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Classification of processing asparagus sections using color images

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ABSTRACT

Impartial classification of Asparagus sections (*Asparagus officinalis* L.), for the purpose of obtaining desired tip to stem pieces ratio in final product, is extremely important to the processing industry. Thus, there is a need to develop a technique that is able to objectively discern between tip and stem pieces, after asparagus has been processed (cut). In this article, a computer vision methodology is proposed to sort asparagus into three classes: tips, mid-stem pieces and bottom-stem pieces. Nine hundred and fifty-five color images from 50 mm length asparagus pieces (cuts) for the three different classes were acquired, using a flat panel scanner. After preprocessing, a total of 1931 color, textural, and geometric features were extracted from each color image. The most relevant features were selected using a sequential forward selection algorithm. Forty-three features were found to be effective in designing a neural-network classifier with a 4-fold cross-validated overall performance accuracy of 90.2% (±2.2%). Results showed that this method is an accurate, reliable, and objective tool to discern between asparagus tips, mid-stem and bottom pieces, and might be applicable to in-line sorting systems.

1. Introduction

Asparagus (*Asparagus officinalis* L.) is a seasonally perennial vegetable that has become very popular around the world (Kidmose and Kaack, 1999; Renquist et al., 2005; Qu et al., 2011; Wei and Ye, 2011; Sánchez et al., 2013). In 2014, approximately 33.7 million kg were produced in the US for the fresh and processing markets (frozen and canned), yielding a total revenue of approximately 73.4 million US$ (USDA/NASS, 2014).

Processing asparagus generally involves the cutting of spears (shoots) into pieces ranging in length of 25–50 mm depending on buyer specifications. Another specification of the final individually-quick-frozen (IQF) product is the ratio of tip to stem pieces, which varies based on the original average spear length and the cut length. The processing industry is recently requiring that processed asparagus contain a higher occurrence of tips to stem pieces than previously specified, as the tips are generally more consumer-desirable from the flavor and texture perspective. Additionally, the asparagus industry, both fresh and processed-frozen, has the challenge of maximizing quality by means of minimizing the occurrence of undesirable stringy or woody-tough fiber. Tough fibrous asparagus is the main complaint of buyers of processed asparagus. It is known that undesirable fibrous pieces are most common in the bottom- or lowest-end of each spear (Werner et al., 1963; Wihelma and Ammerlaan, 1988).

Thus, the opportunity exists to provide a single solution addressing both issues by developing a non-invasive system capable of sorting out the bottom-ends during processing which will decrease the number of stem pieces, and thus increase the ratio of tips to stem pieces, while also reducing the more undesirable fibrous pieces. However, a non-invasive system has never been used to discern between asparagus tips and stems, and there is no methodology that supports the invasive quality assessment of processed asparagus. Because the bottom-ends are often lighter in color and have different textural attributes, it is hypothesized that color imaging can be implemented to classify and sort out less desirable pieces. Computer color vision systems have been used in various foods and agricultural commodities sorting systems today, being objective, reliable, fast, and inexpensive (Brosnan and Sun, 2002; Kumar-Patel et al., 2012). Color computer vision has been effectively used to classify or recognize quality in several agricultural and food commodities including apples (*Malus domestica*) (Paulus and Schrevens, 1999), pistachios (*Pistacia vera*) (Pearson and Toyofuku, 2000), strawberries (*Fragaria* spp.) (Bato et al., 2000), external damage induced by worms in chestnuts (*Castanea* spp.) (Wang et al., 2011), chestnut slices decay (Donis-González et al., 2013), tortillas (Mery et al., 2010), pizza (Sun and Brosnan, 2003b, 2003a), potato chips (Pedreschi et al., 2006), cheese (Wang and Sun, 2001, 2002b, 2002a), and domestic pork meat (Lu et al., 2000; Faucitano et al., 2005).

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The computer vision system is trained from specific patterns of interest extracted from a set of color images, representing different categories (e.g. asparagus tips, middle-, and bottom stems). A pattern or feature is represented by a group of textural, geometric, and image intensity features, which are able to define all of the quality classes. The computer vision system then assigns a new image to a specific quality category or class (Duda et al., 2000). The first step consists in extracting a high number of features (patterns) from the category of known images. After that, features must be selected by their capacity of correctly separating the classes, therefor training the system, and allowing it to automatically classify a new image. Classification is done using statistical and clustering algorithms by assigning each image to its corresponding class (Duda et al., 2000; Mery and Soto, 2008). Complete information regarding statistical pattern recognition methods have been described in several publications, including Jain et al. (2000), Duda et al. (2000), Bishop (2007), and Holmström and Koistinen (2010).

This paper describes a statistical computer vision pattern recognition technique developed to objectively and consistently classify asparagus pieces (tips, middle-, and bottom-stems) using color images. This approach will enable the industry to non-invasively evaluate and dictate the overall pack-out ratio of a processing run of asparagus.

2. Materials and methods

2.1. Sample collection and preparation

Steps used to generate the pattern classification algorithm to discern between tips and asparagus stems (middle and bottom section), using color images are illustrated in Fig. 1. A total of 190 fresh asparagus (c.v. Jersey Giant, a common cultivated hybrid asparagus in Michigan), equal or larger than 150 mm length, were directly hand-harvested from four Michigan commercial production fields (Oceana County, MI) May 2014 and 2015. In addition, with the objective of introducing variability into the color image classifier and experiment, 200 fresh asparagus were purchased from two different Michigan commercial stores. Asparagus were randomized, and manually cleaned with water, with the objective of removing excess dirt. Immediately after cleaning, samples were stored at 4 °C. One day later, color image acquisition was conducted.

2.2. Asparagus section (sample) image acquisition

Immediately after storage, each fresh asparagus was transversely cut into 50 mm sections (segments) using a sharp hand knife. Each asparagus section represented a different sample. Sample distribution for the 3-class-classifier (tips, middle-, and bottom-stems) can be found in Fig. 2. Asparagus samples were manually and randomly set directly over the clean scanner glass (fixed focal point), avoiding the presence of controlled (*e.g. other objects*) and uncontrolled foreign objects (*e.g.* dirt particles). Samples were scanned using a 48 bit color, 9600 × 4800 dots-per-inch (DPI) charge-coupled-device (CCD) scanner (Scan Maker S400, Microtek International Inc., China), using the ScanWizard 5 (Microtek International Inc., China) standard image acquisition software, yielding a tagged image file format (tiff) color image, with a resolution of 816 × 1123 pixels, as seen in Fig. 1. Scan mode was set to true color photo image.

Before every scan, the scanner was thoroughly cleaned, using compressed air in combination with wiping the scanning glass with delicate task wipes, which had been previously soaked in mild non-streak glass cleaner. To avoid variability between images, and to stabilize the intensity of the scanner lamp, the scanner was on for at least 15 min before scanning. The scanner, which was used in this study, is internally calibrated every time it is tuned on, so no calibration and/or calibration targets are required (http://support.microtek.com/product_dtl_2.phtml?prod_id=38).

2.3. Asparagus sample image segmentation

After image acquisition, each asparagus was automatically cropped using Matlab R2012a and its image processing toolbox (The Mathworks, Inc., Natick, MA, USA). Image segmentation was implemented to recognize the region of interest in the image, which is the asparagus in each color image segmented from its background. A combination of simple thresholding (threshold level = −0.05 for values of pixels in normalized images between −1 and 1) and morphologic operations were used to segment each asparagus color image, following the optimized procedure for color image segmentation with an homogenous background, as described in Mery and Pedreschi (2005), and in Donis-González et al. (2013). The segmentation procedure can be found in the "Balu" free toolbox for pattern recognition (Mery, 2015).

2.4. Color image feature extraction and selection

Color components were extracted from color images of each asparagus sample resulting in red, green, and blue (RGB), hue saturation value (HSV), and lightness/color components ($L^*a^*b^*$), using the method proposed by León et al. (2006). In addition, a gray scale image was obtained from each color image (Shapiro and Stockman, 2001). Therefore, ten intensity images were obtained from each asparagus color slice. From these ten images, 1931 features were extracted, as exemplified in Fig. 1. Features were extracted from each of the ten intensity images using the "Balu" toolbox. Extracted features included standard features, invariant shape moments, Haralick textural features (*Tx*), local binary patterns (LBP), and Gabor filters. Extensive information, as well as equations, regarding extracted features can be found in Donis-González et al. (2013). Since rotation invariance is an important criterion for features extracted from the color images, invariance was accomplished for all of the features, by calculating the mean over the four directional feature-matrices (4 offsets).

After extraction and normalization, it is necessary to select the best features to train the classifier (Mery and Soto, 2008). The main objective of the feature selection step, also known as feature reduction, is to obtain a smaller subset of features from the original features that yield the smallest classification error possible (Jain et al., 2000; Zhang et al., 2002). Several feature selection strategies were evaluated using the "Balu" toolbox. Feature selection methods include: (1) The sequential forward selection (SFS) with the Fisher discriminant, k-nearest neighbor (KNN), linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) objective functions; (2) the forward orthogonal search algorithm to maximize the overall dependency (FOSMOD); (3) the rank key features by class sorting criteria (RANKFS), based on the relative operating characteristic curve (ROC); and (4) the student test method (Jain et al., 2000; Bishop, 2007). Steps for all of the algorithms are in depth explained in Jain et al. (2000).

2.5. Classification and validation

A supervised learning approach was used to train the pattern classification algorithm (Duda et al., 2000). Supervised classes, known as labels, were based on three categorical groups assigned by the research team, where each acquired asparagus segment was categorized into one of three section classes (asparagus tips, middle-stem, and bottom-stem sections).

Using the optimized selected features obtained from Section 2.4, decision boundary lines, planes, and hyper planes were implemented using LDA, QDA, Mahalanobis distance (MD), KNN with

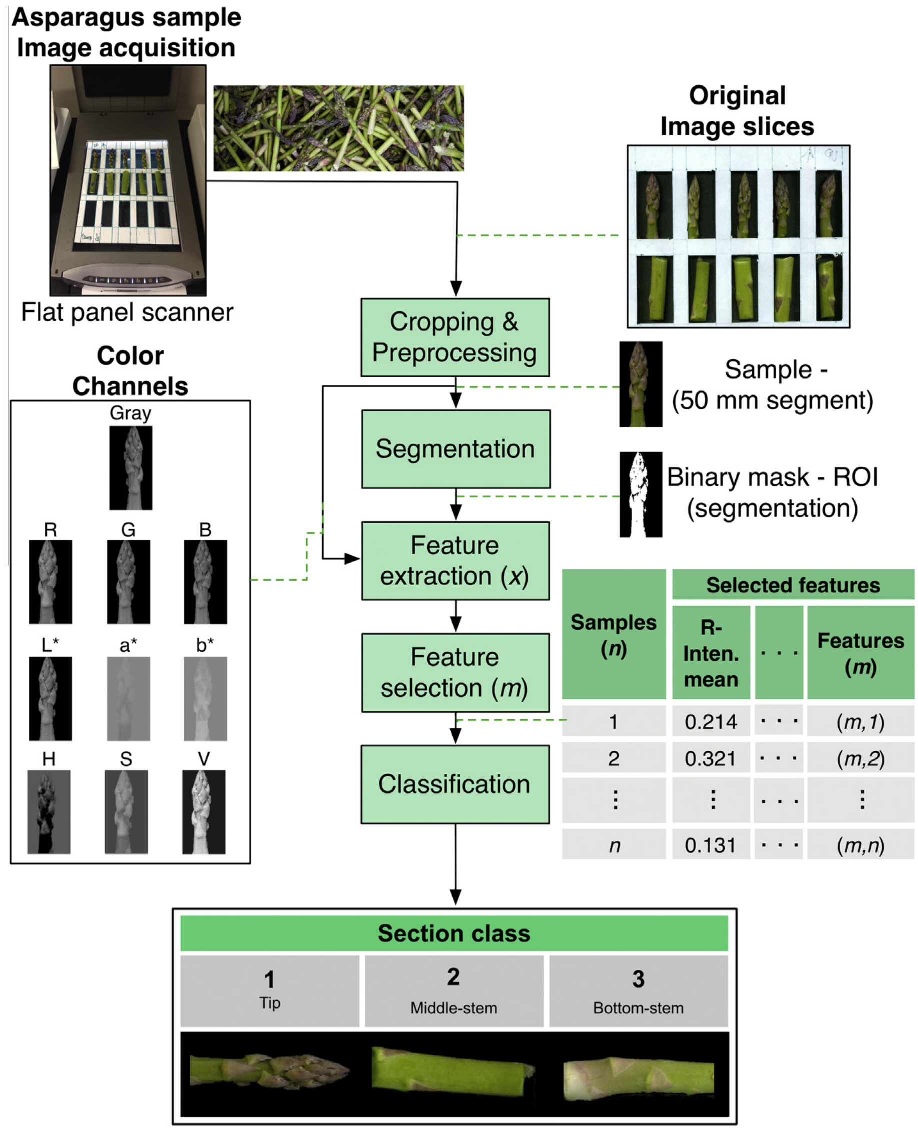

Fig. 1. Procedure used to generate the pattern classification algorithm to categorize asparagus segments (tips, middle-, and bottom-stem). Figure is partially presented in color. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

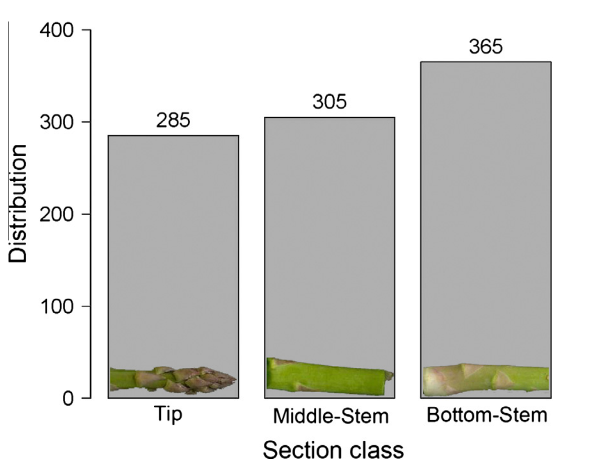

Fig. 2. Overall uniform sample distribution used to train and validate the classifier. Figure also contains an example for each of the 3 categorical classes (tips, middle-, and bottom-stem), representing the section types. Figure is partially presented in color. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5-nearest-neighbors, and neural-networks (NN) following the applied procedure in Ren et al. (2006), Mery et al. (2010), and Leiva et al. (2011) and using the "Balu" toolbox. In general, this step assigns the object (*i.e.* color image slice) to a specific section category. In depth discussion, methodology description, and followed steps for each of the applied classifiers can be found in Duda et al. (2000).

Performance of the classifier was measured as the ratio of correctly classified asparagus in reference to its supervised categorical class (label) to the total number of samples. Classifier validation was implemented using a 4-fold stratified cross-validation technique, therefore yielding an average estimate of classifier performance with 95% confidence intervals for the classification pool (Jain et al., 2000). In the cross-validation, 75% of the samples were used for training and 25% were used for validation repeated four times. Image classification and validation was performed using the "Balu" toolbox.

3. Results and discussion

A total of 955 color images individually categorized into three different section types, containing tip, middle-, and bottom-stem images were used in this study. As seen in Fig. 2, an approximate uniform total distribution was used, containing around the same number of images per section type class, which is important for the appropriate training of the pattern classification algorithm (Duda et al., 2000). Each image was segmented from an original acquired image containing up to 15 samples, following the approach described in Section 2.3. From these samples a set of features were extracted as detailed in Section 2.4 to subsequently train and validate the classifier as described in Section 2.5 (Fig. 1).

After feature extraction, 75% of the samples from each class were selected to perform classifier training (feature selection). The purpose was to select from a large number of extracted features ($x = 1931$), according to the procedure suggested by Mery and Soto (2008), features that are important, and capable of accurately separating asparagus segments into 3-classes. In this study the features were reduced from 1931 to 43 selected features (m) in order to avoid overtraining. This feature reduction was implemented using different algorithms; nevertheless, the SFS method offered the most powerful features, yielding the best classifier performance. The selected features are described in Table 1 where all but one were from the L*a*b* or RGB color components. Reducing overall feature space diminishes the computational time, allowing for possible in-line implementation. The other feature selection methods described in Section 2.4 performed poorly (Results not shown). Even though classifier performance slightly increases after the forty-third feature, it is not recommended to use more than the 43 selected features (m) to avoid classifier over-training, due to overall sample size, as recommended by Duda et al. (2000).

By observing Table 1, it can be seen that the 43 most important features primarily include: (1) LBP features (42%), and (2) Gabor features at different orientation, acquired from different color channels (42%). Lastly, of the selected features, 16% are from basic intensity and contrast features. LBP, and Gabor features are essential because results cannot be credited to a single pixel value, but somewhat to multiple pixels in the image and their interaction. It can be inferred that LBP textural features are among the most important features, because they are invariant to slight monotonic grayscale variations; therefore image noise and imaging irregularity do not play an overbearing role (Ojala et al., 2002). LBP textural features captured the local structure and textural variations between asparagus images. Gabor textural features captured distinctive color image information by means of merging different scaling and orientation elements. Gabor features, extracted from magnitude Gabor filtered images ($I_{rs}(i,j)$), have been found to be suitable for texture representation and discrimination (Zhu et al., 2007), thus it can be inferred that Gabor features offer information to accurately differentiate between tips and stems. It can be inferred that both LBP and Gabor filtered images of an asparagus tip contain a higher level of textural elements in comparison with asparagus stems. In contrast, basic intensity and contrast features, which were less important, couldn't capture significant differences, while trying to discern between tips and stems. While simple image intensity features only account for roughly 16% of the most important features, these features somehow summarize the overall quality appearance changes in the images. Changes in simple intensity features might capture significant difference in the overall color of asparagus, especially when trying to differentiate between middle- and bottom-stem sections. These findings are opposite to that found in Donis-González et al. (2013), as in that study basic contrast features played a higher role for the optimum classification of decayed chestnut slices.

Validation of classification was carried out using a 4-fold stratified cross-validation with 25% of the samples for each fold (repetition). Of the evaluated classifiers, mentioned in Section 2.5, the best overall classifier was found to be the neural-network classifier. Other classifiers were also tested; however, the overall classification performance was lower in all cases (Results not shown). Performance results, using the selected neural-network classifier, for increasing number of features (m) is included in Fig. 3a, where it can be seen that with the 43 selected features (m) the classifier had a high overall performance accuracy classification rate, equal to 90.2% (minimum = 88.1, maximum = 92.4%). Fig. 3b includes the confusion matrix corresponding to the overall neural-network classifier performance using 43 selected features (m). Each column of the matrix represents the occasions in a predicted category, while each row represents the instances in an actual category. This matrix is beneficial, because it visibly documents the misclassified categories (Shapiro and Stockman, 2001). The highest classification error occurs when trying to discriminate between class-1 (tips) and class-2 (middle-stems). This is optimum, as bottom-stems also contain a higher amount of undesirable tough fibrous tissue. Therefore, accurately eliminating bottom-stems will insure a significant reduction of sections containing higher levels of tough undesirable fibrous tissue. Additional classifier results can also be found in Table 2.

Table 1
Forty-three selected features using sequential forward selection (SFS) with the Fisher discriminant objective function, and applying a neural-network classifier as the most effective classifier.

n	Feature	*n*	Feature	*n*	Feature
1	Gabor(7,6)[B]	16	Gabor(2,3)[B]	30	Gabor(4,4)[a*]
2	Gabor(6,6)[G]	17	LBP(1,51)[a*]	31	Gabor(7,7)[B]
3	Gabor(4,7)[B]	18	LBP(1,11)[b*]	32	Gabor(4,4)[B]
4	Gabor(7,6)[b*]	19	Intensity-Kurtosis [G]	33	Gabor(1,7)[b*]
5	LBP(1,23)[G]	20	LBP(1,38)[b*]	34	LBP(1,7)[b*]
6	LBP(1,5)[b*]	21	Gabor(2,3)[G]	35	Intensity-Kurtosis [R]
7	LBP(1,49)[R]	22	Intensity-Kurtosis [L*]	36	LBP(1,33)[G]
8	Gabor(5,7)[G]	23	LBP(1,15)[b*]	37	LBP(1,7)[L*]
9	LBP(1,49)[b*]	24	LBP(1,25)[L*]	38	LBP(1,31)[B]
10	Intensity-Skewness [a*]	25	Gabor(8,7)[G]	39	LBP(1,13)[R]
11	Intensity-Mean [a*]	26	Gabor(8,7)[R]	40	LBP(1,17)[B]
12	Gabor(1,6)[B]	27	Gabor(2,3)[H]	41	LBP(1,40)[G]
13	Intensity-Skewness [G]	27	Gabor(5,7)[R]	42	LBP(1,37)[b*]
14	Intensity-Skewness [b*]	28	Gabor(8,5)[b*]	43	LBP(1,56)[a*]
15	Gabor(1,7)[B]	29	Gabor(1,48)[B]		

Gabor(a,b): Gabor filter, where a is the number of frequency, and b is the number of orientations.
LBP(d,h): local binary patterns, where d is the number of compared pixels with h – neighboring pixels.
Between brackets [] are the color channels used to extract features (L* = lightness, a* and b* = color opponents, R = red, G = green, B = blue, Gray, H, S, V = hue saturation value. For reference, see Section 2.4.

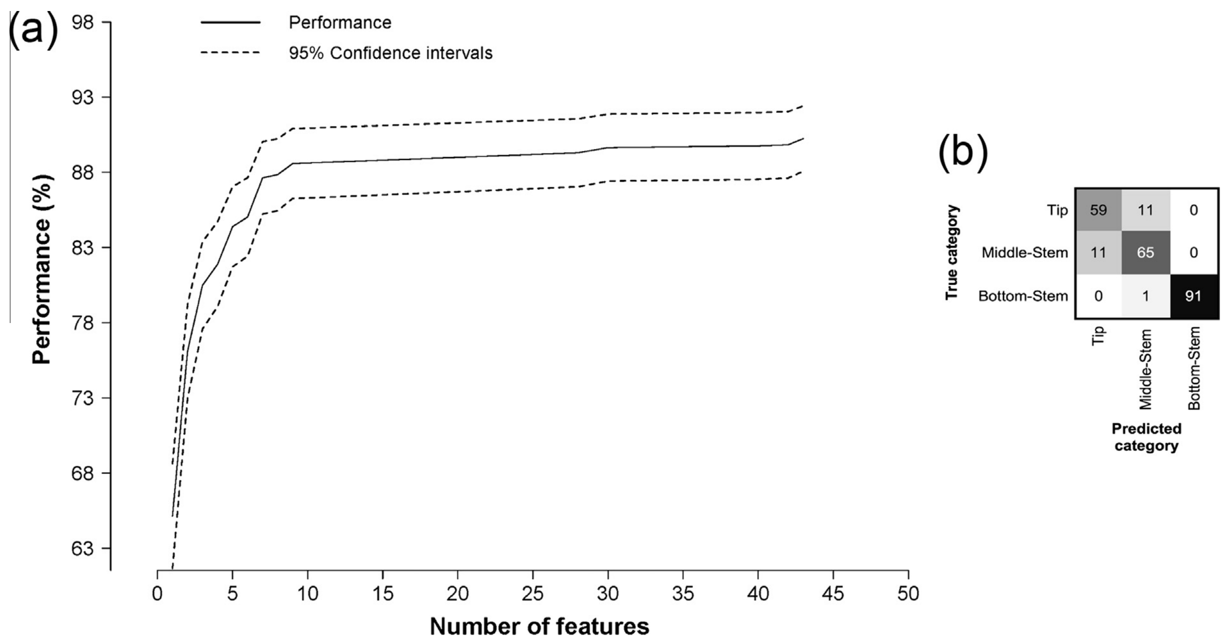

Fig. 3. (a) Neural-network classifier performance using cross-validation with 4-folds in relation to the number of selected features (n). Black line represents the classification mean performance, dotted black lines (---) represent 95% confidence intervals for the cross-validation classification pool. (b) Validation confusion matrix corresponding to the asparagus category prediction using 25% of samples with 43 selected features (overall accuracy rate equal to 90.2%).

Table 2
Classifier performance using selected features (m) with a 4-fold cross-validation.

Classifier	3-classes		
	Mean	UCI[a]	LCI[b]
NN	90.2	92.4	88.1
LDA	89.7	91.5	87.9
QDA	80.5	82.8	78.2
MD	76.1	79.0	73.2
KNN	65.1	68.4	61.8
m	43		

[a] Upper confidence interval.
[b] Lower confidence interval.

Results from this study show that color images, obtained using a commercially available flat panel scanner, were ideal for this experiment; because a true three-dimensional effect is not necessary, as it would be with rounded objects (*e.g.* fresh fruits). This technique objectively, rapidly, and automatically classifies asparagus into 3-classes by measuring different color, and textural features from color images. This high classification rate can be accomplished with a relatively low number of features ($m = 43$) in relation to the available number of images, with appropriate feature selection (*i.e.* = SFS), and classification techniques (*i.e.* = neural-network classifier). Therefore, this study offers a tool, which the asparagus industry and research institutions can use, to objectively differentiate between asparagus tips, middle-, and bottom-stems. It helps the research community to understand which are the features that play an important role in the ideal classification of color images, especially when using two dimensional flat images, like those evaluated in this study. In addition, it creates a general structure that could be used as a reference tool in the development of an in-line sorter of processing asparagus, using traditional computer vision systems (*i.e.* using digital cameras).

4. Conclusions

This study was conducted on a laboratory scale to enhance the present rather subjective evaluation of processing asparagus segments, and therefore objectively rate color images of fresh asparagus. For this, a commercially available flat panel scanner was used to capture the asparagus segment images. Asparagus samples were collected from two different harvesting seasons (2014, and 2015). Individual asparagus sample sections were segmented, and features were extracted from the segmented images. A total number of 1931 features were extracted from the segmented asparagus images. SFS was carried out to reduce the dimensionality of the total image-extracted features. Ultimately, 43 features were used to classify asparagus into 3-classes (tips, middle-stems, and bottom-stems) from the images using a neural-network classifier with a 90.2% (±2.1%) overall accuracy rate.

Although the specific developed classification procedure might not be applicable to other foods or agricultural commodities directly, the methodology is broadly valid. Before applying the classification procedure to other commodities or in-line sorting systems, it will be necessary to correctly train it.

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