Image Segmentation Using Grabcut Based on Anisotropic Diffusion

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***Abstract*— Image segmentation is a technique used to extract the foreground object from background image. In this paper Grabcut framework is used to extract the object from the background. Color and Texture feature is used as discriminating feature for object extraction. Region based image segmentation is done in this paper. For Texture feature extraction, Structure Tensor is used for finding the correct boundary/edge of the needed object. Smoothing is done using Anisotropic diffusion which will preserve the edges from dislocation. If dislocation in edges arises, it is difficult to get proper segmentation. In this paper, details of anisotropic diffusion is given and it tells how the image quality will be increased using this method.**

Keywords-Grabcut, Structure Tensor, Diffusion,Graphcut,MSSIM.

I. INTRODUCTION

In image segmentation, segmentation can be based on the content of the image. Image segmentation is the process of separating or grouping an image into different parts. Label is assigned to each pixel so that pixels with same labels can share certain similar features. An image mainly consists of a foreground object as well as a background image. Extracting the foreground object is the main objective involved in image segmentation. Various features like color, texture is used as discriminating features in a segmentation process. Color images carry more information. There is a lot of information contained in an image which makes it really difficult for manual segmentation and it is time consuming, tedious and for this reason manual segmentation of images is not much preferred[1]. General image segmentation technique should identify the object boundaries and regions automatically or semi-automatically with minimal user input. The image segmentation algorithms are mainly divided into three main categories: feature based, region based and boundary based. Recently the graph based methods are used more frequently and is shown to be more accurate and efficient. In this approach a weighted graph is made in which each vertex represents an image pixel or region and the weight of each edge connecting two vertices represent the similarity between the segments. In anisotropic diffusion, it occurs only along the direction and it is stopped in the direction of the gradient. Structure tensor has been introduced for texture analysis as a fast local computation providing a measure of the presence of edges and their orientation[3]. The nonlinear structure tensors have only advantages in the presence of discontinuities or when delocalization problems appear.

II. GRABCUT

Grabcut algorithm takes the Graph cut algorithm even further. It applies the min-cut algorithm iteratively, inferring unknown knowledge from one iteration to another. This allows it to minimize user interaction to just specifying the background (and not the foreground) pixels. User interaction is therefore minimized to placing a rectangle or a lasso around the object (with respectable distance) instead marking brush-strokes. Moreover, Grab cut generalizes the segmentation to color images by replacing the gray level histograms (based on foreground and background seeds) by Gaussian Mixture Models in (GMMs) RGB. For each GMM, there are Kc components and each component has three parameters, i.e. the vector-valued mean, the symmetric positive definite full-covariance matrix and a real-valued mixture weighting coefficient. Both the color GMMs and texture GMMs are created based on the initial clustering[2].The algorithm is extended to be an "image cutout" (rather then a segmentation) algorithm by using image-mating for opacity values on the objects' borders. This will not be described here as it is beyond the scope of this work.

Below is the full algorithm:

Initialize b (by user),U= $\bar{B}$, F=$\emptyset$. Initialize GMM
parameters w_k,μ_k,ε_k(evenly/randomly)
Repeat(until constant energy) ∀∈U.
Assign the best Guassian => 2K clusters
and for each cluster calculate w_k,μ_k,ε_k => 2K GMMs and find Min Cut as U decreases.

By placing a rectangle around the region of interest, the user specifies the background pixels[2]. Foreground pixels are not specified. This means that only background hard-constraints are used. After the color feature and texture feature are extracted from image, we must choose suited distance measures so as to effectively discriminate these features, which is essential for the accuracy of image segmentation. In order to establish the GMMs, the initial foreground and background produced by placing a rectangle or a lasso around the object must first be classified into Kc clusters based on the color feature and Kt clusters based on the texture feature respectively. Then we will create a total of 2×(kc+kt) clusters[1]. The two clustering processes are independent of each other. In order to take into account the both extracted features, the general energy function is proposed in which α denotes assigned label, with 0 for background and 1 for foreground and ε is the mixing factor used to balance the weights. The equation used is:

$$E(\alpha) = \varepsilon E_C(\alpha) + (1 - \varepsilon)E_T(\alpha) \tag{1}$$

Color and Texture feature are most important discriminating factor. Effectively fusing the two features will greatly improve the performance of the algorithm to segment natural images. An ideal system should adaptively adjust the mixing factor. A mixture fusion technique is proposed which adjusts this parameter depending on the relative discriminative power of texture and color terms. KL distance between the current foreground and background in color and texture fields, the iteration automatically terminates[1]. The minimum of the general energy will yield a globally optimal segmentation for the current iteration of the iterative process or for the refine editing. The iteration automatically terminates. This paper shows that Grab cut method works by just placing a rectangle over the object and a final segmented image will be obtained. It has more computational efficiency. The minimum of the general energy will yield a globally optimal segmentation for the current iteration of the iterative process or for the refine editing. In the process of iterative segmentation, when does the convergence happen. The straightforward criterion is to check whether the labels assigned to the pixels of image change or not after the iteration.

III. PROPOSED METHOD

The flow of the proposed method is given below. Image is given as input. In the proposed method, anisotropic diffusion is used instead of nonlinear diffusion for image smoothing to preserve the edges. The overall image quality is also calculated using MSSIM i.e Mean Structural Similarity Index Matrix and is compared with existing nonlinear diffusion method. The Image quality will increase with the usage of anisotropic diffusion.

Nonlinear Diffusion

Non-Non Linear Diffusion Reduces noise and enhances contours in images. The goal of nonlinear diffusion filtering is to reduce smoothing in the presence of edges[9][10]. The diffusion coefficient is locally adapted, becoming negligible as object boundaries are approached. Noise is efficiently removed and object contours are strongly enhanced. Diffusion stops as soon as object boundary is reached.

A. Isotropic Diffusion

Isotropic nonlinear diffusion means nonlinear diffusion driven by a scalar-valued diffusivity, in contrast to anisotropic nonlinear diffusion, which is driven by a matrix-valued diffusion tensor. The goal of nonlinear diffusion filtering is to reduce smoothing in the presence of edges. This can be achieved by a decreasing diffusivity function g which correlates the amount of smoothing with the image gradient magnitude. Nonlinear diffusion filtering creates a family of simplified images $\{u(x,t)|t\geq 0\}$ of some scalar initial image f(x) by solving the partial differential equation (PDE):

$$\partial_t u = div(g|\nabla u|^2) on \Omega(0,\infty) \tag{2}$$

B. Anisotropic Diffusion

In image processing and computer vision, anisotropic diffusion, is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image[6].

Anisotropic filters are a class of filter that reduces noise in an image while trying to preserve sharp edges. Anisotropic diffusion resembles the process that creates a scale-space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family are given as a convolution between the image and a 2D isotropic Gaussian filter, where the width of the filter increases with the parameter[7]. This diffusion process is a linear and space-invariant transformation of the original image. Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a *non-linear* and *space-variant* transformation of the original image. Anisotropic diffusion can be used to remove noise from digital images without blurring edges. The shapes of the objects in the scene is preserved while the rest is smoothed. In the anisotropic case not only the amount of diffusion is adapted locally to the data but also the direction of smoothing. It allows for example to smooth along image edges while inhibiting smoothing across edges[5]. This can be achieved by replacing the scalar-valued diffusivity function by a matrix-valued diffusion tensor. The diffusion equation used for anisotropic diffusion process is:

$$\partial_t u_{ij} = div\left(g\left(\sum_{k,l=1}^{m} \nabla u_{k,i} \nabla \mathrm{u}_{\mathrm{k,l}}^{\mathrm{T}}\right) \nabla \mathrm{u}_{\mathrm{i,j}}\right) \ (\mathrm{i,j} = 1, \ldots, \mathrm{m}) \tag{3}$$

The MSSIM is used to find the overall image quality. SSIM is the structural similarity index matrix, x_j and y_j are the image contents.

MSSIM equation:

$$MSSIM(X,Y) = 1/M \sum_{j=1}^{M} SSIM\,(x_j, y_j) \tag{4}$$

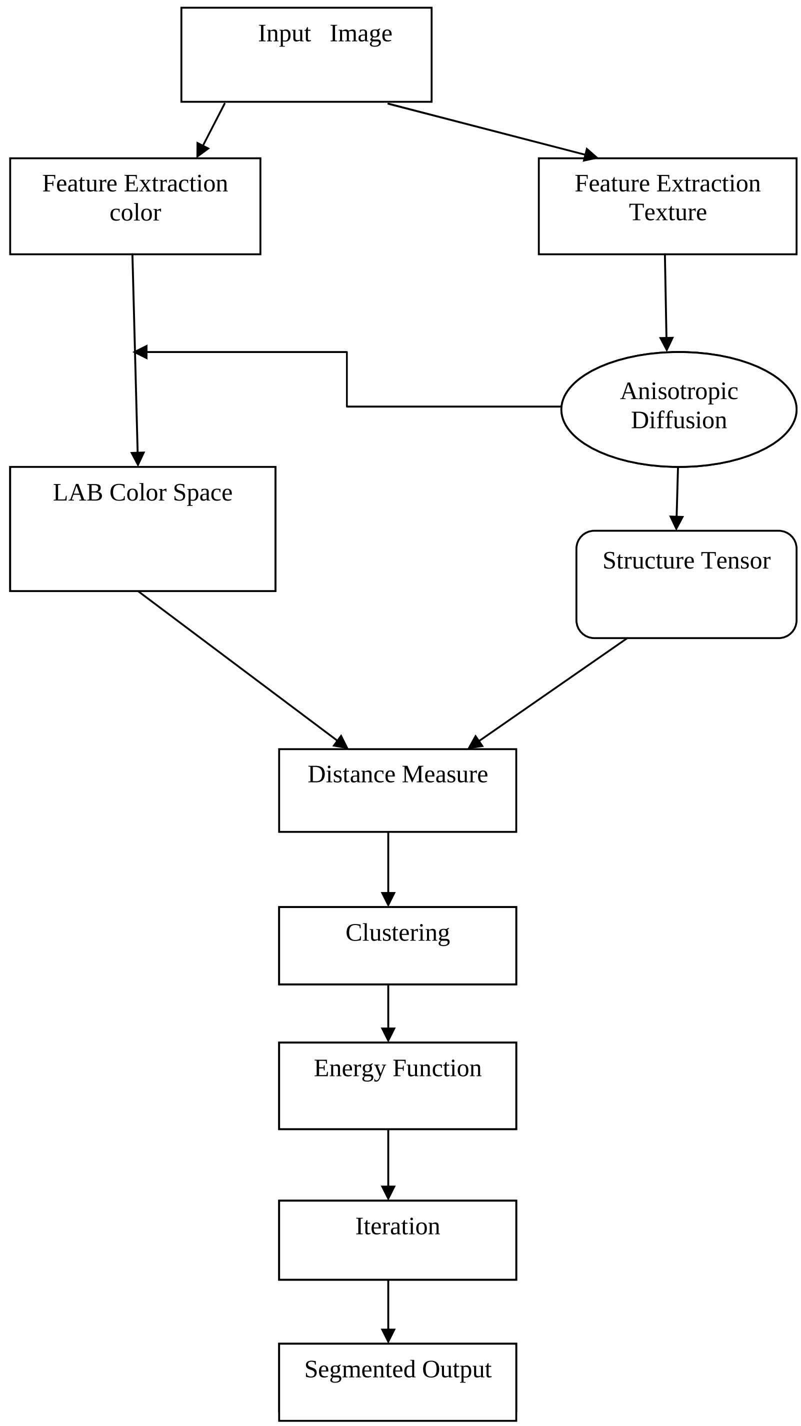

Figure1. Proposed Architecture

The Grabcut algorithm used for anisotropic diffusion works in the way given by the figure shown below:

Figure 2. Grabcut Segmentation

IV. CONCLUSION

In the proposed method, anisotropic diffusion is used than nonlinear diffusion method. Anisotropic Diffusion will preserve the edges more efficiently than nonlinear diffusion. Smoothing is also done for input images. After anisotropic diffusion is applied, segmentation of the image is done using Grabcut framework. Segmented object is got more accurately after using this diffusion. Edges are preserved more efficiently. The overall image quality is also calculated.

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REFERENCES

[1] Shoudong Han, Wenbing Tao, Desheng Wang, Xue-Cheng Tai, and Xianglin Wu, "Image Segmentation Based on GrabCut Framework Integrating Multiscale Nonlinear Structure Tensor." IEEE transactions on image processing, volume. 18, No 10, October 2009.

[2] C. Rother, V. Kolmogorov, and A. Blake, "GrabCut: Interactive foreground extraction using iterated graph cuts," ACM Trans. Graph., vol.23, pp. 309–314, 2004.

[3] Z.Wang and B. Vemuri, "Tensor field segmentation using region based active contour model," in Proc. ECCV, 2004, pp. 304–315.

[4] Perona, P. and Malik, J. (1990) `Scale-space and edge de-tection using anisotropic diffusion', IEEE Transactions on Pattern Anal. Machine Intell., Vol. 12, pp. 629{639.

[5] Sapiro, G. and Ringach, D.L. (1996) `Anisotropic Diffusion of Multivalued Images with Applications to Color Filtering', IEEE Transactions on Image Processing, Vol. 5,pp. 1582{1586.

[6] J. Weickert, Anisotropic Diffusion in Image Processing, B. G. Teubner Stuttgart, 1998.

[7] B. Benhamouda, Parameter Adaptation for Nonlinear Diffusion in Image Processing, Master's Thesis, Dept. of Mathematics, University of Kaiserslautern, P.O. Box 3049, 67653 Kaiserslautern, Germany, 1994.

[8] G. Cong and S.D. Ma, Nonlinear Diffusion for Early Vision, Proc. 13th Int. Conf. Pattern Recognition, ICPR 13, Vienna, August 25 – 30, 1996, Vol. A, pp. 403 – 406, 1996.

[9] F. Catt´e, P.-L. Lions, J.-M. Morel, and T. Coll, Image Selective Smoothing and Edge Detection by Nonlinear Diffusion, SIAM J. Numer. Anal., Vol. 29, No. 1, pp. 182 – 193, February 1992.

[10] Nitzberg and T. Shiota, Nonlinear Image Filtering with Edge and Corner Enhancement, IEEE Trans. Pattern Anal. Mach. Intell., Vol. 14, pp. 826 – 833, 1992.

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