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Automated Extraction of Small Structures in Medical Images Based on Multi Scale Approach

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ABSTRACT

Multi scale techniques coupled with active contours have been widely used to locate the boundaries of structures in noisy images. Significant fine structures have been emphasized through appropriate scale selection. One of the important draw backs of the existing methods incorporating scale selection is that the final result is a combination of fine as well as coarse structures. This is not desirable when the focus of attention is only on selected fine structures and not on the coarse structures. In this paper we propose a method to extract desired structures exclusively. The proposed technique utilizes wavelet edge detection, multi-scale edge linking coupled with a method of classifying relevant edges. Several parameters from the scale evolution of the multiple scale edges detected by a discrete wavelet decomposition of an image are used in a clustering algorithm to classify the edges belonging to various structures. These edges are further processed using morphological techniques to obtain approximate boundaries of the desired structures. This paper presents the approach and preliminary results which are encouraging.

Keywords: multi scale edges, scale selection, wavelet, and small structures extraction.

1. INTRODUCTION

Multi scale techniques have gained wide acceptance in image processing community mainly because of the data reduction they introduce and their similarity to human visual system (HVS) that is strongly multi resolutional [1] [2]. In particular, there are evidences that the brain possibly uses a form of scale-space like analysis to perform preliminary processing on the images before any semantical classification is realized. Thus, scale-space analysis of digital images is a very natural direction of evolution for computer-vision systems. Multi scale techniques have been widely used in medical image segmentation to find the boundaries of anatomical parts in noisy images [3] [4] [5]. These approaches typically find multi scale edges using scale space or wavelet techniques. These edges are then linked through the scales to find approximate boundaries of the regions of interest. The approximate boundary is further refined through active contour techniques or using morphological methods [6], to find a more accurate boundary.

In human visual perception, certain details are more obvious at specific scales [1]. As an example, when a tree is observed from a few meters, one may notice trees, fruits and flowers. When the same tree is observed from far only large branches and the shape of the tree may be of significance. Similarly, in the scale-space analysis of medical images, some tissue structures may only be noticeable at fine scales, and not at coarser levels. For some medical images, it is this fine detail that may carry meaningful information. Researchers have focused on finding the fine detail through scale selection [7]. A major disadvantage of the previously proposed techniques is that the final output contains the result from not only the chosen scale but also the coarser scales. In such case it is not possible to extract desired structures exclusively.

In this research we propose an automated method to extract desired structures exclusively. Our method focuses on automated scale selection and is based on wavelets. It utilizes wavelet edge detection, multi scale edge linking coupled with a method of classifying relevant edges. Several parameters from the scale evolution of the multi scale edges detected by a discrete wavelet decomposition of an image are used in a clustering algorithm to classify the edges belonging to background, structures(s) of interest, other structure(s) and noise. This technique is applied to CT scan images of neck region to successfully delineate several small structures. The following section presents the methodology. Experimental results are reported in Section 3 and Section 4 is devoted to conclusion and future work.

2. METHODOLOGY

Overview of the approach

Figure 1 presents an overview of the proposed method. In this work, edge detection is performed using wavelet transform modulus maxima [8] [9] to obtain multiple scale edges. Noisy edges are eliminated by maxima suppression which produces a collection of local maximum points. This process results in an edge map with edges representing highest intensity changes in the image. The next step is intra-scale edge linking [10] which produces edge segments of varying lengths. The edge segments are further pruned by discarding short edges, which are most likely to be noise. The remaining edges are then linked using an inter-scale edge linking algorithm [11]. After inter-scale edge linking is complete, a feature vector is calculated for each edge segment. These feature vectors contain information about the edge strength, how long an edge lasts through scales and the mean value of the edge strength through scale. These feature vectors, once computed, are clustered using an automatic clustering algorithm. Finally, using morphological processing, the clustered edges are linked to obtain the closed contours of the structures in the image. The following subsections describe feature vector calculation and clustering in detail.

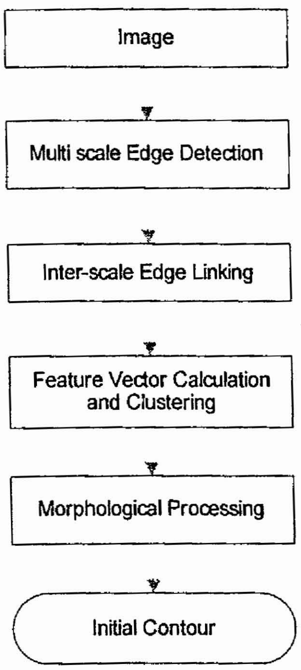

Figure 1: The overview of the proposed approach.

Feature Vector Calculation

Figure 2 illustrates maxima points through scale for a one dimensional signal. This is a typical output from the intra scale edge linking process. Each vertical chain contains the maxima points that are linked through scale and is referred to as maxima chain. Every edge point at the fine scale has one maxima chain associated with it. The length of the maxima chain depends upon the existence of this edge at coarser scales and the slope of the chain at each point is associated with the shift in the edge through scale. The edge magnitude along the maxima chain indicates the strength of the edges. Edges of coarse structures have the longest maxima chains whereas edges of the fine structures terminate at lower scales. Here we hypothesize that classification of the maxima chains based on their length, strength, smoothness may lead to classification of structures in the image. A priori knowledge of the maximum scale of presence of the desired structures may assist in more accurate classification. Therefore features are extracted from the maxima chains to assist in classification.

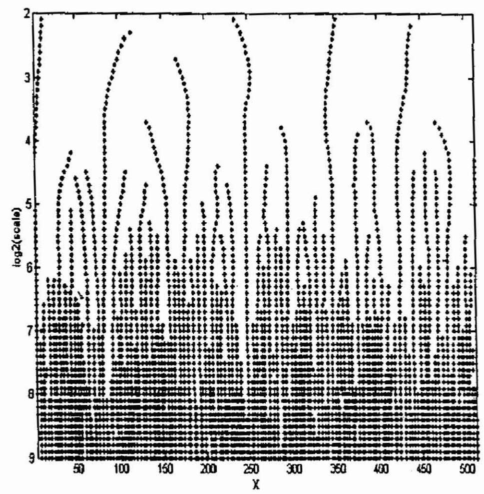

Figure 2: The maxima chains of 1D signal.

In this work we use the expression in Equation 2.1 which is derived from the local Lipschitz regularity theory [8] [9]. This is similar to a curve fitting problem given the points that are to be fitted with the curve. In our case the points to be fitted are the points a_j on the maxima chain.

$$\sum_{j=1}^{J}\left(\log|a_j| - \log(K) - j - \frac{\alpha_0 - 1}{2}\log(\sigma^2 + 2^{2j})\right) \tag{2.1}$$

The expression in Equation in 2.1 is minimized with the variable parameters K, α and σ. These parameters characterizes an edge : K provides information of the strength of the chain, α describes the edge type such as ramp edge and step edge, and σ is the smoothing factor for object size where edges of different object will have different σ.

Other important features that are found to be of significance in extracting desired structures are M and N.

N is the Propagation number being the maximum scale until which a maxima chain exists and M the mean value of the maxima point strength along the maxima chain.

$$M = \frac{1}{n}\sum_{k=1}^{n} x_k \tag{2.2}$$

x_k ... is the magnitude of the kth maxima point.

Clustering

Using the feature vector (K, M and N), the maxima chains are classified using K-means clustering. The three parameters are normalized to prevent favor to any of the three parameters in deciding the output clusters. This algorithm requires a priori knowledge of the number of clusters. This information may be heuristically determined from the image.

The cluster that may represent the desired structure is chosen and the edges in this cluster are further processed by morphological dilation and erosion to determine approximate smooth boundaries. The following section presents the results obtained with a sample image.

3. RESULTS

The output of clustering is shown in Figure 4 and the edge maps associated with each cluster are in Figure 5. Cluster 4 is formed by strong edges that have high propagation number. From Figure 5(a) it is seen that edges from Cluster 4 are clearly the edges of the coarse structure. Figure 5(b) contains the edges of small structures which have weaker edges and not appear at coarse scales. These edges are associated with Cluster 1 of Figure 4. Edges that constitute Cluster 2 are fairly strong but do not appear at the highest scale. It is seen from Figure 5(d) that these edges are associated with the intensity changes within the structures. Finally, Cluster 3 is formed by the noisy pixels with relatively low edge strength. This noise appears only at fine scales. Edges formed by Cluster 2 are depicted in Figure 5(c). Thus, from the obtained results, it may be noted that with the a priori knowledge of the appropriate propagation number of the desired structure, it is possible to identify the associated cluster and isolate the edge map of these structures. After clustering, the edge map may be enhanced using morphological operations such as dilation and thinning. The effect of such morphological operations are illustrated in Figure 6(a) and 6(b).

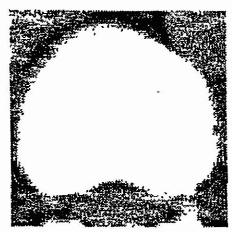

Figure 3: The Original image used in the study.

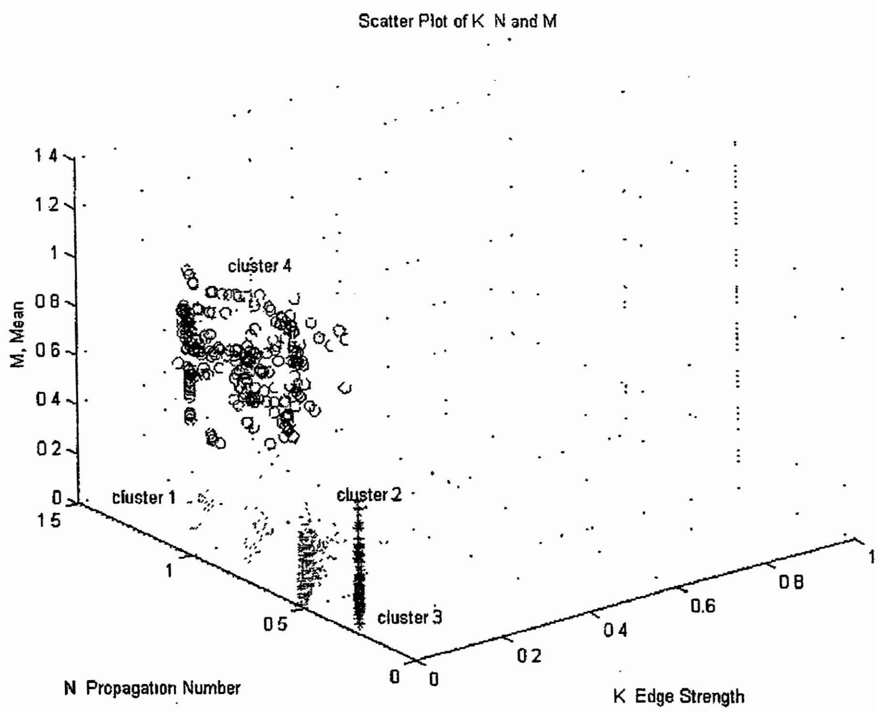

Figure 4: Scatter plot of the K (edge strength), N (propagation number) and M (mean). Cluster 1 is the cluster gives the small structure edges.

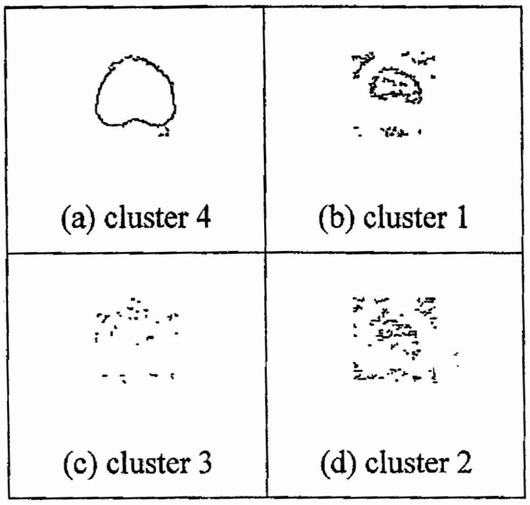

Figure 5: The edges show in cluster 4, 1, 3 and 2.

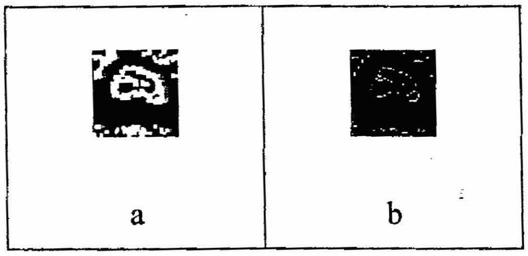

Figure 6(a): The edges after 3 iteration of dilation. (b)The final connected contour after 100 iteration of thinning process.

4. CONCLUSION AND FUTURE WORK

The results of the proposed method are encouraging. The isolated output of the desired structure is very useful for further image analysis. The contours produced in this method may not be accurate. We address this issue in our future work by feeding the output of this method to automatically initialize the boundary in active contour methods.

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References

[1] B. M. t. H. Romeny, **Front-end Vision and Multiscale Image Analysis**, Kluwer Academic Publishers, 2002.

[2] D. Marr, **Vision**, Freeman Publishers, 1982.

[3] A. Laine and X. L. Zong, "Border Identification of Echocardiograms via Multiscale Edge Detection and Modeling", In **Proceedings of The IEEE International Conference on Image Processing**, Vol. III, pp. 287-290, 1996,

[4] N. Lin, W. C. Yu and J. S. Duncan, "Combinative Multi-scale Level Set Framework for Echocardiographic Image Segmentation", **Medical Image Analysis**, Vol. 7, Issue 4, 2003, pp. 529-537.

[5] K. Humnabadkar, S. Singh, D. Ghosh and P. K. Bora, "Unsupervised Active Contour Model for Biological Image Segmentation and Analysis", In **Proceedings of the IEEE TENCON 2003 Conference on Convergent Technologies for the Asia-Pacific Region**, Vol. 2, 2003, pp. 538-542.

[6] V Metzler, C Thies, T Lehmann and T Aach, "Segmentation of medical images by morphological scale-space filtering", **Medical Imaging, Proceedings SPIE 4322**, 2001, pp. 139-150.

[7] A. Petrovic and P. Vandergheynst, "Multiscale Variational Approach to Simultaneous Image Regularization and Segmentation", In **Proceedings of ISPA**, 2003.

[8] S. Mallat, **A Wavelet Tour of Signal Processing**, Academic Press, UK, 1998.

[9] S. Mallat and S. Zhong, "Characterization of Signals from Multiscale Edges", In **IEEE Transactions on Pattern Analysis and Machine Intelligence**, Vol. 14, No. 7, pp. 710-732, 1992.

[10] D. J. Williams and M. Shah. Edge, "Contours Using Multiple Scales", In **Computer Vision, Graphics, and Image Processing**, Vol. 51, pp. 256-274, 1990.

[11] M. Siegel and P. Gunatilake, "Enhanced Remote Visual Inspection of Aircraft Skin", In **Proceedings of the Intelligent NDF Sciences for Aging and Futuristic Aircraft Workshops**, p.p. 101-112, Sept, 1997.