Image Segmentation Based on Fuzzy Method

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Abstract. Image is an important means for human to cognize the world, and image processing technology is also a key research direction in machine learning. In image processing technology, image segmentation is a very critical part of the current academic research hotspot. At present, the fuzzy C-means clustering (FCM) algorithm of image segmentation algorithm uses iterative method to classify samples, which needs less storage space and time. However, FCM algorithm also has many shortcomings, how to use clustering algorithm for real-time, automatic, high-quality image segmentation, has been a problem to be solved. In order to solve the massive data of color image, this paper uses the SLIC method to calculate the super-pixel image over-segmentation. Direct processing of the huge amount of information contained in a color image will degrade the performance of the algorithm. Therefore, image preprocessing is very important.

Keywords: Fuzzy Clustering · Image Segmentation · Super Pixel

1 Introduction

FCM algorithm information technology gradually penetrates into daily life, leading the Hth Industrial Revolution to develop rapidly, the impact is growing. In the 21st century, with the rapid development of computer and microelectronics, the sensor system using W to collect and transmit data has gradually become the most competitive means of production. Image segmentation is an important technique of image engineering, which is used to extract interesting objects from images. Imaging engineering is a new subject, which involves all aspects of imaging. Image engineering can be divided into three interrelated parts [1]: the essence of image segmentation is to classify the pixels of the image, extract the pixel categories we need, and discard the unnecessary categories, which is the fundamental goal of image segmentation. But without prior knowledge, computer can only segment image by texture, edge, space characteristic and interaction of pixels. The difference between computer and human brain makes the distinction between image and background more complex.

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2 Image Segmentation and Clustering Algorithm

In reality, image segmentation often lacks prior knowledge, and there is no segmented image for W. Because the method is based on the information contained in the segmented image itself, the segmentation can be effectively realized by clustering the pixels.

The aim of image segmentation is to replace part of human visual discriminant function with computer and analyze image attributes quantitatively with relevant tools. W can be used to solve the problem of image segmentation because W has two bases: first, the natural image itself has the characteristics of non-uniformity and relationship blur, which is embodied in the pixels of different regions. Therefore, fuzzy clustering is an effective analysis tool for image segmentation and its related fields.

3 Traditional Fuzzy Clustering Algorithm

The traditional FCM method mainly determines the range of each data point according to the size of membership degree, and its advantage is that it can deal with the normally distributed data clusters. This method has better convergence, so the fuzzy membership matrix obtained by this method has better consistency, but its disadvantage is that it can not cluster effectively if the data contains noise. This method is strongly dependent on the initial clustering center, and it is based on the whole situation. It is time-consuming and inefficient under large amount of data.

To solve these problems, this paper proposes several improved fuzzy clustering algorithms. PCM is an exhaustive search algorithm which uses membership constraints to improve clustering performance. However, PCM algorithm must have a good partition to ensure the correct classification. But the complexity of AFCM is also increased, because the clustering algorithm, which changes the scale of data, becomes very sensitive and easy to produce poor clustering effect, so its application range is not large. From the above results, we can see that the improved fuzzy clustering method has its own advantages, but also has its limitations, and needs to be further improved.

4 Algorithms

The use of SLIC is easy to understand. By default, the only parameter of this algorithm is k, meaning those super pixels that are almost the same size. In the classification of CIELAB color images, initialization is carried out at first. Here k initial centers are written into the images, and regular grids with S-pixels are sampled. To generate a superpixel of roughly the same size, the grid spacing is used here. Move the center to the minimum gradient corresponding to the region adjacent to 3×3. This is to avoid placing superpixels on edges and to reduce the possibility of receiving superpixels using noise pixels.

Next, in the assignment phase, each pixel i is associated with the nearest cluster center, which overlaps with the cluster center, as shown in Figs. 1, 2. This is important to speed up our algorithm because the limited search range significantly reduces the number of distance calculations, and each pixel must be compared to the full cluster compared to the traditional kmeans cluster. Only as described in section III-B can D be

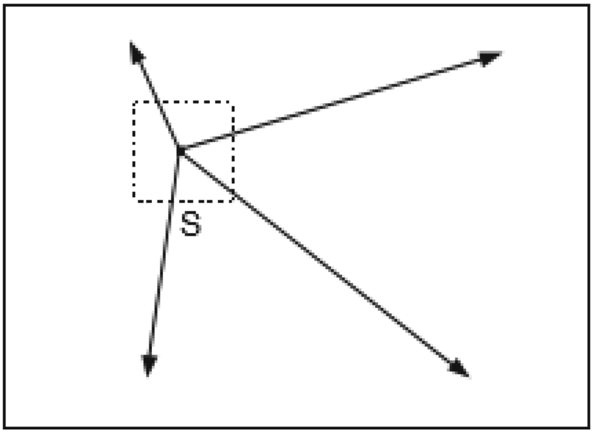

Fig. 1. The entire image is searched with stand k-means.

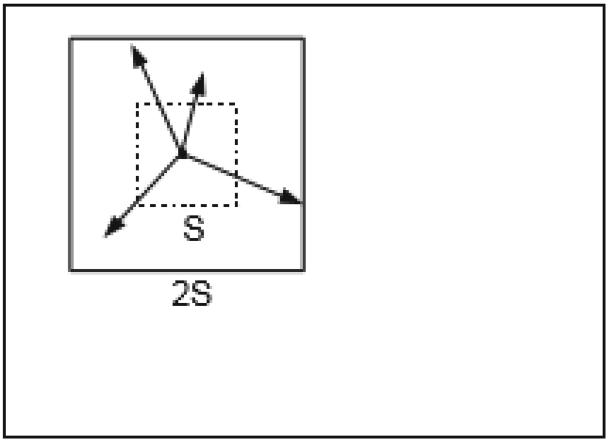

Fig. 2. Slic looks for a confined area.

determined by measuring the distance of the nearest cluster center of each pixel. Because the expected spatial range of superpixels is about the area of S * S, similar pixels are searched within 2Sx2S around the superpixel center.

Figure 2 Narrowing the Superpixel Search Area. When the traditional k- average algorithm is O (kNI), the complexity of SLIC is linear in O (N), where I is the number of repetitions. This provides a search space for each cluster center during the assignment phase. (a) In the traditional k-averaging algorithm, the distance from each cluster center to each pixel in the image. (b) SLIC calculates only the distance of pixels in the cluster center to the 2Sx2S region. Note that the required hyperpixel size is only S * S, represented in smaller squares. The algorithm can not only shorten the distance operation, but also make the complexity of SLIC independent of the number of superpixels.

Once each pixel is related to the nearest cluster center, the update step adjusts the cluster center to the average vector of all pixels belonging to the cluster here to write the image description [lab xy] T. By using L2 norm, the residual error E is calculated for the new cluster center position and the former one. It is possible to assign and update iteratively until the error converges, but we have found 10 iterations that are sufficient for most images. Finally, in the post-processing stage, the disjoint pixels are reassigned to adjacent hyperpixels to realize the connection. This algorithm summarizes the whole algorithm.

Algorithm SLIC super pixel segmentation
/* Initialize */
Initialize Ck = [lkakbk xk yk] with step s sampling pixels.
The cluster center is moved to the minimum gradient of 3×3.
Set flag l (i) = −1 for each pixel i.
Set distance d (i) = ∞ per pixel.
Repetition.
/* Allocation */
For each cluster center Cr.
For each pixel i in the 2S * 2S region around a Ck.
Calculate distance between Ck and i.
IfD < d (i) then.
Set up d (i) = D.
Set up l (i) = k.

SLIC super pixels correspond to clusters on the labxy color image plane. This raises the problem of defining distance measurement D, which is not immediately obvious. In algorithm 1, the distance between pixel i and cluster center Ck is calculated. In the CIELAB color space [ab] ^{T}, the colors of pixels are indicated with a known range of values. On the other hand, the value range of pixel [x, y] ^{T} changes as the image size changes. If D is simply expressed as a five-dimensional Euclidean distance, the clustering behavior of different superpixel sizes will be inconsistent. For large pixels, their spatial distance is greater than the affinity of color, and their relative importance is greater than color. This creates a compact superpixel that does not adhere well to the edges of the image. If it's smaller, the opposite happens.

To combine these two distances into a single measurement, you must use their maximum distance N and N. Used to standardize color proximity and spatial proximity. Write D as.

$$
\begin{aligned}
dc &= [(Lk - Li)^2 + (ak - ai)^2 + (bk - bi)^2]0.5 \\
ds &= [(Xi - Xk)^2 + (Yk - Yi)^2]0.5 \\
d \ &= \ d\_lab \ + \ (m/S) * d\_xy
\end{aligned}
\tag{1}
$$

The expected maximum spacing in a given cluster should correspond to the sampling interval, $N_s = S = \sqrt{N/k}$. It is not easy to determine the maximum color distance for N_c because of the apparent difference in color distance from cluster to cluster and from image to image. Fixing nc to a constant m solves this problem, 1 becomes

$$D = \sqrt{d_c^2 + \left(\frac{d_s}{s}\right)^2 m^2} \tag{2}$$

This simplifies the distance measurement we use in practice

$$D' = \sqrt{\left(\frac{d_c}{m}\right)^2 + \left(\frac{d_s}{s}\right)^2} \tag{3}$$

By defining D in this way, m also allows us to measure the relationship between color similarity and spatial proximity. When m is larger, the higher the spatial proximity, the denser the resulting superpixel (that is, its area to perimeter ratio is smaller).

Within m hours, the resulting superpixels are more likely to stick to the edges of the image, but smaller in size and shape.

If the CIELAB color space is used, the range of m is [1, 40]. Equation 3 sets dc = to dc = suitable for grayscale images. The method can also be extended to deal with 3D supervoxels, for example, in Fig. 3, where the Eq. 3 contains depth dimensions to spatial proximity terms.

$$\mathrm{d}_8 = \sqrt{(x_i - x_j)^2 + (y_i - y_j) + (z_i - z_j)^2} \tag{4}$$

5 Experimental Results and Analysis

SLIC, like other superpixel algorithms, is not required. At the end of the cluster processing, some "isolated" pixels may be retained that are not their cluster centers. To correct this, the nearest cluster center tag is assigned to these pixels using the join composition algorithm.

SLIC avoids thousands of redundant distance operations by locating clusters. Actually, the pixel value is below zero. Near the g cluster centers, SuIc is O (N) complex. In contrast, the conventional k-means algorithm has an upper bound of O (kN), while the actual time complexity is O (kNI), and 1 is an iterative number requiring convergence. At present, there are some schemes, i. e., prime sampling, random sampling, local clustering exchange, and lower and upper bounds, to reduce k mean complexity. SLIC is designed for superpixel clustering. Finally, compared with most of the superpixel algorithms and the K-average algorithm mentioned above, the complexity of SLIC is linear in terms of the number of pixels and independent of k.

6 Concluding Remarks

Superpixels are a very useful tool, and this article introduces you to the features of modern superpixel technology. Five current optimal super pixel algorithms are compared. In addition, a new clustering algorithm based on kmeans is introduced, which is better than the existing super pixel algorithm in every aspect.

The image is segmented by generalized fuzzy clustering method and compared with the traditional fuzzy clustering method. By reducing the initialization requirement, the operation speed is improved and the good segmentation effect of clustering algorithm is ensured, which proves the effectiveness of this method.

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