



ELLIPSE DETECTION ON EMBRYO IMAGING USING RANDOM SAMPLE CONSENSUS (RANSAC) METHOD BASED ON ARC SEGMENT

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Submitted: Mar. 31, 2016 Accepted: July. 21, 2016 Published: Sep. 1, 2016

Abstract- In Vitro Fertilization (IVF) is a method which is used to help couples who have a fertility problem. One of the problems of IVF is the success rate, which is only about 30%. One cause of the problem is the embryo morphology observation done by embryologist manually. Morphologically normal embryo does not mean the embryos are genetically normal. The aforementioned phenomena can be tested by using time lapse recording in which unavailable in the manual observation. Therefore it is very important to establish method for time lapsed recording of the embryos. This can be done by automatic observation on the embryo image, where the first step is to create a system that can automatically detect the embryo. This paper proposed Random Sample Consensus (RANSAC) method based on Arc Segment to automatically detect embryo.

From the experiment that have been conducted, the proposed method can detect single and multiple ellipse on embryo with a better accuracy than the previous method, EDCircles by 6% and 3% for single and double respectively.

Index-terms: EDCircles, RANSAC, Ellipse Detection, Blastomere, Embryo

I. Introduction

In Vitro Fertilization (IVF) technology has been growing rapidly to help couples who have problems (in the reproductive organs) in having children. IVF is conducted by taking a mature ovum from the mother's womb and then it will be injected with a sperm to ensure the fertilization of ovum.

The fertilized ovum is called an embryo. Embryos were observed for approximately 3-5 days and it will be ranked ranging from grade A (highest) to F (lowest) [1]. Embryo with the highest grade will then be replaced into the mother's womb.

Determination of the embryo grades can be done in two methods, manual observation and automatic observation. Manual observation method observe images of the embryo on the first day until the fifth day manually. When the use of IVF technology is becoming more frequent, there problems arise in manual observation method. First of all, the doctor can not follow the cleavage time by looking morphologically only the second, third, fourth, or fifth day after fertilization. Secondly, it is possible that the information will be lost in the manual observation, especially during the cleavage of embryo. The aforementioned problems can be tackled with automatic observation. Nevertheless, automatic observation requires a very high cost to purchase the technology. Therefore, the determination of embryo grades requires a method with more affordable cost. Moreover, it could also provide an important information that can assist the process of selecting an embryo that will be replaced into the mother's womb.

To create a system that can automatically provide the information required by the embryologist, the embryo detection process needs to be done at an early stage, especially detection of blastomere. This process could be used to determine the morphological characteristics of an embryo, such as asymmetrical levels, diameter, fragmentation and the number of blastomere. Observation on the morphology of embryo is the initial stage of embryo grade determination. If the morphology is not in accordance with the desired criteria, then the other factors will not be considered. However, if the morphology is met, then the observation will be continued on the other factors, ie *zona pellucida* and *time-cleavaged* [1]. Thus, embryo morphology plays

an important role in determining the grade. In this paper, we focused on the detection of blastomere with single and multiple ellipse. This approach is used because the shape of blastomere is similar to an elliptical shape, and there are more than one ellipse to be detected (embryo on the second day).

1. Related work

Studies on automatic embryo detection to determine its quality are rarely conducted. Based on the literature review there are three researches with the purpose to detect the embryo conducted by Habibie [2], Elshenawy [3] and Cicconet [4]. Habibie [2] conducted research on 2D image of embryos on the first day embryos. The main method used is Particle Swarm Optimization (PSO) based Hough Transform, where circle detection approach is used to detect an embryo in the first day after fertilization. It presented good results to detect single circle on embryo image. However, this method has drawback because it could not detect multi circle or ellipse on embryo image that will be studied in this research. Elshenawy [3] used embryos images on the second day. The study was conducted by comparing several approaches for embryo detection, like Hough Transform and template matching. It used sobel edge detection method to get the edge from the embryo image. However, the results contained a lot of noise which is extracted as an edge. Cicconet [4] who proposed a method for ellipse fitting of microscopic images which is mouse-embryo. The proposed method can not extract the edge of the embryo image dataset on this paper, so the impacts on poor performance of the ellipse detection.

In contrast to research on embryo detection, studies of ellipse detection has been widely applied by many researchers. It is implemented in various fields, such as surveillance and monitoring, agriculture, industrial, and biomedical applications. Generally, methods for ellipse detection could be divided into three categories [5]. The first category is ellipse detection using least square. Fitzgibbon [6] use Direct Least Square (DLS) method which performs the detection process without iteration so that the computation time is fast. However, this method does not result an optimal solution when all of the point to be estimated is located in an ideal position and it is also not resistant to noise. The DLS method was developed by Kanatania [7] into hyper least square fitting to improve the accuracy of DLS result.

The second category is ellipse detection by Hough Transform voting. One of the studies included in this category is the research that has been conducted by Wei Lu and Jinglu Tan [8] by proposing an Iterative Randomized Hough Transform (IRHT) that improves the Random-

ized Hough Transform (RHT). IRHT using Region of Interest (ROI) to reduce the search area of ellipse with the *k-iteration* until the parameter of an ellipse is converge to indicate that the elliptical has been detected.

The third category is ellipse detection using statistical method, evolutionary algorithm, and combination of the existing methods. One of the studies that is included in this category is the research by H.D Cheng et al [9] which combines the evolutionary algorithm with Hough Transform, and also used Particle Swarm Optimization (PSO) to speed up the computation process by spreading a swarm on edge pixels and the fitness function in this case is ellipse parameter. Swarm will move to the point or parameters which have the highest fitness function, thus the ellipse can be detected. Other studies that are included in the third category is EDCircles [10]. EDCircles use the part of ellipse, which is called arc segment, to detect circular objects or an ellipse. The advantages of EDCircles is low computation time and it is parameter free to extract edge from input image. Akinlar [10] used EDCircles method to detect multi ellipse by extracting edge lines in synthetic and natural images that contain circular objects, like coins, car wheels, watches, and iris. However, the weakness of EDCircles is there are many arc that is missing in the process of arc formation, so it could affect the detection result. Moreover, EDCircles can not detect ellipse with dashed lines. The drawback of EDCircles for embryo detection can be solved by modifying the arc segment, but this modification produced a lot of noise.

Random Sample Consensus (RANSAC) can be used to overcome that noise problems. In this paper, we use RANSAC based arc segment method for multiple ellipse detection from embryo image on the first and second day (which that single and also multiple embryo in the image). RANSAC modification using arc segment is an extension of EDCircles which is resistant to noise, improving the existing methods. It also provided a better result than the previous embryo detection method.

In Fatichah et. al. works [11], they also try to solve the overlapping white blood cell on microscopic blood cell images. In their research, they use mathematical morphology method to determine the structuring element of the cell, especially size and shape. White Blood Cell (WBC) need special treatments by using image segmentation to be detected and counted because the image has different characteristic.

We have already developed a meta-heuristic method for ellipse detection on embryo images by modifying ArcPSO method [12]. The idea of ArcPSO algorithm is based on combining

possible arcs for the ellipse shaped objects and try to find the best combinations using Particle Swarm Optimization technique to find the actual ellipse. The modification that we have already produced is represented in our previous work [13]. In previous research, we proposed an ellipse detection method on single and multiple embryo image by modifying the ArcPSO method on ellipse fitting process and the process on extract the arc segment for ellipse detection.

This paper proposes a method that can be used as part of our big the research. As The main contribution of this paper, embryo detection is the focus on this paper as well as the first stage of our research. The details of this research in general are described in Figure 1.

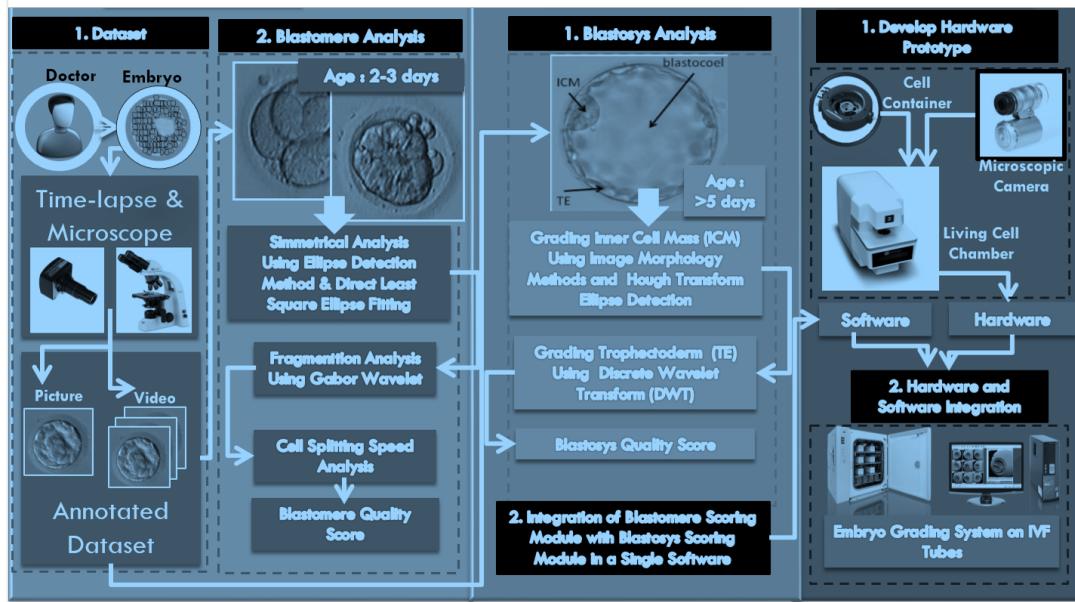


Figure 1: Research on Embryo Grading System

At this early stage, we have done with embryo object detection in the image. The detection of these cells was using RANSAC technique that utilizes statistical aspects. For further development, we will also conduct image segmentation for increasing the accuracy of embryo cell segmentation. Then, by using existing segmentation techniques we will get a better segmentation result. Next, the segmentation results will be assessed by using such a segmentation benchmark as developed by dewanto et.al. [14]. And at the end of this research will aim to make a telehealth system as in Figure 1. To make the system more efficient and effective, the system required compression techniques to transmit data (time-lapsed video) that will be analyzed by an expert (embryologist) in distant places. Then, we need some compression techniques such as in [15], because for each frame of time-lapse embryos video has many similarities that can be reduced by using the compression technique like 3D Set Partitioning In Hierarchical Trees

(SPIHT) algorithm.

The remainder of this paper is organized as follows: In Section 2 we briefly describes the methods used to detect an ellipse (single and multiple) in embryo images. Details of data set, implementation, and experiments is described briefly in Section 3. An analysis and evaluation about the significance of the results in this work are also described in Section 3.

II. Method

1. Data Acquisition

Data used in this paper is an embryo digital image on the process of In Vitro Fertilization (IVF) in the first and second day after fertilization which is performed in Yasmin IVF Clinic, Dr. Cipto Mangunkusumo General Hospital - Jakarta, Indonesia. The dataset consists of 88 embryos where 20 images contains up to one blastomere. There are more than one ways to capture embryo data, such us laser scanning microscopy [16] and camera which used in this research. Each embryo is photographed using Nikon Eclipse Ti equipped with Sony SSC-DC88P and cropped manually to get individual embryo because the image contained multiple embryo. The data captured by the camera is used to monitor embryos development.

2. EDCircles

The foundation of this paper is a research conducted by Akinlar [10] which developed EDCircles method to detects circular and elliptical objects, either single or multiple objects. EDCircles is a real time method which can perform multiple circle and ellipse detection with a fast computational time. This method can also extract edges from the embryo image that are used in this research. EDCircles method uses a grayscale image as an input process and it consists of six main stage as could be seen in Figure 2.

In the first stage after receiving a grayscale image as an input data, edge segment detection will be done using Edge Drawing Parameter Free (EDPF) method [17]. EDPF is an algorithm which uses Edge Drawing (ED) [18] as the main method. ED algorithm is used to connect the edge, where the edge with maximum value will be compared with its neighboring pixels, in the form of dots (as done by a child when drawing an object). The second stage is convert the edge segment, which is the result of the first stage, into line segment using EDLines method [19]. The idea of EDLines algorithm is combining lines, starting from a short line that meets

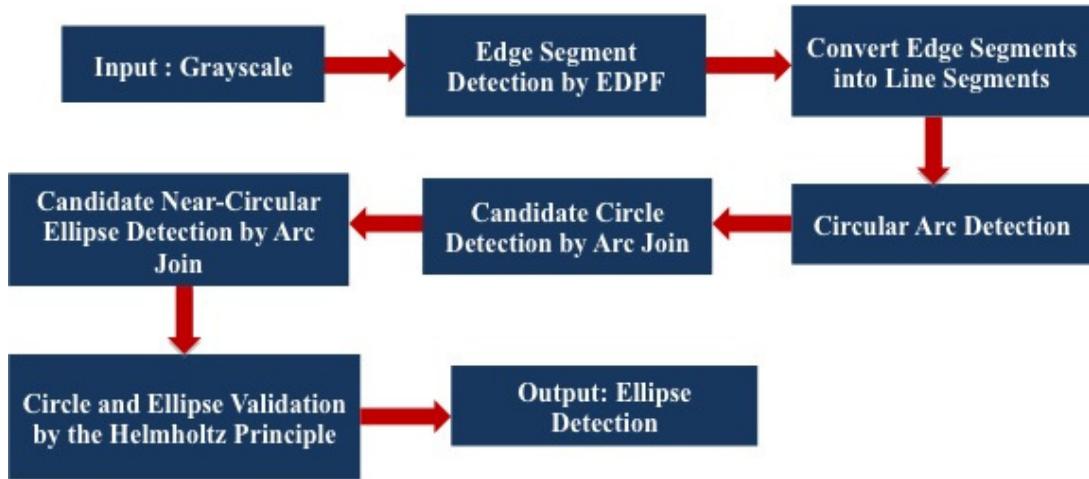


Figure 2: EDCircles main stage

the criteria and then merged with another line as long as possible and the Mean Square Error (MSE) value is less than the threshold.

The third stage is the process of combining the line segment into a circular arc. The idea of this process is to combine at least three lines which have the same direction and the angle between two lines corresponds to the threshold, [10] mentioned that the appropriate angle is in the range of 6 to 60 degrees. In the fourth and fifth stage, the EDCircles algorithm looks for circles and ellipse candidates that meet the specified criteria. There are two necessary criteria to detect circular arc as a circle or ellipse candidate. These two criteria are *radius different* and *center distance constraint*. Radius different constraint is minimum radius of the circular arc so that it can be used as a circle candidate with arc join, that is equal to 25% of another arc radius. For example, as can be seen in Figure 3, radius of A1 is 100 therefore the arc that has a radius in the range of 75-125 can be used as an arc joint candidate. The next criteria is the center distance constraint which is the central point of the arc, so that it can be used as circle candidate, which is not more than 25% of arc radius. For example, radius of A1 is 100 so 25% of A1's radius is 25 pixel, so that the arc whose center point is at 25 pixels from radius of A1 can be used as a circle candidate.

The fifth step has similarities with the fourth step. The difference from the previous step is the criteria that should be met for radius different and center distance constraint is now 50%. Illustration of ellipse candidate search process can be seen in Figure 4. A2 arc in Figure 4(a) can not be an ellipse candidate because the radius difference constraint is more than 50%, thus the A3 and A4 arc are used as an ellipse candidate with A1. In Figure 4(b), A4 does not meet the center distance constraint, so that A1, A2, and A3 will be an ellipse candidate with A1 arc.

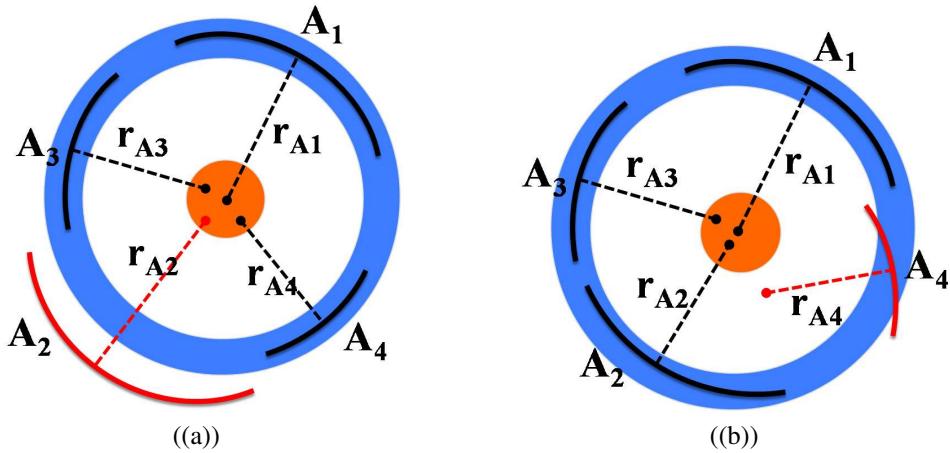


Figure 3: Process to Find The Circle Candidate

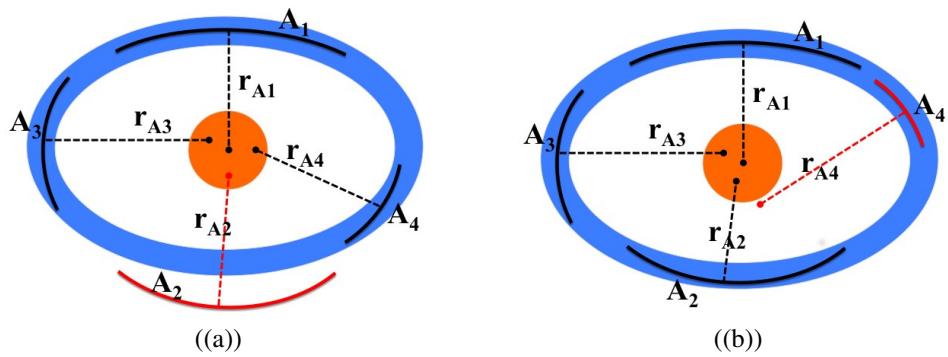


Figure 4: Process to Find The Circle Candidate

In the last stage, circle and ellipse candidate search results will be validated using Helmholtz algorithm [20, 21]. The idea of this algorithm is to find outliers which is the object of a set of background. Helmholtz calculation process is done by calculating the angle between the gradient magnitude and the line angle level at pixel in the (x,y) position. Gradient magnitude of pixel at (x,y) position is calculated with this following formula:

$$g_{x,y} = \frac{I(x+1,y) - I(x,y) + I(x+1,y+1) - I(x,y+1)}{2} \quad (1)$$

$$g_{x,y} = \frac{I(x,y+1) - I(x,y) + I(x+1,y+1) - I(x+1,y)}{2} \quad (2)$$

$$g_x = \sqrt{g_x(x,y)^2 + g_y(x,y)^2} \quad (3)$$

$$\alpha = \angle g_x g_y = \arctan\left(\frac{g_x(x,y)}{-g_y(x,y)}\right) \quad (4)$$

3. Advantages of EDCircles

EDCircles [10] has been proved that has a better performance compared with cvHoughCircles and evolutionary algorithm, such as GRCD-R variant of RCD (Randomized Circle Detection), which uses synthetic and natural images containing circular object as an input image. EDCircles has high accuracy rate when performing circle detection. This is caused by a mechanism that validates the result to detect ellipse that call helmholtz principle. The other advantage of EDCircles is the ability to extract edge segment from input image using EDPF (Edge Drawing Parameter Free). It has also been measured that EDPF [17] produced clean, contiguous and one-pixels wide edges segment compared to canny edge detection and LSD (Line Segment Detection) [22]. Another advantage of EDCircles method is the low computational time to detect circle or ellipse.

4. EDCircles Modification

From the six stages in EDCircles method, we make several modifications on the third stage, while the fourth until sixth stage will be changed to RANSAC ellipse fitting to optimize the detection result. This paper eliminates circle detection arc join process because we will detect embryos with ellipse detection approach. Thus, the process flow of ellipse detection in this study is shown in Figure 5.

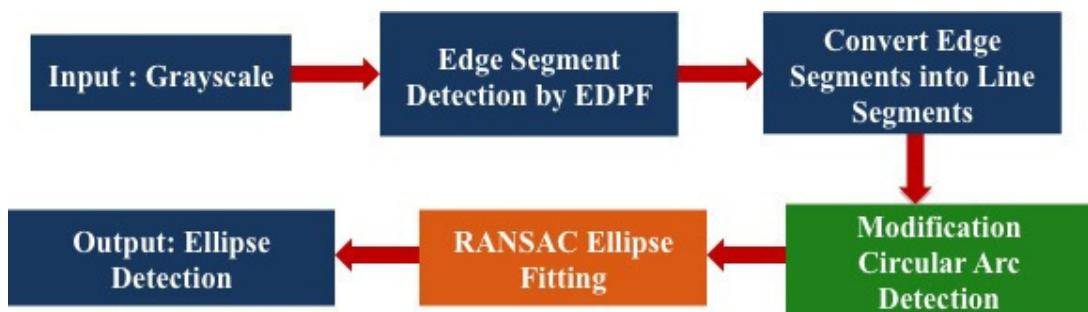


Figure 5: Modified Process of EDCircles

5. Modification of Circular Arc Detection

The standard method used by EDCircles [10] to convert line segment into arc segment is shown in Algorithm 1. From the result of standard arc grouping algorithm on embryo dataset, the generated arc segment has several shortcomings because many line segments are missing as shown

in Figure 6(a), so the standard EDCircles method can not detect an ellipse precisely. Figure 6(b) is an embryo data sample that can not be detected by standard EDCircles method. To overcome that shortcoming, we conducted modification of arc grouping as shown in Algorithm 2.

The different process between Algorithm 1 and 2 is the process to form arc segment. The Algorithm 1 exclude the line segments that does not meet the requirement to form an arc segment in previous step. So it is causes few arc segment formed in some embryo image. Algorithm 2 is made to handle this drawbacks by including all the line segmens that do not belong to any of the arc segment.

Algorithm 1 Standard Arc Grouping

```

1: procedure FINDPOTENTIALARCLINES( $v_1..v_n$ )
2:    $\triangleright v_1..v_n$  is list of line segment  $\triangleright$  MinimumAngle is 6 degrees and MaximumAngle is
   60 degrees
3:    $i \leftarrow 1$ 
4:   while  $i < n$  do  $\triangleright$  Find an initialization line
5:     for  $i \leftarrow 1, n$  do
6:       if  $\Theta_i \geq \text{MinimumAngle} \&&$ 
7:          $\Theta_i \leq \text{MaximumAngle}$  then break
8:     for  $j \leftarrow i + 1, j < n$  do
9:       if  $sign_j \neq sign_i$  then
10:        break  $\triangleright$  The different angle
11:       if  $\Theta_j < \text{MinimumAngle} \parallel$ 
12:          $\Theta_j > \text{MaximumAngle}$  then break
13:       if  $j - i + 1 \geq 3$  then
14:         ExtractArcsFromLines( $v_i..v_j$ )  $\triangleright$  at least 3 lines
15:          $i \leftarrow j$   $\triangleright$  Looking for arc segment again

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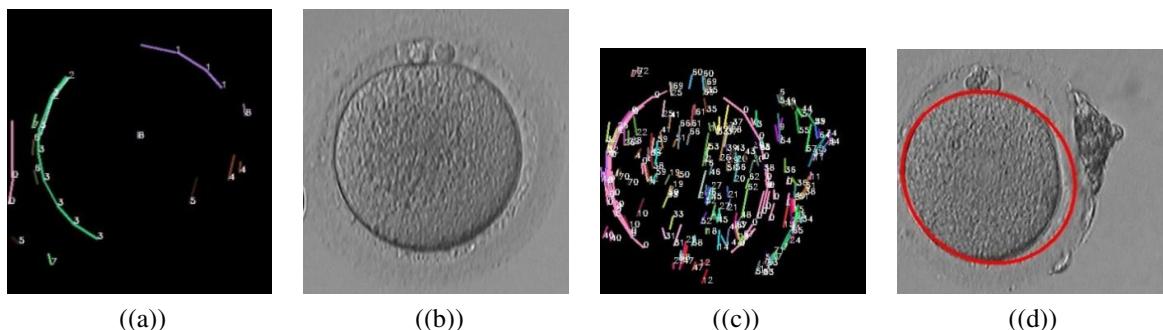


Figure 6: 6(a). Result of Standard Arc Segment, 6(b). Embryo data sample which can't be detected, 6(c). Result of Modified Arc Segment, 6(d). Detection result using Modified Arc Segment

Algorithm 2 Modification of Arc Grouping Part 1

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1: procedure FINDPOTENTIALARCLINESMODIF( $v1..vn$ )
2:    $\triangleright v1..vn$  is list of line segment  $\triangleright$  MinimumAngle is 6 degrees and MaximumAngle is
   60 degrees
3:   for  $x \leftarrow 0, x < n$  do
4:     while  $y < n$  do
5:       if  $statusLoop3 == false$  then
6:         if  $linesegmentdistance <$ 
7:            $distancethreshold$  then
8:             if  $\theta_i \geq MinimumAngle \&&$ 
9:                $\theta_i \leq MaximumAngle$  then
10:               $statusLoop3 \leftarrow true$ 
11:               $addLineSegment$ 
12:                 $\triangleright$  and give a flag to the line that has been processed
13:                break
14:       if  $statusLoop3 == true$  then
15:         for  $zz \leftarrow y + 1, zz < n$  do
16:           if  $linesegmentdistance <$ 
17:              $distancethreshold$  then
18:               if  $sign_y == sign_{zz}$  then  $\triangleright$  different angle
19:                 if  $\theta_j < MinimumAngle \&&$ 
20:                    $\theta_j > MaximumAngle$  then
21:                      $rmse \leftarrow FitCircle(vi..vnow)$ 

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Algorithm 3 Modification of Arc Grouping Part 2

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22:   if  $rmse < 1.5$  then
23:      $addLineSegment$   $\triangleright$  and give a flag to the line that has been
   processed
24:      $statusIncrementLoop2 \leftarrow false$ 
25:     break
26:   if  $statusIncrementLoop2 == true$  then
27:      $yy+ = 1$ 
28:   else if  $statusIncrementLoop2 == false$  then
29:      $statusIncrementLoop2 \leftarrow true$ 
30:   if  $LineSegment \geq 2$  then
31:      $addLineSegmentToListArc$   $\triangleright$  and remove the line that has been processed
            $\triangleright$  Looking for arc segment again
32:    $statusLoop3 \leftarrow false$ 
33:    $yy \leftarrow 0$ 

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Modification of the arc have an impact on the arc results with more noise, as can be seen in Figure 6(c). This will affect the EDCircles's detection results, which is not optimal for detecting ellipses as shown in Figure 6(d), or in some cases is not able to detect an ellipse. Therefore we need a method that can detect an ellipse on the data that has noise. Based on the literature

study, we use RANSAC method to detect ellipse with noise conditions.

6. Random Sample Consensus

Random Sample Consensus (RANSAC) is a sampling method that uses minimal subset to detect model. This sampling method is also robust to noise. The standard algorithm of RANSAC to detect an ellipse consists of five steps:

1. Initialize the number of iteration.
2. Choose five point randomly, then made an ellipse model using that selected point.
3. From the obtained ellipse model, determine how many points which inlier (fit) the model with certain threshold, and insert it into a vector of inlier points.
4. If inlier point satisfy the threshold, the ellipse fitting will be performed on that inlier points along with another points that have been randomized previously.
5. If inlier points does not satisfy the threshold and the iteration is less than a predetermined number of iterations, then return to the second until the fourth step.

7. Modification of RANSAC

In this paper, RANSAC is used to detect an ellipse from the collection of arc segment. The reason for choosing an arc for ellipse detection process is because it can speed up the computation time while processing an image. This is due to the fact that not all of edge pixels in the embryo image are processed. Implementation of RANSAC to detect an ellipse using arc segment is a modification of arc grouping method on EDCircles [10]. The stage of modified RANSAC process can be seen in Figure 7.

1. Determine the iteration that will be used to detect an ellipse in a set of arc segment. Illustration of a set of arc segment can bee seen in Figure 7(a). This image consist of 6 arc segments is A1, A2, A3, A4, A5 and A6. An arc segment is a collection of line segments, consisting a minimum of 2 line segment.
2. To create an ellipse model, three arc segments will be selected from a set of arc segments. Selection of the first arc segment is random. The second arc will be selected based on a threshold distance between the two arc segments. The third arc segment will be selected in the same way as the second arc segment, which is based on the distance of the first or the second arc segment. After getting these three arc segments, the next step is to create

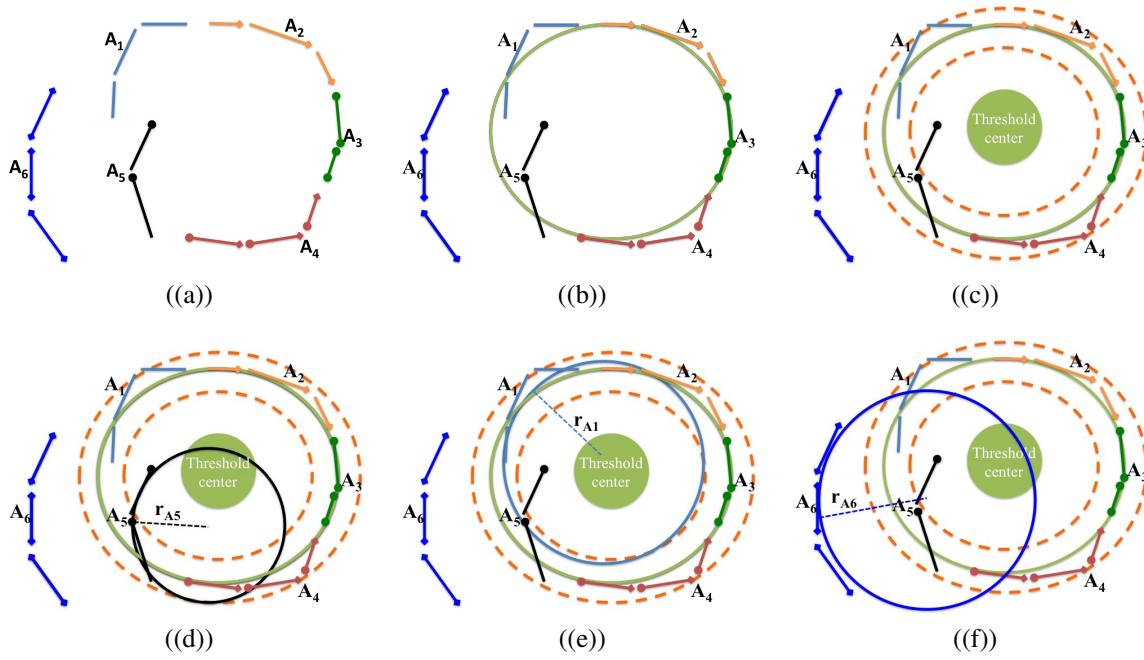


Figure 7: 7(a). A Set of Arc Segment, 7(b). Selection of three arc segment, 7(c). Calculate the threshold of center point and ellipse fitting, 7(d). Detection result using Modified Arc Segment, 7(e). Example of Arc which inlier, 7(f).Example of Arc which not inlier because the radius does not satisfy the threshold

an ellipse model using that arc segment. This selection process can be seen in Figure 7(b). In this image, arc segment A2, A3 and A4 are chosen.

3. The next step is to calculate the threshold of center point and radius by comparing the shortest length of semi-major and semi-minor, then multiplying it by inlier tolerance specified by the user. Illustration of the calculation can be seen in Figure 7(c).
4. After calculating the threshold, the next step is to check the whole arc which inliers to an ellipse model that have been obtained, as shown in Figure 7(d), 7(e), and 7(f). The calculation process of arc which inlier with the model is:
 - a) Perform a circle fitting to an arc, so that the circle parameter will be obtained (xc , yc , and r).
 - b) Calculate the distance between the center point of ellipse and circle in the range that has been determined in accordance with input parameters from the previous step.
 - c) If the distance to the center point satisfies the threshold, calculate the difference between radius of circle and have semi-minor or semi-major on the ellipse which has the shortest length. If the distance between circle radius and major or minor axis satisfies the threshold, that arc will be inserted on inlier vector.

d) After processing the whole arc, calculate an inlier arc segment. If the length of that arc segment satisfies 35% of the first ellipse perimeter's length, which 35% is based on experiment in section 4. After that it is considered valid and do an ellipse fitting to arc which inliers, and it will not be printed. If not, then the RANSAC process will return to the second step, which is the process of selecting arc segment randomly, as long as the iteration is less than the input iteration and arc segments are greater or equal to three. There are two example of invalid ellipse, Figure 7(d) is an invalid ellipse because the radius of the arc segment (A5) is outside the threshold centre and Figure 7(f) is invalid ellipse because the arc segment is outside the inlier threshold center. The Figure 7(e) is a valid ellipse because it fulfills both requirement of radius threshold and inlier threshold.

8. Evaluation Metrics

We evaluate the performance of the algorithm by measuring accuracy, recall, F-measure and execution time with formula as follow:

$$precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \quad (5)$$

$$recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)} \quad (6)$$

$$F - measure = \frac{2 * precision * recall}{precision + recall} \quad (7)$$

True Positive (TP) represents the condition when the algorithm can detect an exist blastomere correctly. False Positive (FP) represents the condition when the algorithm detect a blastomere that does not exist or detect a same blastomere more than once. False Negative (FN) represents the condition when the algorithm failed to detect an exist blastomere. High precision value show that a method gives relevant results (correctly detected) more than irrelevant result (incorrectly detected), and high recall value showed that a detection method gives results which are mostly relevant. While the F-measure is calculated to measure the overall performance of detection methods. The highest value of the F-measure is 1 while the lowest value is 0.

III. Results

Experiment on several scenario were conducted to test the performance of proposed method then compared with EDCircles as baseline methods [10] and fast ellipse detection method [23]. The proposed method is implemented in C++ using IDE Microsoft Visual Studio Professional 2010, OpenCV 2.4.8 library for image processing and EDLines binaries on <http://ceng.anadolu.edu.tr/CV/downloads/downloads.aspx> for line extraction. The EDCircles using demo code on <http://ceng.anadolu.edu.tr/CV/EDCircles/demo.aspx>. The dimension of embryo image is ranging from 300 to 600 pixels for single embryo image and 200 to 400 pixels for multi embryo image.

1. Comparison of Methods

Table 1: *Line Distance Parameter*

Line distance	Validation	Precision	Recall	F-Measure	Stdev-Fmeasure	Mean
10	0.15	0.708573727	0.463235294	0.559931912	0.022920153	0.507408953
	0.25	0.817276498	0.432352941	0.565374062	0.021178969	
	0.35	0.921322396	0.357352941	0.514544932	0.022464674	
	0.45	0.972153423	0.244117647	0.389784905	0.023485707	
20	0.15	0.724893332	0.494117647	0.587148755	0.024546147	0.560294198
	0.25	0.863281449	0.433823529	0.577326312	0.026436421	
	0.35	0.918182435	0.410294118	0.566907149	0.023974814	
	0.45	0.930336342	0.351470588	0.509794575	0.02625684	
25	0.15	0.716764464	0.494117647	0.584230182	0.036660043	0.498846618
	0.25	0.811731419	0.398529412	0.53398532	0.01935425	
	0.35	0.850462236	0.323529412	0.468364813	0.020053979	
	0.45	0.871043176	0.267647059	0.408806158	0.037557828	
30	0.15	0.759706773	0.501470588	0.603748537	0.031128589	0.520385185
	0.25	0.784628354	0.420588235	0.546957904	0.027543047	
	0.35	0.858496092	0.345588235	0.49242352	0.021292967	
	0.45	0.951542228	0.285294118	0.438410777	0.02845287	
40	0.15	0.797516869	0.45	0.575183331	0.020396946	0.490235205
	0.25	0.816544652	0.369117647	0.508062031	0.016665537	
	0.35	0.89437728	0.329411765	0.480145954	0.041389155	
	0.45	0.914661654	0.254411765	0.397549503	0.036619159	

Before comparing the performance, we have conducted experiments to determine the effect of parameters used on the detection accuracy and also to obtain the best parameters for each

Table 2: Inlier Distance Parameter

Inlier Distance	Validation	Precision	Recall	F-measure	Stdev-Fmeasure	Mean
0.1	0.15	0.724893332	0.494117647	0.587148755	0.024546147	0.560294198
	0.25	0.863281449	0.433823529	0.577326312	0.026436421	
	0.35	0.918182435	0.410294118	0.566907149	0.023974814	
	0.45	0.930336342	0.351470588	0.509794575	0.02625684	
0.2	0.15	0.75100556	0.651470588	0.697449717	0.031738271	0.71184328
	0.25	0.862314548	0.647058824	0.738957015	0.026906881	
	0.35	0.888957878	0.635294118	0.740600933	0.029193354	
	0.45	0.914005464	0.529411765	0.670365457	0.032557844	
0.3	0.15	0.914005464	0.529411765	0.670365457	0.032557844	0.741767065
	0.25	0.740527365	0.720588235	0.729817857	0.026130785	
	0.35	0.889953358	0.720588235	0.796117911	0.02107728	
	0.45	0.880826825	0.685294118	0.770767034	0.024655876	
0.4	0.15	0.671247435	0.736764706	0.701993105	0.018623692	0.74059386
	0.25	0.759181452	0.722058824	0.739930005	0.027658831	
	0.35	0.801666319	0.717647059	0.757112389	0.039597276	
	0.45	0.864340779	0.683823529	0.76333994	0.020677103	
0.5	0.15	0.620020397	0.691176471	0.653505869	0.02609165	0.685708498
	0.25	0.65237771	0.669117647	0.660427633	0.035604734	
	0.35	0.723595552	0.680882353	0.701344269	0.027362897	
	0.45	0.768567703	0.691176471	0.727556219	0.027074026	

type of data. Parameters used in this exploration are: (a) *Line segment distance*, a parameter that is used to limit the maximum distance of line segment which will be converted into arc segment; (b) *Arc segment distance*, a parameter that is used as an arc distance constraint to model the first ellipse; (c) *Arc distance that inlier with ellipse models*, a tolerance percentage on the arc segment which is considered inlier with ellipse models; (d) *Validation*, a parameter for determining ellipse detection is valid or invalid. If ellipse detection is valid then ellipse is superimposed to the input image and otherwise. Table 1, 2, and 3 are experiment result in order to select the parameter that gives optimal result on ellipse detection in a single embryo image.

Parameter selection is conducted in 3 scenarios:

1. The first scenario aims to select line distance that has the highest mean average of F-measure. It could be seen on table 1 that line distances with 20 pixels value has the highest mean average, so this value will be used in the next scenario to get another parameter.
2. The second scenario aims to choose inlier parameters, as can be seen in table 2, linear

Table 3: Arc Distance Parameter

Arc Distance	Validation	Precision	Recall	F-measure	Stdev F-measure	Mean
10	0.15	0.740527365	0.720588235	0.729817857	0.026130785	0.76692041
	0.25	0.889953358	0.720588235	0.796117911	0.02107728	
	0.35	0.880826825	0.685294118	0.770767034	0.024655876	
	0.45	0.924047537	0.661764706	0.770978836	0.0242832	
20	0.15	0.559276925	0.825	0.666316745	0.027527533	0.772285854
	0.25	0.760693958	0.835294118	0.795890016	0.032446237	
	0.35	0.805013459	0.804411765	0.804522753	0.026502846	
	0.45	0.858158536	0.789705882	0.822413902	0.03256539	
30	0.15	0.569487574	0.833823529	0.676515529	0.029604299	0.782225036
	0.25	0.739847562	0.847058824	0.789716017	0.03355343	
	0.35	0.823583235	0.841176471	0.832102648	0.034797077	
	0.45	0.855376133	0.807352941	0.830565952	0.028429149	
40	0.15	0.600575361	0.857352941	0.706034118	0.036163298	0.790077756
	0.25	0.736206172	0.852941176	0.790090569	0.044413988	
	0.35	0.820898244	0.847058824	0.83369261	0.031424436	
	0.45	0.833294037	0.827941176	0.830493725	0.017253755	

parameter with 0.3 percent has the highest mean average, so this parameter is chosen and combined with line distance parameter in order to choose the last parameter.

3. The last scenario is to choose arc distance parameter and the result can be seen in table 3. It shows that the arc distance with 40 pixels value give the highest mean average. We then choose the validation parameter with arc distance that has highest F-measure value. From the experiment result on table 3, 0.35 validation value has the highest F-measure value. From this parameter exploration, we obtain four values that represent the best parameter: 20 for line distance parameter, 0.3 for inlier distance parameter, 40 for arc distance parameter and 0.35 for validation parameter. To see the performance of our proposed method using the four parameter that has been selected, the detection results were compared with EDCircles and Fast Ellipse Detection Method. These three values parameter will also be used on the data of multi embryo.

The experiment on multiple embryo detection used the best parameter that give the optimum result on detecting a single embryo. We conducted the experiment 10 times to see whether or not the proposed method is reliable. This is because our proposed method is using random value to choose the arc segment for ellipse detection. The experiment results on multiple embryo can be seen on table 4. The overall performance of our proposed method, which is represented

Table 4: *F-measure Result on Multiple Embryo*

Loop	Precision	Recall	F-measure
1	0.837837838	0.492063492	0.62
2	0.695652174	0.507936508	0.587155963
3	0.756097561	0.492063492	0.596153846
4	0.864864865	0.507936508	0.64
5	0.744186047	0.507936508	0.603773585
6	0.790697674	0.53968254	0.641509434
7	0.75	0.476190476	0.582524272
8	0.8	0.507936508	0.621359223
9	0.794871795	0.492063492	0.607843137
10	0.846153846	0.523809524	0.647058824
Mean	0.78803618	0.504761905	0.614737828
Stdev	0.052580016	0.018020515	0.02305227

by F-measure value average, is 0.614737828. While the reability of the proposed method is represented by standard deviation of F-measure value from 10 experiments, the smaller of standard deviation value it will be more reliable because stdev is used to measure variation of data value set. The stdev value of our proposed method is 0.02305227. This value is small enough because it is near to zero value so it can be said that the proposed method has stable performance to detect multiple ellipse on an embryo image.

2. Performance evaluation

The experiment result on single embryo detection can been seen on Figure 8. In the first input (Figure 8a) both method could detect embryo correctly, but with input Figure 8d and 8g shows that EDCircles failed to detect the embryo. Embryo detection is represented by center, axis mayor, axis minor and angle. The ground truth of ellipses are marked manually using ellipse labeling in <https://sites.google.com/site/dilipprasad/source-codes>. Detection result in single embryo will be regards as a correct detection if the difference between detected parameter and ground truth are less than 13 pixels or approximately 10% of ground truth parameter. But for multi embryo image, it will regards as correct detection if method could detect most region of embryo, because of overlapped and occluded ellipse on an image. So it is very difficult to detect precisely on the multi embryo data. The experiment result on

multi embryo detection can be seen on Figure 9.

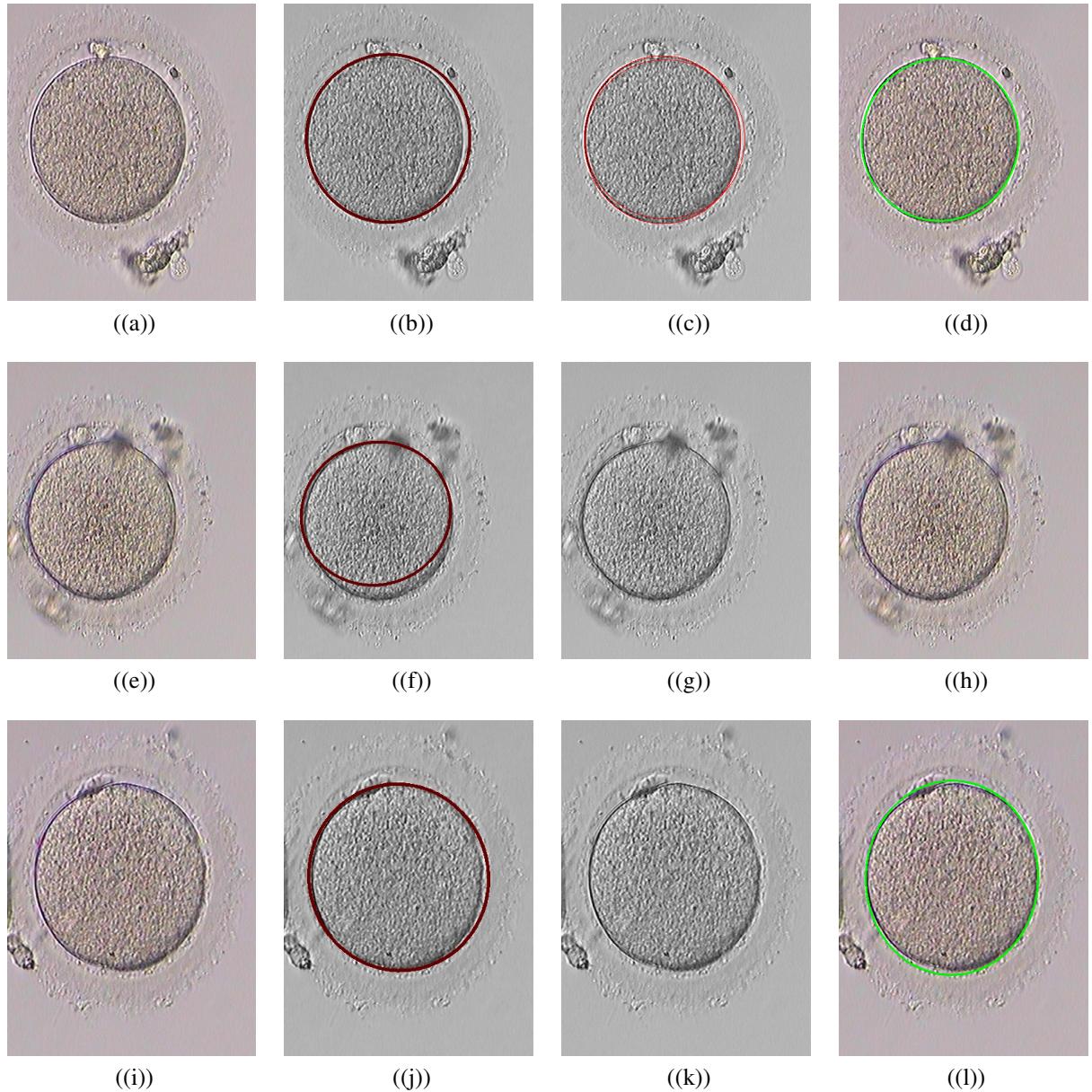


Figure 8: Experiment Result of Ellipse Detection On Single Embryo Image. [8(a), 8(e), 8(i)] Example of input image, [8(b), 8(f), 8(j)] Detection result using the proposed method, [8(c), 8(g), 8(k)] Detection result using EDCircles, [8(d), 8(h), 8(l)] Detection result using fast ellipse detection method.

The performance evaluation of single embryo detection and multi embryo detection can be seen on figure 10(a) and figure 10(b). The overall performance is represented by F-measure value. On the single embryo detection result, the proposed method gave a better result than EDCircles and Fast Ellipse Detection method, with delta accuracy approximately 6%. And on multi embryo detection result, the proposed method give delta accuracy approximately 3%.

The next performance evaluation from both method is comparing the execution time to detect

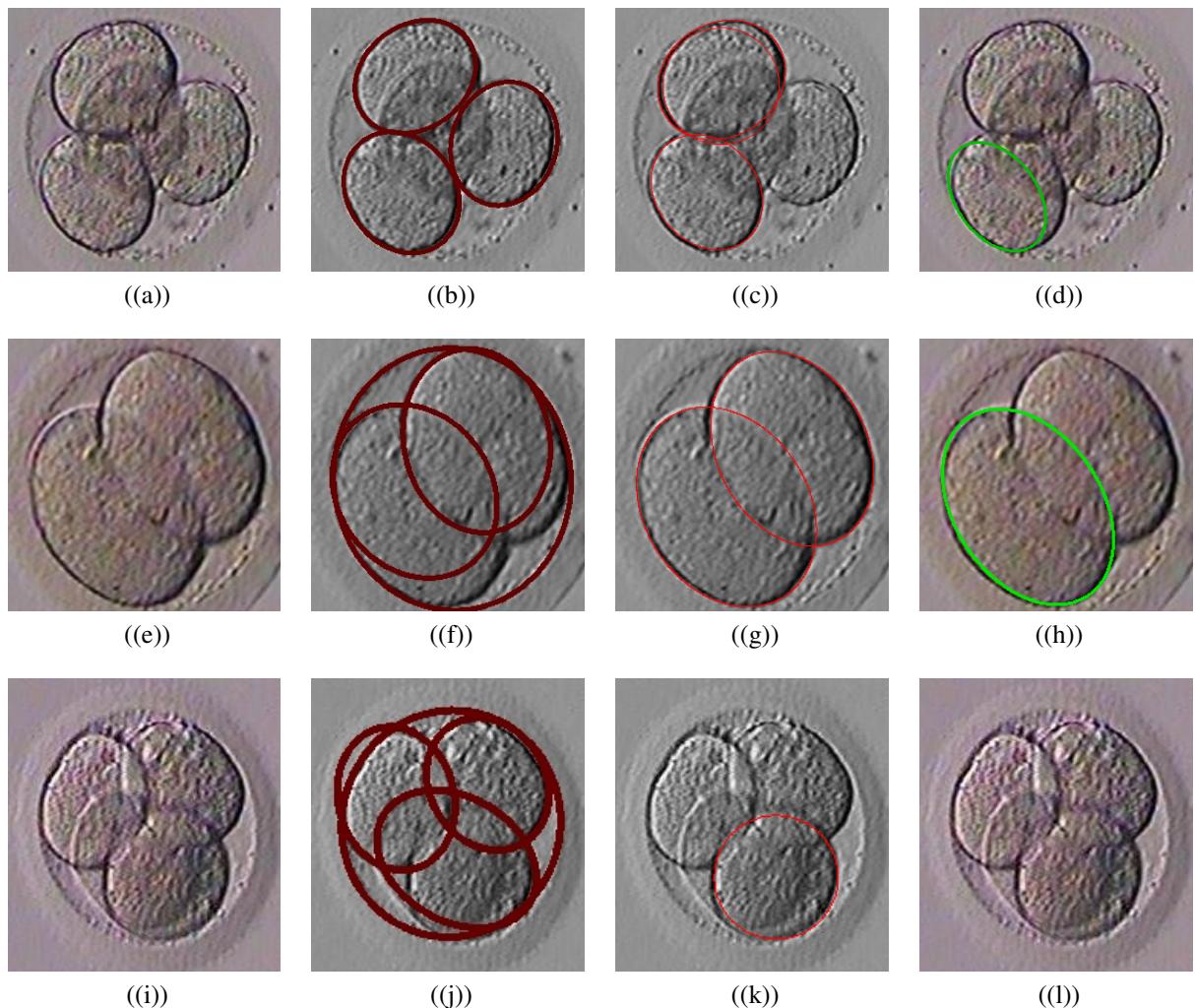
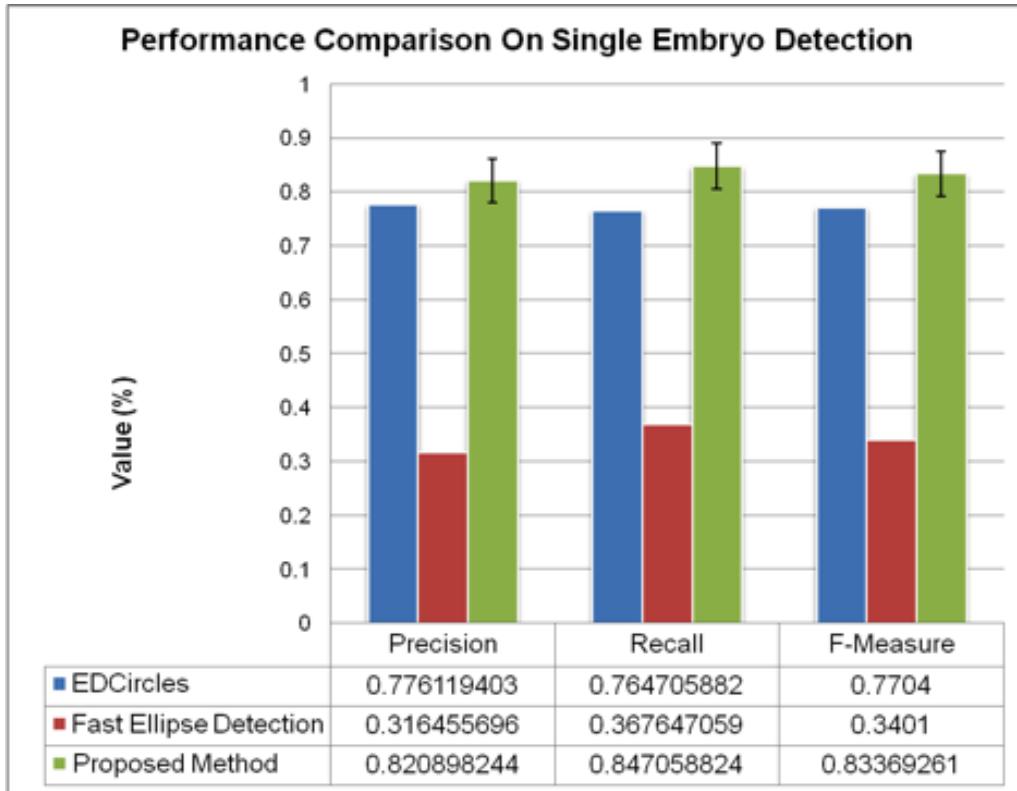
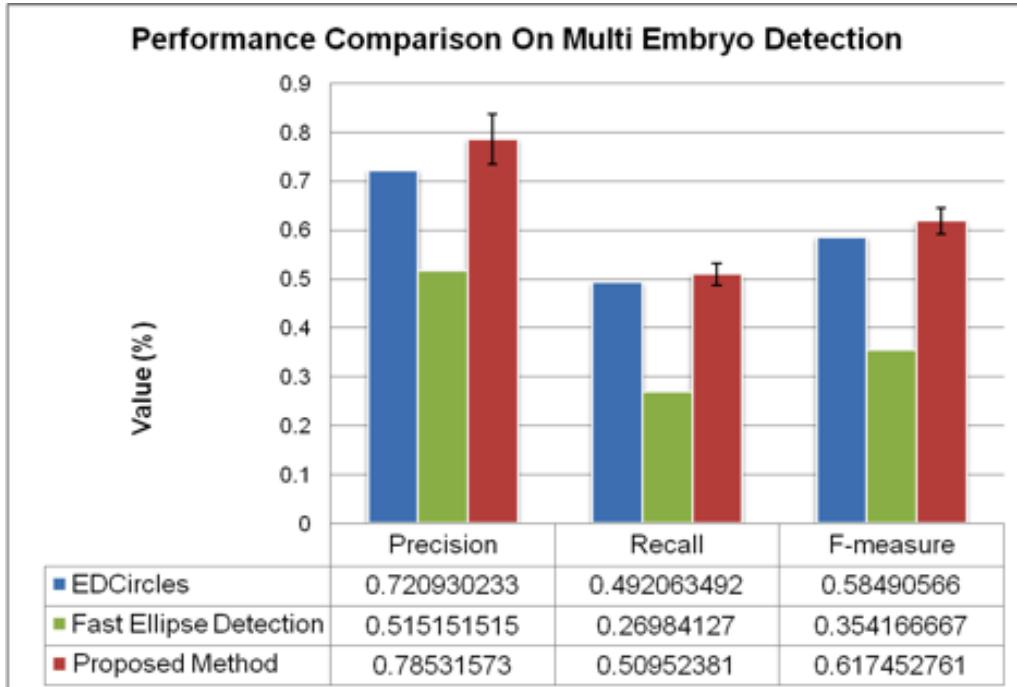


Figure 9: Experiment Result of Ellipse Detection On Multiple Embryo Image. [9(a), 9(e), 9(i)] Example of input image, [9(b), 9(f), 9(j)] Detection result using the proposed method, [9(c), 9(g), 9(k)] Detection result using EDCircles, [9(d), 9(h), 9(l)] Detection result using fast ellipse detection method.



((a))



((b))

Figure 10: Comparison Result in Single and Multiple Embryo

ellipse. The result of execution time can be seen on figure 11. The execution time of the proposed method is slower than EDCircles. This is caused by many arc segment have to be

processed compared with the EDCircles method. Although it is slower than EDCircles, it is relatively fast because it is less than 0.5 seconds and is not very far for EDCircles. And the execution time on single embryo image slower than multi embryo image because the larger dimension of single embryo image.

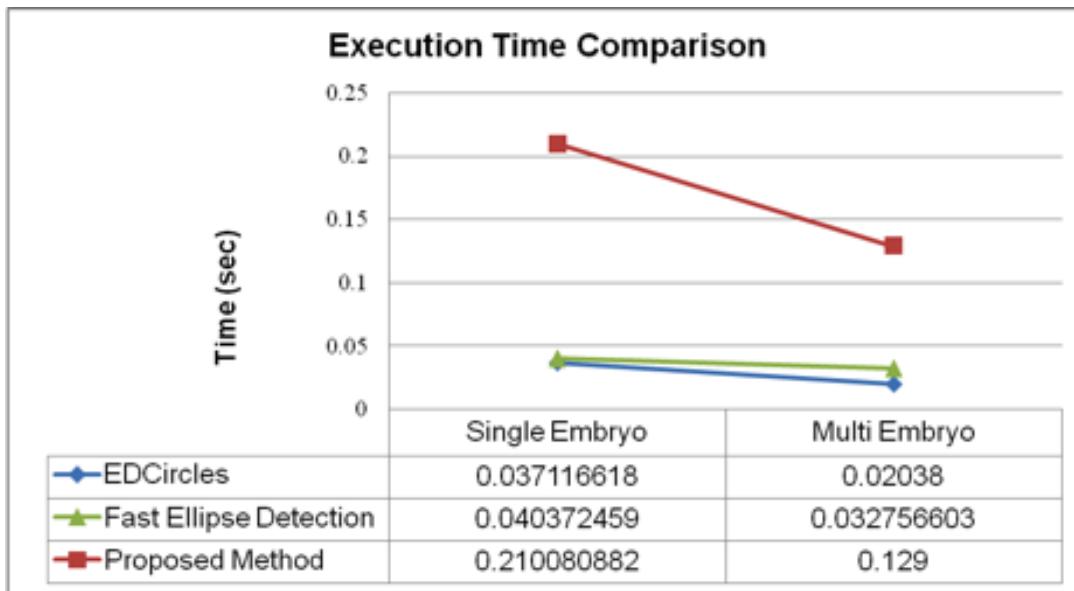


Figure 11: Execution Time Comparison

IV. Conclusion

Randomized Sample Concensus (RANSAC) based arc segment is proposed to improve EDCircles for detecting ellipse on an embryo image. EDCircles is used as a baseline method because EDCircles can extract the edges from input image, especially embryo image that can not be done by standard edge detection like canny edge detection. Based on the experiment it can be concluded that the proposed method improve the performance of EDCircles for ellipse detection on embryo image because it has a mechanism to handle noise of arc segment by using modification of RANSAC method. The proposed method gave the difference F-Measure value 6% to detect single embryo image and 3% to detect multiple embryo image. The accuracy to detect multiple embryo image should be improved if it will be implemented in industry, because the accuracy is still below 70%.

Acknowledgement

This research was supported by Universitas Indonesia and Directorate General of Higher Education, in part of Grant 2013 "Penelitian Unggulan Perguruan Tinggi", entitled "Sistem Peman-tauan Cerdas Penentu Kualitas Embrio Manusia pada Fertilisasi In-Vitro". And also in part of grant "Penelitian Unggulan Perguruan Tinggi" No: 0523/UN2.R12/HKP.05.00/2015, entitled "Pengembangan Sistem Penilaian Kualitas Embrio pada Bayi Tabung".

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