Usually, the upper tracking threshold can be set quite high, and the lower threshold quite low for good results. Setting the lower threshold too high will cause noisy edges to break up. Setting the upper threshold too low increases the number of spurious and undesirable edge fragments appearing in the output. The Gaussian smoothing in the Canny edge detector fulfills two purposes: first it can be used to control the amount of detail that appears in the edge image and second, it can be used to suppress noise. The Canny edge detector allows to find the intensity discontinuities in an image, it is not guaranteed that these discontinuities correspond to actual edges of the object.

3.2.4 Graph cut segmentation

Segmentation is an important part of image analysis. It refers to the process of partitioning an image into multiple segments. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Segmentation by computing a minimal cut in a graph is a new and quite general approach for segmenting images. This approach guarantees global solutions, which always a best solution, and in addition these solutions are not depending on a good initialization. Graph theory is the study of graphs. A graph is an abstract representation of a set of objects, where several pairs of the objects are connected by links. It is a mathematical structure and is used to model pairwise relations between objects from a certain collection. In a graph G = (V, E) , V and E denote the set of vertices and edges of G, respectively.

A weighted graph associates a positive label (weight) with every edge in the graph. A directed graph G consists of a set of vertices V and a set of ordered pairs of edges.

An s-t graph is a weighted directed graph with two identied nodes, the source s and the sink t. An s-t cut , c (s;t), in a graph G is a set of edges E cut such that there is no path from the source to the sink when E cut is removed from G. The cost of a cut E cut is the sum of the edge weights in E cut .

In graph theory, a cut is a partition of the vertices of a graph into two disjoint subsets that are joined by at least one edge. The cut-set of the cut is the set of edges whose end points are in different subsets of the partition. Edges are said to be crossing the cut if they are in its cut-set. In an unweighted undirected graph, the size or weight of a cut is the number of edges crossing the cut. In a weighted graph, the same term is defined by the sum of the weights of the edges crossing the cut.In a flow network, an s-t cut is a cut that requires the source and the sink to be in different subsets, and its cut-set only consists of edges going from the source's side to the sink's side. The capacity of an s-t cut is defined as the sum of capacity of each edge in the cut-set.
Graph-cut is an algorithm that finds a globally optimal segmentation solution. Energy-based segmentation methods can be distinguished by the type of energy function they use and by the optimization technique for minimizing it.Energy function plays a major role in segmentation using graph cuts. A graph G ={V, E}is defined as a set of nodes or vertices V and a set of edges E connecting “neighboring” nodes. A graph cut is the process of partitioning a directed or undirected graph into disjoint sets. The concept of optimality of such cuts is usually introduced by associating an energy to each cut.Graph cut methods have been successfully applied to stereo, image restoration, texture synthesis and image segmentation.

3.2.5 Non Maximal Suppression

Non-maximum Suppression technique is used to extract the centerline of the segmented vessel. Non-maximum supression is a technique combined with the edge detection algorithms it is used. Along the image gradient direction, the images are scanned and if pixels are not included in the local maxima portion those pixels are set to the value zero. This leads to the effect of suppressing the whole information of the images which are not included in local maxima portion. This level is said to be Non-maximum suppression. Then at this stage, edge points set is obtained, as a binary image. At some situation it is said to be thin edges. Non Maximum Suppression technique can set all the pixels in the present neighborhood window which are lesser than the maximum value in that current window to zero (or black). The technique is same as like the Max Filter. In Max Filter, the highest value for the mentioned window size (current ROI area) is evaluated. Then the current pixel is compared to the highest value. If it is lesser value, then it is set to black otherwise the value doesn’t get changed.

3.3 Catheter Detection

3.3.1 Adaboost Classifier

Algorithm based on multi-scale stacked sequential learning(Sequential learning is the discipline of machine learning that deals with dependent data such that neighboring labels exhibit some kind of relationship), which includes pointwise classification method using adaboost classifier and contextual information extracted and refined by stacked classifier. A well known algorithm for classification includes Adaboost algorithm.

Adaboost expands as adaptive since it uses n number of iterations to produce a single strong learner. Adaboost generates the classifier which is well-correlated to the true classifier (i.e., strong learner) by consequently adding a classifier which is lightly correlated to the true classifier (i.e., weak classifier). During each and every stage of training the images, a newly produced weak learner is get included to the ensemble and adjust the weighting vector to impose on misclassified things in past iterations.

Adaptive Boosting (Adaboost) is a machine learning algorithm.It is a meta-algorithm, and can be used in conjunction with many other learning algorithms to improve their performance. AdaBoost is adaptive in the sense that subsequent classifiers built are tweaked in favour of those instances misclassified by previous classifiers.AdaBoost is sensitive to noisy data and outliers. In some problems, however, it can be less susceptible to the overfitting problem than most learning algorithms. The classifiers it uses can be weak (i.e., display a substantial error rate), but as long as their performance is slightly better than random (i.e. their

error rate is smaller than 0.5 for binary classification), they will improve the final model. Even classifiers with an error rate higher than would be expected from a random classifier will be useful, since they will have negative coefficients in the final linear combination of classifiers and hence behave like their inverses.
Contextual means focusing on the relationship of the nearby pixels and misaligned pixels has been classified by the classifier.There are two main approaches to lesion detection by classification: One can either train a classifier to identify image subwindows containing lesions or classify single voxels as belonging to a lesion or not. Focus on difficult data points. The data points that have been misclassified most by the previous weak classifier. Focus on difficult data points. The data points that have been misclassified most by the previous weak classifier.

4. Simulation Result

4.1 Input image

The angiographic image is taken as input for vessel segmentation, centerline extraction and catheter detection.

Figure 2: Input image

4.2 Output images

4.2.1 Preprocessing

Input image is smoothened by Gaussian filter.

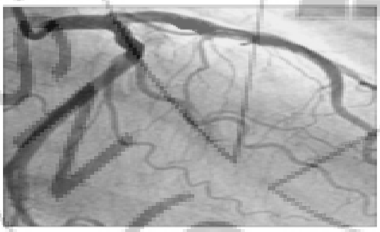

Figure 3: Filtered image

4.2.2 Vessel and Background separation

From the filtered output the Vessel structure and Background are separated, since further processing needs only the vessel structure.

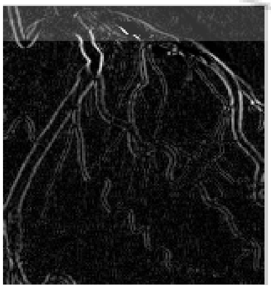

Figure 4: Vessel and Background separation

4.2.3 Geodesic distance map

The geodesic distance map contains the distance of each pixel.The distance is the maximum difference of image gradients and the path is computed by Dijkstra's shortest path algorithm.The vessel region is represented in white and the background region is represented in black on Geodesic distance map.The unary term in Graph cut energy formulation is considered from Geodesic distance map

Figure 5: Geodesic Distance Map

4.2.4 Edgeness map

Canny edge detector algorithm is used to detect the edges. The Boundary term for Graph cut energy formulation is considered from Edgeness map.

Figure 6: Edgeness map

4.2.5 Graph cut Segmentation

By graph cut algorithm, the image is decomposed into N cuts. Each N cuts are taken as vertices and their edges have minimum edge weight. Eigen vectors and Eigen values are taken into account for vessel curvature determination.

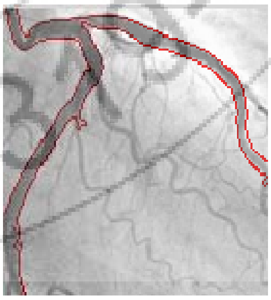

Figure 7: Graph cut segmentation

4.2.6 Centerline extraction and Catheter detection
The vessel centerline is extracted by using Non maximal suppression and the non maximal points are joined by Ridge traversal method. The catheter position is detected by

distinguishing features on centerline by using Adaboost classifier.

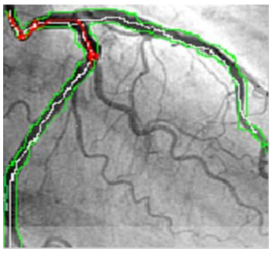

Figure 8: Final segmentation,Centerline extraction and Catheter detection

5. Simulation Result

Segmentation of coronary arteries in angiographic images is a fundamental tool to evaluate arterial diseases and choose proper coronary treatment. An accurate segmentation of coronary artery allows the physician to access different medical imaging information.Segmentation of vessels in angiographic images is done by Graph cut algorithm on analysis of vessel appearance, local connectivity to other vessels(Geodesic distance) and edgeness detection by canny edge detection algorithm. The interventional tool to remove blockages is catheter. Catheter can be of detected using pointwise classification method using adaboost classifier.

References

[1] Y. Y. Boykov and M.-P. Jolly, "Interactive graph cuts for optimal boundary & region segmentation of objects in N-D images," in Proc. Int. Conf. Comput. Vis., 2001, vol. 1, pp. 105–112.

[2] Y. Boykov and V. Kolmogorov, "An experimental comparison of mincut/ max-flow algorithms for energy minimization in vision," in Proc. Int. Conf. Pattern Anal. Mach. Intell., 2004, vol. 26, pp. 359–374.

[3] Y. Boykov and G. Funka-Lea, "Graph cuts and efficient N-D image segmentation," Int. J. Comput. Vis., vol. 70, no. 2, pp. 109–131, 2006.

[4] C. Rother,V.Kolmogorov, and A. Blake, "Grabcut: Interactive foreground extraction using iterated graph cuts," J. ACMTrans. Graph., vol. 23, no. 3, pp. 309–314, 2004.

[5] V. Kolmogorov and Y. Boykov, "What metrics can be approximated by geo-cuts, or global optimization of length/area and flux," in Proc. Int. Conf. Comput. Vis., 2005, vol. 1, pp. 564–571.

[6] S. Candemir and Y. Akgul, "Adaptive regularization parameter for graph cut segmentation," in Image Analysis and Recognition. New York: Springer, 2010, pp. 117–126.

[7] M. Schaap *et al.*, "Standardized evaluation methodology and reference database for evaluating coronary artery centerline extraction algorithms," Med. Image Anal., vol. 13, no. 5, pp. 701–14, 2009.

[8] F. Benmansour and L. Cohen, "Tubular structure segmentation based on minimal path method and anisotropic enhancement," Int. J. Comput. Vis., vol. 92, pp. 192–210, 2011.

[9] D. Lesage, E. D. Angelini, I. Bloch, and G. Funka-Lea, "A review of 3D vessel lumen segmentation techniques: Models, features and extraction schemes," Med. Image Anal., vol. 13, no. 6, pp. 819–845, 2009.

[10] N. Sang, H. Li, W. Peng, and T. Zhang, "Knowledge-based adaptive thresholding segmentation of digital subtraction angiography images," *Image Vis. Comput.*, vol. 25, no. 8, pp. 1263–1270, Aug. 2007.

[11] D. Franchi, P. Gallo, L.Marsili, and G. Placidi, "A shape-based segmentation algorithm for x-ray digital subtraction angiography images," Comput. Methods Prog. Biomed., vol. 94, no. 3, pp. 267–278, Jun. 2009.

[12] K. Krissian, G. Malandain, N. Ayache, R. Vaillant, and Y. Trousset, "Model-based detection of tubular structures in 3d images," Comput. Vis. Image Understand., vol. 80, no. 2, pp. 130–171, 2000.

[13] P. Fallavollita and F. Cheriet, "Towards an automatic coronary artery segmentation algorithm," in Proc. Eng. Med. Biol. Soc., 2006, pp. 3037–3040.

[14] H. Mirzaalian and G. Hamarneh, "Vessel scale-selection using MRF optimization," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Jun. 2010, pp. 3273–3279.

[15] C. Kirbas and F. Quek, "A review of vessel extraction techniques and algorithms," ACM Comput. Surv., vol. 36, no. 2, pp. 81–121, 2004.

[16] M. Schneider and H. Sundar, "Automatic global vessel segmentation and catheter removal using local geometry information and vector field integration," in Proc. IEEE Int. Symp. Biomed. Imag. Piscataway, NJ:IEEE Press, 2010, pp. 45–48.

[17] V. Kolmogorov and R. Zabih, "What energy functions can be minimized via graph cuts," IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 2, pp. 147–159, 2004.

[18] A. Vasilevskiy and K. Siddiqi, "Flux maximizing geometric flows," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 12, pp. 1565–1578, Dec. 2002.

[19] L. Price, B. Morse, and S. Cohen, "Geodesic graph cut for interactive image segmentation," in Proc. IEEE Trans. Comput. Vis. Pattern Recog., 2010, pp. 3161–3168.

[20] R. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," in Medical Image Computing and Computer-Assisted Intervention, (Lecture Notes Computer Science, Vol. 1496). New York: Springer-Verlag, 1998, pp. 130 137.

[21] C. Gatta, E. Puertas, and O. Pujol, "Multi-scale stacked sequential learning," Pattern Recognit., vol. 44, no. 10–11, pp. 2414–2426, 2011.