Superpixel Image Segmentation Based on Improved K-means

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Abstract. Superpixel algorithm is the pretreatment of the image processing steps, in the processing of computer vision, precision of the superpixel algorithm is very important. In order to improve the accuracy of superpixel segmentation, an improved k-means algorithm for superpixel segmentation is proposed. This algorithm uses the improved k-means algorithm to cluster the images. By changing the calculation method of distance, it improves the measurement of similarity, improves the accuracy of segmentation, and improves the quality of segmentation results. Experimental data show that this algorithm performs better than the traditional algorithm and improves the segmentation quality and visual effect.

Keywords: image segmentation, superpixel, k-means.

1. Introduction
Superpixel1 is a block pixel that aggregates most of the similar pixels. Through superpixel segmentation, the segmentation target range can be expanded and the subsequent processing steps can be reduced[1-2]. Compared with ordinary pixels, superpixels have low computational complexity, which is consistent with human eyes' ability to recognize things. However, the boundary of superpixel is more or less rough and the segmentation is not careful[3-4]. As a result, the accuracy of superpixels needs to be further improved. At present, the following algorithms are proposed: superpixel segmentation algorithm2 based on density peak search clustering. By estimating the local density of pixels, the nearest large density pixels are organized into a tree of belonging relationship with them, and the nearest superpixel seeds are searched for assigning marks to them to achieve superpixel segmentation[5-6]. Based on simple linear iterative clustering (SLIC) and fast nearest neighbor region merging algorithm3, this method introduces the nearest adjacency graph on the region adjacency graph, then calculates the dissimilarity function value between each region to be merged and all adjacent regions, and finally merges the region with the least dissimilarity value. Based on RGB three-dimensional histogram and DBSCAN image segmentation method4, this algorithm firstly analyzes the three-dimensional RGB histogram of the image to obtain the initial superpixels with high edge fitting degree, and then selects the appropriate eigenvalues to merge the superpixels with DBSCAN algorithm to generate a large homogeneous region[7-8]. Based on SLIC superpixel adaptive image segmentation algorithm5, this algorithm first uses SLIC to conduct superpixel segmentation of the image, and then takes the five-dimensional feature of the superpixel center as the original data point
through DBSCAN algorithm clustering of adaptive parameters, and then determines the number of multiple subjects and segmentation boundary.

Based on the k-means algorithm, this paper improves the method of measuring distance similarity. Experiments show that this algorithm can better improve the segmentation accuracy.

2. Correlation Algorithm

SLIC algorithm
The algorithm of SLIC (simple linear iterative clustering) firstly uses certain rules to cluster pixels with similar color and distance, then combines the discrete pixels, and finally forms a pixel aggregation block highly consistent with human visual characteristics. The specific process of the algorithm is as follows:

(1) Initialize the center point of clustering. SLIC algorithm can set the number of segmentation according to the needs of users, and the set number of segmentation is the number of clustering centers. If there are N pixels on a picture and the number of segmentation is set to be K, then the size of each superpixel is N/K. Set the seed point at the center of the superpixel and attaches a different number label for each different seed point.

(2) Calculate the distance D between the pixel and the clustering center. Set the clustering center in the center of the pixel block, and each pixel in each pixel of lab color value and spatial distance comparing with a super pixels in the surrounding pixels, and the ratio of the smallest clustering to cluster center, clustering of super block won't appear in the edge pixels, to further ensure the accuracy of the subsequent segmentation.

Formula D of distance measurement between pixel point and clustering center is defined as follows:

\[
d_{xy} = \sqrt{(x_k - x)^2 + (y_k - y)^2}
\]

\[
d_{lab} = \sqrt{(l_k - l)^2 + (a_k - a)^2 + (b_k - b)^2}
\]

\[
D = d_{lab} + \frac{m}{H}d_{xy}
\]

\(d_{xy}\) is the color difference between pixel points, \(d_{xy}\) is the spatial distance between pixel points, D is the spacing of seed points, m is the equilibrium parameter, and H is used to measure the proportion of color value and spatial information in the similarity measurement. The larger D value is, the more similar the two pixels are.

K-means algorithm is a distance based clustering algorithm. It adopts Euclidean distance as the standard to judge the similarity, and synthesizes clusters of objects close to each other. Compact clusters are the result of the algorithm. The algorithm flow is as follows:

1) set a value of K, that is, we need to class the data into K sets;
2) evenly select k data points as the center of mass in the data set;
3) calculate Euclidean distance between each point in the data set and the center of mass, and cluster the center of mass closest to it;
4) the center of mass of each small cluster was recalculated by the mean value method;
5) repeat (3) and (4) until the position of the center of mass is not changed or the number of iterations is reached.

3. SLIC algorithm based on improved k-means algorithm
In the traditional k-means algorithm, the method to measure the similarity is just to calculate the euclidian distance from each pixel to the clustering center, which leads to the insufficient connection between pixels, easy to ignore the similar pixels with distant spatial location, and inaccurate segmentation effect. In order to further enhance the close connection between pixels, this paper improves the method of calculating distance in k-means algorithm to obtain more accurate pixel segmentation.

(1) Find the shortest path each pixel to the clustering center, the shortest path composed of pixels, the distance is measured with RBG color space distance of each pixel, the smallest distance apart pixels into a shortest path, combine all pixels on the shortest path to the clustering center, this reduces the judge similar conditions, and can reduce the number of merge, improve efficiency.

(2) After the initial clustering merger to form the superpixel, there are free pixels between the superpixel and the superpixel, and these free pixels can be divided into two categories: one is a small number of pixels, which exist in the large superpixel, and this kind of pixels adopts the principle of adjacent merger; One is the pixels gathered outside the superpixel, which are too numerous to be adjacent to the superpixel. At this time, it is adopted to merge them into a single superpixel.

4. Conclusion
In this paper, the Berkeley segmentation data set is selected as the sample graph of the experiment. Figure 1 shows the results of SLIC, ERS and the algorithm proposed in this paper in the first to third rows when the number of segmentation is 300. According to the experimental comparison diagram, SLIC algorithm has a regular shape, but produces more outliers, which are clustered together at the edges. ERS algorithm edge distortion and clutter, poor compactness, poor edge fit; In this paper, by improving the calculation method of distance, the outlier pixels are better controlled, so that these pixels are better merged, the edge lines are soft, and the fitting degree is better.

Three evaluation indexes, UE (undersegmentation error), BR (edge recall) and ASA (optimal target segmentation accuracy), were selected for the evaluation content.

UE (Under segmentation Error) is an evaluation index based on segmentation region, which reflects the coincidence degree of artificial segmentation results and superpixel segmentation results, and measures the proportion of segmentation value overflow true value. The smaller the UE value is, the fewer the target objects the superpixel contains, and the smaller the UE value is, the better. BR (Border Recall) is an important index to measure the degree of edge fitting. It refers to the ratio between the number of superpixel edge pixels whose pixels are located within the distance of at least 2 pixels and the total number of true edge pixels. ASA (Achievable Segmentation Accuracy) is a measure of the upper bound algorithm performance, with the maximum overlap area of tags to mark on the true value of each pixel of the best Segmentation Accuracy, ASA, the greater the value is not the more pixels from the signature of the true edge overflow, therefore the ASA value, the greater the edge joint degree, the better.

Three algorithms are used for comparison, and the results of each indicator are shown in table 1. According to the results of the three indexes, when the number of superpixels is 300, the indexes of the algorithm in this paper are superior to the traditional SLIC except BR, with the best performance on the graph.
Figure 1. Results of comparative experiment.

Table 1. Comparison of the method with traditional method

| index | SLIC   | ERS   | Proposed algorithm |
|-------|--------|-------|--------------------|
| ASA   | 0.9818 | 0.9347| 0.9822             |
| BR    | 0.9840 | 0.9686| 0.9844             |
| UE    | 0.2927 | 0.3379| 0.2890             |
This paper analyzes the limitations of the traditional k-means algorithm, and proposes an improved k-means algorithm to address these shortcomings. By improving the measurement method of similarity, an improved superpixel segmentation algorithm is proposed. In order to verify the effectiveness of the super-pixel segmentation method of the improved k-means algorithm, the paper selects the traditional SLIC and ERS algorithms as the experimental reference. Although some indicators are slightly worse, the overall performance is better and the segmentation effect is better.

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