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Novel Vertebral Bodies Segmentation and Classification Approach for Spinal Trauma Diagnosis

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Abstract—Spinal trauma can result severe long-term disability, morbidity and mortality. In this paper we proposed a vital segmentation and classification method for spinal trauma diagnosis in spinal computed tomography (CT) images. First the vertebral bodies (VB) are segmented using pair wise spectral clustering techniques Formation of similarity matrix is the foremost step which considers the intensity and local spatial neighborhood information. Based on the neighborhood information Gaussian weighted kernel function is employed to weight the chi square distance of spatial information which enhance the efficiency of the segmentation then the Gray level co occurrence Matrix (GLCM) texture features are extracted .The type of trauma is classified based on the above features using KNN classifier.

Index terms - CT; Gaussian; GLCM; KNN; Spinal Trauma.

I. INTRODUCTION

The human vertebral column also called backbone or spine is consisting of twenty-four articulating vertebrae, and nine fused vertebrae. It houses and protects the spinal cord in its spinal canal. The first seven vertebrae in the articulating vertebrae are called cervical vertebrae. That allows the neck and heads so much movement. These are the smallest, highest vertebrae and the vertebral foramina are triangular in shape. The next twelve vertebrae are thoracic vertebrae the next five vertebrae are very robust in construction called lumbar vertebrae.

Temporary or permanent change in the shape and function of the vertebrae is called spinal trauma. The main causes of trauma are sport injuries, gunshot, car accident, falls and diseases. Based on the location and type of trauma the treatment differs. In most cases, trauma requires physical therapy and rehabilitation. Spinal trauma is classified into three categories they are cervical trauma, thoracic trauma and lumbar trauma [1]. In India there are about one million people who are affected by spinal trauma per year 10000 new cases are added among then 83% are male belong to under 30 age category [2].

Various approaches have been introduced to tackle the segmentation of spine bones. For instance Mastmeyer et al. [3] presented a hierarchical segmentation approach for the lumbar spine in order to measure bone mineral density. They reported that their algorithm can be used to analyze three vertebrae in less than 10min. This timing is far from the real time required for clinical applications but it is a huge improvement when compared to the timing of 1 - 2h reported. in [4]. Klinder et al. [5] developed automated model-based vertebra detection, identification. The authors reported that the elapsed time for the identification of 12 CT vertebrae in [4].

Other techniques have been developed to segment skeletal structures and can be found for instance in [6, 7, 8] and the references therein. Asem ali et al [9] presented a MAP-based segmentation framework of multimodal images. Empirical distributions of image signals are precisely approximated by linear combinations of Gaussians (LCG) distributions with positive and negative components. This approach is extended to segment 3D volumes.

Fuzzy C Means (FCM) algorithm is one of the widely used algorithms for medical image segmentation [10].The features which depict the image are classified by FCM. The pixels which pose the same characteristics are grouped as clusters. The distance between pixels to cluster centre is called cost function and clustering is done by minimizing the cost function iteratively [11].Graph cut also the widely used segmentation techniques for medical images [13, 14].The eigenvalues and eigenvectors are used for segmentation of weighted graph. The similarity between the nodes of the graph is determined by the edge weight. The image is segmented into regions instead of target object and background. The segmented regions pose the high correlation between pixels [16].Gamio at el [17] proposed Ncut segmentation for MR T1 weighted vertebrae images based on windowed histogram. Though Gamio's algorithm is not efficient since the nearby organ pixels poses the same characteristics of same histogram. So analysis of histogram only not can helpful for accurate segmentation of vertebral bodies.

II. PROPOSED METHOD

In this paper we proposed the novel segmentation and classification approach for spinal trauma detection in computed tomography (CT) images. Formation of the similarity matrix is the foremost step in vertebral bodies (VB) segmentation. A cutoff window is applied around each pixel and the pixel gray values are stacked inside the window as a vector. To differentiate the VB pixels from other organ pixels local histogram is used as a parameter. To reduce the noise and improve the accuracy of the segmentation Gaussian kernel function is used which depict the local spatial information. The built similarity matrix is applied to segmentation process by K means clustering. After segmentation the texture features

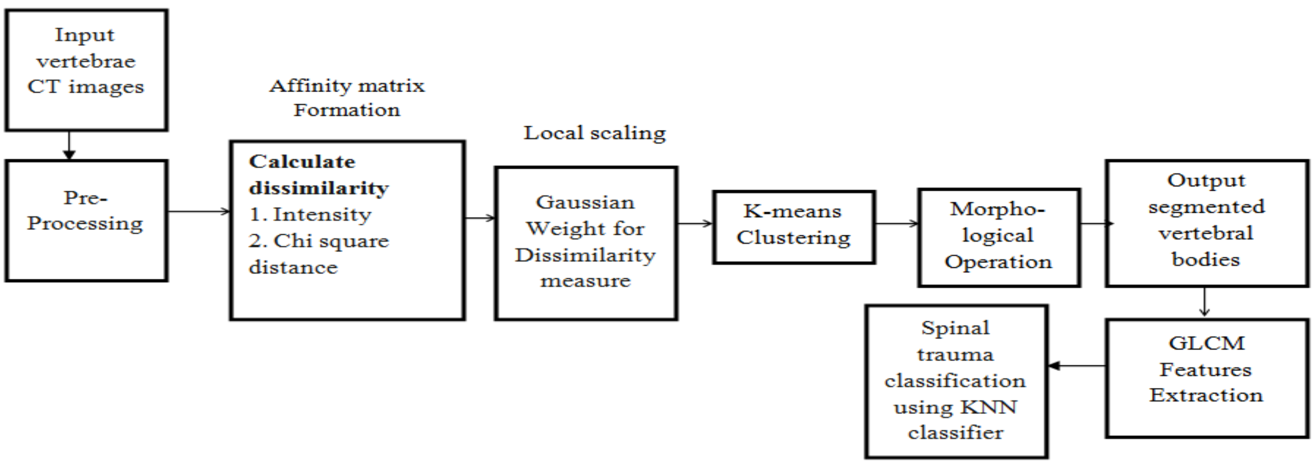

Figure 1. Block diagram of proposed system

of the VB's are extracted by using gray level co occurrence matrix (GLCM) for spinal trauma classification by incorporating KNN classifier.

2.1. Image Data

All input images are vertebral CT images that are collected from radipaedio.com which is the largest database of radiology cases and images. Totally 20 datasets are tested it contains more than 150 images which includes all three major spine trauma cases.

2.2. Pre-Processing

The Input Images are converted into grayscale images which poses the size of 255*255.Then median filter is applied which is used to remove the salt and pepper noise. Each output pixel contains the median value in the 3*3 neighborhood around the corresponding pixel in the input image

2.3. Formation of the Similarity Matrix

NJW algorithm used only the intensity parameter due to the noise and other physical parameters the intensity varies significantly in some organs. The segmented object intensity is close to the organs nearby object. Gamio et al [17] proposed an algorithm which is based on windowed histogram of the intensities as a key parameter so the spatial information is not taken into consideration result in inaccurate result.

Neighboring pixels possess similar characteristics which is the important aspect of the image. So the proposed method extracts the features of the neighborhood pixels to solve the above mentioned problem.

In CT imaging neighborhood pixels have similar features and possibility that correlate to the same cluster is high. This kind of spatial relation is the important aspect of clustering. The spatial function s(i) is defined as

$$s(i) = \sum_{k\in N_n} I_i(k) \qquad (1)$$

Where N_n denotes a local square neighbourhood of the pixel i, n is the number of the square neighbourhood of a fixed size, and I_i (k) is the intensity of the k-th pixel of the local square neighbourhood centred around the image pixel i.

$$d(i,j)^2 = x^2\big(h(i),h(j)\big) = \frac{1}{2}\sum_{k=1}^{n} w_k \frac{(I_i(k)-I_i(k))^2}{(I_i(k)+(I_i(k)} \qquad (2)$$

$$\text{For } \sum_{k=1}^{n} w_k = 1, w_k \geq 0$$

Where w_k is feature weight of the k-th pixel. Weight w_k depends on the Euclidean distance between the centre and the neighbouring pixels. The nearer the distance connecting the adjacent and centre pixel location, the higher the weight value and vice versa.

$$w_k = G_l(p_i(k),p_i(i)) = \frac{1}{\sqrt{2\pi}\,l} e^{-\frac{(p_i(k)-p(i))^2}{2l^2}} \qquad (3)$$

Where pi k is the spatial coordinate of the k-th pixel of the local square neighbourhood centred around the image pixel i, and the decay of the exponential function and decay of weight is the Euclidean function is controlled by the constraint l. It varies between 0.5 and 1.Thus the similarity matrix considers not only the intensity at the single pixel but also the influence.

$$D = \text{diag}\{W\cdot 1\}, \qquad (4)$$

After constructing the Degree matrix constructs the Laplacian matrix called L Find the number of clusters by analyzing the eigenvalues of the Laplacian matrix, the number of eigenvalues of magnitude 0 is equal to the number of clusters k. Find the k first eigenvectors of L (chosen to be orthogonal), and form the matrix U by stacking the eigenvectors in columns. Renormalize each row of U to have unit norm and let V denote the resulting matrix.

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Figure 1(a)Cervical trauma (b) Thorocic trauma (c)Lumbar trauma (Red color circle shows the regions where trauma occurs)

2.4. K Means Clustering

The large collection of objects is divided into groups by the K means method which is based on least square partition. The algorithm repeats over two steps

1. Compute the mean of each cluster.
2. Compute the distance of each pixel from each cluster by computing its distance from the corresponding cluster mean.

Repeat over the above two steps till the sum of squared within group errors cannot be lowered any more. K Means clustering technique is one of the multimodal classification algorithms.

2.5. Vertebral bodies segmentation algorithm

1. Compute the dissimilarity and the local scale σ_i using Eqs. (2) and (3), respectively.
2. Form the affinity matrix W∈ ℜN×N
3. Define D to be a diagonal matrix with $D_{ii} = \sum_{i=1}^{N} W_{ij}$ and construct the Laplacian matrix $L=D^{-1/2}WD^{-1/2}$.
4. Find $x_1,...x_c$ the C largest eigenvectors of L and form the matrix $X=x_1,...x_c \in \Re^{N\times C}$.
5. Re-normalize the rows of X to determine the unit length yielding $Y \in \Re^{N\times C}$, such that $Y_{ij} = X_{ij} \Big/ (\sum_j {W_{ij}}^2)^{\frac{1}{2}}$
6. Treat each row of Yas a point in $\Re^{C}$ and cluster via k-means.
7. Allocate the original point i to cluster c if and only if the resultant row i of the matrix Y was assigned to cluster c.
8. Display the segmented vertebral bodies through the use of morphological operation.

2.6. Perforamance Analyis Of VB Segmentation

To evaluate the accuracy of the segmentation Dice Index [18], Misclassification error (ME) [19] and Hausdorff distance (HD) [20] are chosen. The Dice, ME, HD are given below respectively,

$$\mathrm{Dice} = \frac{2*|F_{\mathrm{Ground\ truth}} \cap F_{\mathrm{Proposed}}|}{|F_{\mathrm{Ground\ truth}}|+|F_{\mathrm{Proposed}}|} \qquad (5)$$

$$\mathrm{ME} = 1 - \frac{|B_{\mathrm{Ground\ truth}} \cap B_{\mathrm{Proposed}}|+|F_{\mathrm{Ground\ truth}} \cap F_{\mathrm{Proposed}}|}{|B_{\mathrm{Ground\ truth}}|+|B_{\mathrm{Ground\ truth}}|} \qquad (6)$$

$$\mathrm{HD}(F_{\mathrm{Ground\ truth}}, F_{\mathrm{Proposed}}) = \max\{h(F_{\mathrm{Ground\ truth}}, F_{\mathrm{Proposed}}), h(F_{\mathrm{Proposed}}, F_{\mathrm{Ground\ truth}}) \qquad (7)$$

Error ratio between manual and proposed sementation is meausred by ME.The dice index value of 1 indicate the best match between manual and proposed segmentation.Maximum distance between two contours is measured by HD.

3. GRAY LEVEL CO-OCCURRENCE MATRIX

Second order statistics of the image texture can be well described by the co-occurrence matrix which is first introduced by the Haralic. A two dimensional histogram is initially constructed by GLCM. It manipulates the spatial relation between different gray level pixels are manipulated. GLCM calculated by how a pixel i with some intensity can correlated with another pixel j at the certain distance d and orientation θ.A GLCM matrix can be specified by the relative frequencies p(i,j,d θ).A co - occurrence matrix can be a function of distance d angle θ and gray scaled i and j.

3.1Texture Features

Set of local statistical properties of pixel intensities is described by texture. The seven common textures features discussed here are angular second moment (ASM) or energy, contrast, inverse difference moment (IDM) or homogeneity, dissimilarity, entropy, maximum probability and inverse

` The sum of squared elements in the image is called energy it is also known as angular second moment (ASM). The texture of the area is depicted by energy. If ASM is equal to one then no discontinuities that mean no fracture in vertebral bodies and vice versa. The local variation of GLCM matrix is measured by contrast.

3.2. Texture K Nearest Neighbour Classification

KNN algorithm classifies objects based on the closest training examples in the feature space. Storing of feature vectors and labeling on the training images done at training phase. The unlabeled query point is assigns label to its k nearest neighbor during classification phase. Each image is converted into feature vector of fixed length with real number. Euclidean distance is used by KNN classifier to find its closest neighbor.

$$d(x,y) = \|x - y\| = \sqrt{(x - y).(x - y)} \quad (8)$$

Table I shows the texture features and their corresponding equations of the gray level co occurrence matrix.

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4. RESULTS AND DISCUSSIONS

All segmentation operations are done in computer with an Intel core i5 processor.The algroithm proposed in this paper is developed and trained using Matlab 2014a Image processing toolbox.For trauma diagnosis the trauma images is classified into three categories.Cervical trauma (I),thorocic trauma (II), lumbar trama.(III)

Subject 1 Patient with lumbar vertebrae fracture A 68 years old male patient with Coronal lumbar vertebral split fracture with endplate depression

The CT slice is outlined by trained radiologist with more than 10 years of clinical experience is considered as ground truth. Specially designed software is used for manual segmentation and the results are saved for validating performance. The radiologist ensures that the segmented images cover the entire vertebral bodies.

Subject 2 : Patient with Thoracic spinal trauma.

A 45 years old male patient with thoracic trauma .The results obtained shown in figure 5.

Fig 3 (a) shows the input image (b) shows the median filtered image after applying preprocessing using intensity and chi-square distance the vertebral bodies region detected clustered. The similar regions are clustered (c) shows the k means clustered image. After clustering the vertebrae region is detected the spinal processes which is not need for trauma analysis is removed using morphological operation. The final binary mask of segmentation is shown in figure (d).The segmented vertebral bodies

Subject 3: Patient with cervical spinal trauma.

A 40 years old male patient with cervical trauma with burst fracture. The results are shown in figure 4

TABLE I COMPUTATION OF TEXTURE FEATURES

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Energy	$F1 = \sum_{i,j=0}^{N-1} P_{i,j}^{\ 2}$
Contrast	$F2 = \sum_{i,j=0}^{N-1} P(i,j) * (i-j)^2$
Homogeneity	$F3 = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2}$
Dissimilarity	$F4 = \sum_{i,j=0}^{N-1} P(i,i) * \lvert(i-j\rvert)$
Entropy	$F5 = \sum_{i,j=0}^{N-1} P(i,j) * [-\ln(P(i,j)]$
Maximum Probability	F6=max i,j P(i,j)
Inverse	F7=$\sum_{i,j=0}^{N-1} \frac{P(i,j)}{(i-j)^2}$

TABLE II COMPARISIONS BETWEEN FOUR ALGORITHMS

Algorithm	Fig	Dice	ME	HD
NJW algorithm	5	0.901617	0.008217	3.3
	7	0.912605	0.006710	4.5
	9	0.947509	0.004050	1.7
	11	0.886505	0.008152	4.2
	13	0.957979	0.004567	1.7
Gamio's algorithm	5	0.926936	0.007644	2
	7	0.894051	0.007421	2
	9	0.890596	0.006543	1.7
	11	0.891325	0.007653	2.8
	13	0.860596	0.006578	2.2
Shi's algorithm	5	0.912664	0.006438	2.2
	7	0.929405	0.005543	2.8
	9	0.930789	0.005654	1.7
	11	0.913751	0.005213	3.5
	13	0.913567	0.005406	1.8
Proposed algorithm	5	0.964549	0.003451	2
	7	0.964315	0.003456	1.7
	9	0.964315	0.002289	1.4
	11	0.962901	0.002678	1.7
	13	0.970673	0.003147	1.7

TABLE III CLASSIFICATION RESULTS OF KNN ALGORITHM

Class	Test Image	Correctly classified image	Incorrectly classified image	Classification accuracy (%)
I	50	45	5	90
II	50	47	3	94
III	50	44	6	0.88

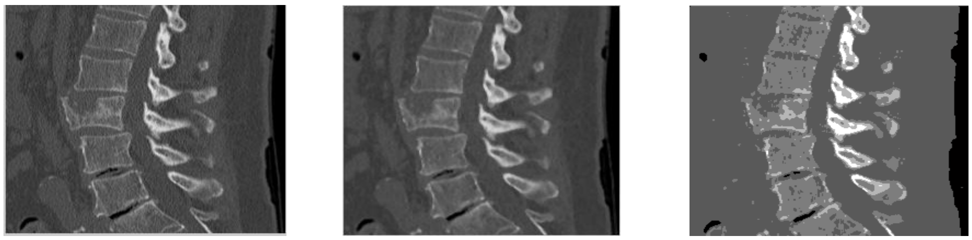
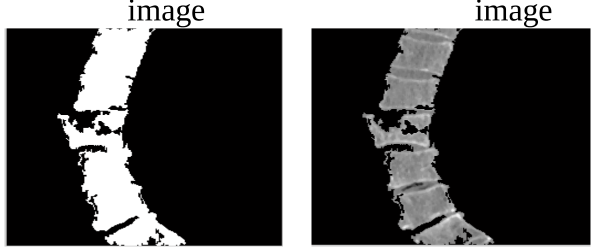


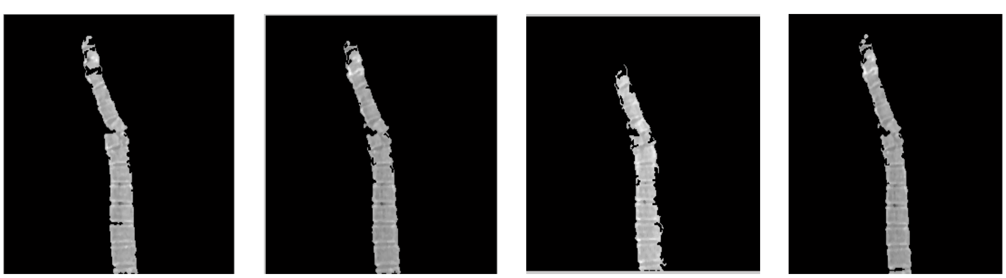
Fig 3(a) Input image (b) Median filtered image (C) k means clustered image



d)Binary mask for segmentation (e) Segmented vertebral bodies

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

Fig 5 (a-d) Thoracic spine trauma Image



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

Fig 4 (a)-(d) Segmented results of Thoracic spine trauma vertebral bodies

TABLE III COMPARISIONS BETWEEN FOUR ALGORITHMS

Type	Auto-correlationn	Contrast	Dissi-milarity	Energy	Entropy	Homo-Geneity	Maximum Probability
I	4.86	1.12	0.16	0.84	0.38	0.97	0.91
I	8.00	2.14	0.31	0.72	0.60	0.95	0.4
I	7.26	0.13	0.19	0.76	0.50	0.97	0.87
I	8.69	0.15	0.22	0.72	0.58	0.6	0.84
II	4.80	0.46	0.07	0.86	0.31	0.98	0.92
II	4.85	0.63	0.09	0.85	0.33	0.98	0.92
II	5.67	0.44	0.06	0.84	0.34	0.98	0.91
II	5.70	0.45	0.06	0.84	0.34	0.90	0.91
III	10.93	1.27	0.18	0.68	0.61	0.97	0.81
III	11.18	1.00	0.14	0.67	0.61	0.97	0.80

5.CONCLUSION

This proposed algorithm describes segmentation and classification of spinal trauma using pairwise spectral clustering and KNN classifier. The proposed system works in two stages first training/learning and secondly testing/recognition. Pair wise spectral clustering techniques used at training stage to segment the VB in CT images. GLCM features are extracted from the concurrence matrix of VB's. The above process efficiently classifies the spinal trauma in CT images. The system can be designed to classify other types of fractures .Improve the KNN classifier is further scope of system.

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