wang et al., 2013) plate (300×165×13.30mm) between the two glass plates, and dark images were acquired by covering the lens of the camera. The relative transmittance intensity value I_R was calculated by:

$I_R = 4095*(I_T-I_D)/(I_B-I_D)$. (1)

I_T: pixel intensity of the transmittance image of a sample

I_D: pixel intensity of the dark image

I_B: pixel intensity of the bright image

The coefficient 4095 is the maximum intensity that the image can express (12-bit image). The bright and dark images were acquired for every 5 samples.

MNF Rotation and Spectra Extraction

Before data processing, images were cropped into 180×250 pixels, in order to remove the large amount of noise around the border caused by mismatching of the raw image and reference images during flat field correction. Minimum noise fraction (MNF) rotation is an algorithm that can reduce the spectral dimension and de-noise in the spatial dimension for hyperspectral images (Xu et al., 2013). This method separates signal and noise of the hyperspectral image before performing the rotation, thus improved image quality and features can be obtained with MNF components (Lu, 2003).

For the images of mixed samples, prior to performing minimum noise fraction (MNF) rotation, the band of the first wavelength 950 nm was removed from the cube, because the band contained unusually high noise values. The 180×250×140 image cube of sample was processed by MNF rotation to assist visual detection and region-of-interest (ROI) extraction, because of difficulties in recognition of foreign matter within cotton. One of MNF component images that showed best contrast between the FM and lint would be selected. Based on this MNF component image, the ROIs of FM and lint were extracted manually, and then mapped on the original image cube to obtain the mean spectra. For the images of FM with the black mask, the mean spectra were directly extracted manually using ROIs method.

After extracting the spectra, normalization (Equation 2) was performed to define the relative transmittance in the range of 0~100%. It was done by dividing the original relative intensity at each band by the maximum intensity value found in the whole spectra sets, including the spectra of FM and FM mixed with cotton. The normalized relative transmittance T_R (%) was generated by:

$T_R = I_R / I_{max} \times 100\%.$ (2)

I_R: the relative transmittance intensity

I_{max}: the maximum intensity

The software ENVI 4.7 (ITT Visual Information Solutions, Boulder, CO, USA) was employed to conduct image cropping, band removal, MNF rotation, ROI selection, and mean spectra extraction of ROIs. For spectra normalization, MATLAB 2014 (The MathWorks Inc., Natick, MA, USA) was utilized to perform the algorithm.

Classification

Linear discriminant analysis (LDA) was employed to classify FM with cotton lint using mean spectra with full wavelengths of a total of 330 samples (30 replicates of 10 types of FM and cotton lint). The discrimination performance was evaluated by the percentage of samples that were correctly classified using the leave-one-out cross-validation. LDA was performed in SAS (SAS 9.4, SAS Institute Inc., Cary, NC, USA).

Support vector machine is a supervised learning model that is widely used for classification and pattern recognition(Foody and Mathur, 2004). SVM classification method was used to classify FM at the pixel level. In this study, the radial basis function was selected as the kernel function, and the values of the two important parameters (gamma in kernel function and the penalty parameter) were optimized by ENVI software. Before performing SVM classification, to reduce spectral dimensionality of the hyperspectral cube, only the MNF components that explained more than 0.5% of the total variation were selected. The selected MNF component images were used to conduct SVM classification. Firstly, ROIs of different types of samples were extracted manually as the validation sets. Then, 30% pixels in each validation set ROI were generated randomly as training sets . Eventually, the SVM method was applied to classify the FM and lint in this image.

Results and Discussion

Spectra Extraction

After acquiring and cropping images, the component images were generated by MNF rotation of raw hyperspectral images. In Figure 4, taking the color image (Fig.4a) of FM without covering lint web as visual comparison, the FM on the transmittance image (Fig.4e) at 1200nm were not clearly identifiable. After MNF rotation, the first three MNF component images (Fig.4b, c and d) revealed more effective information for foreign matter, especially component 1 (C 1). Thresholding was utilized to enhance the visual detection (Fig.4f) of the C 1 image using the gray value of 210. Most of the FM were segmented from the lint. Based on this result, ROIs of each type of FM were selected from the component 1 image (Fig.4g), which were marked by different colors, and then mapped on the original hyperspectral images (Fig.4h) to obtain the mean spectra. For the images of FM without cotton, mean pure spectra were obtained directly by ROIs method.

After spectra extraction, the maximum I_R was found to be 6946. The normalization region was defined to [0 1], by selecting I_{max} = 7000 as the maximum intensity.

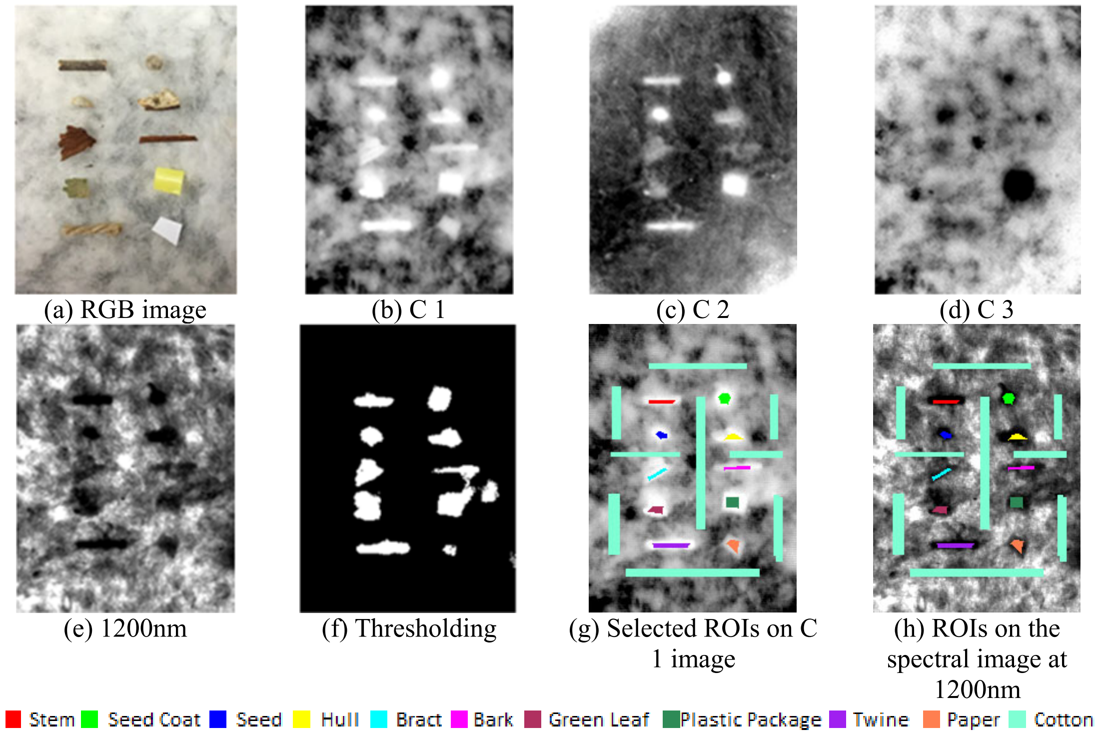


Figure 4. MNF component images and ROIs extraction

Figure 5 showed the mean pure spectra and the mean mixed spectra of each type of foreign matter with the error bar. For stem, seed coat, seed, hull, bark and twine, the intensity of the spectra of mixed samples was higher than that of the pure FM spectra, whereas the cotton layer decreased the spectral intensity for other FM. In general, stem, seed coat, seed, hull, bark, and twine were thicker than the other types of FM and had high density that light can hardly pass through, since they almost completely blocked the light when they were placed on the black mask. In contrast, more light was scattered and reflected by cotton layer around the FM when they were placed between thin cotton lint webs, resulting in higher intensity of the spectra. For thinner FM, more light can pass through FM and the transmitted light was affected by cotton layer's transmitted and scattering light. As a result, the spectra intensity of bract, green leaf and paper in cotton was lower than that of FM examined individually without cotton.

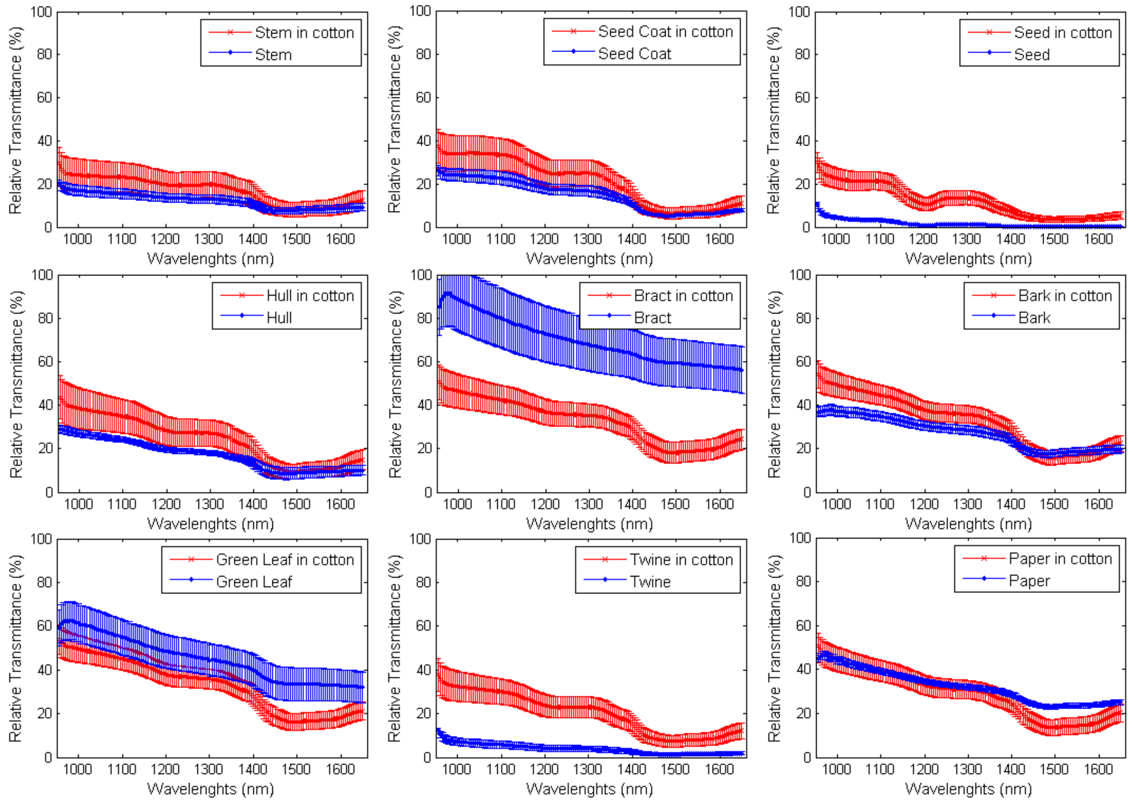


Figure 5. Mean spectra of FM and FM mixed with cotton (error bars indicate standard deviation)

The spectra of most FM had the same trend as the spectrum of cotton, because they were affected by the cotton lint when they were sandwiched between cotton lint webs (Figure 6). For plastic package, seed, and seed coat, their spectra had strong absorption around 1200nm. In the future work, the band 1200nm could be a key feature to analyze. For the spectra of bark and bract, they were pretty close to each other, because they had the same chemical content, similar appearance and thickness.

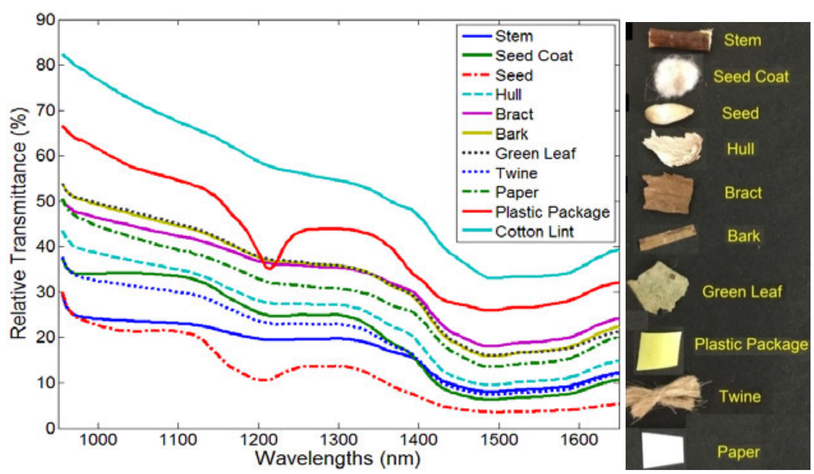


Figure 6. Mean spectra of FM in cotton

Classification at Spectral and Pixel Level

LDA was used to classify various FM mixed with cotton lint based on their spectra. Figure 7 showed the results of classification for each type of foreign matter in cotton lint. For botanical FM, the lowest classification rates were 70%

and 76.67% for bark and bract, respectively, because of their similarities. For stem and hull, the classification results were 83.33% and 86.67%, respectively, since they were both plant tissues with similar structure at the cell level. Green leaf and seed coat had distinct color and thickness, resulting in 90% and 96.67% of correct classification rate, respectively. For non-botanical FM, paper was mostly correctly classified (96.67%) with only one sample being misclassified into stem. The other two non-botanical types achieved 100% classification accuracy. Overall, the average classification rate was 90.91% including cotton lint.

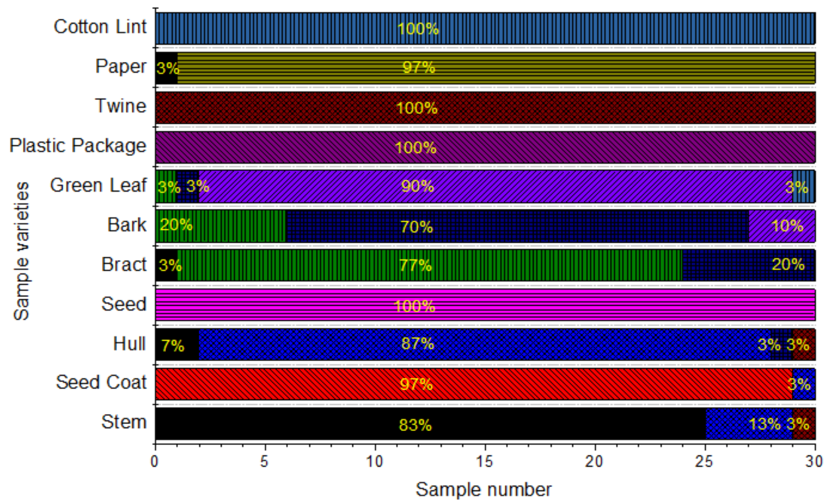
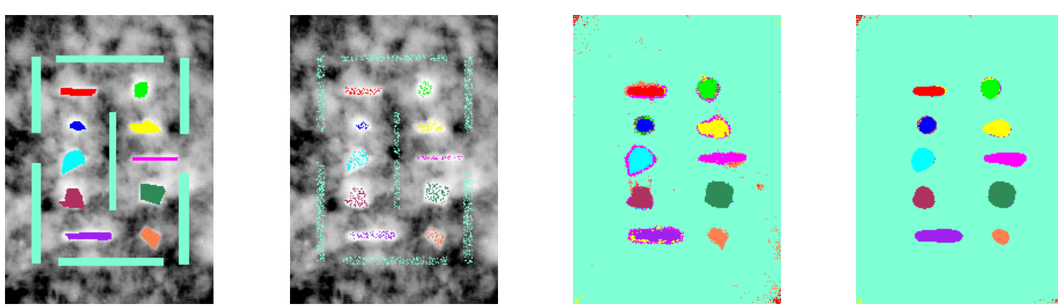


Figure 7. Spectral classification

For the classification at the pixel level, the first 10 MNF component images (eigenvalues were greater than 0.5% of the overall variation) were selected for image classification using SVM. In Figure 8, ROIs were extracted manually as the validation sets (Fig.8a) which were masked with different colors. Then, thirty percent pixels in each ROI were generated randomly from the validation sets as the training sets (Fig.8b). After SVM classification, Figure 8c illustrates that all types of foreign matter and cotton lint were classified well. There were some noises and misclassification around stem, seed coat, seed, hull, bract and twine, so the median filter (kernel size=9) was employed to remove noise of the SVM classification image. In the filtered image (Fig.8d), all types of FM were discriminated from each other and there were less noises and misclassification. The classification results were evaluated by confusion matrix using validation sets as the ground truth ROIs. The average classification accuracy was 95.22% and the overall accuracy was 98.25%. This result indicated that it was promising to classify cotton FM on the hyperspectral transmittance image.



(a) Validation sets (b) Training sets (c) SVM classification map (d) classification map after filtering

Figure 8. SVM classification based on MNF components

Conclusions

This study provided preliminary results of using hyperspectral transmittance imaging to detect and classify ten common types of foreign matter that were sandwiched between cotton lint webs. The MNF component image after thresholding demonstrated good separation between FM and cotton lint when the FM were hidden inside the cotton lint. Correct classification results were 90.91% and 95.22% at the spectral and pixel level, respectively. The preliminary results demonstrated that it was feasible to classify FM using hyperspectral transmittance imaging, when the thickness of cotton sample was less than 5mm.

There were some limitations of this work. The FM used in this study was relatively larger than those found in ginned lint. In addition, image quality was significantly affected by the uniformity of cotton layer that was prepared manually. In future studies, the experiment parameters, as mentioned above, will be optimized. Feature selection methods will be investigated to improve the classification. Online detection and classification will be explored using this method for potential industrial applications.

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