A Survey of Stem Detection Algorithms and A New Algorithm Based on Monte Carlo Method

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Abstract. This paper divided the current algorithms for stem detection into three types, that is, algorithms based on thinness feature, algorithms based on concavity feature and algorithms based on optical property. The basic principles and processes of these algorithms are illustrated and evaluations are given. This paper also proposed a new stem detection algorithm based on Monte Carlo method. Its work objects and all processes are stated. It is proved to be acceptable and practical through computer simulation. The innovation points, conclusion and expectations of this algorithm are presented as well.

Keywords. Stem detection; Machine Vision; Image Analysis; Fruit grading

1. Introduction

China has been the largest fruit production country since 1993, and fruit the yield of China reached 153 million ton in 2004, which accounted for 16% of global overall fruit yield. Grading is an essential process in fruit production, and can distinguish the good fruits with the bad ones, with the indices such as size, shape, color, defect and inner quality. However, this process is traditionally done by experts, which is labor-intensive and introduces many subjective errors, and obviously shows its drawbacks nowadays. It's necessary to apply automatic grading systems to fruit production, in order to reduce the amount of human labor and unify the grading criteria. Machine vision technique is now widely used for detecting the exterior or even interior qualities of fruits.

1.1. Importance and necessity of stem detection

Stem detection algorithm is requisite in a grading system with machine vision mainly for the following three reasons.

The presence of stem in some fruits may be desirable, because stems can help some fruits avoid drying or decay during storage or transportation. Stem integrity is an indicator for good quality of some fruits, such as Huanghua pears.

However, in most cases, the presence of stem is a problem. Stems can produce puncture injures in the process of processing and stocking, and this phenomena is especially severe in some soft fruits like tomato. Stems are sometimes considered as a negative quality factor, for example, in cherry peppers.

What's more, stems can often be confused with defects or blemishes on the skin when machine vision is used. This is because of their similar appearance in visible region. Defects detection is essential, and thus the approach to getting rid of the interference of stems is necessary.

1.2. Current stem detection algorithms

The current stem detection algorithms can be divided into three types according to the unique features of stem they make use of.

The first type is algorithms based on thinness feature of stem. Stems are much thinner in width compared to fruits themselves. According to this characteristic, stems can be detected through 2-D image processing and analyzing. In order to make the thinness feature of stem obvious to find, a profile image of fruit is often required, where the stem appears as a protrusion on the fruit.

The second type is algorithms based on concavity feature of stem region. The stem region of some kinds of fruits is concave, and this 3-D feature can be used to detect the position of the stem region. The performance of these algorithms becomes poor when the stem appears on the edge of the image, and also these algorithms cannot be applied to all kinds of fruits.

The third type is algorithms based on optical property. Stems are usually different from fruit surface in appearance in visible or IR region. These algorithms are normally not sensitive to the position and rotation of the fruit. But as they all use some kinds of statistical methods, training processes are required and have decisive effect on the overall performances.

The detailed information of each algorithm is illustrated in the next section.

1.3. Problems existed in current algorithms

The two key factors to evaluate stem detection algorithms are accuracy and detection time. Low accuracy may lead to mistake stem for defect or inversely, and then lead to errors in grading operation, which will bring much economic loss. Short detection time is also necessary, because the cost of automatic grading machines is limited, and the operation speed is expected to be relatively low. Algorithms with high accuracy often takes more detection time, while algorithms that save time are often worse in performance in respect of accuracy. How to find the balance point between accuracy and detection time is an important topic.

Almost no algorithm can be applied to different kinds or varieties of fruits without modification. That is, the algorithm commonality has to be improved. The algorithms may need different empirical parameters, or new sets of training data. Some algorithms are even not able to be applied to some kinds of fruits.

The requirement for the view is also a limitation. Algorithms based on thinness feature require profile images, while those based on concavity feature usually perform badly in profile images. But the view is difficult to control in some conditions. So many algorithms can only be used in limited conditions.

The cost should be considered as well. Some newly emerged algorithms are of high accuracy, but they uses some advanced devices. It is not practical to apply these algorithms to the design of automatic grading system.

The current solution for the above problems is to use different algorithms in different situations or for different purposes. For example, in situations where high accuracy is required like for research purpose, the detection time and cost may not be main factors that need consideration, but in most practical production situations, relatively low accuracy is accepted to ensure fast-detection and low-cost. Algorithms based on thinness feature are not capable for discriminating stems and defects, and they are often used for measurement of stem length. The other two types of algorithms are used for discrimination in different conditions.

2. A survey of stem detection algorithms

As stated above, stem detection algorithms can be roughly divided into three types. The following subsections illustrate the basic principles and processes of the current algorithms and make brief evaluations respectively, but the specific formulas or numeric results are left out. For reasons of space, the subject of detecting the presence of stem is concentrated on, while measurement of stem length and discrimination between stem-end/calyx and defects are not discussed.

2.1. Algorithms based on thinness feature

2.1.1. Thinning algorithm

In a profile image, the area of fruit is relatively large, while the stem region is thin. Thus when thinning is performed on the image, the stem region will become single layer of pixels firstly. Based on this principle, Pla and Juste (1995) proposed a thinning-based algorithm to detect the stems in profile images of fruits.

In digital image analysis, skeleton denotes a collection of thin arcs and curves rather than pixel areas, and thinning algorithm is to extract the skeleton of a specific object from its binary image by deleting successive layers of pixels from the boundary of the object until there is only skeleton.

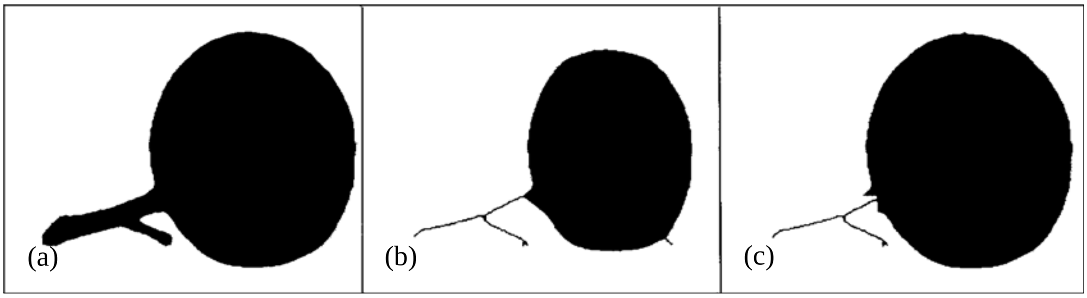

Fig. 1. Orange profile image at different phases of thinning algorithm: (a) initial binary image, (b) after thinning process, (c) after undoing thinning process

Before the thinning procedure, it's necessary to define two kinds of pixels so that the algorithm can decide whether to delete a pixel or not. In a binary image, we assume that the pixels belonging to the object have values of "1", while the others have values of "0". The first kind of pixels is body pixels, among whose neighboring 8 pixels (upper left, upper, upper right, left, right, lower left, lower and lower right pixels) there're at least two adjacent "1"s. Body pixels can be further divided into boundary pixels, whose neighboring 4 pixels (upper, lower, left and right pixels) are not all "1"s, and interior pixels, whose neighboring 4 pixels are all "1"s. The other kind of pixels is skeleton pixels, among whose neighboring 8 pixels there're no adjacent "1"s. Skeleton pixels can also be further divided into four sections, that is, end pixels (only one "1" in its neighboring 8 pixels), arc pixel (two "1"s in its neighboring 8 pixels), T-pixels (three "1"s in its neighboring 8 pixels) and X-pixels (four "1"s in its neighboring 8 pixels).

In the initialization step, computer loads the profile image of the object. After some proper pre-processing, the object region will have large differences from the background region in the grey level image. Then it transforms the grey level image into a binary image with appropriate threshold, which can be determined according to grey level histogram by 2- mode method (*Fig. 1a*). Finally computer labels all pixels of the object as body pixels.

The first step of this algorithm is to perform thinning for N times (*Fig. 1b*). In each iteration, computer scans all pixels of the object, and re-labels the pixels according to their neighboring pixels. If a specific pixel is labeled as boundary pixel, it should be removed, and its coordinate is recorded in a removing list of the current iteration. The determination of the constant N is highly relevant to the resolution of the image as well as the width of the stem. It should be assured that after N times thinning, the stem region becomes skeleton, while fruit region does not become skeleton.

The second step is to undo thinning for N times (*Fig. 1c*). In each iteration, computer scans all pixels in the removing list of the corresponding iteration in the first step. If any of the neighboring 8 pixels of a specific pixel is labeled as body pixel, it is restored and labeled as body pixel (of course boundary pixel). If not, the pixel is discarded.

After these procedures, the fruit region remains its initial shape and area, while the stem region becomes skeleton. Computer can easily detect stems by detecting whether there are skeleton pixels or not. If the second step is not performed, although the stem region becomes skeletons, part of the fruit region that has sharp shape may become skeleton as well. That's why the second step is necessary.

This algorithm can detect stems of fruits that have various shapes and sizes, and the direction of the stems is not compulsory. It can even detect stems with leaves attached. But it requires the profile images of the fruits which are not always accessible. Another serious problem is that this algorithm needs lots of operations and takes much time to process, which does not correspond to the requirement of on-line detection.

2.1.2. Erosion-dilation algorithm

Erosion-dilation algorithm to detect or remove stems is proposed according to the different area of fruit region and stem region. Erosion-dilation algorithm is actually often be used in digital image processing to remove some uneven boundaries, and Leemans et al. (1997) mentioned its application in stem detection.

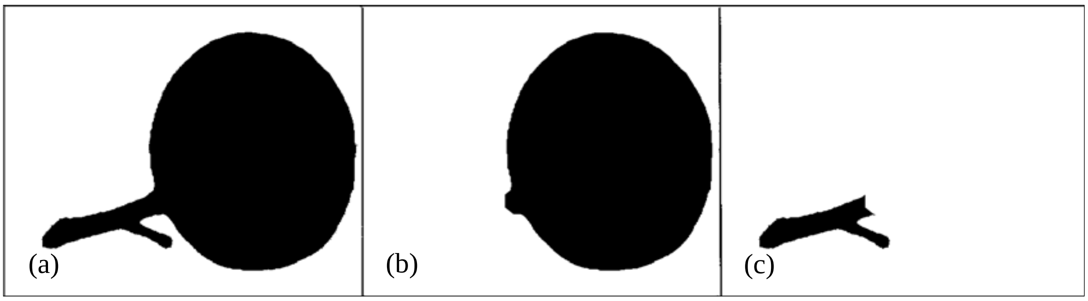

Fig. 2. Orange profile image at different phases of erosion-dilation algorithm: (a) initial binary image, (b) after erosion and dilation process, (c) after subtraction process

The main principle of this algorithm is as follows. Also a binary image of the profile view of the object is required (*Fig. 2a*).

Firstly erode the object region in a binary image, that is, to delete boundary pixels of the object over and over again. Different from the thinning algorithm above, the pixel-deleting process removes all boundary pixels including skeleton pixels. After some times of erosion, there is no stem region in the image, while the fruit region becomes smaller but remains its initial shape.

Then dilate the object region for the same times as in erosion step (*Fig. 2b*). This algorithm does not care about which pixels it removes and whether they should be restored, and it simply adds layers of pixels to the boundary of the object. When this step is done, the fruit region almost recovers its initial shape and area, while the stem region is removed from the image.

By subtracting the post-processing image from the initial one, we can acquire the only stem region in the image (*Fig. 2c*). Through counting the area of the stem region, computer can make decision whether the stem is existed or not, according to a pre-set empirical threshold.

This algorithm is similar to the thinning algorithm, and thus has similar pros and cons. However, it takes less time because there is no need to record the removing lists and to judge the labels. Its results become worse when it performs erosion for too many times, which will cause much information loss and eventually produce a deformed shape. Thus when dealing with fruits with thick stems or with leaves attached, this algorithm may commit some errors.

2.1.3. Contour tracking algorithm

The contour of the fruit region is much smoother than that of the stem region in a profile image. Thus the contour of the stem region has a larger curvature. Ruiz et al. (1996) mentioned an algorithm to detect stems according to the curvature of the contour and the distance to the centroid.

Binary images of the profile view of the objects can be obtained through image sensors and threshold processing. The centroid of the object can also be calculated before the following processes.

The contour of the object needs to be determined using the contour extraction algorithm. Firstly computer scans each pixel of the binary image in certain order (e.g. from left to right and from top to bottom) until it finds the first pixel belonging to the object. Then it checks the neighboring pixel to the most probable direction to find the next pixel on the contour. The most probable direction means the current direction, that is, the direction from the last pixel to this pixel, and if this pixel is not a contour pixel, it turns to the two adjacent directions that have a 45° angle from the current direction. After this tracking procedure, the contour of the object is obtained. However, the contour may have some small projections. Thus computer smoothens the contour curve by eliminating the small inward and outward projections.

Then the contour curve is segmented into many short fragments. Usually 80 to 100 fragments are segmented considering the balance of detection effect and time cost. Assuming that there are N pixels on the contour, and n fragments are to be segmented into, then each fragment has $k = N/n$ pixels.

Instead of accurate curvature calculation, this algorithm uses the difference of slopes between adjacent fragments to reduce the amount of calculation. The fragments can be

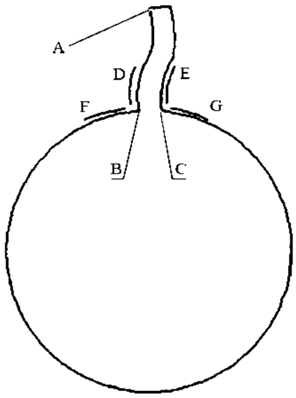

Fig. 3. Apple profile image of contour tracking algorithm where A is regarded as the end of stem, and B and C are regarded as intersection points

viewed as straight lines between the end pixels, because they are short enough. After the calculation of slope differences, the two fragments which have the maximum slope difference can be found. Then computer searches the contour pixels in and near the two fragments, for a pixel that has the largest distance to the centroid. This pixel is regarded as the end of stem. Starting from both sides of this pixel, computer searches for another two key pixels. These two key pixels have the characteristic that the distances of the neighboring pixels to the centroid are almost constant on one side and change strongly on the other side. These two key pixels are regarded as points of intersection between stem and fruit on the contour. Thus stem region can be detected with the above three pixels (*Fig. 3*).

Obviously this algorithm needs less calculation than the thinning or erosion-dilation algorithms, and thus reduces the time cost largely. But it has some critical drawbacks. For example, the stem should be relatively straight protruding. If the stem is bent in harvesting processes, the search for the end pixel may make mistakes.

2.1.4. Square template algorithm

Square template algorithm proposed by Ying et al. (2003) is also based on the fact that the stem is much thinner than the fruit. Different from the above algorithms, this algorithm focuses on the area rather than layer of pixels or the contour.

This algorithm also needs binary images of the profile view of the objects.

Construction of a square template is the first step. This template is an n × n pixel array, and all its boundary pixels are filled with "1"s while interior pixels are filled with "0"s (*Fig. 4*). This template acts as a mask in this algorithm. When it is applied to the binary image, computer simply performs logical AND operations on each pixel. After these operations, the interior pixels are ignored because they all become "0"s, while the boundary pixels becomes the corresponding pixels in the binary image. The constant n is determined according to the maximum width of the stem measured in pixel.

Computer moves the template on the binary image in a certain order, usually from left to right and from top to bottom. The usage of the template is as stated above. Computer counts the pixels on the template boundary that do not belong to the object (i.e. belong to the background). The number of these pixels is recorded and compared with a threshold N. if it does not exceed N, it is assumed that the interior part is fruit region, otherwise it is assumed that the interior part is background or stem region. The threshold N is also relative with the stem width, and usually determined by trial and error.

After the above process, the fruit region can be determined. So the stem region can also be determined through subtraction operation, so that computer can judge whether stem is existed.

The amount of calculation of this algorithm is much less than other algorithms based on the stem shape, and also the accuracy is good enough. It is not sensitive to translation and rotation, and can be applied to different objects with proper constant n and N. But it also has

1	1	1	1	1	1	1
1						1
1						1
1						1
1						1
1						1
1	1	1	1	1	1	1

Fig. 4. Square template used in square template algorithm

the common drawback of profile image requirement.

2.2. Algorithms based on concavity feature

2.2.1. Structured light algorithm

The stem region of many fruits is concave area on the surface. If light stripes are projected on the surface, the stripes will bend for contrary directions on the convex area and the concave area. Thus the structured light algorithm was proposed by Yang (1996), in order to discriminate the damage area and the stem/calyx area.

This algorithm is based on the light striping technique. Due to the efficiency, evenly spaced light stripes are used as the structured light. This kind of structured light can be easily obtained with ordinary light sources and gratings. When the structured light is projected on the surface of the object, an image is acquired by image sensors. The stripe image is then processed into a binary image with threshold processing. Only light stripes remain in the binary image, and all other things including background and fruit surface are removed. Computer then performs thinning on the binary image, and after that, the skeletons of the light stripes are extracted.

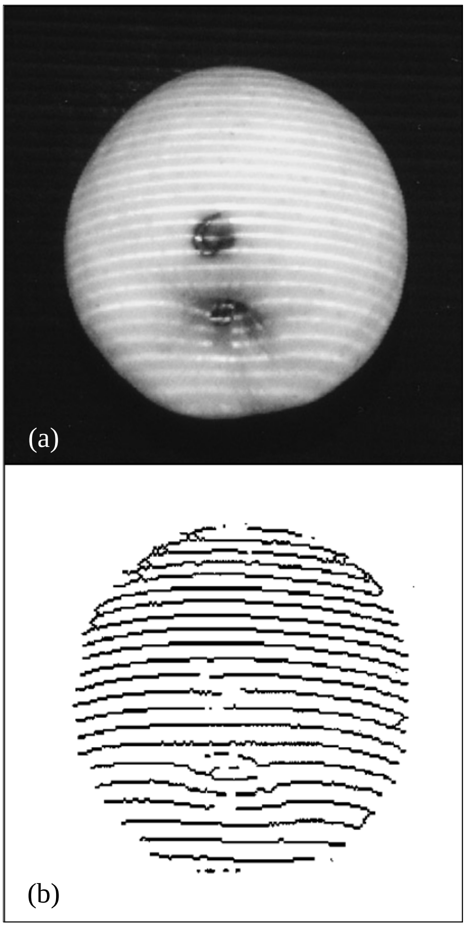

Fig. 5. Apple image of structured light algorithm: (a) light stripes on the apple surface, (b) light stripes after thinning

The shapes of the light stripes reflect the surface conditions (*Fig. 5*). The stripes on convex area, that is, most of the fruit region, are nearly parallel continuous parabolic curves, and their curvature directions are constant. The stripes on flat area, that is, part of the fruit region, are parallel straight lines. However, the stripes on concave area around the stem region are relatively abnormal. Some of them are broken, because the depths of stem and fruit surface are different and non-continuous.

Also their curvature directions change sharply when the surface changes from convex area to concave area or inverse. Through these obvious differences in the shapes of light stripes, computer can recognize the stem region.

Computer can either reconstruct the three-dimensional surface model or only extract essential stripe patterns, in order to find the concave stem area with the above stripe skeleton image. The latter method is more practical due to its time-efficiency. Curvature is used for describing the shapes of the stripes. Before calculating the curvature, computer segmented the fruit image into many small rectangular area. In each rectangular area, the curvatures are calculated. If the curvature changes smoothly and keeps its sign, this area is regarded as the fruit region. And if the curvature varies dramatically and changes its sign, this area is regarded as the stem region.

Some optimization method can be applied to this algorithm. For example, use some segmentation algorithms to find the stem region and the defect region, then apply this algorithm only to these regions to discriminate them. Some improved algorithms are also proposed to substitute the normal curvature calculation. Application of neural network contributes to the accurate detection as well.

This algorithm takes advantage of the 3-D feature of stem area. But this also limits its application, especially in some fruits whose stem areas are not concave. What's more, the calculation of curvature takes much time and

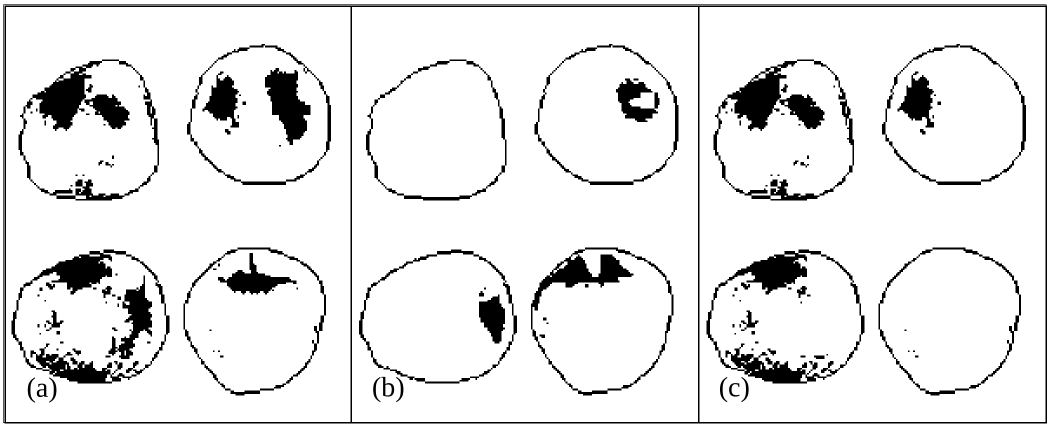

Fig. 6. Apple images at different phases of NIR/MIR dual-sensor algorithm: (a) NIR images after blob analysis, (b) MIR images after blob analysis, (c) final NIR/MIR combination images

the application of structured light sources increases the cost.

2.2.2. NIR/MIR dual-sensor algorithm

According to the different material characteristics and concave shape on both stem-ends and calyxes of apple, the temperature in these areas of the apple is lower than in other parts of the apple surface after being refrigerated. Based on the fact that the mid-infrared sensor is sensitive to the temperature differences on the objects within its field of view, Cheng et al. (2003) proposed NIR/MIR dual-sensor system for online apple stem-end/calyx recognition.

Because this method uses two kinds of sensor, and even the resolution of their images may be different, proper registration is needed to enable effective information compensation.

NIR and MIR images are processed separately and then the combination results were evaluated.

In a NIR image, bright-colored surface, that is, usually the good surface, has higher intensity than dark-colored surface, that is, the defective surface. Different brightness levels may cause detection errors, especially for bright-colored defective apples and dark-colored good apples. A normalization operation is thus applied on the NIR image. Because of inconsistent reflection of the light caused by curved apple surface, the intensity distribution on sensed apples is not uniform. The pixels around the boundary of the apple appear at a much lower intensity than the central pixels, while the defective portions of apples also appear at a low intensity in the NIR image. Adaptive spherical transform method is introduced to solve this problem.

In a MIR image, low-temperature objects present less intensity than high-temperature objects. To extract the stem-ends and calyxes from the original MIR apple images, the background is removed and only the object of interest is considered.

Blob analysis is performed on the processed NIR and MIR images separately to classify the pixels into different regions (*Fig. 6a/b*). The first step is blob identification, which is used to categorize pixels into groups according to the similarity of certain features. The second step is blob labeling, which is used to segment the identified pixels into different blobs according to their spatial positions.

Finally the blob-extracted NIR and MIR images are compared to discriminate stem-ends and calyxes with defects by simply subtraction (*Fig. 6c*).

This algorithm takes advantage of sensor fusion technique, and the results are satisfying. But it can only be used in online grading detection, and it is less reliable when defect region is near stem-end/calyx region. Also the introduction of NIR/MIR cameras greatly increases the cost.

2.2.3. Reflection pattern algorithm

Penman (2001) illuminated apples with blue linear light and used reflection patterns of the fruit acquired by a CCD camera to locate stem and calyx region.

This technique uses the non-diffuse reflection of light from the apple surface. The reflection pattern viewed by a camera is dependent on the spatial disposition of the light sources and the fruit shape. A disturbance from a spherical or other smoothly varying convex surface produces a corresponding disturbance in the reflected light pattern. This enables the concavity surrounding the stem and calyx on apples to be detected.

One obvious drawback of this algorithm is that the accuracy is inversely proportional with the location of stem and calyx's relative to fruit center, and thus images from some limited views are required to improve the accuracy.

2.3. Algorithms based on optical property

2.3.1. Color segmentation algorithm

As the stem region usually has different color compared with the fruit region, it is practical to discriminate stems and fruits according to their colors in some situations. Ruiz et al. (1996) and Blasco et al. (2003) mentioned linear and non-linear discriminant analysis algorithms to detect stems respectively.

In the color segmentation algorithm, Red-Green-Blue (RGB) color space is used because these three color segments can be obtained directly from an image sensor and need less operations than other types of color spaces, and in the meanwhile, RGB color space can give better results (*Fig. 7a*).

Discriminant analysis requires a previous off-line training. At first, several color classes should be defined into which the image will be segmented (*Fig. 7b*). Pixels in identical class should have very similar colors, while pixels in different classes should have very different colors. At least three classes should be defined as background, peel (sound surface) and stem (or/and calyx) According to the specific situations, several other classes may be added, such as damage region and specific feature.

A set of images named training set is required. Images in training set should include various conditions, which makes the classifier more reliable. Before training, it is necessary to manually segment pixels of the images in training set into the pre-determined classes according to subjective experiences by experts. Then computer can calculate the covariance matrix of the red, blue and green variables. Because of the large amount of operations, it is practical to assume that different color classes have equal covariance matrices, and thus the clusters of these classes will be of same shape and size in R-G-B three dimensional graph.

The most important step of this algorithm is to develop classifier. Bayesian classifier is most often used, which is based on Bayesian decision rules. Also the assumption that R, G, B independent variables follow normal distribution should be accepted to use Bayesian classifier. The principle of Bayesian classifier is to calculate the posteriori probabilities, that is, the possibility of one object belonging to one class, according to the priori probabilities with Bayesian formula, and then decide that one object belongs to the class with highest posteriori probability. The specific calculation process is left out. One decision function per class can be obtained after the classifier is developed. The decision functions may be linear or non-linear, according to the different methods. The decision functions have three parameters, that is, R, G and B variables. When deciding the class of a specific pixel, computer just substitute R, G, B in the decision functions with the real values, and calculate the function values. The pixel is then classified into the class

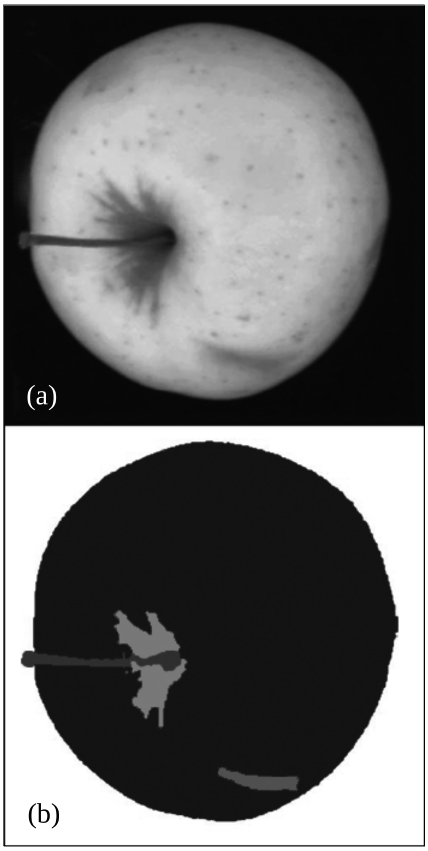

Fig. 7. Apple image of color segmentation algorithm: (a) original image, (b) segmented image showing the peel, russet, stem and damage regions

whose corresponding decision function has the largest value.

In order to validate the performance of the classification model, another set of images named testing set is required. All pixels of the images in testing set are to be classified according to the above classification model and principle. The results are compared with the results that are obtained from manual classification. If the errors are negligible, the model is practical, or it should be re-developed with a larger and more representative training set.

Finally, the number of pixels in stem class is counted and compared with an empirical threshold. If the number exceeds the threshold, it means that stem is existed in the image, and further processing can be performed.

The accuracy of this algorithm is very high, and it can even reach 98% in some conditions. But it requires that the color of stem is very different from that of fruit. The training process also restricts its application, because training is tedious and needs to be repeated when the condition changes.

2.3.2. Pattern recognition algorithm

In Unay et al. (2007), the stem and calyx of Jonagold apples were detected using a correlation pattern recognition technique.

The method starts with background removal and object segmentation by thresholding. Statistical, textural and shape features are extracted from each segmented object and these features are introduced to several supervised classification algorithms. Linear discriminant, nearest neighbor, fuzzy nearest neighbor, support vector machines classifiers and adaboost are the ones tested. Relevant features are selected by floating forward feature selection algorithm. Support vector machines is found to be the best among all classification algorithms tested using selected feature subset.

This algorithm is highly dependent on the training and test set, or rather, the database, which takes much time to build.

2.3.3. Multispectral algorithm

Xing et al. (2007) proposed a hyperspectral imaging system for separating stem-end/calyx regions from true bruises.

Based on principal component analysis (PCA) of the hyperspectral images, multiple effective wavebands were selected. Afterwards, PCA and image-processing techniques were applied to the multispectral images. The stem-end/calyx regions were identified and distinguished from the cheek surfaces by analysing the contour features of the first principal component score images.

The usage of principal component analysis may be regarded as an innovative point, but this kind of method is dependent on the variety of fruits. When the system is applied to another variety, even of the same kind of fruit, the principal components should be re-selected.

3. A new stem detection algorithm based on Monte Carlo method

As stated above, accuracy and detection time are the two main evaluation indices for stem detection algorithm. The current algorithms are almost all based on the scanning method, that is, to scan the image pixel by pixel and make operations or calculations. As the image capture devices used in practical machine vision systems have the resolution of at least VGA (approximate 0.3 million pixels) level now, the amount of calculation is considerable, and the detection time is long. Thus an introduction of Monte Carlo method, that is, to use random numbers to solve calculative problems, seems to be a new way to reduce the amount of calculation. The objective of this research is to shorten the detection time and maintain a satisfying accuracy.

3.1. Work objects

Laiyang pears are chosen as the work objects in the research.

3.1.1. Introduction to Laiyang pears

Laiyang pear is also called Chi pear. It is named after its place of production, Laiyang city in Shandong Province, and is one of the famous specialties of Shandong. It has delicate flesh texture, rich juice, and crisp and sweet mouthfeel, and is thus one of the top-grade breeds of pear.

The sugar content of Laiyang pear is up to 9.76%, 2 to 3% higher than the average pear. It also contains a variety of organic acids, vitamins and other nutrients. Laiyang pears are not only delicious seasonal fruits, and can also be processed into dried pears, pear sauce and canned pears as well as wine and vinegar. What's more, Laiyang pear also has the effect of removing heat from the lung, dissolving phlegm and arresting cough. Laiyang pear ointment and linctus made of it are good medicines for curing bronchitis, colds and coughs.

The cultivated area of Laiyang pear was only over three hundred acres before 1949, and the peak annual output was no more than one hundred tons. Nowadays the cultivated area has expanded to over eighty thousand acres, and the average annual output has exceeded 1.5 million tons. Obviously, the grading process for so many pears cost much human labor every year, and automatic grading systems are required.

According to Standard for Quality Test of Fresh Pears published by Chinese Ministry of Commerce in 1989, stem is an important part of the appearance of pear, and pears of all levels are required to have integral stem. Thus stem detection and measurement is one of the necessary steps in automatic grading systems.

3.1.2. Characteristics of Laiyang pears

Laiyang pears are usually obovate in shape and large in size, and their peel is chartreuse and rough with brown rusty spots on it. Their calyx area is concave, but their stem area is often convex.

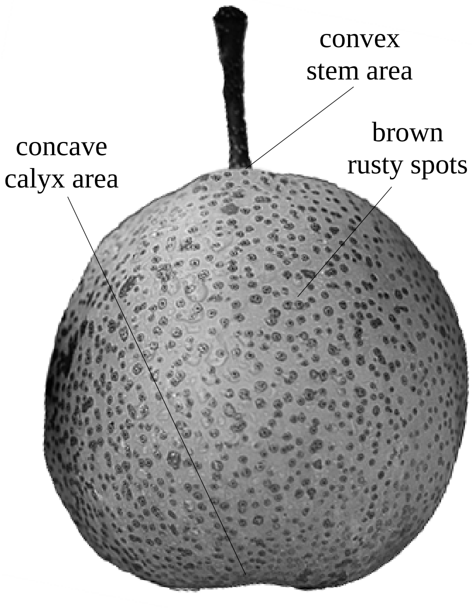

Fig. 8. Profile image of Laiyang pears with some unique characteristics marked

Some of the above stem detection algorithms cannot be used for Laiyang pears because of their unique characteristics.

As the stem area of Laiyang pear is convex rather than concave, the algorithms based on concavity feature are useless for this situation. But these algorithms can be useful for discriminating calyx area with the defects, because the calyx area is concave, though this subject is not discussed in the paper.

The brown rusty spots have a very similar appearance with the stem in color, so some of algorithms based on optical property also perform badly in this situation. The integration of pattern recognition or multispectral technique may improve the performance, but there is no relative paper reporting the results so far.

The algorithms based on thinness feature seem to be the best choice. However, the accuracy and detection time need to be further improved. And also the algorithms should be helpful to the measurement of stem length.

3.2. Image acquisition

The machine vision system consisted of a three charge coupled device (CCD) color camera, a color frame grabber, a host computer, a lighting chamber and an image monitor (*Fig. 9*).

The CCD camera was located on the one side of the conveyor belt. It can capture images for at least 30 times per second, and the images have the resolution of at least 640 × 480.

The color frame grabber digitized and decoded the composite video signal from the camera into three user-defined buffers in red, green and blue color coordinate (RGB). It is connected to the PC bus, and can form color images having 640 × 480 × 24-bit pixel resolution.

Images are acquired, processed and analyzed using a host computer. As this algorithm requires little amount of calculation, low-cost processors are enough for the job.

The lighting chamber is used to provide uniform illumination for the camera. The chamber is like a trapezoid. One side of it is a

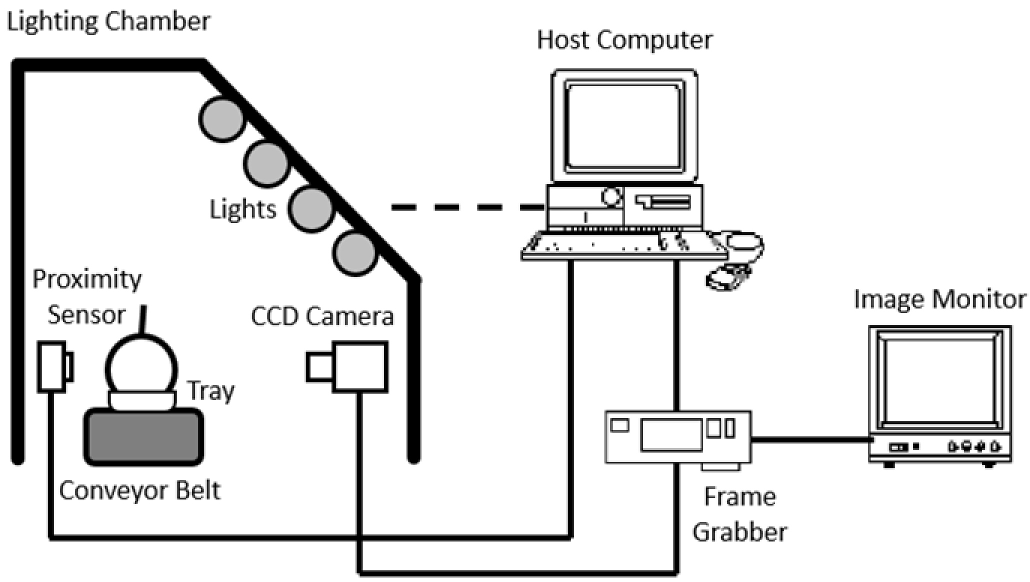

Fig. 9. Schematic diagram of the machine vision system used in the image acquisition process

perpendicular wall, while the other side is a combination of inclined and perpendicular wall, where the CCD camera is located. Lighting is provided by several warm-white fluorescent lamps arranged uniformly on the inclined surface of the chamber above the conveyor belt. The angle between the inclined surface and horizontal is 45 degrees, thus the direct reflected light to the camera can be reduced. The interior surface opposite the camera is roughened and painted black, in order to provide black background for the images and avoid specular reflection. The other surfaces of the chamber are painted flat white to increase the image contrast, provide diffused light reflection and eliminate shadows.

The image monitor is used to observe the situation inside the lighting chamber on-time.

The transportation system is also important. The pears are placed on the tray, and transported by the conveyor belt. Because the calyx area of the pears is concave, the trays can ensure the upright posture of the pears, and thus profile images can be obtained.

A proximity sensor is used to determine the timing when the pear appears in the center of the field of view of the camera. This approach can make the image processing easier.

3.3. Image processing

3.3.1. Image trimming

In an image obtained from the machine vision system, the pear only takes up a small part of the pixels, while the background takes up a large part. In order to improve the efficiency of random points, the portion of the pear should be as large as possible. So some of the background pixels should be trimmed.

The number of pixels that should be trimmed, or rather, the trim boundary, can be determined like this: First, find the boundary coordinate of 100 pears. That is, find the x coordinate of the leftmost and rightmost pixels, and the y coordinate of the topmost and bottommost pixels. Second, calculate the average (Avg) and standard deviation (Std) of the coordinates. Then the top trim boundary can be determined as (Avg_{top} - 3 × Std_{top}), and the bottom trim boundary as (Avg_{bottom} + 3 × Std_{bottom}). Also the left trim boundary can be determined as (Avg_{left} - 3 × Std_{left}), and the right trim boundary as (Avg_{right} + 3 × Std_{right}). This is because more

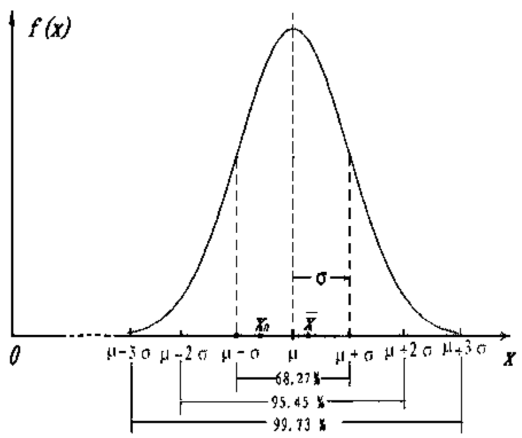

Fig. 10. Probability density function of normal distribution

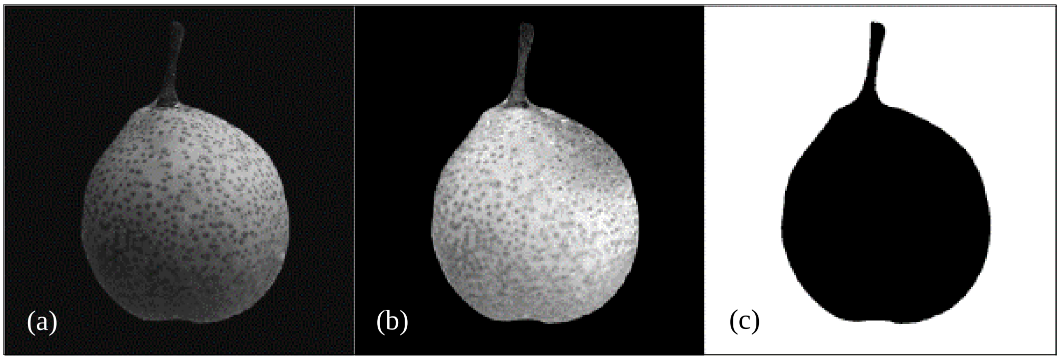

Fig. 11. Pear profile image at different phases of image processing: (a) original image, (b) after image pre-processing, (c) after image thresholding (phase inverted)

than 99% of the pears are believed to appear within these boundaries according to the normal distribution (*Fig. 10*).

3.3.2. Image pre-processing

Image pre-processing is used to make the pear region and the background region have larger differences in intensity. The red, green and blue color channels are separated into three independent monochrome images. Through some arithmetic operations of the intensities of the corresponding pixels in these three images, the differences between background and object can be enlarged.

This process is different because of the variability of the image sensors and illumination. But one key principle should be considered, that both the stem region and the fruit region should be very different from the background region, so that the background can be removed while the fruit and stem remains in the next process. Because both the stem region and the fruit region have higher intensities in red and green channels than in blue channel, and the background region has almost equal intensities in the three channels, a possible pre-processing operation may be like this: Red + Green - 2 × Blue (*Fig. 11b*).

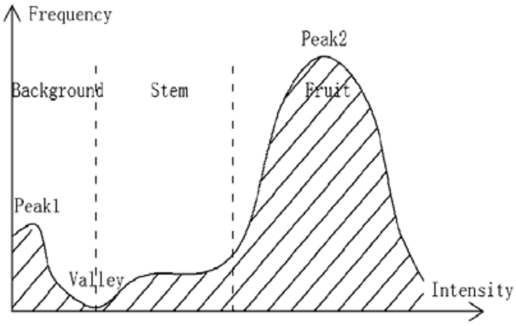

Fig. 12. Grey level histogram of the pre-processed image

3.3.3. Image thresholding

After pre-processing, the object region should be different from the background region in intensity. The threshold needed to generate the binary image can be determined by analyze the pixel distribution. This method is called two-mode method.

First of all, count the frequency of every value of intensity in the image, and plot a histogram. A typical grey level histogram for a Laiyang pear image has two obvious peak-like segments and one relatively even segment (*Fig. 12*). One of the peak-like segment that has low intensities is the background region. After pre-processing, the background region is almost black in color, so it is located at the left side of grey level histogram. The other peak-like segment is the fruit region. As the fruit region is the brightest in the pre-processed image, it is located at the right side. After trimming, the fruit region has a larger area than the background region, so this segment is also larger in area. The middle segment is the stem region as well as the brown rusty spots on the pear surface. Their colors vary a lot, so this segment is relatively even in shape.

Then, find the lowest point between the two peaks in grey level histogram. This point is believed to be the proper threshold for generating the binary image, because it separates the background and the other regions.

After this step, the binary image can be obtained (*Fig.11c*). The object region has the values of “1”, while the background region has the values of “0”.

3.4. Image analysis

3.4.1. Basic principles

This algorithm is based on the fact that the area of the fruit region is much larger than that of the stem region. It also relies on the assumption that the shape of the fruit is approximately a circle, or an upright ellipse, that is, its diameters are parallel to the x and y axes.

When random points are sprinkled on the image, they will be either in the object region or in the background region. Points in the object region are our point of interest, while those in the background region are discarded. Because the fruit region has larger area than the stem region, the overwhelming majority of points are believed to be located in the fruit region, so their statistical indices can reflect the characteristics of the fruit region.

Thus the average (Avg) and standard deviation (Std) of the x and y coordinates of the random points are calculated. The point (Avg_x, Avg_y) will approach the real centroid when the number of random points increases, so it can be regarded as the approximate center of the fruit region. According to the normal distribution, the x coordinates of more than 95% of the random points are in the range from (Avg_x - 2 × Std_x) to (Avg_x + 2 × Std_x), and the x coordinates of more than 99% of the random points are in the range from (Avg_x - 3 × Std_x) to (Avg_x + 3 × Std_x). The condition of y coordinates is just the same.

So an ellipse is drawn with point (Avg_x, Avg_y) as its center, length (K × Std_x) as its x semidiameter and length (K × Std_y) as its y semidiameter (*Fig. 13*). If the coefficient K is proper selected from 2 to 3, this ellipse can surround the fruit region and intersect with the

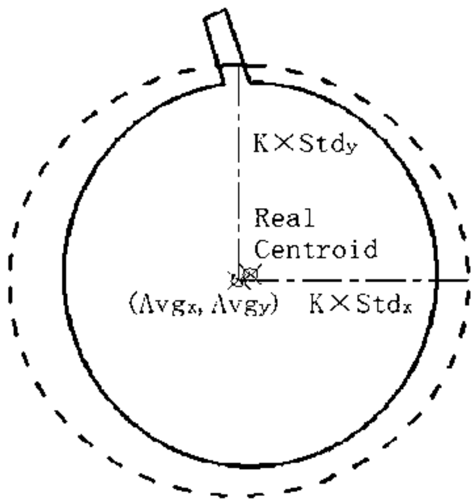

Fig. 13. Ellipse drawn with statistical data

stem region. The pixels on the ellipse are scanned to check whether there are pixels belonging to the object region. If so, the stem is regarded to be existed.

3.4.2. Analysis processes

A simulation program is developed under the environment of C# and .NET Framework 4.5.

The random number generator provided by *System.Random* class is used. One random number is generated in the range from 0 to the width of the image, and used as the x coordinate of the random point. Another random number is generated in the range from 0 to the height of the image, and used as the y coordinate of the random point. Then the corresponding pixel in the binary image is checked. If this pixel belongs to the background region, or rather, has the value of "0", it is discarded. Otherwise, its x and y coordinates are added to two variables (xSum and ySum), and the squares of its x and y coordinates are added to two other variables (x^2Sum and y^2Sum). This process repeats until reaching the pre-set number of times (N), that is, the number of random points sprinkled. The number of random points selected (n) should also be counted in the process.

Then the average (Avg) and standard deviation (Std) of the x and y coordinates of the random points are calculated according to the following formulas.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} = \sqrt{\frac{\sum_{i=1}^{n} {x_i}^2}{n-1} - \frac{n}{n-1}\bar{x}^2}$$

Then Avg_x is (xSum / n), and Avg_y is (ySum / n). Std_x is sqrt(x^2Sum / (n - 1) - sqr(Avg_x) × n / (n - 1)), and Std_y is sqrt(y^2Sum / (n - 1) - sqr(Avg_y) × n / (n - 1)).

With the coefficient K, the ellipse can be drawn according to the parametric equations.

$$x = h + a\cos t$$
$$y = k + b\sin t$$

where (h,k) is the center of the ellipse, a and b is the semidiameters, and t is between –π and π. Thus it is easy to scan the pixels on the ellipse. A progressive variable T is declared. Because the stems normally appear in the top part of the fruit images in this situation, T is designed to change from -135° to +225°, so that the stems

Table 1. Results of parameter determination experiments

Coefficient K	Number of Random Points N 200	400	600	800
2.25	500/1.13	500/2.17	500/3.18	500/4.23
	429/1.50	480/2.56	490/3.55	496/4.55
2.30	500/1.15	500/2.21	500/3.21	500/4.29
	460/1.51	496/2.53	500/3.55	500/4.63
2.35	500/1.15	500/2.12	500/3.25	500/4.22
	490/1.54	500/2.56	500/3.56	500/4.52
2.40	499/1.13	500/2.18	500/3.25	500/4.41
	493/1.53	500/2.56	500/3.58	500/4.59
2.45	498/1.15	500/2.17	500/3.22	500/4.26
	500/1.54	500/2.25	500/3.56	500/4.59
2.50	493/1.19	500/2.17	500/3.17	500/4.42
	500/1.53	500/2.61	500/3.64	500/4.60

can be found quickly. The step length of T is around 1°. The x and y coordinates of the pixels on the ellipse are calculated as ($Avg_x + K \times Std_x \times \cos(T)$) and ($Avg_y + K \times Std_y \times \sin(T)$) respectively. A judgment should be performed to avoid the calculated coordinates appear outside of the image. Finally the pixels on the ellipse are checked one by one, and if there is one pixel belonging to the object region, it means that the stem is found, and subsequent scan is not necessary.

3.5. Algorithm simulation

3.5.1. Simulation environment

For lack of machine vision system, the images used are from the Internet, and edited using Adobe Photoshop CS6.

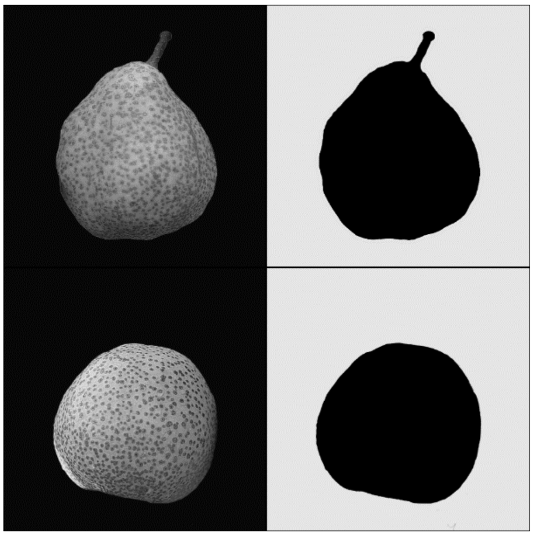

Fig. 14. Experiment sample images with their binary images

The simulation environment is Intel CORE i5 CPU M 450 (dual-core 2.40 GHz) with the operation system of Microsoft Windows 8.

3.5.2. Parameter determination

The parameters N and K should be determined by experiments. Because this algorithm uses random numbers, the results may be different even if it is performed on the identical image for many times. Thus the parameter determination experiments are simply performed for many times on two images (one with stem, and one without stem, *Fig. 14*).

This algorithm is performed for 500 times on each image for every different combination of parameters. The number of correct times and the detection time (in millisecond) is recorded. The results are shown in *Table 1*. Notice that there are four data for every combination of parameters. They are the number of correct times for the image with stem, its average detection time, the number of correct times for the image without stem and its detection time respectively.

Some obvious conclusion can be drawn. The detection of images with stem always takes less time than that of images without stem, because the scan process stops once the stem is found. As N increases, the accuracy increases but the detection time also increases remarkably. K almost has nothing to do with the detection

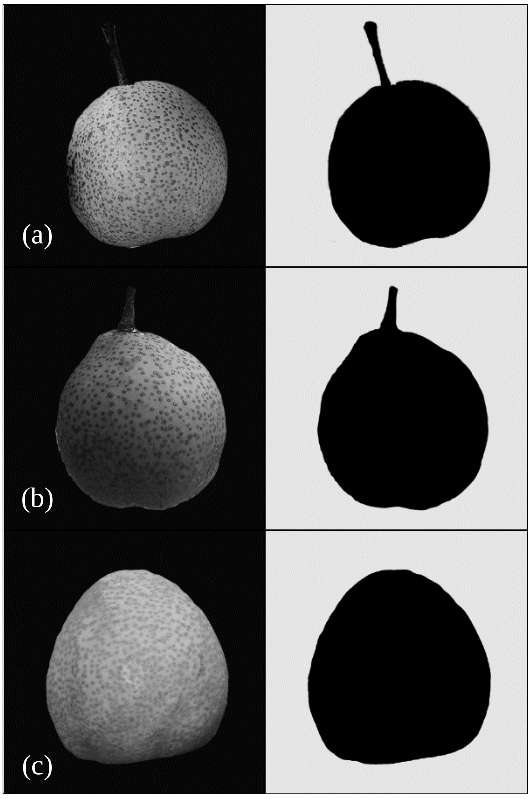

Fig. 15. Validation sample images with their binary images

time, but it influence the accuracy a lot. When K is small, the accuracy of detection for images with stem is good, but for images without stem is quite bad. However, when K is big, the accuracy for images with stem becomes bad, but for images without stem is good. Thus an intermediate K is proper for detection.

Taking both accuracy and detection time into consideration, the best combination in this situation is selected to be 400 as N and 2.35 as K.

3.5.3. Validation

This combination of parameters is then used to detect other three samples for validation. The algorithm is performed for 500 times on each image to test its stability. The results are shown in *Table 2*.

Table 2. Results of validation

Image	Accuracy	Detection Time
(a)	100%	2.03 ms
(b)	100%	2.05 ms
(c)	98.6%	2.45 ms

The results are acceptable, so this algorithm is practical. There are some errors for image (c), mainly because the shape of the pear in this image is relatively far from circle or ellipse.

3.6. Evaluations and conclusions

3.6.1. Innovation points

Instead of the normal scanning method, this paper introduces random number to solve the problem of stem detection. By using Monte Carlo method, the detection time can be remarkably shortened, and the accuracy can also remain high if the algorithm is designed and performed properly. Although the superiority of this specific algorithm cannot be assured, the introduction of Monte Carlo method to stem detection can be a brand-new way of thinking for developing better algorithms.

This algorithm can not only be performed on Laiyang pears, but also be applied to all fruits that satisfy the basic assumptions stated above, such as other varieties of pear. When the condition changes, parameter determination experiments need to repeat.

On condition that the shape of the fruit is approximately circle, this algorithm is not sensitive to rotation. That is, no matter what the direction of the stem is, this algorithm is able to detect it with high accuracy. But the direction of the stem also influences detection time, because the scan process of the pixels on the ellipse is performed from -135° to +225°. Images where stems appear in the top part need the least detection time.

This algorithm can also determine the approximate position of the stem region, because the pixel where the scan process stops belongs to the stem region without doubt. Then some algorithms can be performed on the neighboring area to determine the range of the stem region and other characteristics, instead of scanning the whole image.

What's more, this algorithm is able to determine the approximate area of the object region, which is relative to the size of the fruit. Just divide the number of random points selected by the total number of random points, and then multiply the total area of the image.

3.6.2. Problems and expectations

This algorithm requires profile images because of its basic principles. The problem can be solved by developing appropriate machine vision systems. The machine vision system stated above is only a possible type. It is not perfect because it lacks stability. The pears may fall down on the trays, and profile images are thus unable to be obtained. Some more reliable machine vision system to capture profile images of the fruits should be designed.

This algorithm can only be applied to round or oval fruits, which limits its applications. Therefore, the algorithm can be improved by using other statistical data and fitting methods instead of simple average, standard deviation and ellipse parametric equations.

The accuracy of this algorithm should also be improved without increasing the detection time. This goal can be achieved by modifying the algorithm. A possible modification is like this: After all random points are sprinkled and selected, discard the outlying points according to some statistical rules. Then the averages and standard deviations of the remaining points are recalculated and used for drawing the ellipse. This ellipse is believed to better describe the shape of the fruit region, but this modification takes more time than the original algorithm.

Only detection of the presence of stem is not enough because the length of the stem and its integrity are also important for quality assessment. So the subsequent algorithm should be developed. A possible algorithm to measure the length of the stem is illustrated here (*Fig. 16*). The direction of the stem is believed to be on the ray from point (Avg_x, Avg_y) to the point where the scan process stops. Then a line perpendicular to this direction is formed and scanned from outer to inner. The number of pixels belonging to the object region on the line is counted. When this number changes from 0 to something, this position is regarded as the endpoint of the stem. When this number increases dramatically, this position is regarded as the intersection of the stem region and the fruit region. Then the space between these two lines is calculated as the stem length. However, this algorithm is unable to detect the length of bent stems.

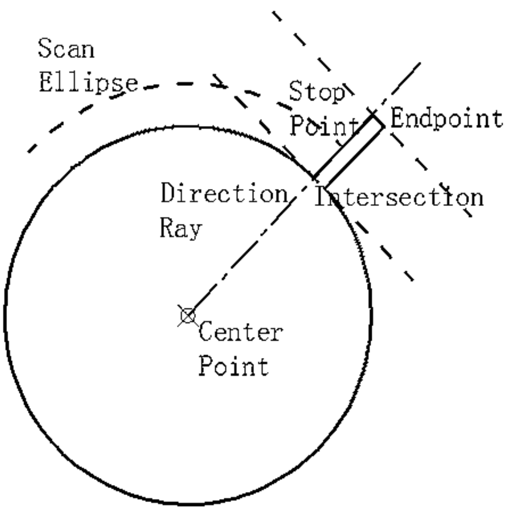

Fig. 16. A possible algorithm for stem length measurement

In addition, some self-adaptive algorithms can be developed to eliminate the manual parameter determination process.

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