Review of Image Processing Techniques to Diagnose Coronary Artery Disease

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Abstract— **Coronary Artery Disease (CAD) is one of the emerging causes of death all over the world , stenosis is a condition related to the narrowing of a vessel or artery. Medical images processing have become increasingly used within the framework of medical care from the diagnose to treatment. As known the segmentation and accuracy of the algorithm lead to successful diagnoses of the images.**

This paper concerned with detection of Coronary Artery stenosis by proposing three different image processing algorithms, Cuckoo's algorithm , Hassian based Frangi Vesselness Filter and Fuzzy C-mean clustering algorithm. 15 patient images has been chosen to carry out the experimental study. Then the performance and the effectiveness of the three different methods evaluated and compared using Receiver operating characteristic chart based on the conditional probabilities sensitivity and specificity.

***Keywords*— Coronary Artery Diseases, image processing, cuckoo algorithm, Hassian metrics, fuzzy c-mean clustering, Receiver Operating Characteristic, Area Under The Curve.**

I. NTRODUCTION

Coronary artery disease (CAD) is a major cause of death worldwide [1][2]. Oxygen and nutrients, which are required for normal heart function, are supplied to the myocardium (the muscular tissue responsible for the contraction of the heart) by the blood traveling through the coronary arteries [2]. If a coronary artery becomes narrowed or occluded owing to the build-up of plaque (e.g. calcium, fat and cholesterol), the amount of blood flowing to the myocardium is reduced and, thus, less oxygen and nutrients are delivered to these myocardial regions. The restriction in blood and oxygen is called ischemia; atherosclerosis is the condition in which plaques build-up in the coronary artery, and the narrowing of a vessel is referred to as stenosis [2].

Various imaging techniques are used to assess and quantify the presence and state of coronary artery stenosis. The choice of which cardiovascular imaging techniques to perform is determined by the patient's history and current symptoms. In current clinical practice Computed Tomography

Angiography (CTA) is the gold standard imaging technique to diagnose CAD. It's provide a high resolution three-dimensional (3D) images of the cardiac and coronary artery anatomy, and allows the interpreter to assess the presence, extent and type (calcified or non-calcified) of coronary plaques.

Different approaches have been proposed to address the challenge of automatically detecting and quantifying stenosis. These methods can be categorized into two groups:

(1) methods that depend on accurate lumen segmentation to compute/estimate healthy and diseased lumen diameters in order to quantify stenosis .

(2) methods that use image features or pattern recognition approaches to detect stenosis .

Pouya D B at el. [3] paper proposed a method to diagnose CAD using cuckoo algorithm which is one of the newest and most powerful evolutionary optimization methods ever introduced.

Supriya Agrawal at el. [4] paper proposes a method for automated segmentation of cardiac stenosis. Pre-processing includes image enhancement and pre-segmentation. Image enhancement is done to remove the noise removal and improves the visual quality. Segmentation of the arteries is done through Hessian based Frangi's vesselness filter.

Bing NanLi at el [5] proposed a method to facilitate medical image segmentation by spatial fuzzy clustering. It begins with spatial fuzzy clustering, whose results are utilized to initiate level set segmentation. Next sections discuss every method in details.

This paper will present methods that focused on stenosis detection rather than plaque detection. In their evaluation stage, binary (healthy or diseased) based on the presence/severity of lumen narrowing rather than presence of plaque. The main objective is how accurately can a significant stenosis be detected by the algorithm.

In order to study the performance for various descriptors, the effectiveness of the three different methods will be evaluated and compared in classification section. The original dataset was partitioned into two subsets; each pair of subsets among the three descriptors was checked separately and serves as input to Receiver operating characteristic.

R.O.C chart is a useful visual tool for comparing classification methods. It shows the trade-off between the true positive rate and the false positive rate for a given model. ROC chart is based on the conditional probabilities sensitivity and specificity.

The dataset of patient images from Tripoli hospital and www.cathlabdigest.com, It consists of male patients and female patients with different levels of blockage of arteries and normal patient of different age groups from 37 years to 73 years old.

Received July 2019, Received in received from October 2019, Accepted December 2019, and Published July 2020

II. Cuckoo's algorithm

This section describes an overview of CS, which is inspired by the life of a bird family, then explain the proposed method followed by the result of Matlab code.

Cuckoo Search (CS) is an optimization algorithm developed from careful observation, mathematical modelling of the craftiness of the cuckoo bird in the egg incubation process [6].

The cuckoo birds prefer to lay their eggs among the eggs of other birds or other cuckoo species. the eggs of the host bird in any given nest represents an optimization solution, while the strange eggs of the cuckoo birds represent new solutions. Through careful manipulation of the cuckoo eggs and those of the host birds, the CS is able to arrive at good optimization solutions to complex optimization problems The CS has enjoyed wide applications to various optimization problems. Some of the successful application areas of the CS includes the travelling salesman's problems, wireless sensor networks, job scheduling, image processing, flood forecasting, classification task in the health sector, etc. The CA essentially works with three important components: selection of the best by keeping the best nests or solutions; Levy's flight search pattern for replacing the host eggs with respect to the quality of the new solutions or Cuckoo eggs produced; and discovery of some cuckoo eggs by the host birds and replacing those eggs according to the quality of the local random walks [7]. Fig .1 shows CA flow chart. The three basic principles are:

1] Each cuckoo lays one egg at a time, and dumps its egg in a randomly chosen nest

2] The best nests with high quality of eggs will carry over to the next generation.

3] The number of available host nests is fixed and the host bird finds the egg laid by the cuckoo having fixed probability. Discovering operate on some set of worst nests, and discovered solutions dumped from farther calculations .

A. Proposed Method:

The proposed method to Diagnose heart disease using cuckoo Algorithm , involves the following steps:

Step 1: Read the given angiogram image, and convert it into a matrix form, where each pixel value is in the range of grey level from 0-255.

Step 2: Apply filtering and noise reduction method.

Step 3: Taking Histogram sample and equalization.

Step 5: Repeat process.

Step 6: Detect the edges of the artery using Cuckoo algorithm to optimize the stenosis.

Step 7: Repeat for the best result.

Step 8: Continue to optimize and update the parameters of Cuckoo algorithm.

Step 9: Repeat.

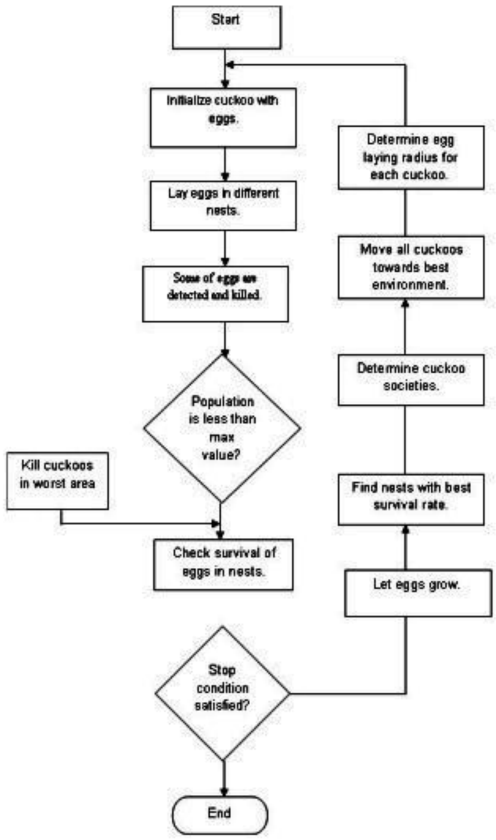


Fig. 1 Cuckoo Algorithm flow chart

TABLE I

Control parameters for the cuckoo search procedure

Parameter	Value
No. of nests	50
Alien egg discovery rate p a	0.25
No. of iterations	25
Lower bound of value for egg	1
Upper bound of value for egg	255

Table 1 above shows the parameters for the CS that has been used in Matlab code, The mutation probability value (pa) decides the fraction of worst nests that are dropped from further calculations and build new one sat new locations via Levy flights. Mutation probability of '1' implies that a host bird recognizes the Cuckoo's egg and throws it or simply leaves its nest. Mutation probability of '0' implies that a host bird does not recognize the Cuckoo's egg and may hatch it. Therefore the range of mutation probability is chosen between 0 and1and a value of 0.25 gives satisfactory results for this experiment.

The lower bound and the upper bound are incorporated in the algorithm according to the constraints of image formation. This experiment has chosen the population size of 50. While

Received July 2019, Received in received from October 2019, Accepted December 2019, and Published July 2020

doing simulation clearly observe that an increase in the number of iterations does not improve the objective function value further. An appropriate value of 25, although tried different values of mutation probability, for example 0.20, 0.25,0.30. But it is observed that $P_a = 0.25$ yields best results in this experiment.

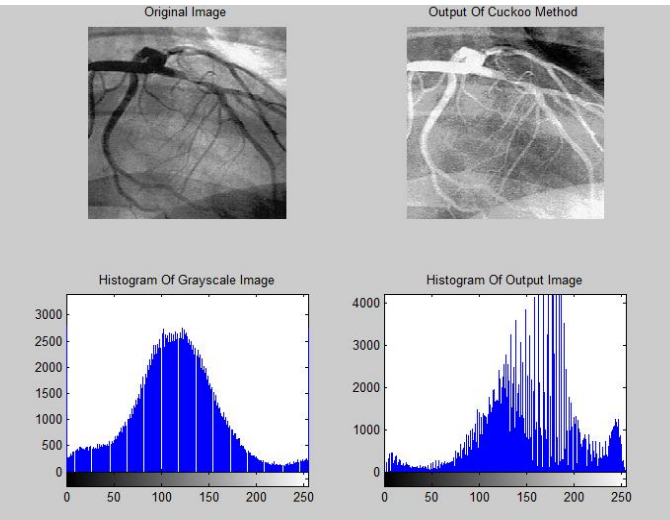


Fig. 2 Experimental results shows the original images , the output of cuckoo method and histogram for each of them.

III. Hassian based Frangi Vesselness Filter

This section will present a 2D image processing method that is based on the analysis of Hessian matrix eigenvalues, inside Vesselness filter between understand and steps . Hessian matrix based method proposed by Frangi [8] for extracting tubular structures from an image is used to determine the Vesselness of any voxel in the data.

The Hessian matrix describes the 2nd order local image intensity variations around the selected voxel [9]. The partial derivatives are calculated as voxel intensity differences in the neighbourhood of the voxel (1).

$$H(f) = \left(\frac{\partial^2 f}{\partial x_i \partial x_i}\right) = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1 \partial x_1} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots\cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2 \partial x_2} & \cdots\cdots & \frac{\partial^2 f}{\partial x_2 \partial x_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \frac{\partial^2 f}{\partial x_n \partial x_2} & \cdots\cdots & \frac{\partial^2 f}{\partial x_n \partial x_n} \end{pmatrix} \quad \ldots(1)$$

where f refers to the image and ∂ is the gradient operator, composed of the respective gradients of the three dimensional image. The calculation of Hessian matrix H is repeated at each voxel location with different scales.

Using these values, a Vesselness value can be calculated The aim is to extract the principle direction in which the second order structure of the image is decomposed.

Vessels appear as white tubular structures in black background. They are brighter than background. Therefore the grey label invariants are calculated as follows:

$$R_A = \frac{|\lambda_1|}{|\lambda_2|} \quad (2)$$

$$R_B = \frac{|\lambda_1|}{\sqrt{|\lambda_2 \lambda_3|}} \quad (3)$$

Where $\lambda_1, \lambda_2, \lambda_3$ are the Eigen values of the Hessian matrix from which RA, RB are calculated [oksuz]. RA and RB contains only the geometric information and therefore a second order structureness is defined as follows:

$$S = \|H\|_F = \sqrt{\sum_{i \leq 3} \lambda_i^2} \quad (4)$$

The measure S is less where there is no structure present and the Eigen values are low due to lack of contrast regions. In high contrast regions the measure will be large and at least one Eigen value will be large. Therefore a Vesselness function is defined as follows:

$$v_0(s) = \begin{cases} 0 & \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ \left(1 - exp\left(\frac{-R_A^2}{2\alpha^2}\right)\right)\left(exp\left(\frac{-R_B^2}{2\beta^2}\right)\right)\left(1 - exp\left(\frac{-S_c^2}{2c^2}\right)\right) & \end{cases} \quad (5)$$

Where: α, β, c thresholds that can control sensitivity of the line are filter to the measures RA, RB and S.

For 2D images the corresponding Vesselness measure is defined as follows:

$$v_0(s) = \begin{cases} 0 & \text{if } \lambda_2 > 0 \\ \left(exp\left(\frac{-R_B^2}{2\beta^2}\right)\right)\left(1 - exp\left(\frac{-S_c^2}{2c^2}\right)\right) & \end{cases} \quad (6)$$

A. *Proposed Method:*

This algorithm presented for the detection of coronary artery stenosis and its follow these steps:

Step 1: Read the given angiogram image, and convert it into grey level image.

Step 2: Apply median filter to remove the noise in the image.

Step 3: Apply Hessian based Frangi's Vesselness filter to segment the artery.

Step 5: Apply global threshold of the output image.

Step 6: Show two results, one with threshold and one without.

Received July 2019, Received in received from October 2019, Accepted December 2019, and Published July 2020

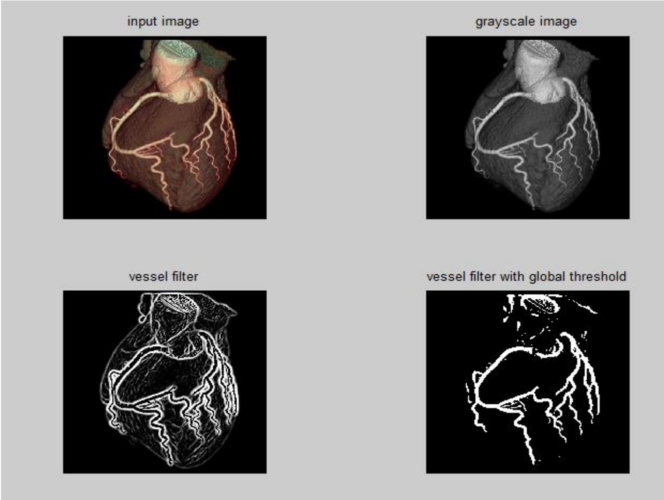


Fig. 3 Experimental results shows the original images and the output of Vesselness filter.

IV. Fuzzy C-means (FCM) clustering methods

In general, cluster analysis refers to a broad spectrum of methods which try to subdivide a data set X into c subsets (clusters) which are pairwise disjoint, all nonempty, and reproduce X. via union. The clusters then are termed a hard (i.e., nonfuzzy) c-partition of X [10].

Fuzzy c-means (FCM)is one of most popular algorithms in fuzzy clustering, and has been widely applied to medical problems [11][12][13].

Fuzzy clustering can be categorized into three categories: hierarchical fuzzy clustering methods, graph theoretic fuzzy clustering methods, and fuzzy clustering based on objective functions [14].

The proposed method is the one that based on minimization of the following objective function:

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (\mu_{ij})^m \left\| x_i - v_j \right\|^2 \tag{7}$$

where m is any real number greater than 1 , μ_{ij} is the degree of membership of x_i in the cluster j, x_i is the i **th** of d-dimensional measured data, c_j is the d-dimension centre of the cluster. and ||*|| is any norm expressing the similarity between any measured data and the centre.

A. Proposed method:

The fuzzy partition matrix (image's pixels)is initialized, then within an iterative loop the following steps are executed: the cluster centers are updated using Eq. (8), then the membership matrix is updated using Eqs. (9,10). The loop is repeated until a certain threshold value is reached [15][16].

B. FCM Algorithm

Input: c : centroid matrix, m : weighted exponent of fuzzy membership, $\in$: threshold value used as stopping criterion, $Y = [y11, y2, ... yn]$: data

Output: c : updated centroid matrix

Randomly initialize the fuzzy partition matrix $U = \left[u_{ij}^{k}\right]$

Repeat

Calculate the membership matrix U^k :

$$c_j = \frac{\sum_{i=1}^{n} \left(u_{ij}^{k}\right)^m y_i}{\sum_{i=1}^{n} \left(u_{ij}^{k}\right)^m y_i} \tag{8}$$

Update the membership matrix U^{k+1} using:

$$u_{ij}^{k+1} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{(m-1)}}} \tag{9}$$

where $$d_{ij} = \left\| y_i - c_j \right\|^2 \tag{10}$$

until $\max_{ij} \left\| u_{ij}^{k} - u_{ij}^{k+1} \right\| \langle \in$

Return c

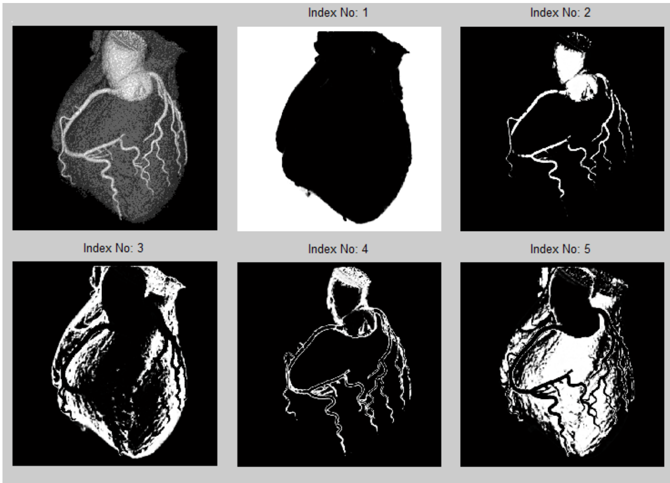


Fig. 4 Experimental results shows the original images and the output of Fuzzy C-Mean cluster method (No. of cluster= 5)

V. Classification

In order to study the performance for various descriptors, the effectiveness of the three different methods will be evaluated and compared. The original dataset was partitioned into two subsets; each pair of subsets among the three descriptors was checked separately and serves as input to Receiver operating characteristic.

In each classifier systems, the dataset must be splitted into two parts: training set and test set which consist of three parts.

The performance of the algorithms is represented in the form of confusion matrix .Confusion matrix is a table with two rows and two columns that reports the number of False Positive(FP) patients who are healthy and predicted as diseased, False Negative(FN) patients who are diseased and predicted as healthy, True Positive(TP) patients who are diseased and predicted as diseased, and True Negative(TN) patients who are healthy and predicted as healthy. Matrix

Received July 2019, Received in received from October 2019, Accepted December 2019, and Published July 2020

confusion allows visualization of the performance of supervised learning algorithms like accuracy.

TABLE. 2 DATA SET

C-Mean	Hessian	Cuckoo	Actual	Disease	Age	Sex	Patiant No.
0	0	0	0	-	37	F	1
0	0	0	0	-	42	F	2
0	0	0	0	-	42	F	3
1	0	1	1	+	50	F	4
1	1	1	0	-	50	M	5
1	1	1	1	+	56	M	6
1	1	1	1	+	62	M	7
1	1	1	1	+	64	M	8
1	1	0	0	-	66	M	9
1	1	1	1	+	67	F	10
1	1	1	1	+	67	F	11
1	1	1	1	+	68	M	12
0	0	0	0	-	69	M	13
1	1	1	1	+	73	F	14
1	1	1	1	+	57	M	15

TABLE 3

CONFUSION MATRICES OF THE THREE METHODS

CONFUSION MATRICS 1

		PREDICTED CLASS		
		15 YES	NO	
ACTUAL	YES	TP=9	FN=0	CP=9
	NO	FP=1	TN=5	CN=6
		RP=10	RN=5	

CONFUSION MATRICS 2

		PREDICTED CLASS		
		YES	NO	
ACTUAL	YES	8	1	CP=9
	NO	2	4	CN=6
		RP=10	RN=5	

CONFUSION MATRICS 3

		PREDICTED CLASS		
		YES	NO	
ACTUAL	YES	9	2	11
	NO	0	4	4
		9	6	

The accuracy can be viewed as in eq.(11) , the percentage of correctly data classified divided by the total number of test. In the other hand it is named recognition rate. performance is typically defined according to the confusion matrix associated with the classifier. Based on the entries of the matrix, it is possible to compute sensitivity (12), specificity(13), Positive Predictive Value(14),and Negative Predictive Value(15). For a single cutoff.

$$Accuracy\ (1 - \text{Error}) = \frac{(T_p + T_n)}{(C_p + C_n)} = P(C), \qquad (11)$$

$$Sensitivity\ (1 - \beta) = \frac{(T_p)}{(C_p)} = P(T_p), \qquad (12)$$

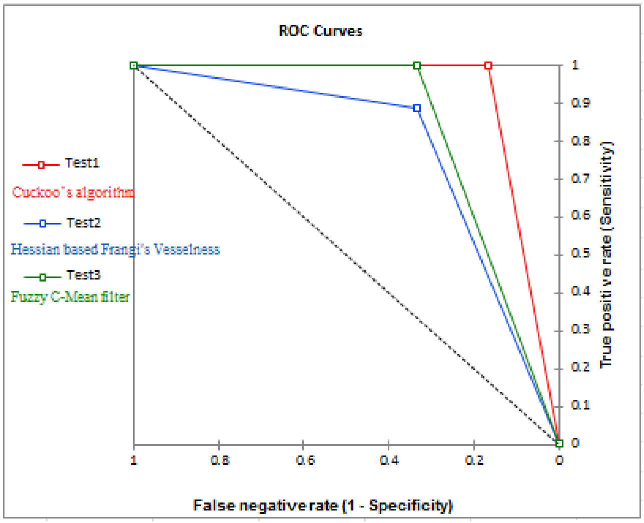
$$Specificity\ (1 - \alpha) = \frac{(T_n)}{(C_n)} = P(T_n), \qquad (13)$$

$$Positive\ \text{predictive value} = \frac{T_p}{R_p}, \qquad (14)$$

$$Negative\ \text{predictive value} = \frac{T_n}{R_n}, \qquad (15)$$

Receiver operating characteristic R.O.C chart is a useful visual tool for comparing classification methods. It shows the trade-off between the true positive rate and the false positive rate for a given model. ROC chart is based on the conditional probabilities sensitivity and specificity [17]. Here XLSTAT has been used (www.xlstat.com) to compute these measures automatically .

Fig. 5 Comparison of the three methods ROC curves



Comparison of ROC curves

At the end its clearly that the best classification has the large AUC which is cuckoo method with value equal to 0.917.

VI. CONCLUSIONS

Therefore, from the algorithms functionality screen shots and output obtained as showed in the results section above, conclude that cuckoo optimization algorithm has the best classification, it shows the improvement of the artery . It was very clear and accepted for vessels tracking. ROC curves showed the accuracy of the algorithm better than the two others methods.

REFERENCES

[1] Roger, V. L., *at el.* , Jan 2012. Heart disease and stroke statistics–2012 update: a reportfrom the american heart association. Circulation 125 (1), e2–e220.

[2] WHO (2011) Cardiovascular diseases, fact sheet 317. World Health Organization

[3] Pouya D B, Mojdeh B, Elham F. Heart Disease Diagnosis Using Image Processing By Cuckoo Algorithm before Surgery. Res Med 2/3

[4] S.Agrawal, S.Mukherjee, "Modeling and Simulation of Blood Flow for Early detection of Coronary Artery Blockage using CCTA imag-es", Proceedings of ISCI-2013, Indian Institute of Technology, Madras,p_id 3, 2013.

[5] B.N.Li,C.K.Chui,S.H.Ong,S.Chang, Integrating FCM and level sets for liver tumor segmentation, in :Proceeding of the13th International Conference on Biomedical Engineering, (ICBME2008),IFMBE Proceeding s23.(2009)202–205.

[6] Yang XS, Deb S (2009) Cuckoo search via Lévy flights. World Congress on Nature & Biologically Inspired Computing, IEEE Publications, India, pp. 210-214.

[7] Xin-She Yang, Suash Deb. Engineering Optimisation by Cuckoo Search. arXiv:1005.2908v3 [math.OC]; 2010.

Received July 2019, Received in received from October 2019, Accepted December 2019, and Published July 2020

[8] Frangi Alejandro F., et al.: Multiscale Vessel enhancement Filtering, in W. M. Wells, A. Colchester, and S. Delp, eds, Medical Image Computing and Computer–Assisted Intervention (MICCAI), volume 1496 of Lecture Notes in Computer Science, pages 130–137, Oct. 1998, available online: http://www.tecn.upf.es/~afrangi/articles/ miccai1998.pdf..

[9] Zuluaga MA, Magnin IE, Hoyos MH, Leyton EJD, Lozano F, Orkisz M (2011) Automatic detection of abnormal vascular crosssections based on density level detection and support vectormachines. Int J Comput Assist Radiol Surg 6(2):163–174.

[10] Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. Computers & Geosciences, 10(2-3), 191–203. doi:10.1016/0098-3004(84)90020-7

[11] K.S.Chuang,H.L.Hzeng,S.Chen,J.Wu,T.J.Chen,Fuzzy c-means clustering with spatial information for image segmentation ,Computerized Medical Imaging and Graphics30(2006)9–15. [5]

[12] W.Cai,S.Chen,D.Zhang,Fast and robust fuzzy c-means clustering algorithms incorporating.

[13] W.K.Lei,B.N.Li,M.C.Dong,M.I.Vai,AFC-ECG:an adaptive fuzzy ECG classifier,in:Proceeding softhe11th World Congress on Soft Computing in Industrial Applications

[14] Xu Y, Liang G, Hu G, Yang Y, Geng J, Saha P (2012) Quantification of coronary arterial stenoses in CTA using fuzzy distance transform. Comput Med Imaging Graph 36(1):11–24.

[15] Yang MS (1993) A survey of fuzzy clustering. Math Comput Model 18:1–16

[16] Ludwig, S. A. (2015). MapReduce-based fuzzy c-means clustering algorithm: implementation and scalability. International Journal of Machine Learning and Cybernetics, 6(6), 923–934. doi:10.1007/s13042-015-0367-0

[17] Marazìa, S., Barnabei, L., & De Caterina, R. (2008). Receiver operating characteristic (ROC) curves and the definition of threshold levels to diagnose coronary artery disease on electrocardiographic stress testing. Part II: The use of ROC curves in the choice of electrocardiographic stress test markers of ischaemia. Journal of Cardiovascular Medicine, 9(1), 22–31. doi:10.2459 /jcm.0b013e32813ef418.

Received July 2019, Received in received from October 2019, Accepted December 2019, and Published July 2020