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Optimized super pixel segmentation for natural image using lazy random walk algorithm

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Abstract *–Image super pixel segmentation approach using the lazy random walk (LRW) algorithm with self-loops has the qualities of segmenting the pathetic restrictions and convoluted texture regions as extremely glowing by the new global probability maps and the transform instance policy. Our technique begins with initializing the seed positions and runs the LRW algorithm on the input image to gain the probabilities of each pixel. Then boundaries of original super pixels are obtained according to the probability and the commute time. Theoriginal super pixels are iteratively optimized by the energy utility, which is defined on the commute time and the texture quantity.The performance of super pixel is improved by relocating the midpoint positions of super pixels and isolating the large super pixels into miniature ones with optimization algorithm. The experimental results have confirmed that our method achieves recoveredact than preceding super pixel approaches.*

Index Terms—*Lazy random walk, commute time, optimization, Superpixel, texture, transform instance policy*.

I. INTRODUCTION

An image can be defined as a two-dimensional function,$f(x, y)$, x and y are spatial coordinates, and the amplitude of 'f' at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point with following properties of an image.

Brightness: - Brightness is an attribute of visual perception in which a source appears to be radiating or reflecting light.

Contrast: - Contrast is the difference in visual properties which makesdistinguishable from other objects and the background.

Resolution: - It is the ability to distinguish fine spatial detail. The spatial frequency at which a digital image is sampled is often a good indicator of resolution. This is why dots-per-inch (dpi) or pixels-per-inch (ppi) are common and synonymous term to express resolution for digital images

Pixels: - The digital image is composed of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and pixels**.** Screens are rated by their number of horizontal and vertical pixels; for example, fig (a) shows 1280×1024 means 1280 pixels are displayed in each row, and there are 1024 rows. Likewise, bitmapped images are sized in pixels: an 350×250 image has 350 pixels across and 250 down .

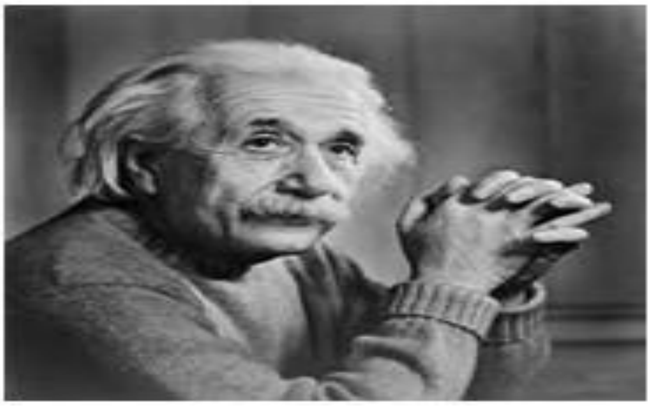


Fig (a) Sample Image **Fig (b) Pixel Image**

In the above picture (b), there may be thousands of pixels,which together make up this image.Zoom that image to the extent that they are able to see some pixels division. It is shown in the image below.

Texture: - It provides the measure of properties such as smoothness, coarseness, and regularity. Texture is another feature that can help to segment images into regions of interest and to classify those regions. In some images, it can be the defining characteristic of regions and critical in obtaining a correct analysis.

Segmentation: - Segmentation is the most important part in image processing. Fence off an entire image into several parts which is something more meaningful and easier for further process. These several parts that are rejoined will cover the entire image.The main motto of segmentation is to reduce the information for easy analysis and also useful in Image Analysis and Image Compression

Segmentation can be classified as follows:

- Region Based
- Edge based
- Threshold
- Feature Based Clustering

Region Based Segmentation

Here pixels that are related to an object are grouped for segmentation .The thresholding technique is bound with region based segmentation. The area that is detected for segmentation should be closed.Region based segmentation is also termed as “Similarity Based Segmentation”.

Edge Based Segmentation

In this edge based segmentation, there is no need for the detected edges to be closed.There are various edge detectors that are used to segment the image using following steps are,

1. To reduce the effect of noise, the surface of the image is smoothened by using Gaussian Convolution.

2. Sobel operator is applied to the image to detect the edge strength and edge directions.

3. The edge directions are taken into considerations for non-maximal

suppression i.e., the pixels that are not related to the edges are detected and then, they are minimized.

4. Final step is removing the broken edges i.e., the threshold value of an image is calculated and then the pixel value is compared with the threshold that is obtained. If the pixel value is high than the threshold then, it is considered as an edge or else it is rejected.

Threshold

Thresholding is the easiest way of segmentation. It is done through that threshold values which are obtained from the histogram of those edges of the original image. The threshold values are obtained from the edge detected image. So, if the edge detections are accurate then the threshold too. Roughness measure is followed by a thresholding method for image segmentation. .

Feature Based Clustering

Segmentation is also done through Clustering. It follows a different procedure, where most of them apply the technique directly to the image but here the image is converted into histogram and then clustering is done on it .Pixels of the color image are clustered for segmentation using an unsupervised technique Fuzzy C. This is applied for ordinary images. If it is a noisy image, it results to fragmentation and It clusters the related pixels to segment the image Segmentation is done through feature clustering and there it will be changed according to the color components.

SuperPixel

A Superpixel can be defined as a group of pixels which have similar characteristics. It is generally color based segmentation. Superpixels can be very helpful for image segmentation. The main merit of superpixel is to provide a more natural and perceptually meaningful representation of the input image.Superpixels are becoming increasingly popular in many computer vision applications. Their benefit is in applications like object recognition,segmentation and automatic photo pop-up methods.

SuperPixel Segmentation

Super pixel segmentation showed to be a useful preprocessing step in many computer vision applications. This led to a variety of algorithms to compute super pixel segmentations, each with individual strengths and weaknesses. Image pixels are the base unit in most image processing tasks. However, they are a consequence of the discrete representation of images and not natural entities.

Fig.1.1SuperPixelImage

II. LITERATURE OVERVIEW

A literature review is a description of the literature relevant to a particular field or topic. It gives an overview of what has been said, who the key writers are, what are the prevailing theories and hypotheses, what questions are being asked, and what methods and methodologies are appropriate and useful

Techniques for SuperPixel Segmentation

This chapter explains about the various papers that are published related to the Super pixel segmentation.

Xiaofeng Ren and Jitendra Malik (2003)presents two-class classification model for grouping. Human segmented natural images are used as positive examples and Negative examples of grouping are constructed by randomly matching human segmentations and images. A set of features for segments, including classical Gestalt cues of contour, texture, brightness and good continuation is defined. These features are evaluated using information-theoretic measures. It prepares a linear classifier to combine these features. Information-theoretic analysis to measure the power of the grouping cues in a model- and algorithm-independent way. This framework has to solve a difficult optimization in the space of all segmentations.

Pedro F. Felzenszwalb and DANIEL P. HUTTENLOCHER(2004)[3] speaks about the problem of segmenting an image into regions. A predicate for measuring the proof for a boundary between two regions using a graph-based representation of the image is defined. And then develop an efficient segmentation algorithm based on this predicate, and show that while this algorithm makes greedy decisions it produces segmentations that satisfy global properties. One important characteristic of the method is its ability to preserve detail in low-variability image regions while ignoring detail in high-variability regions.

A. Levinshtein, A. Stere, K. Kutulakos, D. Fleet, S. Dickinson, and K. Siddiqi (2009)[4]describe a geometric-flow based algorithm for computing a dense over-segmentation of an image, often referred to as super pixels. It produces segments that on one hand respect local image boundaries, while on the other hand limit under-segmentation through a compactness constraint. It is very fast, with complexity that is approximately linear in image size. It shows qualitative demonstrations of high quality results on several complex images.

O. Veksler, Y. Boykov, and P. Mehrani (2010)**[5]**defines A super pixel is an image patch which is better aligned with intensity edges than a rectangular patch. Super pixels can be extracted with any segmentation algorithm most of them produce highly irregular super pixels, with widely varying sizes and shapes. It is formulate the superpixel partitioning problem in an energy minimization framework, and optimize with graph cuts. This method is Computational efficiency.

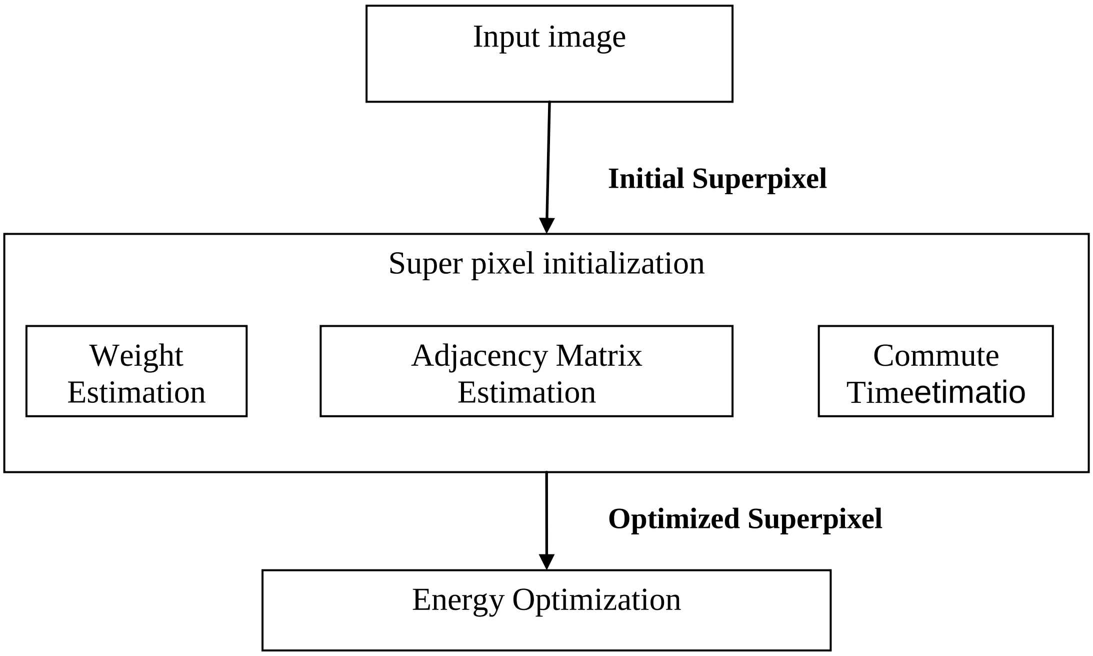
L. Grady(2006) [6] given a small number of pixels with user-defined labels, one can analytically and quickly determine the probability that a random walker starting at each unlabeled pixel will first reach one of the pre-labeled pixels. By assigning each pixel to the label for which the greatest probability is calculated, high-quality image segmentation may be obtained. Theoretical properties of this algorithm are developed along with the corresponding connections to discrete potential theory and electrical circuits.

Wenxian Yang, Jianfei Cai, Jianmin Zheng, and Jiebo Luo (2010)[7]in this paper, the use of multiple intuitive user inputs to better reflect a user's intention random walks algorithm that facilitates the use of three types of user inputs: (1) foreground and background seed input, (2) soft constraint input, and (3) hard constraint input, as well as their combinations. The soft constraint input allows a user to draw strokes to indicate the region that the boundary should pass through. The hard constraint input allows a user to specify the pixels that the boundary must align with. This framework is highly effective and can quickly and accurately segment a wide variety of natural images with ease. It supports multiple intuitive types of user inputs and therefore combines the advantages of different user interactions.

III. METHODOLOGY

3.1 SuperPixel Initialization

The superpixel initialization is computed by commute time. $CT_{ij}$to denote the expected quantities of steps for a lazy random walk that starts at node v_i to reach node v_j and then return to v_i. CT_{ij} is called the commute time. Commute time iscomputed from the Laplacian spectrum using the discrete function. The commute time for image segmentation using the eigenvector corresponding to the smallest Eigenvalue of the commute time matrix. The structural properties of graphs using information conveyed by the Eigenvalues and eigenvectors of the Laplacian matrix (the degree matrix minus the adjacency matrix). So Adjacency matrix for the graph is estimated.



3.2. Graph Construction

Constructing graph with node and edges. Node is corresponding to pixel in the image and the edges connect certain pair of neighboring pixel and selecting the seed point.Points and edges are estimated by using mesh grid.

3.3 Weight estimation

For image segmentation the edge weights in the graph are based on the differences between pixel intensities .First estimating the weight in, a graphG=(V,E) is first defined on a given image $I(x_i)$, which representsa weighted graph containing a set of nodes V and edges connect certain pair of neigh boring pixels. Then every pixel $x_i$is identified uniquely by a nodevertex $v_i \in V$in the undirected graph, where the degree ofeach vertex is computed as

$$d_i = \sum_j W_{ij}$$

For all the edgesthat incident on v_i. The edge-weightcomputation method is used to represent the image intensitychanges. This edge-weight measures the similarity betweentwo neighboring nodes $v_i$and v_j, and thus $W_{ij}$is defined bythe following Gaussian weighting function given in eqn1

w_{ij}=exp($-\frac{\|g_i-g_j\|2}{2\sigma^2}$) (1)

Where $g_i$and $g_j$denote the image intensity values at two nodes,$v_i$and v_j, and σ is the user defined parameter. The value of $2\sigma^2$ is fixed to 1/30 in all the experiments.

3.4 Adjacency Matrix

The neighborhood relations are summarized by the adjacency matrix and it is given eqn2.

$$W_{ij}\begin{cases} 1-\alpha if i=j, \\ \alpha . w_{ij} if i\sim j, \\ 0 \quad otherwise, \end{cases}$$ (2)Where $i\sim j$ means node $v_i$and node v_j are the adjacent nodes, and $\alpha$is a control parameter in the range(0, 1).

After that normalize the adjacency matrix it define the transition probability matrix is given in eqn 3

$$P_{ij}\begin{cases} 1-\alpha if i=j, \\ \alpha . \frac{w_{ij}}{d_i} if i\sim j, \\ 0 \quad otherwise \end{cases} \quad (3)$$

Eqn3 can also be written as P= (1-α)I+αD^{-1}W where D is a diagonal matrix D_{ij} is the degree of the i^{th} vertex v_i.It means that the pixel is stay at the current position the probability is (1- α) and is it walks out along arbitrary edge the probability is$\alpha . \alpha$is the sum of weight of all the edges that incident to v_i.

3.5 Laplacian Matrix

The graph Laplacian directly incorporates a graph structure describing the local neighborhood relation between data points. Theneighborhoodrelation is summarized by the adjacency matrix. The Laplacian matrix is given in eqn 5

$$L_{ij}=\begin{cases} d_i if i=j \\ -\alpha w_{ij} if i\sim j \\ 0 \quad otherwise \end{cases} \quad (5)$$

Eqn 5 can be also written as

$$L=D-\alpha W$$

$CT_{ij}$to denote the expected quantities of steps for a lazy random walk that starts at node v_i to reach node vjand then return to v_i. CT is called the commute time between $v_i$and v_j, which is given in eqn 6

$$CT_{ij}=\begin{cases} L_{ii}^{-1}+L_{jj}^{-1}-L_{ij}^{-1}-L_{ji}^{-1} if i\neq j \\ \frac{1}{\pi} if i=j \end{cases} \quad (6)$$

Where L^{-1}denotes the inverse of the matrix L and then obtained the normalized Laplacian matrix by normalizing the commute time toone that is the sum of commute time from a node to other nodes. Normalized CT is given in eqn 7

$$CT_{ij}=\begin{cases} 1-L_{ij}^{-1} if i\neq j \\ 1 \quad if i=j \end{cases} (7)$$

The commute time is inversely proportional to the probability. The LRW algorithm will be at a pixel xi with the boundary likelihoodprobabilities of label l as given in eqn 8

f_l=(I-$\alpha S)^{-1}yt$(8)

Where I is the identity matrix and S is given by

$$S=D^{-1/2}WD^{-1/2}$$

Here D is the diagonal matrix and W is the adjacency matrix .Finally achieve the labeled boundaries of super pixel from the commute time is given in eqn 9

R(x_i)=$argmin_{lk}$CT(cl_k,x_i)=CT(cl_k,x_i)

Where cl_k denotes the center of the l-th super pixel, and the label l^k *is* assigned to each pixel $x_i$to obtain the boundaries of super pixels. Then the label of the seed with the minimal commute time is assigned to the corresponding pixel as the final super pixel label.

3.6 SuperPixel Optimization

In this module the performance of super pixels is improved with energy optimization function byusing the compactness constraints.

$$E=\sum_{l}(\text{Area}(S_l) - \text{Area}(\mathcal{S})^2 + lWxCTcln,,x2 \quad (10)$$

The first term is the data item adaptively optimizes the positions of seed points to make the superpixel boundaries adhere to the object boundaries well, and the second smooth item adaptively divides the large superpixels into small ones to make the super pixels more homogeneous.

The texture feature of local binary pattern (LBP) to measure the texture information. The LBP value of each pixel is given in eqn 11

$$LBP_i^{q,r}=\sum_{t=0}^{q-1} s(g_t-g_i)2^t \quad (11)$$

Where*q* is the gray level of LBP, *r* is the radius of the circle around pixel *i*, and *g* means the gray value of image. *q* = 8 and *r* = 1 , this values are used in throughout this paper implementation. Based on the LBP texture feature, the area of superpixel is given in eqn 12

$$Area(Sl)= \sum_{i\in Sl} LBP_I, Area(\bar{S})=\frac{\sum_{i\in Sl} LBP_i}{N_{sp}}$$

(12)

WhereArea(Sl)the average area of super pixels and Nsp isis the user defined number of superpixels. The area of superpixel is large when it contains much texture information. The parameter Thcontrols the number of iterations in superpixel optimization process. The ratio of superpixel area and the average superpixel area is greater than threshold; the large super pixel is divided into two small superpixels. After splitting process, the 2 new super pixel and the corresponding two new centers$C_{lnew,}1$, C_{lnew}, 2 is given in eqn 13

$$C_{lnew},1=\frac{\sum_{\{(x-c_l).s>0\}} \widetilde{W_x}\frac{CT(c_l,x)}{\|x-c_l\|}x}{\sum_{\{(x-c_l).s>0\}} \widetilde{W_x}\frac{CT(c_l,x)}{\|x-c_l\|}}$$

(13)

$$C_{lnew},2=\frac{\sum_{\{x|x\in S_l,(x-c_l).s<0\}} \widetilde{W}\frac{CT(c_l,x)}{\|x-c_l\|}x}{\sum_{\{x|x\in S_l,(x-c_l).s<0\}} \widetilde{W}\frac{CT(c_l,x)}{\|x-c_l\|}}$$

IV. RESULT ANALYSIS

4.1 Implementation

4.1.1 Super Pixel Initialization

In this module, first image is chosen for constructing graph with node and edges. Node is corresponding to pixel in the image and the edges connect certain pair of neighboring pixel and selecting the seed point.Superpixel is initialized by commute time.Commute time is the distance between two neighboring pixel in the image.

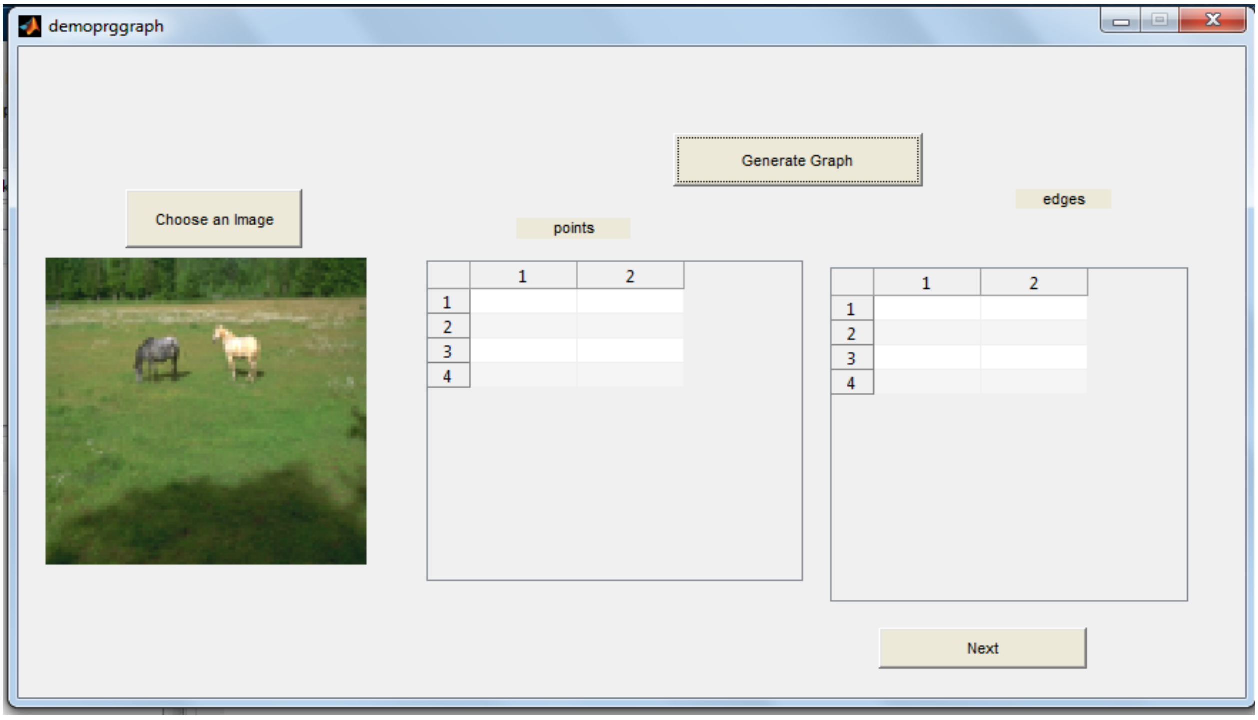


Fig 4.1.1 input image

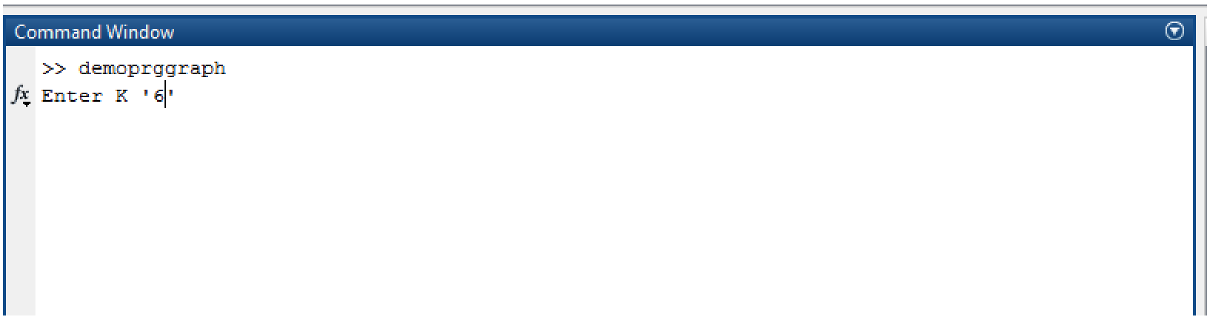


Fig 4.1.2 Seed points

In this module, first seed point kvalue is given as a input to selecting the seed point for initialize the super pixel.

4.1.2 Graph Generation

Fig 4.1.3 Graph Points and edges

In this above figure, the edge and points are estimated for constructing the graph.

4.1.3 Weight Estimation

In this module a weight is computed. A weight is associated with each edge based on some property of the pixels that it connects, such as their image intensities.

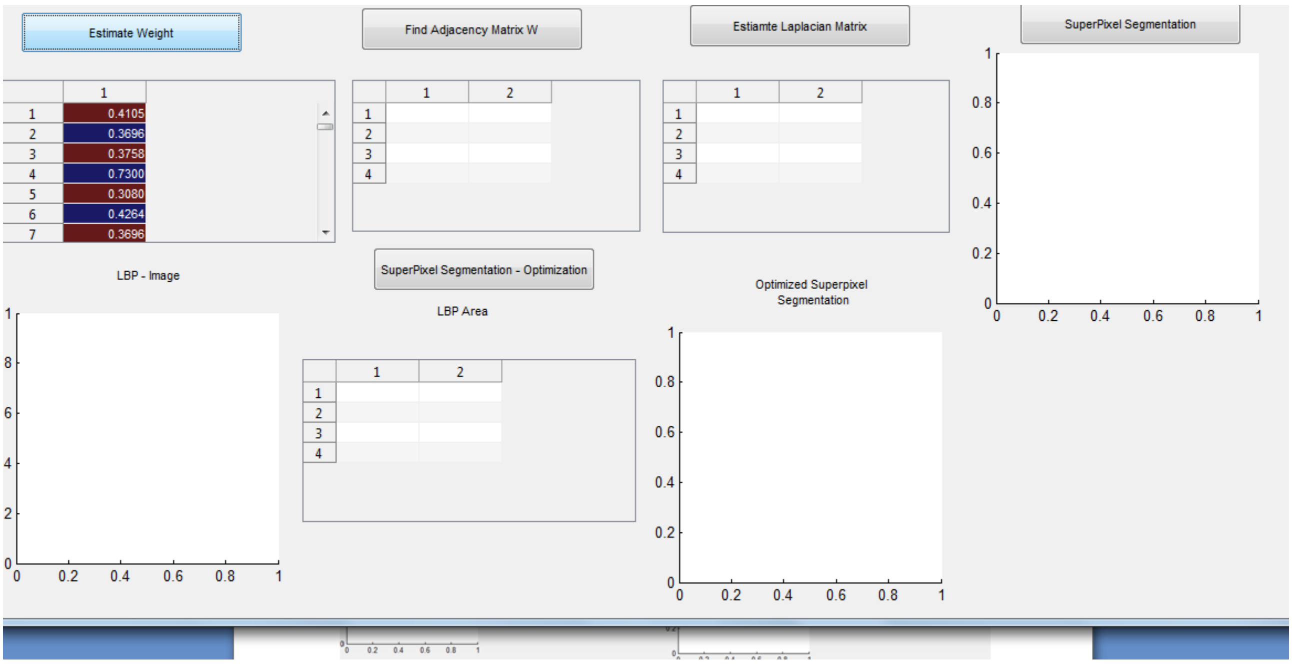


Fig 4.1.4 Weight Estimation

4.1.4 Adjacency Matrix

Adjacency matrix is used to find theneighborhood relation.

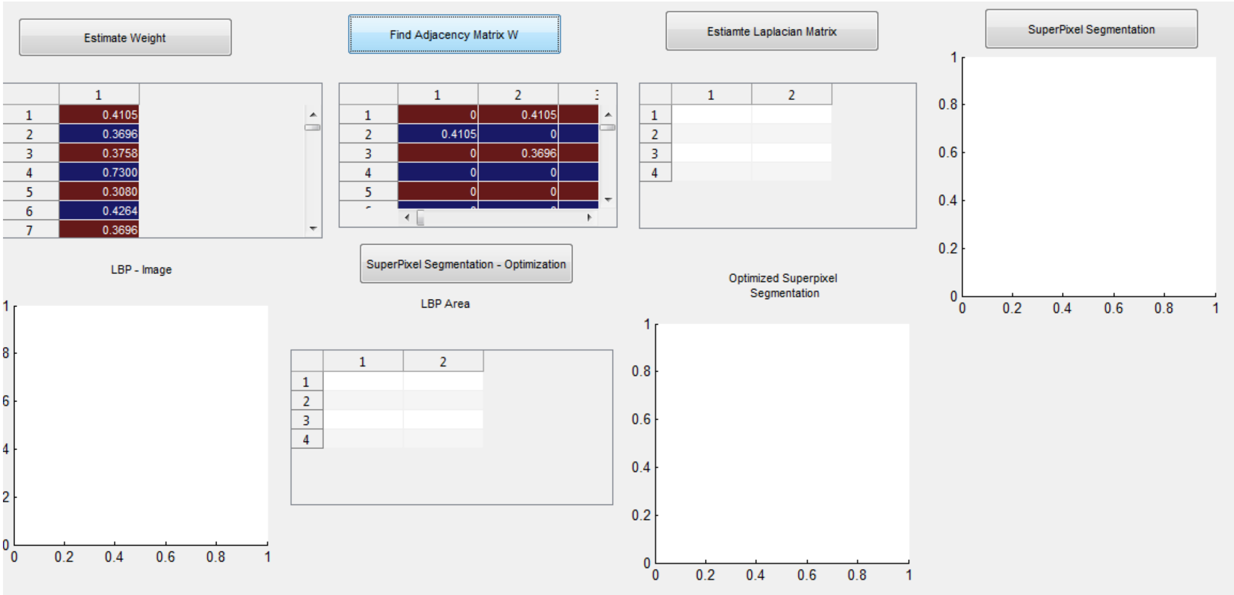


Fig 4.1.5 Adjacency Matrix Estimation

4.1.5 Laplacian Matrix

In this module Laplacian matrix is estimated.

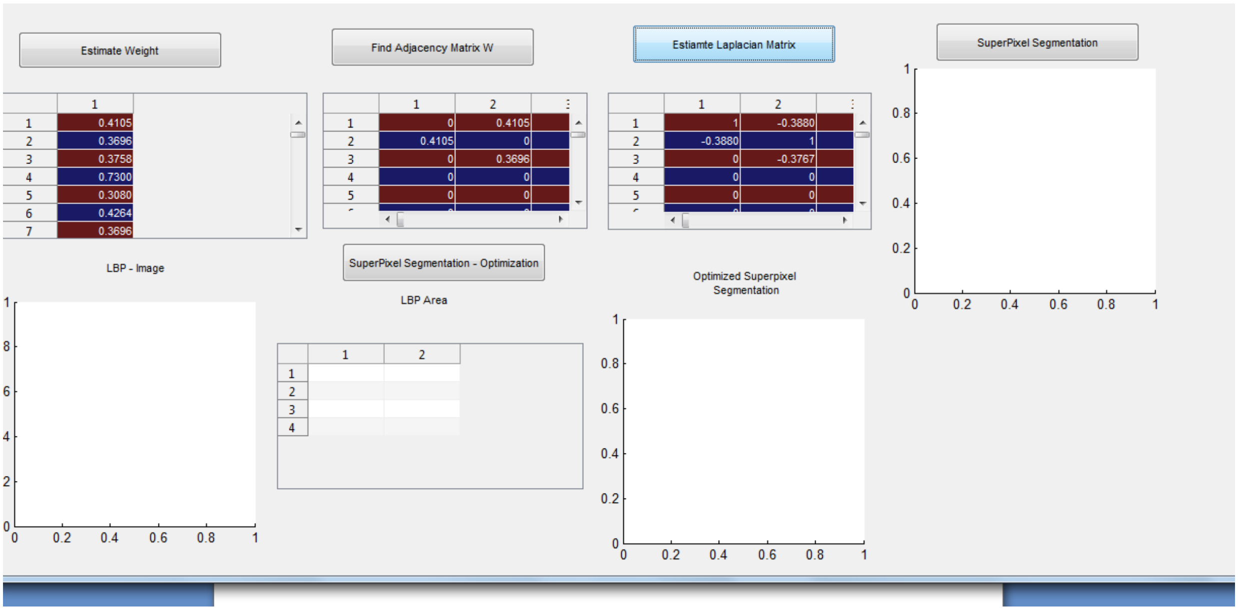


Fig 4.1.6 Laplacian Estimation

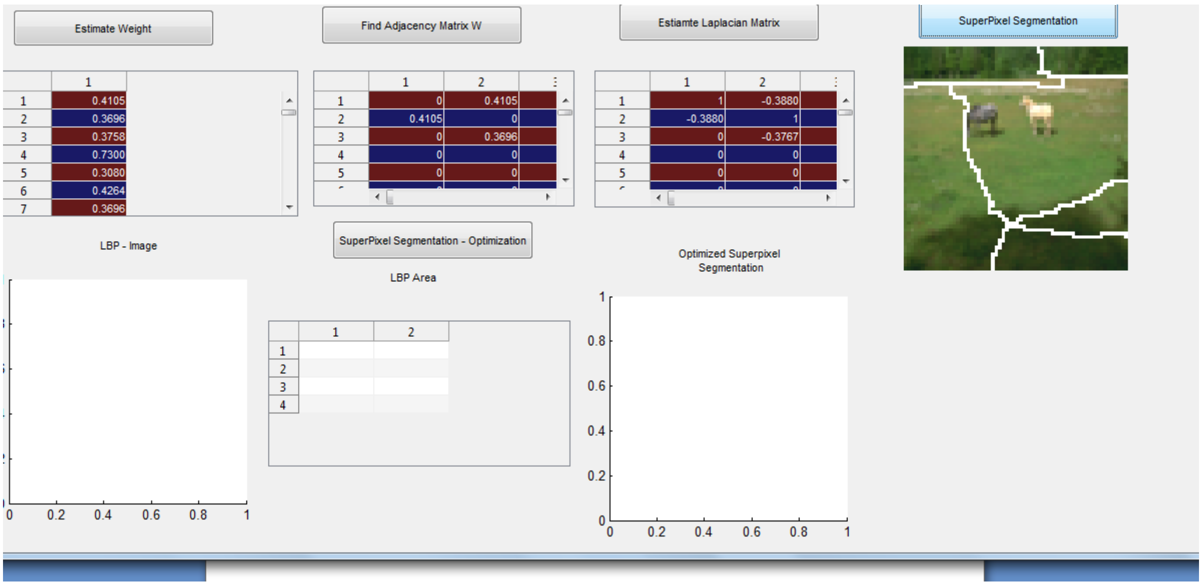


Fig 4.1.7 Initial Super pixel

The final initial superpixel is obtained.

4.2.2 Superpixel Optimization

In this module optimized superpixel are obtained.

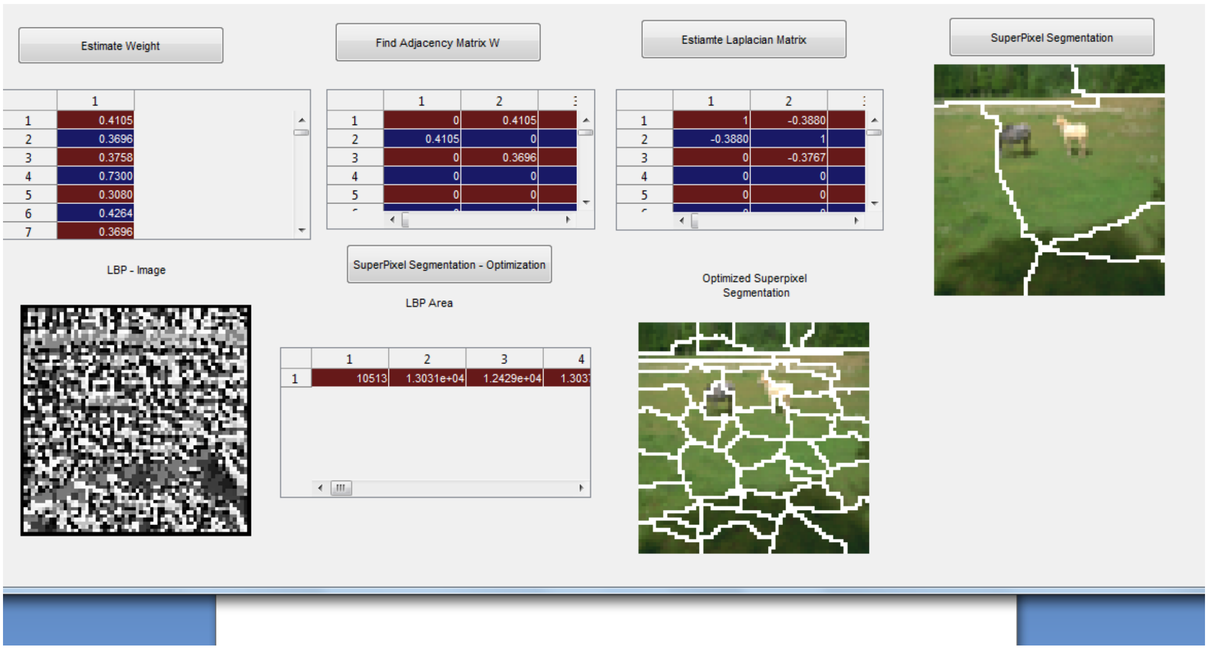


Fig 4.1.8 Optimized Superpixel

4.2 EXPERIMENTAL RESULTS

4.2.1 Under Segmentation Error

The undersegmentation error evaluation measurement checks the deducting area by the superpixel that overlaps the given ground-truth segmentation.

K Value	RW	LRW

20	0.453	0.393
40	0.397	0.301
60	0.321	0.232

Table 4.2.1 Under Segmentation Error

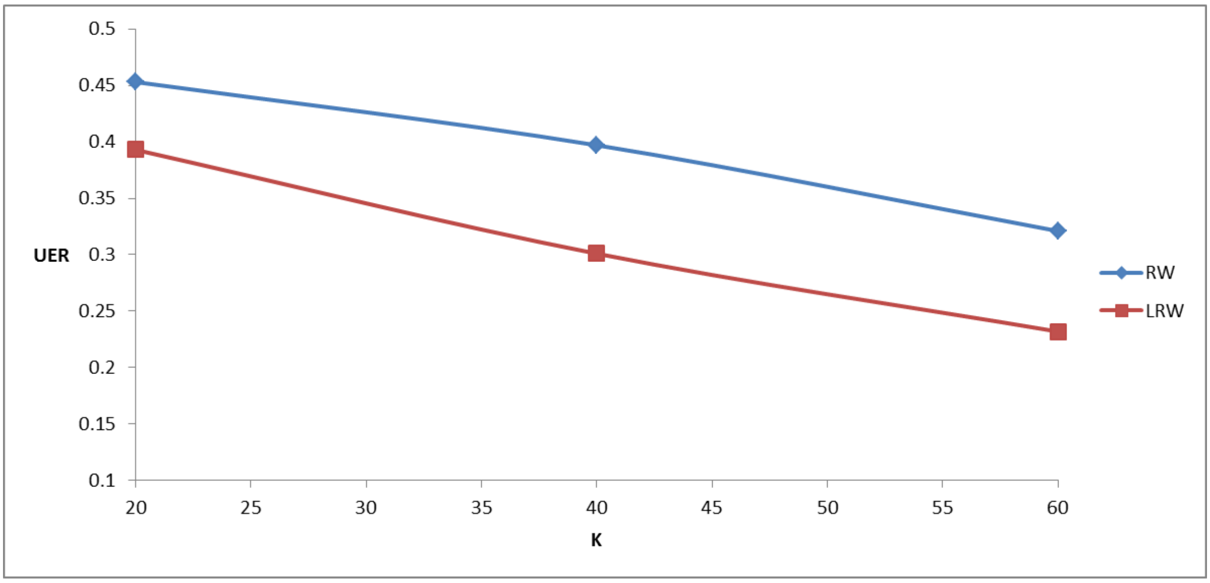


Fig 4.2.2 The Curve of Under Segmentation Error

This graph shows the performance of the LRW algorithm achieves better performance than RW algorithm**.**

4.2.2 Boundary Recall

Boundary recall measurement computes the ratio of the ground truth boundaries that fall within the nearest superpixel boundaries.

K Value	RW	LRW
20	0.423	0.689
40	0.604	0.716
60	0.726	0.835

Table 4.2.2 Boundary Recall

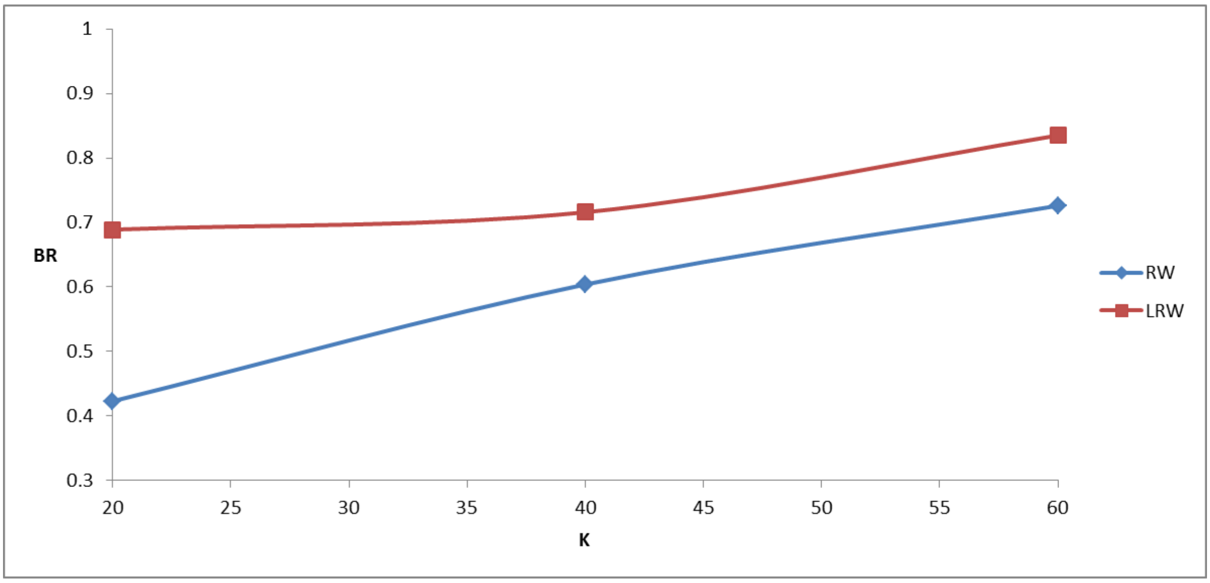


Fig 4.2.3The Curve of Boundary Recall

Lazy Random Walk algorithm precisely calculates the boundary than Random Walk algorithm.

4.2.3 Achievable Segmentation Accuracy

Achievable Segmentation Accuracy computes the highest achievable accuracy by labeling each superpixel with the label of ground truth segmentation that has the biggest overlap area.

K Value	RW	LRW
20	0.543	0.793
40	0.624	0.879
60	0.703	0.926

Table 4.2.4 Achievable Segmentation Accuracy

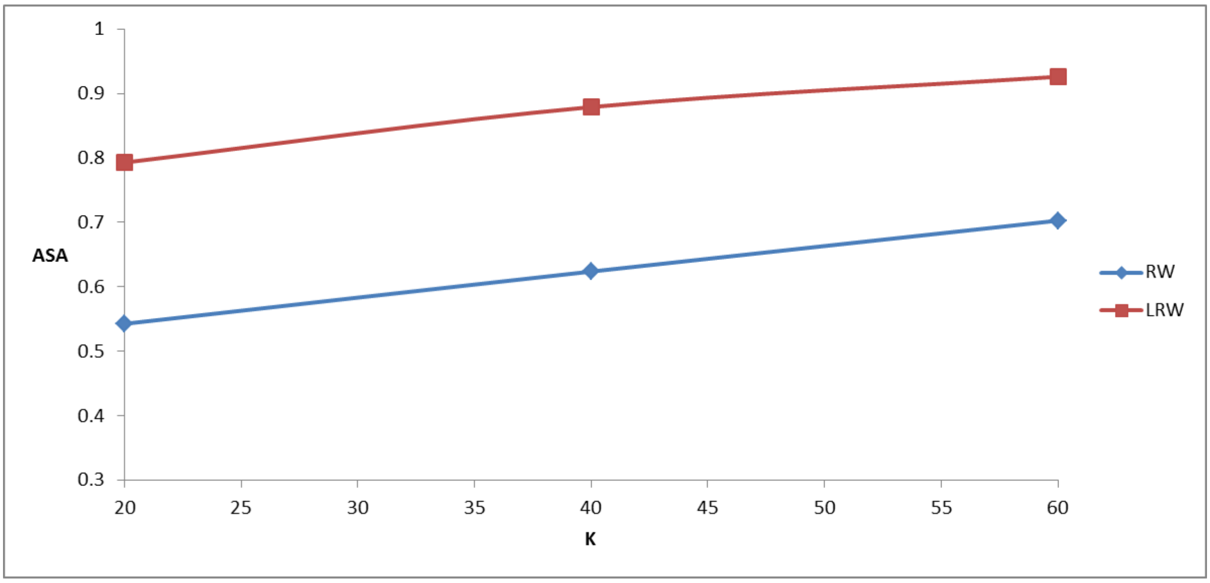


Fig 4.2.5 The Curve of Achievable Segmentation Accuracy

Lazy Random Walk algorithm achieves highest accuracy than Random Walk algorithm.

IV CONCLUSION AND FUTURE WORK

In This method first starts the LazyRandomWalk algorithm to obtain the initial superpixel results by selecting the seed positions on input image. Then it further optimize the labels of super pixels to improve the regularity and boundary adherence performance by relocating the center positions of superpixels and dividing the large super pixels into small uniform ones in an energy optimization framework. The experimental results have demonstrated that the super pixel algorithm achieves better performance than the previous well-known super pixel approaches. This algorithm is capable of obtaining the good boundary adherence in the complicated texture and weak boundary regions, and the proposed optimization strategy significantly improves the quality of superpixels. In future work, optimized Superpixel segmentation can be obtained using various texture feature methods.

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