Heart Atherosclerosis Segmentation Using RWPSO Algorithm

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Abstract

Heart Atherosclerosis disease is one of the world's most critical health issues today. We can detect arterial stenosis and plaque, which are the major causes of this condition, by segmenting and analysing coronary arteries in medical imaging. Manually segmenting coronary arteries is time-consuming and subjective, and most segmentation methods need a suitable starting point, which is challenging to achieve using 3D coronary computed tomography angiography (CTA) data. Medical image segmentation is critical in one of the most difficult sectors of engineering. An imaging modality gives comprehensive anatomical information. It also aids in the detection of the disease and its gradual therapy. In this paper, we used RWPSO (Random Walk Particle Swarm Optimization) segmentation method by combining Random Walk and Particle Swarm Optimization algorithm. By using RWPSO segmentation on medical images we get better Accuracy for Heart Atherosclerosis detection than existing methods.

Key Words: Image segmentation; Random Walk; PSO; RWPSO

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Introduction

Coronary artery disease, or CAD for short, is a primary cause of death in a number of countries throughout the world. Despite the fact that coronary artery disease is a severe danger to millions of lives, millions of dollars are spent on its treatment each year. The diagnosis of cardiac blockage has gotten easier because to the availability of a variety of heart imaging tools. Several daring leaps have been achieved in the field of cardiac imaging technology in recent years [1]. Cardiovascular disorders kill about twice as many people as all malignancies put together. Atherosclerosis is a disease in which plaque forms in the blood artery wall as a result of increased intimal deposition of lipid, protein, and cholesterol esters, resulting in significant blood flow reduction. Atherosclerotic plaques can form in the superficial femoral artery, coronary arteries, carotid arteries, and the infarenal aorta around the common carotid bifurcation, among other places in the vasculature. The expansion of the blood vessel wall in response to the formation of an atherosclerotic plaque generates little or no compression of the lumen at first. The degree of artery stenosis, or narrowing, was once assumed to be a predictor of plaque susceptibility, with full arterial occlusion or a cerebral ischemia event occurring depending on the kind of plaque.The risk of stroke increases as carotid stenosis worsens and decreases after carotid endarterectomy [2]. Cardiovascular disease is one of the most lethal diseases on the planet. Cardiovascular diseases are becoming more common as our living conditions improve, and the beginning age is increasing younger, posing a significant risk to human health Coronary artery heart disease (CAD) is a prevalent sickness also known as coronary artery disease or coronary heart disease. Stenosis is caused by deposits on the coronary artery wall, which causes myocardial ischemia and, as a result, cardiac organic dysfunction. As a result, ischemic heart disease is another name for it (IHD) [3]..

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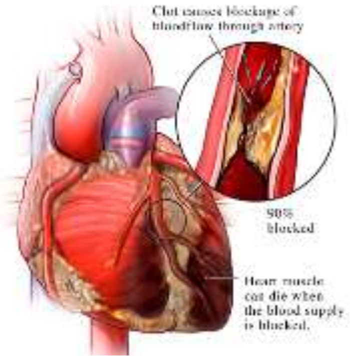

Fig.1 Heart with atherosclerosis

The two types of segmentation are local segmentation and global segmentation. The method of segmenting a subimage using tiny windows on a larger image is known as local segmentation. The term "global segmentation" refers to the process of segmenting the entire image. Global segmentation is generally concerned with rather large numbers of pixels. Local segmentation, on the other hand, deals with fewer pixels than global segmentation. In image processing and computer vision, picture segmentation is a well-known problem. Using image segmentation, we may learn about the principles of digital image processing. Image segmentation is used to improve images and is also beneficial in a variety of medical applications. Picture segmentation can also be used for image analysis and subsequent image pre-processing [4].

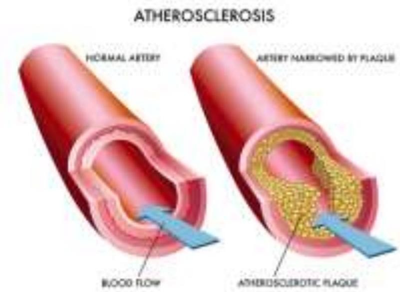

Fig.2 Normal vs Atherosclerotic artery

Cardiovascular diseases are the leading cause of morbidity and death in developed countries. Atherosclerosis, for example, is induced by a sequence of cellular and molecular reactions that develop from the initial inflammatory lesion to advanced lesion stages that are prone to rupture and thrombosis [5]. Particle swarm optimization is a swarm intelligence-based optimization approach similar to fish schooling and bird flocking. The purpose of this strategy is to find the optimal answer from the available options. Kennedy introduced the PSO for the first time in 1995. This method was created in order to address issues that could be solved using actual numbers. Later, it is effectively applied in a variety of study areas [6]. In this paper, we used RWPSO (Random Walk Particle Swarm Optimization) segmentation method by combining Random Walk and Particle Swarm Optimization algorithm. By using RWPSO segmentation on medical images we get better Accuracy for Heart Atherosclerosis detection than existing methods.

Related Works

Qi Zhang et al. [7] Intravascular ultrasonography (IVUS) pictures of atherosclerotic plaques can be used to detect lumen and media-adventitia contours, which can be used to diagnose atherosclerosis. This research presents a method for recognising plaque contours based on previous knowledge of plaque elliptic geometry. They used particle swarm optimization to maximise a matching function. After that, boundary vector field snakes are used to improve the contours. 88 in vivo photographs from 21 individuals were used to test the procedure.

Sarah Saud Alotaibi et al. [8] Coronary Heart Disease has recently become a global epidemic. It has reached a significant number of people. CAD has serious side effects that can cause physical pain as well as worry in the family. Other physical symptoms may raise the patient's risk of mortality in comparison to the general population. As a result, the study focused on establishing a model for predicting the diagnosis of coronary artery disease. Random Walk (RF) and Nave Bayes (NB).

Samra Irshad et al. [9] They devised an objective classification system for retinal vessels that takes into account the size and significance of each characteristic group. The objective function ensures that the chosen feature subset has the smallest number of characteristics and corresponds to the maximum degree of vessel classification accuracy. Support Vector Machines are employed to assess the selected feature subset when the optimization process comes to a standstill. They evaluated the proposed framework's accuracy of retinal vascular categorization to existing state-of-the-art techniques, their method have high accuracy on both healthy and sick pictures. The suggested method's efficacy is validated using both a public and a private dataset.

F. F. C. Morais et al. [10] On CT images produced using traditional coronary calcium score collection methods, they suggested a method for completely automated segmentation of two kinds of cardiac adipose tissues separated by the pericardium. There was a lot of effort put into ensuring that users engaged and repeated themselves as little as possible. A authorization step that approximately adjusts image data to a requirement, a retrieval of aspects relevant to pixel resolution and their nearby areas, and an edge detection step based on data mining classification techniques that determines whether a received pixel is of a certain type are all part of the methodology proposed in this paper.

Tomohiro Kawasaki et al. [11] The fractional flow reserve (FFR) approach is well-established for diagnosing lesion-specific ischemia, despite its invasive nature. The purpose of this study was to investigate how effectively a combined assessment of coronary CT angiography (CCTA) imaging characteristics and CT-FFR could diagnose lesion-specific ischemia when compared to invasive FFR. In the study, 47 people with 60 coronary arteries with stenosis ranging from 30% to 90% were enrolled. There were six anatomic and one functional CCTA descriptors developed. To determine out which descriptors helped identify ischemia-related lesions, researchers utilised a random Walk technique. Model-1 for anatomical CT descriptors and Model-2 for CT-FFR With anatomical CT descriptors were used to create the ROC curves.

Jiayi Wu et al. [12] For segmentation and diagnosis tasks on BB-VW-MRI images, the Deep MAD network is made up of a segmentation subnetwork and a diagnosis subnetwork, with manual labelled lumen area, manual labelled outer wall area, and manual labelled lesion types based on modified American Heart Association (AHA) criteria serving as ground-truth. A deep U-shape CNN with a weighted fusion layer, segmenting the lumen and exterior wall sections at the same time under the supervision of the triple dice loss, provides the vessel wall map as morphological information.

V. R. Elangovan et al. [13] They demonstrated how to use a hybrid segmentation approach with FCM+kmeans combined segmentation algorithm to perform segmentation techniques to human heart atherosclerosis pictures. One of the key causes of coronary heart disease (CHD) is atherosclerosis. Cardiovascular disorders are major causes of death worldwide. The suggested approach for atherosclerosis segmentation in medical images works better, with benefits such as increased sensitivity, specificity, and accuracy of segmentation. As a result, the new merged algorithm's overall performance metrics.

Proposed Method

The recommended strategy is based on coronary artery medical imaging. The Blood vessels like arteries including all other element of the heart is shown in this diagram. These arteries must be split before they can be processed for stenosis detection. The following is the segmentation procedure:

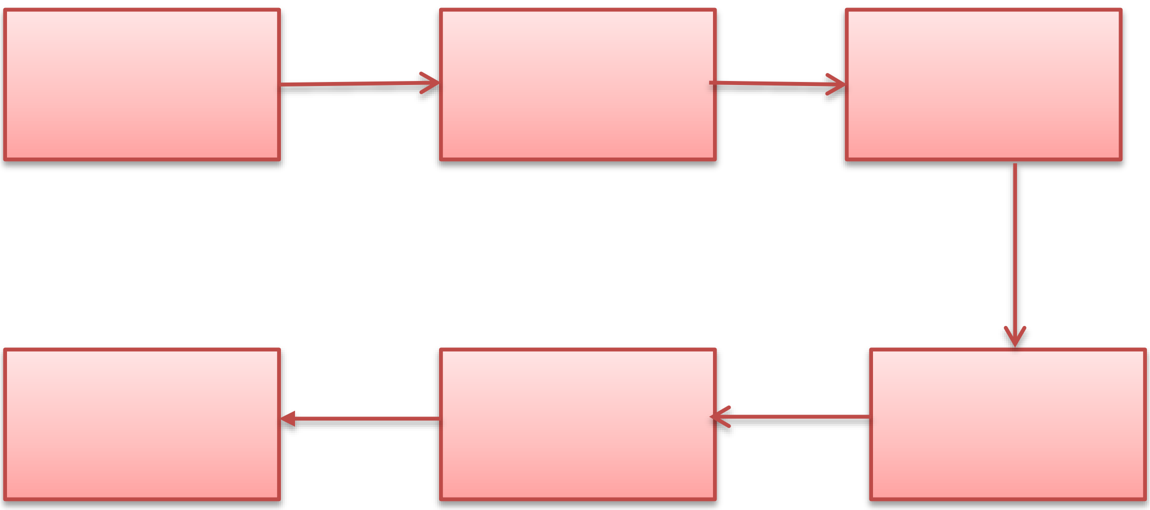

Fig. 3 Proposed Method

Image input

MRI scan image with active blood flow shows actual plague formation in the blood vessel showing atherosclerosis. Since MRI image has be used for processing and detecting atherosclerosis in heart. These images are obtained in jpg format by converting it from DICOM images. Images are appeared to be in gray format and its of variable size according to camera captured or conversion format and methodology.

Fig.4 Input image

Image Preprocessing

Multiple preprocessing techniques are used to the raw picture, making it more suitable for subsequent segmentation. As a result, the system's overall performance increases.

3.2.1 Gray scale conversion

Because input images might be three dimensional or multi plane images, the initial stage in the preprocessing procedure was to convert all input images to grayscale format. Processing time and complexity can be decreased by converting multi-plane images to single plane images. Color information is also not necessary in scan images.

Fig.5 Gray scale converted image

The average of the R, G and B plane pixel values, to convert the color, for example: 0.4R + 0.39G + 0.21B.

Noise removal

The following step in technique is noise reduction. Noise in a picture can develop as a result of the capture, storage, and transmission processes. We performed a performance research on several noise reduction techniques and discovered that the alpha trimmed median filter performs better. A random change in brightness or colour in a picture is referred to as noise. It's the result of a camera or a sensor and scanner circuit.

Alpha trimmed median filter

For monochrome pictures with 24 or 8 pixels per pixel, the alpha trimmed mean filter is a non-linear filter. It makes use of order statistics and may be set up to use a mean or median filter. This filter eliminates both short and long-tail noise, such as Gaussian and salt and pepper noise, as shown in eq. 1.

$$\text{ATMF} = \frac{1}{N-2P+N} \sum_{i=p}^{N+N-P} Ai$$

$$\text{ATMF} = \frac{1}{N-2P+N} \sum_{i=p}^{N+N-P} Ai \qquad (1)$$

Where N is mask square size

Fig.6 Filtered image

Segmentation classification

3.3.1 Random Walk Segmentation

For regression and classification, the Random Walk (RF) approach is utilised. The RF algorithm is a supervised learning approach that makes decisions based on the highest voting output. Furthermore, this approach will choose samples at random from the data and create a decision tree for each sample; as a consequence, the sample's production result will be displayed, and voting on the production result will be implemented. Finally, for classification, the most popular result will be regarded the best, and for regression, the average output of the other trees will be examined.

What are the chances that a random walker starting from this point would be the first to reach each of the k seed spots.

Probability of random walker first reach each of the k seed points.

Graph Gph=(Vij,Eij)

Edge of vertices, Vi, Vj and is denoted by Edge Eij.

Degree of vertices is $D_i = \sum \omega(e_{ij}) D_i = \sum \omega(e_{ij})$ (2)

Assume that this graph is undirected and linked.

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Gaussian weighing function

$$\omega_{ij} = \exp(-\rho(p_i - p_j)^2)$$

$$\omega_{ij} = \exp(-\rho(p_i - p_j)^2) \qquad (3)$$

$\rho\rho$ = a free parameter.

$p_i p_i$= intensity of image pixel. Using

link the picture intensities to the lattice's edge weights

Either interactively or automatically, Pixels are marked with k label and a collection of Vm obtain.

Solve

$$L_u X = -B^T M L_u X = -B^T M \qquad (4)$$

just for the sake of potentials or for the sake of resolving

$$L_u X^8 = -B^T M^8 L_u X^8 = -B^T M^8 \qquad (5)$$

with the exception of the final label,

Give each node, V i, the label that corresponds to max 8 (x i8) to get the final segmentation.

Assign an unseeded pixel to a label in a weighted graph.

Assign the pixel label s if a random walker departing the pixel is most likely to arrive at a bearing label first.

If the seeds are replaced by grounds, assign the pixel to the label with the greatest accuracy while the seeds are "on."

Fig.7 Random walk Segmented image

Particle Swarm Optimization

PSO is a population-based evolutionary computing technique that makes use of biological processes' cooperative and social features. Individuals (or particles) in a population (or swarm) are iteratively moved across the search space until the best solution is found. Particles in the PSO method are made up of cells known as positions. The swarm formed by these particles splits at random in the solution space. The solution set includes every particle in the swarm. The best values of each particle in the swarm, as well as the swarm itself, are aggregated and employed in the following phase to get optimum values.

PSO begins with a set of random particles (solutions) and iterates over generations to find the best one. Each particle is updated every cycle by comparing two "best" values. Currently, the first option (fitness) is the most effective. (In addition, the fitness value is kept.) pbest is the name given to this integer. Another "best" value recorded by the particle swarm optimizer is the best value reached so far by each particle in the population. Gbest, which stands for "global best," is the highest value. When a particle utilises the population as its topological neighbour, the best value is a local best, denoted by lbest.

The particle adjusts its velocity and locations using equations (7) and (8) after selecting the two optimum values (8)

$$v[i] = v[i-1] + c1 * rand(i) * (pbest[i] - present[i]) + c2 * rand(i) * (gbest[i] - present[i])$$

$$v[i] = v[i-1] + c1 * rand(i) * (pbest[i] - present[i]) + c2 * rand(i) * (gbest[i] - present[i]) \qquad (6)$$

$$present[i] = persent[i-1] + v[i-1]\, present[i] = persent[i-1] + v[i-1] \qquad (7)$$

The particle velocity is v[i], and the current particle is persent[i] (solution). As previously mentioned, pbest[i] and gbest[i] are defined. A random number between 0 and 1 is called rand (i). (0,1). Learning factors c1, c2. In most cases, c1 = c2 = 2.

Fig.8 PSO Segmented image

RWPSO – Proposed Algorithm

RWPSO (Random Walk particle Swarm Optimization) is a Random Walk and particle Swarm Optimization combination algorithm.

Gaussian weighing function

$$\omega_{ij} = \exp(-\beta(g_i - g_j)^2)$$

$$\omega_{ij} = \exp(-\beta(g_i - g_j)^2) \quad (9)$$

β= the only variable that may be changed.

$g_i g_i$= represents the pixel's picture intensity.

Using

$$\omega_{ij} = \exp(-\beta(g_i - g_j)^2)$$

$$\omega_{ij} = \exp(-\beta(g_i - g_j)^2) \quad (10)$$

link the picture intensities to the lattice's edge weights

Either interactively or automatically, Pixels are marked with k label and a collection of Vm obtain.

Set $x_i^{-1} = 1 - \sum_{8<f} x_i x_i^{-1} = 1 - \sum_{8<f} x_i$

(11)

Obtain final segmentation by assigning to each node, $V_i V_i$, the label corresponding to $max_8(x_i^8)$ $max_8(x_i^8)$

Given a weighted graph, assign an unseeded pixel

$$v[i] = v[i-1] + c1 * rand(i) * (pbest[i] - present[i]) + c2 * rand(i) * (gbest[i] - present[i])$$

$$v[i] = v[i-1] + c1 * rand(i) * (pbest[i] - present[i]) + c2 * rand(i) * (gbest[i] - present[i])$$

(12)

$$present[i] = persent[i-1] + v[i-1]\, present[i] = persent[i-1] + v[i-1] \quad (13)$$

The particle velocity is v[i], and the current particle is persent[i] (solution). As previously mentioned, pbest[i] and gbest[i] are defined. A random number between 0 and 1 is called rand (i). (0,1). Learning factors c1, c2. Typically, c1 = c2 = 2.

to a label.

Fig.9 RWPSO Iteration

Assign the pixel label s if a random walker departing the pixel is most likely to arrive at a bearing label first.

If the seeds are replaced by grounds, assign the pixel to the label with the greatest accuracy while the seeds are "on."

The pixel is awarded to the label with the highest successful seed placement.

If a 2-tree is randomly selected from the graph, assign the pixel to the label with which it is most likely to remain related. The particle adjusts its velocity and locations using equations (a) and (b) once the randomwalker method finds the optimal values (b)

Fig.10 Segmented image

Results and Discussion

For Segmentation performance measurements, success criteria such as Accuracy, Precision, and recall are calculated and shown in Table 1. Calculation formulas are given

Table 1. Comparison of Hear Atherosclerosis segmentation based PSO, Random Walk and RWPSO.

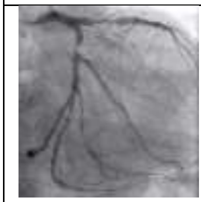
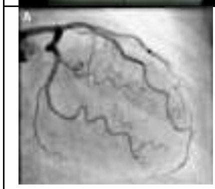
Input Image	proposed RWPSO iteration	RWPSO	RANDOM WALK	PSO
				
				
				

Table 1 (Continued)

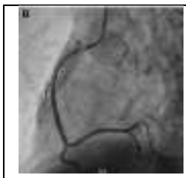
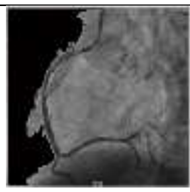
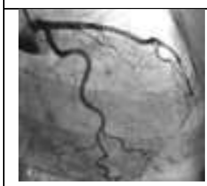
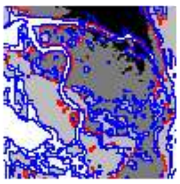
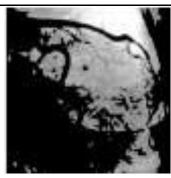
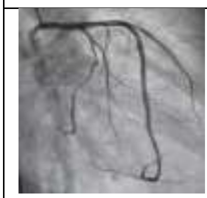
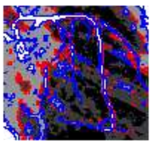
				
				
				
				

Table2 Feature comparison on all three algorithms

	Random Walk		PSO		RWPSO	
	IMG1	IMG2	IMG1	IMG2	IMG1	IMG2
Blood vessel (pixel density)	0.0087	0.0073	0.0083	0.0042	0.0321	0.0808
Pixel Count	571	481	1297	273	457	505
Energy	1	0.9837	0.4330	0.9748	0.9216	0.8816
Contrast	0	0.0138	0.1004	0.0991	0.1214	0.2739
Homogeneity	1	0.9991	0.9836	0.9982	0.9756	0.9951
Correlation		0.9428	0.9358	0.9489	0.9497	0.95044
Kurtosis	15.0482	2.8782	23.6350	11.8701	12.8780	2.6094
Skewness	1.7326	1.0226	0.7310	3.0782	1.2347	0.9370
Standard Deviation	21.2061	11.0461	17.9654	11.9945	21.1867	11.0501
Covariance	2.3835e+06	1.4151e+05	1.7718e+06	1.7498e+05	1.8187+e05	1.4125e+05
Mean	10.2935	1.0748	27.4796	1.4634	2.8754	1.1024
Major axis length	38.0145	35.7636	73.2495	32.0242	38.8402	36.726
Minor Axis Length	27.6619	28.5453	23.3504	25.3783	27.2503	28.066
Eccentricity	0.6859	0.6024	0.9478	0.6099	0.7756	0.64498

The above features are extracted with segmented images of all the three algorithms RW, PSO and RWPSO andthose features are compared against one other where blood vessel pixel density, corellation, and contrast of proposed RWPSO is higher than ithers and Kurtosis, Homogenity, and energy is lower than others. This shows that our proposed method gives good feature on segmentation.

Conclusion

Medical photographs are critical in enabling health care practitioners in gaining access to patients for diagnosis and treatment. In this work, we devised and tested a new computer-based approach for segmenting atherosclerosis in the heart. The use of computer-aided diagnostic technology to segment coronary arteries is therapeutically relevant for detecting and treating coronary heart disease early. In medical image analysis, segmentation is a highly linked process. In this paper, we used RWPSO (Random Walk Particle Swarm Optimization) segmentation method by combining Random Walk and Particle Swarm Optimization algorithm. By using RWPSO segmentation on medical images have better Accuracy for Heart Atherosclerosis detection than existing methods. So RWPSO segmentation proposed method is better than other existing methods.

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