

Performance Assessment of K-Means and KNN Algorithm for the Detection of Borders and Extraction of Plaque Area from IVUS Images

C. Mahadevi, S. Sivakumar



Abstract: The coronary artery vascular disease of atherosclerosis, which made the blood vessel artery wall harden and narrow. The vascular wall disease quantitatively analyzed and diagnosed by an intravascular ultrasound (IVUS) image. The quantitative investigations of coronary atherosclerosis by means of IVUS and manual recognition of wall and plaque borders are restricted by the need for observers with considerable understanding and the tedious environment of manual border detection. To improve and provide more detailed vessel and plaque information for better diagnosis and assessment go for an automated segmentation. An automated construction for the purpose of perceiving lumen and media-adventitia borders in IVUS images was effectively formulated. An effectual unsupervised K-Means clustering scheme refine the borders with morphological operations, later an IVUS data samples area classified using supervised KNN(K-Nearest Neighbor) classifier to extract the plaque feature. The performance of contour metric measurements in terms of Jaccard Index (JI), percentage area difference (PAD), area error (AE), dice index (DI), false positive ratio (RFP), in addition to false negative ratio (RFN) are computed for evaluation and variation.

Keywords: Morphology Operation, Region Props, K-Means Clustering, KNN Classifier.

I. INTRODUCTION

Atherosclerosis is a kind of sickness of the intima level of the artery that characterizes the indispensable trait of arterial pathologies. It is to be noted that Atherosclerosis includes blood cells, multifaceted carbohydrates, lipids fibrous tissues, in addition to calcified dumps generating a commemorative inscription that hinder increasingly the lumen of the blood vessel [1]. Innumerable imaging modalities are present for the purpose of assisting diagnose coronary blood vessel infections.

Out of those, X-ray coronary angiography and intravascular ultrasound (IVUS) correspond to the most frequently utilized problem-solving systems. Selective coronary angiography offers comprehensive images of the vessel lumen, it presents no details regarding the coronary partition. It is to be noted that IVUS is a comparatively new scheme that presents image details that is balancing to that offered through angiography [2]. An IVUS imaging makes possible high-resolution tomographic estimations of the measurements of vessels, in addition to straight assessments of the vessel partitions and fundamental atherosclerotic commemorative inscription morphology [3]. IVUS imaging has established extremely helpful in directing coronary interference methods in accordance with the assessments of lesion harshness, span and morphology prior to stent implantation, at the same time as also optimizing consequences after stent implantation [4]. For the most part commercially accessible border recognition schemes established on accessible IVUS machines are not ideal, in addition, they are in fact moderately unpredictable at present; as a result, medical certified are often enforced to be familiar with the lumen margin and the media-adventitia (MA) boundary by means of portrayal of them through hand in the clinical [5,6]. It must be observed that these two boundaries are extremely significant in identifying the rigorousness of vascular gashes and setting up interventional handling approaches since the positions of these two boundaries can assist in quantifying the measurements of vessels and offer clinically constructive details, for instance, lesion categories based on their division, positions, commemorative inscription and, perhaps, susceptibility to commemorative inscription development [7].

Computer-aided schemes to discovery of the lumen and MA boundaries utilize three categories of information:

- an aforementioned shape restriction on the lumen boundary, in addition to the MA boundary
- the confined form of the lumen-intimae crossing point and the media layer
- dissimilarities in the sharing of image concentration in a range of vascular sections.

The aforementioned figure restriction on the lumen and MA boundaries is described with vessel outline, in addition to commemorative inscription morphology.

The category of information utilized for the purpose of identifying borders is the confined form of audio impedance in the vessel, that completely based on compactness of dissimilar tissues.

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While considering the lumen-intima crossing point, the grayscale rate amplifies considerably from lumen to intima, since the tissue concentration of the lumen is completely lesser than intima.

Additionally, a dark-bright prototype becomes visible in the media level since the tissue concentration of the media is lesser than the intima, in addition to adventitia [8]. The detecting boundaries depend on dissimilarities in the intensity sharing among a variety of vascular sections in IVUS images. Region-dependent schemes and clustering schemes are mutually common for discriminating the lumen, media.

A. Related Work

It is observed that there are numerous image segmentation schemes have been formulated. In view of the fact that, here we are concentrating only on the clustering-based segmentation schemes.

K-means scheme is kind of an iterative approach utilized for the purpose of categorizing the data spots into K factions in accordance with the resemblance among them [9]. Subsequently, several investigators implied it on image segmentation for the purpose of enhancing the performances. A novel scheme for the purpose of clustering segmentation that effectively utilizes K-means clustering integrating region and boundary information [10]. An integrated K-means together with thresholding schemes to execute the segmentation of color image [11]. The Hill-climbing in the company of K-means scheme for the purpose of color image segmentation process formulated [12].

It is to be observed that the image segmentation indicates to a process of separating the given image into more than a few regions in accordance with the visual features shared by the pixels. These schemes project the given image into their respective features spaces initially, subsequently the segmentation is acquired through applying clustering schemes on feature spaces together with giving the cluster numbers. On the whole, K-means clustering schemes in [13, 14] and fuzzy c-means clustering schemes in [15, 16] are the two common clustering schemes. These schemes are extremely capable of generating a partition of images under certain circumstances together with presenting the cluster number earlier. The estimation of centroids from data using K-Means is computationally expensive and not guaranteed to produce satisfactory result. The result of K-Means often suffers from noise, over segmentation and local minima. To overcome the problem the image filtered and sharpened before clustering

Here, an automated frame work is formulated for the purpose of extracting the i.e lumen and plaque segment from an IVUS images through an adaptive region props scheme and an unsupervised clustering scheme and by using boundary trace and morphological operations to trace the borders of IVUS image. This work was effectively assessed with 30 IVUS images got from four patients suffering with coronary artery infection. The performance of manual and automation border trace is compared.

II. MATERIALS AND METHODOLOGY

An IVUS image of region and boundary has some features such as the intensity within the lumen section is

uncomplicated and comparatively harmonized, the concentration gradient of the luminal boundary is moreover elevated, media-adventitia border line has elevated concentration gradient and adventitia tissue has elevated echogenicity and becomes extremely vivid. In accordance with these characteristics of the IVUS images, the segmentation is done effectively. An automatic framework is formulated for the purpose of detecting the Intimae and Media-Adventitia (MA) boundary and get hold of plaque feature for an IVUS image is given in Fig.1.

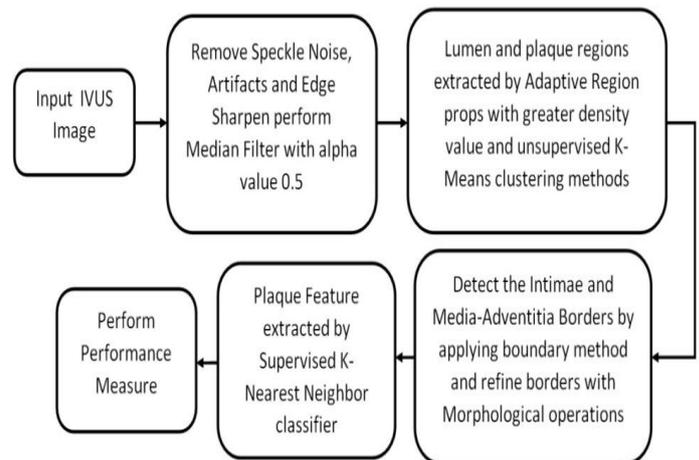


Fig.1. The Framework of an automatically detect an Intimae and Media-Adventitia borders and plaque feature.

A. IVUS Image Data Acquisition

The Volcano S5™ Imaging System of the Eagle Eye Platinum RX Digital IVUS Catheter is used to acquainted the IVUS image. It has the tip size of 3.2 to 3.5F(i.e. 1.2 to 1.5 mm) with 20 MHz transducer is used which will go over 5 to 6F guiding catheter. The Volcano S5™ system produces images in “DICOM” video format with 500×500 pixel size. Each patient this system provide 250 - 500 video frames. These video frames are converted into JPG format by using MicroDicom viewer software tool and stored as Joint Photographic Experts Group (JPEG) file format for processing. An images are kept at 500×500 pixel spatial resolutions. The data set is collected from four different patients and fully cover various ages, genders and additional body factors that possibly will have an effect on vessel heart thickness and outline. For this work 50 images are considered and four different IVUS image datasets are used for border detection and plaque feature extraction process. The image dataset used in this work are exposed in Fig.2., (a) image affected by calcified and shadow artifcats that affect the plaque region, Fig.2. (b) image affected by calcified ring down artifacts that affect the plaque region, Fig.2. (c) image affected by calcified and shadow atrifacts affected plaque region area, Fig.2. (d) image heavily affected by ring down and shadow artifacts that hide the plaque region.

B. Atherosclerotic Plaque

When an atherosclerotic plaque is distorted, this decrease the blood flow in lumen cross sectional area, which in turn causing angina followed the myocardial infarction. In general, small, lipid-rich lesions are more prone to disruption. While fibrotic and calcific lesions tend to be more stable that lead to cause stenosis (i.e. narrowing of the lumen cause the lack of oxygen in the artery). Atherosclerotic process denser the intima and supplementary procedure like fibrosis, calcification, necrosis, and haemorrhage in [17]. The area of cardiology has initiated the phrase ‘susceptible plaque’ which indicates those commemorative inscriptions with a thrombotic impediments, the subsequent speedy development to stenosis and elevated rupture in [18]. The tunica media, which is the bulkiest layer and include largely even muscle cells and elastic tissue in large arteries. Its homogeneous nature implies that, internally echo free and appear as a dark band under ultrasound near the luminal border. Atherosclerotic plaque growth in the artery is shown in Fig.3. that affect vessel heart thickness and shape. So identification of plaques is important to avoid risks prior an angioplasty procedure.

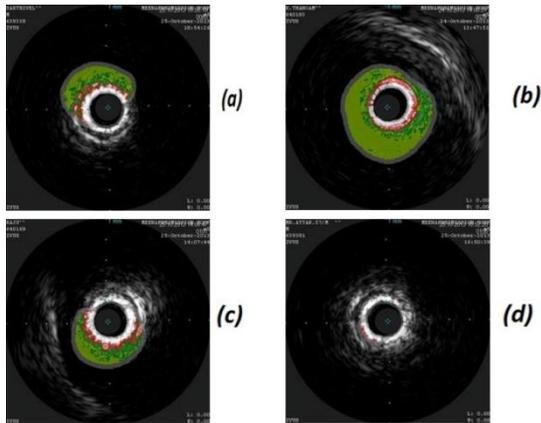


Fig.2. Original IVUS images: (a) Sample IVUS1, (b) Sample IVUS2, (c) Sample IVUS3, (d) Sample IVUS4.

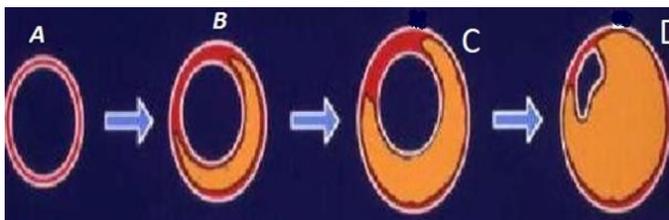


Fig.3. Atherosclerotic plaque growth in the artery: A – Normal Artery , B,C& D- Atherosclerotic Plaque growth

C. Median Filter and Sharpen with fspecial

In digital image processing, the Median filter is a nonlinear digital de-noising method and it is widely utilized as a pre-processing step to take away the noise which preserves edges from the image [19]. The median filter moves along pixel through pixel and substitutes every value along with the neighbouring pixels’ median range. The “window” pattern of neighbouring is used and that transparencies, above the complete image pixel by pixel. The median is considered via initially ordering all values of pixel from the window into the order of numerical, and subsequently replace the pixel along

with the median or middle pixel value. Here the median filter use 3 x 3 window size.

The image sharpened by fspecial function. In matlab the fspecial function generates a two dimensional filter

$$h = \text{fspecial}(\text{'unsharp'}, \alpha)$$

fspecial proceeds h as a correlation kernel, that is fitting generate to utilize with imfilter.

fspecial proceeds a 3-by-3 unsharp contrast augmentation filter, and generates the unsharp filter from the negative end of the laplacian filter with the constraint alpha. This alpha manages the outline of the laplacian with the limit 0.0 to 1.0. The default alpha value is 0.2 but in this work 0.5 alpha value is used to sharpen the edge features of IVUS image.

D. Border Detection and Plaque Extraction

(a) Need of Binarization

To obtain the desired region from an image need to eliminate or remove the background details through binarization process. The binarization transforms grey scale as a binary image as black or white in accordance with certain pre-determined value. The thresholding scheme substitute every pixel in an image with a black pixel in case if the image intensity value of $I_{m,n}$ is less than some fixed constant T1 (that is $I_{m,n} < T1$), for white pixel the image intensity is over and above that constant. The binary image have the value of zero(black) and one(white). The binarization performed on Fig.2.(c) Sample IVUS3, with the threshold value 0.2 applied and the output is shown in Fig.4.(a) image. Through binarization process got the desired region of plaque area and background details more over is eliminated, revealed in Fig.4.(a), the border detected shown in Fig.4.(c). image but without binarization can not get our region of interest area is shown in Fig.4.(b) image and also can not detected the border shown in Fig.4.d. Thus Thresholding take part an imperative position in image segmentation, in the binarized image grey level 1 indicating the plaque region and grey level 0 indicating the background.

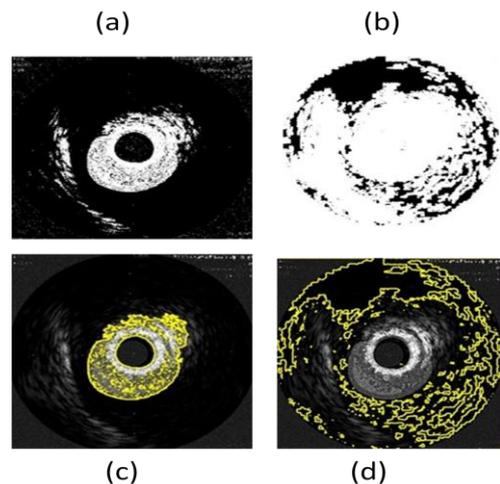


Fig.4. (a) The binarized image with threshold value 0.2, (c) border traced for image (a) , (b) without Binarization image, (d) border traced for image (b).

b) Region props and K-Means clustering

Region-dependent schemes, in addition to clustering schemes are both common for the purpose of differentiating the lumen, media and adventitia in accordance with the pixel intensity distributions.

The IVUS image is intensity based so convert an IVUS image into binary form with the needed threshold value then the regions are labelled after that applied the region props method with the density value greater than 0.5 to detect the desired region and refine the plaque region by Morphological operation .

Clustering is one of the unsupervised learning scheme. K-means clustering is employed for the reason that it is uncomplicated and has comparatively low computational complexity. This scheme is extremely appropriate for the case of biomedical image segmentation, since the number of clusters of K is typically known for images of particular areas of human anatomy. An image data set separated into a number of disjoint clusters. The each pixel in a region is similar concerning certain characteristic, for instance, concentration, or texture and colour. So it is consider as a powerful technique for image segmentation. In accordance with preliminary centroids of cluster, it is effectively employed to take apart related data into groups. With the definition of the algorithm, initially it prefers k data value as preliminary cluster centres, subsequently discovers the distance among each cluster centre and every data value and allocate it to the nearest cluster, update the averages of each clusters, replicate this procedure until the criterion is not equivalent.

To trace the lumen and media-adventitia border, the complete image has four regions - lumen, media, adventitia and background. So take k value as 4 here.

To perform k-means scheme the pre-processed image is given as input and perform the below algorithm

Step 1: Arbitrarily choose from the data set of k points as preliminary cluster centers.

Step 2: In that order compute the distance of every sample to the cluster centers, the sample is placed under the sample from the adjacent class.

Step 3: In accordance with the clustering outcomes, re-compute the distance of cluster center. Subsequently, calculate the mean distance value of the entire data components as the new clustering center.

Step 4: In relation to the new center, re-cluster the entire components of the data set.

Step 5: Replicate Step 4 until the clustering does not transform.

Step 6: Desired region displayed

$T =$

$$\frac{1}{2} \sum_{k=1}^k \sum_{c(i)=k} (\sum_{c(j)=k} d1(X_i, X_j) + \sum_{c(j) \neq k} d2(X_i, X_j)) \quad \text{---(1)}$$

In the equation (1) the d1 and d2 indicates the distance, i and j are variables, first distance $d1(X_i, X_j)$ calculate the distance within cluster W(C) the second distance $d2(X_i, X_j)$ calculate the distance between clusters B(C).

After segment the desired region the intima and media-adventitia border has to be traced by using the

bwboundary trace function that maps out the outside boundaries of objects. It is to be observed that the boundaries of holes within these items. Moreover, it also tumbles down into the furthest items of parents and maps out their offspring i.e. the things entirely covered by the parents.

Morphological procedure is a kind of non-linear compilation process allied to the outline or image morphology characteristics, in which I indicates the image and S represents the outline of a structured component. The morphological procedure employed dilation and erosion as given below

$$(I \ominus S)(x, y) = \min_{(i,j \in S)} \{I(x + i, y + j) + S(i, j)\} \quad \text{---(2)}$$

$$(I \oplus S)(x, y) = \max_{(i,j \in S)} \{I(x + i, y + j) + S(i, j)\} \quad \text{---(3)}$$

Erosion equation (2) also likely to level segments of contour, however, as combat to gap, it commonly blends slight breaks and long thin gulfs, eradicates minute openings, and seals breaches in the contour. Dilation of equation (3) levels the contour, shatters fine isthmuses, and eradicates slim protrusions. In order to diminish the abnormalities of the boundaries in addition to certain small areas in the region of the boundaries, morphological filtering is completed prior to boundary detection. The process of filtering is carried out all the way through the relevance of opening and closing morphological procedures with a disk-structuring component of size 5. The morphological filter trimmed down the abnormalities in the segmented contour and eradicated the minute segmented regions.

c) KNN classifier

KNN is extremely non-parametric scheme which is effectively employed for the purpose of classification. When the fresh training prototype is included to the current training set, there is no necessity for retraining. The productivity can be construed as a posterior prospect belonging to a specific group. At the same time as the k amplifies the confidence. The testing feature vector is perfectly categorized by means of discovering the k adjacent training neighbor vector. Also, the space among the training and testing vector is computed through various distance metric extent scheme. Euclidean distance is employed for the purpose of learning K Nearest Neighbour classifier. The Euclidean distance is provided clearly in equation (4)

$$d(p, q) = \sqrt{\sum_{i=1}^n (p_i - q_i)^2} \quad \text{---(4)}$$

The KNN scheme discovers the adjacent neighbors of the experiment sample and allocates its class label on the majority labels of the nearest neighbors. This scheme presumes that locality in the feature space simply sturdy associations among class labels. It performs in accordance with the minimum distance from the query instance to the training samples for determining the K nearest neighbors Euclidean clustering is used to find objects and segmentation was done after ground removal. The performance varied significantly depending on whether several objects of interest were included in that region or not, with better accuracy when only a single object of interest was included.



The KNN classifier consist of two phases, in Training Phase Data points include labels together with their class. In case of testing phase, the data points are unlabelled and the scheme produces the catalogue of k nearest data point i.e. training data point to unlabelled point and accurately categorizes their class.

The training phase includes only of accumulating the feature vectors and class labels of the training samples. In case of the actual classification segment, the identical features as before are calculated for the experiment sample whose class is not identified. Distances from the new-fangled vector to the entire accumulated vectors are calculated and K closest samples are chosen. The new point is expected to fit in to the most frequent classes contained by the set. The pseudo code is given below

Input: Training samples, test set of samples and the attribute-list.
Output: extract feature of KNN classifier.

- Determine parameter K, the number of nearest neighbours
- For each case in the target data set to be predicted, locate the K nearest neighbours of the training data set by the below formula

$$S = S + ((map(i, j, k) - tn(k), 2, 0.5))$$
- An Euclidean Distance measure calculate each member of the training set

$$D = \sqrt{dx^2 + dy^2}$$
- Sort the distance and determine nearest neighbours based on the Kth minimum Distance

$$MD = 2 \times \exp(-D(2 \times 8/6))$$
- Gather the categories of the nearest neighbours by using the formula

$$mw = mw + MD \times (mw(wx, wy, a) - mw(x, y, a))$$
- Use simple majority of the category of nearest neighbours as the prediction value of the new query instance
- Repeat this procedure for the remaining cases in the target set.
- Extract the plaque area and display

III.RESULTS AND DISCUSSION

An IVUS image has three regions that is lumen, media and adventitia plus neighboring, which are divided through lumen and media-adventitia closed boundaries. At this point, it is to be observed that an IVUS image of region and border has certain characteristics, for instance, the intensity within the lumen region is uncomplicated and comparatively homogeneous, the concentration gradient of the luminal border line is also elevated, media-adventitia border line has elevated concentration gradient and adventitia tissue has elevated echogenicity and emerges extremely intense.

Usually an ultrasound images are affected by speckle noise so need concentration gradient and adventitia tissue has elevated echogenicity and emerges extremely intense. to perform pre-process. An IVUS image not only affected by speckle noise also affected by artifacts that provide undesired information and degrade the image quality. To remove the undesired information of speckle noise and artifacts the median filter is performed and its result shown in Fig.5.(a), need to preserve the edges is an important task to trace the lumen and plaque borders so performed fspecial filter

technique with alpha value 0.5 output shown in image Fig.5.(b), this done on Fig.2. (b) image.

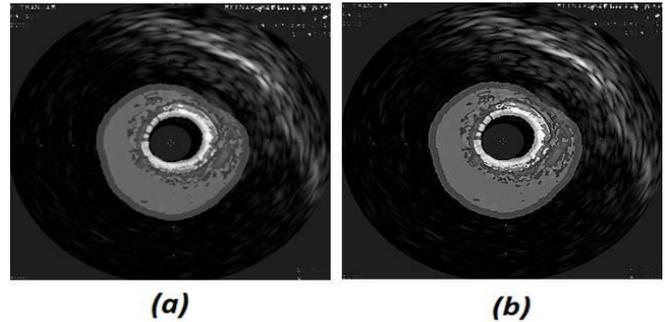


Fig.5. De-noised outputs of original IVUS image Sample IVUS2 in Fig.2. (b): Median de-noised image in (a), Sharpened image in (b).

To detect and trace the borders in an IVUS image is depend on the concentration of dissimilar tissues. By the side of the lumen of intima crossing point, the grayscale value augments considerably from the lumen to the intima since the tissue concentration of the lumen is inferior to the intima. Additionally, a dark–bright prototype emerges in the media level for the reason that the tissue concentration of the media is inferior to the intima and adventitia. The boundary detection is in accordance with the dissimilarities in the intensity distributions among a range of vascular sections. As a result, in accordance with the intensity the plaque region is going to be extracted.

The pre-processed image convert into binary image to get the lumen and plaque region of interest to apply the threshold value 0.2×255 on the image of Fig.2.(b) and the result is shown in Fig.6.(a).Then the regions are labeled then apply the region props method and extract region which density value greater than 0.5. The detected the plaque region refined by morphological operation result shown in Fig.6.(b). Trace the lumen and media border by using morphological operation is shown in Fig.6.(c). inner boundary indicates the lumen border and outer boundary indicates plaque border.

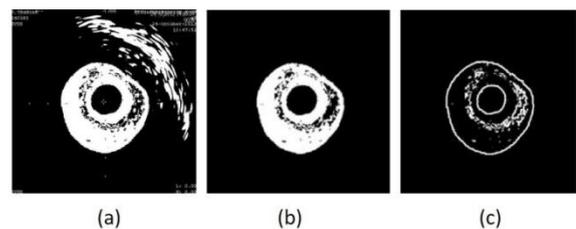


Fig.6. Detect lumen and plaque region and borders from sample IVUS2 in Fig.2.(b): (a) Binarized image, (b) refined the image (a) by morphological operation, (c) the lumen and plaque boundary traced (Inner boundry indicates the lumen border and outer boundry indicates plaque border).

The whole IVUS image presumed to encompass four regions, for instance, lumen, media, adventitia and surroundings or background. The regions are extracted with the assistance of K-means clustering scheme and at each colour layer, the mean and standard deviation values are calculated. In accordance with the mean values of every layer, calculate the mean weight. Based on mean weight, the method measures the distance to identify the closure pixels to produce cluster.

Performance Assessment of K-Means and KNN Algorithm for the Detection of Borders and Extraction of Plaque Area from IVUS Images

Based on the mean weight and mean values the method performs segmentation. This clustering scheme effectively clusters data through iteratively calculating a mean intensity for every class and segmenting the image through the process of classifying each pixel in the class with the neighbouring mean. The amount of classes to be four, indicating lumen, intima, adventitia and background, so here k is taken as 4, this algorithm applied on Fig.2.(b) image and four clustered images are exhibited in Fig.7.(a)., the desired resultant image displayed in cluster 2 which is exposed in fig.7.(b). separately.

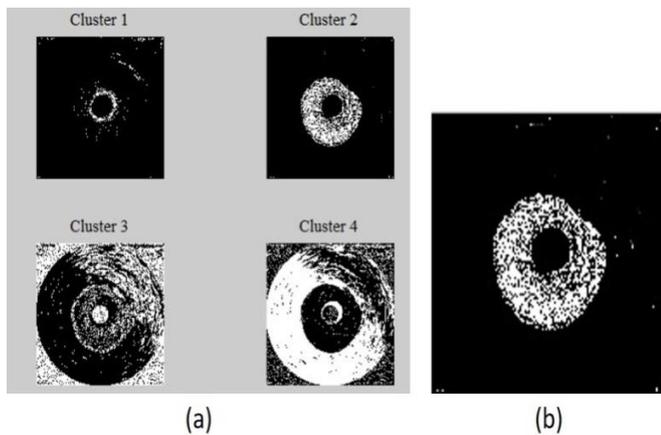


Fig.7. (a) Plaque region extracted by using K-means clustering with 4 clusters for sample IVUS2 in Fig.2.(b), (b) the clustered plaque region.

In K Nearest Neighbour method, the regions are labelled and an image split into classes here the number of class used is 4. By using RGB channel separation method the plaque region extracted from the original image of Fig.2.(b),(c) and its output image displayed in Fig.8.(a) column. The RGB image convert into Lab image, then calculate the mean value for each desired area, categorize every pixel by means of nearest neighbour rule, every colour marker now has average value for that specific required region and can effectively categorize each pixel in the lab image through computing the Euclidean distance finally convert the extracted plaque portion into gray image and reshaped image shown in Fig.8.(b) column by using morphological operation the border traced and displayed in Fig.8.(c).column.

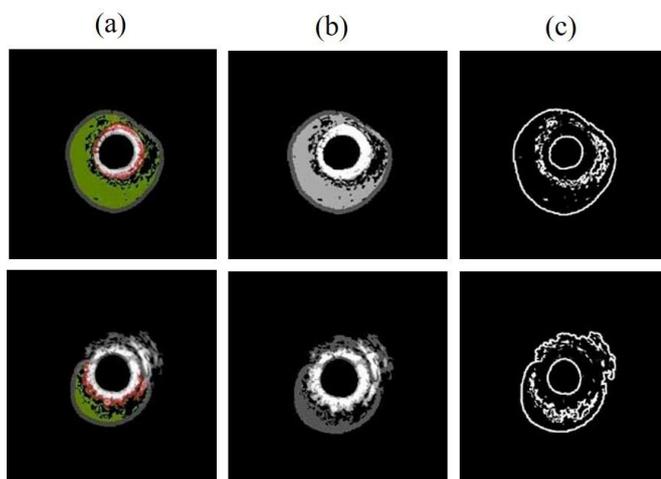


Fig .8. Plaque feature extracted by KNN classifier from Fig.2. Sample IVUS2, Sample IVUS3: column (a) the

plaque region extracted by RGB channel Separation method , column (b) the Plaque region extracted by using KNN method, column (c) the Lumen and Plaque boundary traced.

For the Fig.2. images the intima and media-adventitia border traced and result shown in Fig.9. Row (a) of Fig.9. the borders traced manually by Physician (Intima - blue color, Media-Adventitia - red color), row (b) of Fig.9. image automatically the intima and media-adventitia borders traced, row (c) of Fig.9. image border refined by Morphological operation and media-adventitia broder only traced.

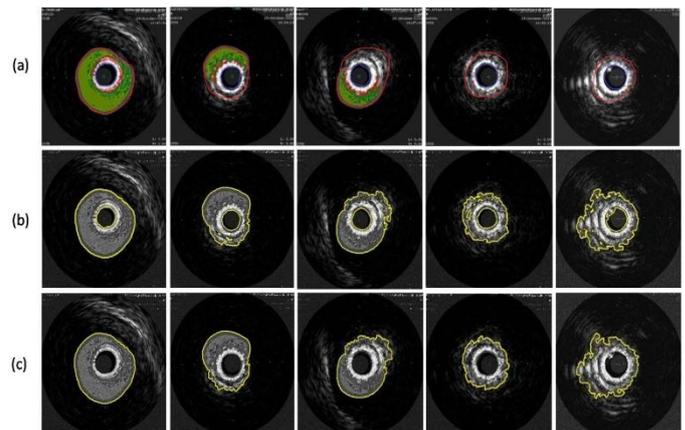


Fig.9. Compare Intima and Media-Adventitia border detection for the Fig.2.: row (a) border traced manually by Physician (Intima - blue color, Media-Adventitia - red color), row (b) Automatically intima and media-adventitia borders traced, row (c) image border refined by Morphological operation and trace media-adventitia broder only.

A. Performance Analysis

The contours got hold through the formulated involuntary segmentation is evaluated to the associated physical tracing prepared through the professional i.e. ground truth delineations were evaluated in accordance with the six measures, for example, Jaccard Index (JI), Dice coefficient (DC), Area Error (AE), percentage of area difference (PAD), Ratio of False Positive (RFP) and Ratio of False Negative (RFN) with the intention of assessing the performance or the quality of the formulated contour detection.

a. Jaccard Index(JI)

JI is worked out in accordance with the two vessel regions contour got hold by the proposed scheme and the associated physical segmentation described with the assistance of specialists. It enumerates the partly cover region among both segmentation as figured out by the (5) below equation,

$$JM = \frac{|I_{auto} \cap I_{manual}|}{|I_{auto} \cup I_{manual}|} \quad \text{----(5)}$$

Where I_{auto} indicates the vessel region segmented through the proposed scheme and I_{manual} indicates the section that is manually segmented with the assistance of specialists

b. Dice Coefficients(DC)

The Jaccard measure is imperative in case of computing the partly cover region recognized by this scheme with regard to equivalent physical description. By the same way, the Dice co-efficient is utilized for the purpose of computing the overlap among the both the type vessel region segmentations by equation (6)

$$DC = \frac{2 * |I_{auto} \cap I_{manual}|}{|I_{auto}| + |I_{manual}|} \text{ ----(6)}$$

c. Percentage of Area Difference (PAD)

PAD indicates the differentiation among the regions of the contour acquired from the automatic segmentation (I_{auto}) and the equivalent manual segmentation (I_{manual}) concerning the region of the physical delineation executed by the equation (7).

$$PAD = \frac{|I_{auto} - I_{manual}|}{I_{manual}} \text{ ----(7)}$$

The plaque region and the APD of the automatic and physical segmentations were also effectively computed. The plaque area is the region within the contour of the wall region and the APD is as given below:

$$APD = \frac{1}{N} \sum_{j=1}^N 2 * r_j$$

d. Area Error(AE)

AE is among the auto segmentation by the prosed method and the physical segmentation as given below (8)

$$AE = |I_{auto} - I_{man}| \text{ ----(8)}$$

Where I_{auto} and I_{man} are two vessel areas characterized by the manually annotated contours

TABLE I: Performance measure using JI, DI, AE, PAD, RFP, RFN for the Fig.2.image.

IVUS Images	JI	AE	PAD	DI	RFP	RFN
Sample IVUS1	0.6035	8008	2200	0.0338	0.0095	0.9827
Sample IVUS2	0.8335	1674	1383	0.6439	0.0702	0.4922
Sample IVUS3	0.6887	2940	1330	0.0977	0.0977	0.9476
Sample IVUS4	0.7683	8400	2666	0.0111	1.9693	0.9834
Sample IVUS5	0.9970	635	635	0.9985	0.0002	0.0028
Mean	0.7782	1.6428e+03	1.6428e+03	0.3570	0.4294	0.6817
Standard Deviation	0.1496	796.6195	796.6195	0.4431	0.8618	0.4328

The segmentation performance of the proposed scheme performed on four sample IVUS images and ground truth is measured using performance measures compare with the ground truth by means of the performance measures such as JI, DI, AE, PAD, RFP, RFN and display in the TABLE I. The Jaccard Index distance compare with the four IVUS samples and its result shown in Fig.10. likewise the Comparison on

false positive and negative ratio for four IVUS samples shown in Fig.11.

The formulated scheme was established to be efficient in identify media-adventitia borders in IVUS images, demonstrating its prospective for application in regular investigation of vascular disease. The proposed algorithm improves the performance of segmentation up to 0.98 and reduces the false ratio up to 0.02.

From the performance measure we obtained 0.7782 as JI value in which the value of one indicates ideal resemblance or the maximum resemblance index. The value of 0.7782, is nearly one means moderately fine. The AE value must be lesser. The PAD have to be 0 to demonstrate extremely superior segmentation, we achieved 1.6428 is exposed in TABLE II, demonstrates the *average measures* acquired from the formulated scheme and the associated ones of comparison. Most of the researchers utilized JI and PAD as performance evaluation in evaluating the dissimilarity. The outcome demonstrates that segmentation by means of the formulated scheme is extremely superior than the Danilo Samuel Jodas et al , equivalent to Mehdi Faraji et al. On the other hand, lower than Lo Vercio et al. Hannah Sofian et al, Destremes et al and Shanhui Sun et al in [20-25].

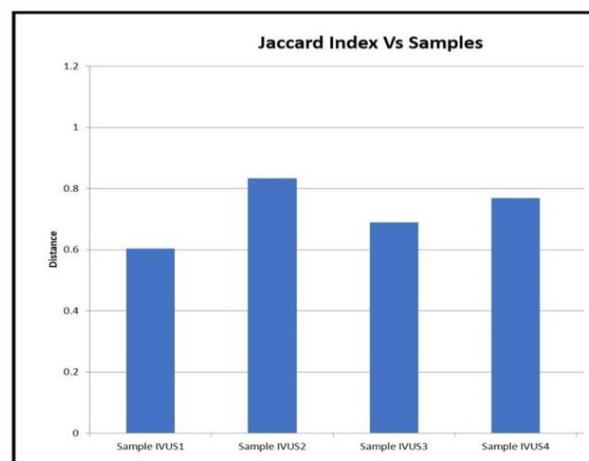


Fig.10. Jaccard Index and IVUS samples compare

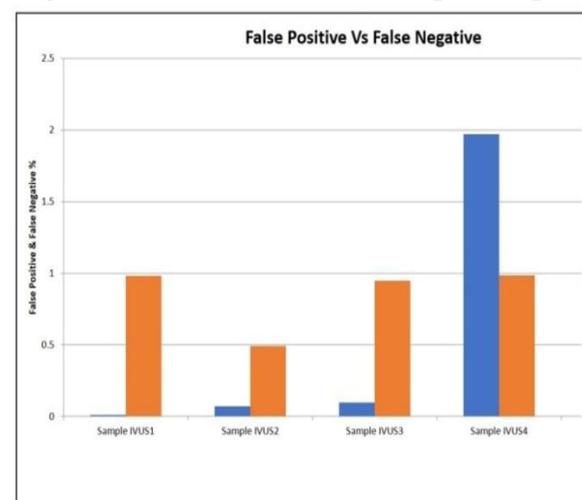


Fig.11. Comparison on false positive and negative ratio

Performance Assessment of K-Means and KNN Algorithm for the Detection of Borders and Extraction of Plaque Area from IVUS Images

Author, Year	Performance Measure						Methods Used
	Jl	AE	PAD	DI	RFP	RFN	
Proposed Method	0.7782	1.6428e+03	1.6428e+03	0.3570	0.4294	0.6817	Jl,AE,PAD,DI, RFP,RFN
Mehdi Faraji et al. 2018	0.77	-	0.19	-	-	-	Jl,HD,PAD
Danilo Samuel Jodas et al. 2017	0.8800	-	0.0900	0.9283	-	-	Jl,HD,PAD,DI
Lo Vercio et al. 2016	0.8300	-	0.1800	-	-	-	Jl,PAD
Hannah Sofian et al. 2015	0.9106	0.8362	0.0733	-	-	-	Jl,AE,PAD,HD
Destremes et al. 2014	-	0.52	-	-	-	-	HD,AE
Shanhui Sun et al. 2013	0.9500	-	0.0300	-	-	-	Jl,HD,PAD

TABLE.II: Average measures achieved from the proposed scheme compare with the previous work.

IV. CONCLUSION

The segmentation of the lumen and media-adventitia areas in IVUS images is a foremost focal point of investigation and takes part an imperative responsibility in assessing the existence and evolution of atherosclerosis. The proposed scheme augments the robustness, effectiveness and automaticity. The quantitative investigation revealed that the segmentation outcomes of the novel automatic segmentation scheme are in relation to the physical delineations. This scheme was found to be efficient in identifying media-adventitia boundaries in IVUS images, representing its prospective for application in regular investigations of vascular disease. The proposed algorithm improves the performance of segmentation up to 0.98 and reduces the false ratio up to 0.02.

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