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Experimental Research Modification of Image Segmentation and Evaluation using Graph Theory

Reshma R.[1], Cheriyachen Joseph[2], Nisha B.S.[3], Vidya Vijayan[4]

[1,2,3,4]*Asst. Professor, Mount Zion College of Engineering, Kadammanitta, Kerala, India*

Abstract - *Graph cuts based interactive segmentation has drawn a lot of attention in recent years. In original graph cuts, the extraction of foreground object from its background often leads to many mistakes and the histogram distribution for energy function is not enough. We investigate the problem of image segmentation based on the colour difference of regions. The aim of the research is to increase the processing speed of the image segmentation and improve the segmentation quality on textured images. We study the aspects of effective implementation of the image segmentation algorithm based on the minimum spanning tree graph, in particular, the use of different data structures for displaying segments. It is shown the dependence of the segmentation result on the colour difference metrics. It is suggested the modification algorithm with the use of an array of singly linked list and with the sorting of the graph edges over linear time, which has resulted in 4 times speed gain. We propose the modification algorithm with the use of super pixelization, which avoids the re-segmentation on the textured areas of the image achieved through the super pixel construction and its use as the graph nodes.*

Key Words: **Graph Theory, Image Segmentation, Graph cut, GrabCut.**

1. INTRODUCTION

Every image is a set of pixel and partitioning those pixels on the basis of the similar characteristics. segmentation is dividing an image into sub partitions on the basis of some similar characteristics like colour, intensity and texture is called image segmentation. The goal of segmentation is to change the representation of an image into something more meaningful and easier to analyze. Image segmentation is normally used to locate objects and boundaries that is lines, curves, etc. in images. Segmentation can be done by detecting edges or points or line in the image. When we detect the points in an image then on the basis of similarities between any two points we can make them into separate regions.

Among different segmentation schemes, graph based algorithm ones have several good features in practical applications. It is more flexible and computation more efficient. A lot of work has been done on graph theory in other applications. The merits of graph based method is re-use existing algorithms and theorems developed for other fields in image analysis.

Graph based image segmentation is based on selecting edges from a graph, where each pixel corresponds to a node in the graph. Weights on each edge measure the dissimilarity between pixels. The segmentation algorithm defines the boundaries between regions by comparing two quantities – Intensity differences across the boundary and Intensity difference between neighbouring pixels within each region. This is useful knowing that the intensity differences across the boundary Literature Review are important if they are large relative to the intensity differences inside at least one of the regions. Graph based image-segmentation is a fast and efficient method of generating a set of segments from an image.

Image segmentation is a partition of an image in an area that is not similar by a certain criterion. The result of image segmentation is a set of areas that collectively cover the entire input image. All pixels in the segment are similar with respect to some characteristics or to computed property (texture, colour, intensity) and probably belong to one material object. The segmentation is one of the first stages of computer vision task and image processing. On this basis the final result of computer vision task depends considerably on the quality of the initial segmentation, and in the decision making system and the system of artificial intelligence the processing speed of the segmentation method is of great concern.

In practice, the segmentation algorithm for color images is applied in various tasks, for instance, in product quality analysis, in defining flooding areas, in yield forecasting, in forest fire prevention, in determining tidal height with the help of aerophoto, in recognition of printed and handwritten text, in identification of malignant tumors and skin diseases, in automatic localization of a person's head on a picture. Existing solutions don't always demonstrate the satisfactory result and the processing speed, that is why new solutions with the use of basic segmentation approaches and their combination are required.

2. RELATED WORKS

The paper [4] addresses the segmentation of a monochrome image. The image is an array $z=(z_1,\ldots z_n,\ldots, z_N)$ of grey values, indexed by the (single) index n. The segmentation of the image is expressed as an array of opacity values α, $\alpha \in \{0,1\}$ with 0 for background and 1 for foreground. The parameters describe image foreground and background grey-level distributions.

The work of Shi and Malik, 1997 [7]; Presents Segmentation based on eigenvector-based methods these methods are too slow to be practical for many applications. In Ratan et al. (1999)[11], method described in this paper has been used in large-scale image database applications. It is fail to capture perceptually important non-local properties of an image. The Work of Urquhart, 1982; Zahn, 1971 [12&6] Presents Segmentation Based on Early graph-based methods. Main disadvantage is Fixed threshold &Local Measures in Computation. Pedro F. Felzenszwalb and Daniel P. Huttenlocher, 2004 [1] it works Based Krusal's Algoritham drawback of this paper is Low Variability image regions while ignoring detail in High variability regions. It is very difficult for users to choose an appropriate value for an expected segmented size. One reason for this interest is that the segmentation quality of Ncuts and other graph-based segmentation methods [2] is very good. The recently-developed isoperimetric method of graph partitioning [3] has demonstrated that quality partitions of a graph may be determined quickly and that the partitions are stable with respect to small changes in the graph (mask). Additionally, the same method was also applied to image segmentation, showing quality results [10].

Among the segmentation based on the representation of an image in the form of a graph, it is necessary to allocate an algorithm based on the construction of the minimum spanning tree [8]. To find the border between the segments it is used the predicate of comparison of a pair of regions, and for building the minimum spanning tree of graph – the Kruskal's algorithm. For this algorithm, several improvements have already been proposed. In the article [9] for the segment representation it is used "Disjoint-set data structure" (DSD) with heuristics "union by rank" and "path compression". In the work [1] it is described how to realize the paralleling calculations for this algorithm, and it is suggested a new predicate to identify the boundaries between regions.

Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals. There are a large number of wavelet transforms each suitable for different applications. The wavelet method applied in our algorithm is mainly based on Mallat's work [5]. The single-level discrete 2-D wavelet is a simple but very efficient method among all kinds of wavelet transform.

There are multi-level wavelet transform or wavelet package, yet one level is enough for our application. The wavelet transform decomposes the image into four independent frequency matrices, cA, cH, cV, cD, which have spatial orientation tuning, and they denote approximation of the original image and the horizontal, vertical, and diagonal textures of the original image.

In our program, for each pixel which is not transformed, a 16*16 square around is obtained and discrete transform is applied on the square. Hence four coefficient matrices: are produced and we utilize three of them: cH, cV, cD. 'Log energy' is computed in the three coefficient matrices by (1). For example, the 8*8 size matrix cD is arranged into a vector S with 64 elements from the first row to the last row. Then,

$$E(cD) = E(S) = \sum_i \log(s_i^2) \qquad (i = 1,2,\ldots,64) \qquad (1)$$

The s_i is intensity of each pixel and $log(s_i^2)$ is entropy. Then other two matrices are obtained as (1). According to this, the textures of horizontal, vertical, and diagonal around a pixel is expressed by three elements.

3. PROPOSED SYSTEM

Fully automatic segmentation may not produce correct segmentation when the image data information cannot discriminate the boundary edges from non-boundary edges. Under such situations, the user's intervention can provide additional information to aid the automatic approach to produce correct segmentation.

3.1 Schema of Algorithm

In the beginning, the user intervention proceeds to identify the object roughly by a user interface. Background is the surrounding of the manual area.

Afterwards, the image is over-segmented by SLIC (Simple Linear Iterative Clustering) superpixels [16]. SLIC clusters pixels in the combined five-dimensional color and image plane space to efficiently generate compact, nearly uniform superpixels, meanwhile the algorithm is easy to use. Generally, the image is divided into 1000 superpixels (regions). After over-segmentation, two vectors v1 and v2 are utilized to represent a region. V1 indicates the color of a region and v2 indicates the color and texture. As proposed in [13], Gaussian Mixture Model (GMM) is applied to classify superpixels. Each GMM, one for the background and one for the foreground, is taken to be a full-covariance Gaussian mixture with k components (typically k = 5).

So,

$$E(\alpha,K)=\boldsymbol{\lambda}R(\alpha,k,\boldsymbol{\Theta},z)+B(\alpha,z)\boldsymbol{\mu} \qquad (2)$$

Then R is replaced by following equation:

$$R(\alpha,k,\boldsymbol{\Theta},z)= -\log\boldsymbol{\Pi}(\alpha,k)+$$

$$\frac{1}{2}\text{logdet}\sum(\alpha,k) + [z - \mu(\alpha, k)] ** (T)\sum (\alpha,k)\text{-}1 \quad (3)$$

Here μ is means of each Gaussian component and $\boldsymbol{\lambda}$ is covariance. The smooth term B is unchanged.

However, the initialization of GMM is another problem. We use K-Means algorithm to classify the foreground and background regions into k clusters respectively (k = 5). Vector v_1 is used only in the stage. GMM components are assigned to regions according to the results of K-Means.

Finally, min-cut algorithm is used to solve *min E(α,K)*, and based on the result, we can adjust the GMM assignment. The process repeats several times until the minimization energy of E converge. The schema is described in Fig 3.1.

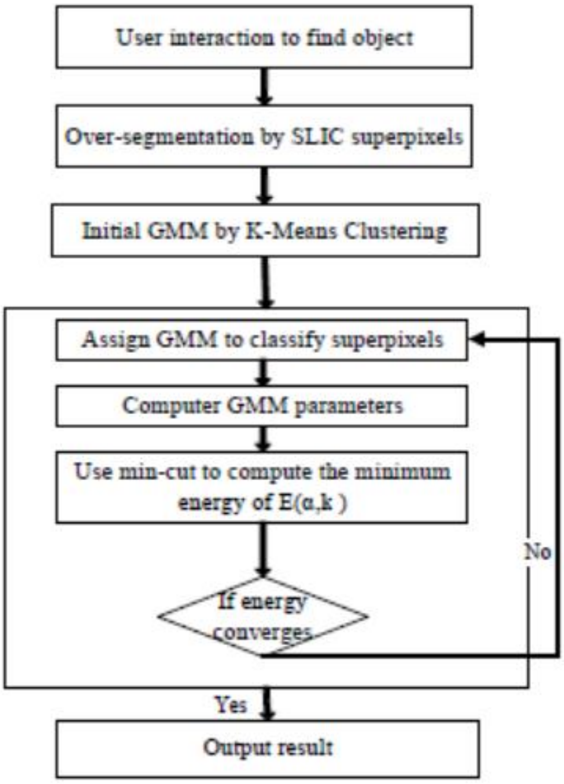

Fig 3.1: *Schema of the ALGORITHM*

3.2 Data Modelling

For each region, the vector v_1 is computed in the RGB mode, then is the mean color of the three R, G, B channels. K-Means are calculated by. Besides the mean color by R, G, B channels, the vector v_2 has other three elements for texture descriptions. First the entropy of each pixel is obtained by (1). Then in a superpixel, the three mean entropies which represent horizontal, vertical, and diagonal textures are computed. Thirdly, for all the vectors corresponding to all superpixels, normalization is proposed.

$$V_{Nor} = v_2/\overline{v_2} \qquad (4)$$

$$\overline{V_2} = [\, \textstyle\sum_{i=0}^{N} |V2| \,]/N \qquad (5)$$

In (5), N is the number of superpixels. The average absolute values of all vectors are obtained. Then after normalize, the values of color model and wavelet entropy can be used in conjunction. V_{Nor} is substituted into (3) to do the energy minimization. By our experiments, when the coefficient $\boldsymbol{\lambda}$ equals 0.5, the IS results are better.

4. RESULT

We compare the proposed iterated graph cuts with the "GrabCut" segmentation method.

In the following, we use four example images to evaluate them qualitatively and show the difference between the two methods. In Fig.4.a and b, the first column is the original images, the second column is the original images segmented by "GrabCut", and the last column is our method's results. Also in Fig.4.c and d, the first row is the original images, the second row is the original images segmented by "GrabCut", and the last row is our method's results.

We get results of the two algorithms with almost the same user interaction, which means that we just drew the objects roughly and then the algorithm converged by themselves.

It is displayed that in Fig.4 (b) and (c), our method can extract the objects entirely and accurately especially at the junction between foreground and background. In Fig.4.(c) and (d), the objects containing weak boundaries due to poor contrast and noise, and some background regions are very close to those of the objects. In such a case, our method can achieve our goals basically.

a

b

Fig 3.2: *The comparision of segmentation results between GrabCut and proposed method*

5. CONCLUSIONS

In this paper experimental research modification of image segmentation is carried out using GrabCut algorithm which belongs to graphical stragies. Image segmentation is a difficult problem in computer vision. It aims to partition an image into constituent regions of interest.

We design software were original algorithm and a number of modifications are implemented. It has been experimentally investigated the dependence of the segmentation quality and processing speed on selecting of pixel metrics, input parameters, graph constructing method, and the method of sorting edges.

Modification using the segments representation in the form of singly linked lists with further approximate sorting of graph edges demonstrates a processing speed value 4 times larger, than the original algorithm.

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BIOGRAPHIES

Reshma R received the Master of Business Administration(MBA) in Marketing and Human Resource from Mahatma Gandhi University Kottayam, Kerala, India in 2017. She is currently working as Assistant Professor in Management studies at Mount Zion College of Engineering, Kadammanitta, Kerala, India. Her primary research interests are in Graph Theory, Artificial intelligence and Marketing Research.

Cheriyachen joseph received the M.Sc in Mathematics from Mahatma Gandhi University, kottayam, kerala, India in 2012. He is currently working as Assistant Professor in Mathematics at Mount Zion College of Engineering, Kadammanitta, Kerala, India. His primary research interests are in Graph Theory, Dynamical systems and differential equations.

Nisha B S received the M.Phil degree in statistics from Bharatidasan university, Tamil Nadu, India in 2008. She is currently working as Assistant Professor in Mathematics at Mount Zion College of Engineering, Kadammanitta, Kerala, India. Her primary research interests are in Graph Theory, Statistics, Calculus and analysis.

Vidya Vijayan received the ME degree in Computer science and Engineering from Anna university, India in 2019. She is currently working as Assistant Professor in the Department of Computer science and Engineering at Mount Zion College of Engineering, Kadammanitta, Kerala, India. Her primary research interests are in graph theory Cloud Computing and data science