ADAPTIVE IMAGE SEGMENTATION BASED ON LOCAL NEIGHBORHOOD INFORMATION AND GAUSSIAN WEIGHTED CHI-SQUARE DISTANCE

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ABSTRACT

We propose a novel affinity matrix for image segmentation in this paper. The affinity matrix is constructed by using the Gaussian weighted Chi-square distance with neighborhood information, in which the vital spatial structure of the image is considered. An adaptive local scaling parameter is used to refine the segmentation rather than selecting a single scaling parameter. We demonstrate that graph-based segmentation approach to solve the automatic segmentation of the vertebral bodies from sagittal magnetic resonance images of the spine is directly impacted by the affinity matrix. The encouraging results indicate that our new algorithm has the advantage of high accuracy and strong robustness.

Index Terms— segmentation, Gaussian weight, neighborhood information, local scaling, affinity matrix

1. INTRODUCTION

Segmentation of vertebral bodies is more challenging and complex in MR images compared to CT due to the relatively lower resolution and artifacts like RF inhomogeneities. Conventional approaches [1, 2] to image segmentation often trap into local optimum, resulting in bad segmentation. Image segmentation based on a graph cut [3, 4] has become prevalent because of its many fundamental advantages. Julio Carballido-Gamio *et al* [5] (Gamio algorithm) applied Normalized cuts to MR T1-weighted sagittal images of the spine using windowed histograms of intensity [6] as the most promising features. However, this method can obtain erroneous segmentation if the two windowed patches share the same statistical characteristics of local histogram. Moreover, statistic features based on the grey value of the pixels, which not refer to spatial information, are unable to depict an image abundantly. The segmented results deviate widely from the object when the soft tissue intensity similar to the vertebral body.

We makes three contributions: (1) we use a cut-off window around each pixel and stack the gray values inside the window into a vector, which introduces spatial neighborhood information; (2) considering the contribution of the nearby pixels to the centered pixel, pixels in the cut-off window can be weighted by the Gaussian kernel function; (3) an adaptive local scaling parameter is used to refine the segmentation rather than selecting a single scaling parameter, so we present a novel affinity matrix. We apply the novel affinity matrix to accomplish the Normalized cut. This algorithm reflects the advantage of segmenting the objects smoothly and clearly in case of vertebral body lesions. It is a general method in segmenting object that can also help in developing segmentation of other tissues and organs.

2. THE NOVEL AFFINITY MATRIX

Graph–based image segmentation is based on the eigenvectors and eigenvalues of a $N \times N$ matrix derived from the matrix of pairwise affinities. N represents the number of pixels in the image. In the case of image segmentation, the elements in V are pixels and the weight of an edge is the measurement of the dissimilarity between the two pixels connected by that edge. The strength of these edges is weighted with an exponential factor.

$$W_{ij} = e^{-\frac{d^2(i,j)}{\sigma^2}} \tag{1}$$

where $d(i,j)$ is the measure of the dissimilarity between nodes *i* and *j*, and σ controls the scale of this measure.

2.1 Neighbor information and the Gaussian Weighted Chi-square Distance

It is crucial for the segmentation to construct an efficacious affinity matrix. Andrew Y. Ng et al. [7] whose algorithm was named as NJW algorithm constructed a matrix through the feature of each pixel's intensity. However, the matrix has a tendency to deliver poor results in object segmentation. The intensity varies significantly in certain tissues and organs because of the noise or is close to the tissues growing around an organ. The segmentation approach by Gamio, J. et al. used windowed histograms of intensity as the feature, thereby missing the spatial distribution information– resulting in incorrect results. We then take into account the values of neighborhood pixels to solve the above problem, resulting to a good spatial structure feature. Fig. 1 shows the comparison; the pixels p and q do not belong to the same tissue. Note that the difference between the histograms of p and q is very small, unlike the intensities of the pixels p and q.

A box of 5×5 pixels centered on each pixel is first used to extract local intensities of 25 pixels. A weighted measurement of intensities is then performed based on the neighborhood intensities. The dissimilarity between a pair of pixels can be written as:

$$d^2(v_i,v_j)=\chi^2(v_i,v_j)=\frac{1}{2}\sum_{k=1}^{n} w_k \frac{\left(v_i(k)-v_j(k)\right)^2}{v_i(k)+v_j(k)} \tag{2}$$

where $v_i(k)$ is the intensity of the *k*-th neighborhood pixel of the *i*-th local intensities; n is the number of the square neighborhood of a fixed size; and w_k is the feature weight of the *k*-th neighbor pixel. Weight w_k depends on the

Euclidean distance between the center and the neighborhood pixels. The closer the distance between the position of the neighborhood and center pixels is, the higher the weight is, and vice versa. The application of the Gaussian kernel function to the neighborhoods leads to the following equation:

$$w_k = G_l\left(P_i(k), P_i(i)\right) = \frac{1}{\sqrt{2\pi}\,l} e^{-\frac{\|P_i(k)-P_i(i)\|^2}{2l^2}} \quad (3)$$

where $P_i(k)$ is the coordinate of the *k*-th neighborhood pixel of the *i*-th local pixels; and the parameter *l* controls the decay of the exponential function. Because the window size is 5×5, *l* should be between 0.5 and 1. Consequently, the decay of the weights is as a function of the Euclidean distances. Neighborhood information is then combined through the Gaussian function, which is less sensitive to noise. Therefore, this affinity matrix not only considers the intensity of a single point but the geometrical configuration in a whole neighborhood. This fact allows a more robust comparison than the other affinity matrices.

2.2 Local scaling

The scaling parameter is a measurement that shows when two pixels are considered similar. Running their clustering algorithm repeatedly (eigenvalues decomposition and *k*-means), NJW algorithm selected σ automatically from a number of values of σ using the criteria of least distorted clusters but this requires a significant calculation, which is expensive. The range of values to be tested should also be set manually. Manor and Perona [8] proposed to calculate a local scaling parameter σ_i for each pixel v_i rather than selecting a single scaling parameter σ. The distance from v_i to v_j as 'seen' by v_i is $d\left(v_i, v_j\right)/\sigma_i$ while the converse is $d\left(v_i, v_j\right)/\sigma_j$. In our paper, we use the Chi-square distance instead of Euclidean distance. Therefore, the affinity between a pair of points can be written as:

$$W_{ij} = e^{-\frac{\chi^2(v_i, v_j)}{\sigma_i \sigma_j}} \quad (4)$$

$$\sigma_i = d\left(v_i, v_K\right) = \sqrt{\chi^2\left(v_i, v_K\right)} \quad (5)$$

where v_K is the K'th neighbor in the image of point v_i. We use a single value of K = 7, which gives good results even for high-dimensional data. The weight W_{ij} is small if v_i and v_j are significantly different. As expected, the weights are high for pixels that should belong together and low if otherwise.

3. EXPERIMENTS AND RESULTS

This study shows how to segment both normal and vertebral body lesions and degenerated discs from sagittal T1-weighted and T2-weighted MR images of the lumbar spine and segment tumor from T1-weighted brain tumor images, with a matrix size of 512 × 512 pixels. We present experimental results obtained from NJW algorithm based on the Equation (4). To evaluate the performance of improved algorithm, we compare our algorithm to NJW and Gamio algorithm. The results obtained by the clinical experts manually are regarded as the as Ground Truth, which is used to validate the feasibility and superiority of the improved algorithm.

Subjects 1: The vertebral bodies of the patient are normal, and the intensities of the vertebral bodies are similar to those of the tissue around the vertebral bodies (T1-weighted).

NJW algorithm: Andrew Y. Ng et al. segment the objects with the use of the intensity of each pixel but without considering the neighborhood pixels. The intensities of the vertebral bodies are similar to those of the fat around the vertebral bodies so this method is most likely to lead to the phenomena of over-segmentation in the joint location (refer to the blue arrow in Fig. 2). Under-segmentation arises in other vertebral bodies (refer to the purple arrow in Fig. 2).

The Gamio algorithm: This algorithm uses the windowed histograms of intensity as the most promising features, thereby missing the spatial information. Moreover, it uses a single scaling parameter so that the segmented results are poor (Fig 2). This algorithm performed well in the vertebral bodies showing high contrast with respect to the intervertebral discs and surrounding structures in the T1-weighted images. However, the performance was poor if the condition was not satisfied. The algorithm's performance degraded when we tested far from the mid-sagittal slice. Moreover, this algorithm cannot obtain good segmented results in T2 high-resolution images.

New algorithm: This approach to the self-acting segmentation of vertebral bodies has encouraging results on the location of the intensities of the vertebral bodies, which are similar to the tissues around the vertebral bodies. The phenomena of over-segmentation and under-segmentation can then be restrained. This improved algorithm segments the vertebral bodies smoothly, clearly, and accurately.

Subjects 2: The vertebral bodies of the patient are normal, and the vertebral bodies show high contrast with respect to the intervertebral bodies and surrounding structures (T2-weighted).

The vertebral bodies are easier to segment compared with other subjects. Fig. 2 shows how the NJW algorithm leads to a few of the phenomena in over-segmentation (refer to the blue arrow in Fig. 2).

Subjects 3: The vertebral bodies of the patient are normal, and the pedicle of vertebral arch is scanned because of the different scanning flip angle (T2-weighted).

The pedicle of vertebral arch is a part of the vertebral body, but only the new algorithm can segment the pedicle of vertebral arch together with the vertebral body accurately (refer to the blue arrow in Fig. 2).

Subjects 4: The patient has vertebral body lesions and disc degeneration (T2-weighted).

Someone will have vertebral body lesions (refer to the blue arrow in Fig. 2) and disc degeneration (refer to the purple arrow in Fig. 2) with advancing age.

The measures for quantitative comparisons are False Negative Ratio (FNR), the False Positive Ratio (FPR), Overlap Ratio (OR) and Hausdorff Distance (HD) [9] to evaluate the performance of segmentation, as Table 1.The

FNR, FPR and OR are defined as:

$$\mathrm{FNR} = \frac{npixelsManual - (npixelsManual \cap npixelsAuto)}{npixelsAuto} \times 100\% \quad (6)$$

$$\mathrm{FPR} = \frac{npixelsAuto - (npixelsManual \cap npixelsAuto)}{npixelsAuto} \times 100\% \quad (7)$$

$$\mathrm{OR} = \frac{npixelsManual \cap npixelsAuto}{npixelsAuto} \times 100\% \quad (8)$$

Table 1 The comparison of the various methods

Algorithm	Data	FNR	FPR	OR	HD
NJW algorithm	1	17.1	3.89	96.1	3.3
	2	1.92	8.24	91.8	1.7
	3	13.6	9.56	90.4	4.2
	4	5.05	3.42	96.6	1.7
Gamio algorithm	1	9.67	5.26	94.7	2
	2	14.48	7.97	92.0	1.7
	3	13.0	14.6	85.4	2.8
	4	9.92	9.55	90.5	2.2
Improved algorithm	1	3.92	3.16	96.8	2
	2	3.68	2.53	97.5	1.4
	3	3.47	3.93	96.1	1.7
	4	2.79	3.07	96.9	1.7

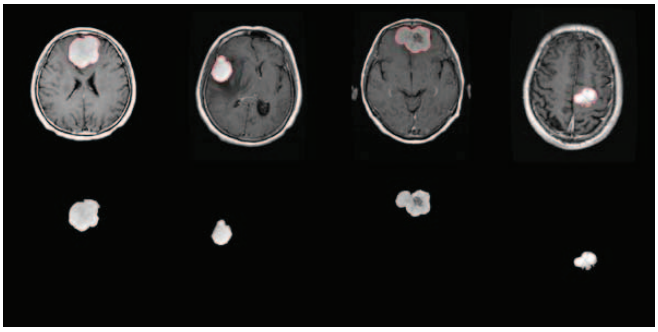
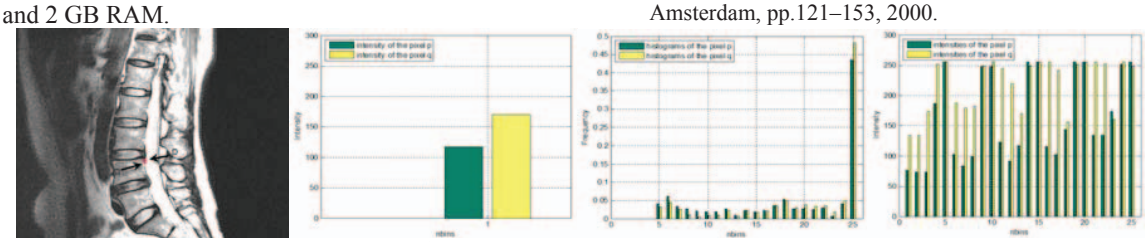


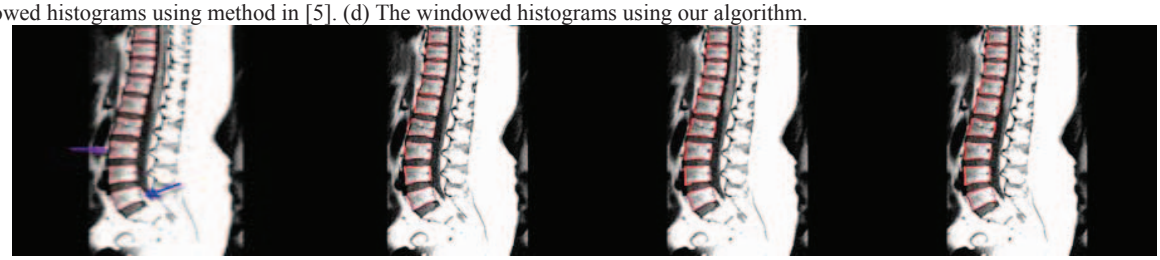
Fig.3. The segmentations of the brain tumors (C=6, l=0.5).

Overall, our algorithm results to robust segmentation of both normal and vertebral body lesions and degenerated intervertebral discs. It is a general method in segmenting object that can also help in developing segmentation of other tissues and organs, as Fig.3. All segmentations are done in a computer with an Intel Core Duo processor, 2.53 GHz, and 2 GB RAM.



(a) (b) (c) (d)

Fig.1. The comparison of the used features. (a) The position of the pixel p and q. (b) The intensity of the p and q. (c) The windowed histograms using method in [5]. (d) The windowed histograms using our algorithm.



4. CONCLUSIONS

The high quality segmentation results could serve image registration and the analysis of spinal deformities. It can also be used in organ location and image-guided vertebra operation, with presumed significant clinical impact.

5. ACKNOWLEDGMENTS

This work was supported by 973 Program of China (No. 2010CB732500) and the National Natural Science Foundation of China (No. 31000450).

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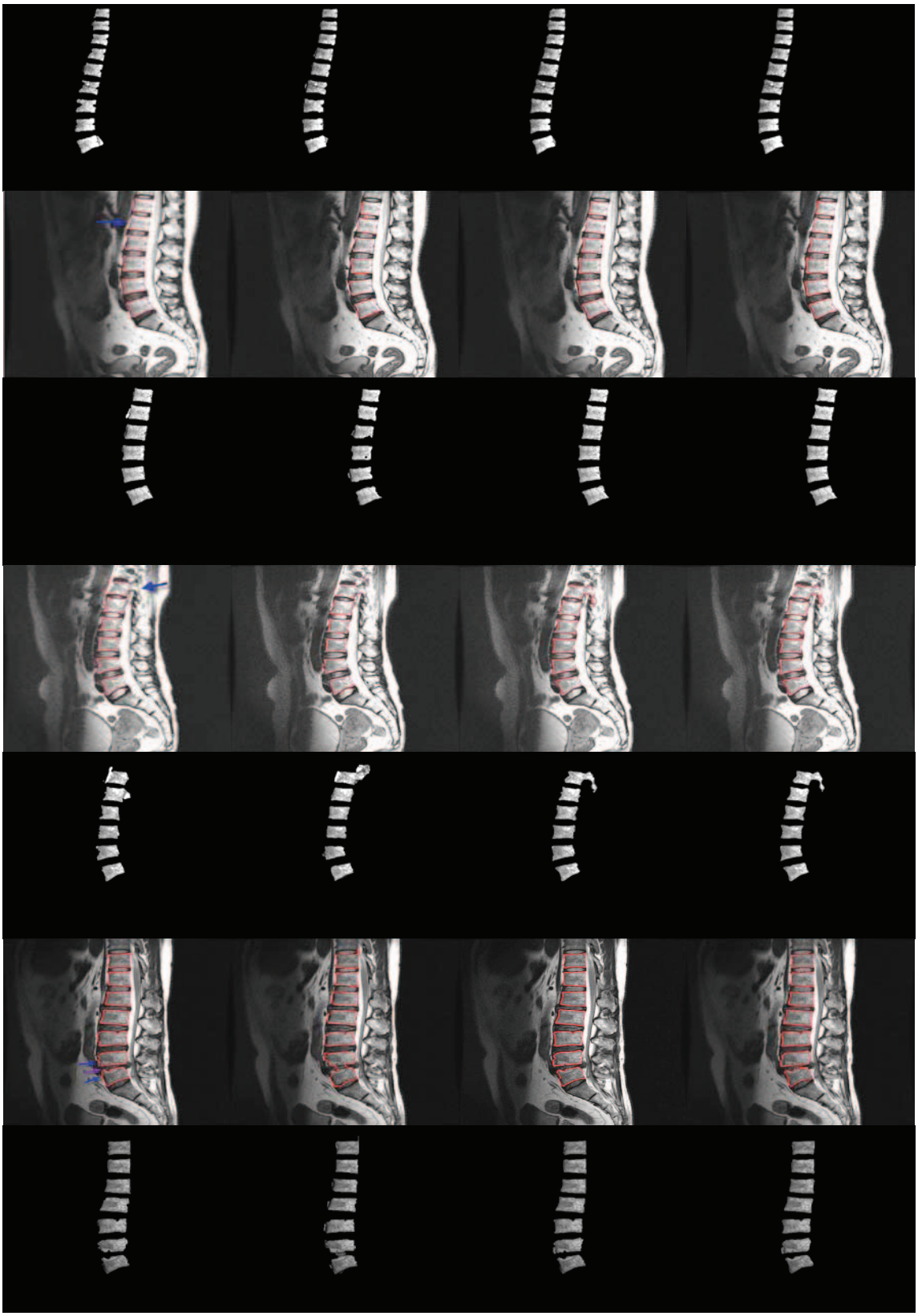
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(a) (b) (c) (d)

Fig.2. The contour (displaying in red line) and the segmentation of the vertebral bodies (C=40, l=0.5). (a) NJW algorithm. (b) The Gamio algorithm. (c) The improved algorithm. (d) Manual segmentation.