A REVIEW OF STUDY ON SEGMENTATION METHODS

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Abstract— A systematic approach has been developed to detect boundaries using edge detection algorithm. The various edge detection algorithms are used. These algorithms outputs are helpful to detect the boundary and to evaluate the further investigation. The research results are beneficial and vital to practitioners to detect the edges of any images.

Keywords— Edge detection algorithm, boundary, canny, sobel, prewitt.

1.INTRODUCTION

The existing study deals with image processing and other areas are discussed. Cai, et al., (2007), incorporated local spatial and gray information together, a novel fast and robust fuzzy c-means framework for image segmentation, fast generalized fuzzy c-means clustering algorithms is proposed. Lei, et al., (2007), introduces an adaptive based on statistical learning theory us proposed to enhance fuzzy electrocardiogram (ECG) classifier with orientation to smart ECG interpreters. Markos, et al., (2008), presented fuzzy rule based decision support system for the diagnosis of coronary artery disease based on easily and noninvasively acquired features, and is able to provide interpretation for the decision made. Li, et al., (2009), proposed a new fuzzy level set algorithm and confirm its effectiveness for medical image segmentation. Bing, et al., 2011, examined an integrating spatial fuzzy clustering with level set methods for automated medical segmentation. The approaches proposed in this paper is the Mumford-shah level set methods for image segmentation. Amatur, et al., (1992), examined the segmentation of magnetic resonance images by optimizing neural networks. This study has demonstrated the applicability of Hopfield net for the tissue classification in MRI. Levinski, et al., (2009), describes the approach for correcting the segmentation errors in 3D modeling space, implementation, principles of the proposed 3D modeling space tool and illustrates its application. Paragios, et al., (2003), introduces a knowledge based constraints, able to change the topology, capture local deformations, surface to follow global shape consistency while preserving the ability to capture using implicit function. Suri, et al., (2002), an attempt to explore geometric methods, their implementation and integration of regularizers to improve robustness of independent propagating curves/surfaces. Yuksel, et al., (2006), reveals the 100% classification accuracy of carotid artery Doppler signals using complex-values artificial neural network. Wendelhag, et al.,

(1991, 1997) results shows variations secondary to subjective parameters when manual measurement methods are employed.

In this proposed method, five different edge detection methods are implemented and compared. As a result canny edge detector is concluded as the best method and the same applied for training and testing in back propagation algorithm.

2. METHODS AND MATERIALS

2.1EDGE DETECTION

Edge detection is the process of finding meaningful transitions in an image. Edge detection is one of the central tasks of the lower levels of image processing. The points where sharp changes in the brightness occur typically form the border between different objects. These points can be detected by computing intensity differences in local image regions. That is the edge-detection algorithm should look for a neighbourhood with strong signs of changes. Most of the edge detectors work on measuring the intensity gradient at a point in the image.

Edge detection is a problem of fundamental importance in image analysis. The purpose of edge detection in carotid artery is to identify areas of an image where a large change in intensity occurs. These changes are often associated with some physical boundary in the scene from which the image is derived. In typical images, edges characterize object boundaries and are useful for segmentation, registration and identification of objects in a scene.

2.2 SOBEL-KERNEL OPERATOR

The Sobel- Kernels are relies on central differences of carotid artery image, but gives greater weight to the central pixels when averaging. The sobel kernels can be thought of as 3 X 3 approximations to first derivatives of Gaussian kernels of the sobel operator are calculated as

$$\mathbf{S}_{\mathbf{x}} = (\mathbf{a}_2 + 2\mathbf{a}_3 + \mathbf{a}_4) - (\mathbf{a}_0 - 2\mathbf{a}_7 + \mathbf{a}_6) \tag{1}$$

$$S_{y} = (a_{6} + 2a_{5} + a_{4}) - (a_{0} - 2a_{1} + a_{2})$$

(2) The above expression implies the emphasis given to pixels closer to the center of the mask. The noise suppression characteristics of a sobel mask is better than that of prewitt mask.

2.3 ROBERT-KERNEL OPERATOR

The main objective is to determine the difference between the adjacent pixels of the carotid artery image, one way to find an edge is to explicitly use $\{+1, -1\}$ that calculates the difference

between adjacent pixels. Mathematically, these care called forward differences. To implement first-order partial derivative is by using cross-gradient operator as

$$\frac{\partial y}{\partial x} = f(i, f) - f(i+1, j+1)$$
(3)

$$\frac{\partial y}{\partial x} = f(i+1, f) - f(i, j+1)$$
(4)

The above expression implies the difference between adjacent pixels. These filters have the shortest support, thus the position of the edges is more accurate, but the problem with the short support of the filters is its vulnerability to noise.

2.4 PREWITT-KERNEL OPERATOR

Prewitt Kernels are based on the idea of central difference. To detect edge prewitt edge detector is a much better operator than the Roberts operator. Here the equation had been formed to consider the central pixels as

$$P_x = (a_2 + ca_3 + a_4) - (a_0 - ca_7 + a_6)$$
(5)
$$P_y = (a_6 + ca_5 + a_4) - (a_0 - ca_1 + a_2)$$
(6)

In the above expression the constant c implies the emphasis given to pixels closer to the centre of the mask. $P_{x \text{ and}} P_{y}$ are the approximations at [i, j]. The Prewitt mask differentiates in one direction and averages in other direction, so the edge detector is less vulnerable to noise.

2.5 LAPLACIAN OF GAUSSIAN OPERATOR

A prominent source of performance degradation in the Laplacian operator is noise in the input image. The noise effects can be minimized by smoothing the image prior to edge enhancement. The Laplacian-of-Gaussian (LOG) operator smooths the image through convolution with a Gaussian-shaped kernel followed by applying the Laplacian operator.

2.6 CANNY EDGE DETECTION METHOD

Canny edge detector is non-isotropic. The canny edge detection algorithm uses first derivative to compute the edge. The canny edge detector is more likely to produce long, thin contours because of non-maximum suppression which thins and hysteresis thresholding which can fill in weak edge gaps. The canny operator works in a multi-stage process. First, the image is smoothed by a Gaussian convolution. Then a 2D first derivative operator is applied to the smoothed image to highlight regions of the image with high spatial derivatives. Edges give rise to ridges in the gradient magnitude image. The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not actually on the ridge top so as to give a thin line in the output, a process known as non-maximal suppression. The tracking process exhibits hysteresis controlled by two thresholds T_1 and T_2 with $T_1 > T_2$. Tracking can only begin at a point on a ridge higher than T_2 .

Tracking then continues in both directions out from that point until the height of the ridge fails below T_2 .

This hysteresis helps to ensure that noisy edges are not broken into multiple edge fragments. The canny edge detector is determined by three parameters

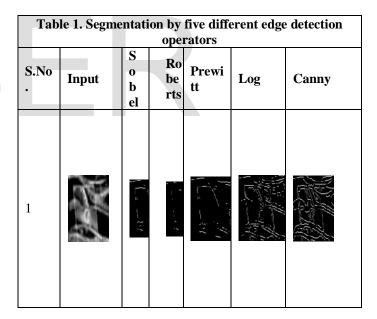
- 1. Width of the Gaussian Kernel.
- 2. Upper threshold.
- 3. Lower threshold used by the tracker.

Width of the Gaussian kernel reduces the detector's sensitivity to noise. The Gaussian smoothing in canny detector works for 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. Usually, upper threshold is set quite high and lower threshold is set to quite low for good results.

3.RESULTS AND DISCUSSION

The image is segmented using five different operators. They are Sobel-Kernel, Roberts-Kernel, Prewitt-Kernel, Laplacian of Gaussian operator and canny edge detector. Among these five edge detection operators, the study suggests, the best edge detector operator is canny edge detection.

Table 1 and Table 2 given below after references helps to conclude that the canny edge detector detects the edges in best way compare to other edge detectors.



4. CONCLUSION

The canny edge detector detects the edges in best manner with less time and less space compare to other edge detectors. This will provide a faster solution and effective way for classification of different pattern of images.

References

- Amartur, S.C., Piraino, D., and Takefuji, Y., 1992, Optimization neural networks for the segmentation of magnetic resonance images, IEEE Transactions in Medical imaging, Vol.II, Issue 2, pp.215-220.
- [2] Bing Nan Li, Chee Kong Chuti, Stephen Chang, and Ong, S.H., 2011, Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation, Computers in Biology and Medicine, Vol.41, Issue 1, pp.1-10.
- [3] Cai, W., Chen, S., and Zhang, D., 2007, Fast and robust fuzzy *c*-means clustering algorithms incorporating local information for image segmentation, Pattern Recognition, Vol.40, pp.825–838.
- [4] Da-Chuan Cehng, Christian Billich, Shing-Hong Liu, Horst Brunner, Yi-Chen Qiu, Yu-Lin Shen, Hans J Brambs, Arno Schmidt-Trucksass and Uwe HW Schutz, 2011, Automatic detection of the carotid artery boundary on cross-sectional MR image sequences using a circle model guided dynamic- programming, Biomedical engineering Vol.10, pp.1-17.
- [5] Levinski, K., Sourin, A., and Zagorodnov, V., 2009, Interactive surface-guided segmentation of brain MRI data, Computers in Biology and Medicine, Vol.39, Issue 12, pp.1153–1160.
- [6] Markos, G., Tsipouras, Themis, P., Exarchos, Dimitrios, I., Fotiadis, Anna, P., Kotsia, Konstantinos, V., Vakalis, Katerina, K., Naka and Lampros K., Michalis, 2008, Automated Diagnosis of coronary artery disease based on data mining and fuzzy modeling, IEEE transactions on Information technology in biomedicine, Vol.12, Issue 4, pp.447-456.
- [7] Paragios, N., 2003, A level set approach for shape-driven segmentation and tracking of left ventricle, IEEE Transactions on Medical Imaging, Vol.22, pp.773–776.
- [8] Santhiyakumari, N., and Madheswaran, M., 2010, Intelligent medical decision system for identifying ultrasound carotid artery images with vascular disease, International journal of Computer Application, Vol.1, Issue 13, pp.32-39.
- [9] Suri, J.S., 2001, Two-dimensional fast magnetic resonance brain segmentation, IEEE Engineering in Medicine and Biology, Vol.20, pp.84-95.
- [10] Wendelhag, I., Gustavsson, T., Suurkula, M., Berglund, G., and Wikstrand, J., 1991, Ultrasound measurement of wall thickness in the carotid artery: fundamental principles and description of a computerized analysing system, Clin Physiol., Vol.11, pp.565-577.
- [11] Wendelhag, I., Liang, Q., Gustavsson, T., and Wikstrand, J., 1997, A new automated computerized analyzing system simplifies readings and reduces the variability in

ultrasound measurement of intima-media thickness, Stroke, Vol.28, pp.2195-2200.

- [12] Yuksel Ozbay and Murat Ceylan, 2006, Effects of window types on classification of carotid artery Doppler signals in the early phase of atherosclerosis using complex-valued artificial neural network, Ultrasound in Medicine and Biology, Vol.37, Issue 3, pp.287-295.
- [13] Li, B.N., Chui, C.K., Ong, S.H., and Chang, 2009, Integrating FCM and level sets for liver tumor segmentation, Proceedings of the 13th International Conference on Biomedical Engineering, (ICBME 2008), IFMBE Proceedings 23, pp.202–205.
- [14] Lei, W.K., Li, B.N., Dong, M.C., and Vai, M.I., 2007, AFC-ECG: an adaptive fuzzy ECG classifier, in: Proceedings of the 11th World Congress on Soft Computing in Industrial Applications (WSC11), Advances in Soft Computing, Vol.39, pp.189–199.

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