Variational Level Set Algorithm in Image Segmentation for Foetus Ultrasound Imaging System

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Abstract **— Segmentation on ultrasound image is difficult when the image is not clear and contains unwanted noise. Since the object to be segmented out can be changing in shape for a period of time, there is a need to apply a computerised segmentation method for future analysis without any assumptions about the object's topology is made. In general, when performing pregnancy ultrasound scanning, seeking a snapshot with best position or angle of the foetus is often a task done by obstetrician. This snapshot is useful for the obstetrician to locate the crown and the rump of the foetus for specific measurement. In this paper, a computerized segmentation using variational level set algorithm (VLSA) is proposed here. Results showed the variational level set contour evolved well on the low contrast and noise consisting ultrasound image.**

Keywords - image segmentation, level set algorithms, foetus ultrasound medical image

I. INTRODUCTION

With the emerging of the computer vision technology, many of the image analyses in various applications including pattern recognition, object detection, and medical imaging require image segmentation. Image segmentation can be defined as partitioning an image into meaningful regions that correlates to particular application that corresponds to individual surfaces, objects, or natural parts of objects. In general, image segmentation is the first stage in image analysis which seeks to simplify the data into its basic component elements or objects within the scene. The goal of image segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyse. This includes identifying an object in a screen for object based measurements such as size and shape.

In this paper, estimation and calculation of the foetus length can be obtained through the segmentation result by obtaining the contour of segmented foetus from the ultrasound image. This can help the obstetrician to monitor whether the foetus is growing healthily.

Image segmentation can be generally categorized into two categories which are parametric and non-parametric image segmentation. Parametric approaches are more generative. Non-parametric method does not require the image regions to have a particular type of probability distribution and does not require the extraction and use of a particular statistic. The image segmentation method that used in the project is a parametric method.

This paper is organised as follows. In section II, various image segmentation methods are briefly described. Explanation of the level set algorithm is presented in section III. In section IV, the experimental results on foetus ultrasound medical image segmentation and discussions are presented. Lastly, section V gives the conclusions of the paper.

II. REVIEW OF IMAGE SEGMENTATION METHODS

There are various image segmentation method available which provide the basis for a variety of more recent methods, these include boundary-based segmentation such as Canny edge detection [1], region-based segmentation such as region growing and global optimization approaches. Andreetto propose a simple probabilistic generative model for image segmentation. The model is principled, provides both hard and probabilistic cluster assignments, as well as the ability to naturally incorporate prior knowledge [2]. In many vision problems, the performance of the segmentation step is highly dependent on the algorithm selection and its parametrisation. These tasks are tricky and time-consuming. Martin and Thonnat present an approach to perform task-oriented segmentation based on segmentation algorithm parameter tuning and learning techniques [3].

W. Tao, H. Jin and Y. Zhang developed a novel approach that provides effective and robust segmentation of colour images [4]. Colour image segmentation methods can be seen as an extension of the gray image segmentation method for the colour images. Nevertheless, many of the original gray image segmentation methods cannot be directly implemented to colour images. J. Tang proposes a colour image segmentation method of automatic seed region growing by combining the watershed algorithm with the seed region growing algorithm. The region growing algorithm is based on the traditional seed region growing algorithm [5]. Michael and Anil propose a method of segmentation by using the object classification subsystem as an integral part of the segmentation. This will provide contextual information regarding the objects to be segmented, and the probability of correct classification as a metric to determine the quality of the segmentation [6]. Z. Wang and M. Yang propose a fuzzy clustering application into image segmentation by viewing clustering as a model of identification process [7]. It is a vital element by classifying things that are sharing the similar properties. The clustering can also be a supportive method for some segmentation algorithm [8].

Geodesic active contour methods are powerful numerical techniques in image segmentation and analysis. C. Liu presented a new region based geodesic active contour method. The new method gives a global view of the boundary information within the image [9]. P. Lin presented a new method integrates the image region statistical information and image boundary statistical information instead of the conventional method that uses spatial image gradient information [10].

At last, for the level set approach, that is first introduced by S. Osher and J. A. Sethian in 1988. It actually originates from computational fluid dynamics. They are designed to handle problems in which the evolving interfaces can develop sharp corners and cusps, change topology and become very complex [11]. Later, Zhong proposed a variational model which is used to locate at the boundary of the object in the designated region. This is done by adding an intersect area term into the model. In this model, an energy functional ε requires the use of two level set functions. One is used to capture the object of interest, the other one indicates image region which should be corrected [12].

III. Level Set Algorithm

The general idea of this level set algorithm is to represent initial object contour as the zero level set of an implicit function defined in a higher dimension (level set function), and then evolve the level set function according to a partial differential equation (PDE). This approach presents several advantages. First, the contour represented by the level set function has the flexibility to break and merge naturally during the evolution. This indicates topological changes are thus automatically handled. Second, the level set function always remains a function on a fixed grid, which allows efficient numerical schemes.

In this research, level set method will be focused in the image segmentation. The variational level set method can totally eliminate the need of re-initialise process. Unlike in the traditional level set method, its re-intialise process can be complicated.

A. Traditional Level Set Method

The basic idea of the level set formulation of active contour is represented by the zero level set function:

$$\Gamma(t) = \{(x, y) \mid \varphi(t, x, y) = 0\} . \quad (1)$$

Γ is the closed curve and $\varphi(t, x, y)$ is the level set function. The set $\{(x, y)|\varphi(0, x, y)$ defines the initial contour. φ is negative when it is inside the object region, and positive when it is outside the interested region. The evolution of the curve Γ in normal direction with a speed F, which is called level set equation, can be written in the following general equation:

$$\frac{\partial\varphi}{\partial t} + F\,|\nabla\varphi| = 0 . \quad (2)$$

During the evolution, ordinary level set function φ can develop spikes (very sharp or flat shape outline) that can cause inaccuracy to the further evolution. Re-initialise or “reshape” are used to counter this problem. This can be done initialising the function φ as a signed distance function before the evolution, and re-initialise the function φ periodically during the evolution. This re-initialise process is certainly crucial and cannot be skipped for this traditional level set method.

B. Variational Level Set Method

The variational level set method focuses on maintaining the level set function to be closed to a signed distance function, and this completely eliminates the re-initialisation procedure. In the process of image segmentation, the active contour (dynamic curve) constantly moves towards the boundaries of an object. This can be done by the external energy which moves the zero level curves toward the boundaries of interest region.

There are few parameters need to be considered in this variational level set method, in order to get the result as accurate as possible. These parameters are the standard deviation of Gaussian distribution, parameter of internal energy, parameter of weighted length term and parameter of weighted area term. Each of them plays an important role in the evolution of level set method. Careful selection of these values of the parameters is needed to maintain the stability of evolution level set equation.

For the internal energy part, there is parameter that controls the effect of penalizing the deviation φ from a signed distance function. The range of the time step τ and the coefficient μ must satisfy $\tau\mu < 0.2$ in order to maintain stable level set evolution. For $\tau\mu < 0.2$, small μ will take longer time to completely segment the image. With the same number of iteration, Fig. 1(b) shows the final evolution of level set curve is far away from boundary of object compared to Fig. 1(a).

The parameter of weighted area term, α can be positive or negative, depending on the relative position of the initial contour to the object of interest. The positive α makes contour to shrink inwards and negative α causes contour to expand outwards.

The value of standard deviation can affect the result of the final contour. The edge-indicator depends on the Gaussian distribution of the input image. The value of Gaussian function is defined based on the standard deviation value. The Gaussian distribution is the basic of large

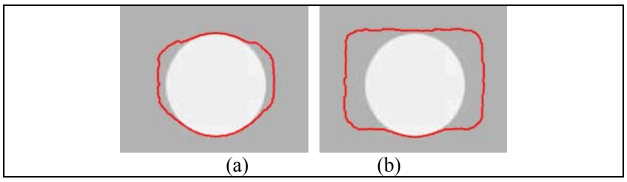


Figure 1. Result of evolution level set with 200 iterations with (a) μ = 0.02, (b) μ= 0.01.

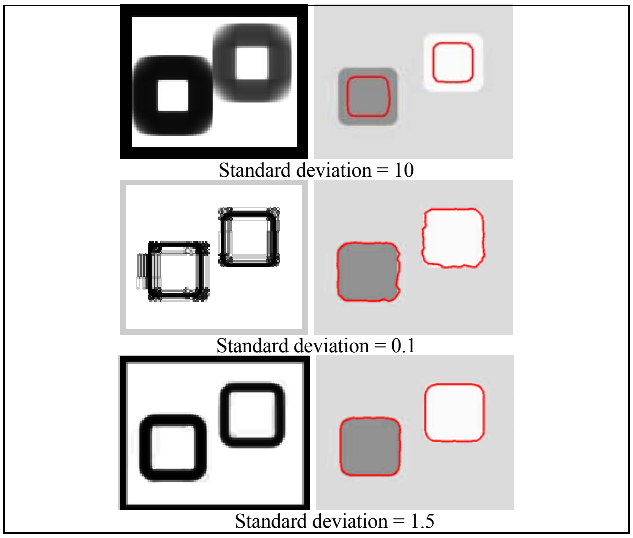


Figure 2. Results for evolution level set with various standards deviation. Images in left show edge-indicator and images in right show complete level set curve.

proportion of statistical analysis. Its averaging almost always leads to a bell-shaped distribution where sometime referred to as normal distribution. In Gaussian distribution, standard deviation reflects the width of the bell. Small standard deviation leads to narrow bell and high peak. Large standard deviation results a wide bell and low peak. Fig. 2 shows the results with different value of standard deviation.

C. Medical Image Segmentation using Variational Level Set Method

Various types of medical images such as X-ray image, MRI (*Magnetic Resonance Imaging*) image and ultrasound image have the variational level set method tested. Fig. 3 shows the evolution of the level set contour on X-ray image of bone. Note that, the level set curve has slowly evolved towards the boundaries of the bone region. It can be seen that the initial rectangle contour evolved well as it follows closely the boundaries of the leg bone at 850 iterations. In addition to it, the level set contour has actually enclosed the shape of the bone. The variational level set method also can handle the sharp corners and cusps of the brain tissue, and it is flexible to the topology change of the brain boundary. Result for evolution level set on MRI image of brain is shown in Fig. 4.

Ultrasound image is well known for the speckle noise in it and its low signal-to-noise ratio. By implementing this algorithm, the obstetrician can rely on this computerised segmentation as it can help to locate the region of interest in the ultrasound image such as the body of the foetus. Fig. 5 shows the evolution of the level set contour on an ultrasound image of carotid artery and its result. Note that the boundary of the carotid artery is unclear. However, the variational level set curve successfully evolved to the object boundaries at 250 iterations. In addition, the shape of the carotid artery is well enclosed by the level set contour.

IV. EXPERIMANTAL RESULTS ON FEOTUS ULTRASOUND IMAGE SEGMENTATION AND DISCUSSION

The foetus body is the region of interest that needs to be segmented out. Foetus ultrasound images have been tested in the segmentation program using the variational level set algorithm. The tested results are shown in the followings.

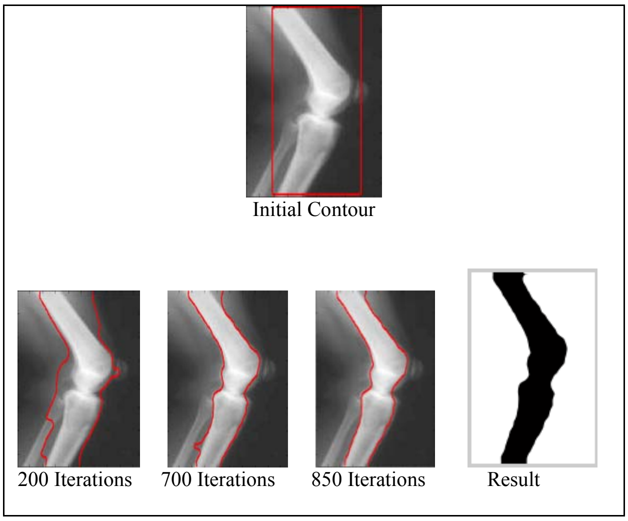


Figure 3. Segmentation on bone (X-ray).

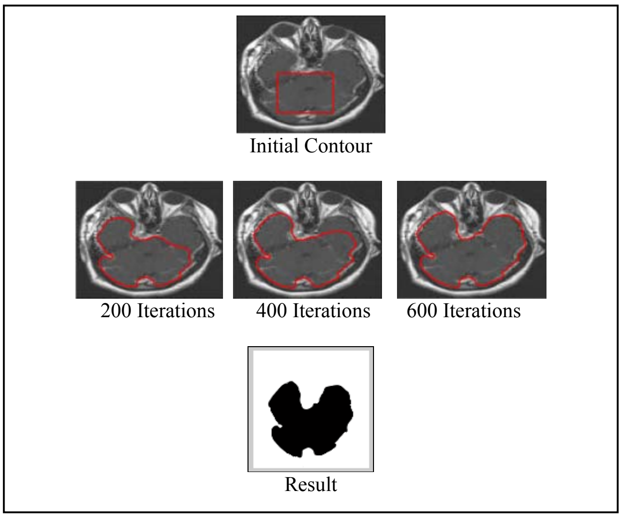


Figure 4. Segmentation on brain (MRI image).

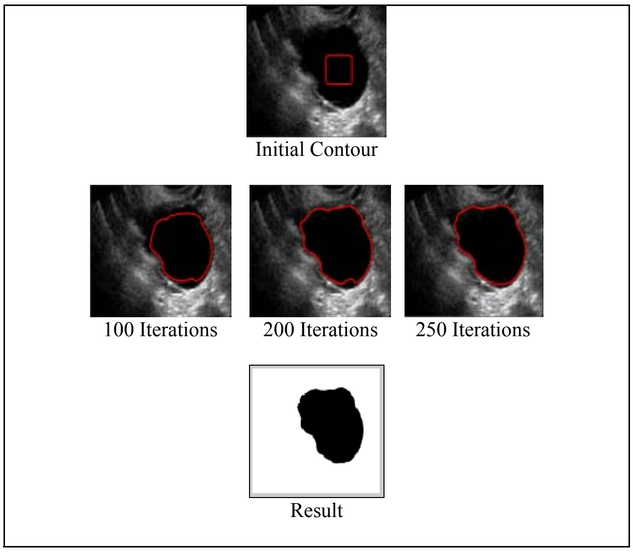


Figure 5. Segmentation on carotid artery (ultrasound image).

Fig. 6 demonstrated the evolution of the level set contour on ultrasound image of a week tenth foetus. The level set curve was evolving towards the boundaries of the target region. The contour evolved successfully from a circular shape to the foetus body shape. This indicates the contour manage to evolve well as the final contour resembles the exact shape of the foetus body. Fig. 7 demonstrates the evolution of level set contour on the week eighth foetus image and week sixth foetus image with their initial contour in ellipse shape. The level set curve has evolved towards the boundaries of the foetus body region and it successfully matches well the shape of the foetus body at the final iteration despite the presence of strong noise.

A. Performance of the Variational Level Set Algorithm

Table I shows the results of the segmentation using variational level set algorithm compared with the results generated from manual segmentation. The difference percentages of the variational level set algorithm segmentation results are very small when compared to the manual segmentation results. Hence, the variational level set algorithm is suitable to be used for foetus ultrasound image segmentation.

B. Foetus Length Measurement

Segmenting the whole body of the foetus can assist obstetrician for further analysis such as estimating the gestational age of the foetus. Gestational age in generally is defined as the age of the baby during pregnancy and its measurement unit is normally in weeks. Measuring the foetus via the ultrasound scanning is mostly accurate in early pregnancy. When the foetus in mother's womb is scanned by ultrasound probe, the obstetrician obtains the measurement of the crown-rump length based on the distance between the two located points and estimate the gestational age.

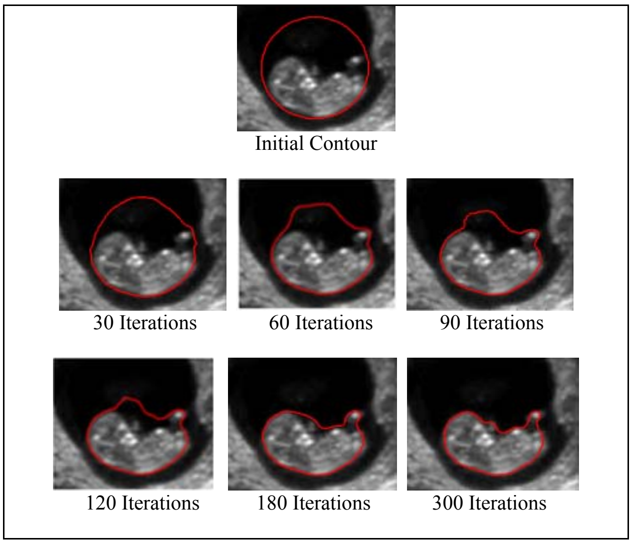


Figure 6. Evolution of the level set contour on week tenth foetus.

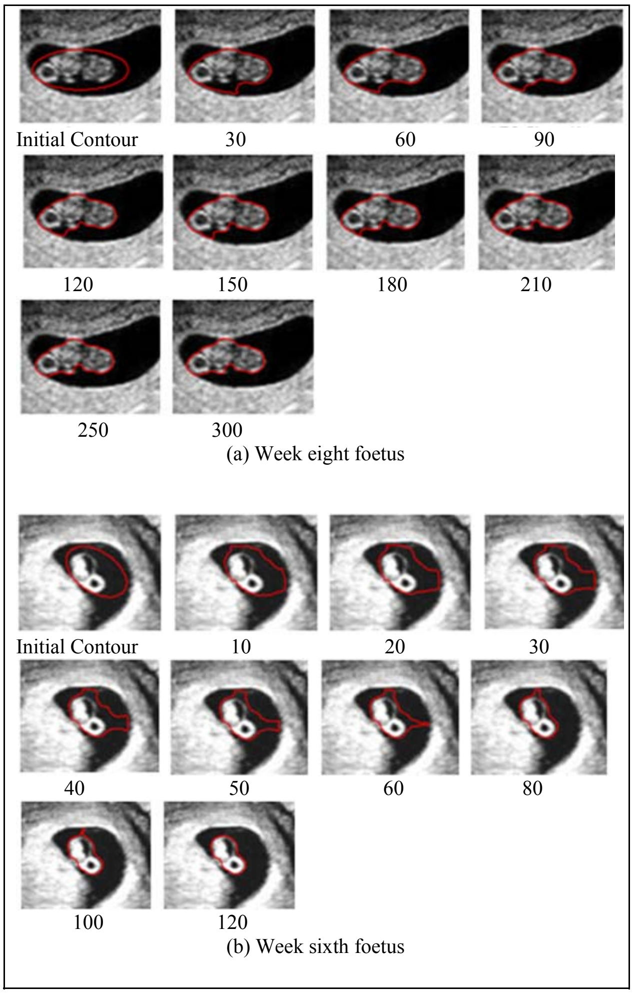
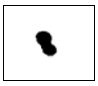
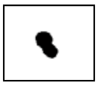
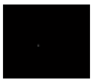
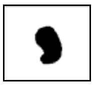


Figure 7. Evolution of the level set contour a week eighth foetus and week sixth foetus (the number depicts the iteration count).

TABLE I. PERFORMANCE BETWEEN THE VARIATIONAL LEVEL SET ALGORITHM SEGMENTATION AND THE MANUAL SEGMENTATION

Manual Segmentation Result	VLSA Segmentation Result	Difference of manual and VLSA	Difference Percentage
			2.383%
			1.183%
			0.717%
			2.392%
			0.283%

Crown-rump length (CRL) is the length of foetus from the top of the head (crown) to the bottom of the buttocks (rump). For example, a foetus crown-rump length of 18 mm denotes a gestational age of just more than eight weeks old. Usually, the obstetrician needs to manually click on the crown and the rump of the foetus, and the foetus length is then calculated. However, with the implementation of variational level set algorithm for the foetus segmentation, locating the points can be computerised as the points can be located based on the segmented contour without the obstetrician's intervene. Thus, the variational level set algorithm brings benefit such that obstetrician can manage more scan foetus images as measurement can be obtained directly without doing the manual measurement.

The length of the foetus is calculated automatically after segmenting the foetus from the ultrasound image. Fig. 8 shows the tested results of the foetus length. The dimension of the size is measured in pixel. For example in Fig. 8, the foetus length based on the segmented week sixth foetus is 26.3 pixels.

C. Feotus Length Measurement at Different Angles

Some calculations at various angles are performed to get the average length. Two different angles of the same foetus is discussed in this section. Fig. 9 is showing the week tenth foetus ultrasound images are used. As the foetus scanning is in continuous time frame, it can be seen that at different time frame will produce a slight difference in length. However, the difference of the lengths would not be too much. Fig. 10 shows another measurement result at second angle for a week tenth foetus. Notice that the foetus of the two angles have almost the same length on Fig. 9 and Fig. 10.

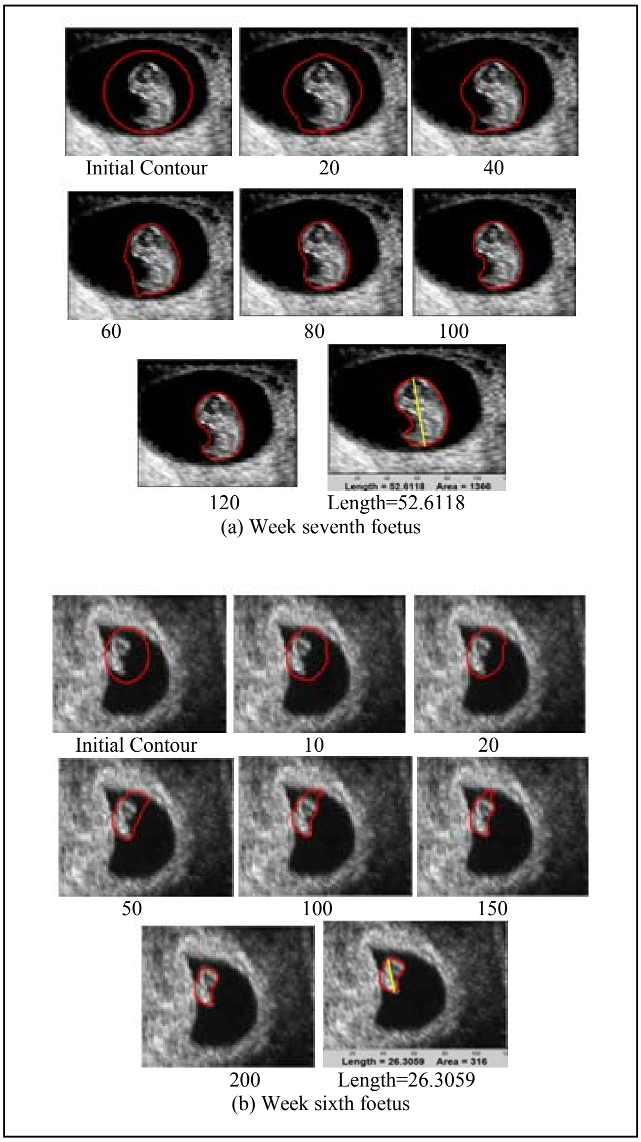


Figure 8. Foetus length.

V. CONCLUSIONS

The level set method has been proposed in this project for medical image segmentation. The variational formulation consists of two energies, internal and external energy. The internal energy term penalizes the deviation of the level set function from a signed distance function and the external energy term drives the motion of the zero level set towards the desired image features, such as object boundaries.

This variational level set formulation has three main advantages. First, a larger time step can be used to speed up the curve evolution. Second, the re-initialize procedure has

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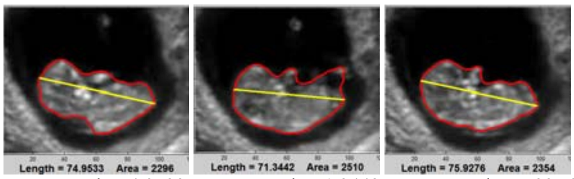
Length=72.111 Length=62.6498 Length=67.6018

Figure 9. Foetus length at first angle.



Length=74.9533 Length=71.3442 Length=75.9276

Figure 10. Foetus length at second angle.

been completely eliminated. Third, the level set curve can be flexible implemented in different object shapes.

In addition, the variational level set algorithm has been successfully implemented in medical image segmentation which including X-ray image, MRI image and ultrasound image. The results showing that the level set contour evolved well on the low contrast and noise consisting medical image, especially the ultrasound image which are well known for the speckle noise and low signal-to-noise ratio. Furthermore, the variational level set algorithm can be applied in foetus ultrasound image segmentation. This can help to do computerised calculation of the foetus length.

However, the unit of the calculated length used in the project is in the number of pixels since the images used here were not in the real time. Thus, the measured length could not be used to estimate the gestational age of the foetus.

In conclusion, the variational level set algorithm program can be embedded in real time imaging system where the images were not resized. Hence, actual foetus length can be measured directly. Moreover, this program may be applied to the machine where the dimension of the screen pixel is in base unit of the length such as millimetre. This enables the measured length of the foetus can be used to estimate the gestational age predictably based on the crown-rump length technique.

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