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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 6 (2): 212-216, 2007
ISSN 1812-5638

Backpropagation Network for Segmentation and Blood flow Velocity Determination in Coronary Angiogram Images

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Abstract: We propose a method for segmentation of vascular structures and determination of blood flow velocity in coronary angiograms. The angiogram images of normal and abnormal-collateral patients are acquired at a rate of 15 frames/sec. In each frame, blood vessel is segmented from background using a backpropagation network. The input is given to two network topologies (121-17-2 and 4-3-2 layer configuration) and tested for their performance. The 4-3-2 configuration was able to classify blood vessel with less number of iterations comparatively and it can detect even small vessels with less computation time. The blood flow velocity in angiogram is determined in two methods. First method is by measuring the distance traversed by the contrast agent in each frame. The second method is based on determining the change in concentration of the contrast agent in two fixed region of interest. By first method, the flow velocity for normal and collateral angiograms are found to be 38 pixels/frame(p/f) and 15 p/f, respectively and by the second method, it is calculated as 45 and 28 p/f, respectively. The results show delayed arrival of contrast in abnormal collaterals than in normal images.

Key words: Angiogram, collateral, neural network, backpropagation network, blood flow, flow velocity

INTRODUCTION

Angiography is used during various catheterization procedures for diagnosis and treatment of patients with blood vessel abnormalities, especially in the area of coronary artery disease. This time sequence of angiograms contains much information about vessel lumen geometry, dimensions and blood flow. However, due to the noise induced by the chain complex imaging and the dynamic nature of the process (heart motion and infusions of the X-ray contrast agent), extraction of such information is not a trivial task. Past research on automated detection of vascular structures has been based on statistical and heuristic methods (Kottke and Sun, 1990; Nekovei and Sun, 1990). Although tracking algorithms (Sun, 1989) have significantly improved vessel identification they often require operator's intervention for selecting parameters such as starting and ending search points. Some algorithms (Pappas and Lim, 1988; Eichel *et al*., 1988) lack the capability of detecting the entire vascular network. None of the aforementioned algorithms has taken advantage of distributed parallel processing.

Blood flow measurement is also important in such applications as imaging cerebro- and cardiac blood flow, perfusion and identification of impaired vascular reserve. In collateral-dependent myocardium, the arrival of the tracer may be delayed compared to normal myocardium. Arteries and arterioles that interconnect coronary artery brances are referred to as (intracoronary) collaterals. The delayed arrival of the contrast agent can lead to inaccurate estimates of myocardial blood flow. In olden days, the severity of vascular disease is assessed by visual examination of stenoses in angiograms. Thus, measurement of flow rates would be useful for evaluation of the significance of stenosis. In addition, flow rates could be employed to determine coronary flow reserve and to evaluate the effect of stenosis. Therefore, a number of investigators (Swanson *et al*., 1986; Fencil *et al*., 1982) have proposed methods for the determination of blood flow rates from angiograms. The determination of time delay in collaterals provides valuable information for identifying collateral dependent myocardium and for assessing the functional capacitance of collateral vessels.

The purpose of this research is to develop a practical approach based on neural network computing for segmentation of coronary angiograms. Also, we present a method for determination of blood flow velocity from real angiographic frames by analyzing the distance traveled by the contrast agent and by analyzing change in contrast agent concentration with respect to time.

MATERIALS AND METHODS

Multilayer feedforward network model using the back-propagation algorithm is one of the well-known neural network classifiers which consist of sets of nodes arranged in multiple layers with connections only between

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node in the adjacent layers by weights. The layer where the inputs information is presented is known as the input layer. The layer where the processed information is retrieved is called the output layer. All layers between the input and output layers are known hidden layers.

NEURAL NETWORK CLASSIFIER

A network window classifier that classifies a relatively small square area in the image is designed. To extract the vascular structures, a window of particular size is chosen. This window is allowed to slide over the entire image. The multilayer feed forward network is used as the window classifier. The input to the neural network is the raw digital data from angiogram images which are subjected to preprocessing. Backpropagation algorithm is used to train the network. The network configuration includes the following categories.

Selection of input window for testing the network: To investigate the role of network topology in this classification problem, it is necessary to evaluate the performance of the window classifier using different network topologies. For this project, there are two nodes (vessel and background) in the output layer. The input nodes are chosen based on the input window. For angiograms, usually the average vessel width is about 9 pixels. For the first training set, a 11×11 window is chosen. With different number of hidden layers the network performance is noted. For the second training set, a 2×2 window is chosen. The network performance is tested for this network also.

Learning rate and momentum term: The network is trained by the delta rule with a momentum term which was introduced by Rumelhart. At (k+1)th iteration during training, the update of network weight Δ_{ij} is based on two components. The first component is proportional to the effect of error signal δ_i, on the output O_j for the neuron sending the activation signal. The second component is proportional to the amount of weight change in the previous iteration (the momentum term).

$$\Delta_{ij}(k+1) = \beta(\delta_i O_j) + \alpha\Delta_{ij}(k) \quad (1)$$

The learning rate (β) controls the rate of convergence for the training process. The momentum term (α) helps to prevent oscillation problem near the solution point. These two parameters are the major factors that affect learning. They also control the tradeoff between the system's stability and classification quality. To obtain fast learning and high performance, a small learning rate (0.05) and a medium momentum rate (0.5) are used.

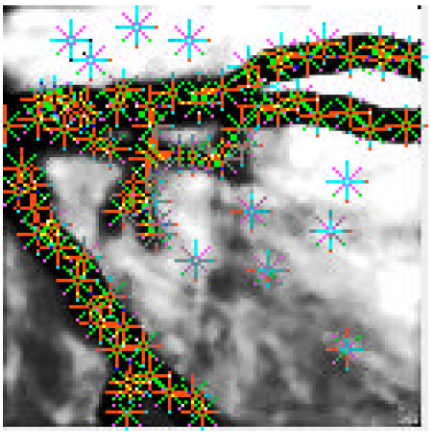


Fig. 1: Manual selection of training samples in angiogram image

Training sample set: It is important to determine how many samples are sufficient for a satisfactory classification. The samples can be selected randomly or manually. The randomly selected sample usually contained very few samples of blood vessel and more samples of background. Therefore, as the training proceeds, the network become biased towards background and tends to ignore vessels. To resolve this problem manual selection (Fig. 1) is done such that the samples contain more number of vessel than background.

Before selection of samples, the input image is subjected to histogram equalization so that the intensity of background is better differentiated from the vessels.

The samples are normalized so that the values of the features are in the range of 0 to 1 and the computational complexity is reduced. The normalization of the samples is done by:

$$X_i = X_i/X_{max}$$

Where:

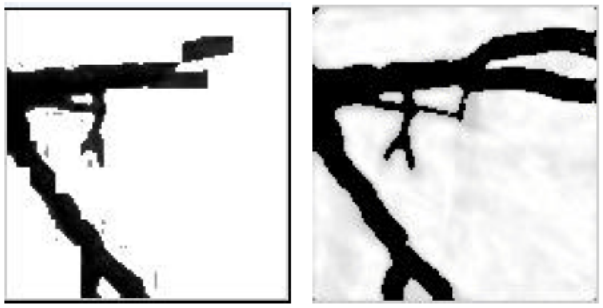
X_i is the value of the sample and

X_{max} is the maximum value of the feature.

The image gray-scale data are taken as feature samples. Out of 128×128 pixels from input angiogram image, 121 values are chosen for first initial training data set and 4 values are chosen for second initial training data set. The data sets are given as input to different network topology. The networks are trained with a fixed learning rate of 0.05 and different momentum rates. The results obtained are shown in Table 1.

Table 1: Results of training sample set

Training with different momentum		Training with different network topology	
Momentum	No. of iteration	Network topology	No. of training iteration
0.2	2372	121-17-2	1603
		121-14-24-2	2071
0.5	2287	121-16-10-2	2672
		121-14-14-14-2	2454
0.9	1168	121-13-13-13-13-2	5128
		4-3-2	103



(a) (b)

Fig. 2: Segmented vessel from configuration (a) 121-17-2 network (b) 4-3-2 network

A larger learning rate is required as the number of hidden layers increases, however a learning rate, which is too large, results in oscillations. Fast learning is achieved with a small learning rate of 0.05 and a medium momentum of 0.5.

For different network topology, data sets are given as input. When the training converges and the Mean Squared Error (MSE) decreases below an acceptable threshold, the window classifier is considered trained and then applied over entire angiogram. The training results show that the number of iterations is less for three-layer backpropagation network. This three-layer network is chosen to test the remaining samples. Each window of size 11×11 is classified as blood vessel if target is [1 0] and as background if target is [0 1].

For angiograms under analysis, the average vessel width of large vessels is about 9 pixels, but small vessel width is about 3 pixels. Using 11×11 window it is possible to segment large vessel but small vessels are not detected, because the number of pixels of blood vessel is less than the background. The Fig. 2a shows segmented image with configuration 121-17-2 results in corrugated vessel edges. Whereas with configuration 4-3-2, it is possible to segment even small vessels (Fig. 2b). Since the train data is less in the second data set, computation time is minimized.

BLOOD FLOW RATE MEASUREMENT

The blood flow velocity in angiogram is determined in two methods. First method is by measuring the distance traversed by the contrast agent in each frame. The second method is based on determining the time taken for the contrast agent to travel the distance between two fixed region of interest (ROIs).

Contrast propagation distance measure: All image frames are acquired with a matrix size of 512×512. Initially segmentation is done for each frame with 4-3-2 network. From the normal and abnormal collateral angiographic frames, a vessel region of interest is manually selected and the centerline of the vessel is determined using thinning algorithm. The following parameters are measured from the frames

- The distance of propagation of the contrast material along the centerline vessel of interest is calculated by counting the number of bright pixels in the selected region.
- The average flow rate between the acquisitions is calculated by subtracting the distance between successive frames. This gives flow rate in pixels/frame.

Velocity determination from contrast agent concentration-time curve: Two region of interest are choosen in the angiogram image where the first ROI is located upstream of the second one. The vessel contrast is determined as the difference between the average pixel value in the central region of the vessel (ROI) and the average pixel value in the adjacent background region. The contrast change is measured at two fixed region of interest. From this the time taken for the contrast agent to travel the distance between two fixed ROIs is determined.

The change in contrast agent concentration with respect to time is determined for normal angiogram image and abnormal collateral image. The collateral images take much time to reach the second ROI, than the normal vessel.

The flow velocity (Shpilfoygel *et al*., 2000) is obtained as:

$$V = \frac{\Delta x}{\Delta t} \quad (2)$$

where:
Δx is the average distance between the two ROIs and
Δt is the time of contrast agent travel between them.

RESULTS AND DISCUSSION

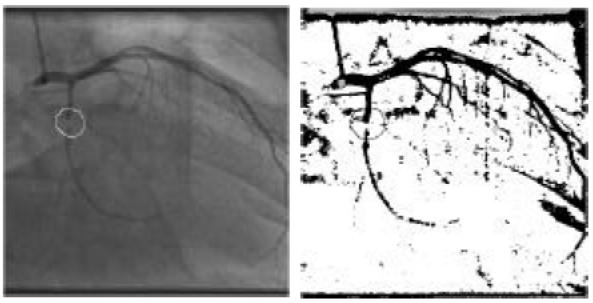
The angiographic frames are acquired at a rate of 15 frames/sec for normal and collateral patients and are segmented using 4-3-2 network. The results obtained by contrast propagation distance measure are as follows.

The Fig. 3a shows input abnormal collateral image frame and Fig. 3b shows segmentation of the collateral image. The segmentation is done for a sequence of frames.

The flow rate for normal and collateral patients are calculated as 38 pixels/frame and 15 pixels/frame, respectively.

The Fig. 4 shows the distance of propagation of contrast agent in a vessel of interest with respect to time.

The Fig. 5 shows the concentration of the tracer increases slowly and decreases after some time. Also, they show variation in tracer concentration for normal and collateral images which gives information about blood flow in stenotic vessel. The contrast agent arrives at the vessel when the curve reaches its maximum peak.



(a) (b)

Fig. 3: (a) Input abnormal collateral image (b) segmented abnormal collateral image (stenotic portion is encircled)

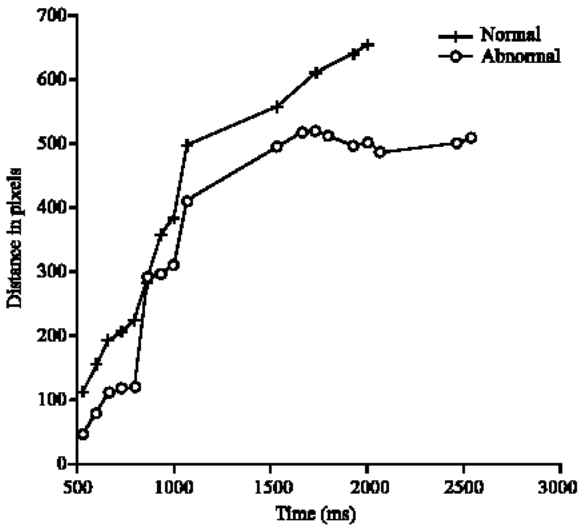


Fig. 4: Time Vs distance curves for normal and abnormal images

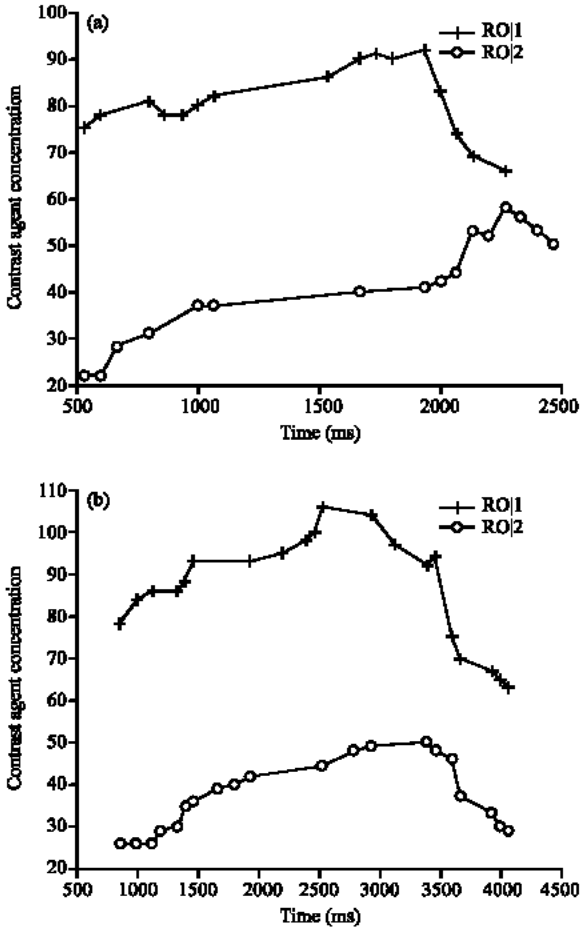


Fig. 5: Contrast agent concentration Vs time curve for (a) normal image (b) collateral image

The flow velocity for normal and abnormal image is 45 pixels/frame and 36 pixels/frame, respectively. The calculated flow velocity of 36 pixels/frame in abnormal collateral image indicates that the time taken to reach the ROI is delayed than the normal vessel.

CONCLUSIONS

The distance of propagation of contrast material is determined, for each segmented frame. Accurate blood flow velocity is calculated by the analysis of the contrast material along the length of the vessel. The blood flow velocity in abnormal collateral image is very less compared to normal images. The delay in contrast agent arrival at collateral region and the blood flow velocity can be used for evaluation and identification of functional significance of stenosis.

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