RESEARCH ARTICLE OPEN ACCESS

A Morphological based Image Matting Model for Segmentation of Blood Vessel in Fundus Images

GUMMADAPU SUSHMITA
PG Scholar, Department of ECE, Andhra University, Vizag, AP, India

ABSTRACT
Automatic detection of retinal blood vessels and measurement of vessel diameter are very much important for the diagnosis and the treatment of different ocular diseases including diabetic retinopathy (DR), glaucoma and hypertension. In this project, we propose a method that first generates trimap automatically by utilizing region features of blood vessels and trimap is generated using morphological operation, then applies a hierarchical image matting model to extract the vessel pixels from the unknown regions. The proposed method has low calculation time and outperforms many other state-of-art supervised and unsupervised methods. The performance of algorithms is analyzed on one database out of three publicly available databases (DRIVE, STARE and CHASE_DB) of retinal images using a number of measures, which include accuracy, sensitivity, and specificity. The experimental results are evaluated using matlab tool.

KEYWORDS: Fundus Image, Image Matting, Image segmentation, Morphological operations, blood vessels

Date of Submission: 20-12-2021 Date of Acceptance: 31-12-2021

I. INTRODUCTION

Blood vessel analysis plays a fundamental role in different clinical fields, such as laryngology, oncology [1], ophthalmology [2], and neurosurgery [3], both for diagnosis, treatment planning and execution, and for treatment outcome evaluation and follow up. The importance of vessel analysis is supported by the constant introduction in clinical practice of new medical technologies aimed at enhancing the visualization of vessels, as endoscopy in Nar- row Band Imaging (NBI) [4] and cone beam Computed Tomography (CT) 3D Digital Subtraction Angiography (DSA) [5]. At the same time, standard techniques, such as Magnetic Resonance Angiography (MRA) and Computed Tomography Angiography (CTA), are constantly improved to enhance vascular tree visualization [6]. Manual segmentation of blood vessels is an expensive procedure in terms of time and lacking intra- and inter-operator repeatability and reproducibility. On the other hand, semi-automatic or automatic vessel segmentation methods require at least one ex- pert clinician to segment or to evaluate the segmentation results obtained. In addition, support for the development and evaluation of such algorithms is still poor as publicly available image datasets with associated Gold Standard (GS) segmentation are currently limited to specific anatomical regions, such as retina [7]. However, automatic or semi-automatic blood vessel segmentation could assist clinicians and, therefore, are topics of great interest in medical research, as demonstrated by the high amount of papers annually published in this field. Indeed, an extensive literature al- ready exists on vessel segmentation and in the past years different reviews on vessel segmentation algorithms have been published, such as [8]. However, due to the strong development in the field, updated reviews are required to analyze and summarize the actual state of the art.

The retinal blood vessels exhibits rough to elegant eccentric distribution and seems like web patch. Its fundamental characteristics viz., thickness, width, branching of vessels plays a significant role in diagnosis, monitoring, encountering at early stage and treatment of various coronary diseases and diseases such as eye strain, red eyes, night blindness. The scrutiny of structural features of fovea central is blood vessels can process encountering and medication of disease when it is in its prompt stage. The analysis of central is blood vessels can assist in interpretation of central is image registration, relationship between vessel tortuosity and hypertensive retinopathy [9], arteriolar narrowing, mosaic synthesis, biometric identification [10], foveal a vascular zone identification and computer-facilitated laser surgery [11].

In [12] author utilizes an AdaBoost classifier feature vector which includes data on local intensity structure, geographical features and dimensions at multiple scales. In [13], contrive a 7-

D vector tranquil of gray-scale and moment invariants dependent characteristics, and then trains a semantic structure for the grouping of pixel, extracts the vessels from the image and uses a Gaussian Mixture Model classifier for vessel segmentation including a group of properties, which are extricated on the basis of pixel neighborhood and first and second-order gradient images engage a semantic structure to extricate blood vessel pixels from fundus images of the eye.

II. IMAGE MATTING

As aforementioned, image matting aims to accurately extract the foreground given a trimap of an image. Concretely, the input image I can be considered as a linear aggregation of a foreground image F and a background image B:

$I = \alpha_z F + (1 - \alpha_z)B$

where alpha matte α_z indicates the probability of the foreground, which ranges from 0 to 1.

After obtaining the user specified trimap, to derive the α_z in the unknown regions, in [14] uses sets of Gaussian distribution to obtain the color models of the foreground and background colors, and estimates the optimal alpha value by using a maximum-likelihood criterion. In [15], Levin et al. derives an effective objective function based on the color smooth hypothesis, and employs this function to obtain the optimum of the alpha matte. In [16], performs image matting based on the local and global learning methods. In [17] author solves a large kernel matting Laplacian, and achieves a fast matting algorithm. In [18] author use an effective cost function to select the optimal (F,B) couple for alpha matte evaluation. In [19] author proposes a matting technique, and obtains an efficient result by leveraging on the preconditioned conjugate gradient method. In [20] author expands the sampling range of foreground and background regions, and collects a representative set of samples for image matting. In [21] author presents an image matting method to assess alpha mattes on sub-images of a light field image. In [22] author proposes a sampling method, and employs a new distance metric to obtain the results of image matting. In [23] author utilizes a deep convolutional neural network to achieve image matting. In [24] designs a novel feature and three-layer graph framework for image matting. In [25] designs an inter-pixel information flow to achieve image matting. In [26] author performs parallel image matting on large images with multiple processing cores.

III. PROPOSED METHODOLOGY

In this section, the process of generating the trimap of an input fundus image automatically is introduced, followed by detailing the proposed hierarchical image matting model.

A. Trimap Generation

Region features of blood vessels have been used for blood vessel segmentation and performed well on segmentation accuracy and computational efficiency. In this paper, the trimap of an input fundus image is generated automatically by utilizing region features of blood vessels. The definitions of regions features are given as follows:

- Area indicates the number of pixels in the region.
- Bounding Box specifies the smallest rectangle incorporating the region. Fig.1(b) gives an example of bounding box.
- Extent represents the region proportion in the bounding box.
- VRatio represents the ratio of the length to the width of the bounding box.
- Convex Hull means the smallest convex polygon incorporating the region. Fig.1(c) gives an example of convex hull.
- Solidity represents the region proportion in the convex hull.

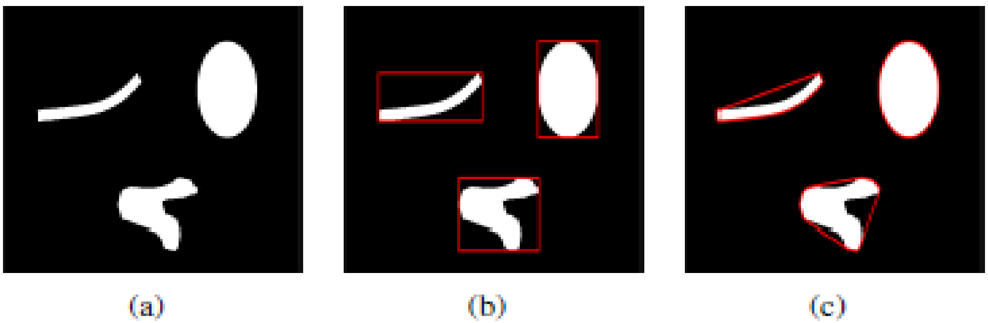


Fig.1 An example to illustrate the bounding box and convex hull. (a) The exemplary image. (b) The image for the illustration of bounding box. The red boxes are the bounding boxes. (c) The image for the illustration of convex hull. The red polygons are the convex hulls.

The proposed model is not sensitive to the above mentioned region features. In other words, these region features can be selected in a relatively large range without sacrificing the performance. In results chapter Sensitivity analysis of threshold values of region features and the weight parameter", empirical study is directed to demonstrate the insensitivity of the proposed model to the threshold values of region features.

Creating the trimap of the input fundus image automatically includes two main steps: 1) Image Segmentation and 2) Vessel Skeleton Extraction. The process of trimap generation is given in Fig.2.

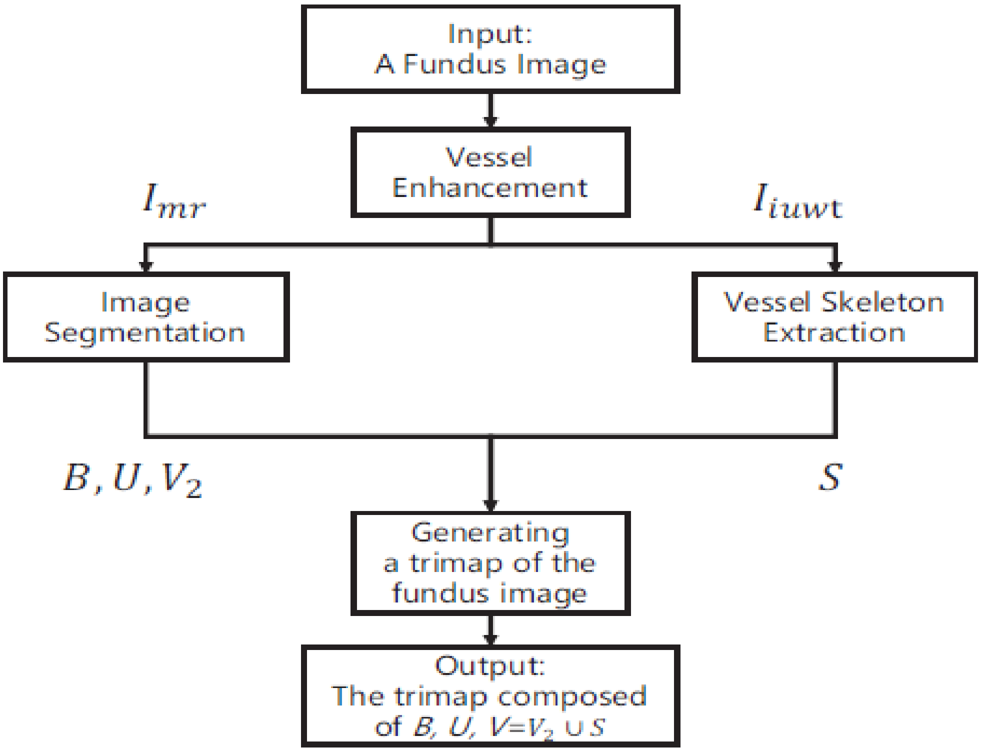


Fig.2 Proposed Trimap Generation

a. Image Segmentation:

Image segmentation aims to separate the input image into three regions: the vessel (foreground), background and unknown regions. Firstly the enhanced vessel image I_{mr} generated by morphological reconstruction [37] is segmented into three regions: the background regions (B), unknown regions (U) and preliminary vessel regions (V_1)

$$I_{mr} = \begin{cases} B \; if \; 0 < I_{mr} < p_1 \\ U \; if \; p_1 \leq I_{mr} < p_2 \\ V_1 \qquad if \; p_2 \leq I_{mr} \end{cases} \tag{1}$$

Where $p_1 = 0.2$ and $p_2 = 0.35$ p1 = 0:2 and p2 = 0:35 restrict the unknown region as thin as possible in order to achieve the better matting result. In order to remove the noise regions in V_1, the regions with Area > $Area > a_1$ in V_1 are extracted firstly (V_1^*). Then regions in V_1^* whose $Extent \leq e_1$ && $V\ Ratio\ \leq r$ && $Solidity\ \geq s$ are abandoned, resulting in the denoised preliminary vessel regions V_2. Fig.4.3 gives an exemplary process of image segmentation.

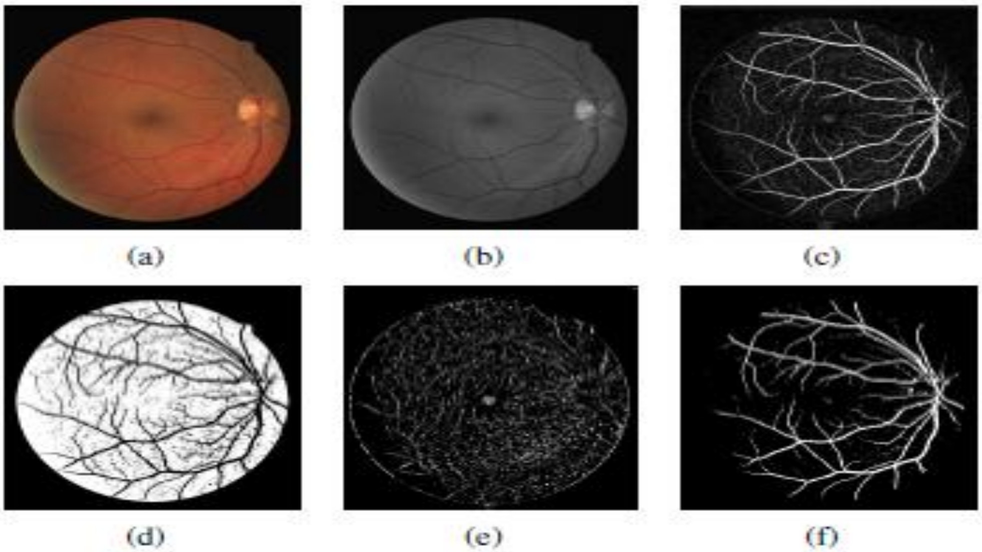


Fig.3. Image segmentation. (a) The fundus image I. (b) The green plane of the fundus image I_g. (c) The enhanced vessel image I_{mr}. (d) The background regions B. (e) The unknown regions U. (f) The denoised preliminary vessel regions V_2

b. Vessel Skeleton Extraction

Vessel Skeleton Extraction aims to further distinguish the unknown regions and provide more information on blood vessels. In results chapter Vessel Segmentation Performance", the effectiveness of vessel skeleton extraction will be presented. Firstly, a segmented image T is generated by thresholding the enhanced vessel image I_{iuwt} generated by the isotropic un-decimated wavelet transform.

$$T = \begin{cases} 1\ I_{iuwt} > t \\ 0\ I_{iuwt} \leq t \end{cases} \tag{2}$$

Then T is divided into three regions according to the Area feature

$$T = \begin{cases} T_1\ if\ 0 < Area < a_1 \\ T_2\ if\ a_1 \leq Area \leq a_2 \\ T_3\quad\quad if\ a_2 < Area \end{cases} \tag{3}$$

In vessel skeleton extraction, the regions in T3 are preserved while the regions in T1 are abandoned. After performing image segmentation and vessel skeleton extraction, the trimap of the input fundus image is generated, which is composed of the background regions (B), unknown regions (U) and vessel (or foreground) regions.

B. Trimap generation using Morphological operations

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image. The primary morphology operators are erosion, dilation, opening, and closing. With erosion, pixels along the edges of an object are removed. With dilation, pixels along the edges of an object are added. Opening is erosion followed by dilation

Dilation adds pixels while erosion removes the pixels at boundaries of the objects. This removal or adding of pixels depends on the structuring element used for processing the image.

Dilation of a by b is defined as,

$$A \oplus B = \{x | (B)_x \cap A \neq \emptyset\} \tag{4}$$

Erosion of a by b is given as,

$$A \ominus B = \{x | (B)_x \cap A^c \neq \emptyset\} \tag{5}$$

By performing these operation and sharp edges can be identified and the results can be improved. After generating trimap, image matting model is proposed to extract the vessel pixels from the unknown regions.

C. Hierarchical Image Matting Model

Hierarchical image matting model is proposed to label the pixels in the unknown regions as vessels or background in an incremental way. Specifically, after stratifying the pixels in unknown regions (called unknown pixels) into m hierarchies by a hierarchical strategy, let u_i^j indicates the $i-th$ unknown pixel in the $j-th$ hierarchy, the segmented vessel image $I_v(u_i^j)$ is modeled as follows:

$$I_v(u_i^j) = \begin{cases} 1 \; if \; \beta(u_i^j, V) > \beta(u_i^j, B) \\ 0 \qquad\qquad\qquad\qquad else \end{cases} \tag{6}$$

The implementation of the hierarchical image matting model consists of two main steps:

Step 1: Stratifying the unknown pixels: Stratify pixels in the unknown regions into different hierarchies.

In this stage, the unknown pixels are stratified into different hierarchies. For the i^{th} unknown pixel in U, its Euclidean distances with all vessel pixels in V are calculated first. Then the closest distance d_i is chosen and assigned to the i^{th} unknown pixel. After that, the unknown pixels are stratified into different hierarchies according to the closest distances. The first hierarchy has the lowest value of the closest distance while the last hierarchy has the highest value of the closest distance. The unknown pixels reside in low hierarchy suggests that they are close to blood vessels; The unknown pixels stay in high hierarchy indicates that they are far away from blood vessels.

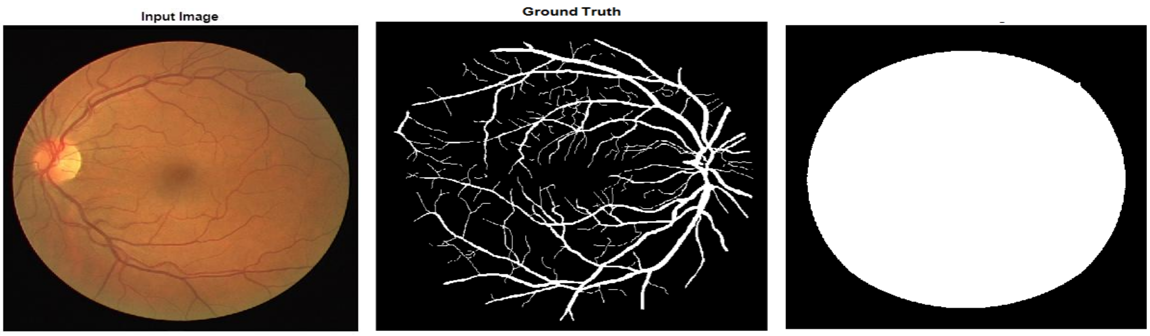
Step 2: Hierarchical update: Assign new labels (V or B) to pixels in each hierarchy.

After performing initialization with the hierarchical strategy, in each hierarchy, the correlations between each unknown pixel and its neighboring labeled pixels (vessel pixels and background pixels) included in a 9 ×9 grid are computed. Then the labelled pixel with the closest correlation is chosen, and its label is assigned to the unknown pixel. After all unknown pixels in one hierarchy are updated, they are used for updating the next hierarchy. The unknown pixels are updated from the first hierarchy to the last hierarchy.

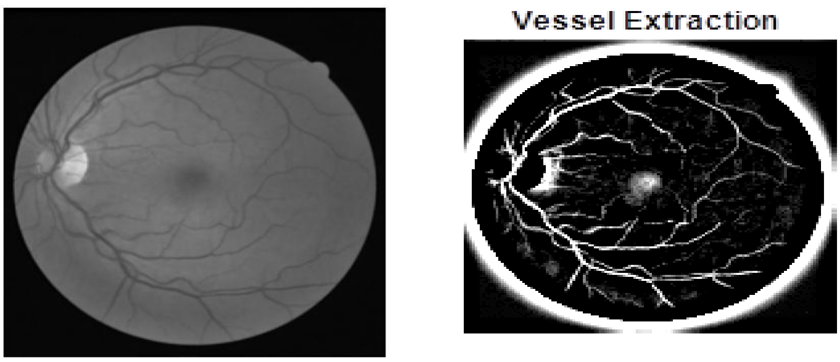
IV. RESULTS AND DISCUSSION

A new study finds that certain morphological changes of the retinal blood vessels in retinal images are important indicators for diseases. Segmentation of blood vessels, which can be divided into the following major categories: supervised and unsupervised methods. Supervised methods require a feature vector for each pixel and manually labeled images in order to discriminate between vessel and non-vessel pixels. Unsupervised methods in the literature comprise the matched filter responses, grouping of edge pixels, adaptive thresholding, vessel tracking and morphology based techniques. Image matting is one of the advanced technique is blood vessel segmentation.

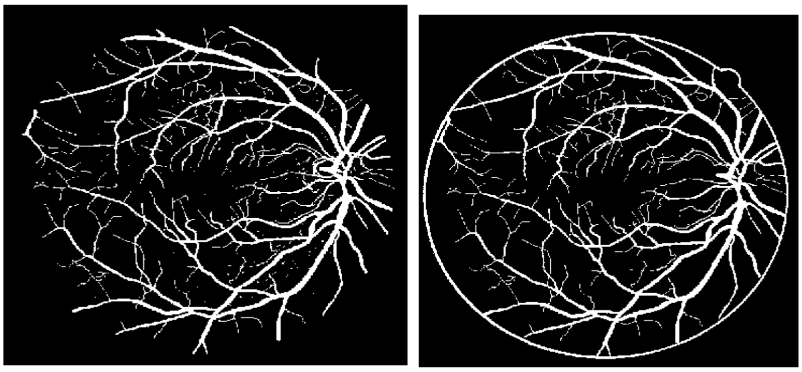
In normal retina, the main function of the blood vessels is to send nutrients such as oxygen and blood to the eye.



(a) (b) (c)



(d) (e)



(f) (g)

Fig.4 Obtained Results (a) Input Fundus Image (b) Ground Truth Image (c) Masking of image (d) Green plane of fundus image (e) Enhanced Vessel Extraction (f) Blood vessel segmentation using Region features Trimap generation (g) Blood vessel segmentation using Morphological Trimap generation

In the case of diabetic retinopathy, the simulation to the growth of new fragile blood vessels is due to the blockage and thickening of the main blood vessels. When the main blood vessels are blocked, new vessels are triggered to grow in an attempt to send oxygen and nourishment to the eye. However, if the blood spatters happen to be on the fovea or macula, sudden loss of vision in that eye occurs as the spatters block all light entering into the eye. The funds images are captured from fundus camera. These images are considered for segmentation of blood vessels from retina. The entire process is evaluated using matlab software results. The obtained results using region features base trimap image matting and morphological operation based trimap iage matting is compared and shown in fig.4

Parametric Evaluation

For vessel segmentation, each pixel is classified as vessels or background, thereby resulting in four events: two correct (true) classifications and two incorrect (false) classifications. To evaluate the performance of the vessel segmentation algorithms, five commonly used metrics are applied.

Sensitivity: $S_e = \frac{TP}{TP+FN}$ (7)

Specificity: $S_p = \frac{TN}{TN+FP}$ (8)

Accuracy: $A_c = \frac{TP+TN}{TP+TN+FP+FN}$ (9)

Precision: $P_e = \frac{TP}{TP+FP}$ (10)

TP- True Positive, FP- False Positive
TN- True Negative, FN-False Negative

Sensitivity (Se) reflects the detecting vessel pixels, Specificity (Sp) is a measure of the identifying background pixels and Accuracy (Acc) is the combination of Se and Sp. So this model is compared with image segmentation model by selecting an operating point from the above mentioned performance metrics.

The performance of the vessel segmentation method is also measured by the area under a receiver operating characteristic (ROC) curve (AUC). The conventional AUC is calculated from a number of operating points, and normally used to evaluate the balanced data classification problem.

$AUC = \frac{S_e+S_p}{2}$ (11)

The Dice scores (D) is applied to evaluate the similarity between the manual segmentations and results of vessel segmentation algorithms:

$D = 2(M \cap S)/(M + S)$ (12)

where M represents the manual segmentation and S represents the segmentation result**.**

Table1. Comparison of results

Parameter/technique	Trimap-Image Matting [27]	Morphological Image Matting
Accuracy	0.944	**0.977**
Precision	0.975	**0.994**
Sensitivity	0.946	**1.00**
Specificity	0.815	**0.90**
D-Score	0.804	**0.998**
AUC	0.865	**0.884**
Times (sec)	4.97	**0.524**

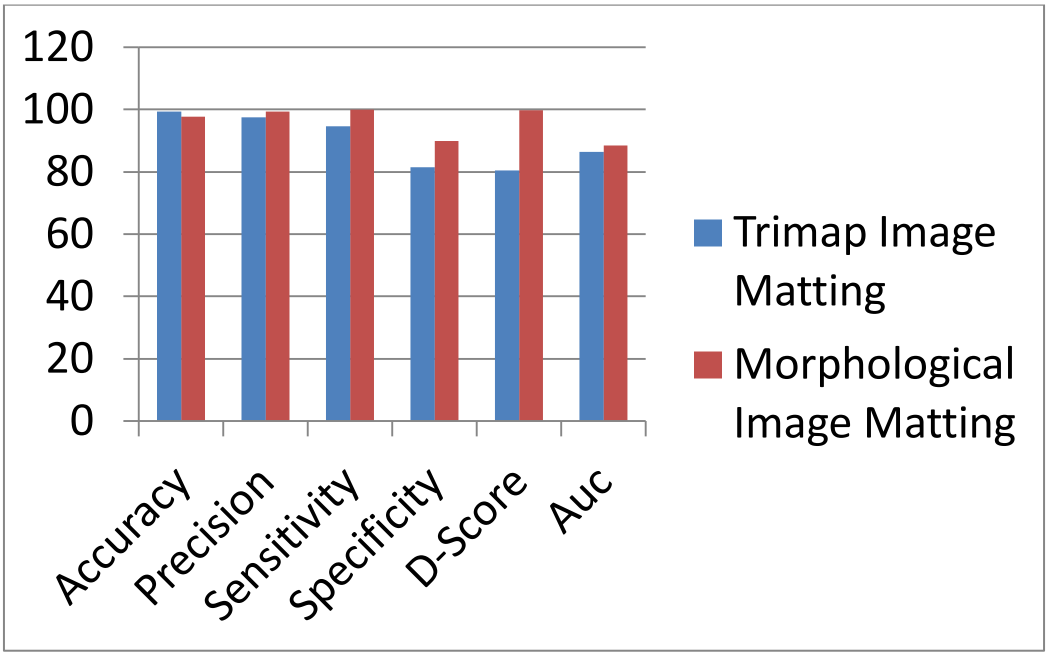


Fig.5 Graphical representation of evaluated results

V. CONCLUSION

Image matting means precisely segmenting the foreground from an image and is crucial in many important applications. The major reason may be that generating a user specified trimap for vessel segmentation is an extremely laborious and time-consuming task. The trimap is generated using morphological operation. In addition, a proper image matting model needs to be designed carefully to improve the vessel segmentation performance. In order to address these issues, region features of blood vessels are first employed to generate the trimap automatically. Then a hierarchical image matting model is proposed to extract the vessel pixels from the unknown regions. The results obtained using region feature based trimap generation and morphological operation based trimap generation is compared. The accuracy obtained using region feature based trimap image matting is 94.4%, whereas while performing morphological operation based rimap the accuracy is 97.7%. The time taken using proposed method is 0.524 sec.

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