A NOVEL CENTROID UPDATE APPROACH FOR CLUSTERING-BASED SUPERPIXEL METHOD AND SUPERPIXEL-BASED EDGE DETECTION

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ABSTRACT
Superpixel is widely used in image processing. And among the methods for superpixel generation, clustering-based methods have a high speed and a good performance at the same time. However, most clustering-based superpixel methods are sensitive to noise. To solve these problems, in this paper, we first analyze the features of noise. Then according to the statistical features of noise, we propose a novel centroid updating approach to enhance the robustness of the clustering-based superpixel methods. Besides, we propose a novel superpixel based edge detection method. The experiments on BSD500 dataset show that our approach can significantly enhance the performance of clustering-based superpixel methods in noisy environment. Moreover, we also show that our proposed edge detection method outperforms other classical methods.

Index Terms— Clustering-based superpixel methods, edge detection, noise-resistance, superpixel segmentation.

1. INTRODUCTION
In 2003, Ren et al. [1] first proposed the concept of superpixel, which refers to a series of regions consists of pixels with adjacent positions and similar color, brightness and texture features. These regions can retain the effective information like the boundary information of objects in the image [2,3,4]. Different from pixel, superpixel can reduce the size of the object to be processed and the complexity of the subsequent processing to a great extent [2,3,4]. Due to these advantages, superpixel methods are usually used as a preprocessing step for many tasks [2,3,4,5].

For the past years, many superpixel methods have been proposed. A good superpixel method should meet many needs like compactness, boundary adherence, computational complexity, controllable superpixel number [2,6]. Each kind of superpixel method has its own advantages and defects [2,7]. Among them, clustering-based methods are widely used for image segmentation tasks [2,8]. Through the clustering process, the number and the compactness of superpixels can be controlled [9]. Simple linear iterative clustering (SLIC) is one of the most commonly used clustering-based methods, which adopts a local K-means clustering method to cluster pixels based on the color and spatial distance [6]. Linear spectral clustering (LSC) is another well-known clustering-based method [10]. Different to the five-dimensional space used in SLIC, it takes a ten-dimensional space and gets a better boundary recall rate than SLIC. Recently, an improved SLIC called simple non-iterative clustering (SNIC) has been developed [5]. Compared to SLIC and LSC, SNIC do not need iterations, so it has higher computational and memory efficiency. However, above clustering-based methods are all sensitive to noise [2]. When the noise exists, they can not maintain the performance as they work in non-noise situation [2].

To solve the above problems of clustering-based superpixel methods, in this paper, we first analyze the features of noise. Then according to the statistical features of noise, we propose a novel centroid updating approach to enhance the clustering-based superpixel methods. Moreover, we propose a superpixel based edge detection algorithm (SBED), which can gain edge of image by detecting edges of superpixels. The contribution of this paper can be concluded as follows,

- We analyze the reason why clustering-based superpixel methods don’t work well in noisy environment.
- According to the features of noise, we propose a novel centroid update approach for clustering-based superpixel methods to reduce the impact of noise.
- Based on superpixel segmentation, we propose a new edge detection method.

2. METHODS
2.1. A novel centroid update approach
When noise exists, value of pixel tends to be singular in the image. While the cluster centroid usually takes the mean

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value of all pixels with corresponding label, the impact of noise will be accumulated in the cluster centroid. Hence noise will affect the cluster centroid, and as we know, the cluster centroid plays an important role in the process of clustering.

Fig. 1. Performance of SLIC in non-noise environment and Gaussian noise environment with different iteration times.

Take SLIC for example, as shown in the Fig. 1 in the early stage of iterative clustering in noise-free environment, the segmentation result has some false boundaries. Generally, the error will reduce and converge with the increase of iteration times. But in noisy environment, the existence of noise will lead to a worse false segmentation, and the false segmentation will then lead to more errors on the clustering centroids as a positive feedback. As Fig. 1 shows, in noisy environment, the difference of cluster centroids becomes ambiguity, and cluster centroids can’t capture the features of the expected object but the mixed region caused by error segmentation. Finally, it will results in a poor segmentation.

Distribution of most noise follows or approximates to the Gaussian distribution as follows:

\[
\text{Noise}(z) = \frac{1}{\sqrt{2\pi}\delta} \exp\left(-\frac{(z - u)^2}{2\delta^2}\right),
\]

where \(z\) is the value of the pixel in an image, \(u\) denotes the average or expected value of \(z\), and \(\delta\) denotes the standard deviation of \(z\).

As Eq. (1) shows, the value of \(\text{Noise}(z)\) is distributed on both sides of \(u\). Hence, most denoising methods take the neighbors of the pixel to eliminate the impact of noise, such as the works in [11, 12], they deal with the noisy pixel by taking the mean value of pixels within a square selected window centered at the current pixel.

Considering the statistical features of noise and inspired by these denoising methods, we propose a novel centroid update approach and apply it to the clustering-based superpixel methods. For an image with size \(M \times N\) and desired number of superpixels \(k\), \(\text{Centroid}_i\) can be computed as follows:

\[
\text{Centroid}_i = [C_{i,1}, \cdots, C_{i,m}, C_{i,m+1}, \cdots, C_{i,m+n}]^T,
\]

\[
C_{i,a} = \frac{\sum_{p_{x,y} \in S_i} q_{x,y}}{|S_i|}, \quad (a = 1, \cdots, m),
\]

\[
C_{i,b} = \frac{\sum_{p_{x,y} \in B_i} q_{x,y}}{|B_i|}, \quad (b = m + 1, \cdots, n),
\]

where \(C_{i,a}\) represents the spatial part (spatial centroid) of the mixed centroid \(\text{Centroid}_i\); \(C_{i,b}\) is the color centroid, and \(S_i\) represents the region of the \(i\)th superpixel, \(|S_i|\) is the number of pixels within \(S_i\), \(q_{x,y}\) is the current coordinate value of pixel \(p_{x,y}\). Because the spatial centroid is not affected by noise, here we still use all the pixels within the current superpixel to calculate it. Different to the spatial space, the color space will be strongly affected by noise. So when calculate the color centroid \(C_{i,b}\) of the \(i\)th superpixel, instead of using all pixels in a superpixel, we use a square block \(B_i\) centered at \(C_{i,b}\) with an adaptive size \(\sqrt{\frac{M \times N}{k \times 2}}\) to select the pixels and calculate it, here \(B_i\) owns approximately half of the pixels within the \(i\)th superpixel. There are two advantages to do like this: (1) it can reduce the effect of noise on the clustering centroids by taking the mean value of pixels within the square block; (2) it also avoids the error caused by false segmentation, most pixels within \(B_i\) used to compute the color centroid can capture the features of the expected object instead of the mixed region caused by error segmentation.

Fig. 2. An overview of our proposed approach.

An overview of our approach is shown in Fig. 2. And the approach can be used for clustering-based superpixel methods. Here for convenience we call our approach Centroid-X, \(X\) indicates a specific clustering-based superpixel method, for example, Centroid-SLIC means that the SLIC method is enhanced by our Centroid-X approach.

2.2. Our proposed superpixel based edge detection

Superpixels can well preserve the boundary of the object, so we can detect the edge of the image based on the edges of superpixels. And here, we use the relationship between superpixels to determine which edges should be reserved and which should be removed.

For a neighboring superpixel pair: superpixel \(i\) and superpixel \(j\), the distance \(D_{i,j}\) between them is defined as follow:

\[
D_{i,j} = |L_i - L_j| + |A_i - A_j| + |B_i - B_j|,
\]

\[
L_i = \sum_{c \in S_i} \frac{l_c}{|S_i|}, \quad A_i = \sum_{c \in S_i} \frac{a_c}{|S_i|}, \quad B_i = \sum_{c \in S_i} \frac{b_c}{|S_i|}
\]

where \(l_c, a_c\), and \(b_c\) is the value of pixel in CIELAB space.

Then we compute the adjacent matrix \(A\) of superpixels (\(A\) is the upper triangular matrix). The \(i\)th row of \(A\) consists of the distance between the \(i\)th superpixel and its neighbors. And for \(A\), its mean value \(\bar{a}\) is the mean of its non-zero elements.
If \( A_{i,j} < \hat{a} \), the edge between \( S_i \) and \( S_j \) should be removed, otherwise it should be reserved.

Finally, we use the gradient of superpixel to further detect the edge point. The whole procedure of SBED is presented in Algorithm 1.

**Algorithm 1 Superpixel based edge detection**

Require: Image \( I \), number of superpixels \( k \)
Ensure: Edge matrix \( E \)

Segment \( I \) into \( k \) superpixels and then detect the edges of superpixels;
Compute gradient matrix \( G \) as Sobel \([17]\), set \( E_{i,j} = G_{i,j} \);
Compute \( A \) using Eq. 3 and gain the average \( \hat{a} \) of \( A \);
for \( i = 1 \) to \( k \) do
  for \( j = i + 1 \) to \( k \) do
    if \( A_{i,j} < \hat{a} \) then
      Eliminate the edge of \( E \) between \( S_i \) and \( S_j \);
    end if
  end for
end for
for each element \( G_{i,j} \in G_{M \times N} \) do
  if \( G_{i,j} < G_{\text{low}} \) then \( E_{i,j} = 0 \); end if
  if \( G_{i,j} > G_{\text{high}} \) then \( E_{i,j} = G_{i,j} \); end if
end for
return \( E \);

3. EXPERIMENTS

In this section, we apply our Centroid-X on three common used clustering-based superpixel methods: SLIC, LSC, and SNIC. We compare the performance of the original method and the enhanced method using our approach on the Berkeley benchmark (BSD500) \([13]\) with three kinds of environment: noise-free, Gaussian noise (zero mean with standard deviation \( \sigma \)) \([0.1,0.2]\)), and salt and pepper noise (noise density range \([0.1,0.2]\)). All the work is run on a personal computer with Windows 10, Intel(R) Core(TM) i7 2.2 GHz 6 cores CPU, and 8 GB RAM.

3.1. Evaluation metrics and parameter settings

We select one standard metric for compactness and two standard metrics for boundary adherence: compactness metric (CO) \([14]\), boundary recall rate (BR) \([15]\), and under segmentation error (UE) \([15]\). Higher BR and lower UE mean a more accurate segmentation, and higher CO means a better compactness of superpixels.

In the experiments, the parameters settings between X and Centroid-X are the same. To keep the fairness, the compactness coefficient are all setting to the same level (SLIC and SNIC take compactness coefficient 30, LSC uses ratio 0.3).

Fig. 3 shows the BR, UE, and CO curves of all methods in noise-free environment. By comparing them, we can find that X (SLIC, LSC, SNIC) obtains better BR than Centroid-X, but the enhanced one obtains better CO, and the UE between them is basically the same. Fig. 4 shows their running time, except SNIC, the speed between SLIC and Centroid-SLIC and the speed between LSC and Centroid-LSC have little difference. Because SNIC takes a non-iterative clustering and its main computation focuses on the centroid update, hence Centroid-X affect the computation of SNIC more than SLIC and LSC. Generally speaking, the difference between X and Centroid-X is not significant in noise-free environment.

Fig. 5 shows the comparison of X and Centroid-X in Gaussian noise environment. We can see that Centroid-SLIC and Centroid-SNIC obtain much better BR, UE and CO than SLIC and SNIC. Although LSC obtains better BR than Centroid-LSC, but its UE and CO are significantly worse than Centroid-LSC. In Fig 6 we can see that the perfor-
mance of LSC in Gaussian noise environment are quite bad (like over-segmentation), so do SLIC and SNIC, while their corresponding Centroid-X can still maintain the approximate performance like in noise-free environment.

Fig. 7 shows the performance of X and Centroid-X in Salt and Pepper noise environment. By observing Fig. 6 we can find that the number of the output superpixels of SLIC and LSC falls sharply (like under-segmentation) in Salt and Pepper noise environment than noise-free environment. But Centroid-SLIC and Centroid-LSC can still maintain comparable number of output superpixels. Although CO of Centroid-X is slightly weaker than X, Centroid-X still obtains much better BR and UE, which illustrates that even in Salt and Pepper noise environment, Centroid-X can still get a robust performance like in noise-free environment.

4. APPLICATION

Here, we apply Centroid-SLIC into our SBED to generate superpixel, and we compare SBED with classical edge detection methods like Sobel [17] and Canny [18]. We take PSNR [19] and SSIM [20] as evaluation metrics like [21] on BSD500. Here we set \( G_{\text{low}} = 0.1 \times \max(G) \), and \( G_{\text{high}} = 0.8 \times \max(G) \). For Sobel and Canny, we set threshold as 0.1.

| Method         | PSNR   | SSIM   |
|----------------|--------|--------|
| Our method     | 6.8372 | 0.0117 |
| Sobel          | 6.5926 | 0.0112 |
| Canny          | 6.1129 | 0.0104 |

Table 1 shows that our method gets better PSNR and SSIM than Sobel and Canny. And Fig. 8 shows that our method can better obtain the edge of image in both noise-free and noisy environment.

5. CONCLUSION

In this paper, we propose a novel centroid updating approach to enhance the clustering-based superpixel methods and a superpixel based edge detection method. Experiments illustrate that our proposed methods can get a much better performance in noisy environment compared state-of-the-art methods.
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