ISSN 2278-3091
Volume 9, No.3, May - June 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse87932020.pdf
https://doi.org/10.30534/ijatcse/2020/87932020

Gestation Age Determination through Optimized Fuzzy Logic Based Edge Detection Algorithm in Fetal Ultrasound Images

Jujjavarapu Sunitha Kumari[1], Usha Rani Nelakuditi[2]
[1]Research Scholar ,Department of Electronics and Communication Engineering , Vignan's University, India
ballekalluneelmoses42835@gmail.com
[2]Professor, Department of Electronics and Communication Engineering, Vignan 's University, India
usharani.nsai@gmail.com

ABSTRACT

The present research proposes an automated technique to determine Gestation age from fetal ultrasound images using BPD biometric factor. Knowing this parameter, the status of the fetal growth is accurately predicted. In advance to the traditional technique, this study significantly focuses on optimized fuzzy logic based LSF algorithm to detect the precise edge information of the images. Gradient values obtained from six directional masks are used as fuzzy input and depending on the fuzzy rules; the system predicts the efficient edges while suppressing the remaining. Fitting an elliptical curve across the edges to determine the necessitate parameter is performed by LSF. Further, filtered LSF is also applied to similar ultrasound images in order to present the effective advantages of the proposed method. Moreover, the observed results are compared with the manual values taken by medical sonographers. From this, it is clearly analyzed that the gestational age predicted by the proposed technique is approximately closer to that of the manual ones when compared to the other technique and this exists mainly due to the inclusion of the fuzzy logic rule specifications.

Key words : fetal images, fuzzy logic, genetic algorithm, gestation age, least square fitting, ultrasound.

1. INTRODUCTION

Accurate prediction of gestation age (GA) plays a significant role in obstetric intensive care unit which enables the success or safety precautions to be influenced in clinical interventions. In addition to this, it also visualizes the fetal growth and detects any abnormalities if possibly present in the fetus [1]. The abnormalities in the growth of fetus may enhance the chance of causing perinatal morbidities and also increases the mortality risks. The failure in presumable low risk pregnancy can be identified through restrictive fetal growth. The above factors make the need for monitoring the fetal growth at every pregnancy [2]. The analysis of fetal growth by gynecologist may results in producing inter-observational error. In order to reduce the time consumption and to avoid manual reliable procedure, it is necessitated to adopt automatic approach for evaluating GA [3]. Among the medical images, Ultrasound images possess lower contrast which results in tedious tasks to achieve segmentation and image extraction process. Further the presence of inevitable noises causes challengeable complexities for isolating the desirable area location and it is needed to apply exactly perfect technique for extracting the edges of the fetal images to estimate the parameters [4]-[6].

Various parametric factors are utilized to determine the gestational age including the bi-parietal diameter (BPD), head circumference (HC), abdominal circumference (AC) and femur length (FL). Among these, the present research uses BPD parameter for estimating the gestation age. Numerous researchers are presented in helping the physician regarding the bi-parietal Diameter (BPD) measure to determine GA and this measurement depends mainly on the image edges.

The edges of the ultrasound images provide accurate information related to the objects present within it and also reveals the information about its boundary [7]. The image contour must be extracted for detecting the entire edge information and this paves the way to establish edge detection as an indispensable process. The obtained edges are utilized as an intermediate result and are provided to interpret the edges of the other approaches [8]. The variation in edges exists based on the image intensities and is detected by calculating the functional derivatives of the intensity with respect to the corresponding pixel values. For relative higher magnitudes of intensities, the pixels present at the respective position will be classified as edge pixels. Significant property of this process lies in its tendency for extracting the accurate edges possessing better orientations with detailed description [9],[10].

Fuzzy relevant canny edge detection technique is adopted for handling uncertainty in the images efficiently by selecting membership function. Type-2 fuzzy logic chooses values appropriately based on the threshold variables which are then utilized by canny edge detector for segmenting gradient images [11]. Fuzzy logic pretends to be a multivalued system that predicts the group of membership degree. Alternative to binary data, fuzzy system logic uses appropriate abilities and approximate information for determining precise edge solution by expressing a group of 'IF-THEN' rules [12].

Integration of the morphological gradient approach with generalized type-2 fuzzy system results in accurate uncertainty model while processing ultrasound images. The main drawbacks in designing the fuzzy system involves the specification of number of inputs, membership function as well as output used, and also need to reveal how accurate the results will be obtained with the usage of fuzzy rules [13]. Therefore, a concern effort is preferred to obtain quality solution through adopting many aggressive and manageable methods. In this Genetic Algorithm based bio-inspired technique is adopted to obtain better solution by overcoming the said disadvantages. The optimization of the fuzzy logic is performed by genetic algorithm to detect the edges accurately [14]. The parametric factors can be determined with the optimization of the edge information. Several other approaches are also followed in the optimized edge output in order to determine the BPD and GA accurately and it is briefly explained in the proposed method.

Numerous researchers are available to measure BPD from ultrasound images. [15] proposes a segmentation-based thresholding canny edge detection technique to estimate fetal weight as well as fetal gender from the ultrasound images with increased accuracy. Fetal sex is determined with respect to the white pixel percentages in the processed images and the weight depends on the estimation of the biometric parameters. For further improvements, this method can be enhanced and applied on two-dimensional ultrasound machine. [16] reveals that the canny edge detection algorithm over performs the other methods like Sobel, Prewitt, Laplacian in estimating the fetal weight and it also recommends to analyze the accuracy of the technique in future. [17] discusses the method to determine fetal weight by processing the input images followed by adopting canny edge detection in which the features are extracted for measuring different biometric parameter. Fetal status can be viewed earlier which minimizes the still births.

[18] develops an automatic fast detection technique for estimating the fetal parameters. The interested regions and its background are well distinguished through trained constrained probabilistic boosting tree in which segmentation is done by traditional technique. Further time consumed by the training process is nearly 2-3 days. [19] Predicts the gestational age from the fetal ultrasound brain images. Spatial and temporal brain developments are characterized by means of regression forest classification technique and feature extraction is performed for capturing sonographic brain pattern which outperforms the clinically evaluated method. [20] adopts convolutional neural network (CNN) to evaluate the fetal parameter automatically from ultrasound images. In this, image classification with respect to different region is performed and the parameter is evaluated through Hough transform with stabilized performance. [21] Presented computer aided detection technique to determine GA and fetal growth automatically. Feature extraction is done for training random forest classifier which then follows Hough transforming to fit an ellipse. The evaluated results show approximately closer when compared to the measurement of clinical sonographer. [22] Different biometric parameters are observed from the selected ultrasound fetal images using an INTERGROWTH-21 tool so that the GA can be predicted accurately. Machine learning genetic algorithm is adopted for image classification with improved accuracy. Reasonable effort must be put-forward for improving earlier initiation in case of underserved patients. Significantly [23] uses Sonography Machine for measuring the BPD and gestation age of the examined patients and the obtained results seems comparably equal with the other techniques.

Further in alternative to the above examination of ultrasound fetal images, suitable edge detection algorithm is literally presented. [24] Novel edge detection method by integrating neural network and fuzzy logic is adopted to obtain fine smoothened edges without the presence of noises. It seems better while comparing with Canny and Sobel operator. [25] Gradient approach dependent fuzzy technique provides better control regarding image gradients with high uncertainty level in the presence or absence of noises for different images. The advantages of fuzzy logic can be clearly understood as dictated in [26]. Optimized type-2 fuzzy logic using cuckoo search algorithm is discussed in [27] to obtain better edges. Only few parameters are tuned in this optimization algorithm which adds a new advantage to the entire technique. Another bio-inspired algorithm known as Ant colony optimization when integrating with fuzzy system provides accurate performance with respect to edge quality and computational time [28]-[31].

Various researchers have discussed the advantages of fuzzy system in different fields. Integration of other optimization or machine learning approaches with fuzzy technique is also presented. But none of the integrated fuzzy logic is used to analyze the edges of the ultrasound fetal images for estimating gestation age. Utilization of traditional edge pattern results in false or complicated edges because of the noisy effect. Therefore, in alternative to this, fuzzy logic system is used in the present research for evaluating gestational age and the results also looks closer to that of the manual sonographer examination.

Paper organization is presented as follows. Section II describes the related works illustrating different technique to estimate the gestational age and also involves the advantage of using fuzzy logic in various fields. Section III indicates the background methodology of the proposed technique. Section IV dictates the reason and aim for motivation of the adopted proposed algorithm. Section V briefly explains the proposed method to determine the fine edge and also includes the fitting technique for estimating the biometric parameter. Section VI illustrates the results and discussion with brief explanation obtained at the output of various methods. Also, comparison with manual value and other technique is dictated. Section VII concludes the paper and also suggest suitable option for further making improvements in future.

2. BACKGROUND METHODOLOGY

Use either SI (MKS) or CGS as primary units. (SI units are strongly encouraged.) English units may be used as secondary

2.1 Edge Detection using PSO Optimized Fuzzy Cellular Automata

An effective edge detection algorithm following the rules of fuzzy cellular automata and further optimized through Particle Swarm optimization technique is discussed. The linear fuzzy parametric membership functional rules are applied to the image datasets for converting gradient magnitude of the image pixel to the fuzzy-cellular automata membership and PSO technique evaluates the better solution. The novel cellular automata approach improves the flexibility of the binary edges. The observed results are compared with traditional Sobel and Canny methods. Detailed edge characteristic is preserved in this method and also involved in detection of slight smoothened, lower contrasted complicate edge pattern. These advantageous characteristics results in compensation of broken weaker edge, providing accurate connectivity but these are predicted with the limited constraints of efficiency and performance. Hence better optimization technique with variation in fuzzy membership rules remains the key challenge [32].

2.2 Gestation Age Determination from Fetal Ultrasonic Image by Measurement of Bi-Parietal Distance

This method automatically measures the BPD that represents the secondary axes length of the elliptical curve in ultrasound fetal images. Initially, the noise present in the images are minimized using Wiener Filter and further objects in the borders are evacuated to obtain enriched higher density regions suppressing the others. Binary form of the image is obtained by Thresholding followed by the Skeletonization process for reducing data points. Least Square Fitting (LSF) algorithm fits an elliptical curve in the desirable region thereby the minor axis length can be measured corresponding to the bi-parietal distance parameter. The evaluated results seem closer to manual values and this helps physician to provide information regarding the health status of fetus, Gestation Age GA, Estimate Date of Delivery EDD, and Fetal Weight. LSF also signifies that it operates fast when compared to Hough transform. However, it necessitates further pre-segmentation of edge points to offer acceptable data distribution [33], [34].

3. MOTIVATION OF THE PROPOSED RESEARCH

Numerous segmentation algorithms are used on the ultrasonic fetal images to extract the biometric parameters for estimating gestation age. The boundary of the segmented portions remains simple and accurate. In case of ultrasound images, irregular boundaries and presence of smaller holes results in challengeable limitations. To avoid this, fuzzy logic-based edge detection algorithm is proposed so that detection task can be achieved accurately [35].

Traditional edge detection technique offers stable edge thickness and seems difficult for implementing the threshold parameter. But in fuzzy logic, the thickness of the edges can be varied with variation in output factor and by changing the fuzzy rules. As fuzzy logic system proves to be an important technique to represent human knowledgeable through expressions defined mathematically, parameter optimization has been pretended to be the yet investigated drawbacks. In order to accomplish this, various techniques are available for optimizing fuzzy system.

Also, the fuzzy logic design suffers from selecting input and output membership function and defining specific inference rules. In general, this implementation necessitates different iterative trials but fails to provide an assurance regarding optimal design. The tuned parameter and the detailed rule description also lead to optimization drawbacks and do not provide precise edge information. The reported limitations improve the requirements to integrate fuzzy with optimization method.

The presented article proposes Genetic algorithm as an option for optimizing fuzzy logic system. Genetic algorithm adopts natural evolutionary mechanisms like selection, mutation. This integrated approach provides a prominent solution in solving various limitations. GA optimizes the edges without using threshold value and offer fast convergence rate to produce optimized solution. The hybrid approach minimizes the processing time with increased qualities in which the BPD measure can be predicted significantly to assist the physician in estimating the gestation age automatically and thus plays a significant role in understanding the growth rate of the fetus.

4. PROPOSED METHOD

The proposed technique involves various steps to be followed for estimating the Gestation age from the lower resolution ultrasound fetal images. Initially, the gradient of the gray scale ultrasound images are computed which is provided as input to the fuzzy logic system by defining membership function and specific interference rules. As the edge information is not provided accurately, optimization of fuzzy logic is given prior importance. Fuzzy logic and Genetic Algorithms are thus two important tools for modeling and managing intelligent and automatic control systems, each with their own advantages. The strengths of Fuzzy Logic lie in its non-linearity and explicit knowledge representation while Genetic Algorithms provide a learning capability with global and local searching process.

4.1 Directional Gradient Approach

The edges detected by gradient methods are not accurate as it uses two and four convolution masks. However, it controls the noise and edges in a smaller amount as it operates in simple manner. The accuracy of detecting edges can be further improved by adopting enhanced gradient approach. In this, the input ultrasound fetal images are convolved with six different masks such as horizontal, vertical, positive left diagonal, positive right diagonal, negative left diagonal and Negative right diagonal to determine the image gradients.

The image gradient is the differences existing between two neighbour pixel intensities belonging to specific structures. The convolution operation involved in determining gradients between mask and input images are represented in (1).

$$D(u,v) = m(x,y) \cdot I(u,v) = \sum_{x=-M}^{M} \sum_{y=-M}^{M} m(x,y) I(u-x, v-y) \qquad (1)$$

$D(u,v)$ *image gradients*
$m(x,y)$ *covolution masks*
$I(u,v)$ *input images*
M *convolution coefficients*

The magnitude and the directions of the gradients signify the maximum intensity variations and greatest increase in intensity values respectively. The maximum directions computed at every pixel point are noted along with the convolution results. The obtained gradients from the ultrasound images in six different directions are used as input to the generalized type-2 fuzzy inference system.

4.2 Fuzzy Logic System

A generalized type-2 fuzzy set (T2 FS) specified symbolically as $\hat{F}$ characterizes the type-2 membership function $\mu_{\hat{F}}(y,v)$ in which $y \in Y, v \in M_y \subseteq [0,1]$ and $0 \leq \mu_{\hat{F}}(y,v) \leq 1$ where M_y illustrate the primary membership of y in $\hat{F}$ and fuzzy set is interpreted as (2).

$$\hat{F} = \{((y,v), \mu_{\hat{F}}(y,v)) | \forall y \in Y, \forall v \in M_y \subseteq [0,1]\} \qquad (2)$$

A. Fuzzification

It defines the process of mapping crisp values to generalized type-2 fuzzy sets in logic circuits. Here singleton fuzzifier is preferred because of its faster computations making it appropriate for fuzzy logic to enable real time computations. In Singleton fuzzification, the crisp inputs are mapped to a fuzzy set possessing single nonzero membership function. In this case, the membership function of crisp input y_q' is given as (3).

$$\mu_{\tilde{F}_q}(y_q') = \begin{cases} 1 & y_q = y_q' \\ 0 & y_q \neq y_q' \end{cases} \qquad (3)$$

$q = 1,2, \dots \dots \dots \dots Q,$ where Q indicates the number of fuzzy inputs. Each gradient value of ultrasound fetal images is considered as fuzzy system input. The input and output linguistic variables in fuzzy logic are defined below.

B. Input and Output Linguistic Variables

The input image gradient D computed from ultrasound fetal images with respect to different masks are specified where each comprises three different membership functions possessing undefined mean values. The input linguistic variables are: low, medium, high. For the purpose of adapting membership functions with gray scale ranges maximum, minimum and middle gradient values are used so that the mean value of such function can be estimated. Using the range of values, the membership functions are constructed for every D input. Every gradient input provides different membership function based on its appropriate value ranges in order to provide varying outputs. Fuzzy interference comprises only one output (i.e) edge. The utilized linguistic variable at the output are edge and no_edge, ranging in the values between 0 and 1. 0 represent the minimum no_edge values whereas 1 dictates the maximum edge values.

C. Fuzzy Rule Specification

After defining the input and output linguistic variables with correspondent membership functions, it is needed to perform the inference process including rule description. Standard Mamdani type structural rules are used in which the antecedents and consequents represents the generalized type-2 fuzzy sets. To model the process using fuzzy logic, rules must be considered for describing the relation existing among the gradients. Figure 1 shows the specification of fuzzy rules used for edge detection. In this D1-D6 specifies the input gradient variables and S denotes the output variables. Fuzzy rules are described depending on the knowledge of experienced researchers in controllable strategies. Further, it also specifies membership degree to the input parameter to produce stabilized adjusted output by performing logical operations with respect to the input. De-fuzzification transforms the inferred fuzzy output to necessitate crisp values. De-fuzzification converts them to the numeric output value. Various de-fuzzification techniques are available among which the centroid de-fuzzification (COD) method is adopted in the presented proposed technique. In this, Fuzzy system fails to provide precise edge information mathematically to determine GA. Thereby optimization and suitable other techniques are followed to analyze the ultrasound fetal images.

If (D1 is HIGH) and (D2 is HIGH) and (D3 is HIGH) and (D4 is HIGH) and (D5 is HIGH) and (D6 is HIGH) then (S is EDGE)
If (D1 is HIGH) and (D2 is MEDIUM) and (D3 is MEDIUM) and (D4 is MEDIUM) and (D5 is MEDIUM) and (D6 is MEDIUM) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is HIGH) and (D3 is MEDIUM) and (D4 is MEDIUM) and (D5 is MEDIUM) and (D6 is MEDIUM) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is HIGH) and (D4 is MEDIUM) and (D5 is MEDIUM) and (D6 is MEDIUM) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is MEDIUM) and (D4 is HIGH) and (D5 is MEDIUM) and (D6 is MEDIUM) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is MEDIUM) and (D4 is MEDIUM) and (D5 is HIGH) and (D6 is MEDIUM) then (S is EDGE)
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If (D1 is HIGH) and (D2 is HIGH) and (D3 is HIGH) and (D4 is HIGH) and (D5 is HIGH) and (D6 is MEDIUM) then (S is EDGE)
If (D1 is HIGH) and (D2 is LOW and (D3 is LOW) and (D4 is LOW) and (D5 is LOW) and (D6 is LOW) then (S is EDGE)
If (D1 is HIGH) and (D2 is HIGH) and (D3 is LOW) and (D4 is LOW) and (D5 is LOW) and (D6 is LOW) then (S is EDGE)
If (D1 is HIGH) and (D2 is HIGH) and (D3 is HIGH) and (D4 is LOW) and (D5 is LOW) and (D6 is LOW) then (S is EDGE)
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If (D1 is HIGH) and (D2 is HIGH) and (D3 is HIGH) and (D4 is HIGH) and (D5 is HIGH) and (D6 is LOW) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is MEDIUM) and (D4 is MEDIUM) and (D5 is MEDIUM) and (D6 is MEDIUM) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is HIGH) and (D3 is HIGH) and (D4 is HIGH) and (D5 is HIGH) and (D6 is HIGH) then (S is EDGE)
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If (D1 is MEDIUM) and (D2 is LOW) and (D3 is LOW) and (D4 is LOW) and (D5 is LOW) and (D6 is LOW) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is LOW) and (D4 is LOW) and (D5 is LOW) and (D6 is LOW) then (S is EDGE)
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If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is MEDIUM) and (D4 is MEDIUM) and (D5 is LOW) and (D6 is LOW) then (S is EDGE)
If (D1 is MEDIUM) and (D2 is MEDIUM) and (D3 is MEDIUM) and (D4 is MEDIUM) and (D5 is MEDIUM) and (D6 is LOW) then (S is EDGE)
If (D1 is LOW) and (D2 is LOW) and (D3 is LOW) and (D4 is LOW) and (D5 is LOW) and (D6 is LOW) then (S is NO_EDGE)

Figure 1: Fuzzy rules specification for detecting edges of ultrasound fetal images

Then the image gradients are further determined for the edges detected using fuzzy techniques for the purpose of highlighting the region with higher spatial derivatives. The region possessing such maximum values are tracked at the output while suppressing the edges with minimum values. This technique is referred as the non-maximum suppression and is considered as one of the class of canny edge detection algorithm. Non suppressed gradient arrays of an image are then reduced through adopting Hysteresis, where two thresholds are used. Edges with magnitude values greater than that of high threshold is produced at the output whereas the remaining edges lying between the two threshold or existing at magnitude values below than that of lower threshold region is signified as zero producing non-edge characteristics. A key consideration in hysteresis technique is that when the

magnitude of gradients lies between the two upper and lower thresholds then in such cases it produces zero output till there exists a path between the pixels of this correspondent region to the gradient pixel located in the region above high threshold.
In spite of its various advantages in threshold fuzzy logic, it suffers from selecting highly valuable relevant membership function. To achieve this, it necessitates complex iterative trials as well as error process but fails to produce optimal solution. Optimization of fuzzy logic results in producing better solution with detailed edge information making it suitable for analyzing fetal ultrasonic images.

4.3 Genetic Algorithm Operators

Genetic algorithms are recognized as an optimization tools enabled suitably to perform direct combinatorial searches. Its main aim is to compute the best solution for a given decision variables effectively which results in minimized objective function. The selected decision variables lie within a constrained value of permissible domain. Genetic algorithm follows various iterations for locating the better decision variables in the search space. Search space defines the set which possibly assigns the entire combination of objective functions.

The utilization of random approach reduces the computational cost with better convergence rate. Its main structural concept involves the initialization of population set, evaluating fitness by means of objective function, performing genetic operator and terminate the criteria while the conditions are met. Genetic operator defines selection, crossover and mutation process and they provide bias to the optimized solution. The procedures involved in optimizing edges using genetic operator are as follows:
Step 1: Initial random population: The edge population is generated randomly with high and low threshold combination possessing maximum and minimum gradients values. Sequenced N individual edges with equal probabilities are selected in random manner from the blurred fuzzy output edges.
Step 2: Fitness value calculation: The external information is not required for GA rather it necessitates fitness values of individual pixels. The fitness values of every gradient pixel are computed as in (4).

$$F = \sum_{(u,v)} \frac{x_{uv}(|\nabla D|)}{u_{uv}(|\nabla D'|)} \qquad (4)$$

x_{uv} dictates the unit vectors and $|\nabla D|$ represents the gradient vector evaluated from the edges obtained at the fuzzy output. Higher probabilities exist for edges with smaller fitness values and is said to be the stronger edges whereas the other is considered as the weaker ones. Stronger edges are selected and further preceded to the next operator.

Step 3: Crossover: Generates operator masks and then smaller regions present in the input strong edge images are swapped based on the masks to offer detailed edges precisely with respect to the normalized crossover rate. This produces better optimized edges at the output when it is significantly found to be greater than the magnitude gradient values. Repeat steps 3 & 4 till it produces optimal solution and the process gets terminated while meeting the satisfactory conditions regarding the pixel values.

4.4 Morphological Reconstruction

Image reconstruction is the process involved in transforming the morphological characteristics of an image using the masks image. Initially masks images are created by defining structural connectivity and then input marker images can be reconstructed with respect to the defined characteristic of masks. Small object removal is one such application that removes the connected objects with pixels smaller than the specified values. Another process involved in eradicating objects that touches the border plays a significant task in reconstruction. One such technique is border clearing algorithm which clears the objects touching the border points. In this, the input image $I(u,v)$ is considered as a mask whereas the marker image is specified as given in (5).

$$M(u,v) = \begin{cases} I(u,v) & \text{if } (u,v) \text{ is on the border of } I \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

The optimal edges are skeletonized before initiating the fitting process and are done mainly to minimize the data points. Further, the generated optimized edges of fetal images are interconnected by combining the extreme points which provides an easier means to determine the gestation age. The approach which is utilized for such connection is convex hull technique. After that least square fitting process is adopted so that an elliptical curve utilized for evaluating the BPD measure of fetal images is obtained which in turn determines the Gestation age.

4.5 Least square fitting algorithm

It is a stabilized numeric non-iterative approach that fits elliptical curve along a data point groups. Its main aim is to reduce the algebraic sum of squared distance among data point and to obtain ellipsoidal curve depending on the specified constraints. Equation (6) describes the elliptical curve and is defined as one of the important cases of conic equation.

$$E(u,v) = au^2 + buv + cv^2 + du + ev + f \qquad (6)$$

In which a, b, c, d, e and f signifies the constant parameter and u, v represents the point coordinates of ellipse. Accurate fitting process can be achieved by reducing the algebraic sum of squared distances between points for a specific ellipse and is dictated with respect to ∂ coefficients given in (7).

$$\min_{\partial}\sum_{i=1}^{M} E(u_i,v_i)^2 = \min_{\partial}\sum_{i=1}^{M} (E_{\partial}(U_i))^2 = \min_{\partial}\sum_{i=1}^{M} (U_i \cdot \partial)^2 \qquad (7)$$

where M indicates the number of data points, $U = [u^2, uv, v^2, u, v, 1]$ and $\partial = [a, b, c, d, e, f]^T$ defines the vector components of ellipsoid. The secondary axes or minor axes length of the elliptical curve represents the BPD measure

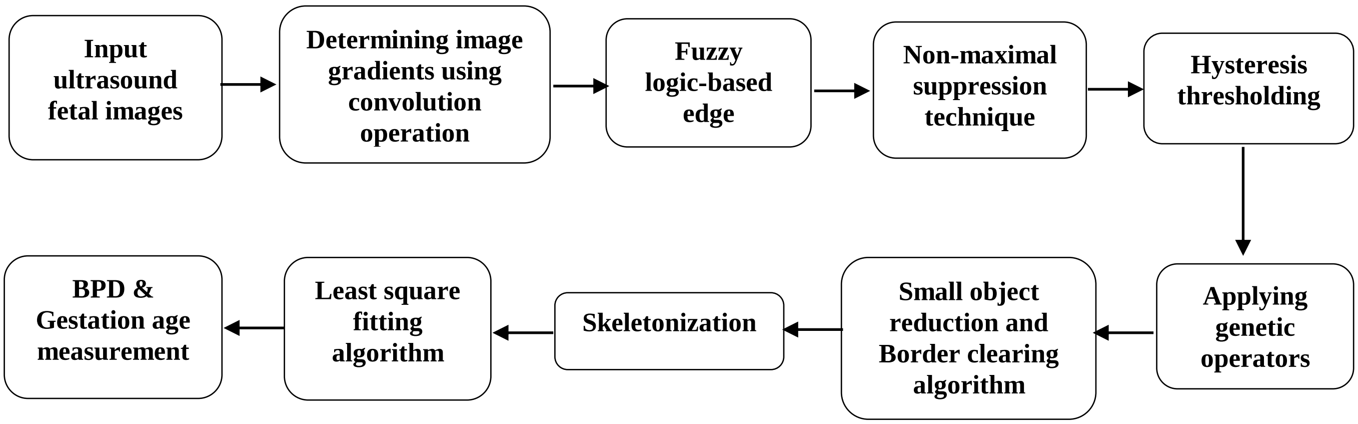

Figure 2: Schematic flow of proposed method to determine gestation age-Step by step procedure

which determines the gestation age of fetal images using a standard formula. Figure 2 presents the overall schematic diagram of the proposed method to measure gestation age of ultrasound images.

5. RESULTS AND DISCUSSSION

The proposed methodological procedures are implemented in different fetal ultrasound images for estimating the gestation age. After determining gestation age, it is compared with the manually evaluated values in order to verify the effectiveness of the observed results. Utilizing the appropriate masks in six directions, the image gradient values are computed by convolving the input images with the masks (i.e) convolution operation. The convolutional masks are suitably found to be small when compared to the original input images. With respect to this, the masks are allowed to get slid across images to manipulate squared pixel in an estimated time interval. For larger Gaussian mask width, the computation of gradient values shows smaller noise sensitivities. Figure 3 show the input fetal images used for evaluating gestation age and are collected from DOI 10.5281/zenodo.1322001.

Then the evaluated gradient value in six different directions is provided as input to the fuzzy logic for detecting edges. Tuning every fuzzy rule result in producing better results and at the same time extracts image edges. Figure 4 presents the images obtained after applying fuzzy logic edge detection technique. The white pixels dictate the preserved edges at the output of fuzzy system. The applied fuzzy rules extract the edge information in precise systematic approach. To estimate gestation age from fetal images, thin edges are required to be preserved excluding neighborhood details. Fuzzy interference system detects the edges that present at the lower contrasted region and this occurs mainly because of the varied results provided by different fuzzy rules. But the edges produced by fuzzy logic seem to be blurred. To provide precise edge characteristics, non-maximal suppression technique is adopted further.

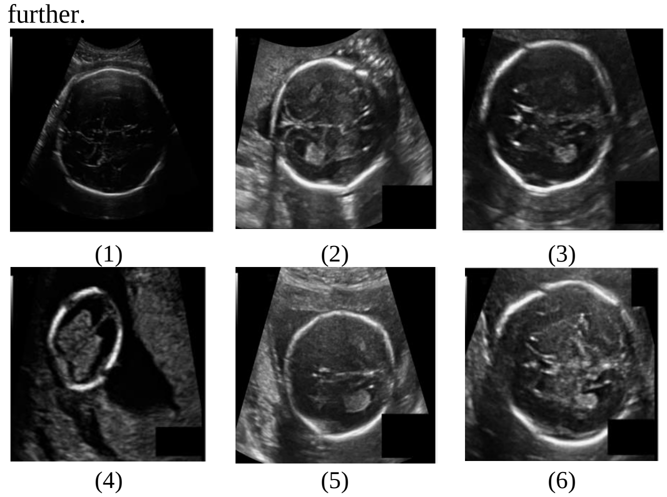

Figure 3: Input Ultrasound fetal images

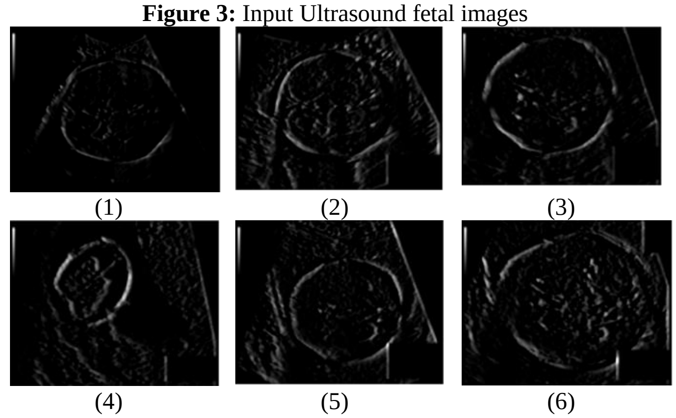

Figure 4: Fuzzy logic-based edge detection of fetal images

Figure 5 dictates the images with applied non-maximum suppression for positioning the edge information effectively. Such technique reveals that the width of every edges is one-pixel. Different directions correspondent to mask are used for evaluating the gradient magnitude and when the magnitude values seems to be high than that of the interpolated results, then it is signified as candidate points whereas in other cases it is represented as non-edge points. After that hysteresis thresholding method is applied for transforming the ultrasound images to binary images.

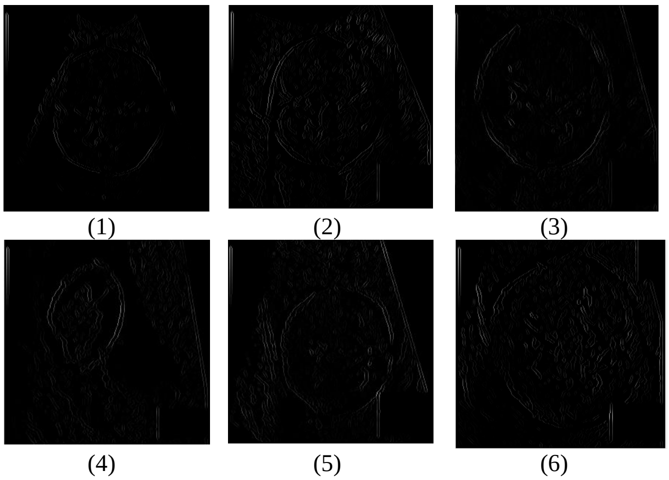

Figure 5: Non maximum suppression of fuzzy edges

Hysteresis thresholding method utilizes two thresholds for selecting the edge points. The calculated values of gradient are higher than that of high threshold then it is considered as an edge whereas if the magnitude values seem to be smaller than lower threshold, then under such case it is signified as a non-edge point. The edges which are lying between the two thresholds is said to be the candidate points and it becomes edge points when connected with higher gradient values. Figure 6 presents the different images obtained after hysteresis thresholding method. The threshold fuzzy logic does not provide optimized edges for estimating gestation age. Therefore, to produce optimal solution, Genetic algorithm-based optimization approach is selected as it optimizes input and output variables effectively, and also processing of the variables is performed at similar time.

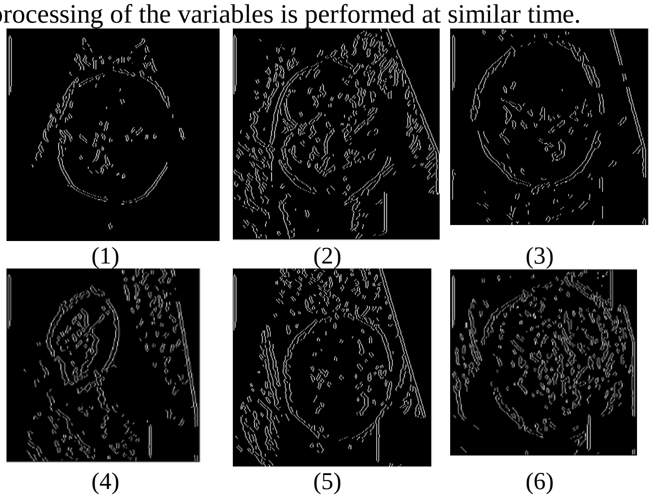

Figure 6: Image Hysteresis thresholding that suppresses lighter edge regions

The genetic operator initially selects a starting point randomly from the fuzzy edges and it comprises both higher and lower threshold edge points. Then the fitness function is computed for every pixel and it dictates the contribution of edges in producing better solution. While considering genetic algorithm, fitness function recognizes the number of smaller region pixel that are perfecting located. Strong edges produce smaller fitness values but the weaker ones possess larger fitness values. This makes it easier to preserve strong edges at the output with removal of the weak or light edges. Operator masks are created with respect to the gradient values of the pixels and smaller region of the preserved edges are further swapped so that the edge information with optimized better solution is produced at the output. Such optimized output of the threshold fuzzy logic is presented in Figure 7.

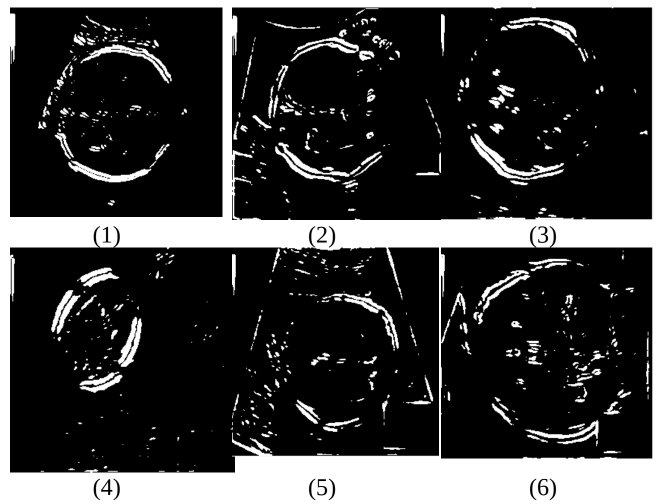

Figure 7: Optimized fuzzy logic using genetic operator

The next step is performing morphological reconstruction which involves small objects removal and border clearing as shown in Figure 8. Small Objects Deleting process, avoids the presence of undesirable small elements in the binary image (all elements will be deleted when its area is less than 100 pixels) and border clearing of input image uses image as a mask, and setting connectivity equal to 26-connected neighborhood. The image border clearing step suppresses structures that are lighter than their surroundings and that are connected to the image border. Border cleared images are shown in Figure 9. Before applying the Least Square Fitting algorithm, we reduce data points amount through morphological Skeletonization process as shown in Figure 10. The application of LSF algorithm yields a single ellipse, where the resulting data points from the Fitting step are located on the edge of output ellipse, so it returns the parameters of this ellipse, including the measurement of secondary axis, which corresponds to BPD measure. The resulted measure is converted to millimeter in order to compute the information about Gestation Age.

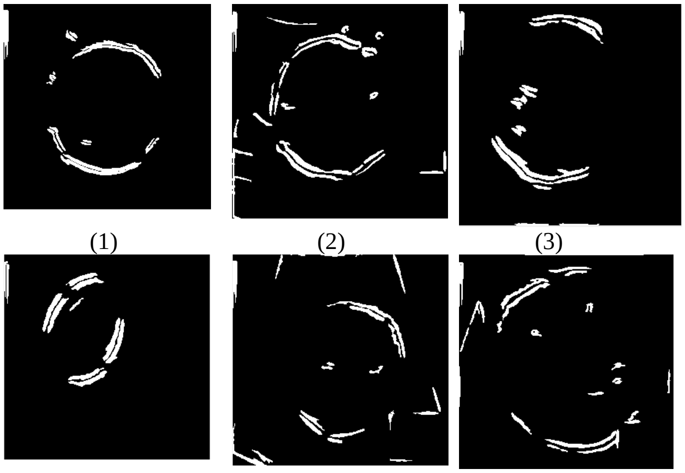

Figure 8: Small object removal of optimized images

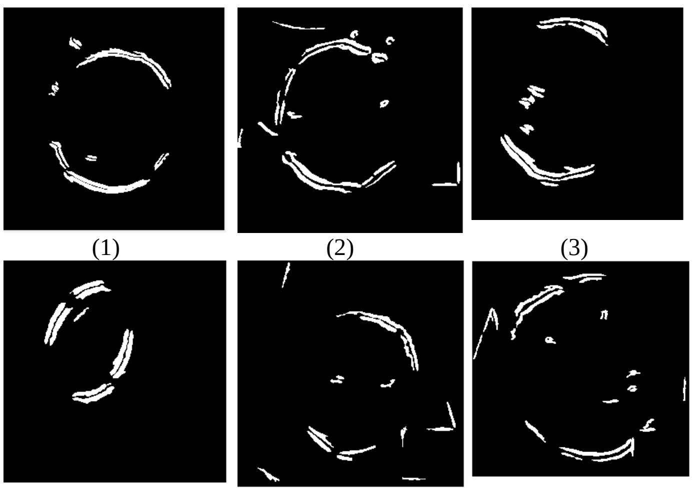

Figure 9: Border clearing algorithm-output

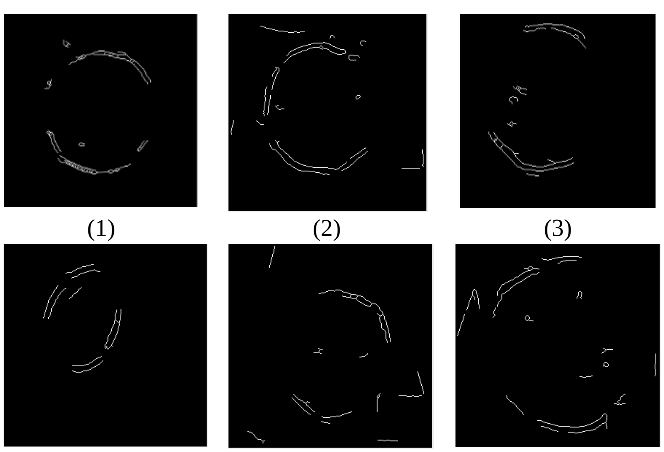

Figure 10: Skeletonization results of optimized fetal images

The present research is conducted mainly to measure the BPD from fetal ultrasound images taken at different weeks of same parents. The BPD is computed from the elliptical curve with respect to its minor axes length. The gestation age is evaluated for each image using BPD measure based on traditional standard regression formula. The proposed algorithm is implemented on 100 fetal images and the calculated gestation age for different images by comparing with filtered LSF traditional technique and the specialist manual measure analyzed using ultrasound device is presented in Figure 11. The comparison is made in order to show the effectiveness of the proposed method. [16] The procedures involved in traditional method involves the filtering of images using Weiner filter, image bordering to strengthen the gray scale images, then adopting skeletonization approach and finally follows the LSF to detect an elliptical curve with respect to the image distribution. The implementation procedures seem similar to that of the proposed method but with a difference in adopting fuzzy logic and genetic algorithm. Similarly, the PSNR value of the images obtained using proposed fuzzy approach is also compared with filtered LSF and is shown in Figure 12. From this, it is observed that the gestation age of the proposed method produces an approximate closer values equivalent to specialist doctor measure when compared to the other method. The accuracy of the proposed method tends to be higher than that of the traditional approach.

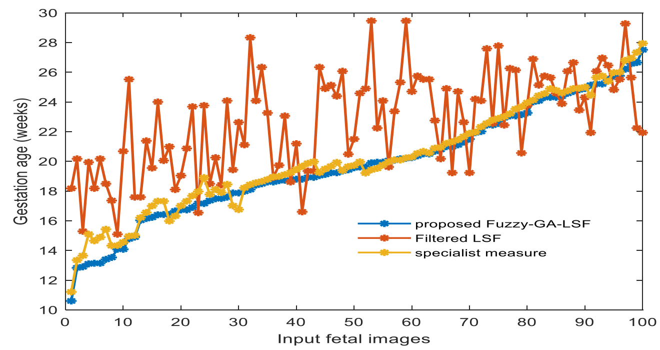

Figure 11: Gestation age comparison of different fetal images

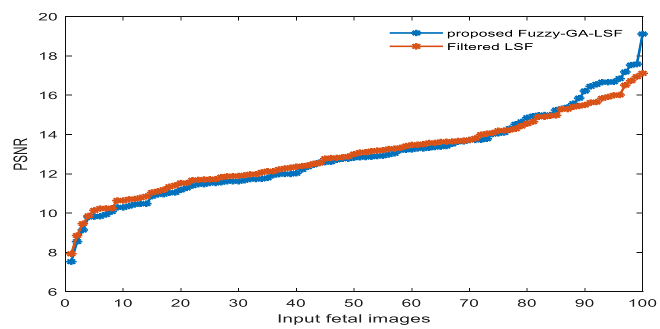

Figure 12: PSNR of different fetal images

The performance of the proposed technique is also validated by using different classifiers by illustrating the manual values with the observed output of the proposed and traditional technique. These methods are compared by means of accuracy parameters and confusion matrix. True positives (TP) and true negatives (TN) represents the total no of samples that are perfectly classified particularly in positive and negative class respectively. Table 1 presents the comparison of proposed fuzzy technique with the traditional and manual measures by means of different accuracy parameters. Recall also known as

Table 1: Comparison of difference technique using accuracy parameters

	True positive rate	**False positive rate**	**Precision**	**Recall**	**F-measure**	**MCC**	**ROC Area**	**PRC Area**	**Classifier**
Specialist measure (Peter W Callen)	0.920	0.120	0.793	0. 920	0. 852	0. 774	0. 949	0. 856	Bayes Bayes
	0. 910	0. 100	0.820	0.910	0.863	0.791	0.969	0.933	Naive Bayes
	0. 560	0.375	0. 427	0.560	0. 485	0.176	0. 628	0. 446	N.B.MultinomialText
	0.910	0.100	0.820	0.910	0.863	0.791	0.969	0.933	N.B.Updateable
Filtered LSF traditional technique	0.130	0.040	0.619	0.130	0.215	0.166	0.691	0.507	Bayes Bayes
	0.470	0.200	0.540	0.470	0.503	0.280	0.730	0.534	Naive Bayes
	0.090	0.110	0.290	0.090	0.137	0.031	0.492	0.336	N.B.MultinomialText
	0.470	0.200	0.540	0.470	0.503	0.280	0.730	0.534	N.B.Updateable
Proposed fuzzy-GA-LSF technique	0. 930	0. 350	0. 571	0. 930	0. 707	0. 549	0. 792	0. 558	Bayes Bayes
	0.650	0.185	0.637	0.650	0.644	0.463	0.830	0.663	Naive Bayes
	0. 520	0. 430	0.377	0. 520	0.437	0.085	0. 586	0. 418	N.B.MultinomialText
	0.650	0.185	0.637	0.650	0.644	0.463	0.830	0.663	N.B.Updateable
Weighted Average	0. 677	0. 162	0. 666	0. 677	0. 670	0. 511	0. 843	0. 710	Bayes Bayes
	0.871	0.130	0.872	0.871	0.871	0.743	0.959	0.960	Naive Bayes
	0.390	0.305	0.365	0.390	0.353	0.077	0.569	0.400	N.B.MultinomialText
	0.677	0.162	0.666	0.677	0.670	0.511	0.843	0.710	N.B.Updateable

Where N.B denotes the Naïve Bayes

Table 2: Parametric result of different classifiers

Classifier	**‘‘Correctly Classified Instances”**	**‘‘Incorrectly Classified Instances”**	**‘‘Kappa statistic”**	**‘‘Mean absolute error”**	**‘‘Root mean squared error”**	**‘‘Relative absolute error”**	**‘‘Root relative squared error”**
Bayes Bayes	198(66%)	102 (34%)	0.49	0.2685	0.3677	60.4095%	78.0077 %
Naive Bayes	203(67.6667 %)	97(32.3333 %)	0.515	0.2691	0.3706	60.5466 %	78.6166 %
N.B.Multinomial Text	117(39%)	183(61%)	0.085	0.4112	0.5174	92.5194 %	109.7656 %
N.B.Updateable	203(67.6667 %)	97(32.3333%)	0.515	0.2691	0.3706	60.5466 %%	78.6166 %

sensitivity indicates the no of positive samples that are identified perfectly by the classifier. Precision represents the proportion of the positive samples which are relatively predicted perfectly. Another parameter referred as F-measure defines the harmonic mean output of recall and precision and provides a stabilized balance among both these parameter in which the classifier performance is reflected. The accuracy enabled by the proposed method is dictated by the parameter signified as ROC Area. The values of the accuracy parameters are significantly greater than the traditional technique and also produce approximate closer measures to the manual ones.

The parametric results of different classifiers based on the proposed fuzzy technique with that of the filtered LSF traditional approach and specialist measure is illustrated in Table 2. Root mean squared error obtained using Naive Bayes and N.B.Updateable classifier seems to be higher with identical values which shows an enhancement in correctly proportioned images. Table 3 shows the comparison of methods by means of confusion matrix.

Table 3: Confusion Matrix for three methods by four classification technique

Bayes Bayes			Naïve Bayes			N.B.Multinomial			N.B.Updateable			
						Text						
a	b	c	a	b	c	a	b	c	a	b	c	
92	7	1	91	9	0	56	9	35	91	9	0	a
18	13	69	16	47	37	40	9	51	16	47	37	b
6	1	93	4	31	65	35	13	52	4	31	65	c

The effective performance of the proposed method in estimating the gestation age is validated using different classifiers. The comparison of automatic resultant measure with the manually evaluated values ensures the effective performance of the proposed technique. Closer equivalent values of the proposed methods with the manual values present a replicable application in research’s and medicine. Smaller minor variations between the two are relatively acceptable since the similar physician can obtain two different measured values for the similar ultrasound images.

6. CONCLUSION

This paper presents optimized fuzzy logic-based edge detection algorithm for automatic measurement of gestation age depending on the BPD value of ultrasound fetal images. BPD represents the minor axes length of elliptical curve obtained through least square fitting algorithm. Optimization of fuzzy logic is done by Genetic algorithm so that the edges can be detected accurately in which the false edges are discarded. Further the observed values are compared with the Filtered skeletonized LSF technique and in order to present its effectiveness different classifiers are used in which its performance is validated based on its measured values of accuracy parameters and confusion matrix. This automatically evaluated measurement provides significantly closer to the manual ones that one of the other LSF technique. Manual values are obtained by sonographers using the ultrasound devices in which the calculated measure of different factor is displayed on the screen. This method proves its ability to present the information accurately by supporting the physician to determine gestation age. Further this can also be enhanced or deeply understood for application in various fields to analyze digital images. More biometric parameter as well as the fetal weight can also be estimated by making suitable modifications in the proposed method.

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