

Research Article

3D Coronary Artery Reconstruction using SVM

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Abstract: Coronary arteries are the vascular structures that supply blood to the heart muscle. Identification of anomalies in the coronary arteries from the 2D slices is a challenging and time consuming process. Segmenting the coronary arteries from the 2D slices and reconstructing into 3D images help in analyzing abnormalities and enable easy diagnosis for medical experts. Hence in this research work, we propose an automated system that extracts coronary arteries from 2D slices of Computed Tomography Angiography (CTA) images using machine learning techniques and reconstruct them into 3D coronary artery tree. Our proposed method extracts statistical features from the arteries and classifies them as coronary and non-coronary arteries using Support Vector Machine (SVM). Classified coronary arteries from 2D slices are reconstructed into 3D coronary artery tree using Maximum Intensity Projection (MIP) algorithm. The performance of our proposed technique is evaluated using Structure Similarity Index Metric (SSIM).

Keywords: Classification, coronary artery segmentation, machine learning technique, MIP, reconstruction, SVM

INTRODUCTION

Cardiovascular Diseases (CVD) are life threatening diseases in the world which includes high blood pressure, Coronary Heart Disease (CHD), congestive heart failure, stroke and congenital cardiovascular defects. Among these, CHD is more prevalent than other diseases. Several imaging techniques are available for diagnosing CHD, Han *et al.* (2008) has proposed Computed Tomography Angiography (CTA) as the best imaging modality. CTA provides greater details about soft tissues and blood vessels and produces multiple images for an organ called as slices. Even though it produces greater details, diagnosing diseases from 2D slices is a complex task. Each 2D axial slice consists of coronary arteries and non-coronary arteries such as aorta, pulmonary artery and veins. The coronary arteries are the vascular structures which supply blood to the heart. Identification of anomalies in the coronary arteries from the 2D slices is very important. So, we propose an automated system which identifies, segments the coronary arteries from 2D axial slices and reconstructs 3D coronary artery tree for easy diagnosis.

LITERATURE REVIEW

During the recent years, segmentation and reconstruction of coronary arteries have played an important role in diagnosis and analysis. An approach for 3D segmentation and reconstruction of coronary arteries from CT images was proposed by Yang *et al.*

(2004). Based on a priori knowledge obtained via Bayes' rule and Maximum posterior voxels were classified as blood-filled regions, lung or myocardium. Arteries in the blood filled region were segmented using active contour model. Kurkure *et al.* (2010) have proposed supervised two stage hierarchical classifier to detect the coronary calcifications in CT images. The method discriminates arterial (coronary and aortic) calcifications among the candidate regions and in the second level the method distinguishes the coronary calcifications from the aortic calcifications. Plourde and Duong, (2012) used machine learning approach to make better Hessian based coronary artery extraction from angiograms. The method divides images into patches of different sizes and extracts features using contour profiling algorithm and classifies using SVM.

Sharma *et al.* (2014) have proposed a work to detect brain tumour based on machine learning algorithms. Texture based features are extracted using Gray Level Co-occurrence Matrix (GLCM) and tumours are classified using Multi-Layer Perceptron and Naive Bayes algorithms. A method for classifying MRI images of brain with neurological diseases such as Alzheimer's Disease (AD) and Autism Spectrum Disorder (ASD) was proposed by Varol *et al.* (2012). Image voxels are ranked based on the voxel wise t-statistics and images are trained using SVM classifier. Liu *et al.* (2012) have presented a hybrid method which used wavelet transform to remove noise and features were extracted with Gabor wavelets along with shape information from T1-weighted MR images and SVM was used to segment tumour.

Manavalan and Thangavel (2011) used clustering with morphological operators to extract the prostate region. They used different Gray Level Co-occurrence Matrix (GLCM) for various distances and directions to extract texture features. They have used SVM to classify the images as benign or malignant using the extracted features. Rahman *et al.* (2010) have proposed a novel image segmentation method to segment left coronary arteries of heart by incorporating statistical information along with structure using Bayesian rule.

Hu *et al.* (2010) have proposed a solution for 3D reconstruction and interaction of medical images. The 3D reconstruction of head, ankle, knee and pelvis was done using marching cube algorithm. Wang *et al.* (2010) have discussed in their work, choosing an appropriate threshold of non-transparency and terminating the calculation when opacity greater than threshold can improve ray-casting algorithm for segmenting the intestine (ROI). Huang *et al.* (2011) have discussed the surface and volume rendering methods based on the VTK and also discussed the initial roaming function based on the information from views. Schroeder *et al.* (2000) have elaborated the basic concepts behind VTK and also provides a overview of the system that helps developers to incorporate VTK in any application. A system for 3D ultrasound image reconstruction for analysis purpose was discussed by Hafizah *et al.* (2010). 3D reconstruction was done using surface reconstruction algorithm like contour filtering and marching cube algorithm and comparison was done. Results proved that marching cube provides better results than the contour filtering algorithm.

In this research work, blobs are segmented from 2D axial slices of CTA images and features are extracted from the blobs. The statistical features such as position, mean intensity, Hu Moments and texture features using Gabor filter are extracted from the segmented blobs and formed as feature vectors. These feature vectors are used to train SVM for classification of blobs into coronary and non-coronary arteries. Marching cube algorithm is applied with the help of VTK pipeline for visualization of arteries. The classified coronary arteries from the slices are reconstructed using Maximum Intensity Projection (MIP) algorithm into 3D coronary artery tree. The reconstructed images are rotated at different angles to generate different projection images of the arteries. These projection images help in diagnosing the abnormalities present in the arteries.

Background: The objective of the research work is to classify and segment the coronary arteries from 2D axial slices of CT images. The classified arteries are reconstructed and rendered based on the volume rendering technique.

Support vector machine: SVM is a machine learning technique used for classification. SVM is a binary classifier and can be extended for multi-class problems. Vapnik (1998) stated that SVM takes labelled data from two classes and generates a model file for classifying the

unlabeled data. SVM separates the two classes with the help of hyperplane which may be linearly separable or non-linearly separable was proposed by Osuna *et al.* (1997). For linearly separable case, the SVM finds the hyperplane that separates the two classes with largest margin using the function:

$$f(x) = wx + b$$

where, w is the weight vector and b is bias. Many hyperplanes may separate the two classes but there is only one optimal hyperplane that best separates the data. The optimal hyperplane is the one with maximum margin between two classes. The support vectors are those that lie close to the decision boundary or the optimal hyperplane which is given by:

$$wx_i + b = \pm 1$$

The optimal hyperplane can be found using Lagrangian formulation and can be written as:

$$f(x) = \sum_{i \in S} \lambda_i y_i (x_i \cdot x) + b$$

where, S is a subset of training sample and are called as support vectors.

Maximum Intensity Projection Algorithm (MIP): 3D reconstruction and visualization of medical images helps clinicians to observe abnormalities in the structures and their positions for diagnostics and treatment. The multi-level and multi-angle view of the anatomy helps doctors to improve the diagnosis. For better visualization and diagnosis, the 3D images are created from 2D slices using 3D image reconstruction techniques. The reconstruction is done by arranging the 2D slices exactly with real spatial positions and can be rendered using rendering technique. The reconstruction algorithm represents the pixels as cube like blocks called voxels. Each voxel is associated with some measured properties of the original object such as transparency, luminosity, density, flow velocity or metabolic activity as proposed by Shahidi *et al.* (1996). The volume rendering techniques represents a volume of data in a bidimensional (2D) plane, preserving the spatial relationships of data was proposed by Pavone *et al.* (2001). To process the CT volumetric data many techniques are available.

The simplest process is to extract one single parameter of the volumetric data by projecting either of the following voxels among set of voxels as proposed by Perandini *et al.* (2010). When the highest Hounsfield value voxels are projected then the projection is called as Maximum Intensity Projection (MIP) or when the lowest Hounsfield value voxels are projected the projection is called as Minimum Intensity Projection (MinIP) and when the median Hounsfield value voxels are projected then they are said to be Average Intensity

Projection (AIP). These projections produce two-dimensional (2D) reconstructions highlighting a desired structure.

MIP is a volume rendering technique, enables the detection of highly intense structures. MIP creates series of 2D images generated from 3D reconstruction by selecting and projecting the voxel with the highest attenuation value at each of several viewing angles. Each angular view in MIP defines 2D projection plane. Let I be the input grayscale 3D image of size $(m*n*1)$. For every pixel in the viewing plane a ray is cast through the volume and the voxel with the highest intensity value is projected onto the viewing plane at that pixel position. Let $D_0, D_1, D_2, \dots, D_N$ are the pixels along the casted ray in the volume image then pixels with highest pixel value is projected onto the viewing plane:

$$\text{value} = \max(D_0, D_1, D_2, \dots, D_N)$$

Let X, Y and Z be the output images representing the maximum intensities in x, y and z directions. X is a 2D image of size $(y*z)$ formed by viewing along the x -axis and selecting the high intensities in the y - z plane. Y image is of size $(x*z)$ formed by viewing along the y -axis and selecting highest intensities in the x - z plane. Similarly, Z image is formed by viewing along the Z axis and selecting highest intensities in the x - y plane and is of size $(x*y)$.

MATERIALS AND METHODS

Proposed methodology: The proposed system consists of three different phases namely segmentation of blobs in the 2D axial slices, classification of coronary arteries in the segmented blobs using supervised learning technique and reconstructing the segmented coronary arteries to 3D. The architecture diagram of the proposed methodology is depicted in Fig. 1.

Segmentation and classification: The axial slices of the CTA image of heart consists of coronary arteries and non-coronary arteries namely aorta, pulmonary artery

and veins. The coronary arteries consist of two main branches Left Coronary Artery (LCA) and Right Coronary Artery (RCA) which supplies blood to the heart muscle. Any coronary artery disorders or diseases can have serious implications on the heart. To identify the diseases in the coronary arteries it is necessary to reconstruct 3D coronary artery by identifying the coronary arteries in each slice.

For better classification, the noises present in the slices are removed by smoothening using Gaussian filter. Detection of ascending aorta and removal of it is the first step in this process. Using a Hough transform hyper-intense circles are detected and its center and radius of the circle is obtained. Using the center, a region growing algorithm is applied and aorta is segmented from the original slices. This process continues for all slices until the detected circle deviates from previous circle locations or if no circles are present. After removal of aorta connected components analysis is done, which scans the image and groups the pixels based on the intensity values which are called as blobs. From the identified blobs the largest blob is removed since pulmonary vein is the largest organ. The remaining blobs consist of both coronary and non-coronary arteries from which coronary arteries alone are to be identified and segmented. To classify the blobs as coronary and non-coronary arteries features such as position of the blob, mean intensity value of each blobs, Hu Moments and texture features using Gabor filter are extracted from the blobs.

Location: The position of each blob with respect to aorta is stored.

Mean intensity: Coronary arteries are considered to be brighter than other non vascular structures. So the mean intensity value of each blob is extracted.

Let b_1, \dots, b_n be the no of blobs in each axial slices. The mean intensity value of each blob is given by:

$$b_i(\text{Avg}) = \sum_{m=1}^N \frac{b_m}{N}$$

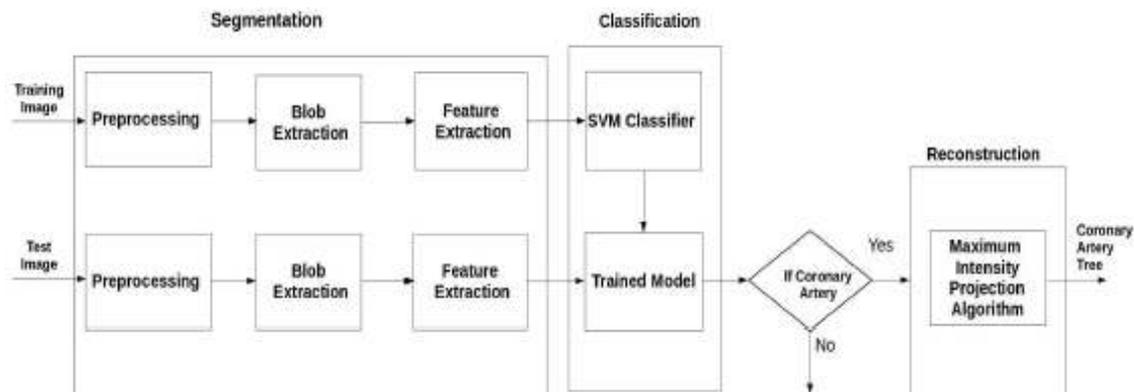


Fig. 1: System architecture

where, m is the pixel value and N is the number of pixels in the blob.

Hu moments: Moment invariants have been extensively applied in image pattern recognition, registration, reconstruction etc. as proposed by Huang and Leng (2010). Hu (1962) first introduced moment invariance and derived six absolute orthogonal invariants and one skew orthogonal invariant based upon algebraic invariants. Hu moments are not only independent of position, size and orientation but also independent of parallel projection. All the seven Hu moments which are based on normalised central moments were used as shape descriptors.

Texture: The variation in the intensity of surface can be quantified by the properties such as regularity, smoothness and coarseness which can be described by texture of the structure. Jain and Farrokhnia (1990) have discussed Gabor filter as a linear filter which is appropriate for texture analysis. The general function $g(x, y)$ of the two dimensional Gabor filter can be represented as follows:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[\frac{-1}{2}\left(\frac{\bar{x}^2}{\sigma_x^2} + \frac{\bar{y}^2}{\sigma_y^2}\right)\right] \exp[2\pi W(\bar{x})]$$

$$\bar{x} = x\cos(\theta) + y\sin(\theta)$$

$$\bar{y} = -x\sin\theta + y\cos\theta$$

where,

σ_x, σ_y = The scaling parameters of the filter

W = The center frequency

θ = The orientation of the filter

Texture features are extracted by convolving the blob b_i with Gabor filter $g(x, y)$. Gabor filter with 2 scales and 3 orientations are applied. Mean and standard deviation of different scale and orientation are taken as features of the blobs.

Statistical model is created by training SVM using extracted features from the segmented blobs. The created statistical model is used to classify the extracted blobs as coronary or non-coronary arteries. The classified coronary arteries alone are reconstructed using reconstruction algorithm.

Reconstruction: The 2D slices of the coronary arteries are stacked in same spatial position which produce 3D volume. This 3D volume has been rendered using MIP algorithm, by projecting the voxels with maximum intensity in the visualization plane. Thus the 2D projection images of the coronary arteries are created from 3D reconstructed images. To create different

projection images of the arteries the created volume is rotated in different angles.

The algorithm of the proposed method is explained below:

1. Let S be the set of slices of a patient.
 2. for all slice s_j in S where $j = 1 \dots n$ do
 3. Apply the Gaussian filter to get the smoothen image
 4. Apply Hough transform to detect the aorta center and radius in the slices
 5. Apply region growing algorithm and segment the aorta from the slices
 6. Apply connected component to the slices and detect the blobs b_k , where $k = 1 \dots m$ are the no of blobs in the slices.
 7. for each blob b_k extract the following features
 - a. Estimate the position of the blob b_k with respect to the aorta.
 - b. Estimate the mean intensity value $b_i(\text{Avg})$.
 - c. Estimate the Hu Moments b_{hu} .
 - d. Estimate Mean and standard deviation for different scale and orientation of the gabor filter $b_{g(x,y)}$.
 end for
 8. Classify the blobs as coronary and non-coronary arteries using the model built by SVM.
 9. Reconstruct the classified coronary arteries using Maximum Intensity Projection Algorithm.
- end for

Repeat steps 1 through 9 for all the patients.

EXPERIMENTAL RESULTS

Experiments were carried out by collecting 2D axial slices of CTA images of 15 different patients from Billroth hospitals, India, in DICOM format. For each patient there are about 220 to 230 axial slices. The images were obtained from SOMATOM 64-slice CT scanner. The DICOM images were converted to TIFF format using Osirix software. The segmented blobs were classified as coronary or non-coronary arteries using LibSVM tool. Visualization Tool Kit (VTK) pipeline is developed and implemented for 3D visualization of segmented arteries. The proposed system was implemented using OpenCV. Performance analysis of the reconstructed images was done with the ground truth created by the medical experts.

Training and Testing of the classifier: Training data were prepared with known labels created with the help of medical experts from the slices of different patients. The training was done using 1500 blobs of non-coronary arteries and 1600 blobs of coronary arteries from six different patients. The statistical features were extracted from the training set and stored in the feature

vector and these feature vectors were used to train SVM. To test the built model, features were extracted from five different patients that were not part of the training set. In this study we have used LibSVM tool introduced by Chang and Lin (2011) for classification. We have used Radial Basis Kernel function (RBF) to train the SVM. To validate the consistency of the classifier cross validation technique was used. The K-fold cross validation divides the training set into k-subset of equal sizes. During first iteration one subset was used for testing and remaining k-1 subsets were used for training. Similarly during the kth iteration, kth subset was used for testing and remaining k-1 were used for training. In the literature 10-fold cross validation was commonly used so we have also used 10-fold cross validation to evaluate the performance of the classifier. With 10-fold cross validation we have obtained cross validation rate of 97.2%. To evaluate the performance of the proposed method we have used precision, recall, accuracy and F1-Score as evaluation criteria.

The formula for calculating precision, recall and accuracy values are presented below:

$$\text{Recall}(r) = \frac{\text{True Positives}}{\text{Total No.of Positive Samples}}$$

$$\text{Precision}(p) = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Accuracy}(acc) = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total No.of samples}}$$

$$\text{F1Score}(F1) = \frac{(2 * p * r)}{(p + r)}$$

Reconstruction: The arteries which are classified as coronary arteries by the classifier for a particular patient are reconstructed. Along with the extracted features position of the blob and slice number where the blob is present is also recorded. The coronary arteries are thus segmented and are saved based on the above information. Thus n different slices with only coronary arteries maintained in the same position as the original slices are created.

These slices are given to the MIP algorithm for reconstruction of 3D volume and renders 2D projection images by projecting the voxels with high intensity onto the viewing plane. These projection images are rotated at different angles and saved in different viewing positions. Thus different projection images are created that help the clinician to diagnose abnormalities in the coronary arteries. The reconstructed output was evaluated using Structure Similarity Index (SSIM) value between the reconstructed images and the reconstructed images obtained from medical experts using MIP. The

SSIM assesses three terms between the reconstructed image x and ground truth image y produced by medical experts. The luminance $l(x, y)$, contrast $c(x, y)$ and structure $s(x, y)$ are given by:

$$l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

$$c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

$$s(x, y) = \frac{\sigma_{(xy)} + C_3}{\sigma_x + \sigma_y + C_3}$$

where, $C_1 = (K_1 L)^2$, $C_2 = (K_2 L)^2$ and $C_3 = (C_2/ 2)$ are small constants

L is the dynamic range of pixel values and K_1 and K_2 are scalar constants. The constants C_1, C_2, C_3 provide spatial masking properties and ensure stability when the denominator approaches zero. Combining these three terms the general form of SSIM is:

$$\text{SSIM}(x, y) = \frac{((2\mu_x\mu_y + C_1)(2\sigma_{(xy)} + C_2))}{((\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2))}$$

RESULTS AND DISCUSSION

The objective of this research work is to extract all coronary arteries since missing coronary arteries leads to poor reconstruction of coronary artery tree. Hence the recall rate should be higher. The classification results of our proposed method are shown in Table 1.

From Table 1 it is evident that the proposed method produces high recall rate. This shows that all coronary arteries are almost detected and only few non-coronary arteries are misclassified as coronary arteries. This misclassification is due to the creation of model with different patients. Since the position and size of the heart varies from patients to patients so that the imaging quality also differs that makes difficult in distinguishing the coronary and non-coronary arteries. The similarity value of five different patients' test images in different rotation angle (60, 120, 240) is listed in Table 2. Higher the SSIM measure greater similarity exists between the images.

We observe from the Table 2 that the value of the index lies between 88 and 94%. This shows a higher level similarity exists between the ground truth image and our reconstructed image. The reconstructed image of a patient is shown below Fig. 2.

Table 1: Results of the test image for different patients

	p (%)	r (%)	acc (%)	F1 (%)
P1	91	100	92.8	95.3
P2	94	95	94.85	94.4
P3	94.39	95.8	95.31	95.08
P4	96.8	98.8	97.6	97.8
P5	93.2	95.6	97.6	94.4

Table 2: Results of SSIM values for different patients for different rotation angle

	R1 (%)	R2 (%)	R3 (%)
P1	90.83	89.21	88.99
P2	89.31	88.78	87.76
P3	90.05	87.05	89.98
P4	93.25	91.05	88.68
P5	88.08	93.96	89.23

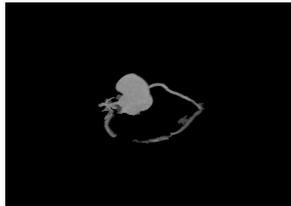


Fig. 2: Reconstructed image

CONCLUSION AND RECOMMENDATIONS

We have proposed a novel method for segmenting and reconstruction of coronary arteries in 3D from 2D slices of CTA images. The extraction of coronary arteries is achieved by classifying the coronary arteries and non-coronary arteries using SVM by extracting the features from the 2D slices of CT images. The MIP reconstruction algorithm is then used to develop the 3D geometric model which provides a comprehensive view of the vascular structures for accurate analysis and diagnoses. Our proposed methodology produced greater than 95% of accuracy for most of the patients and also we have obtained better SSIM values when compared with the ground truth. Future works involves improving the SSIM value by attaining recall value of 100% and also reducing number of false positives. We are also planning to extend the work by measuring clinical parameters from the 3D models so as to estimate the presence of stenosis.

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