Chapter 12
Feature Selection in Fetal Biometrics for Abnormality Detection in Ultrasound Images

R. Ramya, K. Srinivasan, B. Sharmila and K. Priya Dharshini

Abstract Feature selection is a processing step that gives a subset of features required for analyzing an image. The process flow of medical image processing includes pre-processing, image segmentation, feature extraction and feature selection. Medical imaging has been developed predominantly nowadays. It assists the physicians to diagnose the diseases through various medical modalities. Fetal defects are the most common congenital abnormality found at birth. Fetal features are selected and extracted to determine fetal biometrics such as Amniotic Fluid Volume, Bi-parietal Diameter, Head Circumference, Abdominal Circumference, Femur Length and Gestational Age. IntraUterine Growth Restriction remains a challenging problem for both the obstetrician and the pediatrician. The vital role of this approach is to detect abnormalities non-invasively and reduce the risk factors in early stages of pregnancy.

Keywords IntraUterine growth restriction · Fetal parameters · Feature selection Ultrasound image

12.1 Introduction

The feature selection technique is an emerging research topic used in machine learning. This helps to remove the unwanted features in the images and also in enhancing the quality of the system. The feature selection is that the information

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contains numerous highlights that are either excess or inconsequential, would thus be able to be evacuated without bringing about much loss of data. Obstetric Ultrasonography is a non-invasive tool used to analyze the growth of the fetus across gestation. Development of a fetus in its growth is an important factor of prenatal medical care. Analysis of fetal development on ultrasound images is widely performed compared to other modalities such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI).

The common purpose of the ultrasound investigation is to determine the position of the fetus and the placenta, the number of fetuses, Estimated Fetal Weight (EFW), Amniotic Fluid Volume (AFV) Gestational Age (GA) and to detect abnormalities present in fetus. In [1] Support Vector Machine (SVM) is used to detect the outcome of IntraUterine Growth Restriction.

Wang et al. [2] proposed phase based feature selection process exploiting the boundaries of fetal head for the measurement of Bi-Parietal Diameter and Head Circumference. In [3] Haar-like feature is used to extract features from fetal head for the application of Adaboost classifier and the Bi-Parietal Diameter is measured. Yaqub et al. [4] describes Random forest classification framework for segmenting femur and the classification is improved based on selecting strong features. The modified new method gives notable improvement compared to traditional Random Forest. Rahmatullah et al. [5] proposed an automatic method for selecting standard plane for the measurement of fetal biometrics from fetal ultrasound volume. The features are derived from Haar wavelets and feature selection is executed during training process by Adaboost algorithm. Results show that the recall rate is 91.29%.

In [6] innumerable techniques are explained for feature extraction, classification and retrieval and Content-Based Image Retrieval (CBIR). Also analyzed that the features are optimized using Particle Swarm Optimization (PSO). Dorigo et al. proposed Ant colony optimization (ACO) method which can be used for system fault detecting, network load balancing, robotics and other optimization problems [7]. The BPD is measured on a horizontal plane that traverses the thalami and cavum septum pellucidum. An automatic method is implemented that measures Bi-Parietal Diameter of fetal head and length of the femur from ultrasound images. Active contour model is used in measuring the fetal parameters [8]. In [9] morphological watershed segmentation is proposed for estimating the fetal femur length and growth patterns (Fig. 12.1).

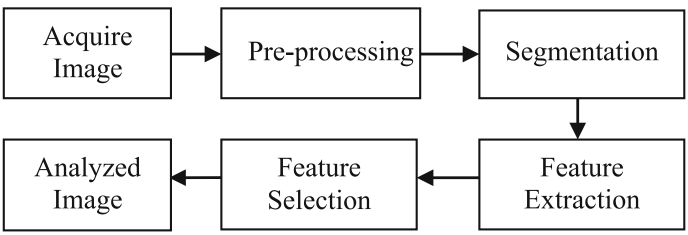

Fig. 12.1 General block diagram of fetal ultrasound images

12.2 Steps Involved in Processing of Fetal Image

The following stages are used for processing a fetal ultrasound image [10].

- Pre-processing
- Segmentation
- Feature Extraction
- Feature selection.

12.2.1 Pre-processing

Image Pre-processing is defined as removing noises from images. The main disadvantage of Obstetric Ultrasonography is poor quality of images due to speckle noise. Speckle is a granular noise that constitutionally exists and degrades the quality of the medical ultrasound images.

Speckle is primarily due to the interference patterns of the returning wave at the transducer aperture. Speckle noise in medical images generally serious, causing difficulties for image interpretation. It is a multiplicative noise that reduces the visual interpretation in fetal ultrasound images. Hence there are many attempts made in researching field to de-noise ultrasound images by developing de-speckling methods. Median filter is widely used to remove speckle noise in fetal ultrasound images.

12.2.2 Segmentation

Segmentation is one of the tedious processes in image processing. Image segmentation is the process that split an image into its constituent parts or segments. The image partitioning process continuous to a level when a particular problem being solved, i.e., the segmentation will end when the objects of interest have been detached in an application. Segmentation algorithms mainly based on discontinuity and similarity. Consequently, the automatic segmentation of anatomical structures in ultrasound imagery is a real challenge due to acoustic interference in these images.

Segmentation in ultrasound images is the process of dividing the structures or organs of fetus such as head, limbs, abdomen, femur, etc. It is carried out by means of many segmentation techniques like thresholding technique, canny segmentation algorithm, etc.

12.2.3 Feature Extraction

Features are quantities which distinctively describe a target such as size, shape, composition, location etc. Quantitative measurement of feature extraction and selection provides comprehensive description of an image. Feature selection and extraction plays a significant role in fetal ultrasound images to evaluate parameters such as Bi-Parietal Diameter, Head Circumference, Abdominal Circumference, Femur Length, Amniotic Fluid Volume and Gestational Age.

12.2.3.1 Estimated Fetal Weight

The fetal weight is an essential component that needs to be estimated for recognition of fetal growth. Fetal weight measurement should be carried out to reduce perinatal morbidity and mortality. IntraUterine Growth Restriction or prematurity is allied with low fetal weight. The fetus will be too small due to uteroplacental insufficiency. Fetal macrosomia refers to a fetus with larger weight and it is due to maternal diabetes. Estimated Fetal Weight is determined using parameters such as Bi-Parietal Diameter, Head Circumference, Abdominal Circumference and Femur Length. Hadlock IV formula can be used to calculate fetal weight.

Bi-Parietal Diameter

The Bi-Parietal Diameter is one of the biometric parameters used to estimate fetal weight. Anisotropic diffusion, otherwise called as Perona–Malik diffusion is a technique used to remove noise in ultrasound images. This technique does not affect the significant parts of the image content mainly edges, lines or other details that are important for the analysis of the image. Anisotropic diffusion is a generalization of diffusion process and it produces a family of parameterized images. Each resulting image is a consolidation between the input image and a filter, based on the local content of the input image. As a result, anisotropic diffusion is a non-linear and space-variant transformation of the input image.

Dilation is one of the two basic operations performed in the sector of mathematical morphology, the other being erosion. It is mostly applied to binary images, but there are versions that work on gray scale images. The basic effect of the dilation operator on a binary image is to gradually expand the boundaries of white pixel regions. Thus enlargement of areas of foreground pixels takes place while holes become smaller within the regions.

The Canny edge detector is an edge detection technique containing algorithm to detect edges in images without loss of information. Canny edge detection is a technique to extract significant structural data for further processing of images from different vision objects. The Blob Analysis technique is used to calculate quantities for labelled regions in a binary image. The blob analysis block provides measurements such as the centroid, bounding box, label matrix and blob count.

Algorithm for Bi-Parietal Diameter Calculation

Step 1: Get fetal head image.
Step 2: Smoothing of image is done by Anisotropic diffusion technique and it is defined as,

$$\partial I \partial t = \nabla c \cdot \nabla I + c(x, y, t\ )\Delta I \tag{12.1}$$

Diffusion coefficient is given by,

$$c(\| \nabla I \|) = e - (\| \nabla I \| \ /K) \tag{12.2}$$

Step 3: Morphological operation (Dilation) is applied to filtered image and it is defined by,

$$A \oplus B = \ \cup b \in BAb \tag{12.3}$$

Step 4: Apply canny edge algorithm to the dilated image.
Step 5: Apply Bounding box by means of blob analysis technique.
Step 6: Bi-parietal diameter is calculated by Euclidean distance formula measuring central axis of fetal head.

Head Circumference

The Head Circumference is evaluated from fetal head image. The circumference of head is calculated by fitting an ellipse model. This method gives quantities such as elliptic equation parameter, angle and major and minor axis of an ellipse. From the parameters, head circumference can be calculated. Li et al. [11] developed a learning based framework for the measurement of Head Circumference. A fast ellipse fitting (ElliFit) method is employed and Random Forest classifier is utilized to detect fetal head.

Algorithm for Head Circumference Calculation

Step 1: Acquire fetal head image.
Step 2: Image pre-processing is done by Median filter.
Step 3: Apply Binary thresholding to the filtered image.
Step 4: Head circumference is calculated by Ellipse fitting process.
Eccentricity is given by,

$$e = \mathrm{sqrt}\left(1 - \left(\left(b^2\right)/\left(a^2\right)\right)\right) \tag{12.4}$$

Circumference of ellipse is given by,

$$h = \left((a - b)^2/(a + b)^2\right) \tag{12.5}$$

$$\mathrm{cir} = \left(\mathrm{pi} * (\mathrm{a}+\mathrm{b}) * \left(1 + \left(3 * \frac{\mathrm{h}}{10 + (4 - 3 * \mathrm{h})^{0.5}}\right)\right)\right) \tag{12.6}$$

Abdominal Circumference

Abdominal Circumference is measured from fetal abdomen image. Circle Hough Transform algorithm is used to measure the circumference of abdomen. Circle Hough Transform (CHT) is a feature extraction technique for detecting circles. It is a specialization of Hough Transform. The aim of this technique is to find circles in imperfect input images. The circle parameters are produced in the Hough parameter space and then the local maxima called accumulator matrix is selected. By measuring the centre of the abdomen, concentric circles are made and the circle appropriate to the outer surface of abdomen is selected. The circumference of the circle gives the measurement of abdomen.

Algorithm for Abdominal Circumference Calculation

Step 1: Acquire fetal abdomen image.
Step 2: Image pre-processing is done by Median filter.
Step 3: Morphological operation (Dilation) is applied to filtered image.
Step 4: Canny edge detection algorithm is applied to the dilated image.
Step 5: After edge detection, Circle Hough transform algorithm is used to measure abdominal circumference of fetus.
In a two-dimensional space, a circle can be described by,

$$(\mathrm{x}-\mathrm{a})^2 + (\mathrm{y}-\mathrm{b})^2 = \mathrm{r}^2 \tag{12.7}$$

Coordinates of centre of a circle and radius is determined using Circle Hough peaks.

Femur Length

Femur is the thigh bone of a fetus. The measurement of length of the femur plays an important role in evaluating fetal growth. The femur length can be measured by means of clustering process namely, K-means clustering technique. The K-means algorithm is an iterative technique that is used to partition an image into K clusters. In [12] entropy based segmentation approach is proposed to segment femur for the evaluation of femur length. Based on the density and height-width ratio of the femur, slim and long object selection is designed.

Algorithm for Femur Length Calculation

Step 1: Acquire fetal femur image.
Step 2: Image pre-processing is done by Median filter.
Step 3: Morphological operation (Dilation) is applied to filtered image.
Step 4: Adaptive K means clustering algorithm is applied to the dilated image.
Step 5: Apply Bounding box by means of blob analysis technique.

Step 6: Femur length is calculated by measuring the maximum length of the clusters.

The gender is detected depending on the white intensity values of the processed image and fetal weight is estimated [13]. Cheng et al. [14] estimated the fetal weight using Artificial Neural Network model and accuracy is increased compared to other methods. The Fetal Ultrasonographic parameters are determined and fetal size is classified by K-means algorithm. The BPD is helpful for dating a pregnancy and in estimating intrauterine fetal weight in weight Eqs. (12.1, 12.2, 12.3), other than that its esteem is constrained and can at times be deluding in the assessment of growth in the fetus. Head circumference value is calculated by ellipse fitting algorithm Eq. (12.6). Sharma et al. [15] formulated a method that shows the results of ultrasound and clinical methods. By Dare's Formula, clinical estimation results in low average absolute error for fetal birth weight below 3500 grams and by Johnson's Formula, it gives the least average absolute error for birth weight above 3500 grams. Fetal weight using six formulae (Shepard, Campbell, Hadlock I, II, III, and IV) is estimated [16, 17]. Hadlock IV formula gives the best positive correlation results between actual birth weight and estimated fetal weight. The commonly used formulae to estimate fetal weight are Shepard, Campbell, Hadlock I, II, III and IV. The formula of Hadlock IV had the highest positive correlation with Actual birth weight among six formulae. Hadlock IV formula to manipulate estimated fetal weight is given by,

$$\begin{aligned} \mathrm{Log10}\,(\mathrm{weight}) = {} & 1.3596 - 0.00386 * \mathrm{AC} * \mathrm{FL} + 0.0064 * \mathrm{HC} \\ & + 0.00061 * \mathrm{BPD} * \mathrm{AC} + 0.0424 * \mathrm{AC} + 0.174 * \mathrm{FL} \end{aligned} \tag{12.8}$$

12.2.3.2 Amniotic Fluid Volume

Amniotic fluid is a liquid constituting nutrients, water and biochemical products that surrounds the fetus in a uterus sac. The amniotic fluid is used to control infection, temperature, develop lung and digestive system and support umbilical cord. A low amniotic fluid volume is one of the factors that indicate the presence of IUGR problem. So measurement of Amniotic Fluid Volume becomes an essential part of fetal ultrasound evaluating fetal well-being. Perinatal death and several perinatal outcomes such as abnormal birth weight, premature rupture of membranes, fetal abnormalities and increased risk of obstetric interventions are allied with abnormal AFV. Fetal Weight is associated with Amniotic Fluid Volume during the first half of gestational period. At first, the ratio of amniotic fluid volume to fetal weight increases till 30 weeks of gestation and then appears to drop. The Amniotic Fluid Volume of a fetus is measured from the evaluation of Amniotic

Fluid Index (AFI) and it is one of the components of biophysical profile. When the amniotic fluid index estimation is less than 5 cm, then presence of anomaly is certain. The largest vertical pocket in each of the four quadrants depleted of fetal parts and umbilical cord of a uterus is detected. The sum of all amniotic fluid indices in four quadrants gives Amniotic Fluid Volume. Normal scale of Amniotic Fluid Index values range from 8 to 25 cm. Rashid [18] proposed Single Deepest Pocket (SDP) to determine AFV. SDP is the largest vertical measurement of amniotic fluid which is free from umbilical cord and other fetal parts.

Algorithm for Estimation of Amniotic Fluid Volume

Step 1: Acquire four quadrant images of amniotic fluid.

Step 2: The input image is subjected to morphological operation (Opening). Opening is the dilation of the erosion of a set A by a structuring element B,

$$A \circ B = (A \ominus B) \oplus B \tag{12.9}$$

where,
$\ominus$ and $\oplus$ denote erosion and dilation.

Step 3: Apply binary thresholding to the image.

Step 4: The maximum vertical pocket is segmented by means of black and white boundary feature.

Step 5: Amniotic fluid index is measured for each of 4 quadrants. Total amniotic volume is given by summation of all index value for 4 quadrants.

12.2.3.3 Gestational Age

Gestational age is the common term used to detect the period of pregnancy. It is measured in weeks. For first trimester, Crown Rump Length is the best predictor of gestational age. For second and third trimester, the fetal parameters such as Bi-parietal Diameter, Head Circumference, Abdominal Circumference and Femur Length are used for the calculation of gestational age.

Steps involved in Measurement of Gestational Age

Step 1: Acquire fetal image.

Step 2: Image pre-processing is done by Median filter.

Step 3: Histogram Equalization is applied to pre-processed image.
The general histogram equalization formula is given by,

$$h(v) = \mathrm{round}((\mathrm{cdf}(v) - \mathrm{cdfmin} - (M \times N) - 1) \times (L - 1)) \tag{12.10}$$

Step 4: The input image is subjected to morphological operation (Opening). Opening is the dilation of the erosion of a set A by a structuring element B.

$$A \circ B = (A \ominus B) \oplus B \tag{12.11}$$

Step 5: The image is subjected to binary thresholding.

Step 6: The boundary of fetus is segmented by means of black and white boundary feature.

Step 7: Gestational age is calculated by,

$$GA = (CRL \times 1.04)0.5 \times 8.05 + 23.7 \tag{12.12}$$

GA for BPD is given by,

$$GA = ((2 * \text{bpd}) + 44.2) \tag{12.13}$$

During routine examinations, the sonographer manually plots minor and major ellipse axes on the ultrasound image and estimates the parameters for automatic detection and measurement of biometric parameters to estimate gestational age. The formula is an approximation that can be used up to 14 weeks of gestational age.

12.2.4 Feature Selection

Image Feature Selection (FS) is a predominant task which affects the performance of image classification and recognition. Feature selection technique increases the classification accuracy by selecting subset of relevant features from the data set. The feature extraction from an image can be accomplished using a numerous image processing techniques. Feature selection aid to minimize the feature space which increases the assessment accuracy and reduces the computation time. This can be attained by removing irrelevant, redundant and noisy features. The feature selection method implemented on three steps which includes screening, ranking and selecting. The screening process removes unwanted predictors having large missing values. Ranking sorts the necessary predictors based on ranks. Selecting process recognize the subset of features by conserving significant predictors [19].

The feature selection techniques for classification process include

- Information Gain
- Relief
- Fisher Score
- Lasso.

Classification is the problem of recognizing to which of a set of group, a new feature belongs based on the training set of data. The images are analysed into a set of features based on a particular model in training phase. The extracted features and label information are utilized by the learning algorithm to learn a classifier. In the testing phase, the classifier will perform on the extracted feature set with the input data and predict the labels.

The classification methods are broadly classified into,

- Linear Classifiers
- Support Vector Machines
- Decision trees and
- Neural Networks (Fig. 12.2).

Features are selected by search algorithms such as Sequential forward Selection, Sequential Backward selection, Genetic Algorithm and Particle Swarm Optimization. For measuring Bi-Parietal Diameter and Head Circumference from fetal head, the outer region of head part should have proper boundaries. This is achieved by phase-based feature selection process. This method is used to detect symmetric (ridge-like) and asymmetric (step edge-like) features. This is achieved by exploiting local phase-based measures computed from a 2D isotropic analytic signal: monogenic signal. Thus the method is used to extract the skeleton of the skull which aids to measure BPD and HC. This can be accomplished with the Multi-Scale Feature Asymmetry (MSFA) and the Multi-Scale Feature Symmetry (MSFS) measure. Good selection of feature will lead to better result of process. For the detection of fetal head in Bi-Parietal diameter measurement, Haar-like feature is used to extract feature from cropping image object and AdaBoost classifier can be used for object detection while Randomized Hough Transform can be applied for biometry measurement [3].

Traditional Random Forest (RF) technique can also be implemented on segmenting femur for the measurement of femur length. The high redundancy of feature selection process is motivated in the traditional RF framework. In the first stage, methods are involved to improve classification by having strong features and

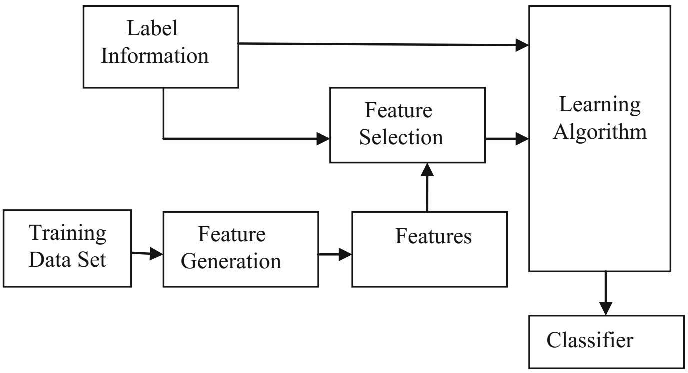

Fig. 12.2 General block diagram of feature selection for classification

neglecting weak ones. Weighting each tree in the forest can be implemented during the testing stage to yield accurate result [4].

Optimization techniques reduce the feature dimensionality by using evolutionary algorithms which includes Genetic Algorithm (GA), Genetic Programming, Evolution Strategy, Evolutionary Programming and Differential Evolution. These algorithms are used for choosing optimal features from the extracted feature set of medical images to diagnose diseases. Genetic algorithm is an optimization technique based on natural selection. It provides solutions to optimization problems depending on operators such as mutation, crossover and selection. GA provides less computational load to classification algorithm. A more important difference between genetic algorithms and other traditional optimization techniques is that population of points at one time is used by GA compared to single point access by traditional optimization methods.

A genetic algorithm needs,

- A genetic depiction of the solution
- A fitness function

Analyse classification process for many diseases with association of GA and SVM techniques for feature selection and classification. Results show that GA-SVM is robust for different medical data set [20]. In prenatal diagnosis application, GA has been used. Fetal macrosomia is one of the complicated fetal features. To differentiate Appropriate Gestational Age (AGA) and Large for Gestational Age (LGA) infants, capillary electrophoresis is used to evaluate amniotic fluid. GA was used for selecting features required for the Bayesian statistics [21]. Fetal weight can also be predicted with the help of GA.

GA is used for reducing the number for features of fetal ultrasound images and these reduced features are further used for classification process that provides better results for abnormality detection.

12.3 Experimental Results and Discussion

The proposed automatic methods were able to measure Amniotic Fluid Volume, Estimated Fetal Weight and Gestational Age. The automatic measurement of fetal biometrics such as Bi-Parietal Diameter, Head Circumference, Abdominal Circumference and Femur Length leads to automatic detection of Estimated Fetal Weight. Automatic detection of Amniotic Fluid Volume shows the fetus suffering with Oligohydramnios or Polyhydramnios. Figure 12.3 shows the processing steps of Amniotic Fluid Volume.

Table 12.1 shows the manual and automatic measurement of Amniotic fluid volume. Presence of abnormality in volume is also shown (Fig. 12.4).

Table 12.2 shows the results of Bi-Parietal Diameter with manual and automatic measurements. Figure 12.5 shows the correlation plot between manual BPD and

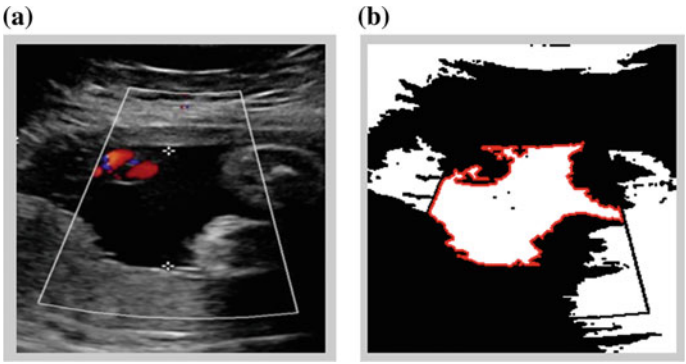

Fig. 12.3 Measurement of amniotic fluid volume **a** input image (I quadrant); **b** boundary segmentation

Table 12.1 Measurement of amniotic fluid volume

Manual measurement (in cm)	Proposed method (in cm)	Status
8.05	8.47	Normal
4.21	4.84	Oligohydramnios
6.75	6.77	Low
24.2	24.7	Polyhydramnios
8.92	8.0	Normal

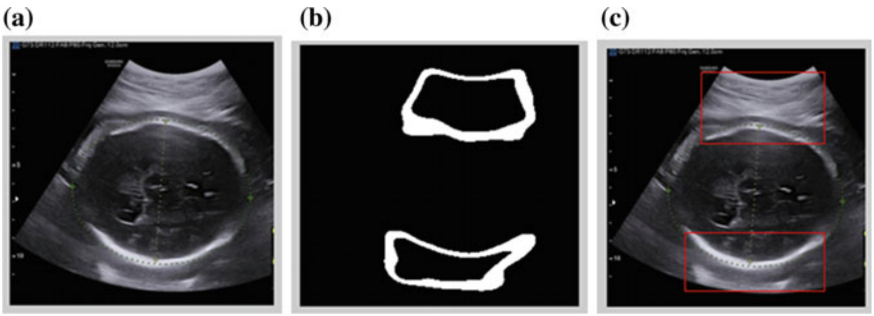

Fig. 12.4 Measurement of Bi-parietal diameter **a** input image; **b** canny edge detection; **c** bounding box image

Automatic BPD. The correlation coefficient is 0.98. Mean value for automatic measurements is 60.67 and error is 1.72 mm and standard error is 60.67 ± 1.7 mm.

The results of Head Circumference with manual and automatic measurements are shown in Table 12.3. Figure 12.6 shows the processing steps for the measurement of Head Circumference.

Table 12.2 Measurement of Bi-parietal diameter

Patient	Manual measurement (in cm)	Proposed method (in cm)
1	7.2	7.4
2	5.0	5.2
3	6.4	6.4
4	7.8	7.6
5	6.5	6.6

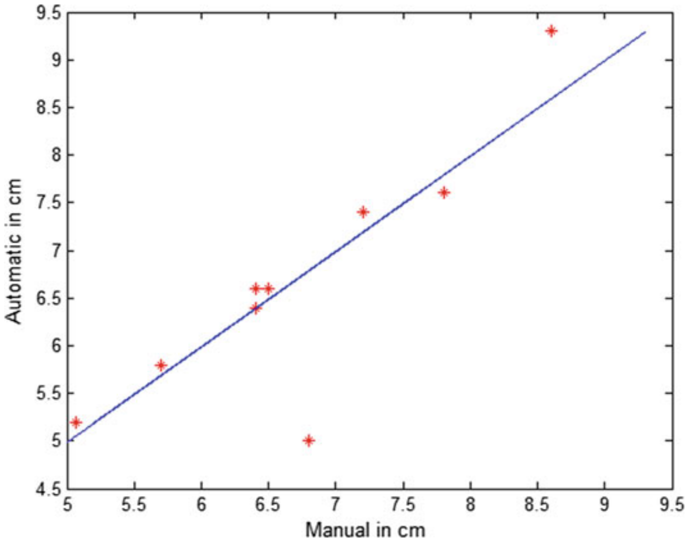

Fig. 12.5 Correlation plot for Bi-parietal diameter

Table 12.3 Measurement of head circumference

Patient	Manual measurement (in cm)	Proposed method (in cm)
1	50.0	54.6
2	24.0	24.5
3	25.0	26.1
4	23.5	23.9
5	24.0	28.6

Figure 12.7 shows the correlation plot between manual HC and Automatic HC. The correlation coefficient is 0.97. Mean value for automatic measurements is 127.87 mm and error is 2.03 mm and standard error is 127.87 ± 2.03 mm (Fig. 12.8).

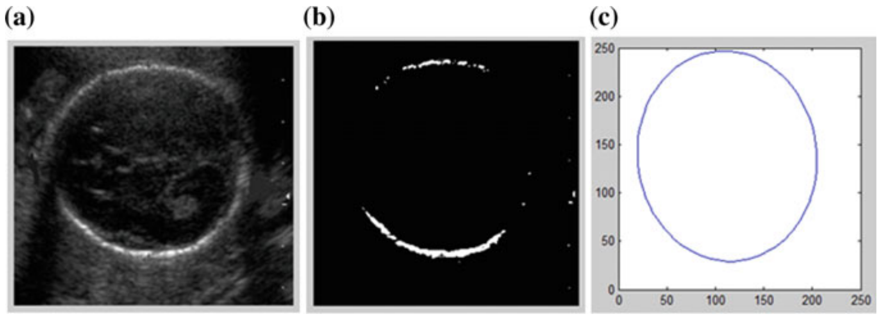

Fig. 12.6 Measurement of head circumference **a** input image; **b** binary thresholding **c** result of ellipse fitting method

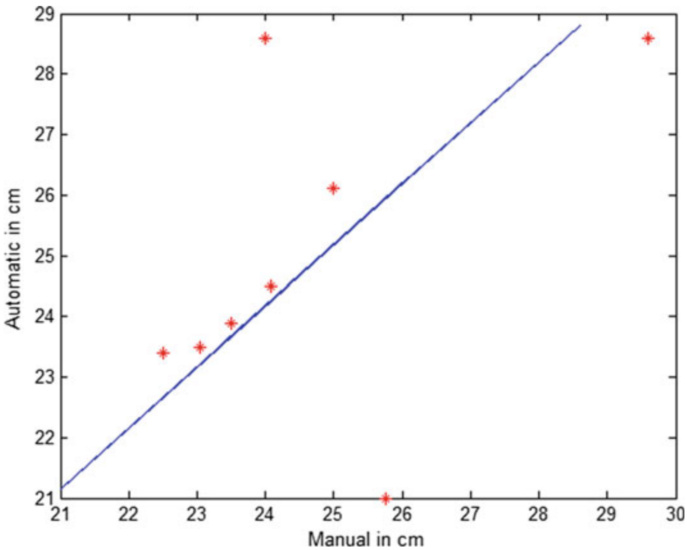

Fig. 12.7 Correlation plot for head circumference

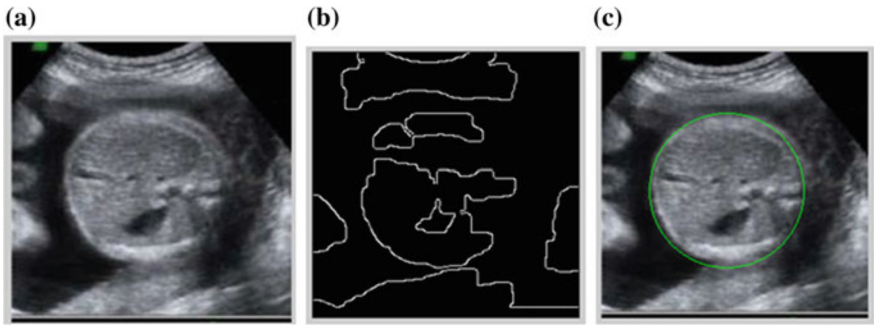

Fig. 12.8 Measurement of abdominal circumference **a** input image; **b** canny edge detection; **c** circle hough transform

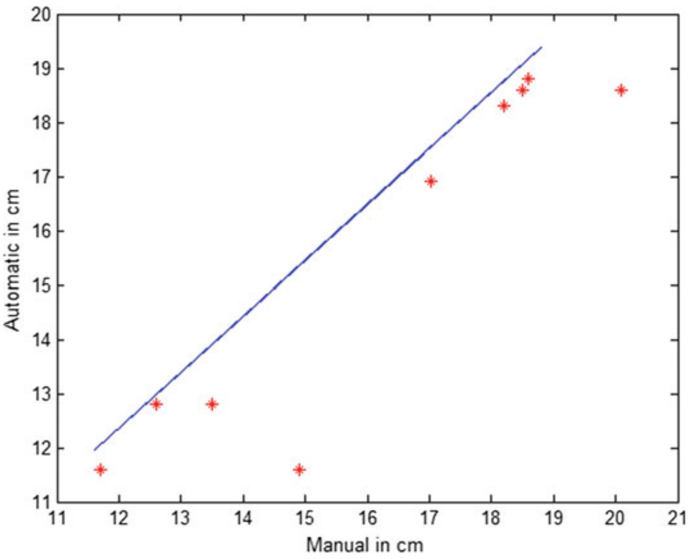

Fig. 12.9 Correlation plot for abdominal circumference

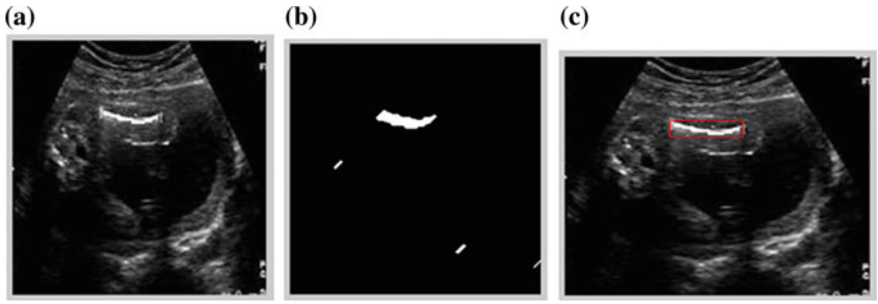

Fig. 12.10 Measurement of femur length **a** input image; **b** adaptive clustering and binary thresholding; **c** bounding box

Table 12.4 Measurement of abdominal circumference

Patient	Manual measurement (in cm)	Proposed method (in cm)
1	18.5	18.6
2	11.7	11.6
3	17.0	16.9
4	12.6	12.8
5	18.6	18.8

Table 12.5 Measurement of femur length

Patient	Manual measurement (in cm)	Proposed method (in cm)
1	2.4	2.6
2	2.2	2.3
3	3.7	3.3
4	3.2	3.3
5	3.8	4.0

Table 12.4 shows the results of Abdominal Circumference with manual and automatic measurements.

Figure 12.9 shows the correlation plot between manual AC and Automatic AC. The correlation coefficient is 0.98. Mean value for automatic measurements is 156.86 mm and error is 2.3 mm and standard deviation error is 156.86 ± 2.03 mm (Fig. 12.10).

Table 12.5 shows the results of Femur Length with manual and automatic measurements. Figure 12.11 shows the correlation plot between manual FL and Automatic FL. The correlation coefficient is 0.94. Mean value for automatic measurements is 31.88 mm and error is 2.2 mm and standard deviation error is 31.88 ± 2.2 mm.

Figure 12.12 shows the correlation plot between manual EFW and Automatic EFW. The correlation coefficient is 0.98. Mean value for automatic measurements is 272 mm and error is 2.8 mm and standard deviation error is 272 ± 2.8 mm. Table 12.6 shows the results of estimated fetal weight with manual and automatic measurements.

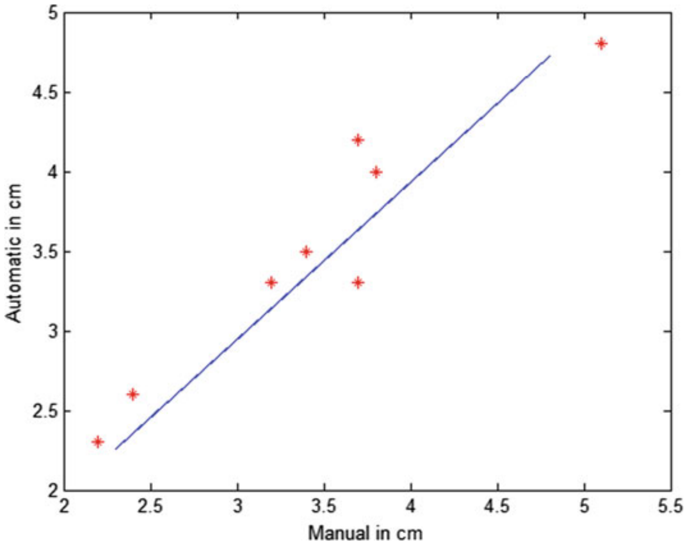

Fig. 12.11 Correlation plot for femur length

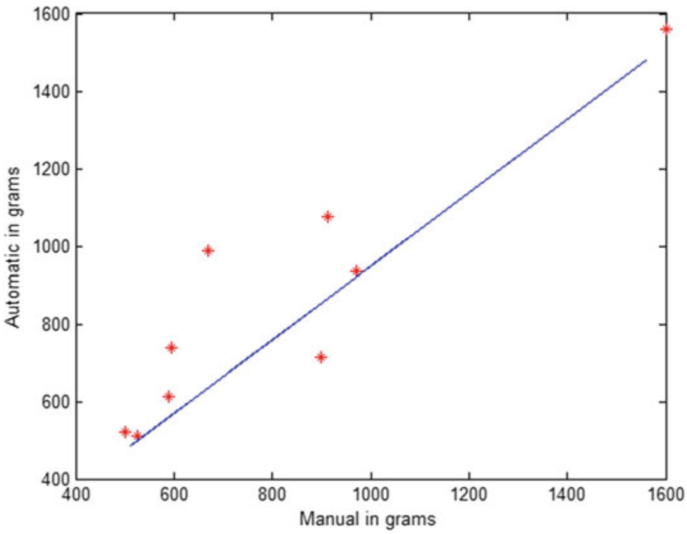

Fig. 12.12 Correlation plot for estimated fetal weight

Table 12.6 Measurement of estimated fetal weight

Gestational age (in days)	Manual measurements (in g)	Proposed method (in g)	Normal/ IUGR
193	590.0	612.0	IUGR
149	525.0	511.0	IUGR
174	594.0	600.0	Normal
197	900.0	875.0	IUGR
177	970.0	935.0	Normal

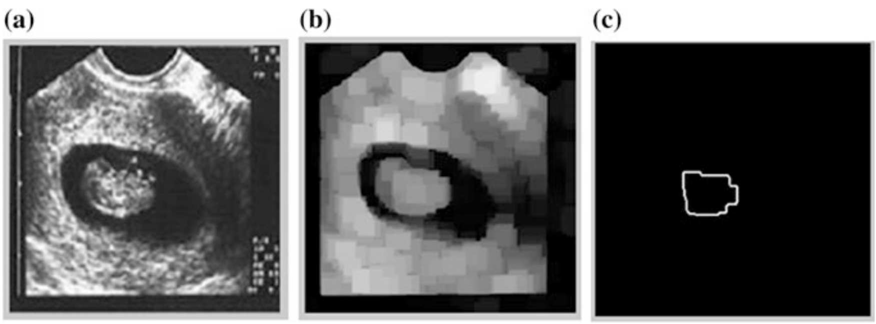

Fig. 12.13 Processing steps of estimating gestational age **a** input CRL image; **b** Histogram equalization and morphological opening; **c** boundary segmentation

Table 12.7 Measurement of gestational age

Manual gestational age	Proposed method for BPD (in mm)	Proposed gestational age
36 weeks 1 day	89.4	36 weeks 5 days
32 weeks 4 days	81.8	32 weeks
37 weeks 6 days	93.2	38 weeks
23 weeks 5 days	60.97	24 weeks
19 weeks 3 days	44.7	19 weeks 6 days

Figure 12.13 shows the processing steps of Gestational Age. The manual and automatic measurement of gestational age is shown in Table 12.7.

12.4 Conclusion

Fetal biometrics for fetal defects were analyzed. A measurement technique for the fetal parameters has been developed and implemented. The evaluation of fetal parameters gives better results for diagnosing the anomalies. Presence of abnormality of Amniotic Fluid Volume such as oligohydramnios and polyhydramnios can also be detected. Prediction of Intra-Uterine growth restricted fetus will be helpful for the obstetricians to take decision regarding the treatment of fetus and this reduces the risk for fetal delivery. This approach can easily identify the child growth restriction, fetal weight, gestational age, whether the fetal is normal or abnormal. For further development of this case having large datasets, optimization techniques can be implemented for optimal solutions using Graphical Processor Unit.

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