CURVELET BASED SEED POINT SEGMENTATION FOR ABNORMALITY DETECTION IN FETUS ULTRA SOUND IMAGES

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***Abstract :** With the advent of computer science and automization performed in several fields, Computer Aided Diagnosis (CAD) has helped scientists and researchers in making decision in the field of biomedicine from Ultra Sound (US) images. With the available extensive knowledge related to the fetus, a host of methods have been designed to study the abnormalities in early stage from US images, resulting in the improvement of accuracy and abnormality detection at an earlier stage. Despite, the advantages recorded, few works have been contributed towards developing fetus spinal cord abnormalities. In this work, a Segmentation using Curvelet-based Seed Point Selection (S-CSPS) method for improving abnormality detection rate for fetus in US images is presented. Correct identification of regions for each pixel that belongs to the objects in US images is obtained through seed point evaluation, reducing the speckle and therefore resulting in the improvement of abnormality being detected. For segmentation of seed points, k-means segmentation algorithm is used. The K-Means Segmentation algorithm preserves the desired information with limited cost factor. The results of applying the introduced method of segmentation of 3D fetal spine images are presented and compared with the results of the other state-of-the art methods. The segmentation accuracy and the abnormality detection rate are regarded in the comparison. The analysis of results shows that the S-CSPS method can be successfully applied for the segmentation of fetal spine US images and provides results in a significantly lesser amount of time without compromising loss in the image segmentation accuracy.*

***Keywords:** Computer Aided Diagnosis, Ultra Sound images, Curvelet, Seed Point Selection, K-Means Segmentation*

1. INTRODUCTION

In recent years, technological developments in US have contributed significantly for screening fatal defects. CAD being an interdisciplinary framework comprises of radiological and digital image processing incorporated with machine learning. Studying how these abnormalities manifest themselves during embryonic development, will require real-time imaging modalities and automated image-processing tools.

Nested Graph Cut (NGC) [1], automatic segmentation method is used for segmenting the objects from Ultra Sound (US) images. It contained multiple objects with nested structure, based on the assumption that each pixel belongs to one of the objects in nested structure. NGC differentiated objects having similar intensity distributions and missing boundaries by assigning weighting coefficients for different nested regions using high frequency US imaging. The advantage of NGC was that it worked well for nested objects without the need for manual selection of initial seeds. However, wrong identification of the regions which does not belong to the nested objects, and falsely labels the regions are compromising the abnormality detection rate.

To analyze the abnormal development of fetal brain, Magnetic Resonance Imaging (MRI)-based method was investigated. The MRI-based detection using Anti Phospholipid Syndrome and Pre Term Birth (APS-PTB) [2] model was associated with symptoms of insufficient placenta and intrauterine growth restriction. These MRI-based methods suggested complement activation to be the footprint for placental insufficiency and cortical fetal brain abnormalities. However, APS-PTB model was non-invasive. Improvement of performance may not be significant in terms of abnormality detection rate where preserving the desired information is in case. At the same time, when it comes to appearance of cerebral morphology to be normal, the metabolism was observed to be abnormal.

The main aim of this paper is to design and develop a method for segmenting and improving the abnormality detection of fetal spine from Ultra sound images by applying Segmentation using Curvelet-based Seed Point Selection (S-CSPS) method. This paper focuses on selecting an appropriate method for each design stage after making a comparative analysis of the various commonly used methods in each category. The various stages involved in the proposed method includes acquisition of US images, seed point selection based on curlvet and finally the segmentation of US images based on the selected seed point.

In this study, a new method for automatic segmentation of fetal spine US images for improving abnormality detection is presented. The proposed Curvelet-based Seed Point Selection (S-CSPS) method for efficient segmentation of fetus spine US images is summarized as follows. First of all, correct identification of regions for each pixel is obtained through seed point evaluation reducing the speckle and therefore resulting in the improvement of abnormality being detected. Next, K-Means Segmentation algorithm is applied to the identified seed point that not only preserves the desired information but also limits the cost factor. Finally, the proposed method is tested on foetus spine US images, and the experimental results indicated that the proposed method had a good performance.

The rest of this research work is organized as follows. Section 2 describes the related works, Section 3 presents the proposed method Segmentation using Curvelet-based Seed Point Selection (S-CSPS) method, Section 4 describes the results and discussions, and finally in Section 5 conclusion of the work presented.

2. RELATED WORKS

In recent years, several works have been reported in the literature for the design and development of methods for segmentation of US images for abnormality detection in fetus. In [3], extensive cervical spine analysis was made to improve robustness and accuracy, two independent techniques are used for the region of interest and measuring the correlation coefficients was applied in [4]. A segmentation based method using Expectation Maximization algorithm was applied in [5] improving the segmentation accuracy for real set images.

Quick and well planned processing of enormous amount of data is considered to be the main challenges to be addressed in medical image processing and analysis. A random walker algorithm was applied in [6] using an extreme amount of time and memory resources from an irregular grid of supervoxels. This in turn resulted in the improvement of segmentation accuracy without loss of data also. Another modified gradient search method was applied in [7] using level set based image segmentation that not only solved the optimization problem in handling noise present in the images but also considering the cost factor involved. Despite, handling noise, the energy minimization was not concentrated. To add this issue, iterating image partitioning by graph cut and identifying region parameters through fixed point computation was presented in [8].

Image segmentation though partitions the image grids into several regions in such a manner that the pixels in each region share similar visual characteristics. Though different methods have been presented in this area, segmentation of natural images in an automatic manner is still considered as a tedious task. In [9], multiple linear reconstructions were applied in windows by obtaining a global optimal labelling minimizing the computational complexity. Though the computational complexity involved in image segmentation was reduced, fetal segmentation for US images remained unsolved. In this regard, a method based on pixel intensity distributions and shape priors was applied in [10], therefore ensuring robustness and minimizing computational cost.

Periodic monitoring regarding the fetus growth is considered to be important to prevent the fetus from growth disorder and also minimize the infant mortality rate. In [11], randomized hough transform method was applied to the fetus US images for detecting the abnormality related to head, femur and abdomen was presented. The application of transform method resulted in the detection of abnormality at an earlier stage. A workshop report on examining fetal skeletons was presented in [12].

Combination of texture and shape features was integrated in [13] to detect pulmonary abnormalities. An automated fetal brain segmentation was performed in [14] using the slice-to-slice volume reconstruction methods, ensuring corrected volume of relevant quality for clinical diagnosis.

The most recent breakthrough in the ultrasound imaging has come with the increasing use of acquiring 2D and 3D data. In [15], automatic measurement of fetal brain and head was presented by applying Sequential Estimation techniques, resulting in the minimum running time. Another region growing segmentation using fuzzy system was applied in [16] using CT images to differentiate between normal, malign or advanced abnormality findings. Despite the findings, noise related issues remain unsolved. A low coverage whole genome sequencing method was applied in [17] to reduce sequencing noise using decision tree model.

A novel K-Means Clustering algorithm was applied in [18], to remove the noise and enhance the images. In [19], abnormality detection rate using pattern matching was performed with client and server model resulting in the abnormality detection. Despite abnormality being detected at a faster rate, brain abnormalities were seen rare in nature. To solve this issue, a discriminative model based on random forest was presented in [20].

In this paper, the proposed method called Segmentation using Curvelet-based Seed Point Selection (S-CSPS) method to segment objects (i.e. seeds) in an image (fetus spine US images) with a nested structure, which means all seeds presented in the US images are spatially-recurring. The seed point selection through curvelet model selects the seed point by obtaining mean value and membership sets by assigning appropriate minimum mean and maximum mean value for different fetal spine US images. Instead of applying the entire image for segmentation, only the seed point selected are segmented using the K-Means Segmentation algorithm. The elaborate description of about S-CSPS method is provided in the following sections.

3. SEGMENTATION USING CURVELET-BASED SEED POINT SELECTION

In this study, a new method is presented for automatically and correctly segmenting fetal spine US images. A seed point is the starting point for region growing that serves as a significant measure for segmentation. Correct identification of regions for each pixel that belongs to the objects in US images is obtained through the proper selection of seed point. In this work, S-CSPS method for US images, incorporating the texture features of a lesion is considered. Figure 1 shows the flow chart of S-CSPS method.

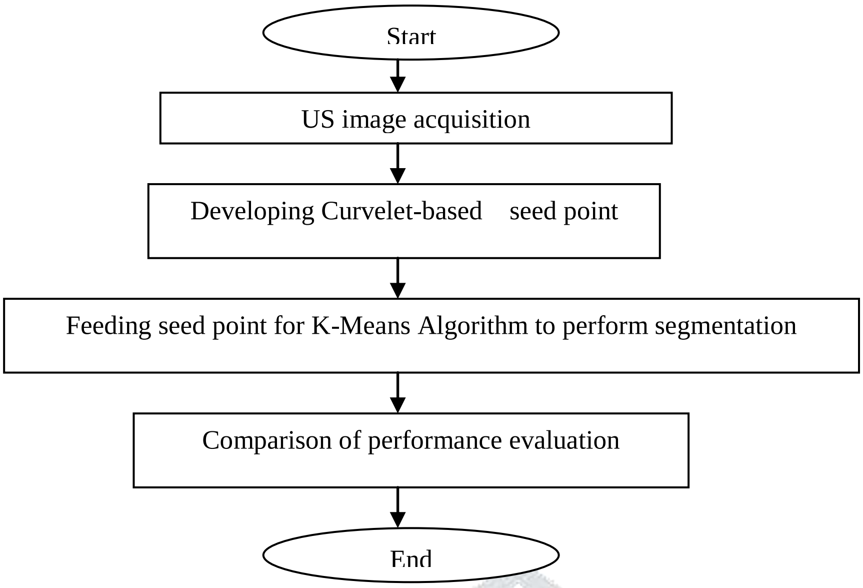

Figure 1 Flowchart of S-CSPS

As shown in the figure 1, the first part is US image acquisition (i.e. fetal spine US images). The algorithm is tested on 35 fetal spine images obtained from the http://www.ultrasound-images.com/fetal-spine/. The processes are carried out using MATLAB 2015b software.

The second part developing a curvelet-based seed point selection method involves frequency analysis of fetal spine images in space and time domains, providing multi-scale image provisioning in a step by step manner which is obtained from the proposed algorithm as mentioned in section 3. The next part involves feeding seed point for K-Means Algorithm to perform segmentation. Finally, the performance evaluation is measured to prove the efficiency of the S-CSPS method.

3.1 Curvelet-based seed point selection

The curvelet-based seed point obtains the seed point for each input fetal spine ultrasound images by subtracting two neighboring pixels due to small changes being observed in the spinal portion between two neighboring pixels. Figure 2 given below shows the Curvelet-based seed point selection model.

The initial location of the fetal spine obtained from 3D region growing is dilated by 2 voxels, where the S-CSPS used HH sub-bands employed for further processes. This is because most of the information on the spinal cord and boundaries were present in the HH sub-bands. To this the S-CSPS measured the mean value with the aid of coefficients of HH sub-bands through window 'w' as given below.

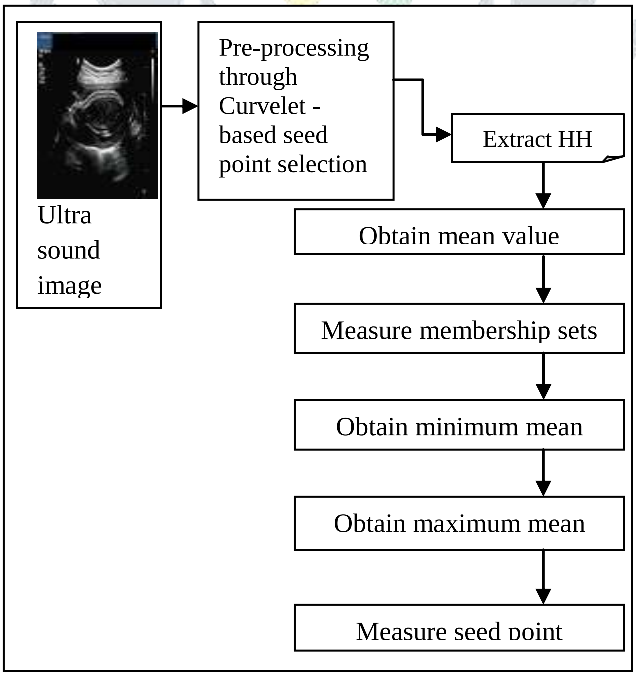

Figure 2 Block diagram of Curvelet-based seed point selection

$$HH'(p,q) = \frac{1}{w*w} \sum_{a=p}^{i} \sum_{b=q}^{j} HH\left(Image(a,b)\right) \quad (1)$$

From (1), the mean value of HH sub-bands is evaluated with the aid of the input fetal spine image '$(Image(a,b))$' and the resultant value is stored in '$HH'(p,q)$'. Higher, the scale more accurate the seed point to be selected, with the lowest frequency being LL and the highest frequency being HH respectively.

$$i = round\ (p + {}^{w}/_{2}) \tag{2}$$

$$j = round\ (q + {}^{w}/_{2}) \tag{3}$$

Next, the sub-bands HH in the S-CSPS is distinguished by 2 representative membership sets 'M_1' and 'M_2' and is expressed as given below.

$$M_{1(HH)}\ (p,q) = \frac{HH'\ (p,q) - HH'_{min}}{HH'_{max} - HH'_{min}} \tag{4}$$

$$M_{2(HH)}\ (p,q) = 1 - M_{1(HH)}\ (p,q) \tag{5}$$

From (4), 'HH'_{max}' symbolizes the maximum mean value of HH sub-bands whereas 'HH'_{min}' symbolizes the minimum mean value of HH sub-bands respectively. It is expressed as given below.

$$HH'_{min} = \min\ (HH'(p,q)) \tag{6}$$

$$HH'_{max} = \max\ (HH'(p,q)) \tag{7}$$

Once the image binarization is accomplished by obtaining the minimum and maximum mean value of HH sub-bands, reduction of speckles is performed to obtain the real lesion region. The real lesion region is extracted by measuring the differences as given below.

$$\alpha\ (p,q) = |HH(p,q) - HH'(p,q)| \tag{8}$$

$$\alpha_{max} = \max\{\alpha\ (p,q)\} \tag{9}$$

$$\alpha_{min} = \min\{\alpha\ (p,q)\} \tag{10}$$

From (8), (9) and (10), the maximum lesion 'α_{max}' extracted using (9) represents the actual lesion candidate list. On the other hand, the minimum lesion 'α_{min}' extracted using (10) represents the region having no intersection and therefore deleted from the lesion candidate list. Finally, the seed point 'SP' is obtained as given below,

$$SP = \{HH'_{max} + \alpha_{max}\} \tag{11}$$

From the above given process, the location of spine information in HH sub-band coefficient is detected by the proposed Spine Texture Differentiation algorithm. This is performed utilizing the texture features of fetal spine ultrasound images with the aid of frequency as presented below. Figure 3 shows the Spine Texture Differentiation algorithm.

Input : Image '$Image\ (a,b)$'
Output: reduces noise
1: **Begin** 2: **For** each input Image '$Image\ (a,b)$' 3:Measure the mean value of HH sub-bands using (1) 4:Measure representative membership sets 'M_1' using (4) 5:Measure representative membership sets 'M_2' using (5) 6:Measure real lesion region using (8) 7:**If** $(\alpha_{max} = \max\{\alpha\ (p,q)\})$ 8:Actual lesion candidate list 9:**End if** 10:**If** $(\alpha_{min} = \min\{\alpha\ (p,q)\})$ 11:Not actual lesion 12:Delete from lesion candidate list 13:**End if** 14:Obtain the seed point using (11) 15:**End for** 16: **End**

Figure 3 Spine Texture Differentiation algorithm

The Spine Texture Differentiation algorithm is used for correct identification of regions (i.e. selecting seed points) for each pixel is summarized as below. For each input fetal spine image, transform a given image into frequency channels by a specified number, i.e., using two decompositions levels. Next, the S-CSPS methods calculate the average membership sets for the two decomposition levels for measuring the real lesion region using (4) and (5). If the maximum of '$\alpha\ (p,q)$' is equal to 'α_{max}', then the actual lesion candidate list generation is obtained. Otherwise, a minimum lesion value is obtained, followed by which no actual lesion is identified. Therefore it will be deleted from the lesion candidate list. The seed point is then obtained and the process is then iterated for other set of regions. In this way, complicated lesion candidate list is removed from the image, therefore concentrating on the lesion portion rather than the entire image, reducing the noise with fairly rapid processing speed.

3.2 K-Means Segmentation

The segmentation of seed point mainly concentrates on separation of regions of interests (affected spine) from background tissues as well as preservation of desired information with limited cost factor. To perform segmentation with the obtained seed point, the S-CSPS applies K-Means Segmentation algorithm that uses pixel labelling. To do this the K-Means Segmentation algorithm evaluates two segmentation measures Random Index 'RI' and Fisher Probable Observed Information 'POI' respectively for each pixel 'i,j' in a given image (i.e. from seed point).

Here a graph '$G=(V,E)$' with vertices 'V' denoting the pixels 'i,j' and bidirectional edges 'E' that connects the neighboring vertices through eight neighborhood structure. Additional edges are represented between the first and last column of the seed point image in order to ensure smoothness when the segmented US fetal spine image is transformed back to their corresponding Cartesian coordinates.

Given a set of 'n' elements '$SP=\{o_1,o_2,\dots,o_n\}$' and two partitions of '*sp*' to compare, a partition of '*sp*' into '*r*' subsets '$P=\{P_{11},P_{21},\dots,P_{r1}\}$',and '$Q=\{Q_{11},Q_{21},\dots,Q_{s1}\}$', a partition of '*sp*' into '*s*' subsets, define the following. Then, the random index between test '$Image_{test}$' and ground truth '*GT*' is evaluated by adding the total pixel pairs with similar label and pixel pairs having different labels in both '$Image_{test}$' and '*GT*' and then dividing it by total number of pixel pairs.

$$\theta = RI(Image_{test}, GT_i) = \frac{1}{\binom{N}{2}} \sum \left[P_{ij}Q_{ij} + \left(1-P_{ij}\right)\left(1-Q_{ij}\right)\right] \quad (12)$$

From (12), the random index 'RI' is estimated with the aid of the seed point 'SP' being an event that describes a pixel pair 'i,j' possessing similar or different labels in the test image '$Image_{test}$' respectively. Followed by this, Fisher Probable Observed Information 'POI' is obtained that is a measure of distance between two partitions 'P_{ij}' and 'Q_{ij}' respectively. Partitioning with partitions is denoted by a random variable '$P=\{1,2,\dots,n\}$' and '$Q=\{1,2,\dots,n\}$' such that the probability values of the two partitions are given as below.

$$Prob\ (P_{ij}) = \frac{|P_{ij}|}{n}; where\ i,j\ \in P\ and\ n = \sum_i P_{ij} \quad (13)$$

$$Prob\ (Q_{ij}) = \frac{|Q_{ij}|}{n}; where\ i,j\ \in Q\ and\ n = \sum_i Q_{ij} \quad (14)$$

From (13) and (14), '$\sum_i P_{ij}$' and '$\sum_i Q_{ij}$' denotes the expected value of observed information between two partitions 'P_{ij}' and 'Q_{ij}' respectively. The Probable Observed Information is represented as given below.

$$\theta_1 = POI\left(P_{ij},Q_{ij}\right) = H\left(P_{ij}\right) = H\left(Q_{ij}\right) - 2I\left(P_{ij},Q_{ij}\right) \quad (15)$$

From (15), '$H\left(P_{ij}\right)$' denotes the entropy of 'P', '$H\left(Q_{ij}\right)$' denotes the entropy of 'Q' whereas '$I\left(P_{ij},Q_{ij}\right)$' is the mutual information between 'P' and 'Q'. Finally, '$POI\ \left(P_{ij},Q_{ij}\right)$' measures how much the partition assignment for a seed in partition 'P' reduces the uncertainty about the seed's partition in partitioning 'Q'.

A pixel labeling through two segmentation measures Random Index 'RI' and Fisher Probable Observed Information 'POI', achieves efficient segmentation, by finding an assignment to '$I_{P,Q}$' that minimizes the amount of two independent experiments as given below. Here, the S-CSPS is therefore designed with the potential that allow us to design segmentation measures to perform this minimization efficiently.

$$I_{P,Q}(\theta,\theta_1) = I_P(\theta,\theta_1) + I_Q(\theta,\theta_1) \quad (16)$$

From the above given process, the segmentation is performed with the located seed points using the K-Means Segmentation algorithm as given in figure 4. This is performed using the two segmentation measures, random index and Probable Observed Information.

Input: Seed Point 'SP_{ij}'
Output: Improved abnormality detection
1: **Begin** 2:**For** each Seed Point 'SP_{ij}' 3:Measure Random Index using () 4:Measure probability value of first partition using (13) 5:Measure probability value of second partition using (14) 6:Measure Probable Observed Information using (15) 7:**End for** 8:**End**

Figure 4 K-Means Segmentation algorithm

As shown in the above K-Means Segmentation algorithm, for each seed point detected through Spine Texture Differentiation algorithm, two segmentation measures are preformed. The two measures used in the S-CSPS are the random index, a measure of similarity between two partitions and Probable Observed Information, a measure of information that minimizes the uncertainty about the seed's partition and therefore improving the abnormality detection rate for fetal spine in US images.

4. EXPERIMENTAL SETTINGS

The proposed method is implemented with MATLAB 2015b, on fetal spine US images on PC with 3.4GHz Intel Core i7 processor, 2GB RAM, and windows 7 platform. For the testing and experimentation purposes, a total of 35 images from the ultrasound images of anomalies of fetal spine are taken. The image distributions based on the fundamental tissue structures in the ultrasound images of anomalies of fetal spine include normal fetal spine in longitudinal section, with main ossification centers in the fetal vertebra i.e., the centrum, the right neural process and the left neural process.

The centrum forms the central part of the vertebral body, whereas the postero-lateral parts of the vertebrae are formed by the right and left neural processes respectively. Randomly selected 35 data/samples were used for testing various segmentation algorithms. The 10-fold cross validation approach was applied in this work to partition the data in training and testing sets. Thus 45 data/samples were used for training purposes and 35 data/samples were used for testing purposes. The images were digitized into a 512x512 rectangular format with 256 gray levels. The proposed algorithm was tested on 35 fetal ultrasound images. The outputs of the segmentation were tallied with markings made manually by an obstetrician to determine correctness.

5. DISCUSSION

Segmentation using Curvelet-based Seed Point Selection (S-CSPS) method is developed in MATLAB platform. By using fetal spine US images and the defined testing method results are compared with existing method. S-CSPS method is compared with the existing Nested Graph Cut (NGC) [1] and MRI-based Molecular Imaging for monitoring Placental and Fetal Brain Inflammation (MI-PFBI) [2]. The experiment is conducted on factors such as noise, segmentation accuracy abnormality detection rate and segmentation time with respect to different number of fetus images.

5.1 Impact of Signal to mean square error

In this work, speckle is considered as noise in the proposed method and try to minimize the speckle preserving the desired information is provided. The signal-to-mean square error (*SMSE*), is employed to evaluate the de-speckle effect and is expressed as given below.

$$SMSE = \frac{\sum_{i=1}^{n} s_i^2}{\sum_{i=1}^{n}(s_i' - s_i)^2} \quad (17)$$

From (17), 'S_i' where is the '$i\ th$' pixel in the original fetus spine US image, 'S_i'' is the pixel in the image after speckle reduction and 'n' represents the image size. A larger SMSE ratio means a better noise suppression effect. The comparison of SMSE is presented in table 1 with respect to the number of patients (fetus US image) in the range of 5 – 35 from 15 male (infant) and 20 female (infant) is provided. With increase in the number of fetus US images, the SMSE also gets increased.

Table 1: Comparative performance of various segmentation methods to measure SMSE

No. of fetus images	SMSE (db)		
	S-CSPS	NGC	MI-PFBI
5	6.33	9.25	12.28
10	11.43	12.35	15.46
15	17.23	20.15	23.26
20	22.31	25.23	28.34
25	28.78	31.68	34.79
30	33.14	36.03	39.14
35	40.29	43.12	46.23

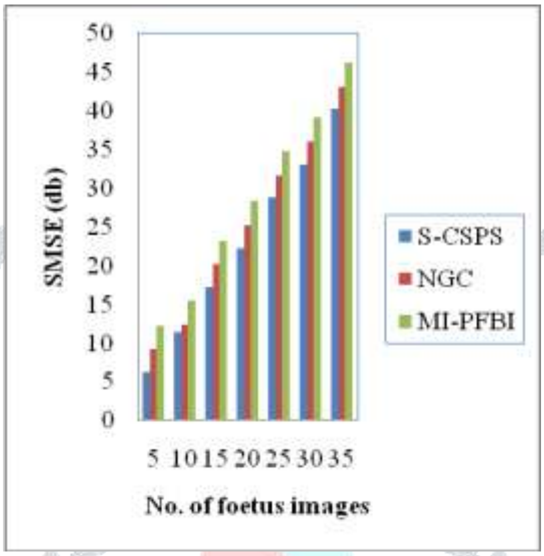

Figure 5 Performance analysis of SMSE

In figure 5, the depicted SMSE attained using 35 fetus images for experimental purposes using MATLAB. A comparison between three methods, S-CSPS, NGC and MI-PFBI is presented, in which the noise observer is recorded. From the figure, it is evident that the SMSE ratio of NGC and MI-PFBI is higher than the S-CSPS method. This is because of the application of Spine Texture Differentiation algorithm. The Spine Texture Differentiation algorithm selects the correct seed points by obtaining the minimum and maximum mean value using the HH sub bands. This in turn reduces the noise using S-CSPS method by 16% compared to NGC. Moreover, by distinguishing between two representative membership sets, separation of lesion candidate list is made in an efficient manner (i.e. separating actual lesion from the abnormal lesion) using the texture features reduces the noise using S-CSPS method by 35% compared to MI-PFBI.

5.2 Impact of segmentation accuracy

The segmentation accuracy depends upon the number of correctly segmented samples (i.e., true negative and true positive) [21] and is calculated as follows:

$$Accuracy = \left(\frac{TP+TN}{N}\right) * 100 \qquad (18)$$

From (18), ‘’ is the measure for segmentation accuracy performed with ‘$N = 35$’ is the total number of samples (fetus spine US images) present in the Ultra sound images. Table 2 gives a comparative analysis of the proposed method with other state-of-the-art methods available in the literature in terms of segmentation accuracy. From Table 2, it can be observed that the proposed method is performing better in comparison to all other methods.

As shown in table, segmentation accuracy is provided using MATLAB simulator and comparison is made with two other methods, namely NGC [1] and MI-PFBI [2].

Table 2: Comparative performance of various segmentation methods to measure segmentation accuracy

No. of fetus images	Segmentation accuracy (%)		
	S-CSPS	NGC	MI-PFBI
5	85.93	77.28	71.90
10	90.21	83.14	77.89
15	94.28	81.45	75.12
20	89.15	82.14	76.28
25	94.18	87.23	81.43
30	96.32	89.74	82.34
35	89.14	82.07	76.14

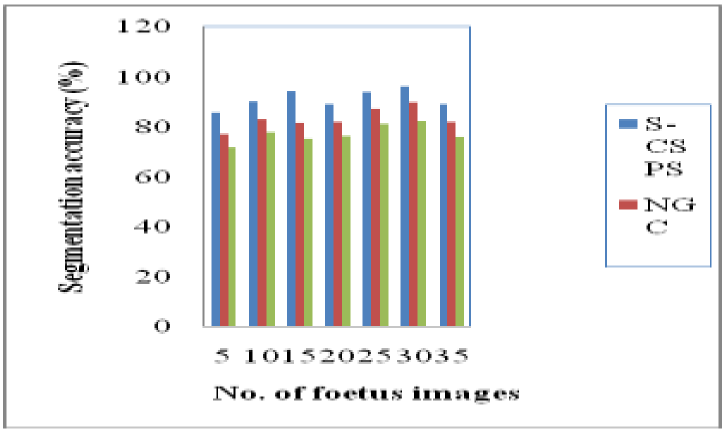

Figure 6 Performance analysis of segmentation accuracy

Figure 6 shows the performance analysis of segmentation accuracy. With the increase in number of feotus images provided as input, the segmentation accuracy is also increased. However, the increase is not found to be linear, that shows the presence of noise in the US images makes the system to compromise the accuracy during segmentation. Despite, non-linearity observed in the figure, segmentation accuracy betterment is achieved using S-CSPS method. For example, when the input fetus image was 15, the sum of true positive and true negative rate observed using NGC and MI-PFBI was observed to be 12 and 11 respectively, whereas it was found to be 14 when S-CSPS was applied with. This, shows an improvement in the segmentation accuracy when S-CSPS was applied with. This is because of the application of K-Means Segmentation algorithm. The K-Means Segmentation algorithm only segments the selected seed points extracted from curvelet based model, therefore ensuring minimum noise and therefore improving the segmentation accuracy. In addition, by using pixel labelling, the segmentation accuracy of S-CSPS method is improved by 9% when compared to NGC [1] and 15% when compared to MI-PFBI [2] respectively.

5.3 Impact of abnormality detection rate

The abnormality detection rate for S-CSPS method is elaborated in table and comparison made with two other methods NGC [1] and MI-PFBI [2] respectively. The method with 35 US images are used for experimental purpose using MATLAB.

Table 3: Comparative performance of various segmentation methods to measure abnormality detection rate

Methods	Abnormality detection rate (%)
S-CSPS	94.23
NGC	89.15
MI-PFBI	82.33

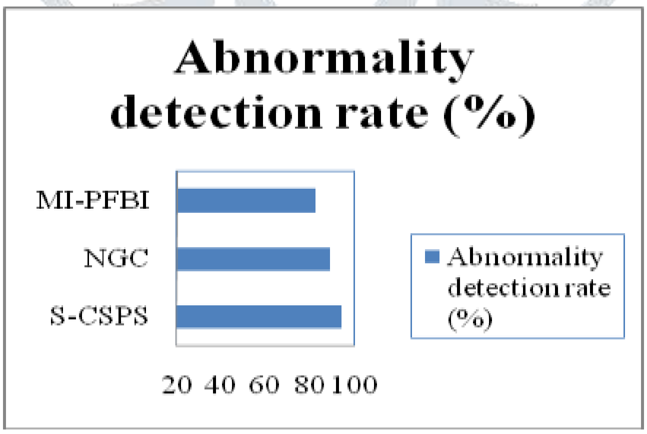

Figure 7 Performance analysis of abnormality detection rate

Table 3 and Figure 7 illustrate the abnormality detection rate versus different fetus spine US images including both male and female patients and simulated in MATLAB. The abnormality detection rate is measured in terms of percentage for experimental purpose conducted using MATLAB. From the figure note the abnormality detection rate is higher by applying the proposed method S-CSPS than when compared to the existing methods NGC [1] and MI-PFBI [2] respectively. This is because of the application of two segmentation measures, random index and Probable Observed Information is to perform segmentation in a significant manner. With these two segmentation measures, accurate separation of region of interests is made, resulting in the improvement of abnormality detection rate using S-CSPS by 5% when compared to NGC. Moreover, by applying pixel labelling, eight neighbouring structure is used that provides smoothness when the segmented image is transformed back to their corresponding Cartesian coordinates and therefore attains an improvement of abnormality detection rate by 7% when compared to MI-PFBI respectively.

6. CONCLUSION

In this work, a Segmentation using Curvelet-based Seed Point Selection (S-CSPS) method for abnormality detection in fetus spine US images is presented. The method reduces the noise rate during the seed point selection with reduced seed point selection time and therefore provides abnormality detection of disease on US images at an early stage. The goal of our US image segmentation is to improve the abnormality detection rate using the training and test images which significantly contribute to the relevance. To do this, first design a curvelet-based seed point selection to select the seed points based on the spinal portion between two neighboring pixels to reduce the noise. Then, based on this measure, the proposed Spine Texture Differentiation algorithm identifies the correct regions and finally obtains the seed point reducing the computational time or seed selection time. With the selected seed points, two segmentation measures, random index and probable observed information are measured for each image with the objective of reducing the segmentation time. In addition, a K-Means Segmentation algorithm based on the pixel labeling with varied training and test images. Through the experiments, the K-Means Segmentation algorithm provided more accurate results compared to existing segmentation methods. The result shows that S-CSPS method offers better performance with an improvement of segmentation accuracy by 12% and improving the abnormality detection rate by 7% compared to NGC and MI-PFBI respectively.

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