

KDC: A Green Apple Segmentation Method

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Abstract Efficient and accurate recognition of apples in the visible spectrum is the key part of realizing orchard production prediction and automatic harvesting. The color of the green target is similar to the background of the branches and leaves. Thus the recognition of green apples becomes a new challenge. In the natural orchard, many complicated environmental factors may affect the accurate recognition of target fruit, such as light, rain, occlusion of branches and leaves, and overlap of targets. The existing recognition methods of target fruit are difficult to realize the real-time and accurate production prediction and automatic harvesting. In order to better realize the recognition of the green target in the natural orchard, a new kernel density clustering (KDC) is proposed. Firstly, the target image is segmented into irregular blocks by the simple linear iterative cluster (SLIC) algorithm, and approximate pixels in a small area are merged into superpixel area. The basic calculation unit is converted from a pixel point to a superpixel area to reduce the complexity. The SLIC algorithm is used to effectively avoid the target fruit contour's blur when simplifying the image data. Based on superpixels, the two-dimensional feature components of the R-B region mean and the G-B region means are constructed, and the color feature space of the green apples for cluster analysis is established. Then, the density peak clustering algorithm calculates the local density and local difference degree of each data point of the green apple image. The precise and accurate local density in different complicated scenes is calculated using kernel density estimation. The high-density area segmented by the low-density area is found more accurately, and the clustering of arbitrary shapes is realized. Finally, a decision graph used to find a cluster center is constructed according to local density and distance. A double sorting algorithm is employed to automatically select cluster centers and efficient segmentation of target fruit. The superpixel area representation of the image is obtained using the SLIC algorithm, and the local density of the data points is obtained using kernel density estimation. The new algorithm greatly reduces the computational complexity and achieves efficient and accurate segmentation of the target images. In order to better verify the performance of the new algorithm, the experiment collects occluded and overlapping target images under multiple lighting, rainy and other complex environments and evaluates them based on segmentation efficiency, segmentation effectiveness, false positives, and false negatives. By comparing the k-means clustering algorithm, mean shift clustering algorithm, fuzzy C-means (FCM) algorithm and density peak clustering algorithm (DPCA), it is finally concluded that the segmentation performance of the new algorithm is the best.

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Introduction

Apple is the third largest fruit crop in the world, but it still adopts the production mode of artificial planting and artificial harvesting. It restricts the flow of labor and the development of the local economy. The solution to the problem is the development of apple's automatic harvesting robot^[1]. The red apple can construct the color difference based on the color feature only, and obtain the segmented image by threshold segmentation because it distinctive color discrimination with the background leaves^[2]. Compared with red apples, green apples and the background are the same color representation. Color approximation leads to blurring of the boundary between fruit and leaves. The traditional method usually distinguishes the fruit from the background based on the texture feature^[3]; and further integrates the color and geometry features to improve segmentation accuracy^[4-5]. Due to the limitations of color camera capture information, spectral phase imaging techniques detect objects of interest based on different wavelengths to distinguish between fruit and background. The thermal imager captures the surface temperature of the object to complete the segmentation^[6].

In recent years, the segmentation of the uniform color fruit has also attracted the attention of many scholars. Li performed Gaussian linear fitting on the foreground image of the green apple under the V channel and used the threshold segmentation to cut the image^[7], which achieved good performance, but the segmentation effect was greatly affected by irregular illumination. A support vector machine is trained to detect and segment green orange, but the occlusion between the leaves and the fruit limits the model's efficiency^[8]. With the rapid advance of image segmentation technology in recent years, mature segmentation algorithms have been applied to the study of fruit segmentation on the same color background. Huang used a graph-based image segmentation algorithm to the green peach recognition model to segment the green peach image into superpixels images by different parameters, and then connected the different segmentation images to obtain the final segmentation result^[9]. However, the effect of the determination of the target boundary is not exact. Wang proposed a gPb-OwT-UCM edge detection algorithm for the green apple detection model based on the SUN detection mechanism^[10]. However, the edge detection algorithm has high time complexity and high requirements for running memory.

In view of the fact that the traditional algorithm is too stiff of the eigenvalue processing leads to an unsatisfactory accuracy rate. This paper proposes a green apple image segmentation algorithm based on density peak clustering. The local density and local difference of each data point are calculated. The decision map is kept separated from the cluster center and other data points. The double sorting algorithm automatically finds the cluster center to accomplish the clustering. The local density is calculated by kernel density estimation (KDE) without considering the manual setting of the cutoff distance, and the pixel level representation of the image is converted into a region level representation according to the SLIC algorithm, which greatly reduces the number of data points and reduces the analysis difficulty. The algorithm can process the boundary blur in the unsupervised and promote accuracy in segmentation results.

1 Image acquisition and method overview

1.1 Method overview

Accurate recognition of target boundaries in green apple image segmentation is still a problem. Boundary blurring creates great difficulty in segmentation problems caused by the approximate color of the apple target and the foliage in the background. This paper uses density peak clustering algorithm to segment green apple image and uses kernel density estimation and double sorting algorithm to optimize clustering algorithm effect.

In this paper, the SLIC superpixel algorithm^[11] is used to process the captured green apple image, and the approximate pixels are formed into irregular blocks of the image. The article analyzes the expression of color features, and the average value of the irregular blocks in the R-B image and the G-B image is taken as the feature component, and the distance between the data points is described. The kernel density estimate is used to calculate the local density of the data points. Compare the local density to get the closest distance from the data point to the larger density point^[12]. Automatic selection of cluster centers is performed using a double sorting algorithm. Finally, non-clustered centers are assigned to the clusters of the nearest higher density points according to local density from high to low, completing the segmentation of green apples. The specific flow chart of the algorithm is shown in Figure 1.

1.2 Image acquisition

The image of the green apple was collected at the Longwangshan apple production base in Fushan District,

Yantai City, Shandong Province. All images were collected under natural light conditions (including front lighting and backlight). The apple variety was fushi and gala. Image acquisition information: Canon SLR camera, the image format

is jpg, the image acquisition resolution is $6\,000 \times 4\,000$. The image data collected in this paper is from orchard images during the day and night, including sunny and post-rain scenes.

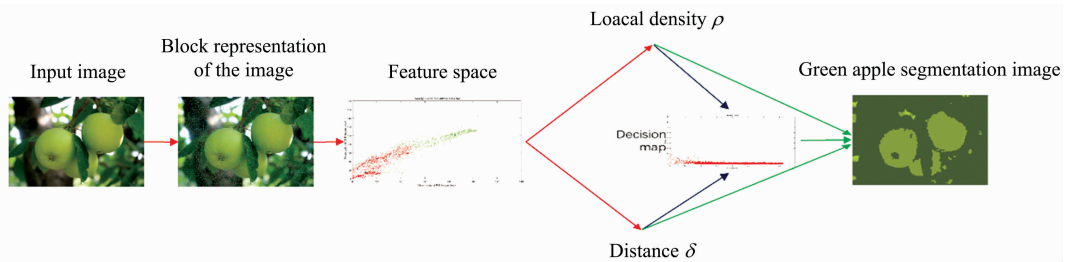


Fig. 1 Flow chart of improved density peak clustering green apple segmentation algorithm



Fig. 2 Green apple image under various real conditions

2 Extract feature components

The basis of the density peak clustering algorithm is the distance between data points, and the distance is the description of the data points based on the feature components. The feature component represents the data point in a dimension of the feature space, which determines the distribution relationship of the data point. In this paper, the SLIC super-pixel algorithm is used to aggregate the approximate pixels to form irregular blocks, and the irregular blocks are used as image data points for cluster analysis. The color relationship between the foreground and the background is analyzed, the R-B image and the G-B image are constructed, and the average value of the pixel points in the irregular block is extracted as the feature component for calculation.

2.1 SLIC Superpixel Blocking

In order to reduce the high complexity of high-resolution images, the SLIC superpixel algorithm is used to aggregate similar pixels in a small area to form irregular blocks, and image blocks are used instead of pixels as a basic unit in

cluster analysis. First, select the seed point evenly in the green apple image and set the seed point to 3 000. Calculate the relative distance from the non-seed point to the seed point, including the color information of the three channels and the two-axis information. According to the relative distance, the non-seed points perform k -means clustering, are assigned to the nearest seed point, and finally obtain the green apple image area represented by the irregular block. The image irregularity block maintains perceptual consistency with the pixel points of the original position. As shown in Figure 3, (a) is the real image input of the green apple, the image size is $6\,000 \times 4\,000$, and the image resolution is tens of millions. (b) There is a green apple image represented by an irregular block, each image irregularity block is a data point in cluster analysis, and a total of 3 172 image blocks. In the density peak cluster analysis, the number of data points has been reduced from tens of millions to thousands.

2.2 Feature components

Since the shape of the image block constructed by the SLIC algorithm is irregular, and the average number of pixels of the image block accounts for only 3/1 000 of the entire image, the consequence of the shape feature and the texture

feature is reduced. Boundary blurring is caused by color approximation, which is manifested in the inaccuracy of the outline of the green apple, and a large number of areas are incorrectly segmented. Figure 4 is a binary image generated by pixel values 130 of three channels R, G, and B in a green apple image, with red lines being the target boundaries. The green apple and leaf areas are shown as approximations on the image, especially in Figure 4(c). The green apple target is completely included in the foreground of a G channel with a pixel value greater than 130, the green apple target is completely included. There is a lot of adhesion between the

target boundary and the background, resulting in complex boundary blurring.

The target areas in (b) and (c) of Figure 4 are full, and the foreground area overlaps with the real green apple target area by 70.98% and 84.40%. Figure (d) is not fully expressed, accounting for only 26.38%. For a background area with a pixel value greater than 130, Figure (c) contains more and Figure (d) has the least. The green apple target is the most abundant in the R channel and the G channel and is not obvious in the B channel. It is most difficult to distinguish the leaf background under the G channel. Under the B channel,



Fig. 3 Green apple image and super pixel segmentation of green apple image

(a): Green apple image, size, 6 000×4 000;

(b): Green apple image after super pixel segmentation, a total of 3172 super pixel regions

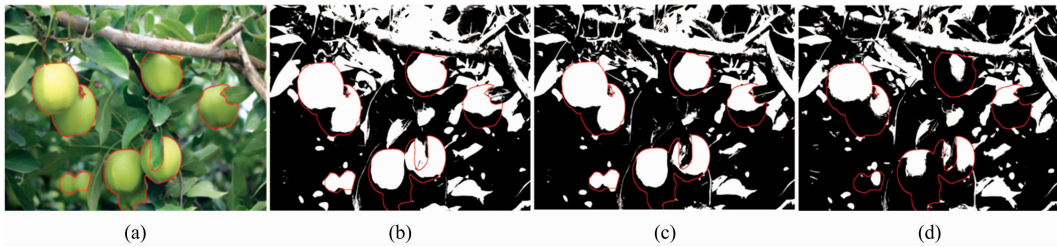


Fig. 4 (a) Original image; (b) Area under the R channel with a pixel value greater than 130; (c) Area under the G channel with a pixel value greater than 130; (d) Area under the B channel with a pixel value greater than 130

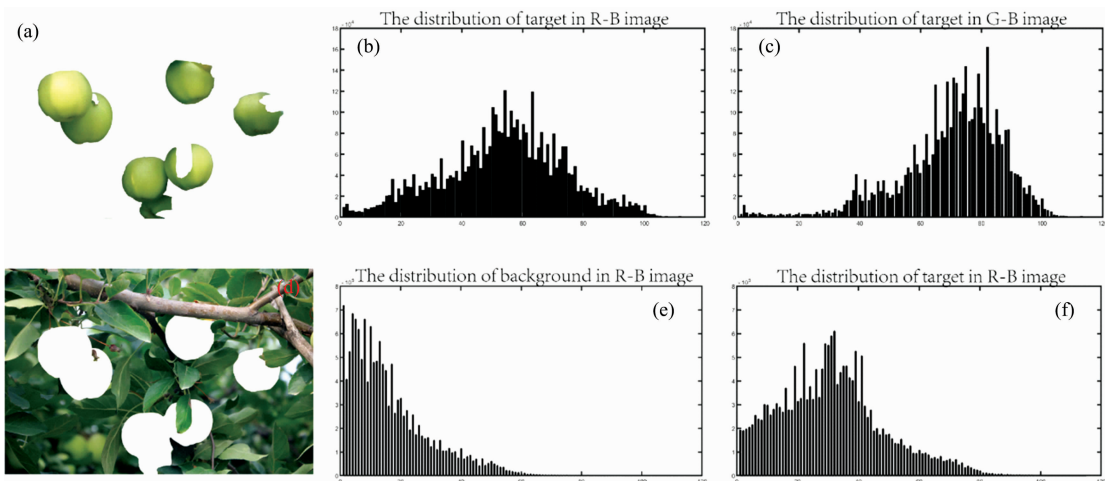


Fig. 5 Numerical distribution of green apple target and background in R-B image and G-B image

the green background is not obvious and is not sensitive to green targets.

From figure 5, the histogram distribution of the target area and the background area of the green apple has a significant distribution difference in the R-B image and the G-B image. In order to reduce the noise and the number of data points, this paper obtains the district-level graph based on the SLIC algorithm, selects the regional mean of R-B image and G-B image as the feature component of the irregular block data point, and the functional space of the clustering segmentation problem of green apple image is constructed. The feature space is shown in figure 6, where the horizontal axis is the average of the R-B regions, and the vertical axis is the average of the G-B regions.

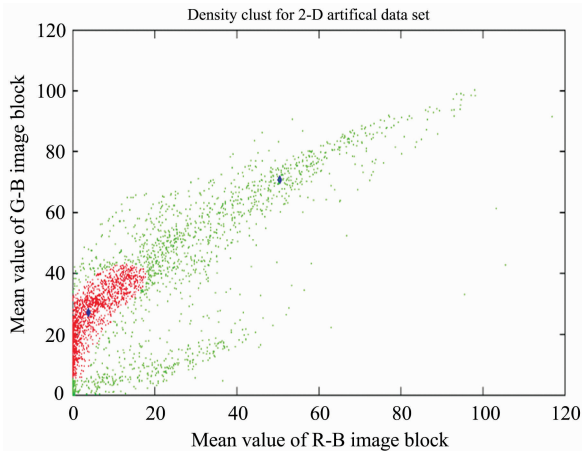


Fig. 6 The regional mean feature space of the green apple image area on the R-B image and the G-B image

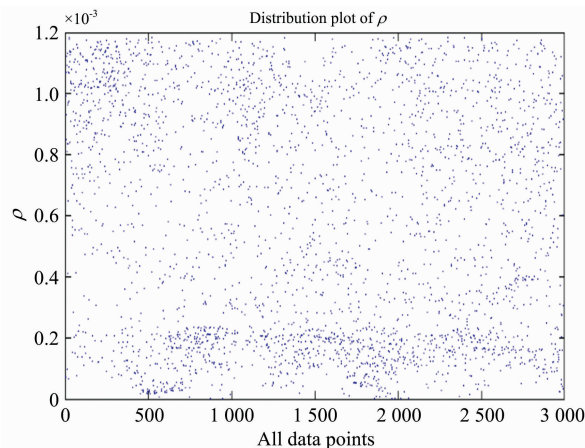


Fig. 7 Local density distribution of data points

Figure 6 is a feature space distribution of an irregular region of a green apple image based on an R-B image, and a G-B image region mean constructed herein. The blue diamond points are the first and second cluster centers of the cluster. The red data points are members of the first cluster class, the black pixel points are non-members of the second cluster

class, and the green data points are members of the third cluster class. The shape of the edges between the clusters is irregular, and the low-density regions are the only intuitive features of the cluster-like boundaries.

3 KDE optimization density peak clustering segmentation algorithm

In the green apple image, the green apple target is similar to the background leaf color, and there is a boundary blur problem in the segmentation. Both are separated by low density regions only in the feature space, as shown in the Figure 6. Traditional clustering algorithms are difficult to deal with clustering problems with unclear boundaries.

The density peak clustering (DPC) algorithm can find high-density regions segmented by low-density regions and cluster clusters of arbitrary shapes. The cluster center of the density peak cluster is fixed, and the cluster category of other data points belongs to the closest local maximum density point. Breaking through the cluster shape must be a spherical limit. However, the density peak clustering algorithm must rely on manual operations, whether it is the setting of the cutoff distance or the choice of the cluster center. In this paper, kernel density estimation is used to analyze the local density, and the double sorting algorithm is used to automatically obtain the cluster center to get rid of the influence of manual setting parameters.

3.1 Principle of DPC

DPC assumes that the cluster center is surrounded by low density values and is farther away from higher density points. For each data point, two parameters are calculated: local density ρ and distance δ from the higher density point. The local density ρ is defined as

$$\rho_i = \sum_j X(d_{ij} - d_c) \quad (1)$$

Where, if $x(\cdot) \leq 0$, then $X=1$; if $x(\cdot) > 0$, then $X=0$. d_{ij} is the relative distance between data point i and data point j . d_c is the cutoff distance and needs to be set manually. The local density ρ_i is equal to the number of data points closer to the data point i than the cutoff distance, and the distribution density of the data is described. The minimum of the distance between data point i and other higher local density data points is the distance δ

$$\delta_i = \min_{j: \rho_j > \rho_i} (d_{ij}) \quad (2)$$

The distance δ_i is the minimum distance from the distance data point i in any other data point greater than the local density ρ_i . Note that the distance δ_i takes the maximum value in d_{ij} only when the local density ρ_i of the data point i is the maximum value. The density peak clustering algorithm can detect clusters of arbitrary shapes, and the clustering process

does not require iteration and has a faster speed. But since the calculation of the parameters depends on the distance between the data points, when the data set is too large, the speed advantage disappears. The manually set cutoff distance affects the accuracy of clustering.

3.2 KDE optimization density peak cluster local density σ

The local density ρ represents the distribution of neighbor data points in the region with the cutoff distance as the radius in the feature space, reflecting the sparseness of the data distribution. The cutoff distance directly impacts the results, and the manually set defects are difficult to solve the boundary problem in the green apple segmentation. Kernel density estimation (KDE) can fully use the data itself to calculate, avoiding the influence of prior human knowledge, and at the same time can approximate the data to the greatest extent. This paper uses kernel density estimation to calculate the local density of data points

$$\hat{f}_w(x, y) = \frac{1}{nw} \sum_{i=1}^n K_w\left(\frac{x-x_i}{w}, \frac{y-y_i}{w}\right) \quad (3)$$

Where K_w is the scaling kernel function, algorithm uses the Laplacian Kernel function $K(x, y) = \exp\left(-\frac{\|x-y\|}{\sigma}\right)$ for the calculation. L2 norm between vectors is adjusted to the L1 norm, which reduces the sensitivity to parameters. w is a smoothing parameter called window bandwidth, set to 0.8. (x, y) is the mean of the R-B region and the mean of the G-B region of the i -th irregular region. The distribution results are shown in Figure 7.

3.3 Distance from larger density points δ_i

The distance δ_i is a description of the degree of difference between the data points and the larger density points over their minimum distance. Calculated by the following formula

$$\delta_i = \begin{cases} \min(d_{ij}) & \exists \rho_j > \rho_i \\ \max(d_{ij}), & \forall \rho_j < \rho_i \end{cases} \quad (4)$$

Where ρ_i is the local density of the data points calculated by the kernel density estimation method, and d_{ij} is the Euclidean distance of the irregular regions i and j in the feature space. The distance δ_i takes the maximum of the distances from any other regions only when the local density of the irregular regions is the largest. The distance δ_i of the remaining area is the minimum of the relative distances of other areas larger than the local density ρ_i .

3.4 Double sorting automatically finds the cluster center

Combining the local density ρ_i and the distance δ_i , the important characteristics of the cluster center are found. The cluster center is a data point having a large local density ρ_i and a distance δ_i . Thus, with the local density as the horizontal axis and the distance as the vertical axis, a decision map for finding the cluster center is constructed. As shown in Figure 8, the data points near the local density axis in the decision

graph are cluster class members, and the distances are small and clustered. Anomalous points near the distance axis are clusters of individual points. The data points located in the upper right corner, called outliers, have a large local density and distance and are the cluster centers of the current data set. In recent years, the automatic selection of cluster centers has been achieved by determining the curve function or tree structure.

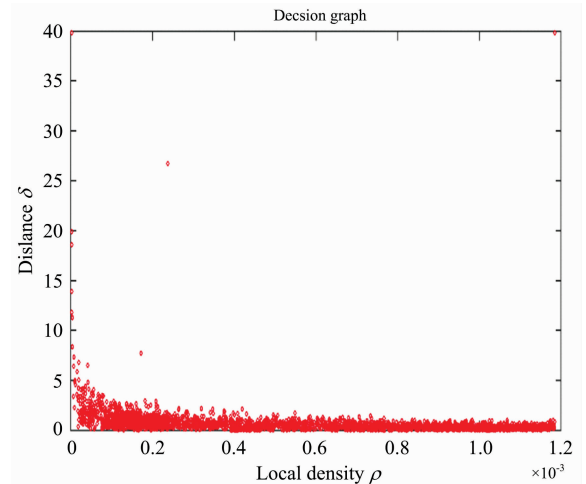


Fig. 8 Decision diagram (the horizontal axis is the local density and the vertical axis is the distance)

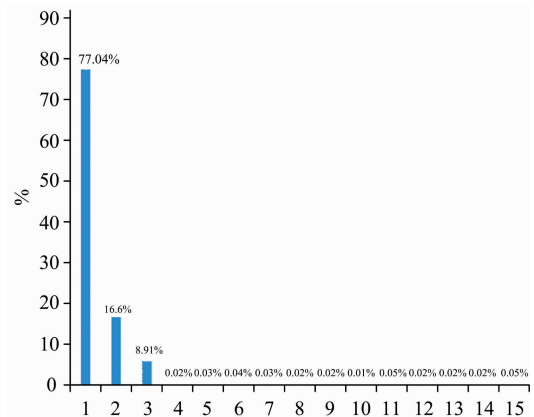


Fig. 9 The ratio of the number of cluster pixels to the total number of pixels (percentage)

The clustering decision of the non-clustered center data points is not completely dependent on the cluster center, that is, the number of cluster centers is not the final number of real clusters. At the same time, the complexity of the green apple image is mainly due to the complex relationship between the position and structure of the object in the image and the difficulty of recognition by the target green apple with the background near color. Image object categories can generally be divided into three categories, green apple target, background foliage, background sky soil and other elements.

The double sorting algorithm is used to select the cluster center automatically. According to the distance values, allirregular regions are arranged in descending order of local density values, and the first 20 are taken out in descending order. The first 15 data points that have been sorted twice are selected as the cluster center. Figure 9 shows the percentage of pixels included in the 15 clusters in the entire image. The

first three clusters contain 98.88% of the total number of pixels. The ratio of the pixels of the remaining clusters in the population is less than 0.03% on average. The clustering error of the target area of the green apple is the judgment of the cluster class boundary, which is related to the first cluster class and the second cluster class. The algorithm results in this paper are shown in the figure 10.

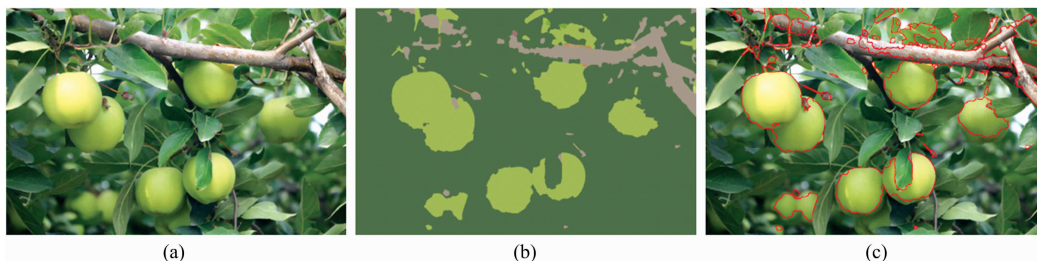


Fig. 10 Algorithm output image

(a): Original green apple image; (b): Improved density peak clustering result map;
(c): Improved density peak clustering segmentation map

4 Experiment

4.1 Experimental design

The collection of 86 green apple images contains various lighting conditions, complex occlusions and overlaps, sunny and post-rain conditions. In this paper, the efficiency of segmentation efficiency (SE), segmentation validity (SV), false positive rate (FPR) and false negative rate (FNR) are used as evaluation indicators to evaluate the effectiveness of the proposed method. In order to better verify the optimized density peak clustering image segmentation algorithm, this

paper compares it with the method in the literature^[13-15].

The operating environment of this research experiment: system environment Win 10, the calculation software is MATLAB2019a, the computer configuration is Inter® Core (TM) i7-6700 CPU @2.50GHz, RAM is 8.0GB.

4.2 Segmentation method verification

In this paper, the improved density peak green apple image segmentation algorithm processes the real-time captured image. For the real scene image including fruit overlap, leaf occlusion, post-rain scene, night environment and other conditions, select multiple segmentation effect maps for analysis. The split effect diagram is shown in Figure 11.



Fig. 11 Segmentation effect diagram of the method

From the perspective of the segmentation effect, the proposed algorithm has excellent segmentation efficiency in various environments. If the leaf occlusion and the fruit overlap cause the boundary to be blurred, the target outline of the green apple in the segmentation map is clear, and the ambiguous division of the target edge and the background region does not substantially exist. The segmentation results were not affected by the irregular refraction caused by the rain

on the green apples after the rain. The algorithm can work in a variety of weather conditions. For nighttime images, even night-time complex images with complex foliage obscuration and many targets in the scene, the target boundary of the green apple in the algorithm segmentation graph are still accurate and clear.

4.3 Results analysis and discussion

The algorithm and k-means, mean-shift, FCM and the

search for image feature density peak are compared. The test results are shown in Figure 12. Our method can obtain the clear outline of the green apple for various environments and green apple image segmentation under various scenarios. From the perspective of the segmentation effect, the green

apple target area has been clearly separated from the background, and compared with other algorithms, the proposed algorithm can distinguish the target area of the green apple from the background to the maximum extent, and the boundary contour is clear.

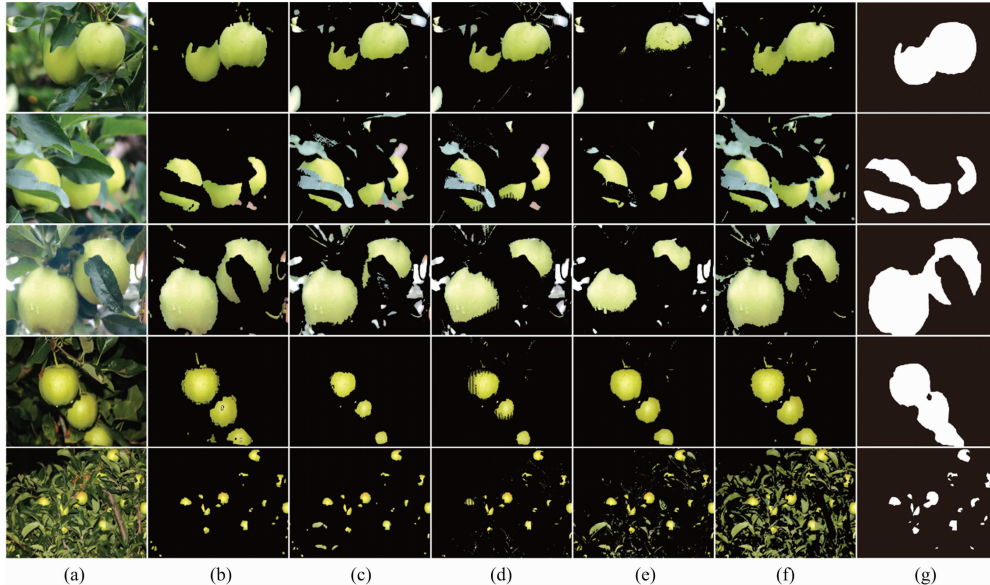


Fig. 12 Results of five clustering segmentation image segmentation algorithms

Table 1 Statistics of evaluation indicators of five clustering segmentation algorithms

METHOD	FNR	FPR	SS	SE
Our method	14.66	2.32	87.69	88.53
K-means	41.83	7.25	62.69	58.16
MeanShift	39.06	13.56	72.48	54.83
Fcm	50.06	3.87	66.58	49.13
Sifdp	23.44	10.52	71.38	76.06

From table 1, the average FNR of the optimized density peak cluster image segmentation algorithm is 15%, which is much lower than other clustering image segmentation algorithms. The average FPR of the proposed algorithm is only 2%, which is the lowest of the five algorithms. The segmentation efficiency and the effective segmentation type are another set of parameters for evaluating the segmentation algorithm, and the algorithm with the higher value has the best segmentation effect. The method of this paper is the highest value among the five clustering segmentation algorithms, whether it is segmentation efficiency or segmentation validity.

5 Conclusion

In order to explore the application of the visual core system of the green apple harvesting robot under unsupervised

conditions, this paper studies the application of the unsupervised density peak clustering algorithm in green apple image segmentation. In the first step, the image of the green apple collected in the natural environment is converted into a regional image representation by the SLIC algorithm, and the region means value on the R-B channel and the G-B channel is extracted to construct the feature space. In the second step, two parameters of density peak clustering are calculated in the feature space. In this paper, the kernel density estimation is used instead of the local density calculation method, which relies on manually setting the cutoff distance, and the data points are recorded between the larger local density data points closest to the distance. The third step is to construct a decision graph and use the double sorting algorithm to select the cluster center. Finally, the non-clustered center data is allocated to the cluster class of the largest local density data point closest to the nearest one according to the order of local density. Complete the clustering.

The algorithm in this paper has ideal segmentation accuracy. The application of an unsupervised algorithm in the problem of green apple segmentation is realized. Compared with other clustering algorithms, the proposed algorithm improves the accuracy and greatly improves the fitting effect of the green apple target boundary.

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基于核优化密度聚类的绿色苹果分割算法

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摘要 苹果的可见光谱目标的高效、精准识别是实现果园测产或机器自动采摘作业的关键, 由于绿色目标果实与枝叶背景颜色较为相近, 因此绿色苹果的识别成为新的挑战。再由于果园实际复杂环境因素影响, 如光照、阴雨、枝叶遮挡、目标重叠等情况, 现有的目标果实识别方案难以满足测产或自动采摘的实时、精准作业需求。为更好地实现果园自然环境中绿色目标果实识别问题, 提出一种新的核密度估计优化的聚类分割算法(kernel density clustering, KDC)。新算法首先利用简单的迭代聚类(simple linear iterative cluster, SLIC)算法将目标图像分割成不规则块, 集结小区域内近似像素点组成超像素区域, 计算单元由像素点转变为超像素区域, 有效降低数据复杂度, 且 SLIC 算法简化图像数据时可有效避免目标果实轮廓模糊; 基于超像素构造 R-B 区域均值和 G-B 区域均值的二维特征分量, 建立针对聚类分析的青苹果颜色特征空间。然后借助密度峰值聚类中心计算绿色苹果图像每个数据点的局部密度和局部差异度, 为解决分割边界模糊问题, 在计算过程中利用核密度估计计算局部密度, 确保局部密度在不同复杂场景中的清晰准确表达, 以更精准找出被低密度区域分割的高密度区域, 实现任意形状的聚类。最后以局部密度和距离构造寻找聚类中心的决策图, 该研究采用双排序算法实现聚类中心的自动选择, 完成目标果实的高效分割。新算法通过 SLIC 算法获得图像的超像素区域表示, 数据点的局部密度通过核密度估计得到, 大幅降低算法的计算量, 实现目标图像的高效、精准分割。为更好地验证新算法性能, 实验采集多光照、阴雨等环境下的遮挡、重叠等复杂目标图像, 以分割效率、分割有效性、假阳性、假阴性等指标进行评价, 通过对比 k-means 聚类算法、mean-shift 聚类算法、FCM 算法和 DPCA 算法, 该研究提出的新算法分割性能均最优。

关键词 绿色果实; 图像分割; 密度峰值聚类; 核密度估计