SEGMENTATION AND LABELLING OF HUMAN SPINE MR IMAGES USING FUZZY CLUSTERING

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ABSTRACT

Computerized medical image segmentation is a challenging area because of poor resolution and weak contrast. The predominantly used conventional clustering techniques and the thresholding methods suffer from limitations owing to their heavy dependence on user interactions. Uncertainties prevalent in an image cannot be captured by these techniques. The performance further deteriorates when the images are corrupted by noise, outliers and other artifacts. The objective of this paper is to develop an effective robust fuzzy C- means clustering for segmenting vertebral body from magnetic resonance images. The motivation for this work is that spine appearance, shape and geometry measurements are necessary for abnormality detection and thus proper localisation and labelling will enhance the diagnostic output of a physician. The method is compared with Otsu thresholding and K-means clustering to illustrate the robustness. The reference standard for validation was the annotated images from the radiologist, and the Dice coefficient and Hausdorff distance measures were used to evaluate the segmentation.

KEYWORDS

Vertebra segmentation, fuzzy clustering, MRI, labelling

1. INTRODUCTION

Image segmentation is a fundamental building block in an image analysis tool kit. Segmentation of medical images is in itself an arduous process where the images are prone to be affected by noise and artifacts. Automatic segmentation of medical images is a difficult task as medical images are complex in nature and rarely posses simple linear feature characteristic. Further, the output of segmentation algorithm is affected due to partial volume effect, intensity inhomogeneity in case of MR images.

Spine is the most complex load bearing structure in our entire human body. It is made up of 26 irregular bones connected in such a way that flexible curved structure results. The vertebral column is about 70cm long in an average adult and has 5 major divisions. Seven vertebrae found in the neck region, constitute the cervical part, the next 12 are the thoracic vertebrae and 5 supporting the lower back are the lumbar vertebrae. Inferior to these, is the sacrum which articulates with the hip bones of pelvis. The entire column is terminated by the tiny coccyx. Intervertebral disc acts as a shock absorber and allow the spine to extend. These are thickest in the lumbar and cervical regions, enhancing the flexibility in these regions. Its degeneration is relatively a common phenomena with aging due to wear and tear and is the major cause for back pain [1]. Herniated disc, spinal stenosis and degenerative discs are a few of the types, to mention. These can be imaged and studied from MRI scans. Also it is prescribed most commonly for

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patients with excruciating back pain. MR imaging of spine is formally identified with IR (Inversion Recovery), T1 and T2 weighted images. While water content appears bright in T2 (in medical lingo, its hyper intense which is clearly seen in the spinal canal), the same appears dark (hypo intense) in T1 images. MR can detect early signs of bone marrow degeneration with high spatial resolution where fat and water protons are found in abundance.

Degenerative lumbar spine disease (DLSD) includes spondylotic (arthritic) and degenerative disc disease of the lumbar spine with or without neuronal compression or spinal instability. Accurate diagnosis remains a challenge without manual intervention in segmenting the vertebral features. It can be seen from fig 1. the degenerated state of L5 vertebrae and the associated intensity changes prevalent. These are primarily due to the end plate degeneration.

Figure 1. Degenerated L5 vertebra in MR sagittal plane

While degenerative changes are a biological phenomena occurring in spinal structure that are imaged using radiological equipments, certain irrelevant processes are also captured. These constitute the artifacts caused due to intensity inhomogenities shown in fig 2. The segmentation process is highly affected by these complexities present in MR images.

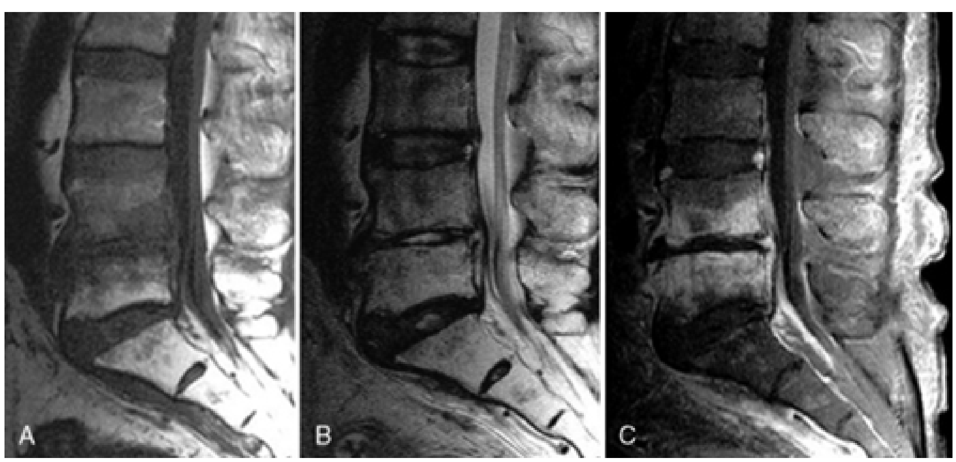


Figure 2. Intensity inhomogenity captured in lumbar vertebrae

The current work deals with segmentation of spinal column from MR image using fuzzy means clustering for identification and labelling of individual vertebral structures. The segmented output can be refined further and used for classification of degenerative state as well as to diagnose deformities.

2. LITERATURE

The commonly used segmentation methods are global thresholding, multilevel thresholding and supervised clustering techniques. In intensity thresholding, the level determined from the grey-level histogram of the image. The distribution of intensities in medical images, especially in MRI images is random, and hence global thresholding methods fail due to lack of determining optimal threshold. In addition, intensity thresholding methods have disadvantage of spatial uncertainty as the pixel location information is ignored[2]. An edge detection scheme can be used for identifying contour boundaries of the region of interest(ROI). The guarantee of these lines being contiguous is very sleek. Also, these methods usually require computationally expensive post-processing to obtain hole free representation of the objects.

The region growing methods extend the thresholding by integrating it with connectivity by means of an intensity similarity measure. These methods assume an initial seed position and using connected neighbourhood, expand the intensity column over surrounding regions. However, they are highly sensitive to initial seeds and noise. In classification-based segmentation method, the fuzzy C-means (FCM) clustering algorithm [3], is more effective with considerable amount of benefits. Unlike hard clustering methods, like k-means algorithm, which assign pixels exclusively to one cluster, the FCM algorithm allows pixels to have dependence with multiple clusters with varying degree of memberships and thus more reasonable in real applications. Using intuitionistic fuzzy clustering(IFC), where apart from membership functions(MF), non membership values are also defined, [4]have segmented MR images of brain. The heuristic based segmentation also considers the hesitation degree for each pixel. A similar study on generic gray scale images is put forth in [5] where the IFC combines several MF's and the uncertainty in choosing the best MF.

The article deals with elementary fuzzy C-means clustering, attempting to segment vertebral bodies(VB) with morphological post processing. Also the VB's are labelled accordingly which can reduce the burden of radiologist while classifying the degenerations involved.

3. METHODS

The proposed method is schematically depicted in fig.3. The input image(s) have been collected from Apollo Speciality Hospitals, Chennai after going through a formal ethical clearance process. The T1 weighted images, served as the initial dataset for the proposed algorithm.

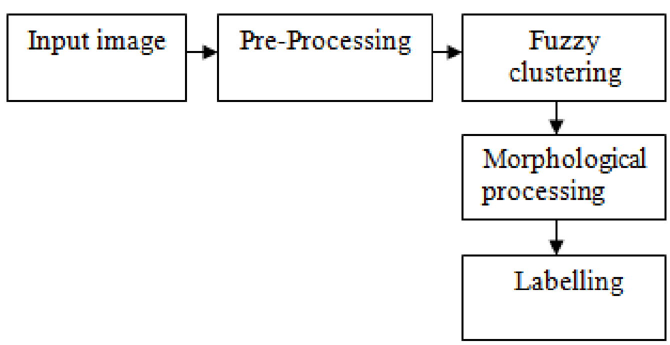


Figure 3. Schematic of the proposed segmentation method

3.1. Pre-Processing

The method first smooths the image using the edge preserving anisotropic diffusion filter presented in. It serves the dual purpose of removing inhomogenities and as an enhancer as well.

3.2. Fuzzy C-Means Clustering

The fuzzy c-means algorithm [2]has been broadly used in various pattern and image processing studies [6]–[8]. According to fuzzy c-means algorithm, the clustering of a dataset can be obtained by minimizing an objective function for a known number of clusters. Fuzzy C-means is based on minimization of the following objective function:

$$J = \sum_{i=1}^{N}\sum_{j=1}^{M} u_{ij}^{k} \, \left\|x_i - v_j\right\|^2, \qquad 1 \le k < \infty$$

where ;

k is any real number known as the weighting factor,

u_{ij} is degree of membership of x_i in the cluster j

x_i is the i^{th} of p-dimensional measured intensity data

v_j is the p-dimensional center of the j^{th} cluster

$\|*\|$ is any norm expressing the similarity between measured intensity data and center

N represents number of pixels while M represents the number of cluster centers

Fuzzy clustering is performed through an iterative optimisation of objective function shown above with update of membership function u_{ij} and cluster centers v_j by

$$u_{ij} = \frac{1}{\sum_{l=1}^{M}\left(\left\|\frac{x_i - v_j}{x_i - v_l}\right\|\right)^{\frac{2}{(k-1)}}}$$

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^{k} x_i}{\sum_{i=1}^{N} u_{ij}^{k}}$$

The algorithm is terminated when $\max_{ij}\{u_{ij}$ at $t+1$ - u_{ij} at $t\} \le \epsilon$ which is between 0 and 1.

3.3. Post Processing

A series of morphological operations are executed for extracting the vertebral bodies (VB) from the clustered output. Hole filling is the preliminary step followed by an erosion to remove islands. An area metric is used to extract only Vertebrae from surrounding muscular region Shape analysis [9] reveals that the aspect ratio of VB varies between 1.5 and 2. This helps in isolating the ligaments and spinal muscles associated with the spine in the region of interest.

3.4. Labelling

The segmented vertebrae are labelled using the connected component entity. Each VB is identified with a group number. Starting from L5(Lumbar), the vertebrae are labelled successively till L1 and then, the thoracic region begin. If the sacrum remains due to improper segmentation, it can be eliminated based on aspect ration or area criteria. A colored schematic is also presented for visual calibration.

3.5. Validation

The proposed method was validated using Dice coefficient (DC) and Hausdorff distance (HD) . The reference standard for comparison was the annotated images from the radiologist. DC measures the set agreement as described in following equations, where the images constitute the two sets. The generalized HD provides a means of determining the similarity between two binary images. The two parameters used for matching the resemblance between the given images are,

- Maximum distance of separation between points, yet that can still be considered close.
- The fraction that determines how much one point set is far apart from the other.

$D(A,B) = \frac{2|A\cap B|}{|A|+|B|}$ (Dice Coefficient)

$D(A,B) = \underbrace{Max}_{a\in A}\{\underbrace{Min}_{b\in B}\{d(a,b)\}\}$ (Hausdorff Distance)

where, *a, b* are points from the images *A,B* respectively.

4. RESULTS AND DISCUSSION

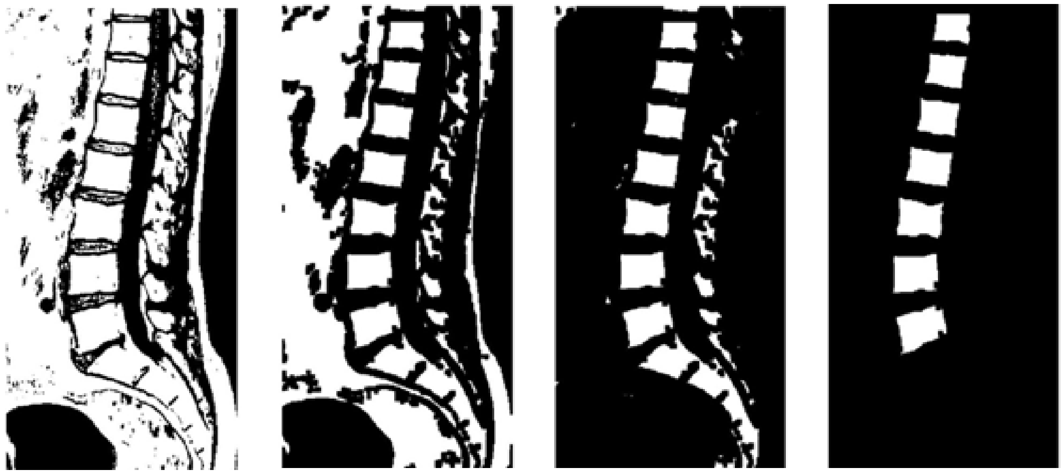
The method is tested on sagittal cross-section of T1-weighted MR images of spine.The goal is to segment the vertebral bodies from the muscular background.

4.1 Fuzzy segmentation

The input MR sagittal slice of spine considered for the current study is shown in fig 4. After the pre-processing stage, the enhanced input is clustered using the Fuzzy C-means technique and the final output derived is shown in fig 5(d).

Figure 4. Sagittal plane MR T1 image

The intermediate steps involving the morphological operations are depicted in fig 4. It can be seen that, the fuzzy clustering provides a closer disjoint VB's owing to which we can erode the muscular region and thus arrive at delineating the same.



(a) fuzzy c-means (b) Erosion (c) Filtering using area criteria (d) Aspect ratio based elimination

Figure 5. Post processed output using morphological operations

4.2 Labeling of VB

Automatic labeling of vertebrae is usually performed to reduce the manual effort put in by the radiologist. It can be seen from fig 6, the labeled vertebrae and its color scheme can help in better diagnosis given that geometric attributes are also extracted.

Figure 6. Labeling of VB after segmentation

4.3 Case study

Around 4 cases were used for the entire study. The patients complained of mild lower back pain and are in the age group between 45-60. The population included 2 female and 2 male. An image overlay of the input and segmented output for various cases is presented in fig 7.

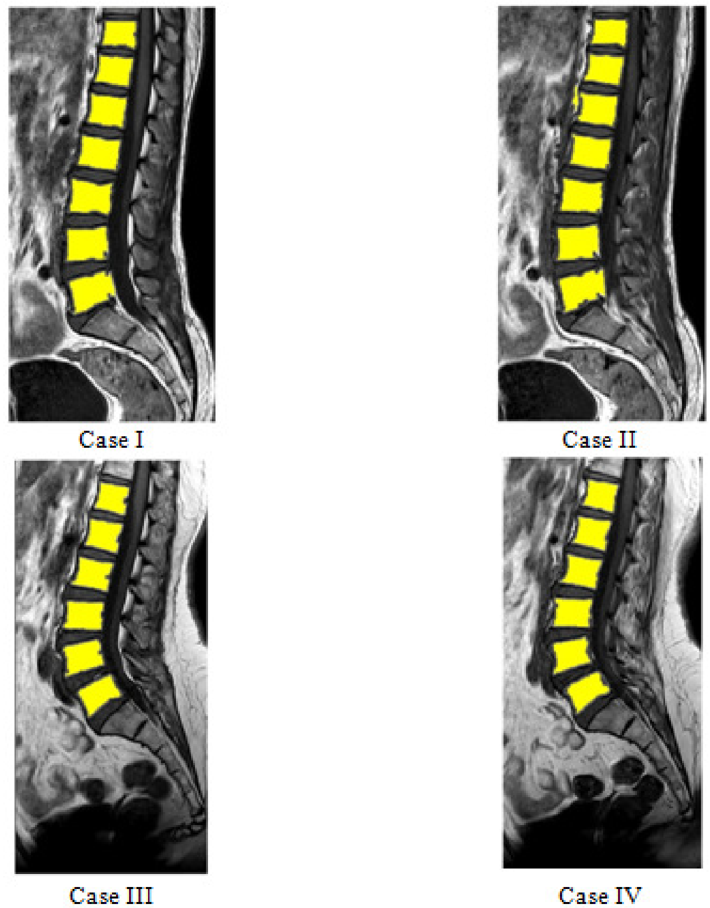


Figure 7. Overlay of segmented image with input for various case studies

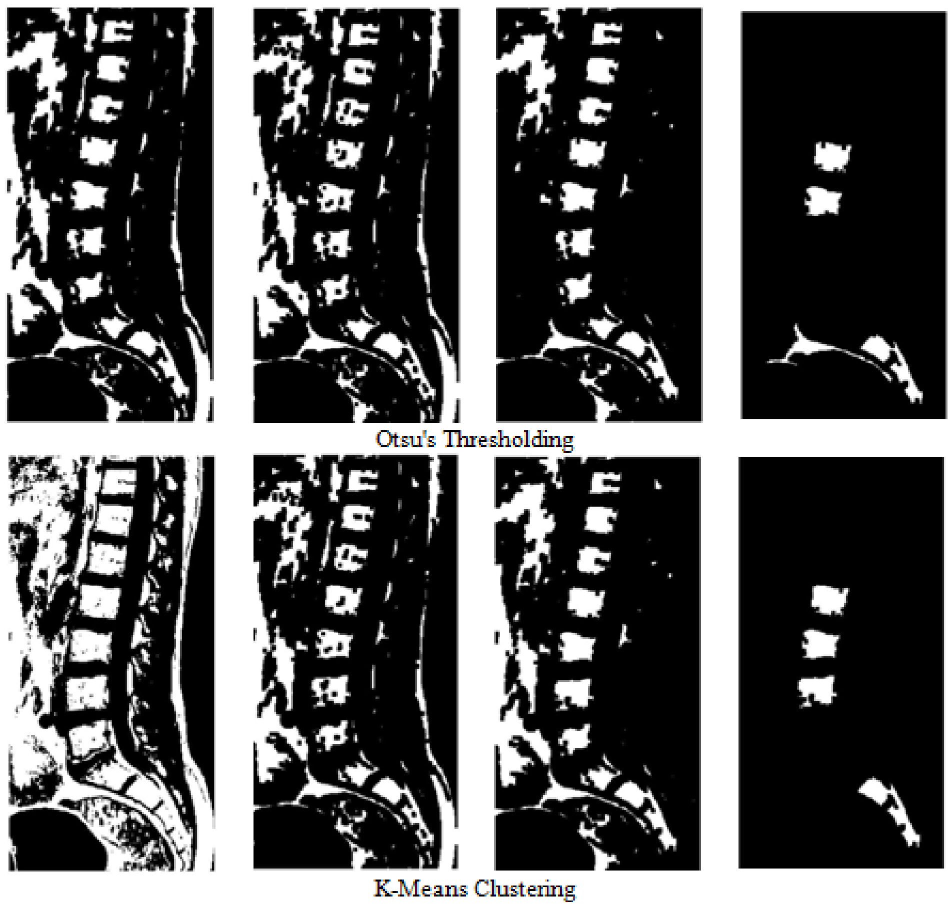
4.4 Comparative Analysis

A comparative tabulation amongst the global thresholding, a simple clustering and the Fuzzy clustering is illustrated in Table 1.

Table 1. Comparison of segmentation methods

Cases	**SI**	**Segmentation methods**		
		Otsu thresholding	K- Means Clustering	Fuzzy C Means Clustering
Case I	DC	0.36	0.622	0.835
	HD	10.23	7.338	3.97
Case II	DC	0.43	0.618	0.90
	HD	16.9	6.142	4.03
Case III	DC	0.57	0.714	0.852
	HD	15.8	5.48	3.62
Case IV	DC	0.437	0.773	0.83
	HD	15.2	5.7	3.95

The ground truth image was manually segmented by the radiologist and is used as the gold standard for validation. It can be observed that the Fuzzy method provides better DC value (closer to 1) and HD value (closer to 0) than compared to the rest thus affirming the robustness in segmentation. Images obtained using Otsu's thresholding and K-means is shown in fig 8.



(a) fuzzy c means (b) Erosion (c) Filtering using area criteria (d) Aspect ratio based elimination

Figure 8. Comparative analysis using Otsu and K-means

4.5 Failure Case

The method was tested on several images and in some images the segmentation failed to provide quality results. The transverse and spinous processes are a part of vertebral bodies. Thus, when they start emerging, with disruption in intensity as well as structure, the fuzzy clustering method fails to adapt to the complex topology. Apart from this, the presence of anterior and posterior ligaments also significantly affects the results of the segmentation. fig 9. shows the results of segmentation of one such case where the ROI has not been delineated clearly.

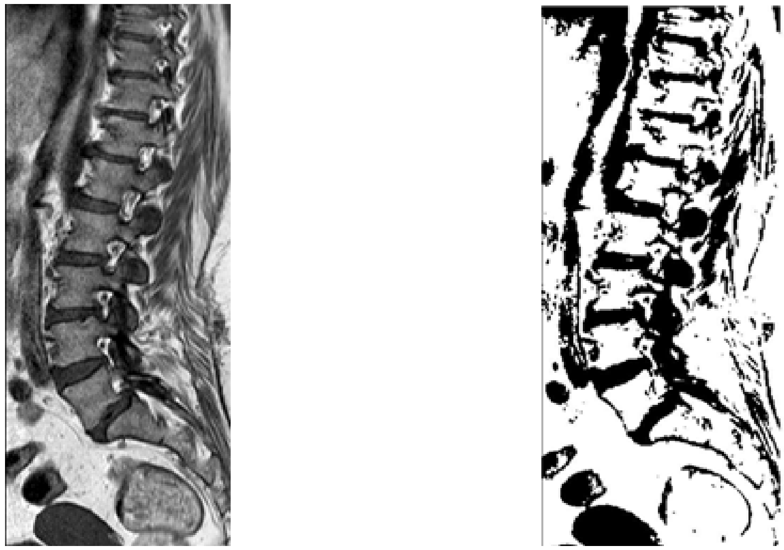


Figure 9. Failure case of proposed segmentation

5. CONCLUSIONS

In this paper, a fuzzy C-means clustering algorithm followed by morphological operations and labelling has been presented for segmentation of spine MR images. It is compared with the simple K-means clustering and Otsu thresholding scheme. Upon validation, it is observed that the fuzzy C-means gives improved segmentation results as compared to the counterparts.As a part of future work, we would like to incorporate intuitionistic fuzzy clustering to check if it can enhance the accuracy. Also extract features from the segmented VB for classifying various deformity.

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