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Patch-based Fetal Heart Chamber Segmentation in Ultrasound Sequences Using Possibilistic Clustering

Chisanai Sardsud
Biomedical Engineering Program,
Faculty of Engineering, Chiang Mai University, Chiang Mai, Thailand
schitsanai@gmail.com

Sansanee Auephanwiriyakul
Senior Member, IEEE
Computer Engineering Department,
Faculty of Engineering, Biomedical Engineering Center, Chiang Mai University, Chiang Mai, Thailand
sansanee@ieee.org

Nipon Theera-Umpon
Senior Member, IEEE
Electrical Engineering Department,
Biomedical Engineering Center, Faculty of Engineering, Chiang Mai University, Chiang Mai, Thailand
nipon@ieee.org

Theera Tongsong
Obstetrics and Gynecology Department,
Faculty of Medicine, Chiang Mai University, Chiang Mai, Thailand
theera.t@cmu.ac.th

***Abstract* — Fetus cardiomegaly, an abnormal enlargement of heart, is one of the early indicators of hemoglobin Bart's disease that is the most dangerous thalassemia in Thai fetuses. The cardiothoracic ratio or CT ratio measurement helps detecting the fetus cardiomegaly. An automatic measuring system is a helpful tool for the physicians. However, in order to do that we need to have an automatic heart chamber segmentation system. In this paper, we developed an automatic fetal heart chamber segmentation system using a patch-based possibilistic c-means. We extracted the region containing heart chambers and ultrasound video frames with the end diastolic and end systolic using the Horn-Schunck's optical flow algorithm. We also extracted the region containing the fetal chest. From the results, we found out that the segmentation error was around 2.17% on the average comparing with the expert's opinion. However, sometimes the system extracted smaller heart chambers. This might be because of the opening operator in the post processing stage.**

Keywords — fetal cardiomegaly; possibilistic C-means; fatal heart chamber segmentation; Horn-Schunck's optical flow

I. INTRODUCTION

Various cardiac abnormalities or failure in fetus especially cardiomegaly (an abnormal enlargement of the heart) can be detected by measuring a fetal heart during prenatal diagnosis. Cardiomegaly is associated with many diseases including hemoglobin Bart's disease which is the most dangerous thalassemia found in Thai fetuses. Tongsong and Tatiyapornkul introduced cardiothoracic ratio (CT ratio) to examine fetus cardiomegaly [1]. Their finding was that the average ratio varied from 0.38 in 11-week normal fetus to 0.45 in 20-week normal fetus. Hence, the average CT ratio value at each gestational week should not be higher than 0.50. If the ratio is higher than 0.5, the fetus has cardiomegaly that might lead to hemoglobin Bart's disease.

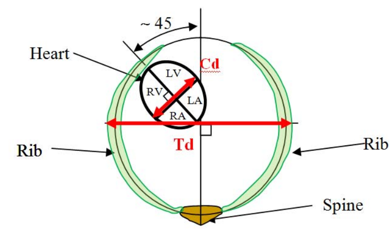

Figure 1. Cardiac and transverse diameter in four-chamber view model.

CT ratio is the ratio of cardiac diameter (Cd) to transverse diameter (Td). These diameters should be measured in the four-chamber view plane with all ribs clearly visible and the heart is at the end diastole stage [2,3] (at the widest Cd frame). Figure 1 shows cardiac and transverse diameters in four-chamber view model.

Normally, a physician determines Cd and Td from sequence of frames of the ultrasound video. To do that, he/she needs to identify the frame with the widest Cd and then measure Cd and Td. Finding the particular frame from the whole ultrasound video is a very tedious work. Moreover, in the first trimester, the fetal heart's size is small and ultrasound image has a low signal-to-noise (SNR) ratio. By looking at ultrasound images, it is not easy for a very skilled physician to detect the heart structure. In order to help a physician, an automatic system of detecting the heart structure is needed. There are several researchers who are working on the area including [4 – 8]. However, they all need a pre-processing methods either by human or machine.

In this paper, we develop an automatic fatal heart structure segmentation using the possibilistic C-means clustering. In particular, we find the frames that are in end diastolic (largest ventricle or widest Cd frame) [9] and end systolic (smallest ventricle or smallest Cd frame) [9] stages using information from motion estimation inside the automatically selected region of interest. Then this region is over segmented into many patches [10] using the possibilistic C-means (PCM) [11]. Finally, these patches are automatically selected and then combined into heart

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chambers. We also compare our results with the segmentation results from an expert.

II. System Description

To find the heart structure from ultrasound video, we need to first extract the region of interest (ROI) where there is a movement. The first ROI is the region that covers only heart chambers (ROI1). The second ROI is the region that supposedly covers chest area (ROI2). Then we need to extract the frames with the least amount of movement as it slows to a stop before changing direction, i.e., from diastole to systole stages or from systole to diastole stages. We then perform the patch-based possibilistic C-means (PCM) on those selected frames. We only perform segmentation inside the ROI2 to speed up the process. The flowchart of the proposed heart structure detection process is shown in figure 2.

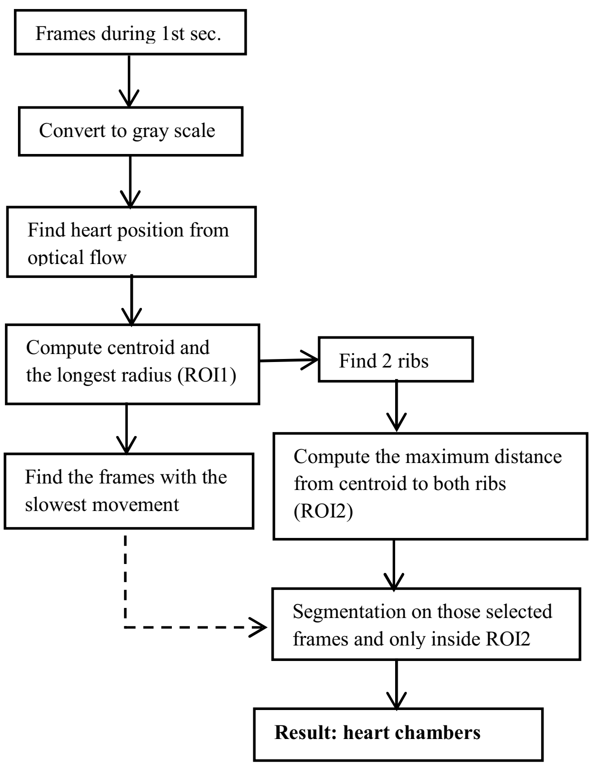


Figure 2. Flow chart of the heart structure detection process.

The ultrasound video is recorded with 20-50 frames/sec. And, since the fetus heart rate is 120-160 bpm or 2-3 bps [12], we only select frames from the first second of the video. Hence, in the first second there must have at least 2 frames that are in the end diastolic stage. Once we have all frames during the first second, we convert the RGB color image to grayscale image using [13]

$$\mathbf{I}(x,y) = 0.2989\mathbf{R}(x,y) + 0.5870\mathbf{G}(x,y) + 0.1140\mathbf{B}(x,y) \tag{1}$$

After that, we have grayscale image sequences, we find the region covering only heart (ROI1). There are 5 steps to select ROI1 as follows.

1. We apply the Horn-Schunck's motion estimation method [14, 15] to the selected sequences.
2. Since only heart chambers and surrounding area move, only the movement area will have a large magnitude value as shown in figure 3(b). We then apply the Otsu's method [13] to binarize each magnitude velocity field image.
3. To enhance the movement area, we add all the binarized images together as shown in figure 3(c).
4. However, movement of the heart surrounding area is not as much as the heart area itself. We then apply Otsu's method [13] again on the addition result. An example of the discovered heart is shown in figure 3(d).
5. We then compute a centroid of the discovered objects (called the heart centroid). Since a fetus's heart is normally of circular shape, we create ROI1 as a circle shape. We then compute the distance between the computed centroid and the farthest boundary of the objects. We call this distance as *Rh*. An example of ROI1 is shown in figure 3(e).

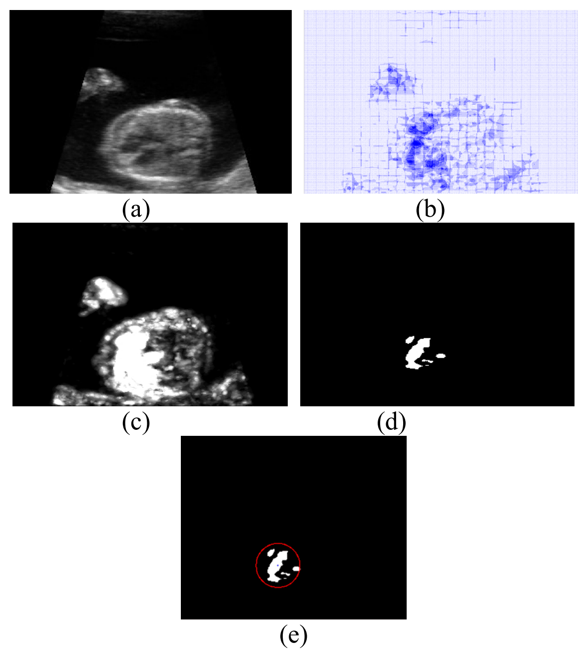


Figure 3. An example of selecting ROI1 (a) original image frame, (b) magnitude velocity field, (c) addition result of all binarized magnitude velocity field images, (d) detected heart chambers, and (e) ROI1 (red circle) of figure (a)

To reduce the processing time, we need to find frames with the end diastolic or end systolic. We assume that during these stages the heart will move slowly or not at all. The maximum fetus heart rate is 160 bpm or 3 bps [12]. Also, in one heart beat, there are 2 stages, i.e., end diastolic and end systolic, that are in slow movement. Therefore, in one second, the maximum number of frames (*MaxFrame*) with the end diastolic and end systolic stages should be equal to 6. Hence for the particular frame sequences, the minimum number of frames that we are looking for (Rs) is

$$Rs = round\left(\frac{FrameRate}{MaxFrame}\right) \qquad (2)$$

For example, if the frame rate is 20 frames per second, Rs will be 3 frames.

We then compute the average of the magnitude velocity field inside ROI1 of each frame as shown in figure 4. There are 3 steps involving with the selection of the frames with the end diastolic and end systolic stages as follows.

1. We compute pairwise difference of the average as

$$D(i) = A(i+1) - A(i) \; for \; i = 1\ldots n-1 \qquad (3)$$

where $A(i)$ is the average of the magnitude velocity field inside ROI1 of image i. And n is the number of frames in the sequence.

2. We first select frames by using the following algorithm.

Let F be an array of selected frame number.
Let k=1.
if $D(1)> 0$
then $F(k) =1$, $k=k+1$ # select frame 1
For $i=2,3,\ldots,n$
  if $D(i)>0$ and $F(k)-F(k-1)>Rs$ and $A(i)<mean\_A$
  then $F(k) =i$, $k=k+1$ # select frame i
where $mean\_A$ is the average of $A(i)$.

3. Then supposedly the selected frame i is in the end diastolic stage. The next stage in before and after this stage will be the end systolic or vice versa. Let *j_after* and *j_before* be the frame numbers that are supposed to be in another stage after and before this stage, respectively. Then *j_after* and *j_before* are

$$j\_after = \frac{round(Rs)}{2} + 1 \qquad (4)$$

$$j\_before = \frac{round(Rs) - 1}{3} \qquad (5)$$

Let K be the number of selected frames in step 3. We utilize the following algorithm to select the right frame

If $F(2) \geq F(1)+j\_after$
Then select F(1) #select first frame 1
For $k=2,3,\ldots,K-1$
  If $F(k+1)\geq F(k)+j\_after$ and $F(k)\geq F(k-1)+j\_before$
  Then select $F(k)$ #select frame number at $F(k)$
If $F(K)\geq F(K-1)+j\_before$
Then select $F(K)$

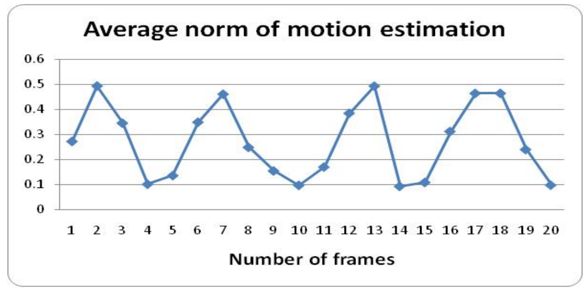


Figure 4. Average of magnitude velocity field insided ROI1 of each frames.

We are now ready to select the region that supposedly covers chest area (ROI2). In this case, we need to first find 2 ribs. Since these 2 ribs are always in the same positions in all image frames, we only perform this step at the first image frame. The first frame is binarized by thresholding with threshold value of 75% of the maximum gray level of the frame. Since a normal heart size is one third of the chest size, we select the longest object with the distance ($d1$) from the heart centroid < $3Rh$. We call this object as Rib1. The second rib (Rib2) is the second largest object that has the distance ($d2$) from the heart centroid < $3Rh$ and also the angle between Rib1 and this object > 90°. The finding Rib1 and Rib2 is shown in figure 5.

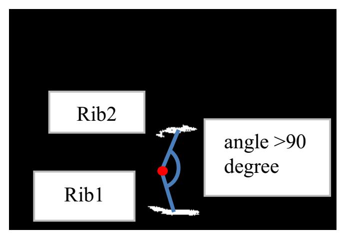


Figure 5. Rib1 and Rib2 of frame in figure 3(a)

The ROI2 is of circular shape with the heart centroid as the center and the radius is the maximum distance between $d1$ and $d2$. An example of selected ROI2 is shown in figure 6.

Figure 6. An example of selected ROI2

Now we are ready to perform patch-based possibilistic C-means. Let we briefly describe on the possibilistic C-means (PCM) [11] as follows. Let $\mathbf{X} = \{\vec{\mathbf{x}}_j \mid j = 1\ldots N\}$ be a set of N feature vectors in p-dimensional feature space. Let

$B = (\vec{\mathbf{c}}_1, \ldots, \vec{\mathbf{c}}_C)$ represent a C-tuple of prototypes each of which characterizes one of the C clusters. The objective function is as follows:

$$J_m(B, \mathbf{U}; \mathbf{X}) = \sum_{i=1}^{c} \sum_{j=1}^{N} (u_{ji})^m \left(d^2(\vec{\mathbf{x}}_j, \vec{\mathbf{c}}_i)\right) + \sum_{i=1}^{c} \eta_i \sum_{j=1}^{N} (1 - u_{ji})^m \quad (6)$$

where $m \in [1,\infty)$ is called the fuzzifier. In our experiment, we set $m = 1.5$. η_i are suitable positive numbers that need to be estimated from the distance statistics. It is calculated as

$$\eta_i = \frac{\sum_{j=1}^{N} (u_{ji})^m \left(d^2(\vec{\mathbf{x}}_j, \vec{\mathbf{c}}_i)\right)}{\sum_{j=1}^{N} (u_{ji})^m}. \quad (7)$$

The update equation of membership of $\vec{\mathbf{x}}_j$ in each cluster i is:

$$u_{ji} = \frac{1}{1 + \left[\frac{d^2(\vec{\mathbf{x}}_j, \vec{\mathbf{c}}_i)}{\eta_i}\right]^{\frac{1}{m-1}}} \quad (8)$$

where $d^2(\vec{\mathbf{x}}_j, \vec{\mathbf{c}}_i)$ is a squared distance between a vector $\vec{\mathbf{x}}_j$ and the center $\vec{\mathbf{c}}_i$. Therefore, the membership u_{ji} is not relative and depends only on the distance of $\vec{\mathbf{x}}_j$ from cluster center $\vec{\mathbf{c}}_i$ rather than on the distance of $\vec{\mathbf{x}}_j$ from all other prototypes. The update equation of the cluster center $\vec{\mathbf{c}}_i$ is

$$\vec{\mathbf{c}}_i = \sum_{j=1}^{N} (u_{ji})^m \vec{\mathbf{x}}_j \bigg/ \sum_{j=1}^{N} (u_{ji})^m. \quad (9)$$

In the experiment, we perform PCM with 20 clusters only on the region that is inside ROI2. After the algorithm converges, we reorder the prototypes in ascending order according to their gray levels and assigning the new label ranging from 1 to 20. Then we need to combine similar patches together to segment the heart chambers as followings.

1. We find the lowest label of the prototype that is inside ROI1, since the heart chambers are needed to be detected. We call this label L. And, the number of patches that will be selected to combine as a heart chambers (N_p) is

$$N_p = round\left((20 - L) * P\right) + L \quad (10)$$

   where P is the percentage of the difference between gray levels of heart chambers and the other areas. In the experiment, we set P=20%. For example, if L equals to 5, then N_p will be 8.
2. Since ROI1 might not cover all the correct heart chamber area, we will fine tune the segmentation by combining all the patches with label 1 to N_p. For example, from the example in step 1, we will combine patches with prototypes of 1 to 8.
3. To reduce some small areas of noise, we apply the opening operator [13] with a disk structuring element (SE) with the size of either 4×4, 6×6, or 8×8 on the result from step 2. We select the size of SE based on the size of ROI2. Let *rr* be 2×radius of ROI2 and *hh* be (3/5)×frame height. Then we select the size from the following algorithm:

```
if rr>hh,
then if rr>frame's height
      then SE's size is 8×8
      otherwise SE's size is 6×6
otherwise SE's size is 4×4.
```

   Then we discard object with the number of pixels less than the number of pixels of the circle with radius of 10% of radius of ROI2.
4. To reduce some noise at the boundary, we discard objects that are connected to the boundary of ROI2 that do not overlap to ROI1.
5. If the maximum distance between the farthest point of the result object from step 4 is less than 40% (this is because normal heart size is approximately one third of the chest size [12] and since our ROI2 is bigger than the chest) of the radius of ROI2, repeat steps 1 to 4 with P increased by 5%.

Now, we are ready to test our system with the real data set. However, to evaluate our segmentation method in this case we compute the segmentation error (E_{seg}) as

$$E_{seg} = \frac{J_1 + J_2}{\textit{Total number of pixels in the image}}. \quad (11)$$

where J_1 is the number of pixels of heart structure from expert's opinion but our system assigns them to non-heart structure. Whereas, J_2 is the number of pixels of non-heart structure from expert's opinion but our system assigns them to heart structure.

III. Experimental Results

The ultrasound videos used in the experiment were collected from the Maharaj Hospital, Chiang Mai University. Since, from [1] the suitable gestational age for measuring CT ratio should not be over 20 weeks, our data set was collected from patient with a single fetus with a gestational age of 14-week to 20-week. Hence, there were 14 ultrasound videos. Again, we only extracted image sequences from the first second of the video, hence there were 70 frames in total in the experiment. Table 1 shows the result of our segmentation method comparing with the expert's opinion. From table 1, we can see that the average segmentation error is around 2.17%. Some of the error occurred because ROI2 covered more area than it was supposed to be. For example, ROI2 of frame from ultrasound video no. 8 as shown in figure 7 covers some other parts that are not parts of fetus's chest. There is a brighter area on those parts, hence, when the algorithm selects the ribs, one of the ribs will be on that part not on the actual rib. This will cause the size of ROI2 bigger than it is supposed to be. And the algorithm will select the wrong size of the SE in the opening operator. Hence, the algorithm will discard some of the correct areas and it will produce smaller heart chambers.

TABLE I. SEGMENTATION RESULTS

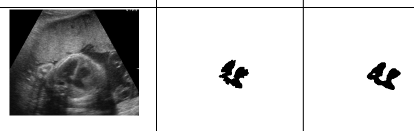
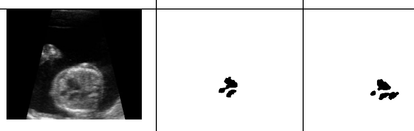
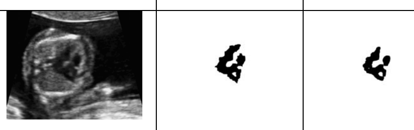
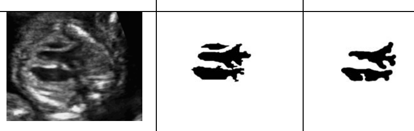
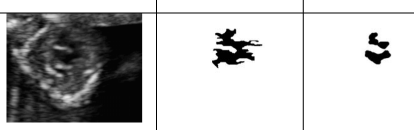
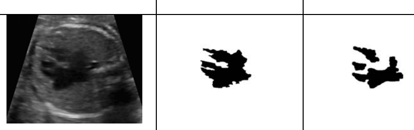
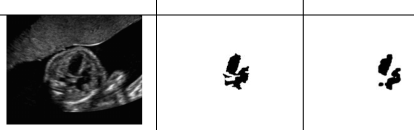
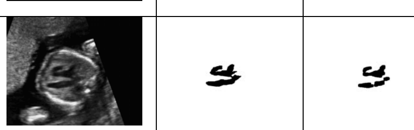
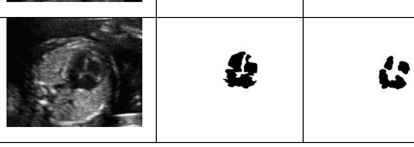
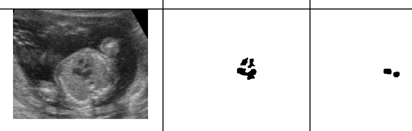
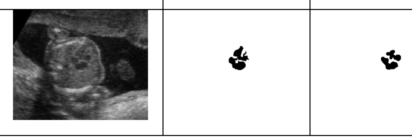
No.	**System segmentation result and expert's segmentation**			
	Original image	***Expert result***	***Our proposed algorithm***	***Segmentation error (%)***
1				0.92
2				0.69
3				0.88
4				3.20
5				2.27
6				2.93
7				3.69
8				1.08
9				1.00
10				2.65
11				0.95
12				3.74
13				1.12
14				0.72
Average Segmentation Error				2.17

Figure 7. Sample error in which ROI2 covers some other parts that are not parts of fetus's chest.

IV. CONCLUSION

An early sign of hemoglobin Bart's disease (the most dangerous thalassemia in Thailand) can be detected early in the fetus with gestational age until 20-week using cardiomegaly indicator. Fetus cardiomegaly, an abnormal enlargement of heart, can be detected by measuring cardiothoracic ratio or CT ratio. The first step in an automatic CT ratio measuring system, the heart chambers segmentation is required. Therefore, in this paper we develop an automatic heart chambers segmentation method using the patch-based possibilistic c-means (PCM). We first utilize the Horn-Schunck's optical flow algorithm to extract the first region of interest (ROI) that is supposed to contain the heart chambers, to find the frames with end diastolic and end systolic. Then we extract the second ROI that is supposed to contain the fetus chest. Finally, we perform patch-based PCM in the second ROI. We compare our results with the expert's opinion. We found out that the algorithm performs well according to the comparison, i.e., approximately 2.17% segmentation error on the average.

However, there are some errors occurring from the post process because of the size of structuring element in opening operator.

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