ISSN: 2455-2631 © February 2019 IJSDR | Volume 4, Issue 2

A Survey on Different Methods for Superpixel Segmentation

[1]Renju J Chandran, [2]Gopakumar G, [3]Shyma S Nair

Image processing,
College of Engineering Chengannur
Kerala, India

***Abstract*: Image segmentation is an important part of image analysis process, since it differentiates between the salient objects and the other objects or from their background. It is the process of dividing digital image into multiple segments and the main aim of segmentation is to pinpoint objects and boundaries. There are different methods for segmenting image, here we are considering the concept of superpixels inorder to segment image. Superpixel can mainly accelerate the successive processing since the superpixels of an image carry more information than a normal pixel. This paper deals with detailed survey on different superpixel segmentation techniques.**

***IndexTerms*: Salient object, Superpixel, Discriminability.**

I. INTRODUCTION

An image is a collection of many pixels and each pixel is used to carry intensity information. Mainly an image has two regions foreground region and background region. So the main aim of segmentation is to differentiate these two regions. Therefore segmentation becomes one of the most important process in computer vision and it can be used as a preprocessing step in image processing. Instead of working with just pixels it is more effective to work with superpixels. The concept of superpixel was firstly presented in [1].

Superpixel is a group of connected pixels which share similar features. Superpixel carry more information than the normal pixel so it make segmentation more easy. Hence it reduces the computational cost. It is one of the main advantage of superpixel segmentation. Superpixels are more meaningfull and all pixels in a superpixel are almost uniform. Superpixel segmentation means dividing an image into many non-overlapping superpixels. Superpixel segmentation can be used as preprocessing step for image segmentation.

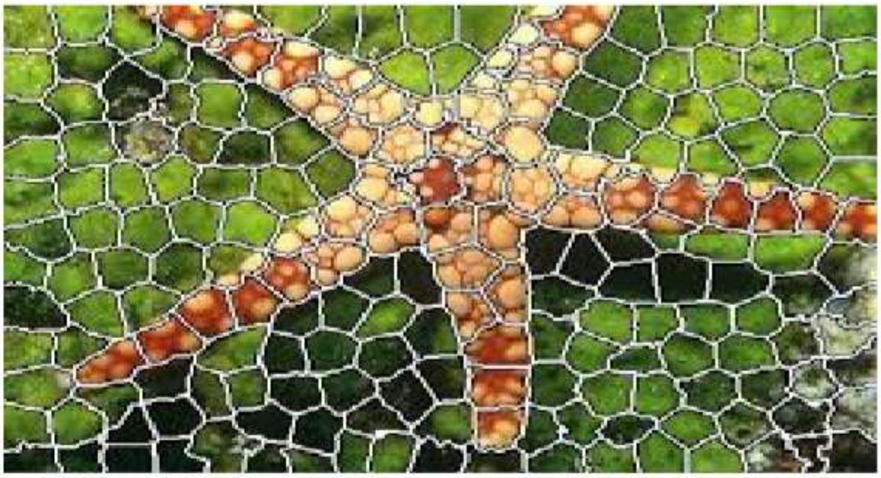

Fig. 1. Example for Superpixel segmentation

Some of the applications of superpixel segmentation in the area of computer vision are image segmentation[2],[3], object recognition[4], object tracking[5],[6] etc. Inorder to use superpixel for different applications it should assure some properties such as : The boundaries of the superpixel should bond well with boundary of the object, superpixel should have regular shape and similar size, it should be computationally efficient and simple to use.

II. LITERATURE SURVEY

This section includes various methods used for superpixel segmentation.

A. Linear Spectral Clustering

The LSC algorithm[8] is mainly based on the relationship between the optimization objectives of weighted K-means and normalized cuts. Instead of highly complex eigen based method simple weighted K-means clustering[9] is used for minimizing the normalized cuts objective function. In LSC superpixel segmentation algorithm first select the desired number of superpixels, K. Then it map image pixels into ten dimensional vector in feature space. Sampling K seed pixels uniformly over the whole image with horizontal and vertical intervals. The feature vector of these seed points are used as initial weighted mean of cluster and then assign each pixel to the corresponding cluster whose weighted mean is similar to pixel vector. After pixel assignment, until convergence, iteratively update weighted mean and search centre of each cluster. Then each cluster will be the superpixel. LSC, provide regular shaped superpixels with linear time complexity and high memory efficiency and achieves both boundary adherence.

B. Simple Linear Iterative Clustering

SLIC[10] is simple and easy to understand. For superpixel generation, SLIC adaptes k-means clustering approach. The image is represented in five dimensional vector space [labxy], where [lab] is the pixel color vector in the CIELAB color space and xy is the pixel position. CIELAB was intended to be perceptually uniform as for human color vision, implying that a similar measure of numerical change in these qualities relates to about a similar measure of outwardly seen change. The distance between the two colors in the CIELAB space is limited and spatial distance xy depend on the image size. The algorithm begins by selecting the desired the number of superpixels and it can be K. And then initialize K cluster centres. For an image of size N, the size of each superpixel will be N/K. Here the grid interval is S=$\sqrt{N/K}$ to produce equally sized superpixels.

Fig. 2. Segmented superpixel using SLIC of size 64, 256, and 1024 pixels[10]

Each pixel is associated to the nearest cluster center and an update step adjusts the cluster centers to be the mean [l a b x y] vector of all the pixels belonging to the cluster. The assignment and update steps can be repeated iteratively until the error converges, Here using Euclidean distance which cause inconsistencies in clustering for different superpixel sizes. This can produce compact superpixels and also they do not bond well to the image boundaries. Because, for large superpixels spatial distances may be greater than color proximity that means giving more relative importance to spatial proximity than color. So instead using Euclidean distance measure, a different distance measure is used.

$$d_c=\sqrt{(l_j-l_i)^2+(a_j-a_i)^2+(b_j-b_i)^2}$$

$$d_s=\sqrt{(x_j-x_i)^2+(y_j-y_i)^2}$$

$$D'=\sqrt{(\frac{dc}{Nc})^2+(\frac{ds}{Ns})^2}$$

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

where D′ indicates the sum of the (lab) distance and the xy plane distance. A variable m is used to control the compactness of a superpixel. This value can be in the range [1,20].The greater the value of m, the more spatial proximity and the more compact the cluster.

C. Superpixels using the Shortest Gradient Distance

Superpixel using the Shortest Gradient Distance[11] uses bilateral filtering[12] which is applied to the texture rich regions. Then, a distance function which uses the shortest gradient distance is considered to enhance boundary adherence. Instead of using the simple Euclidean distance, the proposed combined distance function can be used which can increases the accuracy of associating a pixel to a cluster.

Segmentation begins with selecting the initial image and then represent each pixel in CIELAB color space. Then initialize K cluster centres and assign each pixel into its nearest cluster centre. After this process, the barycenters of the clusters are adjusted as the mean of all the pixels belonging to the same cluster. The texture regions in the image such as grass wood etc may have an negative effect because of the dramatic color variations. So this approach introduce bilateral filtering for preserving edge and provide better result. Bilateral filtering applied only on texture rich region and hence the edges are protected. After that this approach propose shortest gradient distance to achieve better boundary adherence. It start from converting the input image into a grayscale image and extracting its gradient magnitude (GM) map by Sobel operator. Therefore, the GM map is considered as a weighted undirected graph. For a given point p, its shortest minimum cost path to the cluster center Ck can be obtained using the Dijkstra shortest-path algorithm.

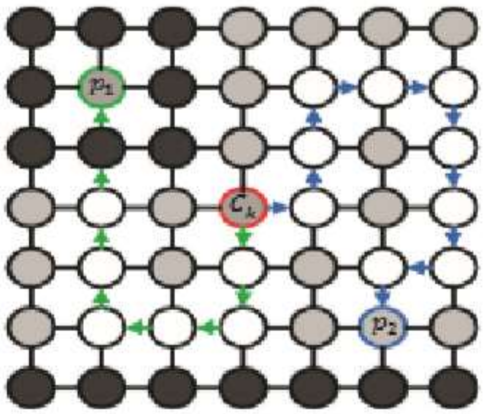

Fig. 3. Searching window in the GM map

The cluster center Ck searches the shortest path to point p1 and point p2 and the these three pixels are represented with red, green and blue boreder respectively. p1 is encompassed with edges. Eventhough p1 and p2 have the same Euclidean distance to Ck.

D. Gaussian mixture mode

GMM[13] is defined as a weighted sum of Gaussian functions, each superpixel describe the density of each pixel represented by a random variable. The weights are constant. Gaussian functions in the weighted sum are subsets of all the Gaussian functions which have the same weights, and results in an algorithm of linear complexity. For each individual pixel, pixel related GMM is applied which allows the superpixels to spread locally over an image and provide a lower computational. Gaussian distribution has the same probability of being selected, which means Gaussian functions are summed with the same weight, so the superpixels will be of similar size. This approach provide better accuracy. This approach used two lower bounds to eliminate the eigen values of the covariance matrices and control the regularity of superpixels.

E. Using morphology

Morphology based operators[14] are used to segment superpixels. This approach is faster and memory efficient. The morphology based method is adapted from the watershed segmentation algorithm. The edges are differentiate by the intensity transitions in the image. Various gradient operators are used to detect these edges, large gradients indicate points where there is a rapid intensity change. Morphological closing operator is used to suppress spurious gradients in the gradient image when there is no prior information about the shape of an object in an image, to preserve isotropy morphological closing is usually applied with a disk shaped structuring element. The closing operation is then followed by watershed segmentation to obtain the segmented image, which is a popular segmentation algorithm, it divides the gray level image into regions that are each associated with one local minimum. The watershed lines are then defined to separate the adjacent regions. The watershed segmentation algorithm is applied to the area closed gradient image to obtain the desired superpixels. The watershed lines are obtained by applying the watershed segmentation algorithm onto the original image.

F. Superpixel hierarchy

Superpixel hierarchy[15] algorithmis used to generate efficient multiscale superpixels . To provide better segmentation accuracy efficient edge detectors are directly integrated with the proposed algorithm. This superpixel hierarchy method provide number of superpixels in a tree structure. Here the image is represented using an n directed graph consist of n vertices. Each pixel is associated with a vertex and the edge is assigned with a weight which represent the dissimilarity between two vertices.

Boruvka algorithm[16] is used here to extracting superpixels. It computes a minimum spanning tree in a bottom up manner. A graph with n trees is considered in which each vertex itself is a tree. Then nearest neighbor of each tree is calculated. An auxiliary graph is built after the nearest neighbor search. In the graph each vertex represent a cluster and each edge associated to one choosen light edge. These edges are distinctive. The connected components can be find out using deep first search. This algorithm will be continue merging until one tree left. Each tree is contract to a single vertex rather than maintaing a forest of trees.

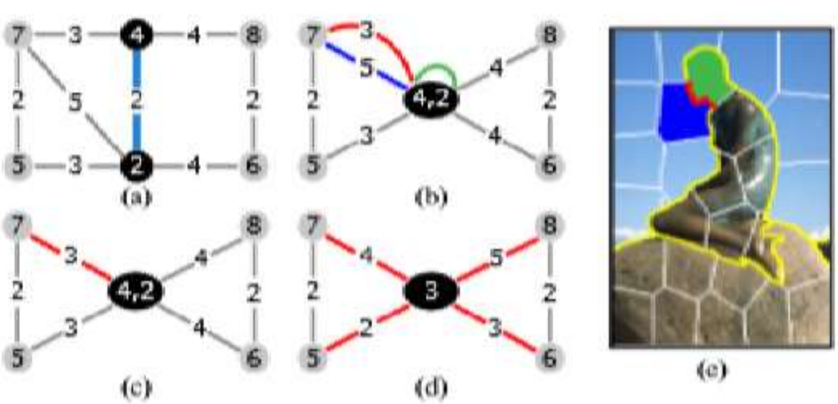

Fig. 4. Illustration of edge contraction and feature aggregation[15]

At each vertex in the figure of edge contraction, a number denotes the attributes (e.g., pixel intensity). The absolute distance of the attributes at two ends are calculated and that will be the weight of each edge. First vertex 4 and 2 is considered. Between these two vertex edge contraction is performed after that vertex 4 and 2 become a supervertex, which create a self loop and two parallel edges. Then remove the selfloop (green line)and replace parallel edges (blue line)with the lightest one. After each iteration feature aggregation is carried out by gathering features from newly formed clusters and then updating edge weights (red lines).Then combine both color and edge features.

G. Content-Adaptive Superpixel Segmentation

[17] offers a new feature representation that include color, contour, texture, and spatial features. Some of the work use only color and spatial features but it is hard to get an accurate result mainly in regions with low color contrast. Inorder to improve segmentation and separating ability new feature representation is used .

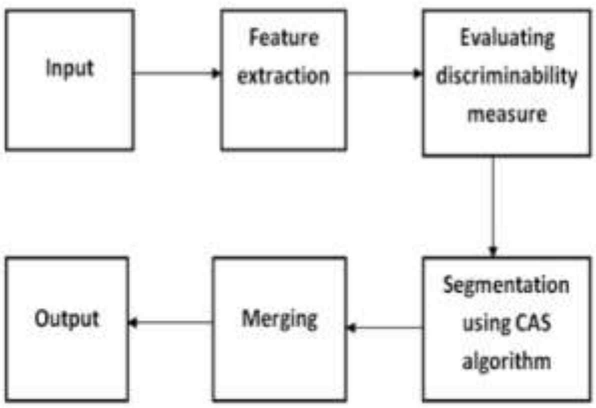

Fig. 5. Flowchart of CAS Algorithm

Here each pixel is represented by a seven dimension feature vector for example p = [l,a,b,x,y,g,u]^T, where [l,a,b]^T measures the color property of a pixel, [x,y]^T is the spatial feature, g and u are the contour and texture features, respectively. The color features are calculated in CIELAB color space. This color space provides distance measurement to distinguish the regular changes of human perceivable colors using the euclidean distance between two colors of pixels. In CIELAB space the color feature is represented by vector [l,a,b]^T, where l stands for lightness and a and b are the color dimensions. Then spatial features are calculated using Euclidean distance. This paper use the image gradient to create contour feature. Image gradient measures the intensity changes in the image, and its magnitude is calculated through the square root of the sum of the squared directional signal changes. Then to construct texture feature WLD [18]descriptor is used .After calculating these features then clustering will be performed.

The discriminability of different features are evaluated using a discriminability measure. Based on their discriminability on the current partition of pixels the weights of different features are automatically adjusted. Several iterations are performed to obtain the final segmentation result. In each iteration, first set the pixels to their nearest centers, creating a section of the image instance. Then, based on the current section, the discriminability of different features are calculated, and therefore reset their weights correspondingly. These weights will be updated in next iteration. Unconnected superpixels are then merged to their most similar neighbors.

Method	Advantage	Disadvantage
Linear Spectral Clustering	**Time efficient**	**Color and spatial features only used. Their performance is decreased when color feature is inadequate.**
Simple linear iterative clustering	**Time efficient**	**Color and spatial features only used. Their performance is decreased when color feature is inadequate.**
Shortest Gradient Distance	**Achieve better boundaries adherence**	**Lack of compactness**
Gaussian Mixture Model	**Allows fast execution on parallel computers**	**Irregular shape of superpixel**
Using Morphology	**Memory efficient and faster execution**	**Not efficient when object are very close to each other. Blurring of the point spread function interfere.**
Superpixel Hierarchy	**Efficient in generating hierarchy of superpixel**	**Time consuming**
Content-Adaptive Superpixel Segmentation	**Provide better segmentation, Since It uses more features.**	**Time consuming**

Comparison of different methods

III. CONCLUSION

In computer vision, image segmentation is an important task and is the process of partitioning an image into multiple segments. The purpose of segmentation is to simplify or change the image representation to something more useful and easier to analyze. But in this work we consider Superpixels for image segmentation since it carry more information than a normal pixel. So superpixel segmentation is more effecient. In this paper, we have briefed various methods for superpixel segmentation. Different methods are LSC, SLIC, shortest gradient distance, morphology, superpixel hierarchy, content-adaptive superpixel segmentation. Content-Adaptive Superpixel Segmentation take time to extract features but it provide better segmentation result compared to other methods since it uses different features.

REFERENCES

[1] X. Ren and J. Malik "Learning a classication model for segmentation ",in IEEE Int. Conf. Comput. Vis, vol. 24, p. 10-17, 2003.

[2] J.Malik,S.Belongie,T.Leung,andJ.Shi "Contour and texture analysis for image segmentation ",in IEEE Int. Conf. Comput. Vis, vol. 43, p. 7-27, 2001.

[3] X. Wang, Y. Tang, S. Masnou, and L. Chen "A global/local afnity graph for image segmentation, ",in IEEE Transactions on Image Processing ,April. 2014.pp. 1451 - 1462,Vol. 24

[4] C. Wang, Z. Liu, and S.-C. Chan "Superpixel-based hand gesture recognition with Kinect depth camera ",in IEEE Trans. Multimedia , 2015.pp. 29 - 39,Vol. 17

[5] F. Yang, H. Lu, and M.-H. Yang "Robust superpixel tracking ",in IEEE Trans. Image Process , 2014.pp. 1639 - 1651,Vol. 23

[6] S. Oron, A. Bar-Hillel, D. Levi "Locally orderless tracking ",in Int. J. Comput. Vis , 2015.pp. 213 - 228,Vol. 111

[7] J. Xiao, R. Stolkin, and A. Leonardis "Single target tracking using adaptive clustered decision trees and dynamic multi-level appearance models ",in Proc. IEEE Conf. Comput. Vis. Pattern Recog , 2015.pp. 4978 - 4987.

[8] Zhengqin Li ,Jiansheng Chen "Superpixel Segmentation using Linear Spectral Clustering ",in Proc. IEEE Conf. Comput. Vis.Pattern Recog. IEEE ,2015.pp. 1356 - 1363

[9] I. Dhillon, Y. Guan, and B. Kulis. "Weighted graph cuts without eigenvectors: a multilevel approach ",in IEEE Trans. on PAMI ,2007.pp. 1944 - 1957,Vol. 29(11)

[10] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk "SLIC superpixels compared to state-of-the-art superpixel methods",in IEEE Journal, p. 2-8, 2012.Vol.6

[11] Ning Zhang and Lin Zhang "SSGD:Superpixel using the shoertest gradient distance ",in IEEE ICIP, p. 3869-3873, 2017.

[12] C.TomasiandR.Manduchi "Bilateral filtering for gray and color images",in ICCV, p. 839-846, 2002.

[13] Zhihua Ban, Jianguo Liu, Member, IEEE, and Li Cao "Superpixel Segmentation Using Gaussian Mixture Model ",in IEEE Transactions on Image Processing, vol. 27, p. 4105-4117, 2018.

[14] Sree Ramya s. P. Malladi, Sundaresh Ram and Jeffrey J. Rodriguez "Superpixels Using Morphology for Rock Image Segmentation ",in IEEE on Image Processing, p. 145-148, 2014.

[15] Xing Wei, Qingxiong Yang, Yihong Gong, Narendra Ahuja, and MingHsuan Yang "Superpixel Hierarchy ",in IEEE Transactions on Image Processing, vol. 27, pp. 4838–4849, 2018.

[16] D. B. West et al " Introduction to graph theory ",Prentice Hall, 2001.

[17] Xiaolin Xiao, Yicong Zhou, Senior Member, IEEE and Yue-Jiao Gong, Member, IEEE "Content-Adaptive Superpixel Segmentation ",in IEEE Transactions on Image Processing, vol. 23, p. 1-14, 2018.

[18] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen, and W. Gao, "WLD: A robust local image descriptor ",in IEEE Trans. Pattern Anal. Mach. Intell, vol. 32, pp. 1705–1720, 2010.

[19] Lei Zhu, Dominik A. Klein, Simone Frintrop, Zhiguo Cao*, and Armin B. Cremers "A Multisize Superpixel Approach for Salient Object Detection Based on Multivariate Normal Distribution Estimation ",in IEEE Transactions on Image Processing ,Dec. 2014.pp. 5094 - 5107,Vol. 23

[20] Arun M. Saranathan,Student Member, IEEE, and Mario Parente, Senior Member, IEEE "Uniformity-Based Superpixel Segmentation of Hyperspectral Images ",in IEEE Transactions on Geoscience and remotesensing ,Mar. 2016.pp. 1419 - 1430,Vol. 54

[21] Jianbing Shen, Senior Member, IEEE, Yunfan Du, Wenguan Wang, and Xuelong Li, Fellow, IEEE "Lazy Random Walks for Superpixel Segmentation ",in IEEE Transactions on Image Processing ,April. 2014.pp. 1451 - 1462,Vol. 23

[22] Jian-Jiun Ding, Chia-Jung Lin, I-Fan Lu, and Ya-Hsin Cheng "Real-time Interactive Image Segmentation Using Improved Superpixels ",in IEEE , 2015.pp. 740 - 744,Vol. 23

[23] TitinuntKitrungrotsakul1,Xian-HuaHan1,andYen-WeiChen1,2"Liver Segmentation using Superpixel-based Graph Cuts and Restricted Regions of Shape Contrains ",in IEEE ICIP , 2015.pp. 3268 - 3371.

[24] Jianbing Shen, Senior Member, IEEE, Yunfan Du, Wenguan Wang, and Xuelong Li, Fellow, IEEE "Cartoon Image Segmentation Based on Improved SLIC Superpixels and Adaptive Region Propagation Merging ",in IEEE International Conference on signal and image processing, April. 2016.pp. 277 - 281.