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A Video Image Segmentation System for the Fruit-trees in Multi-stage Outdoors Orchard under Natural Conditions

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ABSTRACT

Segmentation is an important part of each machine vision system that has a direct relationship with the final system accuracy and performance. Outdoors segmentation is often complex and difficult due to both changes in sunlight intensity and the different nature of background objects. However, in fruit-tree orchards, an automatic segmentation algorithm with high accuracy and speed is very desirable. For this reason, a multi-stage segmentation algorithm is applied for the segmentation of apple fruits with *Red Delicious* cultivar in orchard under natural light and background conditions. This algorithm comprises a combination of five segmentation stages, based on: 1- L*u*v* color space, 2- local range texture feature, 3- intensity transformation, 4- morphological operations, and 5- RGB color space. To properly train a segmentation algorithm, several videos were recorded under nine different light intensities in Iran-Kermanshah (longitude: 7.03E; latitude: 4.22N) with natural (real) conditions in terms of both light and background. The order of segmentation stage methods in multi-stage algorithm is very important since has a direct relationship with final segmentation accuracy. The best order of segmentation methods resulted to be: 1- color, 2- texture and 3- intensity transformation methods. Results show that the values of sensitivity, accuracy and specificity, in both classes, were higher than 97.5%, over the test set. We believe that those promising numbers imply that the proposed algorithm has a remarkable performance and could potentially be applied in real-world industrial case.

Keywords: Background; Daylight; Machine vision; Natural condition; Texture; Color space

1. Introduction

Machine vision systems are used to perform different duties in agriculture and industry, among others. These systems have an automatic segmentation part that plays a main role in their accuracy. In environments with complex backgrounds including a wide variety of colors and textures, segmentation is the most sensitive part of a machine vision system (Rahimi-Ajdadi et al 2016; Rahimi-Ajdadi et al 2018). In these conditions, a wrong segmentation is caused when main object is considered as a background object that has to be removed, so the accuracy of machine vision systems is reduced (Slaughter et al 2008). Orchards are an example of environments

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with complex backgrounds. So in order to design a machine vision system to estimate the yield, spraying in proportion to the density of fruits, and fruit picking, segmentation operation has to be performed with high accuracy. There are various objects such as, leaves, different branches with different colors, cloudy or clear sky, among others. Therefore, the skill of programmer and the use of different segmentation methods such as color based segmentation, texture based segmentation and a combination of them, are very important often. Several researches have proposed different methods for in site-specific spraying, to combat weeds (Onyango & Marchant 2003; Montalvo et al 2013; Arroyo et al 2016; Sabzi et al 2017b; Sabzi et al 2018; Sabzi & Abbaspour-Gilandeh 2018; Sabzi et al 2018), plant segmentation in agricultural fields (Bai et al 2014; Hernández et al 2016; Sabzi et al 2017a), fruit segmentation (Liu et al 2016), determining the growth stage (Kataoka et al 2003) and in detecting plant diseases (Camargo & Smith 2009). Aquino et al (2017) proposed a segmentation method to count the number of 18 different cultivars of grape berry under artificial light. They used 152 images (126 images for training and 26 images for testing) to design a segmentation algorithm. The segmentation algorithm had two main steps: 1. general segmentation step to separate the grape cluster from the background, and 2. recognition each grape berry over each cluster. Results showed that the segmentation accuracy based on two classifiers including support vector machine (SVM) and artificial neural network (ANN) were 0.9572 and 0.8705, respectively. In another study, a segmentation method to detect immature green citrus in citrus gardens was proposed by Zhao et al (2016). They used a combination method of sum of absolute transformed difference (SATD) and color features. A total of 126 images, including 58 training image and 68 testing images, were used in the development of detection algorithm. Results showed that SVM classifier had a detection accuracy of 83%. Liu et al (2016) developed an apple segmentation algorithm based on artificial light with low brightness with 20 apple fruits. They used RGB and HIS color space components for training of ANN. They also consider the color and position of the pixels surrounding the segmented area in order to complete the segmentation. The estimation of number of citrus on trees based on image processing was studied by Dorj et al (2017). They stated that the estimation of performance is nowadays often done manually with low accuracy. For this reason, they used 84 images that were taken from 21 different trees. Their proposed algorithm had 6 main stages: 1- converting RGB color space to HSV color space, 2- thresholding, 3- identification of orange color, 4- noise removal, 5- applying watershed segmentation, and 6- final counting. The results showed that the determination coefficient between samples identified manually and with automatic algorithm was 0.93. Behroozi-Khazaei & Maleki (2017) studied the possibility of ripe grape clusters segmentation from leaves and the background based on color features using the combination of ANN and genetic algorithm. They used 129 images of ripe grape clusters that were directly taken from orchard. After training of proposed algorithm, results showed that their algorithm had an overall accuracy 99.4%. The probably of identification of cotton in the field based on an algorithm that was trained under supervised and unsupervised conditions was proposed by Li et al (2016). Their algorithm consisted of two main steps. The first step employed simple linear iterative clustering (SLIC) and density-based spatial clustering of applications with noise (DBSCAN) on Wasserstein distance and second step color and texture features were extracted from these regions based on texture. They used 42 images for training of the proposed algorithm. Results showed that the proposed algorithm had an average error within 4 years of 0.75 days.

It can be observed that most researches focus over processes of high quality images under artificial light also with a controlled background. In practice, in order to design a machine vision system being able to work in real orchard in picking of fruit, and estimating the number of fruits, a robust segmentation algorithm is needed. Since in any orchard different objects with different color and texture exist, segmentation algorithm often needs to be a combination of different segmentation approaches. The aim of this study is to develop a new segmentation algorithm consisting of various color-based, texture-based, and threshold-based methods, for separation of apple fruits under real conditions.

2. Material and Methods

Given that in a number of orchard operations, such as estimating the number of fruits, the camera has to move across orchard, video processing was used. Video processing is harder than image processing since the frames are lower quality than common still images. The segmentation algorithm was trained under real environment and natural variable light conditions. Figure 1 shows a global outline of different stages to design a new algorithm for apple color segmentation in garden.

2.1. Data collection

Since weather conditions and light intensity change from sunny to very cloudy during day, segmentation algorithms should be trained under various light intensities to offer high accuracy in all possible conditions. For this reason, different videos were recorded in nine different states using a DFK 23GM021, CMOS, 120 f s^{-1}, Imaging Source GmbH, Germany, digital camera equipped with an appropriate lens (Computar CBC Group, model H0514-MP2, f= 5 mm F1.4, 1/2 inch type megapixel cameras, Japan). Table 1 shows light intensity values and the number of frames used in each time of filming. Filming was performed during different states of growing of apple cultivar *Red Delicious* in different orchards of Iran-Kermanshah (longitude: 7.03E; latitude: 4.22N) under natural conditions. The speed of filming was inside a range of 10 cm s^{-1} to 35 cm s^{-1}. Figure 2 shows two illustrative sample frames from different orchards.

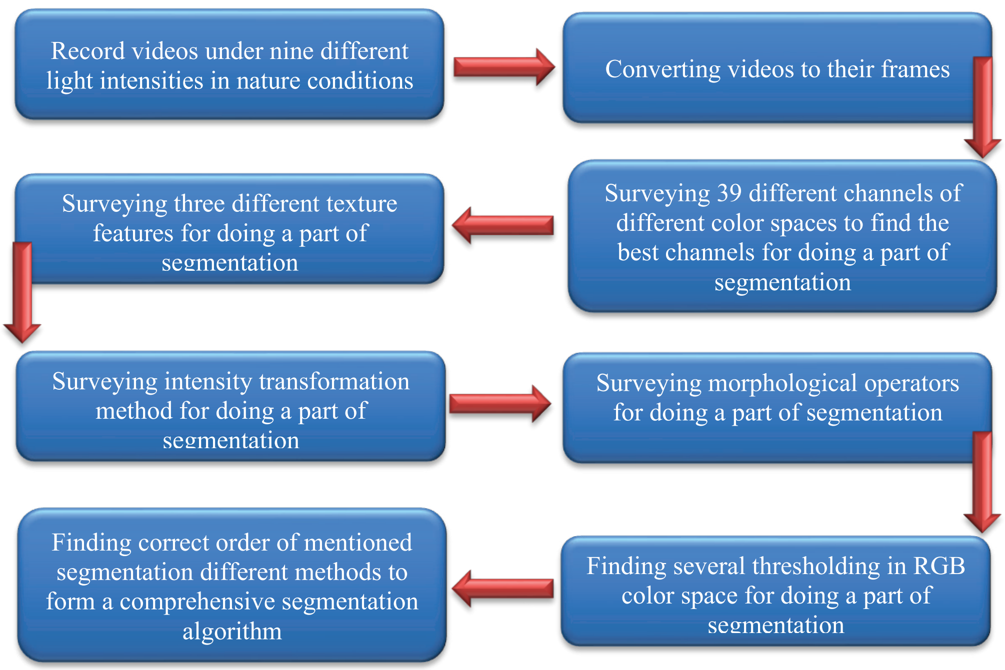


Figure 1- Different steps to form a comprehensive segmentation algorithm

Table 1- Light intensity and number of frames used in each video time state of filming

Video	*Light intensity (lux)*	*Number of video frames*
First	385	725
Second	628	439
Third	815	1264
Fourth	1120	694
Fifth	1386	496
Sixth	1593	583
Seventh	1793	1020
Eighth	1920	873
Ninth	2013	921

2.2. A survey of different color spaces

Difference researchers have surveyed the effect of the various color space in segmentation problems. They found that the finding of optimal color spaces increase the accuracy of segmentation (García-Mateos et al 2015). For this reason, A total of 13 different color spaces include: YIQ, L*a*b*, HSV, L*u*v*, YCbCr, CMY, HIS, JPEG-YCbCr, YDbDr, YPbPr, YUV, HSL, and XYZ that comprise a total of 13×3= 39 color channel, were investigated in this study. The aim of this survey is to find a suitable color space and channels for proper image segmentation. Figure 2 shows a sample video frame in different color spaces including RGB, CMY, L*a*b and L*u*v* color spaces. As it can be seen, each color space shows pixels with different colors. At this point, finding a color space that has minimum number of colors is very important since the possibility of main objects (apples) pixel elements is then reduced. On the other hand, background pixels need to be removed. Figure 3 shows that in L*u*v* color space there exists a minimum number of pixel color variations. Thus, we conclude that L*u*v* is a suitable color space to perform proper video frame segmentation.

2.3. The role of texture features in final segmentation

The use of texture features can offer useful information to detect background pixels in a segmentation process, since each kind of object can have different types of typical textures. These features have different outputs based on the texture of different objects. Texture is defined differently in different perspectives. One of the most common subdivisions is soft and hard texture. In fact, soft texture is the one with homogeneous object pixels, and hard texture is the one with heterogeneous object pixels. Because background of extracted frames from videos have different objects, and each object has a unique structure, using these features is useful for removing background objects from images. For this reason, local entropy, local standard deviation and local range were investigated to find the proper texture features for doing part of the segmentation work. Figure 4 shows the results of applying various local texture features over a sample video frame. As it can be seen, this method is very useful for pixel elements related to soil and plants that are dense.

Figure 2- Two sample video frames from different apple orchards

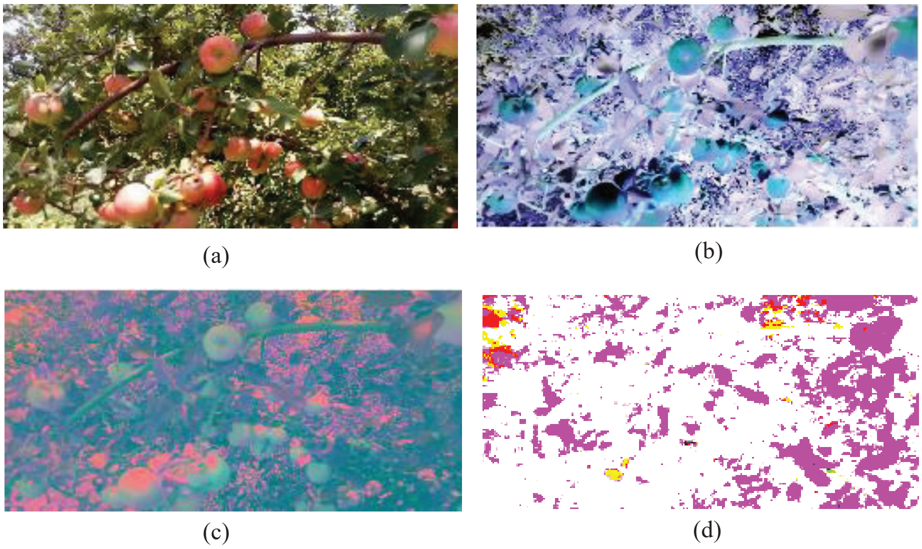


Figure 3- A single sample video frame displayed in different color spaces. (a), RGB color space; (b), CMY color space; (c), L*a*b color space; (d), L*u*v* color space

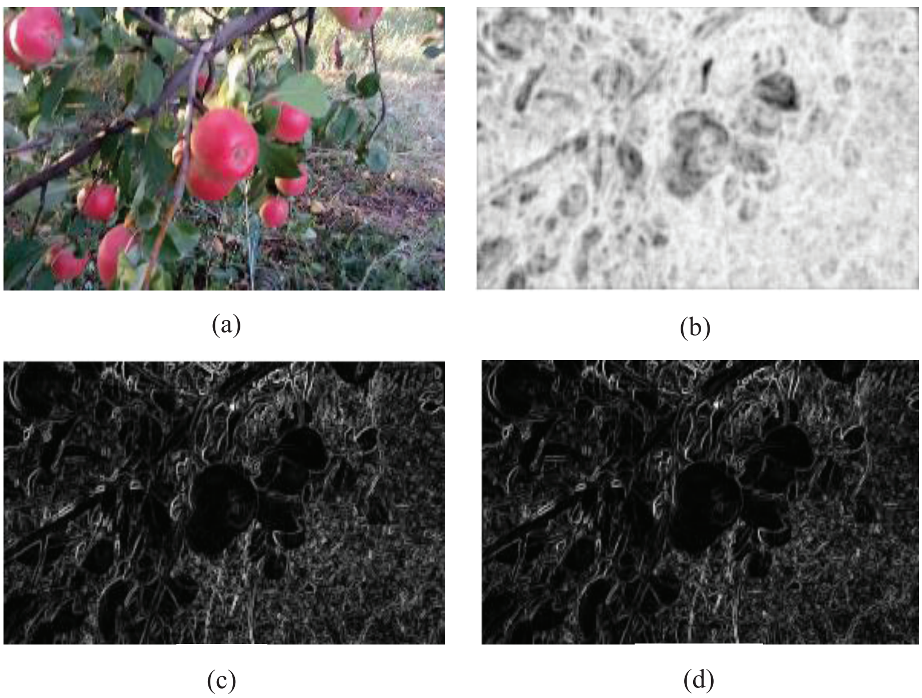


Figure 4- Results of applying texture features over a sample video frame. (a), original frame; (b), result frame after applying local entropy feature; (c), result frame after applying local range feature; (d), result frame after applying local standard deviation feature

2.4. The use of intensity transformation method is segmentation

The use of intensity transformation method can be offer valuable information in segmentation, since changes in pixel intensity range on gray images lead pixels to either bright or dark modes. This is the case of the current problem, where apple pixels have more bright intensities than many objects in the background, thus allowing thresholding to remove some pixels not of interest in frames. Figure 5 shows the effect of applying the intensity transformation method over a single sample video frame. Based on this method, applying thresholding afterwards, part of the segmentation work was performed.

2.5. Partial segmentation based on morphologic operators

Morphologic operators play a key role in outdoor segmentation since in outdoor variable daylight conditions, different noise levels are present due to sunlight, and dust. Based on different morphologic operators such as the removing of object borders, filling holes and thickening removal of objects with a value less than the specified threshold, variable noise is conveniently removed (Gonzalez et al 2004). Thus, three morphologic operators of filling holes, labeling of connected components, and removal of objects with a thickness number less than the specified threshold, have been used in this study. The threshold used at different stages of the algorithm was set to 100, meaning that objects with a number of pixels less than 100 are to be deleted. Later threshold value was selected based on trial and error.

2.6. RGB color space thresholds to final stage in segmentation

After using different segmentation methods, some background pixels still remained in frames. After studying and working on various frames, 30 thresholds in RGB color space were used to complete the final segmentation of video frames.

3. Results and Discussion

As mentioned in previous sections, comprehensive segmentation algorithm is a combination of several segmentation methods. The selection of optimal state of each segmentation method guarantees the accuracy of segmentation algorithm.

3.1. An optimal color space partial video frame segmentation

Since the color of some pixels of background and apples are similar, the use of a simple threshold is not possible for performing complete segmentation. But it can be proven that thresholding can help solve a large part of the problem, by removing pixels which are clearly outside the color range of apple fruits. After studying different color spaces, L*u*v* color space was selected as a suitable color space to do part of segmentation. In fact, among all color spaces, L*u*v* color space showed how most of pixels in different frames were displayed with only 4 main colors: white, purple, red, and yellow. For this reason, with lower error, background pixels are removed optimally. Equation 1 shows the exact threshold used in L*u*v* color space:

(a) (b)

Figure 5- The effect of applying the intensity transformation method over a sample video frame. (a), original frame; (b), original frame after applying the intensity transformation method

Luv1(i, j)>90, Luv3(i, j)>90, Luv2(i, j)>90 (1)

This equation implies that if all components of a pixel in L*u*v* space are more than 90, they belong to background and have to be removed from image. Figure 6 shows the result of applying L*u*v* color space threshold over a sample frame. As it can be seen in Figure 6, without deleting pixels of the main objects (apples) various background pixels were conveniently removed.

3.2. An optimal texture feature partial video frame segmentation

Since background includes different objects such as trunk of the trees in front of the sun, tree trunk in the shade, leaf in the sun, narrow branch, leaf in the shadow, petiole, thick branches in the sun, thick branches in the shadow, clear sky, cloudy sky, soil, green plants, yellow plants, dense leaves, mountains, wheat, straw, broken branches of trees, dried leaves on trees, flowers and weeds in the orchard, it often has sharper textures that produce higher texture values. On the other hand, apples skin show low values in all texture descriptors due to soft nature. So, based on this difference of texture value, a part of segmentation can be done based on texture features. Among next three texture features, local entropy, local standard deviation and local range, local standard deviation was selected to do part of the segmentation. In fact, any texture feature capable of removing the higher number of pixels possible from background with no damage to foreground (apple) pixels is a suitable texture feature. This is done by converting each texture structure image to a binary image, so that each pixel with value of 1 is considered as the background and will be consequently removed from frame image. Figure 7 shows the result of applying the second method of segmentation, the local standard deviation feature, over a sample frame. Figure 7b clearly shows that most part of background pixels were removed from image after thresholding.

(a)

(b)

Figure 6- Result of applying L*u*v* color space segmentation threshold over sample video frame. (a), original frame; (b), same frame after applying L*u*v* color space thresholding segmentation

(a)

(b)

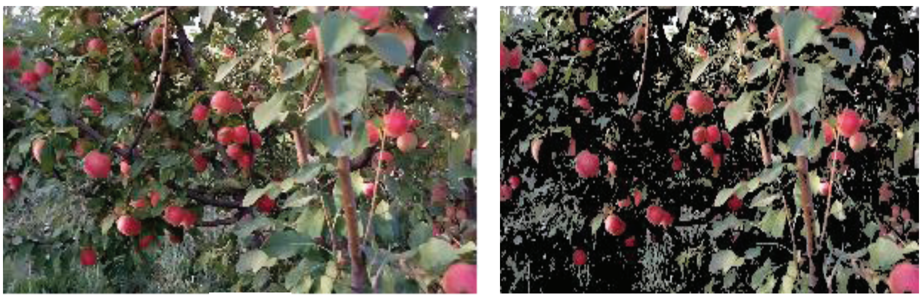
Figure 7- Result of applying the second method of segmentation (local standard deviation feature) over a sample frame. (a), original frame; (b), sample frame after applying the threshold of local range feature

3.3. An optimal threshold based on intensity transformation for partial video frame segmentation

Figure 8 shows the result of applying intensity transformation method over a sample frame. Figure 8b shows that most background pixels were eliminated from image frame without deleting apple foreground pixels, meaning that the method is remarkable robust. Frames were at first turned into gray images, and then pixel intensity range changed from {0, -1} to {0, -0.4}. Since images were in *uint8* data class, pixels were first multiplied by 225. Second, a threshold of value 75 was applied to perform part of segmentation. This threshold was obtained under a trial and error approach. This threshold assigns pixels greater than 75 to the background of frame image and thus should be removed. It is interesting to note that despite the different light intensities, with this thresholding method most of the darkest pixels belonging to the background, such as thick branches in the shadow, leaf in the shadow and petiole, were removed. This proves that this threshold was robust and fixed with high accuracy.

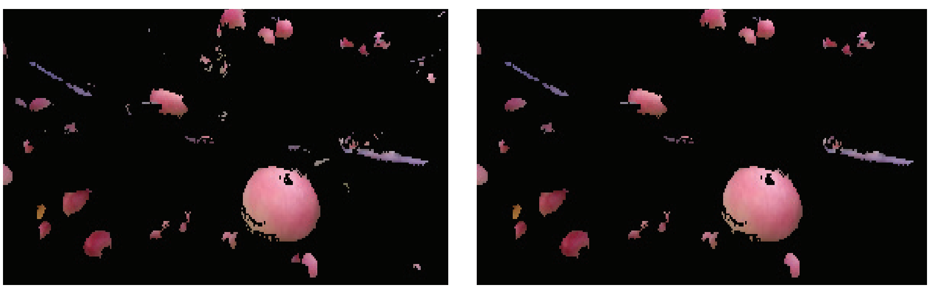
3.4. Optimal morphologic operators for partial video frame segmentation

Figure 9 shows the result of applying morphologic operators over a sample frame that was partially segmented by other segmentation methods. Figure 9a shows that some objects have the number of pixels less than 100. These objects have to be removed since they have not useful information and they reduce processing speed. Figure 9b shows the resulting frame after removing noise objects. The use of this operators cause that the speed of processing of segmentation algorithm rises. Since videos are taken in real conditions in garden and



(a) (b)

Figure 8- Result of applying intensity transformation method over a sample frame. (a), original frame; (b), result frame after applying the threshold using the intensity transformation method



(a) (b)

Figure 9- Result of applying morphologic operators over a sample frame that was partially segmented by other segmentation methods. (a), original image; (b), result frame after using morphologic operators

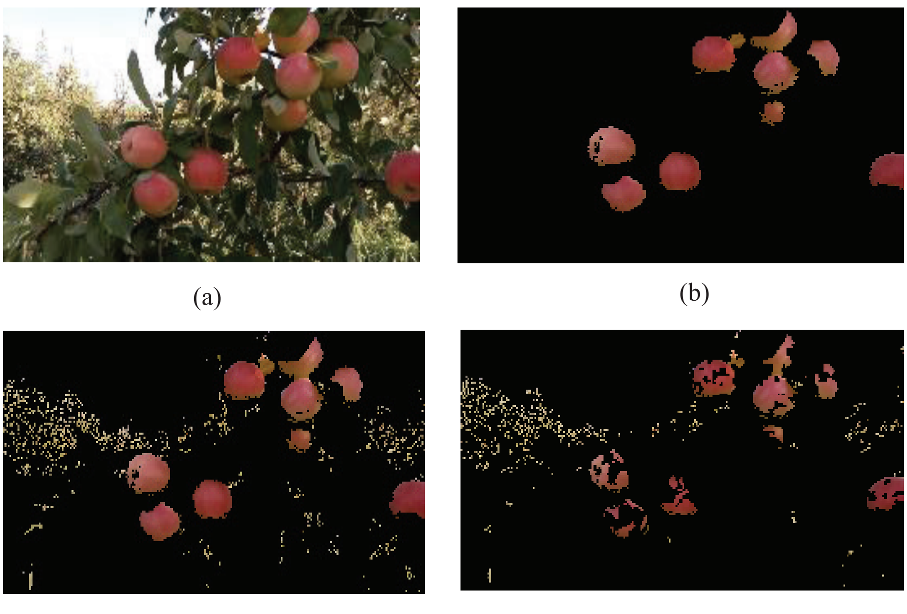
different objects in the background may exist, in each stage of segmentation a lot of pixels include noise. If noise is not removed, accuracy of results will be degraded for obvious reasons.

3.5. Best ordered combination of partial video frame segmentation methods

The order in which the segmentation methods are applied in the complete multi-stage segmentation algorithm is very important. In fact, each segmentation method can remove only part of background pixels from image, so the correct order in complete multi-stage algorithm of segmentation can cause removal of most background pixels. Figure 10 shows the effect of three different ordered segmentation methods in complete algorithm. As it can be seen in Figure 10b, the best order of segmentation is based on color, texture and intensity transformation methods. In other ordered methods, some noise still remains after final stage. This noise causes the use of additional segmentation steps thus increasing processing time. For online applications, time restrictions are very important, so processing time is a limitation factor.

3.6. Final color thresholds stage to complete multi-stage segmentation procedure

We tested that there were still few noise pixels after application of the different stages of segmentation. In order to remove noise, 30 thresholds in RGB color space were used as a final stage. Table 2 shows 11 RGB color thresholds definitions among 30 color thresholds to complete the segmentation process, which should be applied in an ordered fashion. For instance, first row in Table 2 means that if the first, second and third component of RGB color space are between 225 and 235, 170 and 180 and 135 and 145, respectively, and also the absolute difference between the second and third component of RGB color space is less than



(a) (b) (c) (d)

Figure 10- Results of three different ordered segmentation stages in complete multi-stage algorithm. (a), original image; (b), segmented image based on color, texture and intensity transformation ordered stages; (c), segmented image based on intensity transformation, texture, and color ordered stages; (d), segmented image based on texture, color, and intensity transformation ordered stages

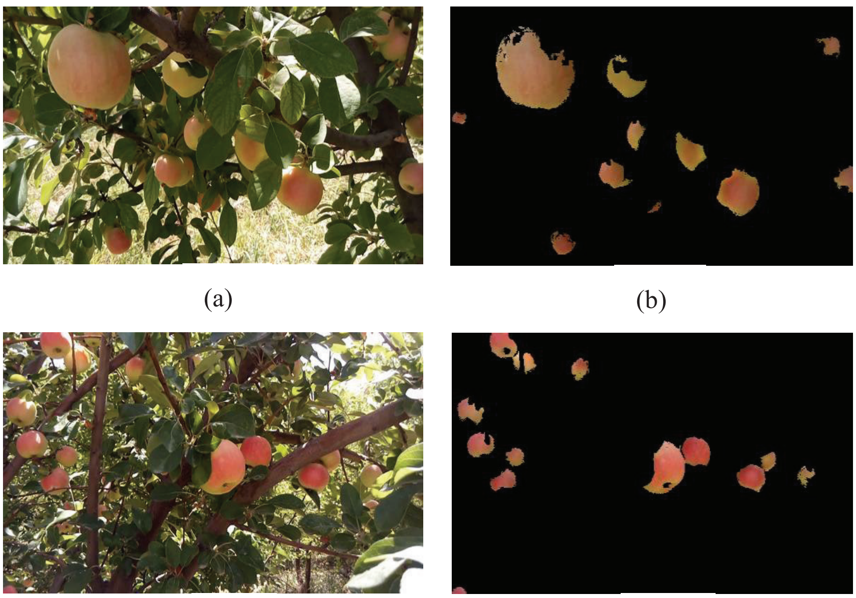
40, then that pixel belongs to background and has to be removed from image. Figure 11 shows two sample frames before and after segmentation based on segmentation by the complete multi-stage segmentation algorithm here proposed. Figures 11b and d show how background pixels were completely removed from image.

3.7. Accuracy and speed of algorithm

Table 3 shows confusion matrix and the accuracy in detection of fruits in image for the here proposed multi-stage video frame segmentation system, over the test set. This table shows that 1.69% of apple samples were incorrectly detected as background objects (from 23359 apple pixels, 394 where misclassified

Table 2- Definition of 11 RGB color thresholds to complete final segmentation stage

1	FR(i,j)>225 & FR(i,j)<=235 & FG(i,j)>170 & FG(i,j)<180 & FB(i,j)>135 & FB(i,j)<145 & abs(FG(i,j)-FB(i,j))<40;
2	FR(i,j)>250 & FR(i,j)<=255 & FG(i,j)>200 & FG(i,j)<210 & FB(i,j)>170 & FB(i,j)<180 & abs(FG(i,j)-FB(i,j))<35;
3	FR(i,j)>220 & FR(i,j)<=245 & FG(i,j)>170 & FG(i,j)<200 & FB(i,j)>150 & FB(i,j)<180 & abs(FG(i,j)-FB(i,j))<30;
4	FR(i,j)>155 & FR(i,j)<=160 & FG(i,j)>130 & FG(i,j)<165 & FB(i,j)>110 & FB(i,j)<150 & abs(FG(i,j)-FB(i,j))<20;
5	FR(i,j)>178 & FR(i,j)<=185 & FG(i,j)>125 & FG(i,j)<140 & FB(i,j)>105 & FB(i,j)<125 & abs(FG(i,j)-FB(i,j))<25;
6	FR(i,j)>195 & FR(i,j)<=220 & FG(i,j)>185 & FG(i,j)<210 & FB(i,j)>135 & FB(i,j)<155 & abs(FR(i,j)-FG(i,j))<15;
7	FR(i,j)>195 & FR(i,j)<=215 & FG(i,j)>165 & FG(i,j)<195 & FB(i,j)>120 & FB(i,j)<140 & abs(FR(i,j)-FG(i,j))<35;
8	FR(i,j)>215 & FR(i,j)<=230 & FG(i,j)>155 & FG(i,j)<170 & FB(i,j)>130 & FB(i,j)<150 & abs(FG(i,j)-FB(i,j))<30;
9	FR(i,j)>195 & FR(i,j)<=210 & FG(i,j)>160 & FG(i,j)<185 & FB(i,j)>125 & FB(i,j)<150 & abs(FR(i,j)-FB(i,j))>50 & abs(FR(i,j)-FB(i,j))<70;
10	FR(i,j)>215 & FR(i,j)<=220 & FG(i,j)>183 & FG(i,j)<190 & FB(i,j)>135 & FB(i,j)<140 & abs(FR(i,j)-FG(i,j))<35;
11	FR(i,j)>220 & FR(i,j)<=235 & FG(i,j)>195 & FG(i,j)<215 & FB(i,j)>150 & FB(i,j)<180 & abs(FR(i,j)-FG(i,j))<30;



(a) (b)

(c) (d)

Figure 11- Two sample frames before and after segmentation based on the multi-sage segmentation algorithm. (a and c), original frames; (b and d), segmented frames after use of the multi-stage segmentation algorithm

as background and removed from image) and also 1.91% of apple samples incorrectly detected as background objects (from 16336 background pixels, 313 where misclassified as apple pixels and kept in image). These misdetection values show a well-balanced and homogeneous of classification errors among the two classes, since the number of apple color pixels misclassified as background objects is similar to the number of background color pixels misclassified as apple samples. Three commonly used criteria for analyzing the performance of a binary classification algorithm are sensitivity, accuracy and specificity. By definition, sensitivity expresses the wrong assignment of samples of the relevant class and specificity indicates the wrong assignment of the samples of other classes into the relevant class. Finally, accuracy is the percentage of total samples correctly classified in their corresponding classes (Wisaeng 2013). Table 4 shows the results of the algorithm performance in terms of sensitivity, accuracy and specificity, over the test set. As it can be seen in Table 4, all these three criteria have the value higher than 97.5% in both classes, implying a remarkable accuracy in segmentation and potential application under real conditions in industry. The speed of data processing in online application is important. For this reason, algorithms with high speed and accuracy are most useful. In this study, a laptop with processor Intel Corei3CFI, 330M at 2.13GHz, 4GB of RAM, Windows 10 and MatLab 2015b was used. The average processing time per video frame was 0.795 seconds, including image reading and full multi-state segmentation. Since the proposed method in this study is new and there is no similar case, there is no direct comparison of the results obtained in this study with the results of other researchers. However, comparing the results of this study with other studies reveals the importance of the method used here. For this reason, the proposed segmentation method is compared with two similar previous studies by Hernández-Hernández et al (2016) and Aquino et al (2017). These two studies focused on the segmentation of corn in agricultural land, and on counting the number of grape cubes with an artificial background, respectively. Table 5 shows the results of comparing our method with two

Table 3- Confusion matrix and the accuracy of the detection of the proposed multi-stage video frame segmentation system, test set

Classes	*Apple*	*Background*	*All data*	*Misdetection (%)*	*Correct detection (%)*
Apple	22965	394	23359	1.69	98.22
Background	313	16023	16336	1.92	

Table 4- Performance of the multi-stage frame image segmentation algorithm classification in terms of sensitivity, accuracy and specificity (%), test set

Class	*Sensitivity (%)*	*Accuracy (%)*	*Specificity (%)*
Apple	98.31	98.22	98.66
Background	98.08	98.22	97.60

Table 5- Compares the success rate of the different methods for segmentation

Method	*The number of samples*	*Accuracy rate (%)*
Proposed model	39695 (testing data)	98.22
Hernández-Hernández et al (2016)	182	97.00
Aquino et al (2017)	152	95.72

other methods. As it can seen, our method has higher accuracy. We believe that one of the most important reasons for high accuracy in our method is the use of a combination of several segmentation methods, while two other methods used only one single segmentation method. When using only one segmentation method, thresholding may be rather sensitive.

4. Conclusions

In current study, a segmentation algorithm to segment fruits over trees in outdoors garden under natural condition was proposed. This algorithm is formed from a combination of different methods. Due to different challenges in nature/real conditions in open field, the use of a combination of different methods may obtain higher accuracy. In fact, we believe that when only one segmentation method is used, threshold set value is very sensitive, since it may be altered by the pixels of main foreground objects. Also, in order to achieve methods that are able to work in real time, video input should be used instead of static still pictures, thus producing lower quality images. The order of segmentation methods in comprehensive algorithm plays also an important role in accuracy, so that an unsuitable order reduces segmentation accuracy. To conclude, we want to state that the accuracy of the final multi-stage segmentation algorithm in detecting background and apple objects was rather remarkable in 98.22%, over the test set.

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