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A Survey on Segmentation of Spine MR Images Using Superpixels

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Abstract - Image processing contains a necessary step of Image Segmentation, which forms a tedious task in medical field. There are various deformities and abnormalities available in human spine, which can be detected using segmentation of MRI images. Various methods are available and studied to perform spine image processing .Superpixels is an approach used for segmenting spine MRI images of human body. This approach helps in reduction of image complexity and makes the detection of vertebral body contour easier. Applying superpixels may miss to cover all the boundaries of the image, so this is handled by performing post-segmentation using thresholding method. Region growing technique is applied for final segmentation by manually selecting the seeds points by the specialists.

Keywords: Superpixels, segmentation, lumbar, clustering.

I. INTRODUCTION

In human body there are five separate vertebrae available which are named according to their location in vertebral column. This lumbar spine is labelled as L1 to L5 which is located between the thoracic vertebrae and the sacrum of the spine. In human body the lumbar spine forms a very important weight bearing portion of the spine. Among all the vertebrae within human spine the lumbar vertebrae is having a complex structure and contains many anatomical parts.

There are various computational methods through which different characteristics of the lumbar spine can be studied and can be worked on. The very important step by which we can scan the individual subjects of the vertebrae is through Image Segmentation. In segmentation process the image contains labelling of pixel the image, then according to the assigned label classifying that pixel to the class to which it belongs. Segmentation in medical images can be done manually but it takes a lot of time as medical images are presented as stack called slices, which requires proper estimation of each and every slice of the image stack. By applying semi-atomic process a good result of segmentation can be obtained from a huge dataset of images.

The medical field has many instruments like magnetic resonance imaging (MRI), Computed Tomography (CT), Ultrasonography (US.) through which human body image can be captured. Among all this MRI images forms a great development part for the medical research work.

MRI images has many benefits like it has high resolution, nonradioactive contamination, it does not provide exposure to any kind of harmful radiation. For using raw MRI images it is very important to preprocess that images to satisfy the segmentation purposes. Pre-processing of the image contains many steps like de-noising, skull-stripping, intensity normalization etc, so it is very important to preprocess the MRI images which can remove noise and brighten the image contrast.

Vertebral bodies segmentation detects various defects available like vertebral fractures, scoliosis, spon dylolisthesis in human body[1]. From the point of view of segmenting the vertebrae from MRI images there are various methods

available for semi-automated and automated segmentation of vertebral bodies[1]. Vertebral bodies segmentation can be effectively addressed by using Superpixels which is very widely used approach. Superpixels are beneficial for reducing the complexity of the image which is becoming a crucial approach for computer technology[1]. They have become the base for computer vision activities such as object localization, depth estimation and segmentation.

II. LITRATURE SURVEY

A. Superpixel Segmentation Methods

a) Graph-Based Methods

In[7] this method every pixel is treated as a node in a graph and the edge weight between the two nodes is proportional to the neighboring pixels on the basis of similarity.

b) Normalized Cuts algorithm [NC05]

In[3] this algorithm all the pixels of the graph are partitioned using the contour and texture, which minimizes a cost function applied on the edges of the boundaries. The output of this is, we get good amount of superpixels which is regularly produced. The segmentation quality is relatively high but the running time is slow.

c) GS04

Here[3] to generate superpixels an alternate graph-based method is applied. Agglomerative clustering of pixels as node is done on a graph so that each superpixel is the minimum spanning tree from all the other available.GS04 is found to be well suited to cover the image boundaries, but there is problem of irregularity of shape and size during generation of superpixels. Also there no control over the number of superpixels and their compactness.

d) SL08

This method[3] divides the image into small sized vertical or horizontal regions to find most favorable paths using a graph cut method for creating superpixels. The pre computed boundary maps is not taken into consideration during superpixels generation which causes quality effect problem and even the speed of the output.

e) GCa10 and GCb10

In this approach[3] superpixels are generated by stitching together overlapping image patches in such a way that each pixel should belong to only one of the overlapping regions. This method uses optimization approach which is very much similar to texture synthesis. GCa10 is used for generating compact superpixels which has control over the number superpixels and also it is useful for generating supervoxels. It has got three parameters which can become difficult to set them.GCb10 generates superpixels which are more compact than GCa10.Constant Intensity superpixels is used as a variant in this method.

B. Gradient-Ascent-Based Methods

In these algorithms at prior stage clustering of pixels is done repeatedly to refine clusters until some convergence criterion is met to generate superpixles.

a) MS02

MS02 is an earlier method [3] of generating superpixels. An iterative mode-seeking procedure for locating local maxima of a density function, is applied to find modes in the color or intensity feature space of an image. Pixels that converge to the same mode define the superpixels[7]. Superpixels generated by using this method are not properly shaped and are improperly sized.

This method is too complex and slow, it doesn't allow for amount, size, compactness of superpixels.

b) TP09

In turbopixel[3][5], approach a number of seed points of image are selected using level-set-based geometric flow, in which a curve is formed to obtain superpixel boundaries. This algorithm has a certain amount of control over number of superpixels and processing speed is very good as compared to others. Superpixels generated using TP09 has got same size, are compact, and cover boundaries of the image preety well. This algorithm is slowest among all and have poor boundary adherence.

c) WS91

The watershed algorithm[3][5] performs a gradient ascent starting from local minima to produce watersheds, lines that separate catchment basins. This approach is fast but does not have control over the amount of superpixels or their compactness. The superpixels are irregular in size and shape and do not support to boundary adherence of images.

d) QS08

Quick Shift[4][5] is a clustering method which uses mode seeking segmentation procedure. Here segmentation is achieved by using mediod shift approach. Parzen density is increased by moving each point in feature space to the nearest neighbor.QS08 covers the boundary of the images very well and even it is good in under-segmentation error.QS08 was used prior for localization and motion segmentation.

QS08 is an example of a mode seeking algorithm, which attempts to associate each data point with a mode of the underlying probability density function. This algorithm initiate by computing the kernel density estimate of the data.

$$P(\mathbf{y}) = \frac{1}{N}\sum_{i=1}^{N} K(\mathbf{y}_i - \mathbf{y})$$

where K is a suitable kernel function and the features are usually the image intensity values. Each of the data points is then moved towards a mode of the density by following the direction of highest gradient from the current point. The points that converge on the same mode form a cluster. This algorithm has good increment of density function as it moves each data point to the closest neighbor. A tree of data points is constructed having branches that denote the distance between the data points .Branches which are formed contains superpixels of the image which have greater distance than a threshold value[10].

Quick shift has disadvantage that it is very slow, it do not have control over size and number of superpixels. The superpixels compactness is not satisfactory and it requires many parameters for tunning.QS08 showed poor segmentation and source code doesn't provide proper assurance that the generated superpixels are attached components or not which results into a problematic situation.

e) SLIC SUPERPIXELS

The Simple Linear Iterative Clustering (SLIC)[2],[3],[5] algorithm is very important method to partition the image into superpixels. The SLIC algorithm generates superpixels by clustering pixels based on their intensity values and spatial proximity in the image. It is very much similar to K-means for generating superpixels but differs in two ways:

i.) Here the search space is reduced to only region space which is proportional to the superpixel size because of which number of distance calculations is reduced.

ii.) Color and spatial proximity is combined as a measure in weighted distance, simultaneously providing control over the size and compactness of the superpixels.

SLIC is relatively simple and easy to understand. At the beginning the algorithm assigns the cluster centers to the regularly spaced grid. The 3 × 3 pixel neighborhood is provided around each center of the cluster so that lowest gradient center point is searched, that can reject noisy regions and avoid placing center on the edges. Then comes the assignment step were each pixel of the image is assigned with the nearest cluster center, which has the smallest distance within the local region. When all the pixels are associated the updated cluster center are found and the same process is continued till all the pixels are covered of the image. In final step, connectivity of the superpixel regions is enforced by detecting any disjoint segments sharing the same label and assigning the smallest segment to its largest neighbouring cluster. As compared to other methods SLIC is preety much faster, it is more memory efficient, it generates compact and equable superpixels. The boundary details of image are well preserved by this method. The problem with superpixels is for compact structure it is unable to cover complete object and the sematic level information is not preserved.

C. Threshold-based methods

This[8] is the segmentation method where the comparison of intensities is done with one and more than one intensity

thresholds. Thresholding methods are categorized as local and global thresholding. Global thresholding is done when image contain objects with homogeneous intensity and background is high. Local thresholding is done by recognizing a threshold value for the different regions from intensity histogram.

D. Region-based methods:

This[8] segmentation methods takes pixels from images and creates disjoint regions by merging neighbor pixels with homogeneity properties depending on similarity criterion. The region growing and the watershed segmentation methods are part of the region-based methods. It is effective method and have less computation.

III. PROPOSED SYSTEM

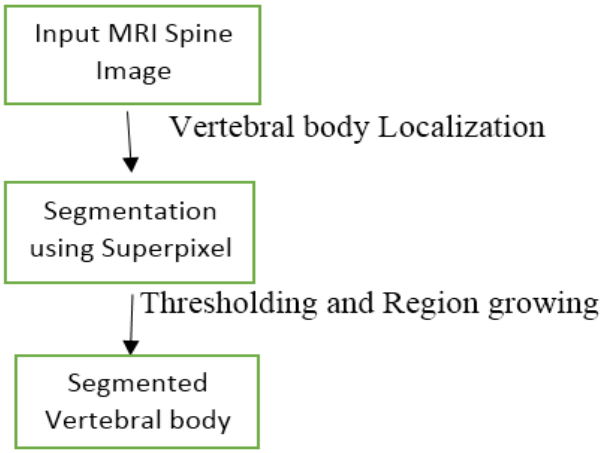

Fig. 1 Proposed System

As we discussed above all the methods regarding segmentation using superpixels each have some benefits and some drawbacks. Thus this method has been introduced as an effective segmentation technique developed to extract the vertebral bodies from spine MRI[1]. The image using a superpixel technique is used to cluster homogeneous pixels while reducing the complexity of the image. The input to it is the MRI images which is given by selecting the seed points by the specialist. The segmentation is performed using superpixels technique and as a result we get the segmented vertebrae of the MRI spine[9].

IV. CONCLUSION

It is very important in medical field to perform vertebral body detection and segmentation from MRI images[1]. Many spine abnormalities or deformities can be detected from vertebral shapes and positions. There are various methods and techniques available and studied to perform spine image processing. Here superpixel technique is used for segmenting the vertebral body. The benefit of using superpixel is it reduces image complexity and makes the detection of each vertebral body contour easier.

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REFERENCES

[1] A. Suzani, A. Rasoulian, S. Fels, R. N. Rohling, and P. Abolmaesumi, “Semi-automatic segmentation of vertebral bodies in volumetric mri images using a statistical shape pose model,” Proc. SPIE 9036, Medical Imaging, vol. 9036, pp. 1– 6, 2014.

[2] R. Achanta, “Finding Objects of Interest in Images using Saliency and Superpixels,” Ph.D. dissertation, IC, Lausanne, 2011.

[3] R. Achanta, A. Shaji, K. Smith, and A. Lucchi, “SLIC superpixels compared to state-of-the-art superpixel methods,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 11, pp. 2274–2281, 2012.

[4] C. M. Schmit BD, “Quantification of morphological changes in the spinal cord in chronic spinal cord injury using magnetic resonance imaging,” IEEE Eng Med Biol Soc, vol. 6, pp. 4425–4453, 2004.

[5] R. C. Gonzalez and R. E. Woods, Digital Image Processing (3rd Edition). Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 2006.

[6] Shiyong Ji, Benzheng Wei, Zhen Yu, Gongping Yang, and Yilong Yin ," A New Multistage Medical Segmentation Method Based on Superpixel and Fuzzy Clustering", Volume 2014.

[7] Ivana Despotović, Bart Goossens, and Wilfried Philips," MRI Segmentation of the Human Brain: Challenges, Methods, and Applications", Volume 2014.

[8] Marko Rak 1 · Klaus D. Tönnies," On computerized methods for spine analysis in MRI: a systematic review", 28 August 2015.

[9] N. Otsu, "A Threshold Selection Method from Gray-level Histograms," IEEE Transactions on Systems, Man and Cybernetics, vol. 9, no. 1, pp. 62–66, Jan. 1979.

[10] P. G. B. G. M. D. A. S. Coulon O, Hickman SJ, "Quantification of spinal cord atrophy from magnetic resonance images via a b-spline active surface model." MagnReson Med, vol. 47, pp. 1176–1185, 2002.

[11] Z. Xue, L. R. Long, S. Antani, and G. R. Thoma, "Spine X-ray image retrieval using partial vertebral boundaries," in IEEE Symposium on Computer-Based Medical Systems, 2011,pp. 14.

[12] S. Antani. R. Long, and G.Thoma, "Bridging the gap :Enabling cbir in medical applications," in Proceedings of 21st IEEE International Symposium on Computer-Based Medical Systems, 2008. CBMS '08., June 2008, pp. 4–6.

[13] T. C. Mann RS, Constantinescu CS, "Upper cervical spinal cord cross-sectional area in relapsing remitting multiple sclerosis: application of a new technique for measuring cross-sectional area on magnetic resonance images," J Magn Reson Imaging, vol. 26, pp. 61–67, 2007.

[14] A. Vedaldi and S. Soatto, "Quick Shift and Kernel Methods for Mode Seeking," Proc. European Conf. Computer Vision, 2008.

[15] O. Veksler, Y. Boykov, and P. Mehrani, "Superpixels and Supervoxels in an Energy Optimization Framework," Proc. European Conf. Computer Vision,2010.

[16] A. Moore, S. Prince, J. Warrell, U. Mohammed, and G. Jones, "Superpixel Lattices," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2008.

[17] J. Shi and J. Malik, "Normalized Cuts and Image Segmentation," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 8, pp. 888-905,Aug. 2000.

