Retraction

Retraction: Texture based Clustering Technique for Fetal Ultrasound Image Segmentation (J. Phys.: Conf. Ser. 1916 012014)

Published 23 February 2022

This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

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IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1

Retraction published: 23 February 2022
Texture based Clustering Technique for Fetal Ultrasound Image Segmentation

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Abstract. Segmentation of fetal ultrasound image is an important and necessary task in the automation of fetal biometric measurement. Fetal ultrasound image segmentation is tedious because of the fuzzy nature and textured appearance of fetal structures. Hence, texture based Clustering is proposed for segmenting fetal ultrasound images. Clustering is performed using texture properties of the images which are used for segmenting ultrasound images of fetus. Texture based clustering technique can be used for segmenting all fetal anatomies specifically abdomen, the boundaries of which are very vague and difficult to delineate. Synthetic, simulated ultrasound images and 120 ultrasound fetal images were used for validating the method achieving an accuracy of 90%.

1. Introduction
Fetal growth has to be monitored during pregnancy to diagnose any anomalies. At present, obstetricians manually measure all the fetal parameters such as crown rump length, head circumference, bi-parietal diameter, femur length and abdominal circumference. This is a time consuming and challenging task because of the sensitive nature and fuzziness of the appearance of these anatomical structures. Automation of fetal bio-metric measurements are being performed to overcome the drawbacks of manual measurement. Clustering algorithm based on texture is proposed for segmenting ultrasound images of fetus.

The paper is divided into following sections: Existing fetal ultrasound segmentation is discussed in Section 2. Texture based clustering technique is dealt in Section 3. The quantitative metrics used for assessing clustering based on texture features is given in Section 4. Section 5 gives results and concluded in Section 6.

2. Existing Techniques for Fetal Ultrasound Image Segmentation
Many fetal ultrasound image segmentation techniques were proposed specific to different anatomies. A general method for segmenting all fetal structures is only few. [1] proposed head segmentation for fetus based on active contour model. 4 D hough transform was used on binary image by [2] to segment head by fitting ellipse. [3] used K-means clustering, morphological operations and object recognition and later an iterative randomized Hough transform
was used find the ellipse of the head of fetus [4]. Rough segmentation using thresholds based on shape features and then chamfer matching followed by Hough transform was proposed by Mathews M. et al. [5] for head segmentation.

[6] proposed morphological operators based on shape features for femur segmentation of fetus. Class separable method was given by [7]. Entropy based segmentation was proposed by [8] for segmenting head. [9] made use of texton features obtained for each of fetal structures using a multi scale and multi oriented filter bank. An iterative randomized hough transform was proposed by [10,11] for fetal abdomen. Classification of fetal structures using constrained probabilistic boosting tree was given by [12] for each of fetal structures. Extended absolute fuzzy connectedness (AFC) approach using an affinity function from local phase features was given by [13].

3. Texture based Clustering Technique

Clustering methods are robust when compared to other unsupervised segmentation techniques. Clustering methods provide good results if the number of clusters is known beforehand. K Means, EM and Fuzzy C Means (FCM) algorithms are some of the commonly used clustering techniques. Among clustering techniques, FCM is efficient in terms of segmentation accuracy, less sensitive to noise and allows pixels to belong to different clusters using membership functions. Clustering based on texture features is proposed for segmenting ultrasound images of fetus. Texture properties are obtained from the fetal ultrasound images. These properties are used for segmentation using various clustering techniques and their performance is evaluated[14].

3.1. Texture Energy Images

Texture is periodic arrangement of basic patterns that is used to identify different objects. Ultrasound images lack discrete boundaries; In this scenario, texture can be used for forming continuous edges at the boundary of regions identified by texture properties [15]. A set of features are obtained which characterize the texture of the image. The intensity based pixel distribution in an image has regularity and mutual relationship. Texture based segmentation is used to identify region boundaries by identifying the regions with different texture properties. The ultrasound images are characterized by their fine texture content. It is rather difficult to find the basic texture unit or texton of these ultrasound images. Hence, the neighborhood texture content of each and every pixel is considered along with its intensity. Thus, the fetal abdomen which is considered to be fully textured structure compared to femur and head, is efficiently clustered considering the texture properties of the pixels. In the proposed method, a total of 8 texture features are used for obtaining texture energy images which are given below in Table 1.

Table 1. Texture energy images

| Texture extraction technique                      | Texture features               |
|--------------------------------------------------|--------------------------------|
| Statistical features                             | Variance                       |
| Haralick’s features based on Grey-Level Co-occurrence Matrix | Correlation, Sum of squares |
| Neighborhood Gray Tone Difference Matrix         | Strength                       |
| Statistical Feature Matrix                       | Coarseness, Contrast           |
| Law’s texture energy measures                    | LE texture energy image        |
| Fourier power spectrum                           | Angular spectrum               |

The above textures are used to obtain 8 texture feature images. Textures are derived for each and every pixel of the input image using 5 x 5 neighbourhoods. Texture features cannot be calculated for a single pixel. So a texture window is considered for every pixel. The texture features are calculated for the texture window region, which is considered as the texture feature of the corresponding centre pixel.
The $k^{th}$ texture feature image, $g_k(i,j)$, is then used to calculate the sample mean and deviation around each pixel according to Equation (1).

$$s_k(i,j) = \frac{1}{(2n+1)^2} \sum_{u=-n}^{i+n} \sum_{v=-n}^{j+n} |g(u,v) - \text{mean}_k|$$

where $n=5$ and mean of the $k^{th}$ feature image with size $M \times N$, mean$_k$ is given by Equation (2).

$$\text{mean}_k = \frac{1}{MN} \sum_{i,j} g(i,j)$$

The resulting images $s_k(i,j)$ ($k=1..8$) are "energy" measures, which are used in clustering technique for segmenting fetal structures.

### 3.2. Clustering Techniques

#### 3.2.1 K Means Clustering:

K-Means method is the most popular unsupervised algorithm. This divides the pixels into different groups based on the distance between them. The objective of k-means algorithm is to find the minimum of the sum of squared distances between cluster centres and all pixel values. K-means method is statistical clustering algorithm [16].

#### 3.2.2 Expectation Maximization Clustering:

The algorithm estimates the maximum likelihood parameter of data modelled based on latent variable. In this method, alternatively Expectation (E) and Maximization (M) steps are iteratively done till convergence of results. The expectation step estimates the likelihood of the observed latent variables and maximization step estimates the maximum likelihood by maximizing the expected result found on the previous step. The results of maximization step are used as the starting point of another E step, and iteratively performed until convergence. The EM method results in $K$ multivariate distributions for each cluster. The EM algorithm is statistical technique which is performed iteratively to find the probability that pixel belongs to particular cluster [16].

#### 3.2.3 Fuzzy C Means Clustering:

The Fuzzy C Means [17] divides a set of data $X=\{x_1, x_2, x_3 \ldots x_n\}$ into a number of clusters by minimizing the following objective function as given in Equation (3).

$$J_{FCM} = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \|x_i - v_j\|^2$$

where membership $u_{ik} \in [0,1]$ represents degree of pixel $x_k$ belonging to the cluster $i$, $m$ is the fuzzy parameter which gives the level of cluster fuzziness, $d_{ik}=\|x_i-v_j\|$ is the distance between pixel $x_k$ and the centroid $v_i$ of $i^{th}$ cluster.

The objective can reach a local minimum by changing the fuzzy membership function $U=\{u_{ik}\}$ and cluster centers $V=\{v_1, v_2, v_3 \ldots v_c\}$ as given in Equations (4) and (5) respectively.

A General FCM method follows the below procedure:

1. Initialize $c$, $m$ and stopping criteria.
2. Set arbitrary values for partition matrix $u_{ik}$.
3. Initialize $b=0$.
4. Compute cluster centers using $v_i$.
5. Calculate membership values using $u_{ik}$
6. If max $\{U^{(b)} - U^{(b+1)}\} < \varepsilon$ (stopping criterion) then stop, otherwise, $b=b+1$ and go to step 4.

### 4. Evaluation Metrics

The quantitative metrics used for evaluating the proposed segmentation technique is given in this section. A number of existing ultrasound image segmentation techniques utilize these metrics for
validation. Let X be the manual delineation of the input image J by the expert, Y be the proposed technique result obtained using clustering based on texture features.

4.1. Jaccard Index (JII)

This is overlap-based metric which measures similarity between segmented image (B) and ground truth (A) as given in Equation (6). A higher value indicates a better result [18].

\[
Jaccard\ Index(X, Z) = \frac{|X \cap Y|}{|Y| + |X| - |Y \cup X|} \quad (6)
\]

4.2. Segmentation Accuracy (SA)

SA is defined as given in Equation (7)

\[
Segmentation\ Accuracy = \frac{SS}{P} \quad (7)
\]

where SS is the correctly classified pixels and P is the total pixels in the region. If all the pixels are in the right region, we have Segmentation Accuracy is 1.

4.3. Variation of Information (VoI)

This computes the common information between ground truth, X and segmentation using proposed method, Y by calculating the information that is lost or gained when changing from one to another. A lower variation of information relates to better segmentation. Variation of Information gives the distance between two partitions based on average conditional entropy [19].

5. Results and Discussion

The proposed texture based clustering technique has been implemented in MATLAB 9.2 (R2017a). The performance of the proposed technique is evaluated using synthetic image, simulated ultrasound images and clinical ultrasound images of fetus.

5.1. Synthetic Images

The synthetic image which is given in Figure 1(a) is corrupted artificially with Speckle noise of variance such as 1%, 3%, 5%, 7% and 9% and segmentation is performed using k means, EM, FCM using texture energy images.

The results of the clustering techniques on the segmenting noisy synthetic image are shown in Figure 1. It can be seen that the FCM clustering has higher segmentation quality in comparison with K means and EM techniques. Though all segmentation techniques give good results for noiseless and less noisy images, FCM technique performs better in high noise density images when compared to other segmentation methods. In addition to this, the FCM technique gives good results for all densities of noise compared to EM and K means method.

5.2. Simulated Ultrasound Images

The proposed segmentation technique is validated using simulated ultrasound images. Simulated images are formed using Field II, Ultrasound simulation software. The qualitative evaluation of the texture based FCM, K means and EM clustering is given in Figure 2. From the results, FCM clustering gives better results compared to K Means and EM methods.

5.3. Clinical Fetal Ultrasound Images

The texture based clustering is performed on 200 ultrasound fetal images (50 femur images, 100 head images and 50 abdominal images of fetuses). The images are obtained using Phillips ultrasound machine. The clinical images are resized to 780 x 615. The qualitative evaluation of the texture based
clustering is given in Figure 3 for segmenting fetal head, abdomen and femur. Table 2 gives the quantitative metrics. The results show that FCM method gives better results for fetal head segmentation. Segmentation of femur and abdomen using FCM method gives slightly less accurate results because these structure has varying shapes for different fetus.

The computation time for each of the segmentation technique is analyzed in Table 3. Given that the texture images and no. of clusters computed beforehand, the proposed FCM technique requires lesser computation time compared to other techniques since it converges faster with lesser number of iterations.

Figure 1. (a) Original image (b) – (d) 3%, 5%, 9% speckle noisy image (e) – (h) k-means clustered images (i) – (l) EM clustered images (m) – (p) FCM clustered images
Figure 2. Clustering results for simulated cyst image (a) Original image (b) K means clustering (c) EM clustering (d) FCM clustering.

Figure 3. Clustering results for fetal abdomen, femur and head (a), (e), (i) Original image (b), (f), (j) K means clustering (c), (g), (k) EM clustering (d), (h), (l) FCM clustering.
Table 2. Quantitative Evaluation for Clustering techniques for segmenting clinical ultrasound images

| Clustering technique | Quantitative Metrics |
|----------------------|----------------------|
|                      | SA       | JI      | VoI     |
| K means              | 0.9386   | 0.9236  | 0.3456  |
| EM                   | 0.9398   | 0.9377  | 0.3324  |
| FCM                  | 0.9576   | 0.9434  | 0.3244  |

Table 3. Computation time for Clustering techniques for segmenting clinical ultrasound images

| Fetal Structure   | Computation time in seconds(Number of iterations) |
|-------------------|-----------------------------------------------|
|                   | Determination of No. of clusters             |
|                   | Texture energy image(Subtractive clustering) |
|                   | K means  | EM   | FCM  |
| Abdomen           | 1051     | 2981 | 4.04 | 14.3 | 39.58(100) |
| Femur             | 1019     | 4910 | 0.95 | 10.1 | 39.61(100) |
| Head              | 1143     | 3414 | 1.24 | 13.1 | 40.7(100)  |

6. Conclusion
A texture based clustering technique is proposed for segmentation of fetal ultrasound image in this paper. Eight texture energy images are used for segmentation using different clustering methods. The texture based clustering method is evaluated using synthetic, simulated and clinical ultrasound images. The evaluation metrics such as SA, JI, and VoI are used for validating the performance. K-means clustering using texture energy images takes less computation time but gives less accurate result. FCM dives better result compared to other clustering methods in terms of accuracy.

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