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Automatic Detection of Lumbar Spine from Ultrasound Images Using Fuzzy Clustering Techniques.

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ABSTRACT

Spine is an important part of skeletal system which is responsible for the movements of the body. It supports the weight of the body and protects the spinal cord. Any change in the structure of the spine or a poor spinal health may affect the nervous system which in turn reduces the capability to lead a normal, active life. So it is important to monitor the condition of the spine. This paper deals with the automatic detection of lumbar spine from the ultrasound images. There are many techniques available for imaging the lumbar spine. Ultrasound technique is becoming the most preferred imaging technique, since it is safer than the other imaging techniques like, X-ray, MRI and CT. So far ultrasound images of spine have not been used for detection and diagnosis because of the noise and poor quality. The ultrasound image of lumbar spine is enhanced by image preprocessing. Noise removal has been carried out by filtering and the quality of the image is enhanced by contrast adjustment. The preprocessed image is segmented using fuzzy clustering techniques viz. Fuzzy C Means and Reformed Fuzzy C Means. The spectral signature of lumbar spine is extracted from the segmented image. The lumbar spine alone is separated from the extracted image. By comparing the two fuzzy clustering techniques, it is found that the detection of lumbar spine by Reformed Fuzzy C Means is more complete than the Fuzzy C Means technique.

Keywords: Lumbar spine, Ultrasound Images, Clustering, Reformed Fuzzy C Means, Fuzzy C Means

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INTRODUCTION

The spine is one of the most important components of the human body. It provides structure and support to body. Without a backbone we could not stand up at all. It also protects the spinal cord and nerves from damage and it is a direct path to the brain. Protecting the spinal cord is probably one of the more well known functions of the backbone.

The spinal cord is a bundle of sensory and motor nerves that transmit signals from the brain to the rest of the body. Any damage to the spine can cause injury or damage to the spinal cord. Depending on the area of damage, this could cause sensation loss and paralysis in certain parts of the body. Ribs are connected to the spinal cord and create a cage that protects other organs such as the heart, lungs, and stomach. Hence, the health and structure of the spine is crucial for the health of the human beings and monitoring the changes and damages to the spine is important for their welfare.

The spine can be classified into cervical vertebrae, thoracic vertebrae, lumbar vertebrae, Sacrum and Coccyx. The lumbar spine is meant for load bearing and it bears most of the weight of the human body. Lateral flexion, extension and rotation are possible because of the lumbar vertebrae. The lumbar spine is connected to the pelvis, where most of the weight bearing and body movement takes place. So too much pressure is placed on Lumbar spine while lifting up a heavy box or carrying a heavy object. This causes repetitive injuries that can lead to damage to the parts of the lumbar spine. For monitoring the condition, it is essential to detect the lumbar vertebrae from the medical images.

Various modalities are used for imaging the spine such as X- ray, MRI and CT. All modalities use the ionizing radiation. The ultrasound imaging is the one which have no harmful or ionizing radiation and can be used in real time For spine surgeries, understanding anatomical characteristics of the spinal column is very important. Fluoroscopic technique is used for identifying the positions of specific anatomical structures during surgery with the use of ionizing radiations. This causes health hazards to the patients as well as the surgeon as both are exposed to those radiations. So this cannot be used for continuous real time monitoring. Hence the ultrasound technique is introduced to provide radiation free viewing of the lumbar region.

Aslan et.al used the CT images for detection and segmentation of lumbar vertebrae [1]. Ghosh et.al detected lumbar spine from CT images for fracture diagnosis [7]. Kelm et.al applied iterated marginal space learning to MRI and CT images for spine detection [8]. Zhan et.al applied hierarchical learning and local articulated model to MRI images for spine detection [13]. Stefan et.al used parts-based graphical model for labeling the vertebrae [12] using MRI images. Punarselvam [9] et.al utilized edge detection methods for segmenting lumbar spine. Fabian et. Al applied Multi-Class SVM for Automatic Vertebra Detection in X-Ray Images [6].

MRI scan is done in an enclosed space and is noisy. Moreover it involves a really high amount of electric current supply. X-rays increases hydrogen peroxide level in blood cells which could damage the cell. The exposure to X-rays may cause cancer and change the DNA base. As the exposure to radiation is more in CT scan, there is higher risk of getting cancer. Compared to these techniques ultrasound is safer and it has the advantage of portability.

The aim of the current research is to detect the lumbar spine from ultrasound image. The quality of the ultrasound images are poor compared to other imaging techniques. It is really a challenging task to extract the useful information from ultrasound images. Image preprocessing is done to enhance the details in the ultrasound images. Fuzzy clustering techniques are applied for segmenting and the unwanted details are removed by morphological opening to extract the lumbar spine.

The rest of the paper is organized as follows. The anatomy of human spine is described in section II. Section III presents a detailed insight into the methodology. The image preprocessing method used for enhancing the ultrasound image of the lumbar spine is also explained in this section. In section IV Fuzzy Clustering techniques are discussed in detail. In Section V the performance of automatic detection system is analyzed. In Section VI concluding remarks are given.

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THE ANATOMY OF HUMAN SPINE

The human spine also known as backbone is the vertebral column of the human skeleton. It consists of 24 articulating vertebrae and 9 fused vertebrae in the sacrum and the coccyx. Spine is formed from individual bones called vertebrae. It makes the spinal canal, which encloses and protects the spinal cord. The articulating vertebrae can be classified into cervical vertebrae, thoracic vertebrae and lumbar vertebrae

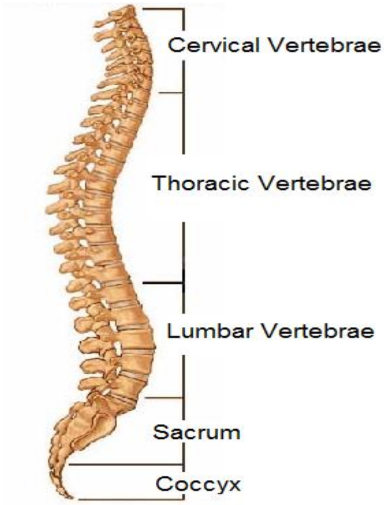

Figure 2.1

Cervical Vertebrae

Cervical vertebrae are the top seven vertebrae in the spine immediately below the skull. It starts developing when the infant begins to lift its head. It supports the head and the neck, protects the neck and moves the spine,

Thoracic Vertebrae

Thoracic vertebrae are the 12 vertebrae which lie below the cervical vertebrae. The pairs of ribs are connected to them. It is present at the time of birth itself. It holds the rib cage and protects the heart and lungs.

Lumbar Vertebrae

There are five or six articulating vertebrae below the thoracic vertebrae. They are called lumbar vertebrae. It starts developing when the infant starts to walk. The main function of lumbar spine is to support the body weight.

The fused vertebrae are classified into Sacrum and Coccyx.

Sacrum

The 5 fused vertebrae below the lumbar spine are called the sacral vertebrae. They are fused together to form the single wedge-shaped bone known as Sacrum. It connects the spine to the hip bones

Coccyx

The 3 to 5 fused vertebrae below the Sacrum are called the coccygeal vertebrae. They are fused together to form a small triangular bone at the base of the spinal column known as Coccyx. It acts as an attachment spot for tendons, ligaments, and muscles.

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METHODOLOGY

The increased resolution and raised level of detail in the medical images has made the automatic detection of lumbar spine from the ultrasound images viable. The flow diagram of automatic lumbar spine detection system is shown in Figure 3.1.

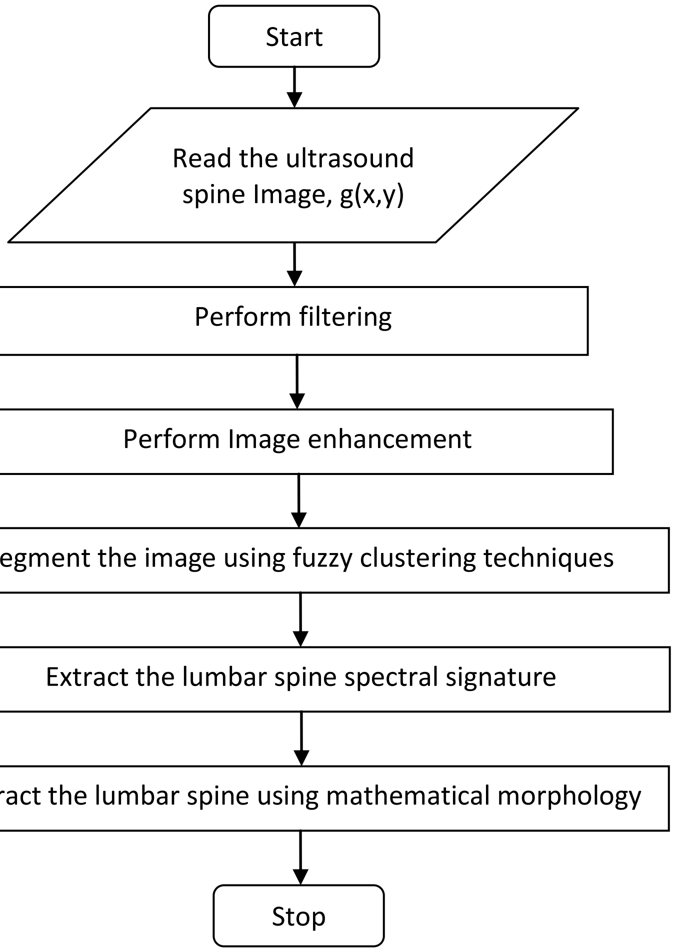


Figure 3.1

The ultrasound image of lumbar spine is read by the automatic lumbar spine detection system. The image is enhanced by image preprocessing which involves filtering and contrast stretching. The goal of image preprocessing is to increase both the accuracy and the interpretability of the image data during the image processing phase by eliminating the noises. There are two steps involved in image preprocessing, viz. image filtering and contrast stretching.

Image Filtering

The usefulness of ultrasound imaging is degraded by the presence of signal dependent noise known as speckle [3]. Speckle noise is multiplicative in nature. This type of noise is an inherent property of medical ultrasound imaging and because of this noise the image resolution and contrast become reduced, which affects the diagnostic value of this imaging modality. Image smoothening reduces the effect of speckle noise. This work utilizes averaging filter for smoothening the image. Through repetitive tests it has been found that 3×3 template proves to be effective in eliminating speckles in the imagery.

Contrast stretching

Contrast stretching stretch the gray level ranges where more information is desired. The slope of T(r) function in this range is above 1. It compresses the gray level ranges that are of little interest. The slope of T(r) function in this range is less than 1. The reason for low contrast are poor lightning, Low dynamic range of image sensors and the wrong setting of lens aperture of camera. The piecewise linear transformation function T(r) is shown in Figure 3.2.

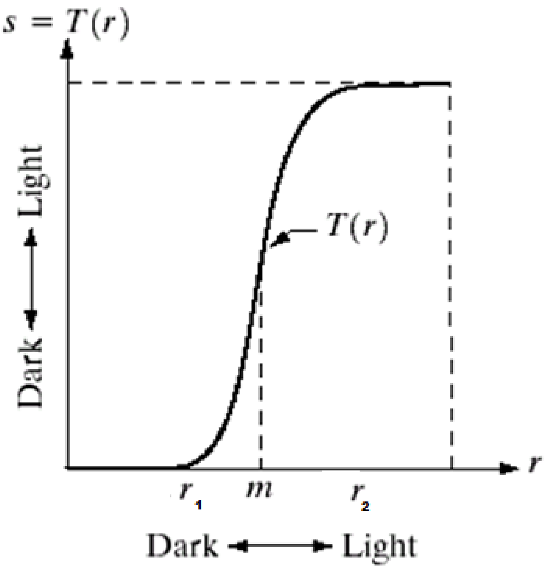


Figure 3.2

If the input gray level is below r_2 or above r_1 then the transformation is a linear function which does not alter the input. When the input gray level is between r1 and r2 the input contrast between r1 and r2 is stretched. The piecewise linear transformation function is single valued and monotonically increasing.

It preserves the order of gray level of the input image and prevents the intensity artifacts. Since, the preprocessing step is simple, quick and automatic, it can be applied to high resolution images of huge volumes. The preprocessed image is segmented into three clusters using fuzzy clustering techniques. As the spine has the highest gray level in the clustered image, the spectral signature of spine alone is extracted.

Mathematical morphology

Mathematical morphology is an image processing tool used for extracting features of interest. The mathematical morphology tools used are granulometry and trivial opening. A granulometry analysis of labeled objects in the image is performed and the size information of them is obtained. By morphological operations involving opening of labeled parts the lumbar spine is separated and extracted.

Morphological Trivial Opening [10] is defined as one, which provides a practical mean of object detection and identification. It does not affect the shape and size of the objects of interest. Let X be an image, {X(n)|n = 1, 2, 3, …,N} is a series of connected components in the image, x(i) is a point in X. The trivial opening is defined with a criterion T, as,

$$TO = \begin{cases} x(i) & \text{if } x(i) \text{ satisfies the criterion } T \\ \emptyset & \text{otherwise} \end{cases}$$

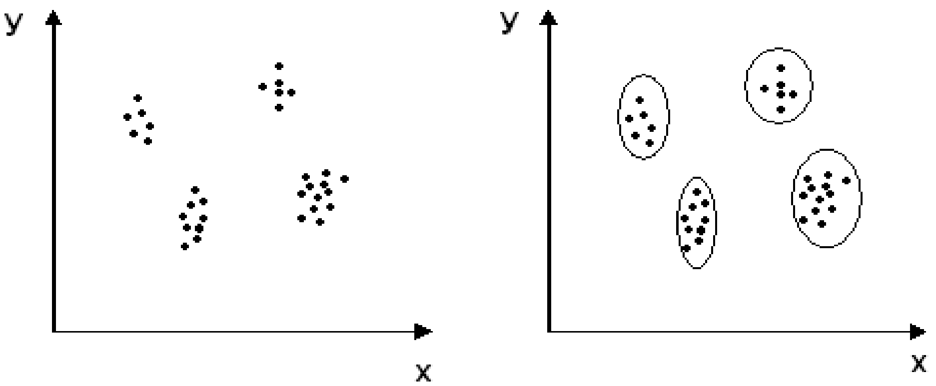
where TO is the trivial opening associated with criterion T. A structural element of horizontal line of length 8 is chosen for trivial opening.

The labeled parts having area below 50 pixels and above 5000 pixels are eliminated and the remaining parts are labeled again. The last labeled part is one of the lumbar vertebrae and is extracted. The image is rotated in clockwise direction by 270^O and labeled again. The first labeled part is one of the lumbar vertebrae and is extracted. The extracted vertebrae are combined into single image.

FUZZY CLUSTERING TECHNIQUES

Unsupervised Clustering is the natural grouping of data by unsupervised learning. It is also defined as the problem of grouping a given collection of unlabeled patterns into meaningful clusters. For an unsupervised learning, the training data consist of input training patterns only. The goal is to group the objects into clusters based only on their observable features, such that each cluster contains objects that share some important properties. Clustering is useful in several exploratory pattern analysis, grouping, decision making, and machine learning situations, including data mining, document retrieval, image segmentation, and pattern classification. The goals of unsupervised clustering is to group the data into clusters in such a way that,

(i) Data within a valid cluster are more similar to each other
(ii) Data belonging to different clusters are as dissimilar as possible.



(a) (b)

Figure 4.1

An example of unsupervised clustering of data is depicted in Figure 4.1. The input data points are shown in Figure 4.1(a), and the desired clusters are shown in Figure 4.1 (b). Unsupervised clustering methods are broadly classified into hard and fuzzy clustering methods depending on the type of output. In hard clustering each data point is allocated to single cluster. Fuzzy clustering allocates each data point to two or more clusters with varying degree of membership functions.

Fuzzy C means algorithm

This method was first proposed by Dunn [5] and it was later improved by Bezdek [2]. This algorithm is frequently used in segmentation of medical images. In FCM the sum of membership values of a data point in all the clusters must be equal to one. Hence the outlier points are poorly handled [4].

The steps involved in the Fuzzy C means algorithm are as follows.

Let n be the length of the image data and c be the no. of clusters

1. Receive the image data matrix X
2. Initialize the number of clusters, c ($2 \leq c \leq n$)
3. Initialise the partition matrix, U(r) = [ujk]. U is the c x n fuzzy c-partition matrix, containing the membership values of all samples in all clusters.
4. Determine the cluster centers, Y

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$$y_j = \frac{\sum_{k=1}^{n} (u_{jk})^m x_k}{\sum_{k=1}^{n} (u_{jk})^m} \quad \text{for all j}$$

5. Calculate the Euclidean distance matrix, D using equation

$$E_j = \left\| x_k - y_j \right\|^2$$

6. Update the partition matrix, U(r) by

$$u_{jk} = \begin{cases} \left(\sum_{l=1}^{c} \left(\frac{E_j(x_k)}{E_l(x_k)} \right)^{2/m-1} \right)^{-1} & if\, E_j(x_k) \rangle 0 \ \forall j,k \\ 1 \ \ if \ \ E_j(x_k) = 0 \ \ and \ \ u_{jk} = 0 \ \ \forall l \neq jk \end{cases}$$

7. Check for convergence

If max | U(r) - U(r+1) | < ε stop else repeat steps 4–6

Reformed Fuzzy C means algorithm

As FCM handles outlier points poorly, an improvement has been suggested by Sowmya and Sheelarani [11]. The probabilistic constraint is removed by equating sum of membership function in a cluster to n.

$$\sum_{j=1}^{c} (u_{jk}) = n$$

The steps involved in the Fuzzy C means algorithm are as follows. Let n be the length of the image data and c be the no. of clusters

1. Receive the image data matrix X
2. Initialize the number of clusters, c (2 ≤ c ≤ n)
3. Initialise the partition matrix, U(r) = [ujk]. U is the c x n fuzzy c-partition matrix, containing the membership values of all samples in all clusters.
4. Calculate the neighbourhood influence parameter γ. γ is determined by convolving original image with a template of 3x3 matrix of ones.
5. Determine the cluster centers, Y

$$y_j = \frac{\sum_{k=1}^{n} (u_{jk})^m x_k}{\sum_{k=1}^{n} (u_{jk})^m} \quad \text{for all j}$$

6. Calculate the Euclidean distance matrix, D using equation

$$E_j = \left\| x_k - y_j \right\|^2 e^{-\gamma k}$$

7. Update the partition matrix, U(r) by

$$u_{jk} = \begin{cases} n * \left(\sum_{l=1}^{c} \left(Z_j(x_k) E_j(x_k) \right)^{2/m-1} \right)^{-1} & if\, E_j(x_k) \rangle 0 \; \forall j, k \\ 1 \quad if \quad E_j(x_k) = 0 \quad and \quad u_{jk} = 0 & \forall l \neq jk \end{cases}$$

where Zj is , $$z_j = \sum_{k=1}^{c} \frac{1}{E_k}$$

8. Check for convergence

If max | U(r) - U(r+1) | < ε stop else repeat steps 5–7

PERFORMANCE EVALUATION OF AUTOMATIC DETECTION SYSTEM

Four ultrasound test images of lumbar spine are used for evaluating the results of the fuzzy clustering techniques. The test images are shown in Fig. 5.1

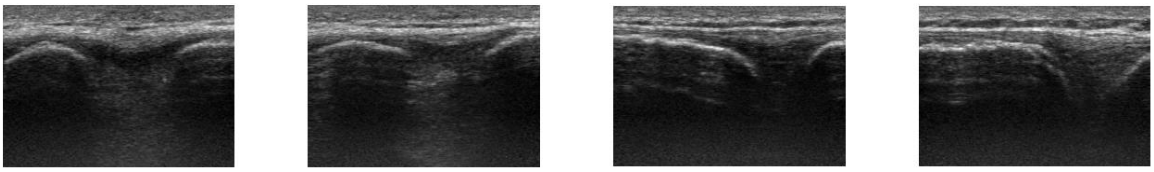

Figure 5.1

The images are enhanced by image preprocessing technique involving filtering and contrast stretching. The enhanced images are shown in Fig.5.2. The result of image segmentation by FCM is shown in Figure 5.3 and image segmentation by RFCM is sown in Figure 5.4. The lumbar spine spectral signature from image segmented by FCM and RFCM are shown in Figure 5.5 and Figure 5.6 respectively.

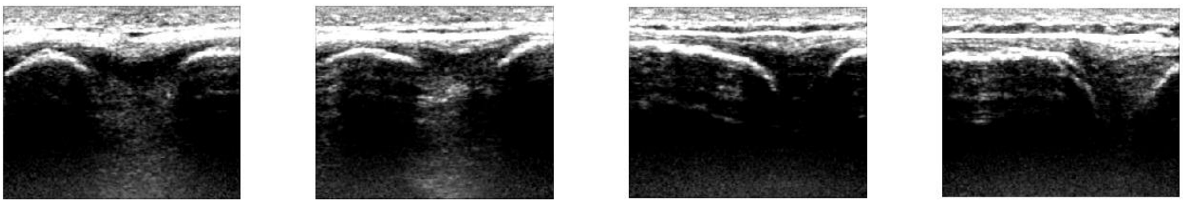

Figure 5.2

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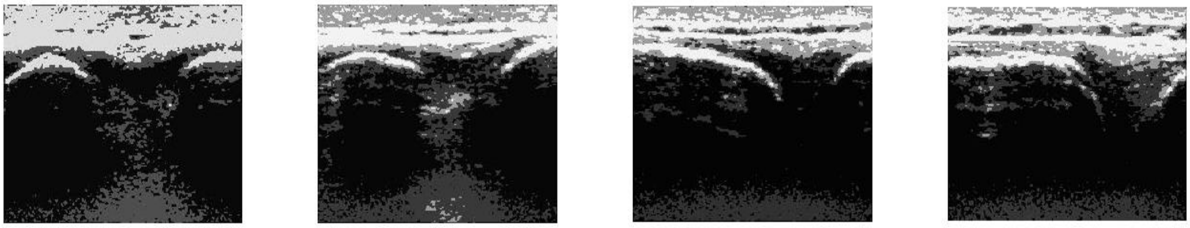

Figure 5.3

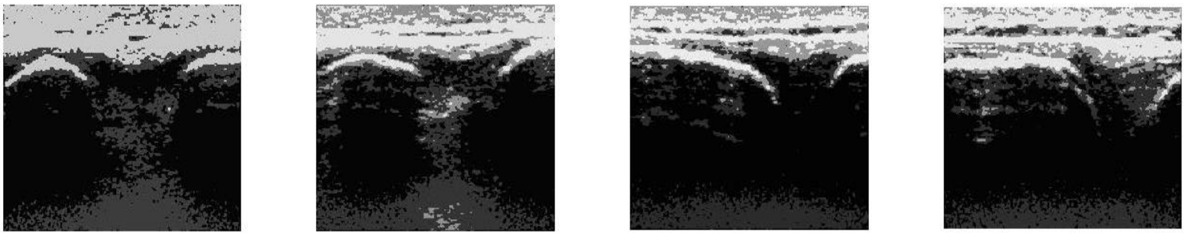

Figure 5.4

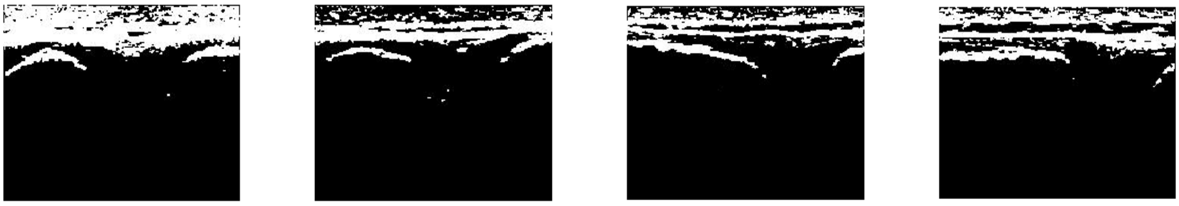

Figure 5.5

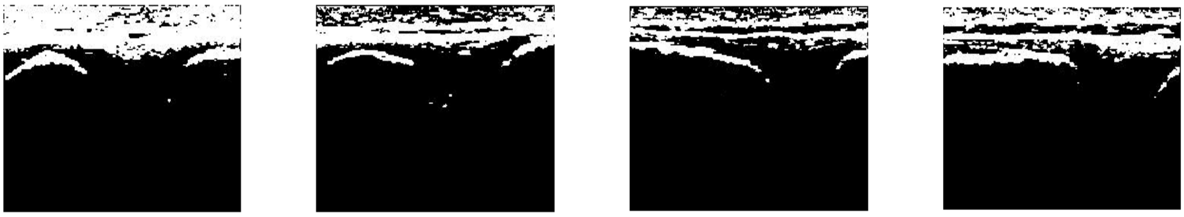

Figure 5.6

The lumbar spine extracted from the spectral signature images by FCM and RFCM are shown in Figure 5.7 and Figure 5.8 respectively.

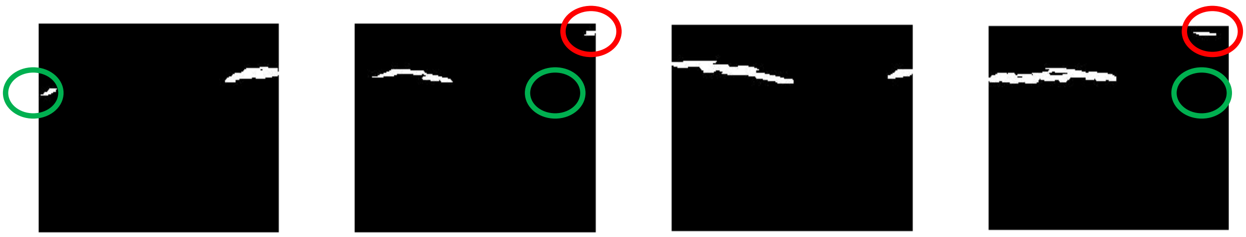

Figure 5.7

The green circles in Figure 5.7 show the portions where the FCM algorithm failed to detect the lumbar spine and the red circles show the portion where it has wrongly identified the portion as the lumbar spine. It is seen from Figure 5.7 and Figure 5.8 that the detection of lumbar spine by RFCM is more complete than by the FCM technique.

Figure 5.8

CONCLUSION

In this paper a detailed description of extraction of lumbar spine from the ultrasound images using fuzzy clustering techniques is presented. As ultrasound images are poor in quality, they are enhanced by image filtering and contrast stretching. The preprocessed image is segmented by two fuzzy clustering techniques viz. Fuzzy C Means and Reformed Fuzzy C Means.

The spectral signature of lumbar spine is extracted. From the spectral signature, by mathematical morphology lumbar spine alone is extracted. Extraction by RFCM technique is better compared to FCM technique in terms of correctness and completeness.

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