Red to far-red multispectral fluorescence image fusion for detection of fecal contamination on apples

Chun-Chieh Yang, Moon S. Kim, Sukwon Kang, Byoung-Kwan Cho, Kuanglin Chao, Alan M. Lefcourt, Diane E. Chan

1. Introduction

As a result of many outbreaks of foodborne illness related to contaminated fruits and vegetables that were reported in the US during the past decade (Mead et al., 1999; FDA, 2001, 2006), interest in methods and technologies for detecting contamination and preventing foodborne illness has grown significantly in the food and agricultural industries and in government regulatory agencies. Rapid and direct detection of pathogenic bacteria on freshly harvested products in the field or on processing lines is a difficult problem, but one approach to assist in risk reduction and food safety assurance is to screen products for indicators of potential contamination. Pathogenic bacteria are closely associated with fecal matter, which can come in contact with food crops and processing operations due to proximity to livestock or wildlife intrusion (Armstrong et al., 1996; Mead et al., 1999; Xicotencatli-Cort and Chacon, 2009). Implementation of real-time, non-destructive online inspection methods to detect fecal matter on the surfaces of fresh produce is one way to help protect public health from potential contamination on fruits and vegetables (Cody et al., 1999; Crohn and Bianchi, 2008). Detection of fecal matter as an indicator for potential contamination allows for further measures to be taken promptly on processing lines to help prevent or minimize potential safety risks. For example, potentially contaminated food products might be subjected to additional washing steps or entirely removed before the packing and distribution operation stages (Kim et al., 2003; Yang et al., 2010). For practical implementation, inspection methods must be easily implemented and cost-effective as well as accurate, so that fresh produce companies can supply safe products without the need to dramatically raise prices.

A variety of non-destructive machine vision systems have been developed to target the rapid inspection of food products for food safety and quality (Cheng et al., 2003; Lu, 2003; Unay and Gosselin, 2007; Yang, 1996). Among these, hyperspectral line-scan imaging systems have recently demonstrated great potential for direct application to food processing lines (Jun et al., 2009; Kim et al., 2005; Yang et al., 2010). Hyperspectral line-scanning systems are now capable of rapid imaging at high speeds matching those of typical commercial food processing lines, and can acquire images at as many precisely selected narrow bandwidths of light as needed from within the broad range of the visible and near-infrared spectrum that is available. Use of full spectrum hyperspectral data can also be implemented, but acquiring and processing excessively large amounts of possibly redundant data simply increases computation time without benefit. Use of selected bandwidths that are not narrowly precise enough can result in less effective differentiation and detection, since finer differences in spectral charac-

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Abstract
This research developed and evaluated three multispectral algorithms derived from hyperspectral line-scan fluorescence imaging using violet LED excitation for the detection of fecal contamination on Golden Delicious apples. The algorithms utilized the fluorescence intensities at four wavebands, 680, 684, 720, and 780 nm, for computation of simple functions for effective detection of contamination spots created on the apple surfaces using four concentrations of aqueous fecal dilutions. The algorithms detected more than 99% of the fecal spots. The effective detection of feces showed that a simple multispectral fluorescence imaging algorithm based on violet LED excitation may be appropriate to detect fecal contamination on high-speed apple processing lines. This fast and non-destructive method for detection of fecal contamination can be implemented in the food and agricultural industries to help in risk reduction and food safety assurance for preventing or minimizing the potential foodborne illness.
teristics might be lost. With these considerations, high-resolution full-spectrum hyperspectral data acquired by a line-scan imaging system can be analyzed to carefully select essential wavebands relevant to the targeted inspection task to develop a multispectral inspection algorithm suitable for rapid online use. Then, if that multispectral algorithm can be implemented using the very same line-scan imaging system, effective inspection can be achieved while bypassing difficulties posed by cross-system calibration requirements typically required for transferring a hyperspectral-derived algorithm for use on a separate multispectral system (Yang et al., 2009, 2010).

There are multiple factors to consider for hyperspectral and multispectral line-scan imaging for food products on a moving processing line, both for the development of effective multispectral methods and for practical real-world implementation (Kim et al., 2003; Yang et al., 2010). Food processors typically operate high-speed processing lines; spectral imaging cameras must be both fast and able to perform sensitive low-light imaging for online use on processing lines. Any illumination source for imaging must provide relevant spectral wavebands for differentiating the inspection target from background product or equipment, and be appropriately selected to best highlight and enhance relevant differences and also to disregard irrelevant attributes. Multispectral inspection algorithms should be fairly simple, to enable rapid real-time computation and potential simultaneous performance of multiple algorithms if needed.

The subject of this study is the development of a simple multispectral algorithm to detect fecal contamination that was applied to apple surfaces. This work continues previous research in developing multispectral food safety inspection methods, with special consideration of the new use of violet LED lights for fluorescence excitation and the analysis of the resulting spectral emissions. A previously developed hyperspectral imaging system was equipped with the new violet LEDs and the hyperspectral fluorescence images were analyzed to develop three simple algorithms that were evaluated for their effectiveness in detecting fecal contamination spots created on Golden Delicious apples.

2. Materials and methods

2.1. Sample preparation

This research used Golden Delicious apples from the Rice Fruit Company (Gardners, PA), with the specific selection of “tree-run” apples to which no wax or other coating was applied after harvest. The apples were transported to the Environmental Microbiological and Food Safety Laboratory (EMFSL), Beltsville Area Research Center (BARC), Agricultural Research Service (ARS), United States Department of Agriculture (USDA) in Beltsville, MD, and stored in a 4°C cold room. Fresh feces of Holstein cows from the Dairy Operations Unit, BARC, ARS, USDA, were also collected for this research, and stored at −4°C prior to use for the experiment.

Four spots of fecal contamination were applied to the surface of each of 59 Golden Delicious apples. The spots were applied using aqueous dilutions of the fecal material at four different concentrations, 1:2, 1:10, 1:20, and 1:50, which contained 0.5, 0.1, 0.05, and 0.02 g, respectively, of fecal material per ml of water. The generally round contamination spots each had a diameter of approximately 5 mm.

2.2. Line-scan imaging system

The major components of the hyperspectral line-scan imaging system used for fluorescence imaging in this research consisted of an electron multiplying-charge-coupled-device (EMCCD) camera, an imaging spectrograph, lens, and a pair of customized light-emitting-diode (LED) line lights. Fig. 1 shows a diagram of the hyperspectral line-scan imaging system. A Luca DL 604M EMCCD camera (Andor Technology PLC, Belfast, Northern Ireland) was used with a Hyperspec VS imaging spectrograph (Headwall Photonics, Fitchburg, MA) with 60 μm slit, attached with a Schneider-Kreuznach Xenoplan 1.4/23 C-mount lens (Schneider Optics, Hauppauge, NY). The two LED line lights, spaced 230 mm apart and 270 mm above the sample-holding surface, provide near-uniform illumination to the linear field of view (FOV) for fluorescence excitation at 410 nm, and were built in-house using 20 violet 410-nm 3-watt LEDs (Sailux Inc., Gwangju, South Korea) for each line light. These violet LEDs were used because fecal material has been demonstrated to exhibit a maximum fluorescence emission at 680 nm under 410-nm excitation (Kim et al., 2003; Pelet et al., 2004), which should provide useful contrast between fecal material and the fruit surfaces. Spectral line-scan imaging in the laboratory is facilitated by the use of a motorized precision positioning table (Velmex, Bloomfield, NY) to incrementally move samples transversely, step-by-step, across the linear field of view, simulating sample movement on processing lines. In this study, the apples were positioned, with contamination spots facing up, on a tray lined with non-fluorescent black cloth and placed on the positioning table. Spectral line-scan imaging was conducted using incremental steps of 0.5-mm.

2.3. Line-scan image acquisition

Each line-scan image acquired by the hyperspectral imaging system contains spectral data along one axis and spatial data along another axis. The EMCCD camera used in this research can produce images sized at 1002 (spectral) × 1004 (spatial) pixels. However, preliminary study found that such high resolution images did not help to detect feces but did make for more difficult waveband selection and longer times for data transfer to the computer. The image size was then reduced by binning both the spectral and spatial dimensions.
special dimensions by two, to 501 × 502 pixels in the buffer of the camera, before transfer of the image data to the computer. The preliminary trial-and-error study also showed that of the 501 available spectral channels spanning 481–780 nm (with an approximate 4 nm interval), analysis of only 76 channels was necessary for waveband selection. The remaining spectral channels could be discarded for their lack of information relevant to feces detection. Thus, the line-scan image size was further reduced to 76 × 502 pixels. Generally, 220–230 line-scan images were acquired to complete the scan of one apple (top-facing side only).

After hyperspectral fluorescence line-scan imaging was completed for the 59 apples, the images of eight apples were randomly selected for a calibration group and the other 51 apple images for an evaluation group. The hyperspectral images of the calibration group were analyzed to select optimal wavebands and to generate a multispectral imaging algorithm using the selected wavebands. For each apple image in the calibration group, 50 pixels were manually selected from areas of uncontaminated normal apple surface and 25 pixels from each of the four spots of diluted fecal contamination (1:2, 1:10, 1:20, and 1:50). Thus, spectral analysis of the calibration group included a total of 400 pixels for normal Golden Delicious apple surface and 200 pixels for each of the four fecal contamination dilutions applied to the apples. The average spectra calculated for apple surface and for the four fecal contamination dilutions are shown in Fig. 2.

2.4. Hyperspectral image analysis

As shown in Fig. 2, the spectra show little in characteristic features between 481 and 648 nm useful to differentiating between apples and fecal contamination, so these spectral channels within this region were excluded from analysis. There were two spectral characteristics between 648 and 780 nm that clearly indicated differences between apples and fecal contamination, regardless of the degree of fecal dilution. First, the peak observed at 684 nm for normal apple surfaces was shifted to 680 nm for fecal contamination, because of the maximum fluorescence emission at 680 nm of feces resulting from 410 nm excitation (Kim et al., 2003). Second, the fecal contamination spectra show a “shoulder curve” between 700 and 740 nm that was absent from the normal apple spectrum. The apple spectrum shows a sharp intensity decrease from the peak at 684 nm to about 700 nm, and then a continued but more gradual decrease between 700 and 780 nm. The feces spectra also show a sharp intensity decrease between 684 and 700 nm and also a more gradual decrease between 730 and 780 nm, but in contrast to the apple spectrum, the feces spectra show a plateau between 700 and 720 nm followed by a sharper decrease from 720 to 730 nm. This shoulder curve around 720 nm was observed for all the fecal dilutions, and not observed for apple. These two spectral characteristics, the peak shift and the shoulder curve, were used for the analysis to select optimal wavebands. This analysis, using the calibration dataset of eight apples, treated all 800 sample pixels of fecal contamination as one group in contrast to the 400 pixels of normal apple surface, because predicting specific concentrations of fecal contamination was not the goal of this research.

2.5. Development of algorithm for peak shift

The fluorescence peak shift was examined independently for the fecal contamination pixels and the apple pixels using the intensities at 680 and 864 nm—\(I_{680}\) and \(I_{864}\), respectively. Linear regressions showed a high correlation between \(I_{680}\) and \(I_{864}\) for the apple group and, separately, for the feces group, but the regressions were significantly different between these two groups, as shown in Fig. 3. The correlation coefficient of the linear regression was 0.9963 for apples and 0.9884 for feces. The linear regression function for apples \(y = 1.1969x - 146.77\) was selected, due to higher correlation coefficient, for calculation of the distance value of a pixel sample, \(D_{PS}\). This value is the vertical distance as calculated between the regression function and the coordinates of a sample pixel \((I_{680}, I_{864})\)—i.e. the difference between \(I_{864}\) intensity of a sample pixel and the calculated value of the regression function using the \(I_{680}\) intensity of the sample pixel, as shown in Eq. (1):

\[
D_{PS} = I_{864} - (1.1969 \times I_{680} - 146.77)
\]

The lower the \(D_{PS}\) value, the higher the chance that the pixel is located within an area of normal apple surface. However, this value cannot be used alone to precisely differentiate between apples and feces, particularly for low-intensity pixels. It can be seen in Fig. 3 that the coordinates for some feces pixels were very close to those for apple pixels.

2.6. Development of algorithm for shoulder curve

The spectral characteristics of the shoulder curve were examined using the pixel intensities at 684, 780, and 720 nm. These val-

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**Fig. 2.** The average spectra for normal apple surface pixels for Golden Delicious apples and for feces pixels from contamination spots on apples for four fecal dilutions, 1:2, 1:10, 1:20, and 1:50.
ues, $I_{684}$, $I_{780}$, and $I_{720}$, respectively, were used to calculate two two-waveband ratios: $I_{720}/I_{684}$ and $I_{720}/I_{780}$. The distribution of the sample pixels based on these two ratios is shown in Fig. 4.

Unlike Fig. 3, Fig. 4 shows more overlap between apple and feces pixels and less correlation between two ratios, both for apples and for feces. Also in contrast to Fig. 3, Fig. 4 shows second-order polynomial regression relationships between the two ratios, and the correlation coefficient is higher for feces (0.6591) than for apples (0.2520). Using the feces regression curve, the vertical distance $D_{SC}$ between the curve and the coordinates of any sample pixel were calculated ($I_{720}/I_{684}$, $I_{720}/I_{780}$) as shown in Eq. (2) to describe the spectral characteristic of the shoulder curve:

$$D_{SC} = \frac{I_{720}}{I_{780}} - \left( -2.5188 \times \frac{I_{720}}{I_{684}} \right)^2 - 1.5994 \times \left( \frac{I_{720}}{I_{684}} \right) + 5.4332$$

Values of $D_{PS}$ and $D_{SC}$ were calculated for all sample pixels in the calibration set. Fig. 5 shows that the apple pixels and feces pixels can be separated more easily using $D_{PS}$ and $D_{SC}$ in contrast to using only the $I_{680}$ and $I_{684}$ fluorescence intensities based on the peak shift as shown in Fig. 3, or only the $I_{720}/I_{684}$ and $I_{720}/I_{780}$ band ratios based on the shoulder curve as shown in Fig. 4. Taking into account both peak shift and shoulder curve by using $D_{PS}$ and $D_{SC}$, no areas of overlap occurred between the apple and feces pixel clusters in the calibration set.

2.7. Development of separate algorithms

Based on Fig. 5, three separate algorithms were developed using calibration set data to detect feces on apples, and then evaluated using data for the 51 apples in the testing set. Each algorithm cal-

Fig. 3. The intensities at 680 nm and 684 nm of 400 apple surface pixels and 800 feces pixels, and the linear regression functions for apples and feces and their corresponding correlation coefficients, respectively, for the calibration data set.

Fig. 4. The fluorescence ratios of $I_{720}/I_{684}$ and $I_{720}/I_{780}$ of 400 apple surface pixels and 800 feces pixels, and the second-order polynomial regression functions and their corresponding correlation coefficients for apples and feces, respectively, for the calibration data set.
culated a single value output for each pixel in the line-scan image, with outputs greater than zero indicating fecal detection.

The first algorithm was developed based on the manual drawing of a simple straight-line boundary on Fig. 5 that separates the apple pixels and feces pixels. The output of this algorithm, \( O_F \), was calculated as shown in Eq. (3):

\[
O_F = D_{SC} - (0.0032 \times D_{PS} - 0.6)
\]  

(3)

The second algorithm was developed using a boundary based on the shape of the cluster of apple pixels in Fig. 5. Three pixels near the outermost edges of the cluster of apple pixels were manually selected and a second-order polynomial regression was fitted to these pixels to form the boundary. The output of this algorithm, \( O_A \), was calculated as shown in Eq. (4):

\[
O_A = D_{SC} - (-0.000002 \times D_{PS}^2 + 0.0038 \times D_{PS} - 0.8313)
\]  

(4)

The third algorithm was developed using a boundary based on the shape of the cluster of feces pixels in Fig. 5. Unlike \( O_F \) and \( O_A \), this third algorithm required use of two second-order polynomial regressions to form an effective boundary for the cluster of feces pixels. Three pixels near the outermost edges of the cluster of feces pixels were manually selected to form one portion of the boundary and another four pixels were manually selected to form the remaining portion of the boundary. The pixel with lowest value of \( D_{SC} \) was selected twice for both boundary determination and was the joint of the two portions of the boundary. In this research, the joint had the \( D_{PS} \) of \(-347.9978\) and the \( D_{SC} \) of \(-1.2531\). When the value of \( D_{SC} \) of the pixel in the image was higher than the \( D_{PS} \) value the joint, the output of this algorithm, \( O_F \), was calculated as shown in Eq. (5):

\[
O_F = D_{SC} - (0.000002 \times D_{PS}^2 + 0.0134 \times D_{PS} + 0.9802)
\]  

(5)

Otherwise, the algorithm calculated \( O_F \) as shown in Eq. (6):

\[
O_F = D_{SC} - (0.00000007 \times D_{PS}^2 - 0.00001 \times D_{PS} - 1.2716)
\]  

(6)

2.8. Detection of fecal contamination

For this experiment, in which spots of contamination were applied to apple surfaces, fully successful detection of fecal contamination by a detection algorithm would produce a higher-than-zero output value for at least one pixel within the area of each of the 204 contamination spots on the 51 apples in the testing group. Successful detection of normal apple surfaces would be achieved with no false-positive detections for pixels within areas of normal apple surfaces.

3. Results and discussion

Three feces-detection algorithms were evaluated using 51 Golden Delicious apples, each of which had four diluted fecal contamination spots, \( 1:2, 1:10, 1:20, \) and \( 1:50 \). Fig. 6 shows example images of the \( O_F \), \( O_A \), and \( O_L \) detection results for eight apples. The white areas in the images indicate pixels detected as feces. The images of 51 apples were visually compared to observations of the real apples for evaluation. In Fig. 6, the \( O_F \) and \( O_L \) algorithms (straight line and apple-boundary algorithms, respectively), generated similar results, detecting all of the fecal spots on the apples. However, the \( O_A \) algorithm had several false-positive detections on normal apple surfaces for 49 of 51 apples—the successful recognition of apples was only 2%. The \( O_A \) algorithm had such false-positive detections on all 51 apples. Fig. 6 also shows that these two algorithms could not adequately remove the image background around the apples areas.

To improve the performance of these two algorithms regarding the background problem, a waveband was selected for use in background removal by thresholding. Since apple spectra and feces spectra both showed peak or near-peak fluorescence intensities at 684 nm (Fig. 2), this waveband was selected to serve for background removal. From previous examination of the spectra, the threshold intensity was set at 600. Pixels with 684 nm intensity less than or equal to 600 could be treated as background and discarded. Fig. 7 shows the improved performance as a result of this background removal step—the \( O_F \) and \( O_L \) algorithms successfully removed background from the images without changing the detection performance within the apples areas.

In contrast, the \( O_A \) algorithm, based on the boundary drawn around the cluster of feces pixels in Fig. 5, generated a result very different from those of the other two algorithms. The \( O_A \) algorithm detected only 202 (99%) of the 204 fecal spots, failing to detect two.
spots of the 1:50 fecal dilution, but had a much higher rate of detection for normal apple surfaces (detection without false positives), correctly detecting 31 (61%) of 51 apples. This is a much lower rate of false positives than that demonstrated by the other two algorithms, and the numbers of false positives on each apple that the OF algorithm did find on the remaining 20 apples were also much lower. Furthermore, this algorithm successfully removed background from the images without using the additional waveband thresholding method that was applied to the other two methods to improve them. Also, the results of the OF algorithm were observed to lack occurrences of false positives related to apple stem areas in the images, which did occur with the other two algorithms.

It can be seen in Fig. 7 that most false-positive detections were for pixels scattered about the apple surface. To further improve the performance of three algorithms, image filters of various sizes were applied to remove the scattered false-positive detections. Each image filter contained $n \times n$ pixels, in which $n$ must be an odd integer since it is the center pixel to which the effects of the filter are applied. The intensities of all pixels surrounding and including this center pixel within the filter were averaged, to replace the original intensity of this pixel. The filter sizes tested were $n = 3, 5, 7, \text{ and } 9$. Further increasing the image-filter size would unacceptably degrade the image resolution. Figs. 8 and 9 compare the results of using these image filters for detection of feces and for differentiation of apples from feces, respectively.

In Fig. 8, the OL and OA algorithms detected all of fecal contamination spots regardless of image-filter size. In contrast, the third algorithm missed one more fecal contamination spot with the $3 \times 3$ image filter (compared to no filter at all) and then missed another spot when the filter size increased from $7 \times 7$ to $9 \times 9$. Overall, the performances of all three algorithms for the detection of feces were very close. The OF algorithm detected 98–99% of the fecal spots with or without any filter while the other two algorithms detected 100% of the 204 spots.

In great contrast to Fig. 8, Fig. 9 shows that the OF algorithm consistently recognized normal apples at a much higher success rate than the other two algorithms did. Moving up from the use of no filter at all, the successful recognition of apples by the OF algorithm increased from 61% to 80% ($3 \times 3$ image filter), 86% ($5 \times 5$ image filter), 90% ($7 \times 7$ image filter), and 94% ($9 \times 9$ image filter). Although increasing the image filter size helped to improve the successful recognition of apples by the OL and OA algorithms, the recognition only increased up to 29% for the OL algorithm, and to 63% for the OA algorithm.

For all three algorithms, instances of false positives—the incorrect detection of feces—were observed scattered randomly across the apple surfaces, instead of aggregating near the peripheral rims of apples where the fluorescence intensities were lower than other apple surfaces. This showed that non-uniform illumination of the apple surface due to uneven shape or curvature would not cause difficulty to any of the three algorithms. This can be of practical benefit in applying these developed algorithms for real-world detection of feces.

From the above results, the OF multispectral algorithm, using a cluster boundary based on six sample feces pixels to separate feces and normal apple surfaces, has the highest potential of the three
algorithms to be effectively implemented by the line-scan imaging system for the detection of fecal contamination on Golden Delicious apples on a processing line. This algorithm required the intensities from only four wavebands, 680, 684, 720, and 780 nm, to utilize four simple functions as shown in Eqs. (1, 2, 5, and 6). In order to implement the selected wavebands to the imaging system, the band interval must be equal to or less than 4 nm in order to be able to distinguish the shift between the peak at 684 nm for apples and the peak at 680 nm for feces on the surface of apples. This algorithm obtained the highest successful recognition of normal apples, almost equally high successful detection of feces spots, and needed no extra image processing work for background removal. To increase the successful recognition of apples, the 7 × 7 image filter could be used to obtain the highest recognition rate for apples when the detection of feces was already higher than 99%. To improve further the performance of this algorithm, more sample images will be collected in the future research, as this algorithm may be an important consideration for real-world applications of non-destructive food safety inspection methods.

In this study, apples were placed on a tray lined with a non-fluorescent black cloth and were illuminated by the violet LED lights. Throughout all the imaging analyses, none of the pixels from the black cloth background caused any false positives for the $O_F$ algorithm. This benefit could help to simplify the detection of feces and the recognition of apples, which may also further increase the computation speed. Should it be necessary to detect the edges of the apples and to count the number of processed apples automatically at the same time, the 684 nm waveband selected by the algorithm could be used with a simple threshold of 600 since the highest intensity difference between apples and the black cloth background was obtained at this waveband. Because counting apples or detecting the edges of apples was not the goal of this particular research, it will be considered for future work.

![Graph](image1.png)

**Fig. 8.** Comparison of the successful detection of feces by three feces-detection algorithms, $O_L$ (first), $O_A$ (second), and $O_F$ (third), with the use of image filters.

![Graph](image2.png)

**Fig. 9.** Comparison of the successful recognition of apples by three feces-detection algorithms, $O_L$ (first), $O_A$ (second), and $O_F$ (third), with the use of image filters.
The EMCCD camera used in the hyperspectral imaging system allows for both hyperspectral and multispectral high speed imaging with high resolution despite low-illumination environments. For each pixel in an individual line-scan, the imaging spectrograph disperses light to form a full-spectrum measurement detected by the EMCCD camera. Compilation of the line-scan images produces a complete hyperspectral image of the target. These hyperspectral images can be analyzed to select specific wavebands useful to a specific application, such as the detection of fecal contamination in this study. The hyperspectral imaging system can then be configured, by software controls, to perform multispectral imaging by transferring only data at selected wavebands from the EMCCD camera to the computer, while discarding the remaining spectral data in the camera buffer. This function avoids the typical need for cross-system calibration required when using two different imaging systems—one hyperspectral, one multispectral—to develop multispectral methods. This function also significantly increased image acquisition speed, and was very helpful for effective spectral scanning of food products on high speed processing lines.

In this research, the use of violet LED lights presented a significant benefit over other fluorescence imaging methods that utilize UV excitation. The violet LED lights result in a high fluorescence emission at 680 nm from feces and not from the food products. Also, there is no need to carry out flat-field calibration as a reference. This simplifies the imaging process and increases the efficiency of the imaging system. The line-scan hyperspectral imaging system was operated in a darkened room during the research to prevent the camera from possibly detecting any other ambient environmental light sources. Consisting of an EMCCD camera, spectrograph, lens, and line lights as shown in Fig. 1, this system could be easily made portable for simple installation on a food processing line. In a real-world application, using such a system and method to detect fecal contamination could create cost savings for the food industry by reducing safety risks of fresh food products and maintaining or increasing the efficiency of food processing.

4. Conclusions

A hyperspectral line-scan imaging system consisting of an EMCCD camera, spectrograph, and lens was equipped with a pair of violet LED line lights for acquiring fluorescence images of Golden Delicious apples to which spots of fecal matter had been applied. A simple multispectral algorithm was developed to detect the different dilutions of fecal contamination on the apple surfaces and to differentiate uncontaminated apple areas from feces. The spectral analysis showed two relevant spectral characteristics: the shift from the peak at 684 nm for normal apple surfaces to the peak at 680 nm for feces on apples, and the shoulder curve formed along the 684, 720, and 780 nm wavebands for feces. The algorithm thus required the intensities from four wavebands, 680, 684, 720, and 780 nm, for simple computation. Six sample pixels of feces were selected to form the boundary to separate the output values of apples and feces. The algorithm detected 99% of fecal contamination spots on apple surfaces. With the help of an image filter, the successful recognition of apples could be improved to more than 90%. The high detection accuracies demonstrated in the study suggest that the simple fecal detection algorithm and nondestructive imaging inspection method may have significant potential for use to help ensure food safety, increase efficiency, and reduce costs for the food industry.

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