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Comparative Study of Clustering Algorithms in Order to Virtual Histology (VH) Image Segmentation

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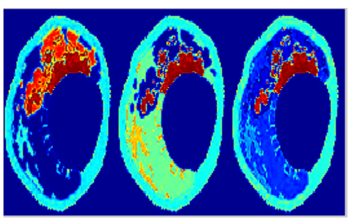
Graphical abstract



Abstract

Atherosclerosis is the deadliest type of heart disease caused by soft or "vulnerable" plaque (VP) formation in the coronary arteries. Recently, Virtual Histology (VH) has been proposed based on spectral analysis of Intravascular Ultrasound (IVUS) provides color code of coronary tissue maps. Based on pathophysiological studies, obtaining information about existence and extension of confluent pool's component inside plaque is important. In addition, plaque components' localization respect to the luminal border has major role in determining plaque vulnerability and plaque–stent interaction. Computational methods were applied to prognostic the pattern's structure of each component inside the plaque. The first step for post-processing of VH methodology to get further information of geometrical features is segmentation or decomposition. The medical imaging segmentation field has developed to assist cardiologist and radiologists and reduce human error in recent years as well. To perform color image clustering, several strategies can be applied which include traditional hierarchical and nonhierarchical. In this paper, we applied and compared four nonhierarchical clustering methods consists of Fuzzy C-means (FCM), Intuitionistic Fuzzy C-means (IFCM), K-means and SOM artificial neural networks in order to automate segmentation of the VH-IVUS images.

Keywords: Atherosclerosis plaque, VH-IVUS, TCFA, segmentation, clustering

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1.0 INTRODUCTION

Atherosclerosis causes two types of stable and vulnerable plaques. Stable plaques led to stenosis in coronary artery and chronic myocardial ischemia; and Vulnerable Plaque (VP) is prone to rupture and cause Acute Myocardial Infarction (AMI) and sudden death [1]. The phrase of vulnerable plaque descriptions, was introduced 20 years before [2]. According to recent estimated study, Cardiovascular diseases are causes of almost 23.6 million deaths by 2030 [3]. Recently, characterization of Vulnerable Plaque is growing in order to acute coronary event prevention [4]. The Providing Regional Observations to Study Predictors of Events in the Coronary Tree study (PROSPECT study) organization is an international multicentre prospective research center that is responsible for adverse conditions of coronary events by evaluating plaque types in VH-IVUS images [5].

Unfortunately, available methods do not provide clinical relevant information about the pattern of plaque structure, plaque composition, geometric position of each component, location and distribution of plaque components toward the boundaries of lumen [6, 7].

This paper is divided into three sections as follows: section 2 describes the related works; section 3 defines the concepts of vulnerable plaque and finally, comparison between four segmentation methods based on clustering is presented in section 4.

2.0 RELATED WORK

Generally, clustering algorithms have classified into four main categories which are partitioning methods (k-means and FCM), hierarchical techniques (agglomerative approach), density-based models (Gaussian mixture models), and grid-based methods (self-organizing feature maps (SOM)) [8].

Ricckard *et al*., in [9] utilized SOM in order to breast region segmentation. Extracted global image properties were used as SOM training samples for image segmentation. Classification of ambiguous pixels near the skin line is performed by applying trained a SOM.

Chang and Teng in [10] developed image segmentation approach toward region of interest (ROI) detection by SOM. Their proposed method significantly reduces the impact of noises and identifies a proper set of dominant colors. Several tests have been conducted on three types of MRI, X-ray, and ultrasound medical images. Results showed that the efficiency of the proposed method is better than active contour algorithm for segmentation.

Iwamoto *et al*., in [11] proposed automatic IVUS classification method based on SOM and multiple spectrum parameters. SOM were used in two stages including supervised-SOM in order to learn blood, catheter, shadow, and outer lumen and unsupervised-SOM to classify remaining data. The second SOM uses K-means clustering for categorization of data. At last, the tissue color-coded maps were reconstructed based on each plaque component values.

In [12] a hybrid segmentation approach based on Hierarchical self-organizing map (HSOM) and FCM has been proposed for MRI image to detect brain tumor. At first, initial cluster selected using HSOM clustering algorithm. Then, actual cluster center and final converges that is necessary for FCM, achieved by several iterations. They tested their experiments with various neighborhood pixels for MRI image segmentation.

Ying in [13] proposed a hybrid approach for image segmentation based on SOM and hierarchical agglomerative clustering. In the pre-processing step, local features were extracted from the MR image as SOM input vectors. Then, hierarchical agglomerative is applied for further clustering the output prototypes that were representative of cluster centre.

To perform brain tumor segmentation in apparent diffusion coefficient (ADC) images, a computer-assisted technique has been implemented by means of SOM and hierarchical multi resolution wavelet [14]. Based on experiments conducted, trained SOM can determine several types of the tissue such as high or low grade tumor, edema, necrosis, CSF, and normal tissue. Their results were compared with manual segmentation with 0.86% sensitivity and 0.93% specificity.

In [15], SOM has been implemented in MATLAB software to analysis the biomedical images (high-resolution CT). Segmentation and edge detection have been applied in order to abnormal structure detection or identifying tissue type. They verified their software by detection of Granulo-matosis with polyangiitis (GPA) disease using high-resolution of CT images.

Fuzzy c-means (FCM) algorithm has been used in image segmentation as it is the most popular scheme due to deal with ambiguity and can hold more data than the hard segmentation approach [16]. Based on studies and experiments done in [17], FCM algorithm showed high performance and stability even against outliers and overlapping.

Giannoglou *et al*., in [18] has been applied FCM to determine the fuzzy degrees of patterns to every class. Feature selection phases were done by FCM in order to classify components of plaque into four classes: calcium, necrotic core, fibrous and fibro-fatty. The overall accuracy achieved by FCM-based was more than first order (FO-SVM) method.

Lazrag *et al*., in [19] has been proposed a new automated method based on FCM and level-set for detecting the luminal border. First, FCM is applied for regions of interest (ROI) extraction in IVUS image. Then, a novel level-set active contour is used for segmenting and detecting of luminal boundary.

A fully automated method is presented in [20] in order to segmente IVUS images based on Gray-Level Co-Occurrence matrices (GLCM) and FCM Clustering. At the first phase, FCM categorizes the features extracted by GLCM using five levels FCM clustering. Then, two levels FCM were applied to classify spatial zone. Their proposed algorithm achieved 83% and 91% of specificity and sensitivity respectively.

Biswas *et al*., in [21] applied FCM and Harris corner detection algorithm to segment the IVUS image into Region of Interest (ROI) and Region of Non-Interest (RONI).

Chaira in [22] applied IFCM to discover abnormal parts in the brain using CT scan image. Four sets of CT scan image were tested and segmented into four clusters. The three components of each pixel are considered include gray value, mean and standard deviation. They compared their method with FCM and Type 2 fuzzy clustering scheme.

Juang and Wu in [23] presented a method to tumor objects tracking for magnetic resonance imaging (MRI) brain images by utilizing K-means clustering along with color-converted segmentation algorithm. Their application can separate exactly brain regions related to a tumor or lesion from the colored images. In addition, it shows outstanding results to measure lesion size and region exactly.

3.0 CONCEPT AND VULNERABLE PLAQUE

3.1 Virtual Histology-Intravascular Ultrasound (VH-IVUS)

Several invasive and the non-invasive clinical imaging techniques have been used in development to detect VPs, such as X-ray angiography, ultrafast Computed Tomography (UCT) and Magnetic Resonance Imaging (MRI) as non-invasive; and invasive techniques including Intravascular ultrasound (IVUS), optical coherence tomography (OCT), computed tomography, and magnetic resonance imaging (MRI) [5].

Intravascular ultrasound (IVUS) and spectral analysis of the radio frequency signal provide an in vivo tissue characterization of atherosclerotic plaques. Figure 1 (a) demonstrates an IVUS catheter along with yellow dashed curve of the transducer when grayscale images of cross-sectional are obtaining. Figure 1(b) indicates the cross-section of Atherosclerosis plaque. In order to reconstructing a typical frame of IVUS, polar (r, θ) domain is converted to (x, y) Cartesian coordinates. Different companies produce transducers with distinct frequencies to generate and display IVUS images. Figure 1 (c, d, e and f) shows four different frames that are generated by dissimilar frequencies [24].

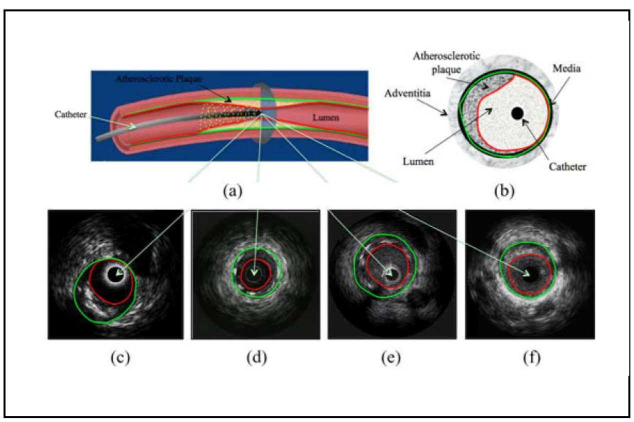

Figure 1 Catheter, Atherosclerosis and IVUS image

Lately, virtual histology (VH) has been proposed based on the 20 MHz IVUS platform to analysis of image into special tissue components [25].

Plaque's components can be discriminated into three classes based of echogenicity in VH-IVUS image [26]. Four types involve Dense Calcium (DC), Fibrotic Tissue (FT), Fibro-Fatty Tissue (FFT) and Necrotic Core (NC) that is shown in Figure 2 [12].

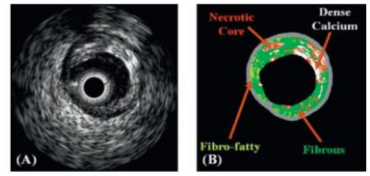

Figure 2 VH-IVUS color code [14]

3.2 Classification of Plaque

Different type of lesion consists of Fibrotic plaque (FT), Fibrocalcific plaque (FC), Fibro Atheroma (FA), Pathological intimal thickening (PIT), Thin-capped fibroatheroma(TCFA) are shown in Figure 3 [26, 27].

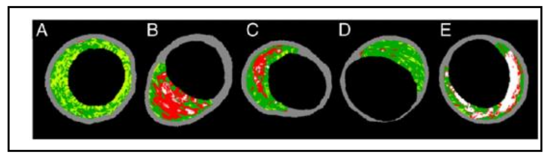

Figure 3 Classification of Coronary Artery Plaque by VH IVUS, (A) Pathological Intimal Thickening (PIT). (B) Virtual Histology Intravascular Ultrasound (VH-IVUS) – derived Thin-Capped Fibroatheroma (VH-TCFA). (C) Thick-Capped Fibroatheroma. (D) Fibrotic plaque (FT). (E) Fibrocalcific Plaque (FC) [14]

3.2 Necrofic Core

TCFA lesion along with its high risk of rupture and thrombosis widely contributes to sudden cardiac death. Based on histological studies, three major criteria contribute to define TCFA lesions as follows: the thin fibrous cap <65μm thicknesses, a large lipid pool, and macrophages in the region of or inside the fibrous cap [13].

Plaque characterization is required to accurately describe the vicinity of necrotic core (NC) component as a major characteristic of Thin cap fibroatheroma (TCFA) and lumen borders in VH-IVUS image. Nevertheless, this criterion is currently assessed visually and manually due to lack of automated application [6].

4.0 SEGMENTATION

The essential step in plaque characterization is segmentation. Performing medical image segmentation manually is a difficult, individual, time-consuming procedure, and it depends on observer ability [29, 30].

Segmentation approach for color image is categorized based on pixel colors distribution or color domains. In order to obtain the segmentation map, connected pixels of color domain class are labeled [31, 32]. Generally, medical segmentation methods can be classified based on their principal methodologies into three main categories include thresholding techniques, clustering algorithms and deformable models [33]

In order to specify the spatial intra-plaque distribution of VH–IVUS components and determine the position of the NC component respect to the luminal border, a decomposition approach should be developed.

4.1 Clustering Method

Image segmentation clustering has been applied to classify objects or patterns into k groups such that pixels belong to a cluster are homogeneous. However, segmentation may be dealing with issues such as low spatial resolution, poor contrast, intensities overlapping, noise that decrease the effectiveness of hard (crisp) methods. Fuzzy clustering has been widely applied in image segmentation as a soft method [8, 16, 32]. Usually, similarity between objects calculated by a distance degree function, for instance, Mahalanobis distance or Euclidean distance [34]. The shortcomings of clustering method consist of (a) the number of clusters should be specified non-automatically, (b) noise can be considered as a segments of the image and (c) time-consuming approach and (d) Incorporating spatial information makes it less general.

4.2 Fuzzy C-means (FMC) Clustering Algorithm

According to Bezdek in [35], the most widely image segmentation algorithm in order to analysis of feature, clustering applications, and classifier strategies is fuzzy c-means (FCM) algorithm. During different iterations, centroids (cluster centers) are calculated by minimizing the dissimilarity function. FCM Algorithm regularly updates the center of each cluster and the membership grades of pixel in order to assign the centers of the cluster to the "right" location [21].

The number of clusters is given by c, matrix U is c×n where, c indicates the number of rows and n is the number of columns and the range of its values is between 0 and 1[32]. The membership matrix (U) = [u_{ij}] initializes randomly to achieve fuzzy partitioning as follow:

$$\sum_{i=1}^{c} u_{ij} = 1, i = 1,2,\ldots,n \quad (1)$$

Where, uij relates to data point membership function degree of ith cluster. The performance index (PI) of U matrix and ci's is shown in Equation 2.

$$J(U, c_1, c_2, \ldots) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \quad (2)$$

The *uij* value is between 0 and 1, ci is the centroid of cluster, is dij the Euclidian distance between *ith* centroid (*ci*) and *jth* data point. $m \in [1,\infty]$ is weighting exponent. To minimize of dissimilarity function, tow conditions are satisfied as follow:

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \quad (3)$$

$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}} \forall k,i \quad (4)$$

FCM algorithm is implemented using MATLAB software. The results with considering various numbers of clusters were different. Figure 4 shows the result of clustering algorithm with 4 clusters. Because the number of clusters is inappropriate, FCM is not able to separate the components properly. Figure 5 shows the result of clustering algorithm with 7 clusters.

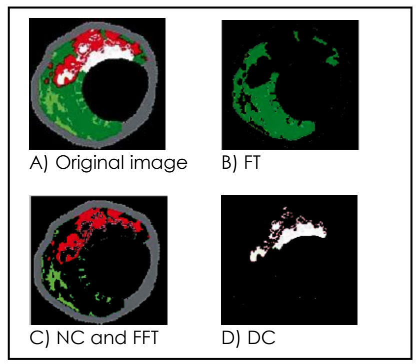

Figure 4 FCM with 4 clusters

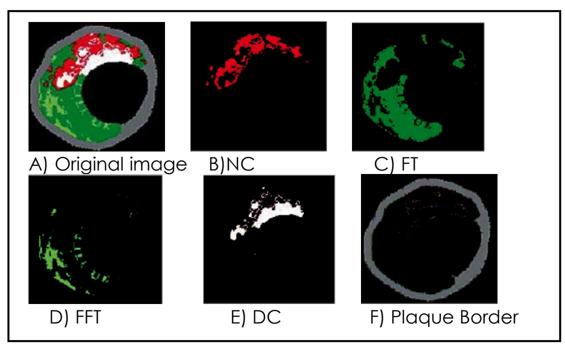

Figure 5 FCM with 7 clusters

4.3 Intuitionistic Fuzzy C-means Algorithm (IFCM)

In defining the membership function, some kind of hesitation is existed as membership degrees are imprecise and depend to person's choice. Therefore, Atanassov's in 1983 has been introduced a higher-order fuzzy set that is named intuitionistic fuzzy set (IFS).This scheme considers both membership and non-membership degree [22]. Dividing distinctive homogeneous groups of image, including color and texture for classifying different patterns called as clustering. Clustering method is based on crisp or fuzzy. Although, each pixel of a distinct cluster (i.e. zero or 1) in non-fuzzy or crisp clustering is belonged to one group, in fuzzy clustering method, membership value is associated with each pixel could be a member of several clusters [36].

In IFCM algorithm, X is a nonempty fixed set and A in X is an object which defined as:

$$A := \{ < x, \mu_A(x), \nu_A(x) > \mid x \in X \} \qquad (5)$$

For each x, μ_A: X→[0,1] consider as the value of membership function .Also, the degree of non-membership group is ν_A: X→[0,1]. For every x , μ_A and ν_A satisfy Eq.6:

$$0 \le \mu_A(x) + \nu_A(x) \le 1 \qquad (6)$$

Unlike traditional fuzzy, the summation of μ_A and ν_A is not necessarily had to be one. IFCM function sums two equations: (i) conventional FCM objective function, which is modified by IFS, and (ii) IFE, which shows entropy of intuitionistic fuzzy. Minimizing objective function using IFCM is:

$$J_{IFCM} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{*m} d_{ik}^{2} + \sum_{i=1}^{c} \pi_i^{*} e^{1-\pi_i^{*}} \qquad (7)$$
$$u_{ik}^{*} = u_{ik} + \pi_{ik},$$
$$\pi_i^{*} = \frac{1}{N}\sum_{k=1}^{n} \pi_{ik}, \quad k \in [1, N]$$

Where the intuitionistic fuzzy membership is ,the *kth* data in *ith* class. μ_{ik} belongs to conventional fuzzy membership and π_{ik} is Hesitation degree in this equation:

$$\pi_{ik} = 1 - u_{ik} - (1 - u_{ik}^{\alpha})^{1/\alpha}, \alpha > 0, \qquad (8)$$

Yager's intuitionistic fuzzy complement used as follow equation:

$$N(x) = (1 - x^{\alpha})^{1/\alpha}, \alpha > 0, \qquad (9)$$

Finally, intuitionistic fuzzy set equation is:

$$A_{\lambda}^{IFS} = \{x, \mu_A(x), (1 - \mu_A(x)^{\alpha})^{1/\alpha} \mid x \in X\} \qquad (10)$$

The algorithm is implemented using MATLAB software. The results with considering various numbers of clusters were similar to FCM.

4.4 K-means Clustering Algorithm

K-means objective function provides feature vectors distribution of clusters based on similarity and distance measures [23]. K-Means algorithm clusters naturally input vectors by means of squared Euclidean distance [37, 38]. During the stage of minimizing objective function, all input points are collected into separate centers: $\mu_i \forall i = 1..k$, $x_j \in S_i$

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 \qquad (11)$$

While, K is the number of clusters S_i , i=1,2,…,*k* and μ_i show the center of all point. K-means algorithm starts with computing the intensity distribution. Then, k random intensities are produced as initial centroid. Next, in an iterative stage, points are clustered by means of intensities.

$$c^{(i)} := \arg\min_{j} \left\| x^{(i)} - \mu_j \right\|^2 \qquad (12)$$

Now, new center are computed for all clusters based on follow equation:

$$\mu_i := \frac{\sum_{i=1}^{m} 1\{c_{(i)} = j\} x^{(i)}}{\sum_{i=1}^{m} 1\{c_{(i)} = j\}} \qquad (13)$$

K-means algorithm is implemented using MATLAB software. As seen in Figure 6, the K-means clustering algorithm is not able to accurately separate the four components of VH.

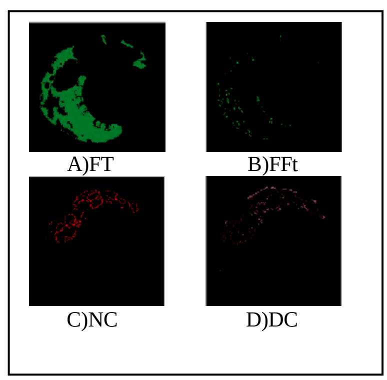

Figure 6 K-means with 7 clusters

4.4 Self Organizing Map(SOM)

SOM is unsupervised feed-forward neural network and has been proposed by Kohenen. Each node is related to a weight vector (w_i) with similar dimension in the map space. A similarity measure is used for finding the most similar node (namely best matching unit (BMU)) in each iterative learning process [39]. Similar input patterns in the input space are kept close together in the output map [13]. A prototype vector $w_i=(w_{i1}, w_{i2}, \ldots w_{im})$ is exists for each node i. A winner node (c), for each input sample x is selected by the similarity rule as follow:

$$\|x - w_c\| = \min_i \|x - w_i\| \qquad (14)$$

The winner weight (c) along with their neighbors is updated as follows:

$$w_i(t+1) = w_i(t) + h_{ci}(t)[x(t) - w_i(t)] \qquad (15)$$

t: iteration of the training process

x *(t)* : input sample of current iteration t

h_{ci}: neighborhood function of the winner node c

The neighborhood function h is defined by the following equation:

$$h_{ci}(t) = \alpha(t)h(\|r_c - r_i\|, t) \qquad (16)$$

a(t): learning rate

r_i: positions of the node i

r_c: Winner node c

SOM algorithm is implemented using MATLAB software. The result with 1000 iteration is shown in Figure 7.

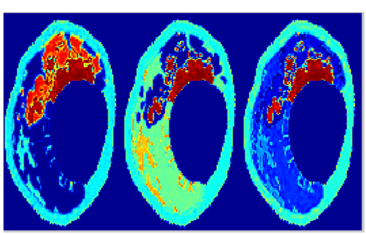

Figure 7 Iteration=1000

5.0 CONCLUSION

Medical image segmentation persist a challenge since lack of resolution, characteristics of imaging, motion, adjustable pathology and anatomy. Based on our experiments, performance of the clustering algorithms depends on the number of clusters. K-means cannot divide VH-IVUS with 7 numbers of clusters whereas FCM can visualize four plaque components with 7 clusters. In addition, the result of IFCM and FCM are similar based on our experiments. Moreover, SOM algorithm is not applicable in this case and should be combined with other algorithms because the amount of each color component in the detection of vulnerable plaques is important.

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