# Automatic Identification of Early Miscarriage Based on Multiple Features Extracted From Ultrasound Images

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**Abstract**

Ultrasound is one of the most widely used multipurpose imaging modalities that is ideal for monitoring and diagnosing early pregnancy events. The first sign and measurable element of an early pregnancy is the Gestational Sac (GS). Currently, the size of GS is manually measured from an ultrasound image of the GS. This paper argues that the Mean Sac Diameter (MSD) derived from the manual measurements results in inter- and intra-observer variations, which may lead to difficulties in diagnosis. The paper proposes a fully automated diagnosis solution to accurately identify miscarriage cases in the first trimester of pregnancy based on currently used MSD as well as alternative geometric features extracted from the image. Our experimental results show that the perimeter and volume of the GS are effective features where the perimeter can outperform the MSD. Furthermore, our study shows that the identification accuracy of early miscarriage can be further improved by combining the perimeter, volume and MSD of the GS.

# 1 Introduction

Medical imaging techniques have been increasingly deployed in the past decades to diagnose various types of diseases. Among medical imaging modalities, ultrasound imaging is considered to be safe, non-invasive, portable, accurate, and cost effective. These advantages have made the ultrasound imaging the most common diagnosis tool deployed hospitals around the world [1]. Ultrasound imaging is also considered as an effective modality particularly for monitoring pregnancy because of its safety without hazard of radiation [2].

The first three months, known as the first trimester, are the most crucial period in pregnancy. Monitoring pregnancy within this period enables clinics to evaluate the development, growth, and wellbeing of the foetus [3]. The first sign and measurable element of an early pregnancy is the Gestational Sac (GS). The American College of Radiology guideline defines miscarriage as being an empty GS with a Mean Sac Diameter (MSD) greater than or equal to 16 mm [4, 5]. However, the Royal College of Obstetricians and Gynaecologists of the United Kingdom first recognised miscarriage as being an empty sac with MSD greater than or equal to 20 mm, but later concluded that an empty GS with MSD greater than or equal to 25mm should be introduced as a new guideline to minimize the risk of false positive diagnosis of miscarriage [6].

Estimating the size of the GS is currently done manually. The manual process involves multiple subjective decisions when three diameter measurements on the GS are taken from an ultrasound image to establish the MSD [6]. The subjective decisions increase the inter- and intra-observer variations which may lead to difficulties and even errors in the diagnosis stage. Therefore an automated way of measuring the size of the GS from a given ultrasound image is desirable. Unlike other types of medical image, ultrasound images are corrupted by speckle noise that tends to reduce image resolution and contrast, and consequently reduce the diagnostic value of the image. Therefore speckle noise reduction is an important requirement whenever ultrasound imaging is used.

A large amount of research into ultrasound image de-nosing has been undertaken [7,8,9], but the research in the area of gestational sac segmentation and enhancement is very limited. In [10], Chakkarwar et al. presented an automatic method for GS segmentation using a database of 12 images with average accuracy of 83.3%. Their method starts by de-speckling the image using a combination of contrast enhancement, low pass filter and wiener filter, followed by thresholding. Zhang et al. [11] proposed a three-step automatic detection method for GS from a video using AdaBoost method to detect the GS in each frame followed by an efficient method exploiting the local context to reduce false positive detection. The algorithm was tested on 31 videos and achieved a GS detection rate of 87.5%.

This paper proposes an automatic solution for accurate segmentation and quantification of GS. Besides MSD, the proposed solution also extracts some geometrical features from GS images such as volume, perimeter, area, circularity, compactness, solidity and eccentricity from two most important planes - transverse and Sagittal for GS that may be relevant to miscarriage identification. We have used k Nearest Neighbor (kNN) classifier to identify early miscarriage cases based on the extracted features. To verify the performance of the proposed solution, we have conducted experiments on a data set of 68 ultrasound images. Our experimental results show that the proposed solution can achieve a higher level of accuracy using the perimeter compared with the MSD. We also showed that combining the perimeter, volume and MSD features can further improve the accuracy of miscarriage diagnosis.

# 2 Materials and Methods

## 2.1 Materials

A database of 68 ultrasound images for GS was prepared to cover both Normal (44) and Miscarriage (24) cases. Each image was captured from two planes - transverse and sagittal for GS. The database was labeled by experts in early pregnancy department, Queen Charlotte's and Chelsea Hospital, London, UK.

## 2.2 Methods

Figure 1 shows the block diagram of the underlying process of the proposed solution for automatic identification. Each stage of the process will be explained in detail in the following sub-sections.

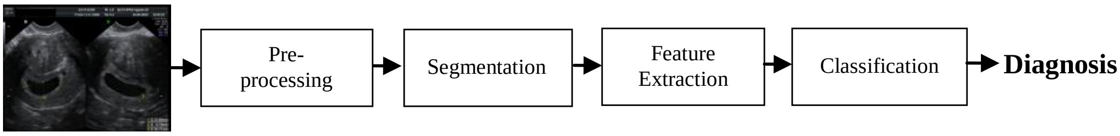



Figure 1: Block Diagram of the Major Steps of the Proposed Method

### 2.2.1 Pre-processing

Ultrasound images of GS are very dark and hence the accuracy of GS segmentation can be badly affected. We first separate the sectional images as shown in Figure 2 (a) and (b), and then brighten each image by using the following adaptive method: if the mean of all pixels intensity values of the image >=55, the intensity value of each pixel is multiplied by 2; otherwise it is multiplied by 4. Unlike histogram equalisation, this transformation gives more weight for the dark pixels (where the detailed information lays) by stretching them over the whole grey-sale range. The enhanced image is shown in Figure 2 (c).

### 2.2.2 GS Segmentation

Step 1: A simple method to extract an object from its background is through thresholding. The Otsu method [12] is typically used to automatically select the best threshold. However, this method did not perform well on most of the images in our database because our database contain images where are very different intensity. Therefore, we chose the mean pixel values of the original image as an alternative threshold. This simple solution is effective on almost all type of images (bright and very dark) in our database as illustrated by the example in Figure2 (d).

Step 2: A median filter with a window size of 15x15 is applied to smooth the boundary of the binary object without losing its original shape in addition to filling holes and removing small outlier regions. The result is shown in Figure2 (e).

Step 3: The best-fit ellipse is then found to estimate the shape of the GS due to the fact that GSs are usually round in the early pregnancy, but as the sac grows it often appears more elliptical. Figure 2(f) shows the ellipsoid shape on the GS

Step 4: To extract the border of GS, the morphological operation erosion is first applied. The resulting image is then subtracted from the binary image from step 2. The border of the GS is illustrated in Figure2 (g).

Step 5: The border extracted in step 4 is superimposed on the original image to clearly visualize the segmented GS as shown in Figure2 (h).

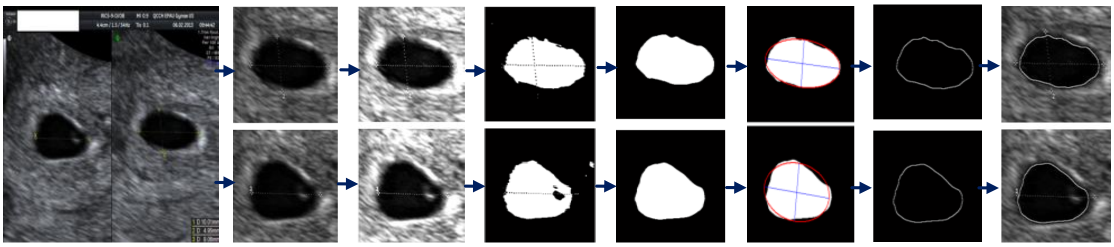
### 2.2.3 Feature Extraction

As explained earlier, each GS is visualised in two perpendicular sections/planes. Our algorithm first finds the best fitting ellipse for the segmented GS in each plane. Assuming the GS has ellipsoid shape in 3D, the three principal axes of the ellipsoid can be estimated by the major axis (A), minor axis (B) of the ellipse from the first plane and the depth (C) from the second plane. After that, we extracted the following geometric features from each GS:

1. The Mean Sac Diameter (MSD) : Based on the three principal axes A, B, and C, the MSD is given by:
$$MSD = \frac{A+B+C}{3}$$
2. Volume: The volume of the GS can be estimated using the three semi-principal axes as follows:
$$Volume = \frac{4}{3}\pi\ ABC$$
3. Perimeter: It can be accurately calculated by simply counting the number of pixels around the boundary of the GS, and then taking the average of the perimeter from both sections to produce a single perimeter measure.

### 2.2.4 Classification

At this stage, a classifier is normally derived from a set of examples. In principle, any suitable classifier can be trained and deployed in this step. In this study, we particularly used a simple kNN classifier to test the effectiveness of the extracted features.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 2: (a) Original Image in two sectional, (b) Cropped image GS (c) Enhanced Images, (d) Binarized image (e) Border of the GS smoothed (f) Border extracted (g) Superimposed the border on the original image (h) Result of segmented GS with best fitted ellipsoid

# 3 Experiment Results & Discussion

## 3.1 Experiments and Results

In our experiments, a stratified cross-validation was employed and a random sample was drawn 15 times. For each sample, 24 random normal and 24 miscarriage cases were chosen. We report the average accuracy, the average sensitivity and the average specificity. The results in Figure 3 illustrate that when the automatically extracted MSD feature is used, we obtained an overall accuracy of 98% with sensitivity (miscarriage) 97% and specificity (normal) 99%. When the Volume feature is used, the level of accuracy is marginally lower with a larger discrepancy between sensitivity 95.5% and specificity 100%. The Perimeter feature has achieved a better sensitivity of 98.6% while specificity remains at 99%. The difference between the sensitivity and specificity has also been narrowed, indicating an overall improvement over the MSD and the Volume features. Perimeter is a more robust feature which is automatically measureable from each single image of the GS. Furthermore, the results in figure 3 also show that combining the three features will further improve the performance (accuracy, sensitivity and specificity) to 99.5% through complementing the strengths of the individual features.

## 3.2 Discussion

In order to further understand the applicability of the extracted features in classification, we also tested the features using two other types of classifiers: decision tree (DT) and support vector machine (SVM) as well as kNN [13] when k=1. Figure 4 shows a consistent pattern of performance of MSD and perimeter across the classifiers, but the performance of volume feature deteriorates for SVM classifier and for kNN , k=1 classifier, due to some border line cases which make the decision very sensitive.

We also have investigated into other features such as area, compactness, circularity, solidity and eccentricity [14]. Area is another indicator of GS size and is calculated by first finding the actual number of pixels in the GS region (GS) and then converting the number of pixels to area measurement in $mm^2$. The classification test on this feature shows an inferior performance compared to the other three features. Compactness, solidity, circularity and eccentricity are indicators of roughness, irregularity, and the shape of GS borders. Our experimental result shows that these features have little diagnostic value for miscarriage cases except the area. Figure 5 illustrates the classification results for these features. The reason for the poor performance of these features may well be due to the images in our data set where most sacs, miscarriage or normal, have regular and smooth borders. Initial investigation on replacing the MSD with the three measurements , major axis (A), minor axis (B) of the ellipse from the first plane and the depth (C) from the second plane separately to be fed into the classification scheme did not show any improvement over the MSD. However, more images of various border characteristics are needed in future investigations to draw solid conclusions.

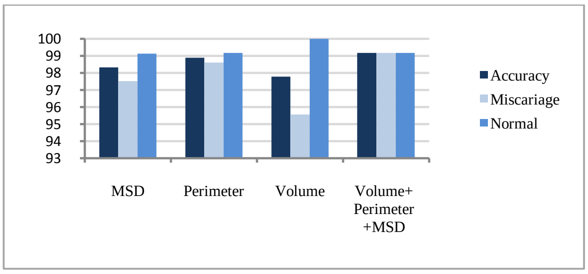



Figure 3: Comparing miscarriage classification accuracy, sensitivity and specificity based on MSD, perimeter, volume and multi features using kNN, k=3

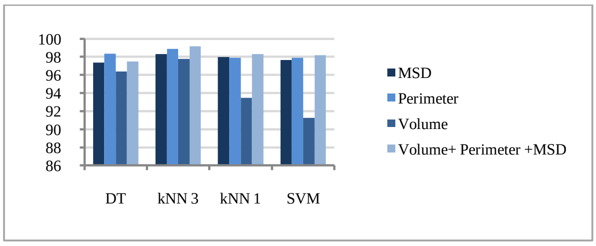



Figure 4: Classification accuracy based on MSD, perimeter, and volume using 4 different Classifiers

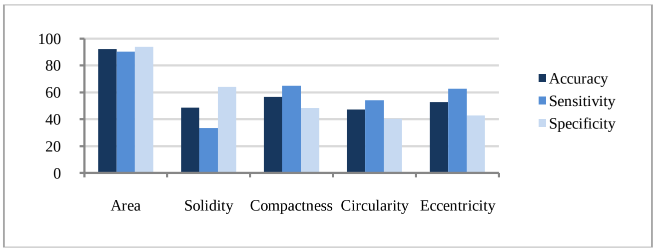



Figure 5: The system performance based on area, compactness, circularity, solidity and eccentricity using kNN, k=3

# 4 Conclusions

In this paper, an automatic computer based solution for segmenting, quantifying and classifying the GS has been proposed for miscarriage diagnosis in a very early stage of pregnancy. Firstly, our results show that our preprocessing task was successful for segmenting the GS. Secondly, we have investigated the effectiveness of new features such as perimeter and volume to further improve the classification accuracy. The result shows that using perimeter as a single feature outperforms the use of MSD in terms of miscarriage classification accuracy. Thirdly, our study shows that the combining perimeter, volume and MSD can improve the classification accuracy even further. Finally, we establish that the contribution of other features such as area, solidity, circularity, compactness, and eccentricity in diagnosis is very limited. Our future work includes segmentation, quantification and classification of other types of miscarriage cases such as GS with Yolk or Embryo inside.

# 5 References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