Almond Dispersion Detector for a New Almond Picker Apparatus using Coupled Image Segmentation and Genetic Algorithm

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ABSTRACT
The objective of this study was to develop a machine vision system for detecting almond drop from trees on the ground during the harvesting stage. To attach this goal, in the machine vision system, the segmentation technique was coupled by genetic algorithm technique. The proposed method consists of three steps; Preprocessing included conversion images to gray level, noise reduction and edge dissimilarity enhancement; Image segmentation included K-means clustering algorithm, connected components labeling and remove small region; Region merge procedure using GA. The developed method was compared with usual image segmentation, thresholding and color segmentation. The results of fruit detection in the images showed that the developed method could detect 93% of all fruits in the images. While fruit detections using segmentation-thresholding and color segmentation in the images were 80% and 78%, respectively. The results confirmed that our method is found to be suitable, and effective for detecting almonds.

Keywords
Almond, almond picker, image processing, segmentation, genetic algorithm, merge procedure.

1. INTRODUCTION
Almond (*Amygdalus communis L.*) is one of the most popular tree nuts in the worldwide. It is perennial plant growing in the Mediterranean and cold climates of Iran. The almond and its kernel play an important role as a source of protein (21.22 g/100g) in human diet [1, 2]. In 2011, Iran with 170×103 tones almond production was the third main producer country after USA and Spine in world. One of the most important processing steps in almond production is almond harvesting that its mechanization gives the most promise of reducing costs. Records show that knocking costs per acre vary widely between orchards. Such variations are caused more by differences in size of trees, varieties, maturity of nuts when knocked, times of day, efficiency of crew and method used than by differences in yields.

Experimentally, various types of mechanical shakers are being tried but as yet none has been proven to be practical. After shaking the tree, nuts fall on the ground. Therefore commercial harvester should use a picker part to gather the nuts. Modern commercial pickers use mechanical fingers or brushes to sweep the nuts up from the ground so they can be elevated through the machine to be sacked, or dumped into a bulk trailer. The use of a mechanical picker usually requires extra land preparation. The land must be as level as practicable for the most efficient operation. Extra annual ground preparation costs for mechanical picking generally range from $200 to $600 per acre in Iran. Soil type is an important factor affecting this cost. Most farmers try to level the ground with scrapers and then roll and pack the soil to get away from clods that can be picked up by the picker. Sticks and leaves falling to the ground during shaking or knocking operation may cause difficulties to the mechanical picker. Excessive leaves on the ground may clog the picker and materially slow down the operation. Clods or rocks if not removed may cause damage to the huller. For most almond orchards mechanical picking involves an additional capital outlay for new equipment of from about $3000 to over $6000 in Iran. This covers only the picker, additional land leveling and smoothing equipment, and trailers. Other equipment usually required at the huller pre-cleaner, de-rocker ranges from about $1800 to $2200. Because of the lower labor requirements bulk handling of the nuts has become general practice with mechanical pickers. Where bulk handling is used, additional equipment bins, elevators, conveyors which may cost from $1200 to $3600, usually must be installed at the huller. Thus the changing over to mechanical picking could involve a total capital outlay of from around $6000 to more than $12000 exclusive of any changes in hulling practices.

For savings in costs, the pickers should be modified by a detecting system of almond position using automated systems such as image processing techniques. Prototype machine vision based harvesters are increasingly being developed such as nut [3, 4], fruit [5, 6, 7, 8], vegetables [9], citrus [10, 11].

Until now, several studies have been conducted to detect fruit position using image processing techniques. However, most of these techniques require thresholds for features such as color, shape and size. In addition, their performance strongly depends on the thresholds used, although optimal thresholds tend to vary with images [9]. Their developed method did not require an adjustment of threshold values for fruit detection from each image because image segmentation was conducted based on classification models generated in accordance with the color, shape, texture and size of the images. The challenges in developing a fruit harvesting robot are recognizing the fruit in the foliage and detaching the fruit from the stems and leaves without damaging them [5]. They developed a real-time fruit detection system using machine vision and laser ranging sensor and an end effecter capable of detaching the fruit similar to the human picker. The machine vision recognized the fruit and the laser ranging sensor determined the distance of the fruit.

According to the researches in an automated picker system the following operations are needs: (1) Recognize and locate the fruit; (2) Reach for the fruit by detecting the distance between apparatus and fruit; (3) Detach the fruit from soil, leaves, debris and so on. One of the low cost, rapid and strong method to attach these goals is image processing technique. The techniques in image processing can be divided into spectral-based or shape-based analysis. Spectral-based analysis is effective for fruits with reflectance different from the background [12] while shape-based analysis is used to look for a specific shape of the fruit [13]. One of the most encountered problems in fruit detection is uneven lighting condition [14]. This condition can affect the reflectance of objects which can result in not detecting the fruit or detecting a non-fruit object. In some shape-based approach, leaves are detected as fruit. The third problem is occlusion where fruits are partially hidden by other fruits, leaves and stems. Some researchers have reported methods to detect occluded objects. One of the popular methods is the image segmentation using thresholding [10] which is effective for more round fruits but the leaves generated false detection, image segmentation using color features [11, 15] which has false detection in uneven lighting conditions and blob-based segmentation [9] which is computationally intensive and will pose a challenge for real-time application. Therefore the objectives of this study were recognition the almond on the ground after shaking the tree using new technique of image segmentation i.e. coupled dynamic region merging and genetic algorithm (GA) techniques and compared the detection results with color and thresholding segmentation methods.

2. MATERIAL and METHODS

2.1 Image Acquisition

The pictures were taken from some groves of Chaharmahal and Bakhtiari province in Iran (situated between 31° 09' North latitude and 32° 48' East longitude, located at the center of Zagros Mountains) after shaking the almond trees in the phase of harvesting (Fig 1). The pictures were imaged in different position of groves and in different lighting conditions using a webcam located on an equipped displaceable leg with two wheels for recording the images from different position and distance of almonds.

2.2 Image Processing

The software written in Matlab code was used to execute the algorithms spending an average of 8 seconds to recognize the fruits in each image. The software was not compiled to generate a faster code, so the timings reported could be improved to cope with the requirements of a real-time application. The software was designed using image processing-segmentation and GA toolboxes. The segmentation of complex images is one of the hardest tasks in image processing. The precision of the segmentation determines the success or failure of other analysis procedures. Consequently, special care must be taken to improve the techniques and achieve accurate segmentation results. The presented evolutionary image segmentation approach consisted of three phases; preprocessing filters, split procedure and merge procedure using genetic optimization. In the first step of our segmentation approach, original input image was transformed into a gray-level intensity image, its noise was reduction using 'Average', and 'Gaussian' filters, respectively, and edge dissimilarity was enhanced using 'Unsharp' filter.

Fig 1: Almond scattering with different amount and position on the ground

2.2.1 Split Process

The split procedure included the following steps: (a) Clustered pixels of the image by K-means clustering algorithm; (b) Identified different regions using connected component labeling; (c) Removed small regions in order to prevent over-segmentation.

After applying the preprocessing steps and the split procedure, an initial segmented image was formed which was subjected to optimized merge procedure by means of a GA. In order to cluster the entire pixels of the image into several groups, the original input image was divided into several regions using the K-means clustering algorithm (Fig 2).

2.2.1.1 K-means Clustering Algorithm

K-means is an applicable method to divide the image pixels into a variety of clusters based on histogram technique which is a representation of number of pixels in each intensity level [16]. K-means algorithm categorized pixels together whose features were similar to each other. In the first iteration of K-means algorithm, a number of predefined pixels were selected randomly as the center for each cluster. The final result illustrated several clusters that every cluster indicated a specific interval in the histogram (Fig 3).

The main benefit of this technique is to avoid the complex threshold setting by using an iterative procedure. Furthermore, the segmented contours are continuous and one-pixel-wide, which is another advantage of this method. However, over-segmentation problem may take place [17]. Therefore, a merge procedure was further applied in order to solve the problem.

2.2.1.2 Connected Component Labeling

K-means clustering cannot provide a distinguished object of an image because there may be some pixels in one cluster, which are not connected to each other. Due to some disconnected pixels of a cluster, the number of regions may be more than the number clusters after the split process. In our approach, clustered image was defined by a matrix in which, pixels of each cluster had the same value. Thus, in order to label the connected pixels as a region, the connected component label algorithm was applied on the image. Afterwards, the initial segmented image with separated region labels was achieved. Due to noise and spatial property of an image, there were some regions that may contain only a few pixels [18]. Small regions were neglected if their pixel sizes were less than 15 pixels for an image with the size of 270×340. In order to ignore small regions, they were merged with one of their neighbors. Then, small regions were removed by merging with their best neighbor based on some predefined criteria. The number of inappropriate regions would be reduced by removing small regions. The process of optimization for image segmentation is shown in Fig 2, in which original input image is influenced by mentioned preprocessing techniques and then detected objects are attained after the merge procedure containing a GA.

2.2.2 Merge Procedure Using GA

An evolutionary merge procedure was further applied on initial segmented image in order to ignore inappropriate regions. In this context of GA, there were three primary states to design an evolutionary merge procedure as follows; 1) An effectual chromosome encoding model; 2) A suitable fitness function; 3) A powerful evolutionary algorithm.

2.2.2.1 Chromosome Encoding Method

A chromosome encoding method was used to represent a segmented image. Each gene of the chromosome indicated a separated region of the image. Assumed that the segmented image had R regions (r_1, r_2, r_3,… , r_R), the chromosome $\alpha = \alpha_1, \alpha_2, \alpha_3, \dots, \alpha_N$ was an integer string, which represented the number of genes. The length of the chromosome (number of genes) was equal to the number of regions in segmented image [19].

2.2.2.2 Neighbor Selection for Merge Procedure

To decide which neighbor is the best one to merge, dissimilarity distances must be compared between a region and all of its neighbors. In this study, the dissimilarity distance was based on the region variance. If the variances of two adjacent regions are close, then they are candidates for merging. Therefore, variance distances were calculated between a region and all of its neighbors. Dissimilarity distance was calculated by measuring the Euclidean distance between variances of one region and all of its neighbors. In this approach, Euclidean distance was computed in the scale of regions variance. As a result of the K-means clustering algorithm, each region involves a number of connected pixels (x), with similar gray level intensity (g). Consequently, in order to calculate the Euclidean distance of variances (d_i), all pixels (x) of region R must be substituted in Eqs. (1-3).

$$\sigma_R^2 = \frac{\sum_{i=1}^{n}(g_i - \bar{g})}{\bar{g}} \qquad (1)$$

$$\bar{g} = \frac{\sum g_i}{N}, for\ i = 1{:}N \qquad (2)$$

$$d_i = \sqrt{|(\sigma_{r_i}^2)^2 - |(\sigma_{N_i}^2)^2|} \qquad (3)$$

Where σ_R^2 represents variance of region R, g_i represents the gray-level intensity of pixel i (for i=1: N, while N is the number of pixels in the considered region) and $\bar{g}$ indicates the mid-point of the region which is based on the gray-level intensity of pixels.

In order to undertake the merge procedure, considering the dissimilarity distance as the only condition was not enough. Therefore, to have a desired merge procedure, a threshold value was also taken into account. The lower variance distance should be smaller than the predefined threshold value to satisfy enough similarity between two adjacent regions [20].

2.2.2.3 Fitness Function

In this representation, the K-means algorithm was based on the properties of the pixels in a region. Consequently, the fitness function was also related to the overall properties of the regions in an image. We can define the fitness function with two main objectives, namely: regions contrast (dissimilarity distances between regions) and region size. Therefore, the fitness function for each chromosome was based on the summation of all variance distances between the merged regions (Eq. 4). Fitness value was computed to evaluate the quality of each individual. Based on the predefined fitness function, better fitness values identified better individuals.

$$F = \sum_{i=1}^{N} \frac{1}{d_i * s_i}, i = 1{:}N \qquad (4)$$

Where i represent the candidate regions which should be merged with their best neighbors, s_i indicates the size of removed region and d_i represent the Euclidean distances between the removed regions and their closest neighbor based on variance. The smaller value of s_i and d_i produce better fitness value [21].

2.3 Genetic Algorithm

To select the best pair of chromosomes, the fitness value is an essential parameter to generate the next population. In this study, a selection operator was applied based on the Roulette Wheel Selection approach [22]. In this approach, each individual occupied a portion of roulette wheel, with respect to its fitness value. Individuals with better fitness values taken longer slot from the roulette wheel. It was clear that the longer slot had the higher priority to be selected. In our research, two chromosomes were selected. Consequently, to produce new chromosomes, crossover and mutation operations were applied. In this implementation, two-point crossover operation was applied on the selected chromosomes (parents), to produce two offspring. Through the crossover operation, a fixed interval with a random selected start point was defined as the crossover interval. The length of crossover interval depended on the number of separated regions in the segmented image. In our representation, mutation operation caused to change the region label into one of its neighbors. In this method, random numbers of genes (regions) were selected from the offspring. The selected regions would be merged with one of the adjacent neighbors as an extra merge procedure. As a result of this method, in order to produce one uniform region, the boundaries between two merged regions would be removed [21, 23].

In order to take more advantages from GA optimization technique, the elitism strategy was used during the generation approach. In canonical GA, in order to produce the next population, all of the individuals from the current population must be participated. Therefore, the entire individuals from previous population would be replaced by the new generation [24]. Thus, the convergence rate of canonical GA was found to be very low. On the other hand, in elitism strategy, the best individual from the current population always survives into the next population [24]. As a result, CPU time was lower and the individual with the best fitness value would be unchanged in the next generations.

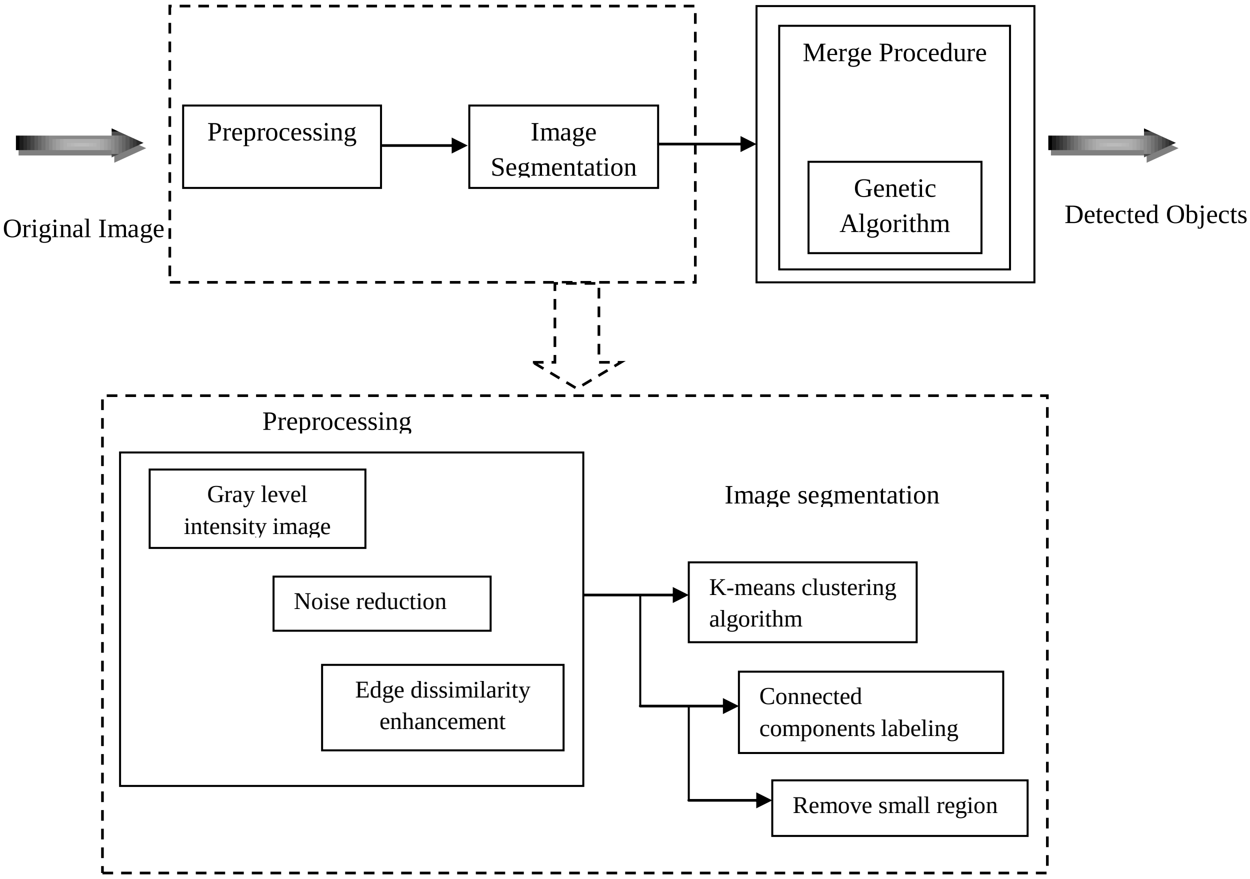

Fig 2: Optimization image segmentation process

(a) **(b)** **(c)**

Fig 3: (a) Original image; (b) K-means clustering image; (c) Histogram of the original image

3. RESULTS AND DISCUSSION

The proposed GA optimization for image segmentation was implemented using Matlab programming on an Intel core (TM) i3CPU computer. The procedure was completed when the fitness value of the best chromosome remained unchanged during 5 generations. As a result, total of 40 sub images of almond separation with different amount of almond and position were detected by this algorithm. As it is illustrated in Fig 4, the presence of other objects in the scene such as sticks, clods, rocks, leaves and so on can cause high occasion. The biggest challenge of occlusion is false detection, which will affect the accuracy of the picker system. Therefore in this study, the main focus was to determine if the segmented portions were almond or an occluded fruit and treat the single fruit as the fruit to be picked. In this way, false detection could be avoided and the probability of picker the fruit successfully was increased.

Our developed method was able to recognize each one of the safe almonds but obviously less of the rocks and clods were detected due to their minor difference with the color of the almonds. False detections were appeared to detect the leaves because of their similarity with color of almonds.

Table 1 and Fig 4 describe the results of fruit detection from the images. The developed method using GA could detect 93% of all fruits in the images, while fruit detection using segmentation-thresholding and color segmentation was 80% and 78%, respectively. Missed fruit detection was analyzed by comparing with manual counting. The missed detected fruits were the fruits which existed in the image but failed to be detected by the algorithm or the rocks, clods, sticks and leaves which were incorrectly detected as almonds. The most miss detections were from sticks and leaves due to their similarity with the color of almonds (Table 1). Miss detections by using segmentation-thresholding method from sticks and leaves were nearly similar to rocks and clods because of using object sizes in the images but to detect the objects in the images using color segmentation, the color features of objects were used. False positive detection is incorrectly detected background object as fruit by the algorithm. This factor was calculated by summing the number of estimated clods and rocks with number of estimated sticks and leaves. The percentages were calculated with dividing the false positive count by total count. The result showed that false positive count for segmentation-thresholding, Segmentation-GA and color segmentation were 220 (18%), 65 (5.4%) and 272 (23.8%), respectively. Furthermore the most false positive count attached for sticks and leaves detection.

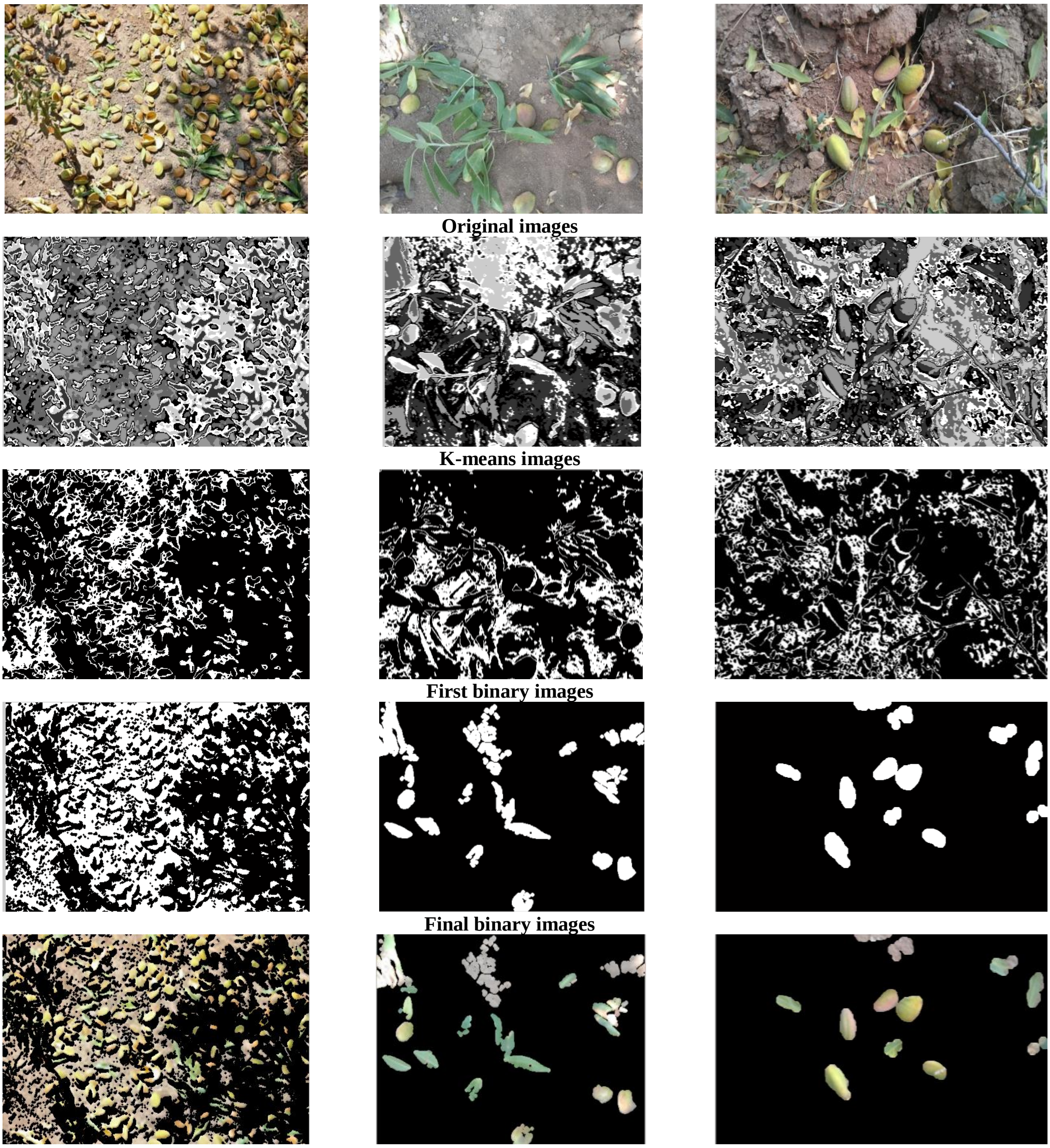

Fig 4: Different stages of image processing to detect the almonds

Table 1. Performance of different algorithms for almond detecting

Algorithm	Num of images	Num of almonds by manual counting	Num of rocks and clods by manual counting	Num of sticks and leaves by manual counting	Num of estimated rocks and clods	Num of estimated sticks and leaves	Num of estimated almonds
Segmentation-thresholding	40	1650	1242	1150	100 (8%)	120 (10%)	1320 (80%)
Segmentation-GA	40	1650	1242	1150	30 (2.4%)	35 (3%)	1532 (93%)
Segmentation-color	40	1650	1242	1150	108 (8.6%)	164 (15.2%)	1301 (78%)

It can be concluded that coupled image segmentation and GA could produce a new technique for detection the almonds separating on the ground after shaking. Indeed, coupled image segmentation and GA is a superior, cheaper and faster optimization technique for detecting the almonds and their distances for the processing machines when compared to the experimental methods. Therefore, the integrated image segmentation and GA approach is an appropriate method which can reduce the missed detection in a picker machine and increase its performance. This method can help the researchers and factories in the future for improving the almond picker machines and other automated machines.

4. CONCLUSION

In order to detect better almond separation in ground after shaking the tree, a new image processing algorithm was used in this research. The new technique was made by coupled image segmentation and GA. Of course this algorithm was compared with two general segmentation methods, segmentation using thresholding and color segmentation. The proposed method consists of three steps; 1- Preprocessing included conversion images to gray level, noise reduction and edge dissimilarity enhancement; 2- Image segmentation included K-means clustering algorithm, connected components labeling and remove small region; 3- Region merge procedure using GA. At the first and second steps, pixel-based segmentation was conducted to roughly segment the pixels of the images into classes composed of fruits, leaves, stems and backgrounds and eliminated misclassifications generated at the initial segmentation. At the third step, merge procedure was applied to detect individual fruits in a fruit cluster. The developed method did not require an adjustment of the threshold values of each image for fruit detection. The results of almond detection in the images showed that our method could detect 93% of all almonds in the images, while almond detections using segmentation-thresholding and color segmentation in the images were 80% and 78%, respectively. This indicates that our approach can be a useful tool to find the almond separation for designing the gathering machine to reach the optimal efficiency of gathering the almond, which is considered as a very tedious and time-consuming task.

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