Different cotton foreign matter causes various levels of damage to textile products and decreases the monetary value of cotton. Hyperspectral imaging technique has shown the capability of discriminating the foreign matter, but its large amount of information which is mostly correlated and redundant limits the classification accuracy and processing speed. The goal of this study was to explore a new method of feature selection (minimum Redundancy Maximum Relevance algorithm) to select optimal wavelengths from the visible to near infrared spectra of the hyperspectral imaging data for cotton foreign matter classification. A spectral dataset containing 480 samples was collected from hyperspectral reflectance images of cotton lint and 15 types of foreign matter. Each sample was represented by a mean spectrum containing 256 wavelengths ranging from 400 nm to 1000 nm. The dataset was pre-processed by removing the noise, and the number of wavelengths was reduced from 256 to 223 by removing those with a signal to noise ratio lower than 10 dB. The optimal wavelengths were selected from the pre-processed dataset by a two-stage approach. The first step was to rank the features using the minimum Redundancy Maximum Relevance algorithm and to provide only the top ranked features for the following feature selection. In the second step, the sequential backward elimination was applied to the top ranked wavelengths to select the optimal wavelengths for foreign matter classification. The generality of the selected wavelengths was evaluated by comparing the classification performance using the Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Artificial Neural Networks (ANNs). A total of 12 wavelengths were selected as the optimal feature set for foreign matter classification. Eight wavelengths from the visible range were related to the natural or artificial pigments of foreign matter, and the other four from the near-infrared range were related to the proteins or nutrients in foreign matter. The selected wavelengths achieved average classification rates of 91.25%, 86.67%, and 86.67% for the LDA, SVM, and ANNs, respectively, indicating the generality of the selected features. This study explored a new method for hyperspectral imaging optimal wavelength selection and the selected wavelengths can be used with different classifiers for cotton foreign matter classification.
addition, the shape features are not reliable because the shape of the FM changes over time (Xu et al., 1999). To improve the aforementioned issues, spectroscopic methods have been conducted, including Near-Infrared (NIR) (Fortier et al., 2011; Jia and Ding, 2005a), Mid-Infrared (MIR) (Loudermilk et al., 2008), and Fourier-Transform Infrared (FT-IR) (Himmelsbach et al., 2006). These systems provided extra spectral information for FM classification, but they were impractical for industrial quality inspection due to lack of the FM spatial information.

Combining the strengths from both the color imaging and spectroscopy, hyperspectral imaging provides both spatial and spectral information and has been widely used in food quality and safety evaluation and recently in cotton contamination detection (Jiang and Li, 2015). The preliminary results showed that 14 out of 15 types of FM usually found in U.S. cotton were statistically different from each other, indicating the capability of using the hyperspectral imaging to classify them. However, the data analysis methods of the system have not been fully investigated yet. Typically, each pixel in hyperspectral images contains information from several hundreds of wavelengths, which is much larger than that in traditional color images. Thus, a key aspect for the classification system based on hyperspectral imaging is to reduce the spectral dimension through feature selection (Qin et al., 2013).

Over the past few decades, a large number of feature selection approaches have been proposed and they can be grouped into three categories: filter mode, wrapper mode, and embedded mode (Saeyes et al., 2007). The filter mode ranks the features by assessing their relevance using the intrinsic properties of the data. The lower ranked features are removed and the remaining features are used to form a new subset as the input for classification or other processing. Representative methods of this mode include correlation-based feature selection (CFS) (Hall, 1999), mutual information (MI) based selection (Dhillon et al., 2003), and ReliefF (Robnik-Sikonja and Kononenko, 2003). These methods are easily applied to high-dimensional datasets, computationally simple and fast, and independent of the classification algorithm (Wang, 2012). However, the effects of the selected subset on the performance of classifiers are not considered by this mode (Wang, 2012). To address this issue, the wrapper mode is designed to select the optimal subset by utilizing a specific classifier to evaluate the candidate datasets. Classic approaches using this mode include sequential forward selection (SFS) (Kittler, 1978), sequential backward elimination (SBE) (Kittler, 1978), and genetic algorithm (GA) (Lanzi et al., 1997). Although the subset selected by these methods improves the classification performance, the wrapper-based method is computationally intensive because it has to run cross validation to avoid overfitting. The embedded mode as the third method embeds the feature selection within classifier construction, such as ID3 (Yceba and Aydn Son, 2014) and C4.5 (Lin and Chen, 2012). Both ID3 and C4.5 are decision tree algorithms whose paths from root to leaf represent classification rules. In the paths, the leaf nodes serve as the classification result, whereas the non-leaf nodes mean the features. Typically, more important non-leaf nodes are closer to the root position, and thus this importance order can be used for feature selection as well. However, the generality of the selected subset is limited due to the high dependency on the specifically designed classifiers (Wang, 2012). Recently, a hybrid approach has been proposed to select features by the minimum Redundancy Maximum Relevance (mRMR) (Peng et al., 2005). The mRMR ranks features by minimizing their redundancy and maximizing their relevance. It can be extended with a two-stage mode which firstly reduces the number of features by ranking and then selects the top ranked features by wrapper-based approaches. Since this approach can take advantage of both filter- and wrapper-based modes, it has been widely used for feature selection.

In addition to feature selection algorithms, it is important to validate the generalization of the selected features. Typically, the generalization is tested by the classification performance using different classifiers. The classification models can be divided into two groups: unsupervised and supervised. The unsupervised methods classify new data by finding hidden structure in unlabeled data, whereas the supervised models are first trained by the known data before they are used to predict the classes of unknown data. Since the supervised methods take advantage of the prior knowledge of dataset, their classification performances are relatively better than the unsupervised ones (Kotsiantis, 2007). Thus, in most cases, researchers prefer supervised models. The commonly used supervised classifiers include Linear Discriminant Analysis (LDA) (Martinez and Kak, 2001), Artificial Neural Networks (ANNs) (Mcculloch and Pitts, 1990), and Support Vector Machine (SVM) (Cortes and Vapnik, 1995). The LDA searches a linear combination of features which characterizes or separates two or more classes of the data. Because no parameter optimization is needed, the LDA is considered as the simplest model for classification tasks, but its performance could suffer from non-linear tasks. An important solution to non-linear dataset is ANNs which are a set of statistical learning algorithms inspired by biological neural networks. The ANNs utilize the features as model inputs and determine categories of unknown data by the hidden layers which can compute values from the inputs. Thanks to the hidden layers, the ANNs can process non-linear tasks, and one hidden layer is enough for most non-linear problems (Heaton, 2008). Although the aforementioned models are able to handle both linear and non-linear problems, they could be overfitting when the number of training data is too small. This is because both the LDA and ANNs are based on the empirical risk minimization (ERM). The ERM minimizes the loss (classification error) on the training data, and thus if the training set is too small to represent the sample population, the trained models may perfectly perform on the training set but poorly generalize to the new data. In order to solve this issue, the SVM has been proposed based on the structural risk minimization (SRM). The SRM provides a trade-off between hypothesis space complexity and the quality of fitting the training data. Because of the balance, the SVM can be better generalized to the new data than other models (Meyer et al., 2003). But the parameters used in the model have to be optimized for specific tasks, otherwise, the model performance could degrade significantly. In addition, since the SVM is originally designed for binary classification, it needs to be extended with other strategies for multi-classification, such as one-against-all or one-against-one. The one-against-all constructs k (the number of classes) SVM models for each class, and an unknown sample is classified as the class which its classifier provides the maximum decision value. Whereas, the one-against-one trains k(k-1)/2 SVM models for each pair of classes, and an unknown sample is classified as the class which has the most votes from all classifiers (Lin, 2002). These classifiers based on different strategies are suitable for testing the generality of the selected wavelengths.

The overall goal of this study was to select and justify the optimal wavelengths from the hyperspectral images for cotton FM classification. The specific objectives were to: (1) select and analyze the optimal wavelengths using the mRMR-based method, (2) assess the generalization of the optimal wavelengths by evaluating the classification performance using LDA, SVM, and ANN.

2. Materials and methods

2.1. Spectra of cotton foreign matter and lint samples

A spectral dataset was collected from hyperspectral reflectance images of cotton lint and 15 types FM (Fig. 1). The FM included...
bark inner and outer, stem inner and outer, brown leaf, bract, hull, twine, seed coat inner and outer, seed, green leaf, plastic bag, plastic bale packaging, and paper (Jiang and Li, 2015). There were 30 replicates for each type of samples, and each replicate was represented by its mean spectra extracted using a region-of-interest based approach. Thus, the spectral dataset consisted of 480 mean spectra of the samples.

Prior to processing the dataset, the number of wavelengths was reduced from 256 to 223 based on the criterion of signal-to-noise ratio (SNR). The wavelength with SNR less than 10 dB was considered as noise and removed from the dataset. Thus, the dimension of the resulting dataset was $480 \times 30 \times 223$.

Subsequently, the dataset were equally divided into training and test sets by a partition method provided in MATLAB (MATLAB R2014a, The MathWorks, Inc., Natick, MA). Since the partition method randomly separated the dataset using class information, both training and test sets had 15 replicates for each class. To obtain an unbiased performance evaluation, the training set was used for the feature selection and classifier training, and the test set was used for the performance evaluation of classifiers.

### 2.2. Optimal wavelength selection

Each wavelength was considered as one feature of the sample spectrum, and then the feature selection algorithm was applied on the dataset to extract the optimal wavelengths. The feature selection algorithm was performed in MATLAB.

#### 2.2.1. The mRMR-based feature selection

The minimum Redundancy Maximum Relevance (mRMR) is a feature selection approach based on mutual information (Peng et al., 2005). In information theory, mutual information can be considered as the reduction in uncertainty about one random variable given knowledge of another. Given two random variables $x$ and $y$, their mutual information is defined in terms of their probabilistic density functions:

$$I(x; y) = \int \int p(x,y) \log \left( \frac{p(x,y)}{p(x)p(y)} \right) dx dy;$$  \hfill (1)

Based on mutual information, the feature relevance and redundancy are defined as

$$\text{Relevance}(S,c) = \frac{1}{|S|} \sum_{f \in S} I(f;c)$$  \hfill (2)

$$\text{Redundancy}(S) = \frac{1}{|S|^2} \sum_{f \in S} \sum_{f' \in S} I(f,f')$$  \hfill (3)

where $S$ is feature set, $c$ is sample class, $f$ is individual feature in $S$.

The mRMR ranks features by simultaneously minimizing the redundancy and maximizing the relevance. This operation is implemented by an operator $\Phi$.

$$\max \Phi(\text{Relevance, Redundancy}) = \text{Relevance} - \text{Redundancy}$$  \hfill (4)

The mRMR can be either directly used or combined with other wrapper-based approaches as a two-stage feature selector. The two-stage mode has been widely used for practical applications because it enhances the wrapper feature selection by filter-based methods, achieving both high accuracy and fast speed. Therefore, the present study used the two-stage mode combining the mRMR with the SBE. The SBE was used because it is less computationally intensive compared with randomized wrappers (e.g. GA) and it performs better compared with other deterministic wrappers (e.g. SFS) (Saeys et al., 2007).

The optimal wavelengths for cotton FM classification was extracted using the two-stage framework containing four steps (Fig. 2). The first stage is the filter-based selection of potential features, which consists of three steps. In the first step, all 223 wavelengths of the training set were ranked by the mRMR to form a new feature set $\Omega$. In step 2, 223 sequential feature subsets ($S_i$) from the $\Omega$ set were generated. For instance, the $x$th subset contains the first $x$ features in the $\Omega$. This leads to $S_1 \subset S_2 \ldots \subset S_i \ldots S_{222} \subset S_{223} = \Omega$. The third step is to select the
potential features for SBE selection by determining the $S_k$ which provides the best performance and the most features. The performance was evaluated using the mean misclassification error (MCE) of the 10-fold cross-validation calculated by the LDA. In order to remove the trivial performance fluctuation, the difference in MCEs less than 0.01 was considered as providing the same performance. The last step in the second stage is to select the optimal wavelengths from the $S_k$ by the SBE. The SBE tried to form a new subset $S_{k-1}$ by eliminating one feature from the current subset $S_k$, with the constraint that the eliminated feature provided the least contribution (largest MCE) to classification. The SBE stopped until all features in the $S_k$ were removed and $k$ subsets $S_{k-1}, \ldots, S_1$ were generated. The performance of the $k$ subsets was evaluated by the mean MCE of 10-fold cross validation calculated by the LDA. The subset with better performance and less features was considered as the final subset, and thus the wavelengths in the subsets were the optimal wavelengths for cotton FM classification.

2.3. Classification of cotton foreign matter

Three representative classifiers were applied to classify cotton lint and 15 types FM: the Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Artificial Neural Networks (ANNs). All classifiers were performed using the test set in MATLAB.

2.3.1. Linear discriminant analysis

The LDA constructs a linear combination of features which characterizes or separates classes of observations. The LDA used in the present study was the Fishers linear discriminant analysis which provided by MATLAB. The method uses the mean spectra of each type of samples to train a linear model which maximizes the variance between classes and minimizes the variance within individual classes.

2.3.2. Support vector machine

The SVM is a supervised classifier and has successfully demonstrated in many research areas. The approach is designed for binary classification, which creates a hyperplane separating two classes. Since the cotton trash classification is a multi-class problem, the SVM model used in the current research is based on one-against-one strategy and implemented by an open source package LIBSVM (Chang and Lin, 2011). Besides, the radial basis function was used as kernel function allowing the model to process the non-linear class boundary. In order to obtain the best performance of the classifier, two parameters needed to be optimized: the penalty ($C$) of the model and the gamma ($\gamma$) of the kernel function. According to the package guideline, a grid-search approach was applied to the training dataset to search for the best $c$ and $\gamma$ for each selected feature subset. Prior to training and testing, the dataset were normalized by mapping the row minimum and maximum to the range $[-1, 1]$.

2.3.3. Artificial neural networks

ANNs are computational models presented as systems of interconnected “neurons” which can compute values or make classifications from inputs. In ANNs, there are supervised, unsupervised, and reinforcement approaches. A supervised learning method, the back projection neural network (BPNN), was used in this research. All selected wavelengths were used as the input for the BPNN model, and the categories of samples were the output. The parameters of the BPNN framework were set by default except the size of the hidden neuron. The optimal size was obtained by exhaustively searching from the potential range from 1 to $2 \times k$, where $k$ is the number of the input.

2.3.4. Evaluation standards

Two standards were used to evaluate the performance of the classifier with the selected feature subsets: accuracy and true positive rate (TPR). The accuracy was for evaluating the performance of detecting the FM from the cotton lint, whereas the TPR was for evaluating the performance of classifying FM from each other. Because the FM detection is the first step for the FM classification, and any false negative means misclassification. The accuracy and TPR were calculated by the following equations.

\[
\text{Accuracy} = \frac{\text{\# test true positive samples} + \text{\# test true false samples}}{\text{\# total number of samples}} = \frac{\text{\# test true lint samples} + \text{\# test true FM samples}}{\text{\# total number of samples}} \quad (5)
\]

\[
\text{TPR} = \frac{\text{\# test true positive samples}}{\text{\# labeled true positive samples}} = \frac{\text{\# test type X of FM}}{\text{\# labeled type X of FM}} \quad (6)
\]

3. Results and discussion

3.1. Selected optimal wavelengths

3.1.1. Criteria for determining the optimal subset

The MCE of $S_{99}$ achieved the global minimum, and it was kept relatively consistent in the minimum until $S_{150}$ where the MCE started to significantly increase (Fig. 3(a)). The feature set $S_{150}$ was selected because it provided similar performance (difference in MCE less than 0.01) with the feature set $S_{99}$ but contained more features. Since the performance of the feature subsets from $S_{99}$ to $S_{150}$ was similar, all wavelengths in these subsets contributed to classifying cotton foreign matter. Therefore, the more wavelengths used for the wrapper-based stage, the higher the possibility of selecting the optimal wavelengths would be achieved. The top 150 ranked wavelengths were used for selecting the optimal wavelength in the second stage.

At the second stage, the SBE sequentially removed one wavelength with the least contribution to the classification from $S_{150}$ (Table S2 shows the order of the wavelength elimination). This
Fig. 3. The misclassification error (MCE) of 10-fold cross validation calculated by the LDA: (a) for the subsets generated by mRMR ranking, and (b) for the subsets produced by sequential backward elimination (SBE).

Fig. 4. The spectral responses of the foreign matter and lint at the 12 selected wavelengths.

Fig. 5. Selection of optimal classifier parameters according to classification performance: (a) the optimal C and g for the SVM and (b) the optimal hidden neuron size for the ANN.
led to generating 150 subsets $S_{1}^{150}$ where $S_{150}$ contained 150 wavelengths. The MCE reached the global minimum (MCE is 0.0867) when 112 wavelengths were eliminated, started to increase smoothly until removing 138 wavelength, and then sharply increased when 139 or more wavelengths were removed (Fig. 3(b)). Feature subset $S_{139}^{150}$ (MCE is 0.0987) was selected as the optimal wavelengths because compared with $S_{139}^{150}$, feature subset $S_{139}^{150}$ sacrificed only 0.012 in MCE (13.8% increase in MCE) but eliminated 26 more wavelengths (68.4% reduction in the spectral dimension). The computational efficiency improved by the dimensional reduction was more than the increase of the MCE. Besides, the MCE of using the $S_{139}^{150}$ was acceptable for the classification. Therefore, the 12 wavelengths in $S_{139}^{150}$ were selected as the optimal features to be used for cotton FM classification.

3.1.2. Analysis of the selected wavelengths

The cotton lint and FM showed difference due to their various light absorption properties at the 12 selected wavelengths (Fig. 4). The 12 wavelengths can be categorized into visible and NIR range. The visible range contained 8 wavelengths including 437 nm, 459 nm, 481 nm, 540 nm, 651 nm, 658 nm, 676 nm, and 689 nm, and they were related to the natural or synthetic pigments in the FM. Most botanical FM (e.g. bark, leaf, etc.) contained primary pigment (e.g. chlorophyll a) and accessory pigments (e.g. phlophrytin, carotenoids, anthocyanins). Chlorophylls in acetone solution have strong absorption peaks at 430 nm in the violet-blue range and at 662 nm in the red range (Lichtenthaler and Buschmann, 2001). This correlated to the selected wavelengths at

![Graphs showing classification results](image-url)

**Table 1**
The overall classification performance of the LDA, SVM, and ANN with the selected wavelengths.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy of foreign matter detection (%)</th>
<th>Average TPR (%)</th>
<th>No. of types with TPR &gt; 90%</th>
<th>No. of types with TPR &lt; 60%</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDA</td>
<td>100</td>
<td>91.25</td>
<td>11</td>
<td>0</td>
</tr>
<tr>
<td>SVM</td>
<td>99.58</td>
<td>86.67</td>
<td>10</td>
<td>2</td>
</tr>
<tr>
<td>ANN</td>
<td>99.17</td>
<td>86.67</td>
<td>9</td>
<td>1</td>
</tr>
</tbody>
</table>

Fig. 6. The classification result calculated by the LDA with the selected wavelengths. The test set contained 15 replicates for each type of the samples.
437 nm and in the red range including 651 nm, 658 nm, 676 nm, and 689 nm. Besides, pheophytin also absorbs light of the longer wavelengths in the red range, which is specifically correlated to 676 nm and 689 nm (Milenković et al., 2012). Carotenoids typically have a broad absorption range from 450 nm to 500 nm, which was supported by the selection of 459 nm and 481 nm (Lichtenthaler and Buschmann, 2001). Wavelength 540 nm was selected because of anthocyanins (Gallik, 2015). The anthocyanins are complementary to that of green chlorophyll in photosynthetically active tissues and absorb light in the green range. Since they are mainly distributed in leaves, the green leaf also showed relatively low reflectance at 540 nm. In addition to the botanical FM, the colored non-botanical FM contained artificial pigments, for instance, the yellow pigment in the plastic bale packaging. This yellow pigment absorbed light in the blue range and reflected red and green, which led to the selection of 437 nm, 459 nm, and 481 nm.

The NIR range contained 4 wavelengths including 793 nm, 859 nm, 945 nm, and 985 nm. The FM with similar appearance in the visible range showed difference in the spectral response at these wavelengths. For example, plastic bag was transparent and showed similar color with the background (lint) in the visible range. However, the spectral response of plastic bag was different from that of lint at the NIR wavelengths due to their different chemical compositions. The plastic bag was made of polymers, whereas lint consisted of cellulose. This was consistent with the previous study where the NIR range was used to differentiate plastics from lint (Jia and Ding, 2005a). Since other FM contained various types and amount of chemical compositions (e.g. nutrients or proteins), they could have different spectral responses at the 4 wavelengths in the near infrared region, which can be used for classification.

3.2. Classification using the selected wavelengths

3.2.1. Optimal parameters for classifiers

Optimization of penalty C and gamma g were carried out for the SVM (Fig. 5(a)). For both C and g, the search range were from $2^{-10}$ to $2^{10}$ with step of 0.1 (Hsu et al., 2010). The optimal C ($2^6$) and g
(2⁻⁰.³) were found for the selected wavelengths, when they provided the highest average TPR of the 5-fold cross-validation on the training dataset. Additionally, the optimal hidden neuron size (HNS) of 17 was determined for the ANN (Fig. 5(b)).

3.2.2. Classification performance

All three classifiers provided promising and comparable classification result on the test set, but the overall classification performance of the LDA was better than that of the SVM and ANN (Table 1). The differences in FM detection accuracy of the three classifiers were less than 1%, so it can be considered that they provided the same performance on detecting FM from lint. For the other three performance indicators, however, the LDA performed better than SVM and ANN. This was probably because of the bias in the feature selection. Since the LDA was used as classifier in the wrapper, the selected wavelengths were supposed to be more suitable for the LDA, providing better classification performance than the SVM and ANN. But it is noteworthy that the LDA only classified brown leaf and hull better than the SVM and ANN. In fact, compared with the LDA, the SVM and ANN provided same or similar TPR for most FM and better TPR for bark outer. Therefore, the selected wavelengths are not highly dependent on the LDA but can be generally used by most representative classifiers.

Although the least average TPR was 86.67%, 5 types of FM were frequently misclassified by all three classifiers, including bark outer, stem outer, brown leaf, bract, and hull (Figs. 6–8). One possible reason for these misclassifications is that the samples shared similar spectra. Bark was often misclassified as stem outer, because it was essentially the outer layer of the stem and shared the similar spectra with stem outer. Besides, brown leaf shared the similar spectra with bract, and they were misclassified with each other. Another reason for the misclassification is the spectra variation. Since hull consisted of a dark and hard edge and a bright and soft central part, its spectra varied significantly when they were extracted from different position. For example, the edge was...
similar to twine and the central part was similar to stem inner. Thus, the spectra of hull were mixed with several types of FM, resulting in being misclassified as several FM.

In addition to the sample spectra, the mechanism of classifiers could also affect the misclassification of the five types of FM. The LDA classifies samples based on linear combination of the original features, so it could incorrectly classify one sample if the features of one sample are highly similar to those of other types. For example, bark outer was misclassified as stem outer, and brown leaf and bract were misclassified with each other. In contrast, the SVM transforms the samples from the original feature space into higher dimensional space where the samples are linearly classifiable, and thus the samples could be misclassified if they are similar in the higher dimensional space. Besides, the ‘one-against-one’ strategy could cause misclassification due to the majority voting. For instance, if most SVM models misclassify the sample, the final result should be wrong. Therefore, some samples were misclassified as one type by the SVM but as another type by the LDA or ANN. Although the ANN transformed the samples into higher dimensional space (original feature size was 12, hidden neuron size was 17), it directly classified the sample without voting strategy, and thus resulting in misclassifying stem outer as hull brown leaf.

3.3. Perspectives on an online classification system

The selected wavelengths with commonly used classifiers showed promising classification accuracy, and thus opening an opportunity of implementing an online classification system of cotton foreign matter. The data volume of the hyperspectral images was reduced to 5.4% using the selected wavelengths (12 out of 223 wavelengths). For data acquisition, the hyperspectral imaging system can be reduced to a multispectral one by simply using band filters only corresponding to the selected wavelengths or by using more advanced cameras such as electron-multiplying CCD (EMCCD) (Yoon et al., 2011). For data transfer and processing, special software architecture and data structure need to be considered to simultaneously acquire, transfer, and process the hyperspectral images such as the multithreading technique and circular buffer strategy. Parallel computing technologies could be considered to further speed up the classification such as GPU-based machine learning framework. Additionally, classification performance at the pixel-level needs to be evaluated and explored to ensure the practicability of the system for industrial applications.

4. Conclusions

This study explored a new two-stage approach for hyperspectral imaging optimal wavelength selection. A total of 12 wavelengths in the visible/NIR range were selected for cotton FM classification, including 437 nm, 459 nm, 481 nm, 540 nm, 651 nm, 658 nm, 676 nm, 689 nm, 793 nm, 859 nm, 945 nm, and 985 nm. They were correlated to the chemical properties and compositions of the FM and their generality was validated by three commonly used classifiers. The selected optimal wavelengths could be used for online FM classification system. Future study will be focused on implementing automatic FM image segmentation and classification method using the selected wavelengths.

Acknowledgments

This study was funded by the Cotton Incorporated and Georgia Cotton Commission.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2015.10.017.

References


