Reinforcement of Edge Detection by Concurrent Segmentation on Images with Elongated Structures

Özlem Mutlu ,H. Kevser Bayraktar
Bilgisayar Mühendisliği Bölümü
Yalova Üniversitesi
Yalova, Türkiye
{ kevser184, ozlem-mutlu1 }@hotmail.com

Yrd.Doç.Dr. Ali İSKURT, Doç.Dr. Müfit Çetin
Bilgisayar Mühendisliği Bölümü
Yalova Üniversitesi
Yalova, Türkiye
{ ali.iskurt, mufit.cetin }@yalova.edu.tr

***Abstract*—It is well known that edge detection and segmentation are complementary techniques, one can be deduced and enhanced from the result of the other retrospectively. However, their simultaneous processing can be arranged as well to produce better edges. This paper has proposed a new approach that makes great enhancement on edge detection specifically on noisy images where standard edge detection algorithms based on gradients, fail to track the boundary or branch to a false positive edge. In these cases where the weakened gradients precludes from going ahead, the segmented regions come up on dual sides of already detected edges, and supply needed information to discover the lost clues of edges. The experimental results show that both accuracy and recall values get incremented by 30% utmost on some very noisy images and about 20% on the whole image set.**

***Index Terms*—Segmentation, edge detection, noise, reinforcement, gradient**

I. INTRODUCTION

The success of many computer vision and image processing applications mostly rely on finding the edges. Though being studied much, there is not a robust algorithm for edge detection since many factors like illumination, noise, apriori information for ap-plying thresholds etc affect the accuracy. Thus, researches continue to grow at this low level vision area. For instance, almost all algorithms use empirically determined thresholds which will affect the resultant edge figures when disturbed a little bit. Inevitably, noise will cause all of them to fail at some regions [1, 2, 3, 4] .

Those considerations make edge detection still hot, and the researches seem to continue [5, 6, 7, 8]. Three decades passed after Canny's master thesis and improvements are tried by many recent researches even on this particular detection method. A recent paper describes the properties of a good edge detector [9], and during the last decade, many new researches are added . A recent comparison of various techniques is listed by Maini et al [10]. A Survey of them for segmentation is done by Rajedsh [11] and performance of edge detectors can be found in [12]. Enhancements on well known detectors continue as well, for instance, on canny edge detector many studies are made [13,14,15]. Segmentation, as a subject of artificial intelligence and computer vision, benefits very much from the extracted edges [16]. The reverse case is mentioned by [1] saying segments reveal the boundaries of objects in the images but rarely studied in the literature. Thus, any reference to such papers couldn't be found and is not attached to the reference list here. As it is, the proposed technique which is a reinforcement of the edge detection by concurrent segmentaion (RES) stands fairly novel which utilizes the segmentation to trace the true edges. Moreover, segmentation and edge processing is combined to overcome the most difficult problem of noise where the gradients originated from the intensity contrasts are lost by famous edge detectors. This is done by a very interesting and logical method as will be described shortly.

II. METHOD

The method of RES can better be explained by showing which shortcomings it addresses and how this is done by visualization on the images. For instance, it can be tested on medical imaging of coronary angiography or satellite images where the patterns to be extracted are obviously arteries and roads. In Figure1-a, a typical angio image is given where primary artery is manually marked. A region of the manually drawn artery is zoomed in where it gives three branches in Figure 1-b. Even normal person who is not an expert can notice and mark these small branches till the intensity contrast fully disappears and this is drawn in Figure 1-d showing what we expect from an ideal edge detector. It also serves as the ground truth shown in yellow color overlapped on the blue dots of Canny edge detector.

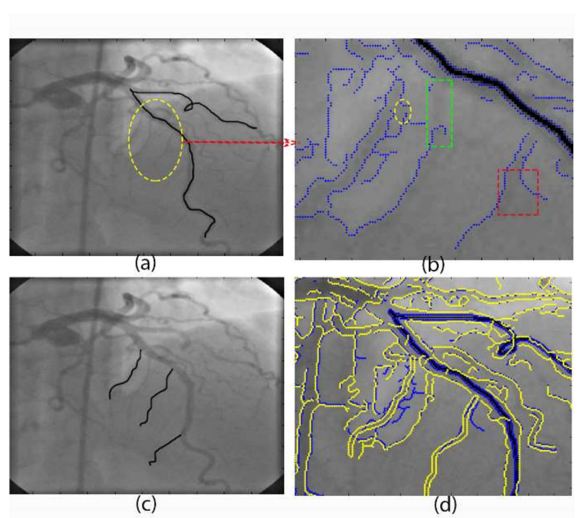

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Figure 1. Shortcomings visualized on a medical coronary angiography image. Human can keep track on small braches attached to primary artery in (a) but edge detectors cannot follow the edges. (c) manually drawn small branches (d) Ground truth and edges detected together.

This paper gets close to the ground truth which reveals the missing items and shortcomings. The description of how it does this will also summarize the explanation of the method. The method can be understood by looking at the point where the edge detector fails to catch up with true edge and why? The answers get obvious while monitoring the gradients and their orientations at zoomed in images on the failed regions as given in Figure 2.

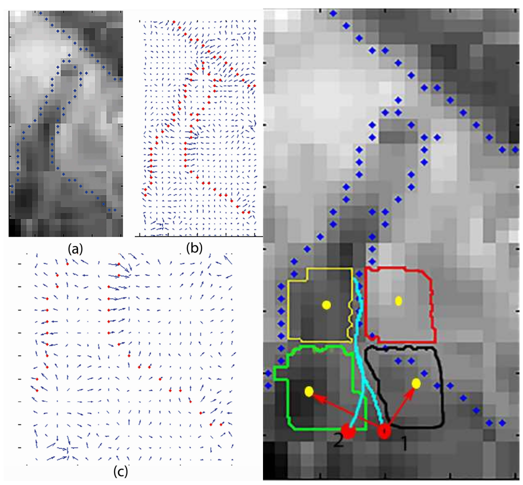

Figure 2. Elucidating why edge detectors fail to follow the true boundary (a) Zoomed in small artery (b) Gradients of pixels there (c) Point where diverging to false direction because of small gradients below the lower threshold. Thus, RES starts and four subregions centered at the error point are formed as in the rightmost image.

The gradients of strong edge dots which are vertically aligned in red color are nearly horizontal as expected and at one point they change their directions diverging from the true edge. This is because of the gap where no strong gradient magnitude (strong meaning having a value over even the lower threshold of Canny's hysteresis thresholding algorithm) exists on the true way and clues are lost. Here this paper says there is another clue present in this region. It is the regional intensity information. Till to the diverging point, the edge found has already separated and formed two segmented areas on each side.

It is critical that looking for big gradients in the front window to bypass the gap will not be reasonable. They may be caused by other contrast differences which belong to two different segmented regions. However, it is reasonable to seek for the same intensity somewhere in front of the diverging point will probably belong to the same segment couple. And as it is seen in Figure 2-c, even at this region with insufficient gradient magnitude , there exist many similar intensity pixels being scattered in an area because of noise and thus couldn't give rise to a sufficiently high magnitude of gradient for edge detectors to follow. The method is simply based on this reasonable fact.

A. Dividing into Subregions at Critical Points

In order not to affect the true edges extracted by edge algorithms, the exact time must be determined where the enhancement and fine tuning must take place. Otherwise no action must be carried out. For this, the whole edge points are traced and at each point a window as in rightmost image of Figure 2 is constructed and oriented according to the direction of the edge. It consists of 4 subregions. Size of this window is heuristically chosen. That size can be adapted according to the width of the elongated structure dealed with. Two subregions in yellow and red contours refer to already segmented regions by the edge. Their means and standard deviations are calculated according to intensities of pixels inside the regions and these two parameters characterize the subregions well as Gaussian distributed gray levels. Since there is an edge between them, means have to be found different.

The remaining two subregions in front of the current edge point are separated by the interpolating spline in cyan color and are used for future estimation of possible edges. The number of similar intensities are counted in these regions and expected to be over a predefined threshold value if there is really an edge there. N_{R1} equals to the number of the image pixels such that

$$I(x,y)_{R1} \leq |\mu_1 + \sigma_1| \tag{1}$$

Where I(x,y) is the image intensity, μ_1 is the mean value of the intensities of pixels in region R_1 , and σ_1 is the standart deviation. Similary, for region R_2 , N_{R2} denotes the number of the image pixels s.t.

$$I(x,y)_{R2} \leq |\mu_2 + \sigma_2| \tag{2}$$

Then, the following condition is checked

$$T_1 < N_{R3} < T_2 \text{ or } T_1 < N_{R4} < T_2 \tag{3}$$

Where T_1 is the lower threshold that denotes the minimum required number of pixels with similar intensity and T_2 is the upper limit that avoids working on already found true edges. Met condition guarantees that similar intensities are found in the upcoming regions which resemble to already separated parents. Thus, the edge have to continue. The identification of the direction of this new edge is not ambiguous. It will be logical that the new direction of the edge will be towards to the centroid of the region with bigger number. The distance of centroids to the extrapolated spline point is thus important. The centroids try to pull the spline towards themselves as seen in Figure 3. New red dot position will identify the new edge direction.

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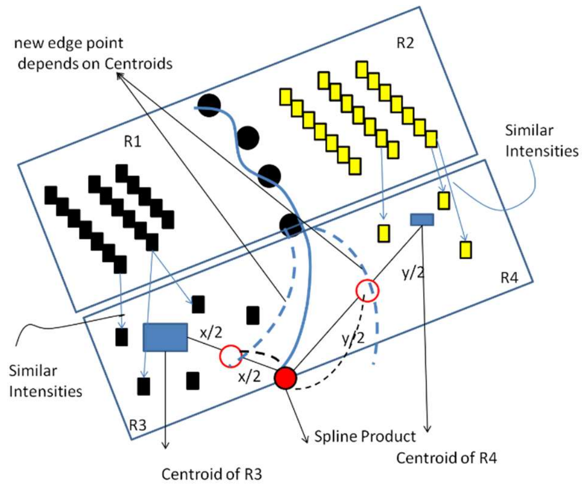

Figure 3 25x25 window at one critical point with four subregions The red dot tends to move to heavier centroid nearby changing edge direction from false direction to more accurate one. Means of R_3 and R_4 are blue rectangles. Similar pixels are connected on each side of the edge.

In Figure 3 , ‘x’ is the distance from centroid of R_3 to the final spline point shown as red dot. Similaryl ‘y‘ is the distance from centroid of R_4 to the same final spline point. These quantities are multiplied with related number of pixels, N_{R1} and N_{R1} , and the products are subtracted and divided by 2. Although no similarity appears on one side of the subregion R3 or R4, one with adequate number of pixels is sufficient and the resulting spline point will be on half the way at a distance x/2 or y/2 to the centroids.

$$\frac{\left(N_{R1} \times x - N_{R2} \times y\right)}{2} \tag{4}$$

This is only one simple way for the direction of the newly found points. Then, these new edge points are added and the edge get extended.

An outline of the algorithm can be summarized as follows;

- Get results of any edge detetion algorithm on images with mostly elongated structures to be extracted (vessels, roads, pipes, trees, etc)
- Get each separate edge as a contour. If applicable, divide into branches, and get each branch as a contour to be processed
- Obtain pixel coordinates of the contour in an array set S.
- Sort the coordinates in S in an order so that each subsequent point in the array is also graphically the successor.
- For all points in S are processed do:

  -For each point P in S, form a directed window centered at P. The direction of window will be compatible with the direction of the previous points of the edge.

  - The candidate edge is initially set to a curve fit to these last 3 or 4 points shown as red dots in Figure 4-c

    -Calculate variances and means of 4 subregions

    -Apply the criteria to detect whether RES algorithm must start

    - If the start criteria is met,

      - find center of gravities of forward subregions on both sides of the edge used for enhancement

      - bend this edge towards the weightier center direction of new points and record their coordinates

      -Update the contour set, S with new points

and continue recursively untill all points are exhausted. The progress of RES is shown on a real coronary artery in Figure 4.

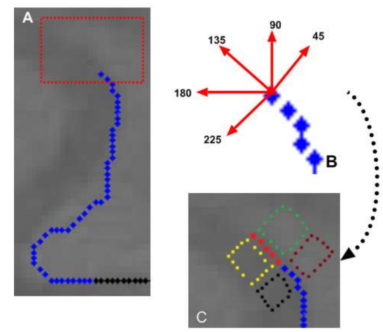

Figure 4. Tracing the detected Canny edge, an alarm condition is met by comparing the subregions. Missing edge points in red dot are produced and added in the correct direction.

III. RESULTS

The database of images mostly consists of biomedical angiography images. There are some synthetically produced test images, in-door images of letters on papers, cups and satellite images. For revealing the efficiency of the technique better, the results are chosen from the subset of harder images with much noise where the best edge detection algorithms will fail. Sobel and mostly Canny algorithms are applied on these images. Human’s perfect perception intelligence will visually track the black elongated vessel structures in Figure 5 till the contrast totally disappears.

As machine vision, this goal can only be kept up with learning algorithms and artificial intelligence with some supervised techniques which is not the subject of this paper. Thus, edge detection algorithms stop earlier in blue dots leaving many false negatives behind. The reinforced edge detection with segmentation (RES) extended these edges with green additions as observed in Figure 5.

In Figure 6, some in-door objects are photoed and edges are detected. The letter ‘E’ is written on a paper and photoed in a weak illuminated scene. This results in pure detection of edges especially by Sobel. Paper-background contour is expected to be rectangular but one fourth of the edge is caught by Sobel. The left side of the paper can not be distinguished from the background by Canny which is shown as white edges in Figure 6. RES starts from the point they stop and adds red lines by managing even to turn around the paper corners and maintain the contour continuity. Moreover, RES does not corrupt already found edges by these detectors. In the first row, a cup image is given where Sobel misses the closer curve at the brim. RES fully reveals it but adds some useless lines (maybe not artefacts) also. RES is currently being developed to address this issues as a future work. In fact, it is an interpretation whether these extra lines are artefacts since

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shading and illumination degrading exist there. Then, they can be preserved.

Edges of Canny on the cup image are good but they are discontinuous at the brim of the cup. On the other hand, RES again gets a closed contour without discontinuity. RES finalizes the contour of brim correctly as a whole elliptic shape by utilizing the segmential information there.

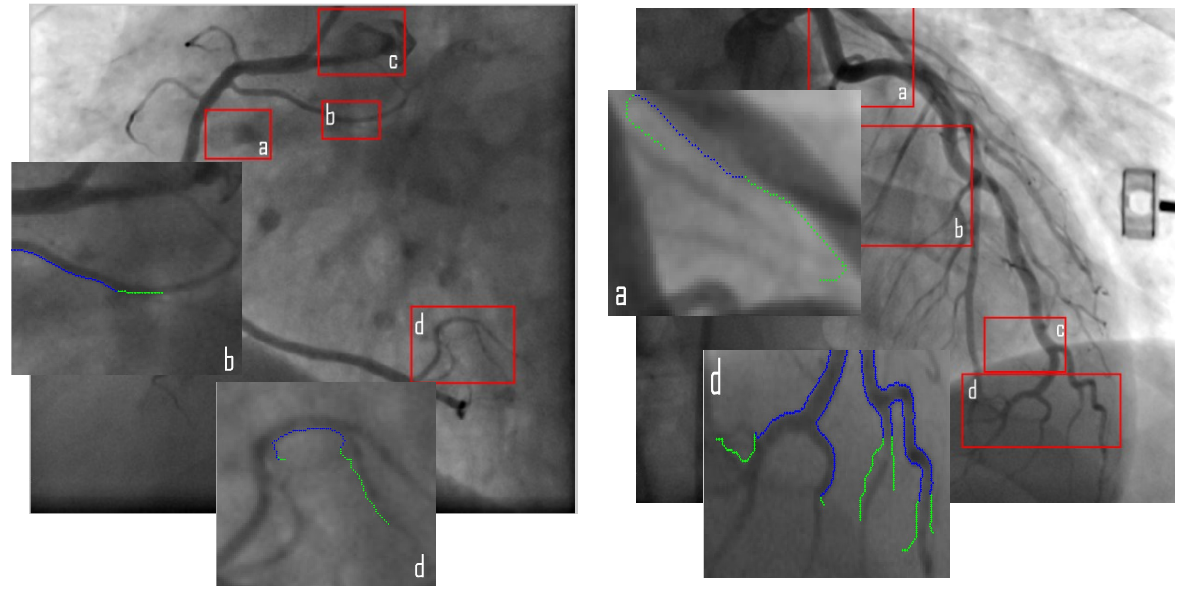

Figure 5. Angiogram noisy coronary images. By the reinforcement of edge detection with region segmentation, green edges are added to those blue edges extracted by Canny. Human intelligence can visually track the black elongated vessel structures well in zoomed out regions further of course.

Figure 5. In-door test images. First row shows an original cup and its edges obtained by Sobel, Sobel+RES, Canny , Canny+RES respectively. The second row is the photo of a big letter 'E' on a paper, and its edges as in the first row. RES not only extends the unfound/missing edges but also fills the gap between the disjoint edges and completes the contour continuity.

IV. CONCLUSION

Human uses the intelligence grown up from childhood by adding many relevant (similar to images seen before) information about the images/environment to extract the borders and to recognize the objects. What is expected from a good edge detection algorithm is to approach to this human vision ability by including some global features instead of just relying on the local gradient changes.

This paper stands at some point trying to fill the gap between ordinary edge detectors like Canny, Sobel, Haralick, vs. and perfect vision of human. It includes some human insight by utilizing segmented region information for supporting the edge detection algorithms. Thus, RES is able to get closed contours instead of isolated edges and continue to keep track of the edges where contrast and intensity gradients diminish too much.

RES has been tested on medical coronary images and enhanced the artery borders. The algorithm does not delete the wrongly found artery edges but it adds undetected ones which means an increment in true positive edges and a high decrease in false negatives. Thus, both accuracy and recall values increase about 30% on some very noisy medical images and about %20 on the average. RES produces some artefacts which are thought to be originating from some execution errors and can be fixed. On the other hand, its advantages are obvious since tracing the edge points iteratively, the algorithm does an enhancement because;

- RES finds further edge points that really exist in the front regions where common detectors stop for some reason
- RES discovers edges with better direction than the detectors suggest at critical points
- the criteria of RES based on the compatibility to parent regions will discover the wrongly found edges (false positives)
- RES will at the same time strengthen the belief to true edges passing that criteria and will supply a clue for elongated regions.

Further researches continue to apply the technique at images taken from different modalities like satellite, hyperspectral and thermal, medical imaging. The performance of RES will then be measured under different enviroments with real and artificially produced noise and inhomogeneities.

Conflict of Interest: The authors declare that they have no conflict of interest.

REFERENCES

[1] M. Shah, Fundamentals of Computer Vision, UCF, 1992.
[2] M.D. Heath, S. Sarkar, T. Sanocki, K.W. Bowyer, “A robust visual method for assessing the relative performance of edge-detection algorithms, “ IEEE Trans. Pattern Analysis and Machine Intelligence 1997; 19:1338-1359. http://dx.doi.org/10.1109/34.643893
[3] M.C. Shin, D. Goldgof, K.W. Bowyer, “Comparison of edge detector performance through use in an object recognition task, “ Computer Vision and Image Understanding 2001; 84:160-178. http://dx.doi.org/10.1006/cviu.2001.0932
[4] T. Peli, D. Malah, “A Study of Edge Detection Algorithms, “ Computer Graphics and Image Processing 1982; 20:1-21. http://dx.doi.org/10.1016/0146-664X(82) 90070-3
[5] P.A. Khaire, N.V. Thakur, “ Image edge detection based on soft computing approach, “ International Journal of Computer Applications 2012; 51:12-14. http://dx.doi.org/10.5120/8061-1426
[6] C.T.N. Suzuki, J.F. Gomes, A.X. Falcao, J.P. Papa, “Hoshino-Shimizu S, Automatic segmentation and classification of human intestinal parasites from microscopy images, “ IEEE Transactions on Biomedical Engineering 2013; 60:803–812. http://dx.doi.org/10.1109/TBME.2012.2187204
[7] J. Vasavada and S. Tiwari. “An Edge Detection Method for Grayscale Images based on BP Feedforward Neural Network, “ International Journal of Computer Applications (0975 –8887) Volume 67– No.2, April 2013. http://dx.doi.org/10.5120/11368-6627
[8] M.G. McGaffin, J.A. Fessler, “Edge-Preserving Image Denoising via Group Coordinate Descent on the GPU, “ IEEE Transactions on Image Processing 2015; 24:1273-1281. http://dx.doi.org/10.1109/TIP.2015.2400813
[9] W. Xiao, X. Hui, “An improved canny edge detection algorithm based on predisposal method for image corrupted by gaussian noise, “ World Automation Congress 19-23 Sept. 2010; 113-116.
[10] R. Mainin, H. Aggarwal, “Study and comparison of various image edge detection techniques, “ Int Journal of Image Processing 2009; 3:1-12.
[11] M. Roushdy, “Comparative study of edge detection algorithms applying on the grayscale noisy image using morphological filter, “GVIP Journal 2006; 6:17–23.
[12] M. Juneja, P.S. Sandhu, “Performance evaluation of edge detection techniques for images in spatial domain, “ Int Journal of Compt Theory and Engineering 2009; 1:1793-8201. http://dx.doi.org/10.7763/IJCTE.2009.V1.100
[13] Y. Mei, S. Yang, B. Mo, “ Improved edge detection algorithm based on Canny operator, “ Laser & Infrared 2006; 36:501-503. http://dx.doi.org/10.1109/ISDA.2007.6
[14] W. MCIlhagga, “Canny edge detector revisited, “ Int. Journal of Computer Vision 2011; 91:251-261. http://dx.doi.org/10.1007/s11263-010-0392-0
[15] B. Ramamurthy, K.R. Chandran, “Content based image retrieval for medical images using Canny edge detection algorithm, “ Int Journal of Computer Applications 2011; 17:32-37. http://dx.doi.org/10.5120/2222-2831
[16] S.S Al-Amri, N.V. Kalyankar, S.D. Khamitkar, “Image segmentation by using edge detection, “ Int J of Compter Sci Eng 2007; 2:804-807.