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Automatic Active Contour-Based Segmentation and Classification of Carotid Artery Ultrasound Images

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Abstract In this paper, we present automatic image segmentation and classification technique for carotid artery ultrasound images based on active contour approach. For early detection of the plaque in carotid artery to avoid serious brain strokes, active contour-based techniques have been applied successfully to segment out the carotid artery ultrasound images. Further, ultrasound images might be affected due to rotation, scaling, or translational factors during acquisition process. Keeping in view these facts, image alignment is used as a preprocessing step to align the carotid artery ultrasound images. In our experimental study, we exploit intima–media thickness (IMT) measurement to detect the presence of plaque in the artery. Support vector machine (SVM) classification is employed using these segmented images to distinguish the normal and diseased artery images. IMT measurement is used to form the feature vector. Our proposed approach segments the carotid artery images in an automatic way and further classifies them using SVM. Experimental results show the learning capability of SVM classifier and validate the usefulness of our proposed approach. Further, the proposed approach needs minimum interaction from a user for an early detection of plaque in carotid artery. Regarding the usefulness of the proposed approach in healthcare, it can be effectively used in remote areas as a preliminary clinical step even in the absence of highly skilled radiologists.

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Introduction

Carotid arteries are main blood suppliers to the brain. Narrowing of carotid artery generally blocks the blood flow into the brain and thus may cause a serious brain stroke. Consequently, early detection of the plaque in the arteries may help in preventing brain strokes. Noninvasive diagnostic techniques in medical profession are invaluable. Ultrasound imaging is an attractive technique due to its noninvasiveness. However, ultrasound images are of poor quality due to the presence of speckle noise and wave interferences. As a result, carotid artery ultrasound images need considerable efforts from radiologists to detect the plaque. Further, manual intima–media thickness (IMT) measurement produces results that may not be reproducible. Thus, a computer-aided diagnostic (CAD) technique for segmentation, plaque detection, IMT measurement, and classification of segmented images is highly desirable for carotid artery ultrasound images. This may help the medical experts to extract significant information about the plaque in determining the stage of disease [1, 2].

Most of the CAD techniques require user intervention at certain level. Sometimes intervention from an inexperienced user may lead to false results. Snake-based method [3], dynamic programming [4], and combination of both [5] have been used for automatic IMT measurement. In [6], authors have proposed a semiautomatic snake-based method for the segmentation of carotid artery images. In their approach, a seed point is needed from the user to segment lumen of the carotid artery. Special care is required during seed point initialization since inappropriate snake initialization may lead towards misleading results. This seed point selection is the basic shortcoming of the snake-based method. One of the major contributions in this research work is an automatic initialization of snakes to segment the carotid artery ultrasound images.

In this work, we have developed an automatic technique for carotid artery ultrasound image segmentation, based on active contour approach followed by classification through support vector machine (SVM). The possible presence of plaque depends upon the thickness of the arterial wall. IMT measurement is used to assess the thickness of arterial walls. Decision about normal or abnormal carotid artery is based on IMT measurements. In this experimental study, we have employed SVM for classification of normal and diseased carotid artery images. Four different features are extracted from the IMT values and a feature vector is formed to train and test the SVM classifier. Experimental results show the effectiveness of the proposed methodology.

Rest of the paper is organized as follows. First, The Proposed Approach Section describes the proposed approach. Results and Discussion Section then presents the experimental results and discussion. Finally, conclusions and future work are described in Conclusions Section.

The Proposed Approach

The proposed scheme of automated carotid artery image segmentation and classification consists of the following steps: dataset acquisition, preprocessing, image alignments, carotid artery image segmentation, IMT measurement, and classification of segmented images. The graphical representation of the proposed approach is shown in Fig. 1.

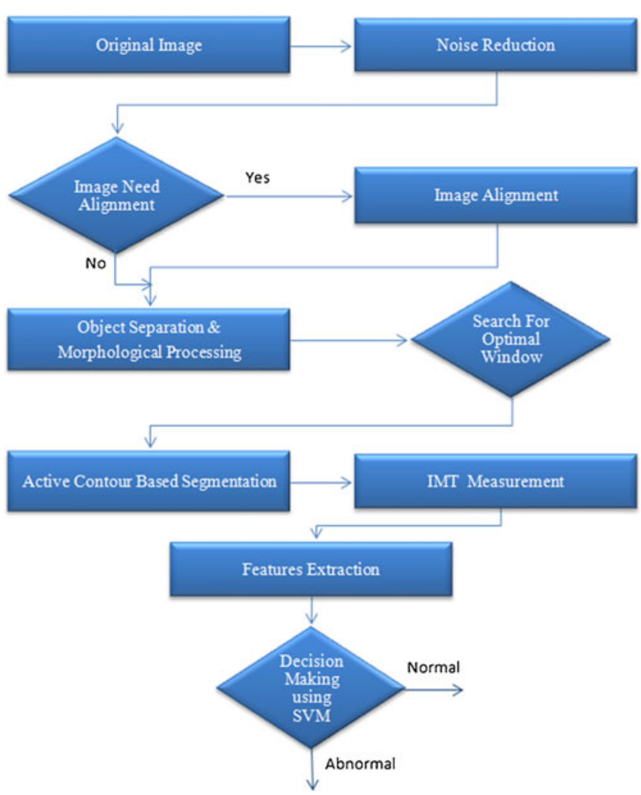

Fig. 1 Flow chart of the proposed approach

Datasets

The dataset is obtained from Shifa International Hospital, Islamabad, Pakistan. Toshiba Xario XG ultrasound machine equipped with linear probe transducer with a frequency range of 7–8 MHz was used in the said hospital for carotid artery ultrasound. The videos were recorded for 10 s and these videos were converted into frames employing video decompiler. Original images have dimensions of 800×600 with resolution of 72 PPI. The images are cropped from borders and converted into grayscale before further processing. These cropped images have reduced dimensions of 350×380. A dataset of 250 (114 normal and 136 abnormal) images has been developed to test the performance of the proposed approach. The age of the patients in the image dataset ranges from 38 to 78 years. Overall mean age and standard deviation for the whole dataset are 60.34 and 8.78 years, respectively. The obtained images have been categorized into normal and abnormal with the help of medical experts. SVM is used for classification of the segmented images. To check the performance of the classifier, classification results were compared against already labeled images. All computations are performed on an Intel Core i7 Pc with Matlab 7.12 (2011a).

We have obtained data from Shifa International Hospital and have carried out an experimental study on human subjects with the permission of concerned management of the hospital. Further, patient's privacy has been protected by labeling the data with numeric dummy values and keeping patients' credential undisclosed.

Image Preprocessing

The major negative aspects of ultrasound images are their poor quality, presence of speckle noise, and wave interferences [7–9]. To obtain better segmented images, noise must be removed. For this purpose, we have used median filter for noise removal as image preprocessing step because in case of carotid artery ultrasound images, it has been observed that it smoothes out noise and preserves image details in better way as compared to average and bilateral filters [10].

Carotid Artery Ultrasound Image Alignment

During our experiments, we have found that all images are not aligned. It is due to the fact that during the imaging process, ultrasound transducer has continuously been moved around the carotid artery. Patient movement is another factor for nonuniform imaging. Ultrasound transducer and patient movement thus result in images which may not be aligned.

It is easy for a human expert to locate the region of interest (ROI) and obtain IMT measurements. However, automatic detection of ROI by computer is not an easy task. It requires aligned images for accurate ROI identification. To handle rotation, translation, and shearing transformation in carotid artery ultrasound images, we have incorporated the image alignment as a preprocessing step in the proposed approach.

The main objective of image alignment is to present two or more images in the same orientation. Usually, one of the undistorted images is taken as a base (reference) image. The image which needs transformation due to any reason is considered as an input. This input image is required to be aligned with reference image before further computation. One of the possible approaches to align the images is the use of control points. These control points are also called corresponding points. Location of the control points should be known in input and reference images. In our approach, we have applied iterative process to select the control points. For example, four control points are selected in both input and reference images, respectively, for estimating the transformation function. The transformation function estimation is one of the modeling problems [11]. The bilinear-based approximation model is given by

$$x = c_1u + c_2w + c_3uw + c_4 \tag{1}$$

and

$$y = c_5u + c_6w + c_7uw + c_8 \tag{2}$$

where (x, y) and $(u, w)$are control point coordinates of reference and input images, respectively. In both images, if we have four corresponding pair points, eight equations have to be defined based on Eqs. (1) and (2). These equations are used to solve eight unknown coefficients $c_1, c_2, c_3, \ldots, c_8$.

The accurate alignment of images is greatly influenced by the selected control points. Inappropriate selection of control points may lead to false results. For accurate control point selection, we have incorporated the concept of spatial information of input control points. In this regard, cross-correlation is calculated between the selected input and reference control points. The advantage of incorporating spatial information is accurate input control point selection and consequently a better aligned image. This accurate image alignment plays a significant role in automated carotid artery image segmentation.

Snake Initialization

The major shortcoming of active contour model is the initialization of snakes [12]. The initial selected window greatly affects the segmentation results. In this paper, window is selected in an automatic way for snake initialization to segment the carotid artery ultrasound image. Snake initialization in an automatic manner is one of the main contributions of this research work. The input to this step is a preprocessed image. Automatic window selection methodology is described in detail in the following subsections.

Separation of Objects from Background

First of all, we have to find the objects in the carotid artery ultrasound image. For this purpose, we have used Otsu's method [13] to separate the objects from the background. The Otsu method is an automatic method of histogram-based thresholding. It is a nonparametric and unsupervised threshold selection method. Our goal is to separate out the objects from background by considering it as a two-class problem. The algorithm calculates optimal threshold to separate the objects from background so that intra-class variance becomes minimal using the following equations:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \tag{3}$$

where σ_i^2 is the class variance, ω_i denotes the probabilities of the classes separated by threshold t. Expression (4) is used to minimize the inter-class variance.

$$\sigma_b^2(t) = \sigma^2 - \sigma_\omega^2(t) = \omega_1(t)\omega_2(t)[\mu_1(t) - \mu_2(t)]^2 \tag{4}$$

where μ_1 and μ_2 are the means of class 1 and class 2, respectively. The probability of class $\omega_1(t)$ is computed from the histogram at t using Eq. (5):

$$\omega_1(t) = \sum_0^t p(i) \tag{5}$$

where $p(i)$ is the probability of a pixel belonging to respective class, whereas the mean of the class is computed using Eq. (6):

$$\mu_1(t) = \sum_0^t p(i).x(i) \tag{6}$$

where $p(i)$ is probability of the variable $x(i)$ in the respective class.

The objects and background are separated from the carotid artery ultrasound images. Some noisy patterns may remain there. These noisy patterns have to be removed by morphological opening operation using expression (7). The morphological opening operation is usually used for smoothing object contours and for elimination of thin protrusions [11]. The opening of f by the structuring element b is denoted by $f \circ b$ and defined as:

$$f \circ b = (f \Theta b) \oplus b \tag{7}$$

where the symbols Θ and $\oplus$ denote the erosion and dilation operations, respectively.

After the morphological opening operation, area inside the artery walls has to be intelligently identified. For this purpose, we take negative of the segmented image using expression (8).

$$s = 1 - r \tag{8}$$

where s is the resultant negative binary image and r is the segmented image using Otsu's approach.

An advantage of image negative is that it can be used effectively in finding the area inside the arterial walls. After finding area inside the artery, the algorithm intelligently decides the location and size of the window for snake initialization. The height of the initial window will be the distance between the upper and lower arterial walls. Location and size of window vary from image to image depending upon the objects in the carotid artery ultrasound images. Once the window is determined, active contour method can successfully be applied to segment the carotid artery ultrasound images.

Segmentation of Carotid Artery Ultrasound Images

In our study, we have employed active contour method to segment the carotid artery ultrasound images in an automatic way. Active contour model is proposed by Kass et al. [14] and is widely used in computer vision applications. It is based on the energy minimization function. The advantage of active contour model for segmentation is that the snakes are autonomous and self-adapting in search of a minimal energy state and can easily be manipulated. The active contour model can be used to track objects in both spatial and temporal domains.

The governing equation of the snake is based on the internal and external energy components. Liang et al. [15] proposed that snake is a time variant parametric curve $\mathbf{v}(\mathbf{s},\mathbf{t}) = (\mathbf{x}(\mathbf{s},\mathbf{t}),\mathbf{y}(\mathbf{s},\mathbf{t}))^{\mathrm{T}}$ located on image surface $(x, y) \in \Omega$, where x and y are coordinate functions depending on the parameter s and t. The expression (9) is used as the governing equation of active contour model.

$$E(\mathbf{v}) = \underbrace{\int_0^L \alpha(s)\left|\frac{\partial \mathbf{v}}{\partial s}\right|^2 + \beta(s)\left|\frac{\partial \mathbf{v}^2}{\partial s^2}\right|^2 ds}_{S(v)} + P(\mathbf{v}) \tag{9}$$

The parameters α and β are used to control the internal energy, and $S(v)$ shows the contour stiffness and elasticity. The gradient of image is calculated to find the external energy $P(v)$. Minimum energy is obtained when contour approaches at the edge of interest.

Practically, N piecewise polynomials are used to assemble the contour. Space-independent shape function like B-spline has been used to build each polynomial [16] weighted by the node parameters. The energy function, expression (9), is minimized corresponding to Euler–Lagrange partial differential equations.

$$\mathbf{M}\frac{d^2\mathbf{u}(t)}{dt^2} + \mathbf{C}\frac{d\mathbf{u}(t)}{dt} + \mathbf{K}\mathbf{u}(t) = \mathbf{q}(\mathrm{t}) \tag{10}$$

where $\mathbf{u}(t)$ is the vector of N terminals and $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ are mass, damping, and stiffness matrices, respectively. The external forces are represented by $\mathbf{q}$ [15].

The motion Eq. (10) is solved with the replacement of time gradients and its discrete approximations. By discretizing time variable t, Eq. (10) results in the following difference matrix equation.

$$\mathbf{F}\mathbf{u}_\xi = \mathbf{A_1}\mathbf{u}_{\xi-1} + \mathbf{A_2}\mathbf{u}_{\xi-2} + \mathbf{q}_{\xi-1} \tag{11}$$

where discrete time is represented by ξ and

$$\mathbf{A}_1 = 2\mathbf{M}/(\Delta t)^2 + \mathbf{C}/(\Delta t), \tag{12}$$

$$\mathbf{A}_2 = -\mathbf{M}/(\Delta t)^2, \tag{13}$$

$$\mathbf{F} = \mathbf{A_1} + \mathbf{A_2} + \mathbf{K} \tag{14}$$

The computational cost of expression (11) is very high because of F inverse calculation. An alternative formulation has been proposed by Weruaga et al. [17] for translation of the energy function (9) in frequency domain. In this procedure, matrix inversion is avoided because in frequency domain, it becomes a point-wise inversion.

To get the final solution smoother, B-splines are utilized as a shape function [15], and at each update of the contour, some additional calculations are performed. To get better execution time ratio, cubic B-splines have been used in this study [18]. Cubic B-spline interpolation technique has been applied at node parameters u to achieve the active contour v.

Classification of the Segmented Images

Carotid artery disease diagnosis greatly depends upon accurate artery image segmentation and classification of the segmented images. Segmented images are classified into normal or abnormal. In this study, we have used SVM classifier for classification of the carotid artery images. Four different features are extracted from the IMT values obtained from carotid artery-segmented images to train and test the SVM classifier.

Feature Extraction

The following four commonly used statistical features are extracted from IMT measurements of the segmented carotid artery image. These features are normalized in the range of [0 1] and then used as input to the SVM classifier. Classification accuracies are observed to be the best using these features for the given dataset. Mathematical description of each feature is as under:

$$\mathrm{Average} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{15}$$

where $\{x_1, x_2, \ldots, x_n\}$ are the observed values and n is the total number of observations.

$$\mathrm{Var(X)} = \frac{1}{N}\mathrm{E}\left[(X_i - \mu)^2\right] \tag{16}$$

where $\{x_1, x_2, \ldots, x_N\}$ are the observed values, μ is the mean of the observed values, and N is the total number of observations.

$$\mathrm{SD} = \sqrt{\frac{1}{N}\mathrm{E}\left[(X_i - \mu)^2\right]} \tag{17}$$

Standard deviation is the square root of the variance defined in Eq. (16).

$$\mathrm{Skewness} = \mathrm{E}\left[\left(\frac{X_i - \mu}{\sigma}\right)^3\right] \tag{18}$$

where μ shows the mean of x and expected value of quantity is represented by E.

SVM Classifier

The SVM classifier is a supervised learning algorithm, which is successfully being used for classification and analysis of data. It is a binary classifier, but with kernel method, it can be utilized for multi-class problem as well. For instance, to classify data in two classes, SVM finds a new hyperplane with the help of support vectors and margins. SVM selects the hyperplane having maximum separation between the classes. Quadratic optimization is used to solve the classification problem. Classification error is minimized at each new training example to find the optimal linear hyperplane [19, 20].

Different kernel functions are available for SVM to classify the data. In the current research, we have used SVM-radial basis function for classification of the segmented images into normal or diseased. LIBSVM 3.11 toolbox is used to train and test SVM [21]. For training and testing the SVM classifier, we have used tenfold cross-validation.

Classification Performance Measurements

In statistical prediction, to check the effectiveness of the method, different types of cross-validation techniques are in practice. Among the cross-validation methods, jackknife is a popular one. It gives unique results for a given dataset. It is being used by the analysts to validate the accuracy of prediction. In our work, we have also used jackknife validation technique to examine the quality of the classifier. According to jackknife test, $N-1$ samples are used for training and one of the data sample is used for testing. The class of the test pattern is predicted by the classifier based on the $N-1$ training samples. The sampling process is repeated for N times and the class of each sample is predicted. The true positive (TP) and true negative (TN) are the number of correctly classified positive and negative classes. The false positive (FP) and false negative (FN) are those images which are incorrectly classified. To evaluate the performance of the classifier, the following measures are used.

Accuracy

This measure is used to assess the overall usefulness of the classifier. Accuracy can be determined by the following expression:

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \times 100. \tag{19}$$

Sensitivity

Sensitivity is used to check the ability of a classifier to recognize the positive class patterns. The following equation is used to calculate the sensitivity of the classifier:

$$\mathrm{Sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \tag{20}$$

Specificity

It is used to check the ability of a classifier to recognize the patterns of negative class. It can be calculated using expression (21).

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{21}$$

Matthews Correlation Coefficient

Matthews correlation coefficient (MCC) is used as a measure of classification in binary classes and have values from −1 to +1. The value +1 means perfect pattern prediction (classifier never commit a mistake), 0 means a random prediction, and −1 means that classifier never predict a correct label. It can be obtained using the following equation:

$$\mathrm{MCC} = \frac{\mathrm{TP} \times \mathrm{TN} - \mathrm{FP} \times \mathrm{FN}}{\sqrt{((\mathrm{TP} + \mathrm{FN})(\mathrm{TP} + \mathrm{FP})(\mathrm{TN} + \mathrm{FN})(\mathrm{TN} + \mathrm{FP}))}}. \tag{22}$$

The F measure

F measure considers precision and recall to measure the accuracy of the test. *F* measure ranging from 0 to 1 is a weighted average of the precision and recall, whereas 0 shows worst score and 1 shows best score. The *F* measure can be calculated using the following formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{23}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{24}$$

$$F\ \text{score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{25}$$

Negative Predictive Value

The negative predictive value (NPV) measure is used to show the performance of the diagnostic testing. High value of NPV illustrates that the probability of a patient becoming free from the disease against the test was conducted [22]. It can be calculated using the following expression:

$$\text{NPV} = \frac{\text{TN}}{(\text{FN} + \text{TN})} \times 100 \tag{26}$$

where TN and FN are true negative and false negative, respectively.

ROC and Area Under the Curve

Receiver operating characteristic (ROC) curve is a graphical representation of true positive vs. false positive rates. It is one of the effective measures in disease diagnostic tests. It has widely been used in radiological tests to evaluate the performance of the medical test. It is usually used for binary class problems. ROC is used to show how an observer performs some detection task. The ROC is obtained utilizing true and false positive rates (1-specificity), which are described in Sensitivity and Specificity Sections, respectively.

Several indices can be associated with ROC in which one popular diagnostic performance measure is area under the curve (AUC) [23]. It is used to measure the overall performance of diagnostic test and represents the average value of sensitivity and all possible values of specificity. Its range is between 0 and 1. AUC value close to 1 shows better diagnostic performance. To check the performance of the proposed approach, we have obtained the ROC and have calculated the AUC.

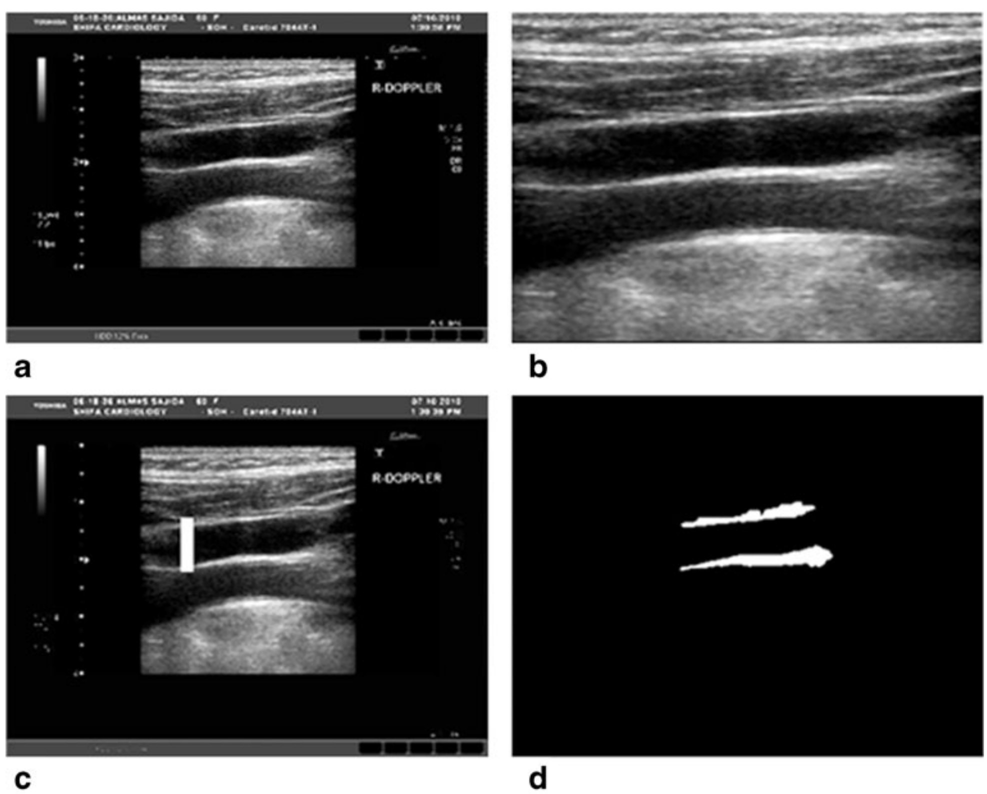

Fig. 2 **a** The original carotid artery ultrasound image. **b** The cropped median-filtered ROI. **c** The automatically selected window for snake initialization. **d** The segmented carotid artery ultrasound image using active contour method

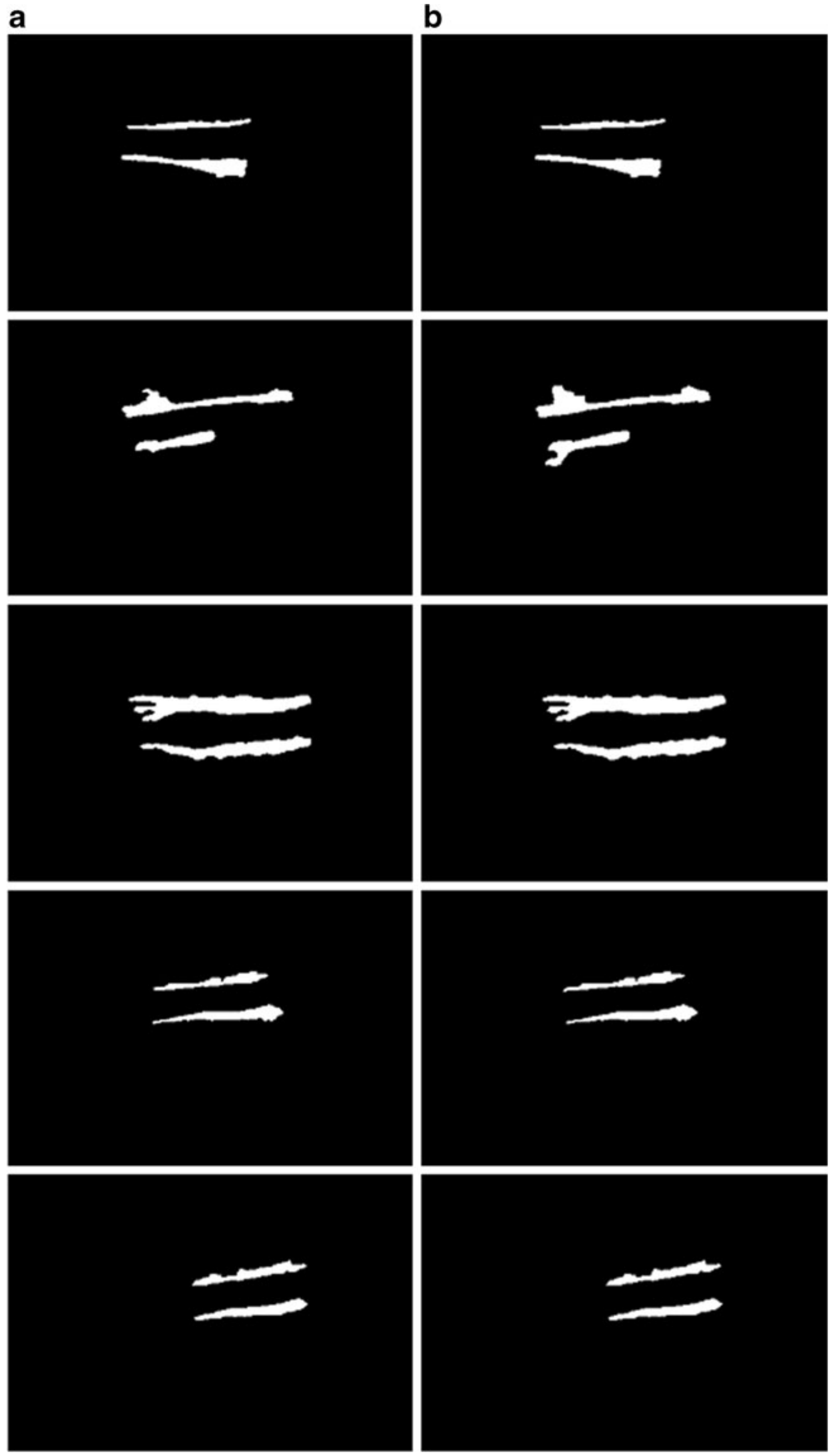

Fig. 3 *Column a* shows segmentation results using our proposed approach of automatic snake initialization and *column b* shows the image segmented by manual initialization of snakes

Results and Discussion

The carotid artery ultrasound images are segmented and classified by our proposed technique. Figure 2a shows one of the original carotid artery ultrasound images. The ROI is selected from the original image. Figure 2b shows the selected ROI. To reduce the speckle noise and wave interferences, median filter is applied on the original image. As described in Snake

Table 1 The IMT measure of upper and lower wall of carotid artery in terms of millimeter

Segmented carotid artery (Fig. 4)	IMT (mm)
Upper artery wall (min)	0.149
Upper artery wall (max)	0.298
Lower artery wall (min)	0.149
Lower artery wall (max)	0.447

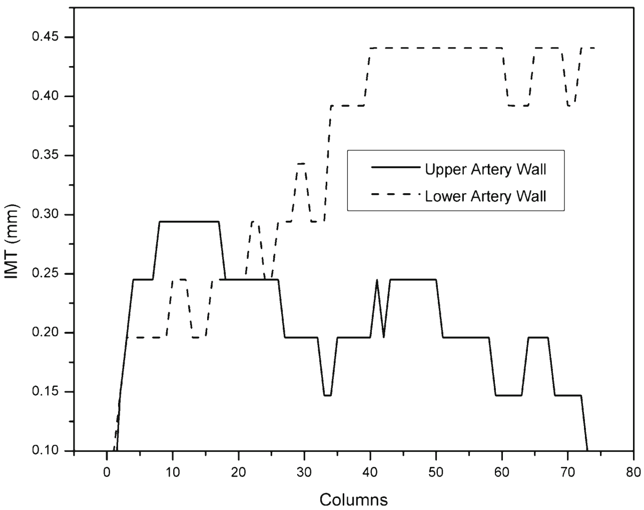

Fig. 4 Graphical representation of IMT measurement of a normal carotid artery ultrasound image

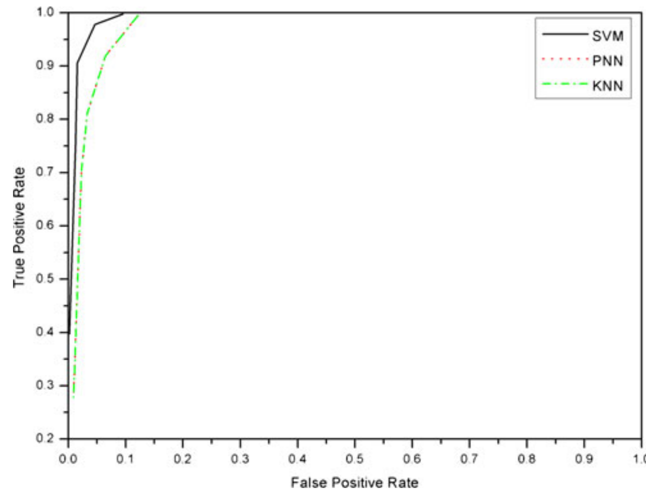

Fig. 5 ROC curves of SVM, KNN, and PNN showing true positive and false positive rates at different thresholds

Initialization Section, a window for snake initialization has been determined automatically using the said procedure. The selected window for snake initialization is shown in Fig. 2c. The carotid artery ultrasound image is segmented using active contour approach as shown in Fig. 2d. From Fig. 2d, it can be observed that the image is segmented accurately by the active contour method. Accurate segmentation of carotid artery ultrasound images using active contour approach greatly depends upon the window initialization. If initialization is done well, one can get significant results. In our proposed approach, we have developed a technique for automatic initialization of snakes to segment carotid artery ultrasound images. As described earlier, manual initialization may lead to false segmented results. Hence, there is need of such a mechanism in which minimum interaction from user is required. Our proposed approach to segment the carotid artery ultrasound images is automatic and hence no user intervention is required.

A comparison of manual and our proposed approach of automatic snake initialization have been made for segmentation of carotid artery ultrasound images. The proposed approach shows promising segmentation results for carotid artery ultrasound images. Figure 3 column a shows the carotid artery images of different patients segmented by our proposed approach using automatic initialization of snakes and Fig. 3 column b shows results through manual snake initialization. The last row of Fig. 3 shows one of the normal carotid artery ultrasound image segmented by the proposed and manual initialization techniques, respectively. From Fig. 3, it can be observed that images segmented by the proposed and manual initialization approach do not have any difference, which shows the effectiveness of our proposed approach.

The problem in automatic initialization of snakes arises when images are not aligned. The images may become rotated, sheared, and translated during ultrasound imaging process. Such images are required to be aligned before snake initialization. To cope with this problem, we have incorporated the concept of image registration. The advantage of image registration is that it aligns two or more images. It requires the input image to be aligned with the base image. Accurate registration needs precise selection of control points. To deal with this problem, we have incorporated spatial information for control point's selection. The spatial information helps to correlate base and input image control points. It increases the corresponding points matching and results in the form of better registered image.

Table 1 shows the IMT measurement (in millimeter) of maximum and minimum of one of the normal carotid artery ultrasound images. The graphical representation of upper and lower arterial wall IMT measurement (in millimeter) is shown in Fig. 4. IMT is one of the effective measures, which show the seriousness of a disease.

IMT measurement is one of the effective techniques for the detection of plaque in the carotid artery. One of the

Table 2 Performance comparison of the proposed approach with other approaches

Techniques	Accuracy (%)	F score	MCC	Sensitivity	Specificity	NPV (%)
KNN	98.40	0.9799	0.9600	0.9839	0.9762	98.4
PNN	98.40	0.9799	0.9600	0.9839	0.9762	98.4
SVM	98.80	0.9879	0.9763	1.0000	0.9766	100

normal carotid artery IMT measurements is shown in Fig. 4, which is obtained from the image segmented by our proposed scheme. We have measured the IMT of every normal and abnormal image. Four features, namely, the average, variance, standard deviation, and skewness, are extracted from measured IMT values. These features are used to train and test SVM classifier. Table 2 shows the classification results based on four features of IMT. It can be observed from Table 2 that carotid artery image classification using these features shows significant performance.

Further, we compare the performance of the proposed approach in terms of ROC and AUC. Figure 5 shows ROC curves obtained for the TP and FP rates using SVM, k-nearest neighbor algorithm (KNN), and probabilistic neural network algorithm (PNN) classifiers, respectively. From Fig. 5, it can be observed that SVM ROC is close to *y*-axis and there is small deviation in ROC compared to both KNN and PNN. Variation in ROC shows misclassification. Table 2 shows that KNN and PNN generate the same results and hence ROC of PNN and KNN overlaps in the graph. We have obtained 98.80 % classification accuracy through the proposed approach. ROC curve shows some variation at *y*-axis and this variation represents the misclassifications when the threshold for classification is very strict. To check the overall performance of the classifier, we have also calculated AUC. The AUC is calculated from the ROC curve. The AUC is 0.98 which is close to 1. The value of AUC close to 1 shows the overall better diagnostic test. The better diagnostic test confirms the superiority of the proposed approach. The NPV of our proposed approach using SVM classification is 100 %. The resulting high value of NPV means that the probability of a patient has become risk free for which the test was conducted. Therefore, it can be concluded that our proposed approach can be used effectively for diagnostics of plaque into carotid artery ultrasound images.

In addition to this, performance comparison of the proposed scheme in terms of size of feature vector for classification has been carried out with other techniques. Minghao et al. [20] have used SVM classification with 22 different features obtained from IMT measurements. They have reported an *F* measure of 0.98 using their own dataset. While a large feature vector dimension may affect the classification accuracy because of the redundant features, in our proposed scheme, we have used only four features and got better *F* measure ~0.99 compared to 22-feature dataset. The reduced features may save classification time and resources. Further, the proposed scheme outperforms using given features.

Results obtained through the proposed technique are also compared based on overall accuracy. Santhiyakumari et al. [24] have employed multilayer backpropagation neural networks for classification and have reported a maximum of 96 % classification accuracy. In their approach, IMT measurement is used to train the neural networks. Further, they did not mention feature extraction strategy and it may be difficult to reproduce the results. On the other hand, in our proposed scheme, we have utilized a straightforward approach to classify the segmented carotid artery ultrasound images and obtained 98.8 % classification accuracy. The statistical results show the effectiveness of our proposed approach.

Furthermore, to check the performance of our proposed approach, we have applied KNN and PNN on the given dataset. The detail of KNN and PNN can be found in [25] and [26], respectively. Table 2 shows comparison of different methods at different quality measures. From Table 2, it is

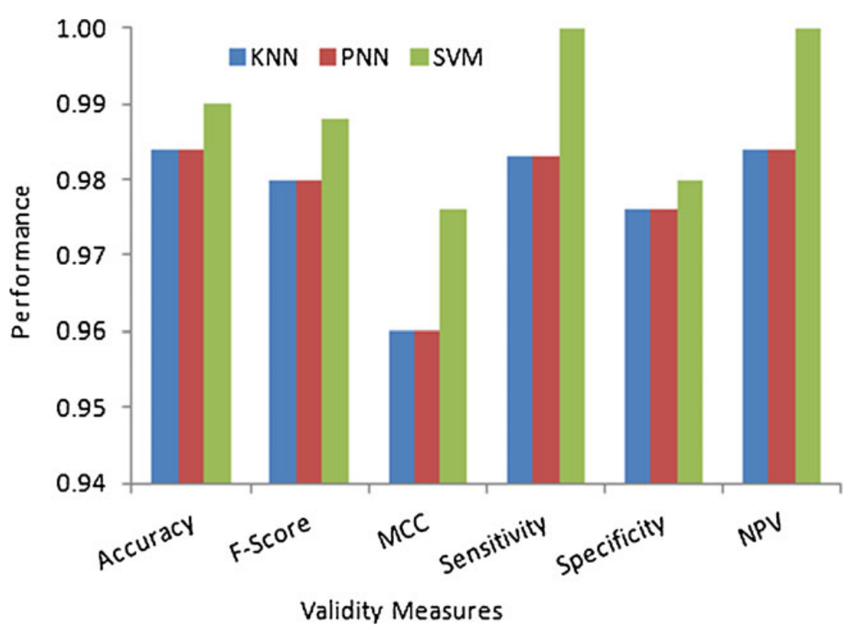

Fig. 6 Performance comparison of KNN, PNN, and SVM classification techniques at different classification validity measures

clear that SVM offers superior results compared to other techniques. Statistical analysis of results represents the usefulness of the proposed approach. Figure 6 shows the graphical performance comparison of PNN, KNN, and SVM at various classification validity measures. Classification using SVM offers superior performance compared to other techniques at all validity measures.

Carotid artery ultrasound images segmented through our proposed approach do not show any difference compared to manual snake initialization approach. The advantage of our proposed approach for carotid artery ultrasound image segmentation is that it requires minimal user intervention. Image classification is one of the most important steps to know about the presence of plaque in carotid artery. In our proposed approach, we have used SVM for the classification of normal and abnormal images. Statistical analysis shows that the proposed approach outperforms other techniques at hand.

Country like Pakistan, where there is lack of health facilities to the people, the proposed approach might be useful to check the possible presence of plaque in the carotid artery. Further, the proposed approach can be successfully used as an initial diagnostic tool for the carotid artery diseases. It can also be used by minimal experienced users and early detection of plaque in artery may prevent serious brain strokes.

Conclusions

In this paper, we have proposed automatic initialization of snakes for carotid artery image segmentation. Images need to be registered, if two or more images are not aligned. Performance comparison of the proposed approach has been carried out with the manual initialization of snakes. Using manual initialization, window is set empirically and it requires the window to be placed at right location. However, if user has less experience and initializes the window at improper place, results may not be accurate. The proposed approach of automatic snake initialization window shows the effectiveness of the method. IMT is measured to show the seriousness of plaque in blood vessel. Four different features are extracted from IMT-measured values for training and testing of SVM classifier. In our proposed approach, we have used SVM for classification of normal and abnormal images. Different types of validity measures are calculated to show the effectiveness of the proposed approach. Using SVM classification, we have obtained 98.8 % classification accuracy. A numerical comparison is made with other approaches at different validity measures. Statistical analysis shows that the proposed approach outperforms other techniques at hand. In the future, we intend to extend the automatic snake initialization at different types of medical images for effective medical image segmentation and plaque classification to show the seriousness of disease. Further, we intend to explore various types of features, which may be used to improve the accuracy of the classifier.

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