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SIMM: A Stratified Image Matting Model for Blood Vessel Segmentation with a Fuzzy C-Means Trimap in Fundus Images

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Abstract:- The vascular network of human eye is having variable size of blood vessels, contrast variations and outlier presence in pathological cases. For the better management of vascular diseases, automatic detection of vessel structures is required which is of great importance for its early diagnosis and treatment. A new model for blood vessel segmentation from fundus images based on stratified image matting is proposed. Generally, the image matting models requires an input trimap. The trimap generation is a time consuming task, also the accuracy of segmentation results depends upon the quality of input trimap. Therefore, a new method for generating a high quality trimap in less time, based on the application of kirsch template is incorporated in this image matting model, for accurate matte estimation. First, the good quality trimap is generated automatically by applying the Kirsch template which includes three parts: Blood Vessel Extraction Using Kirsch's Template, Co-fusion and Fuzzy C-Means Clustering. Then, for better segmentation performance, vessel pixels from unknown regions are extracted using the multi-level image matting model.

Keywords:- *Global Contrast Normalization (GCN), Conditional Random Field(CRF), Support Vector Machine, Patch Alignment Manifold Matting(PAMM), K-Nearest Neighbor, Fuzzy Multi-Criteria Evaluation (FMC).*

I. INTRODUCTION

The essential anatomical structures that are visible in the retinal images are blood vessels. For the analysis of most cardiovascular and retinal diseases, retinal blood vessel segmentation has been widely used. Thus, it is of great importance to have a proper vessel segmentation technique that automatically detects the retinal diseases like diabetic retinopathy and cataract. Retinal vessels are the fundamental anatomical framework distinguishable in the eye fundus image. The manual detection of vessels and segmentation is an immensely tedious process. There are numerous vessel segmentation features involving length, width, junction points and curving. For early discovery and treatment of retinal diseases, the manual inspection of these features is incredibly a difficult task. Also, manual division is cost devouring and time-consuming effort that needs eyes specialist for the segmentation process. Therefore, automatic vessel extraction and its segmentation in the medical computed tomography images has became progressively more significant for determination and evaluation of vascular illness, planning of surgery , and the flow simulation that varies for every patient.

Matting refers to the foreground object extraction process from an input image. For applications like image and video editing, matting is of great significance. A "matte" is produced as a result of matting task that can be utilized to separate foreground object from the background in a given image. Matte can also be used for integrating a given foreground on an independent background in order to generate new conceivable image.

II. LITERATURE SURVEY

Cheng et al. [1], proposes a model based approach of vessel segmentation that is based on the centerline and cross-section models. In this category, the vessel surface is demonstrated with deference to a centerline curve, that follows generalized cylinder techniques. The vessel walls are characterized as two dimensional cross-section contours that breadths along the centerline. The extraction technique of vessels is simpler in the cross-section models, based on the centerline estimation. The position, shape and size constraints are incorporated into the B-snakes for accurate vessel segmentation. The boundary surface of the vessel is deformed on the cross sections under restricted motions, and is voxelized to create the complete segmentation of the vessel. Vessels within the problematic region are completely segmented with a better precision.

Zhao et al. [2], proposes a new infinite active contour model for automated vessel segmentation that automatically detects the blood vessel structures for managing different vascular diseases. This strategy utilizes composite information of regions within the image. The local phase-based enhancement map is utilized because of its predominance in maintaining the vessel edges and the intensity information will assure the segmentation of the right feature. This method is useful for the accurate segmentation of objects with crooked boundaries. It also provides better accuracy for images with actuating intensity levels and helps to avoid potential outliers in the images. IPACHI is sensitive in recognizing finer vessels, capable of eliminating the noise, the cornering effect and the resolution of the image.

A method for the automatic segmentation of retinal blood vessels using deep neural network is mentioned by Liskowski et al. [3].The segmentation of vascular network of human eye in fundus images is a non-trivial task due to the varying size of the vessels, lower contrast range, and existence of pathologies in diseases like microaneurysms and hemorrhages. In order to address this issue, a supervised

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segmentation technique is used that utilizes the deep neural network. The backpropagation extended with drop out is used, with which a subset of network that where temporarily switched off during the training phase are drawn. These disabled units are trained separately to accomplish the desired functionality with every disabled sub-network. Using this method the central vessel reflex can be resisted and it is also capable of detecting finer vessels.

Orlando et al. [4], proposes a new methodology for vessel segmentation using the fully connected CRF model in fundus photographs. This method deals with delicate and longer structures. Structured output SVM is used for automatically learning the parameters of this method. The structured output Support Vector Machine, a supervised technique is used in various machine learning applications for the structured prediction. Conditional Random Fields are a probabilistic framework useful for segmenting structured data, in which images are drawn into graphs. This method adopts fully connected CRFs, in which each node is connected to all pixels of the specific image. Finally the CRFs is learned with structured output SVM to accommodate non-linear boundaries. Misclassifications in the bright central reflex in the high resolution images might occur with the use of this methodology.

A new sampling-based alpha matting methodology is proposed by Karacan et al. [5]. Various image and video editing applications requires the precise estimation of the foreground and background layers. The sparse subset selection problem addressed, is diminished by adopting an entirely new approach that produces the small representative samples' set that defines the unknown pixels. These candidate samples corresponds to the known foreground and background region. A dissimilarity measure is used to compare two samples. This method does not miss any true samples, discovers the best foreground and background pair and then finds its alpha matte value. It is capable of exploiting the interrelations between the known and unknown regions in an efficient way, handles spatially disconnected regions also avoids the need for local samples.

Lee et al. [6], presents a divide and conquer strategy that is used for performing the closed form matting. It addresses the problem of computational complexity that emerges while applying the alpha matting to large images. This issue of matting, that is characterized for an input image is solved by breaking it into system of linear equations that are defined for every tiny blocks of specific image. The size of the tiny systems is to be sufficiently small to obtain solutions efficiently utilizing a direct sparse linear equations system resolver. Matting is carried out on fan-shaped subdivisions that parallel's on more than one processing cores in order to assign equal number of blocks of images for achieving load balancing with faster processing speed. This method determines high quality alpha mattes for large images with stable the memory requirement and computational complexity also scales well for parallelization.

Li et al. [7], presents a matting model that uses unified manifold framework known as Patch Alignment Manifold Matting (PAMM) for the purpose of extracting the foreground object from the input image. Color to alpha space transformation is an image matting process. For the extraction of foreground object, an alpha matte value is to be estimated which lies in the range of [0,1]. In general, the PAMM model involves each individual part modeling and the entire process of alignment. The local patch alpha reconstruction error is produced by utilizing the part modeling. For achieving the entire alpha reconstruction error, whole alignment process is used. The prior information that are necessary to study the definite foreground, background and unknown region are offered along with the trimap for the problem to be optimized. Then Nesterov's algorithm is used to iteratively resolve the optimization problem to obtain the alpha mask and the image foreground is extracted.

A deep CNN for image matting is proposed by Cho et al. [8]. The input to this strategy includes the multiple initial alpha mattes and RGB color images that are normalized. The two initial alpha mattes are obtained as the result of using the closed form and the KNN methodologies for foreground extraction. In terms of local and non-local principles they complement each other. For obtaining alpha mattes with higher quality than the supplied inputs, the local and non-local principles are combined that corresponds to the closed form and the KNN matting models respectively. Thus, it is capable in detecting different image structures in the local area. Deep CNN is used for training in which errors are propagated backwards to every layer as weight updates. For handling the JPEG block artifacts, RGB guided artifacts' elimination networks are created.

Liang et al. [9], proposes a new methodology that optimizes the pixel pairs for the extraction of foreground objects' opacity for a specific trimap. For several applications like image and video editing, the process of extraction of foreground object is getting evolved with the rapid growth of advancements and requirements. The opacity of foreground objects are estimated by the proper selection of a pair of pixels (F,B) for every unfamiliar pixel, in this sampling-based methodology. In the neighborhood grouping strategy, the high dimension decision variable is grouped into N groups based on the spatial correlation from which the pareto optimal front for each sub-vector is obtained. Finally, a dominated solution will be obtained as the pareto front of high dimension decision variable. This method precisely evaluates the pixel pairs even in uncertain cases where the satisfaction degree is lower and results in good visual quality alpha mattes.

Huang et al. [10], proposes a discrete multiobjective sampling at pixel level, novel methodology for image matting. In pixel level discrete multiobjective sampling, multiple optimization objectives correspond to various sampling criteria, with an aim to find a solution for the issues that arises in sampling criteria that may results in the missing of true samples problem. The sampling criteria for the color sampling of unknown pixels includes color, spatial closeness and texture criteria. MOP is optimized for each unknown sample to obtain the independent samples, which results in numerous

MOPs to be resolved. To overcomes the problem of missing true samples, candidate samples are obtained from colors of all pixels rather than from the mean colors of super pixels. The Fast Discrete Multiobjective Optimization Algorithm is an exact optimization method. For a given discrete MOP, FDMO ensures to get all of the Pareto optimal solutions. In each iteration, FDMO is intended to find a Pareto optimal solution and to avoid the unnecessary computations, it removes the solution that is dominated by another. PDMS has its strength in minimizing both color difference and spatial distance between known and unknown pixels.

III. SYSTEM DESIGN

From the studies being conducted in the area of vessel segmentation and image matting, it is found that the vessel segmentation which is performed by incorporating a multiple level image matting results in a better extraction of vessel pixels from regions that are unknown. The image matting models is intended to separate the image that is given as input into three different regions: (1) Foreground region i.e., blood vessels, (2) Background region and (3) Unknown regions. Usually the image matting model requires an input trimap. Creating a trimap manually is extremely a laborious and prolonged work. Also, the quality of segmentation results depends upon the quality of input trimap. Trimap of very good quality is engendered by employing Kirsch's template.

The figure 1 illustrates the proposed framework for the Stratified Image Matting Model. The proposed model consists of two main steps: (1) Trimap generation and (2) Matting model. In the trimap generation, an uncomplicated and decisive approach is used to spawn a good quality trimap from a given input image. Trimap generation includes three processes: Blood vessel extraction through Kirsch's template application, Co-fusion and Fuzzy C-Means clustering. Initially the blood vessels are extracted from the input fundus image by applying the kirsch template that uses a mask of 3x3. As a result, eight filtered results will be obtained for the application of filter, Kirsch's convolution kernels. Then, the maximum values of eight filtered results' is fused together to obtain a better result. The Fuzzy C-Means Clustering groups the pixel values into three different clusters based on the values as: foreground pixels, background pixels and the unknown pixels for obtaining an accurate trimap. In the second step, pixels in the unidentified regions are labelled as vessels or background. The unknown pixels are arranged to be in various strata at multiple levels based on the Euclidean distance. Then the correlation between pixels is determined with which labels to the pixels of the unknown region are assigned either as vessel or as background.

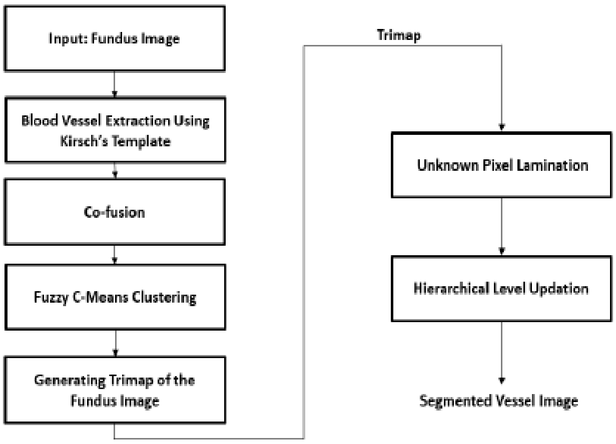

Fig.1. Proposed SIMM Framework

In the second step, pixels in the unidentified regions are labelled as vessels or background. The unknown pixels are arranged to be in various strata at multiple levels based on the Euclidean distance. Then the correlation between pixels is determined with which labels to the pixels of the unknown region are assigned either as vessel or as background.

IV. IMPLEMENTATION

A. Language Used

The programming language used for this system is MATLAB, a high-level technical computing language. It provides an interactive environment for algorithm development, whole data visualization, data analysis and numeric computation. Using the MATLAB product, technical problems in computing can be solved more quickly than with traditional programming languages, such as C, C++ and Fortran. The MATLAB application is developed around the MATLAB scripting language.

B. Dataset

DRIVE [12] is the dataset used for this technique. The DRIVE dataset mainly consists of 40 images of the fundus. These images are taken by a Canon camera at 45 degree field of view (FOV) where each image is of 584x565 pixels and the DRIVE dataset is separated into two sets: a training set as well as a test set each including 20 fundus images and the training set is marked by two observers whereas the test set is marked by two independent observers [11].

C. Modules

1. Image Pre-processing

The fundus images may be suffering from non-uniform brightness, so pre-processing is the essential step to be taken before blood vessel extraction to get better segmentation result. It is important to eliminate the impact of noise artifacts and irregular illumination in addition to improving the contrast between the background and the retinal blood vessels. Color fundus image is first transformed into a gray-scale / green-channel image to promote the segmentation of the blood vessels along with minimizing the processing time by supplying less details for each pixel. Only the luminance information is given by the gray-scale image followed by abolishing the hue and saturation. Optimum local contrast is furnished by green-channel image between the foreground and context. A mask image is also produced, which is set to zero in the resulting image when added to another binary or to a gray-scale image of the same size, while all other pixels that are zero in the mask remain unchanged. The pre-processing phase encompasses: Contrast Limited Adaptive Histogram Equalization (CLAHE) and median filtering.

The contrast in between the foreground blood vessels and the background retinal tissue is relatively low in fundus images. CLAHE is a productive method used to restrict the maximum slope of the contrast enhancement feature in the transformation function. CLAHE divides the whole area into several diminutive regions of the same dimensions and works on each and every section where the contrast of every small region is improved such that the histogram represented by the distribution parameter in correspondence with the histogram of the output image. Another method, called Isodata, which provides an automatic binarization threshold value is also used.

The future treatments' features is upgraded by definite prior-treatment step, the noise reduction which is achieved by the application of a non-linear digital filtering method called median filter. The median filter removes the salt and pepper noise, in order to smoothen the picture. The pixel here is substituted by the median value of the neighboring pixel ie., the center pixel of a MxM neighborhood shall be replaced by the corresponding window median value. The following figure shows the input and the output image obtained after pre-processing.

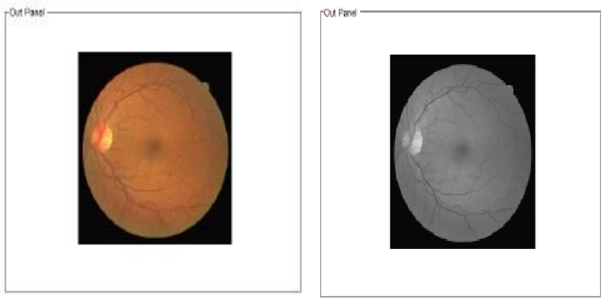

Fig. 2 and Fig. 3 Input Fundus Image and Grayscale Image

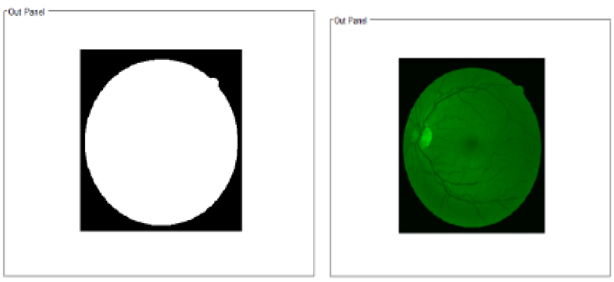

Fig. 4 and Fig. 5 Mask and Green Channel Image

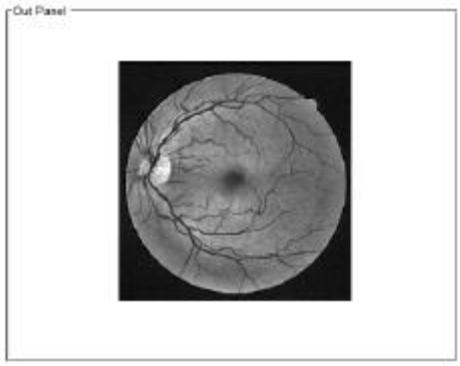

Fig. 6 Enhanced Image

2. Trimap Generation

A trimap is a rough pre-segmented image consisting of three subregions of foreground, background and unknown [24]. A trimap acts as the major inputs for most of the image matting models. The quality of the segmentation result of the given fundus image depends on the quality of the trimap. Therefore the precision of the result is also affected. In this methodology, the trimap is generated using the kirsch's template and the Fuzzy C-Means Clustering. The trimap generation mainly comprises three phases. First, the blood vessels are extracted from input fundus images using the Kirsch's template by using a 3x3 mask that rotates in eight directions at 45 degree increments. The information of a pixel and its neighboring pixels are included within the matrix. The aim of Kirsch's algorithm is to detect the edge and its direction. Second, Co-fusion is carried out. To produce a better performance, the maximum values of eight filtered results obtained by the Kirsch application template to the retinal images input are fused together. Eventually, the Fuzzy C-Means Clustering (FCM), an unsupervised clustering algorithm, is used to group the pixel values into three separate clusters: foreground, background and middle depending on the threshold values in order to produce the Trimap as shown below fig. 7.

Fig. 7 Trimap

3. Image Matting Model

The matting model incrementally defines the pixels in the unknown regions. These unknown pixels are labelled as vessel or background. The application of this image matting model mainly involves two phases: 1) Unknown Pixel Lamination: Stratify pixels into various hierarchies in the unknown regions. 2) Hierarchical Level Updation: Allocating

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labels either vessel or background to the unknown pixels in every hierarchy.

Unknown Pixel Lamination and Level Updation

The unknown pixels are stratified into varying hierarchies at this stage. Initially, the distance between all the unknown pixels to the vessel pixels are estimated. For this, the Euclidean distance between the unknown pixels and the nearest vessel pixels are calculated. Based on the closest distance value the unknown region pixels' are stratified into disparate hierarchical levels. Unknown pixels with lower distance value resides in the top level of hierarchy indicating that they are closer to the blood vessels whereas, unknown pixels with higher distance value resides in the bottom level of hierarchy indicating that they are far from the blood vessels.

Different labels (vessel or background) are allocated to pixels in each hierarchy. Correlation between the unknown pixel and the adjoining labeled pixels incorporated in a 9x9 grid are measured for this purpose. The labeled pixels can be either a vessel pixel or a background pixel. The unknown pixel is allocated with the label of the known pixel having the nearest correlation based on the computed value. This updating process progresses in such a manner that initiates from the first level to the last level of hierarchy by labeling all the unknown pixels in a particular level of hierarchy. The segmentation result is shown in figure 8.

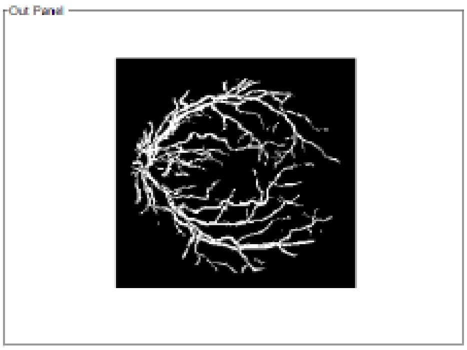

Fig. 8 The segmentation result

V. RESULTS AND DISCUSSION

The pixel is marked as vessel or background for vessel segmentation, producing in four events: two correct (true) classifications and two incorrect (false) classifications as shown in Fig. 9.

	Vessel Present	Vessel Absent
Vessel detected	$TruePositive(TP)$	$FalsePositive(FP)$
Vessel not detected	$FalseNegative(FN)$	$TrueNegative(TN)$

Fig. 9 Four Events of Vessel Classification

Three widely used metrics are used here to determine the performance of the vessel segmentation algorithms [11] as shown in fig. 10.:

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Fig. 10 Sensitivity,Specificity and Accuracy

Where TP, TN, FP and FN indicates the true positive, true negative, false positive and false negative. The TP is the number of correctly identified abnormal vessel segments whereas TN is the number of correctly identified normal vessel segments. The FP is the number of incorrectly identified abnormal vessel segments whereas FN is the number or incorrectly identified normal vessel segments [23].

Sensitivity (Se) and Specificity (Sp) represent the capability of the algorithm to detect pixels of the vessels and background pixels. Accuracy (Acc) is a global measure of classification performance combining both Se and Sp [11]. With the calculated values, the accuracy, sensitivity and the specificity graphs are plotted as shown in fig.11, 12 and 13.

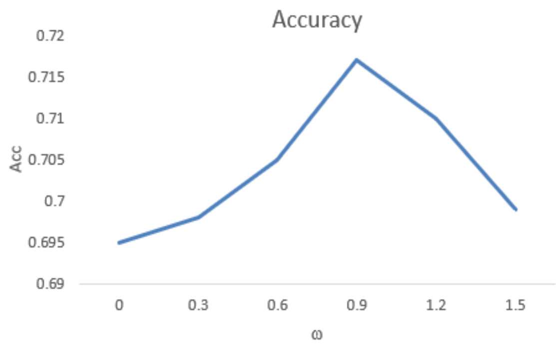

Fig. 11 Accuracy Graph

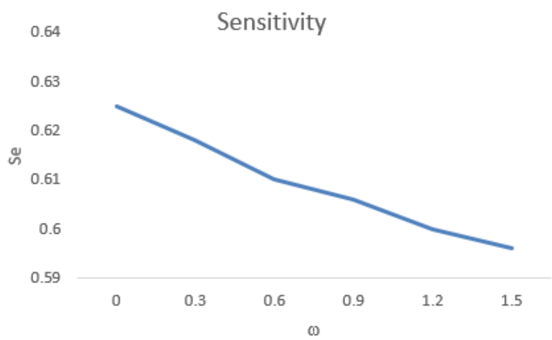

Fig. 12 Sensitivity Graph

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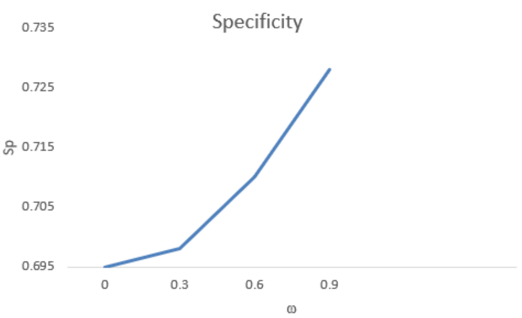

Fig. 13 Specificity Graph

From the experiment result, it is possible to see that, using Kirsch's template, this system can produce a high-quality trimap resulting in high-quality image matting results. The high specificity can avoid introducing the noise. Sensitivity is higher on DRIVE database. Besides, with the good accuracy on DRIVE database, this system can achieve a satisfactory segmentation results.

VI. CONCLUSION

Accurate vessel segmentation is of remarkable significance in various clinical applications, for the recognition and treatment of diverse angio-cardiopathy and ocular diseases like vein occlusions and stroke. It is useful for revealing the important information regarding the systemic disease and assists the identification and treatment processes. As the accuracy of segmentation results is highly dependent upon the quality of trimap, it is necessary to produce a good quality trimap. Most of the existing systems do not produce a good quality trimap, which is one of the major input requirements for the image matting model. The proposed method utilizes multiple level strategies for the extraction of the foreground objects that is incorporated with good quality trimap generation using kirsch template. This approach yields segmentation results with good accuracy and performance.

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