NSLIC: SLIC SUPERPIXELS BASED ON NONSTATIONARITY MEASURE

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ABSTRACT

Superpixels become more and more popular as image preprocessing step in computer vision applications. In this paper, we propose an improved simple linear iterative clustering (SLIC) superpixel approach based on nonstationarity measure (NS-M), which is called nSLIC. An adjustive distance measure is developed in the five-dimensional $[labxy]$ space. The nSLIC superpixel replaces the predefined fixed value of compactness parameter by the nonstationarity measure map of each image, which exploits the image information and is therefore adaptive to the color feature of the image. It also avoids the difficulty of pre-setting compactness parameter and reduces the parameters needed setting to only one indeed. The nSLIC superpixel improves not only segmentation quality bust also computational efficiency by the way of achieving faster convergence. Experiments done on BSD500 dataset show that nSLIC adheres better to image edges meanwhile producing regular and compact superpixels as much as possible, compared to various popular versions of SLIC.

Index Terms— nonstationarity measure, nSLIC, superpixel

1. INTRODUCTION

Superpixels algorithms are popular image segmentation for further processing in computer vision. They group pixels into superpixels which carry more information than pixels and adhere better to image edges than simple box image patched. Up to now, there are many superpixels generating algorithms proposed which are mainly divided into graph-based methods, gradient-ascent-based approaches and watershed algorithms, which are compared in [1], [2]. Among them, because of producing high quality as well as low number of parameters to be set and low computation complexity, SLIC (Simple Linear Iterative Clustering) propsed in [2] is the most popular and powerful prophase for further image segmentation, classification and registration. It is used for image segmentation [3], [4], parsing the hand in depth images [5], saliency detection [6], [7], object contour detection [8], object localization [9], online human trachking [10] and many other fields.

However, the compactness parameter of the distance measure is required to be predefined in SLIC superpixels [2], which is chosen by user trying different values of it and same for all superpixels of each image, resulting in SLIC producing smooth regular-sized superpixels in a smooth image while highly irregular superpixels in a textured image. It may result in wrong superpixels segmentation during the iteration of k-means and therefore increases iteration number. The adaptive SLIC namely ASLIC presented in [2] adaptively chooses the assumed maximum color and spatial distances within each cluster which comes at the price of obviously decreasing in segmentation quality, without any optimization in runtime. Many other researches for SLIC focus on improving computational efficiency with different compromise on segmentation performance, at the same time even introducing more parameters needed setting, such as reducing simply iterations numbers in [11], computing in parallel on GPU in [12] and operating within multi-thread on CPU in [13], accelerating color space conversion in [14], respectively.

In this paper, we proposed an improved SLIC superpixel based on nonstationarity measure, called nSLIC. In nSLIC, the nonstationarity measure is introduced into distance measure instead of the predefined compactness parameter. Unlike the fixed value of compactness parameter, the nonstationarity meausre varies according to the local image features. Therefore, compared to SLIC [2], nSLIC not only improves the superpixel segmentation quality but also reduces the computational complexity. In addition, nSLIC avoids the problem of setting compactness parameter. The comparison of the superpixel segmentation results on BSD500 [15] benchmark shows that nSLIC outperforms various SLIC approaches [2].

2. ALGORITHM

The proposed nSLIC approach improves SLIC by introducing nonstationarity measure into similarity distance measure, which is adaptive to image features. The nSLIC achieves better superpixel segmentation as well as reduces the computation complexity.

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This research is supported by NSFC, China (No: 61375048).

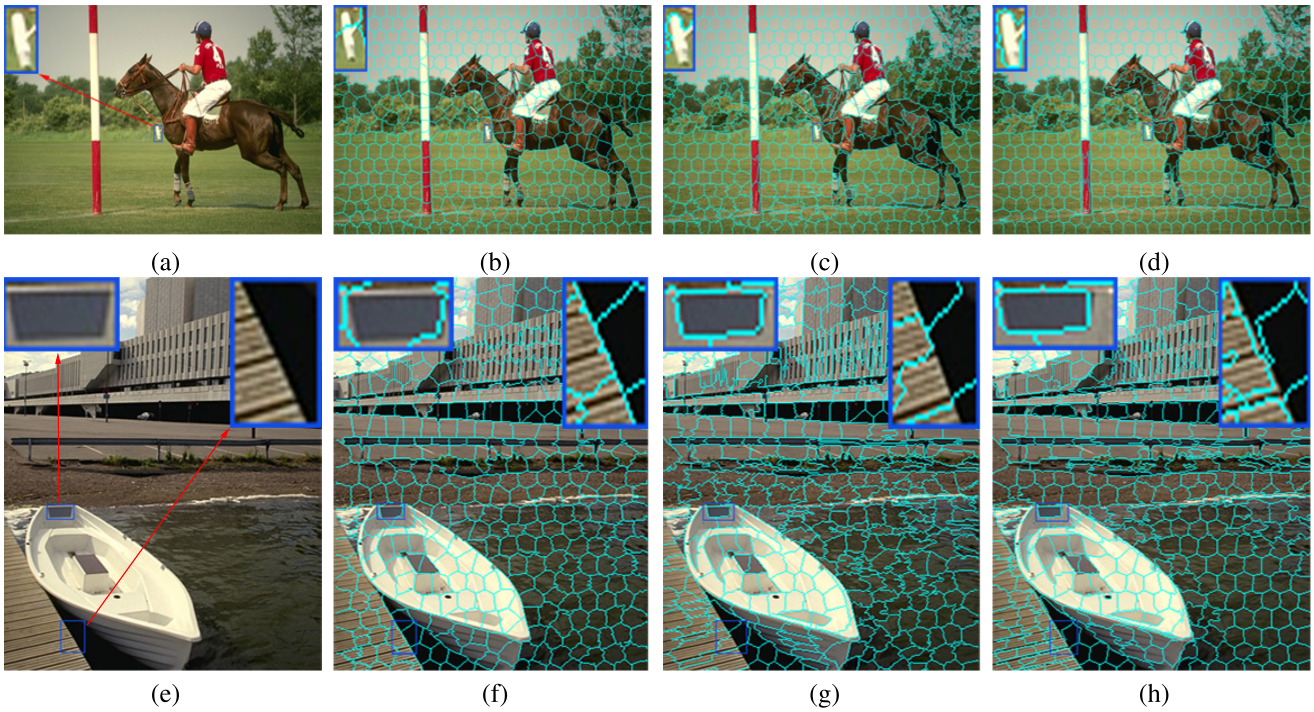


Fig. 1. Visual comparison of different versions of SLIC with 500 superpixels. (a) and (e) Sample images. We select three regions amplified for further discussion in detail as examples. Superpixels generated by four methods: (b) and (f) ASLIC, (c) and (f) original SLIC (the compatness parameter is 10 as default in [2]), (d) and (h) our approach. We can see that superpixels of our algorithm adhere best to image edges meanwhile generates more regular superpixels than original SLIC.

2.1. SLIC superpixels

SLIC [2] adapts the conventional k-means algorithm for superpixels generation based on color similarity and spatial proximity of N pixels in an image with two parameters needed setting: the superpixels number k and compactness factor m. The 5D Euclidean distance measure in $[labxy]$ space between pixel j and cluster center $C_i = [l_i, a_i, b_i, x_i, y_i]$ for pixels clustering follows below formula:

$$\begin{aligned} d_c^2 &= (l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2 \\ d_s^2 &= (x_j - x_i)^2 + (y_j - y_i)^2 \\ D^2 &= d_c^2/m^2 + d_s^2/S^2. \end{aligned} \tag{1}$$

where S^2=N/k stands for the expect average area of each superpixel.

2.2. Nonstationarity Measure

The notion of NSM proposed by [16] stems from the conception of "stationary" in the feild of random process theory about signal processing. They consider that nonstationary describes a variation in statistical characteristics of any signal segment.

Supposing the statistical parameter of an 2D image is λ, then the NSM can be calculated by

$$\begin{aligned} nsm(m,n) = &\sum_{i=m-W}^{m+W} \sum_{j=n-W}^{n+W} g(i-m, j-n) \cdot [\lambda(i,j)]^2 \\ &- \left[\sum_{i=m-W}^{m+W} \sum_{j=n-W}^{n+W} g(i-m, j-n) \cdot \lambda(i,j) \right]^2 \end{aligned} \tag{2}$$

where W designate the half length and half width of a square 2-D sliding window.

If the parameter λ is estimated by a linear operator mask h, (2) can be simply expressed as a convolution form

$$nsm = g * (h * f)^2 - (g * h * f)^2. \tag{3}$$

where g and h both are 3×3 Gaussian filter mask.

2.3. nSLIC Algorithm

We combine NSM with SLIC for superpixels segementation. Because of the compactness parameter replaced by nonstationarity measure map of an image, the only parameter of our algorithm is superpixels number k. We follow the below five steps in detail to implement our algorithm:

(a) Preprocessing step: we convert the color image of N pixels into the CIELAB color space and compute the NSM

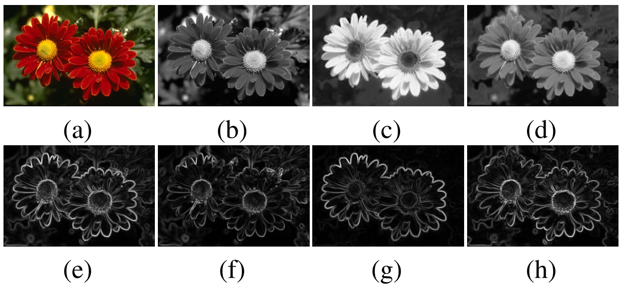


Fig. 2. Illustration of NSM map and edge map. (a) sample color image and corresponding lab channel images and their NSM maps are shown in (b) and (f), (c) and (g), (d) and (h). The edge map of the color image is summation of absolute NSM value of each channel shown in (e).

map of each channel in CIELAB color space firstly, which is efficient according to (3) and image adaptive, as shown in Figure 2. Then normalize the NSM map to the range $(0, 1)$ so that the corresponding value of the homogeneous pixels are small, nearly zero. We define that the edge map of the color image is summation of absolute NSM map value of each channel.

(b) Initialization step: k initial cluster centers $C_i = [l_i, a_i, b_i, x_i, y_i]$, where $[l, a, b]$ is the pixel color vector in CIELAB color space and $[x, y]$ stands for pixel position, are sampled uniformly with fixed grid interval S which is superpixel size and equals to $S{=}\sqrt{N/k}$. Then it is necessary to move the centers to the lowest gradient magnitude locations in a 3×3 neighborhood according to edge map for avoiding locating a center on an edge pixel and reducing the impact of noisy pixel.

(c) Assignment step: we just replace the companess parameter m in (1) with nsm map value as the weighting coefficient of corresponding pixel for each channel. For color image, each pixel j of a 5D vector is labeled by the nearest cluster center according to the weighted Euclidean distance measure D

$$\begin{aligned} D_c^2 &= nsm(l_j) \cdot ||l_j - l_i||_2 + nsm(a_j) \cdot ||a_j - a_i||_2 \\ &\quad + nsm(b_j) \cdot ||b_j - b_i||_2 \\ D_s^2 &= [||x_j - x_i||_2 + ||y_j - y_i||_2] / S^2 \\ D^2 &= D_c^2 + D_s^2. \end{aligned} \tag{4}$$

in a search region $2S \times 2S$ around the superpixel center which significantly improves computing efficiency.

Simply speaking, when a pixel is similar to its 8 neighborhood pixels, the nsm value corresponding to channel tends to be small near zero. Therefore, the D_c is small near zero and the superpixel is regular. Conversely, nsm value has a larger value when the pixel locates near the boundary and D_c value can not be ignored. Thus, the distance measure pays more attention to spatial proximity in a homogeneous region while attaches more importance to color proximity close to the boundary. Consequently, the superpixels adhere well to image boundaries under the condition of ensuring the nearly same low segementaion error.

Moreover, we can further improve the computational efficiency just by replacing the compactness parameter m with edge map based on nsm map of an image with slightly descreasing in segmentation performance. Then the formula for D_c is expressed:

$$D_c^2 = edgemap(j) \cdot [||l_j - l_i||_2 + ||a_j - a_i||_2 + ||b_j - b_i||_2] . \tag{5}$$

For grayscale image, we simply adapt D_c to D_g as follows:

$$D_g^2 = nsm(l_j) \cdot ||l_j - l_i||_2. \tag{6}$$

(d) Update step: recompute the the mean of the pixels belonging to the same superpixel label to update the cluster center. Since nonstationarity measure map is image adaptive, and better responses image boundary than just the same compactness parameter, the cluster centers achieve convergence only through 3-5 iterations, which improves much in efficiency compared to different kinds of SLIC.

(e) Postprocessing step: the unconnected small regions which belong to a superpixel but not connected to it are assigned to nearby superpixels.

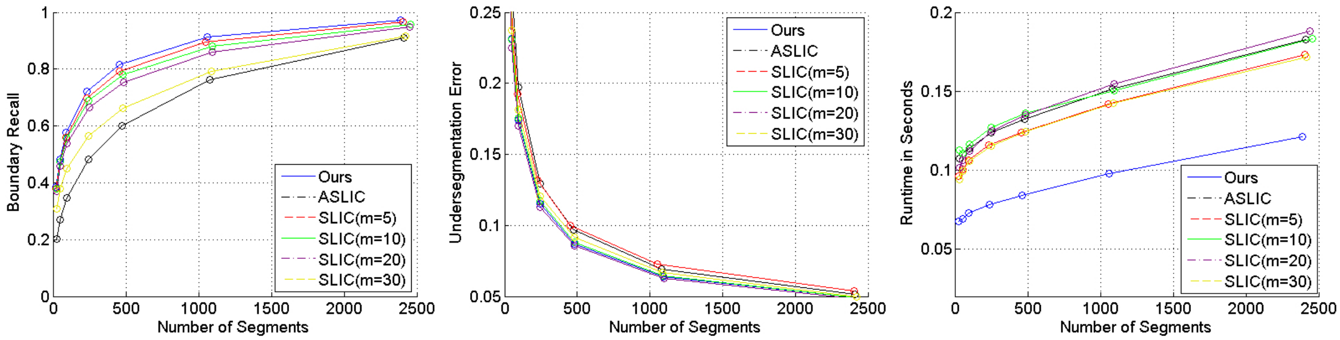
3. RESULTS AND DISCUSSION

We evluate the algorithm on the BSD500 dataset [17], which contains 500 images and hand-segmented contours for boundary and segmentation serving as ground truth. Then compare it with original SLIC of different compactness parameters and the adaptive compactness parameter version ASLIC, according to three metrics: Boundary recall, Undersegmentation error and Runtime.

All metircs are evaluated on each of the 500 images with a given requested number of superpixels. For all the experiments, the number of superpixels are set in the range (25,100,250,500,1000,2500) and the compactness parameter m for different SLIC are set in the range (5,10,20,30), as well as the iterations are set 10 for SLIC and ASLIC, and 5 iterations for nSLIC.

3.1. Segmentation Quality

Boundary recall measures the fraction of hand-annotated edges that fall within at least two pixels of a superpixel boundary. As shown in Figure 3.a, we can see that boundary recall increases progressively with decreasing the compactness parameter m for original SLIC. In other words, SLIC behaves best when m=5 and yet worst when m=30. Besides, ASLIC has the lowest boundary recall because of its dynamically choosing the maximum observed color distance as the compactness parameter m from the previous iteration within each cluster. While our algorithm achieves the highest



(a) Boundary Recall (b) Undersegmentation Error (c) Runtime

Fig. 3. We compared different versions of SLIC with various compactness parameters, ASLIC and nSLIC on the BSD500 dataset. (a) Boundary recall increases with decreasing compactness parameter m and the highest is nSLIC while lowest is ASLIC. (b) Undersegmentation error decreases with decreasing compactness parameter m in the range $(20, 30)$ while shows the opposite trend in the $(5, 20)$. The extremum is at the value of 20 and nSLIC shows nearly the same as it. (c) Results show that nSLIC saves nearly a third of runtime compared to different versions of SLIC including ASLIC.

boundary recall for the reason that NSM is image adaptive and detects image boundary well, which is completely different in principle from ASLIC.

Undersegmentation error (UE) measures how much area of superpixels flood over the hand-annotated segmentation edges. As shown in Figure 3.b, we can see that SLIC performs best when m=20 and yet worst when m=5 accompanied with ASLIC. However, our approach ahieves nearly the same lowest as the optimum condition of SLIC. It is explained that we adjust the original SLIC to adhere better to image boundary by introducing nonstationarity measure of an image as prior information.

From the sample images in Figure 1, our algorithm adheres better to image boundary than the most two popular versions of SLIC (m=10) and ASLIC. In detail, the edges of polo mallet as boxed and enlarged in Figure 1.a are missed least of our algorithm. Another typical examples are selected in Figure 1.e, ASLIC and SLIC (m=10) can adhere well to image boudary for one region while bad for another. However, our algorithm behaves well for two regions in Figure 1.d. Moreover, it is obvious that the regularity and compactness of superpixels from our algorithm fall in between SLIC (m=10) and ASLIC.

3.2. Runtime

Runtime, shown in Figure 3.c, is an especially important measure for superpixels generating algorithms. Since our algorithm is image adaptive and takes more image information into consideration for clustering, it needs less iteration numbers leading to improving nearly 33% in efficiency. We implement all the algorithms on the source code provided by [2] without any code optimization and run on the BSD500 database based on a machine with Intel Core i5-4570 3.2GHz and 8GB RAM.

3.3. Discussion

Generally speaking, the ability to image boundaries adherence and runtime are standard measures when evaluating a superpixels method. Good superpixels method is able to combine performance with efficiency. The above analysis has fully shown our algorithm outperforms ASLIC and various compactness parameters of SLIC.

By solving efficiently the two remaining problems of the compactness parameter m and the iteration numbers, our algorithm, which is much different with previous optimization measures for SLIC, achieves better performance with much higher computational efficiency because of faster convergence. Hence, all of the optimization algorithms based on SLIC can be transplanted to our algorithm to further improve SLIC.

4. CONCLUSION

SLIC superpixels have become widely used in more and more computer vision applications, and we introduce nonstationary measure into the distance measure of SLIC to improve its performance and efficiency. Moreover, we reduce the parameters the user needs to set to only one indeed. We have shown that the proposed nSLIC algorithm acquires better performance and higher efficiency compared to different versions of SLIC including ASLIC based on BSD500 dataset, since the nonstationarity measure map is image adaptive and takes greater advantage of more informatin in an image.

In future, we will focus on combining nSLIC with machine learning methods, such as random forest, for object contour detection, as well as trying to apply it into other applications in computer vision.

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