Automatic Fetal Head Detection in Ultrasound Images by An Improved Iterative Randomized Hough Transform

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***Abstract*—This paper describes an improved iterative randomized Hough transform (IRHT) method for automatic fetal head detection on ultrasound images. The traditional IRHT method iteratively updates a region of interest in the image space based on the latest ellipse parameters estimated by randomized Hough transform (RHT). The noise pixels are gradually excluded from region of interest during the iteration process, and the estimation becomes progressively close to the target. However, owing to the absence of considering the number (N) of pixels on ellipse, the parameters of final detected ellipse are relatively volatile and the iterative time is also unstable. For this reason, the result for each iteration in our improved IRHT method is selected as the detected ellipse with the maximal number of pixels on ellipse, which is picked from the top-M peaks in the accumulators of the whole detected ellipse samples. The experiments on fetal ultrasound images demonstrate that the proposed method achieves more robust and accurate results, and has a better performance for fetal head detection than IRHT method.**

Keywords- fetal ultrasound image; fetal head detection; ellipse detection; iterative randomized Hough transform (IRHT)

I. INTRODUCTION

Fetal head detection and segmentation on ultrasound images is an important primary step for many clinical applications, such as fetal growth evaluation [1], gestational age estimation [2], fetal weight estimation [3], and obstetric diagnosis [4], etc. However, owing to the discontinuity and irregularity of fetal head skulls, low resolution and signal-to-noise ratio of ultrasound images, it is quite challenging for surgeons to recognize it manually and also manual analysis is always time-consuming. Therefore, automated or semi-automated medical image processing [5-9] should be used to ensure a better effective, precise and consistent measurement.

Hough transform (HT) [10], Randomized Hough Transform (RHT) [11] and Random Sample Consensus (RANSAC) [12] are several typical techniques for ellipse detection, but they may fail when the strong noise can corrupt the curve peaks in the parameter space. An novel method named iterative randomized Hough transform (IRHT) [8] was proposed for the detection of incomplete ellipses under strong noise conditions. Though the traditional IRHT method can detect an incomplete ellipse with strong noise successfully, its efficiency and accuracy can still be enhanced further. In this research, we introduce the number (N) of pixels on ellipse to propose an improved IRHT method for fetal head detection. Then, the result for each iteration in the improved IRHT method is selected as the detected ellipse with the maximal number of pixels on ellipse, which is picked from the top-M peaks in the accumulators of the whole detected ellipse samples. The experiments on fetal ultrasound images demonstrate that the proposed method achieves more robust and accurate results, and has a better performance for fetal head detection than IRHT method.

The rest is organized as follows: Chapter 2 introduces the improvements on pre-preocessing, the traditional IRHT method, and improved IRHT method, Chapter 3 presents the experiments on fetal ultrasound images, and also provides the comparison of two methods, Finally, Chapter 4 gives a conclusion.

II. ALGORITHM

A. Pre-processing

For fetal head detection on ultrasound images, the skeletons of fetal head skulls should be extracted as the bright object in pre-processing. On the other hand, because speckle noise is often superimposed into ultrasound images, a bilateral filter [13] with a 5×5 window is exploited to reduce the speckle noise and preserve edge by a nonlinear combination of nearby image values. Subsequently, a white top-hat transform in mathematical morphology is operated to increase the contrast through a 11×11 structuring element.

After that, K-means clustering algorithm [14] is applied to distinguish the bright object from gray object and background, which aims to segment all image pixels into k clusters where each pixel belongs to the cluster with the nearest mean. In this way, the mean value μ_i and standard deviation σ_i $(i = 1, \dots, k)$ of each cluster can be calculated from segmentation results. Since K-means method is sensitive to noise, the bright object separated from segmentation results will be corrupted by much noise. Through considering the detection of incomplete ellipses with strong noise via IRHT method, we only need to extract the basic skeletons of fetal head skulls. Therefore, it is not essential to extract the whole bright object comprising much noise.

In order to suppress the noise impact in K-means method, we make use of a global thresholding to convert the intensity image into a binary image, then the bright object can be extracted from the background by a simple operation that compares image gray values with a threshold value *T*. The following threshold value *T* verified in experiments, is adapted to extract bright object.

$$T = \mu_{k-1} - 0.75 \times \sigma_{k-1} \tag{1}$$

Where, μ_{k-1} is the mean value of bright object, σ_{k-1} is the standard deviation of bright object (Here, we suppose the bright object is classified into *k-1* cluster).

As for binary image, a binary morphologic opening operation with a 2×2 structuring element is used to remove small bright objects. Morphologic dilation with a 1×1 structuring element and closing with a 2×2 structuring element are used to smooth the boundaries of large bright objects. After a series of pre-processing, the skeletons of bright object are extracted by distance transform [15].

B. Iterative randomized Hough transform

On ultrasound images, fetal head skulls often appear as the bright object with some gaps, because fetal head skulls are not completely closed. Besides, some other structures also may generate bright spots in an image. Furthermore, various artifacts and noise are usually present on ultrasound images. Consequently, a useful head detection algorithm must effectively deal with these disturbances. The iterative randomized Hough transform (IRHT) [8] was recently developed for the detection of ellipse with large gaps and strong noise, derived from randomized Hough transform (RHT) [11] method. The following parts will make a brief description of the RHT algorithm and IRHT algorithm.

1) Randomized Hough transform (RHT)

In a binary image, the curve to be detected can be modeled by $f(c, z) = 0$, where $c = [\alpha_1, \ldots, \alpha_2]^t$ comprises *n*-dimensional parameters, $z = (x, y)$ represents the coordinates of pixels on the curve. The RHT first randomly takes a sample of *n* pixels, $z_i = (x_i, y_i), i = 1, \ldots, n$, and maps this sample into one point $c \in R^n$ in the *n*-D parameter space by solving a set of *n* equations $f(c, z_i) = 0$. If *c* is valid for ellipse, the counter at c is increased by one in the parameter space and stored in its corresponding accumulator. This process is repeated until a predefined number of valid samples (K) are processed. The location of the counter peak in the accumulators denotes a remarkable possibility of the curve in the image. For ellipse detection ($n = 5$), the following equation is suitable to be utilized [16, 17] :

$$x^2 + y^2 - U(x^2 - y^2) - V2xy - Rx - Sy - T = 0 \tag{2}$$

where, the five parameters, $[U, V, R, S, T]^t$, can be converted into standard ellipse parameters $c = [x_0, y_0, a, b, \phi]^t$, (x_0, y_0) are the center coordinates of the ellipse, a and b are its major and minor semi-axes, and ϕ is the angle of rotation, then the ellipse eccentricity is given by $e = b/a$ and

$$U = \cos 2\phi \frac{1-e^2}{1+e^2} \tag{3}$$

$$V = \sin 2\phi \frac{1-e^2}{1+e^2} \tag{4}$$

$$R = 2x_0(1-U) - 2y_0V \tag{5}$$

$$S = 2y_0(1+U) - 2x_0V \tag{6}$$

$$T = \frac{2a^2b^2}{a^2+b^2} - \frac{x_0R}{2} - \frac{y_0S}{2} \tag{7}$$

U and *V* depend only on ϕ and *e*. In particular, for a circle, *U* and *V* are zero.

2) Transform Formulas

In order to obtain the standard ellipse parameters $c = [x_0, y_0, a, b, \phi]^t$, we deduce the following formulas based on (3) – (7).

$$x_0 = \frac{SV + R + RU}{2(1-U^2-V^2)} \tag{8}$$

$$y_0 = \frac{RV + S - SU}{2(1-U^2-V^2)} \tag{9}$$

$$a = \sqrt{\frac{2T + x_0R + y_0S}{2(1-\sqrt{U^2+V^2})}} \tag{10}$$

$$b = \sqrt{\frac{2T + x_0R + y_0S}{2(1+\sqrt{U^2+V^2})}} \tag{11}$$

$$\phi = \frac{1}{2}\arctan\frac{V}{U} \tag{12}$$

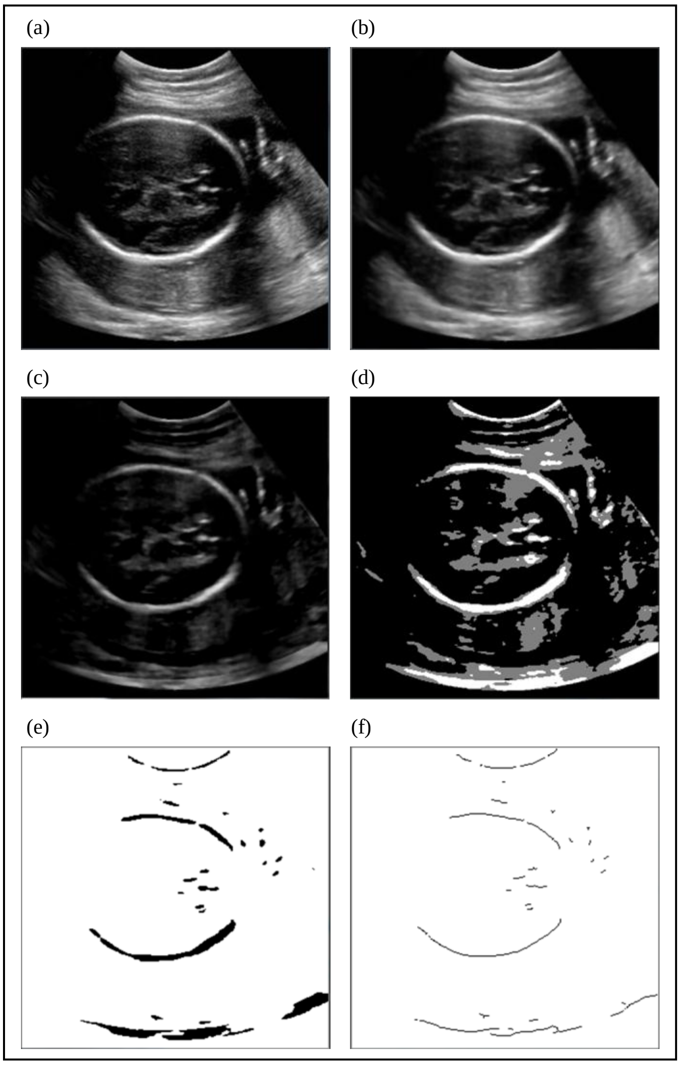
3) Improved iterative randomized Hough transform

Region of interest (ROI), as a new technique was imported into IRHT method with the purpose for reducing noise interference of the whole image. In RHT method, ROI delimited to a whole image does not change all the time, which makes RHTs select samples with equal probability from all pixels including noise pixels. In IRHT method, ROI shrinks into a smaller rectangular region enclosing detected ellipse from last iteration rather than all pixels in the image, and then an improved detection would be achieved since the probability of selecting pixels from the curve is increased.

On the basis of the principle of IRHT method, we further introduce the number (N) of pixels on detected ellipse, and the detected ellipse with the maximal number of pixels on ellipse, which is picked from the top-M peaks in the accumulators of the whole detected ellipse samples, is accepted as the result on each iteration for updating the region of interest (Herein, M is selected as 10). In addition, a slightly larger rectangular region is drawn as ROI to compensate for uncertainties in the detected ellipse. This iterative process continues until the size difference of ROI between two iterations is very small, and the detected ellipse in the final iteration is the terminal result. Moreover, the convergence conditions in this process are as follows, less than 2.5° in ϕ; less than 2 pixels in each of $x_0, y_0, a\ and\ b$; and less than 6 pixels total in $x_0, y_0, a\ and\ b$.

III. EXPERIMENTS

Fetal ultrasound images are provided by Nanjing Maternity and Child Health Care Hospital in China, which had been achieved the consent of each mother in this research. For the purpose of enhancing the performance of the algorithm, the priori information, reported by Hadlock et al. [2], is applied into our improved IRHT method, which shows that the eccentricity $e = b/a$ of the human fetal head has a mean (μ_e) of 0.783 and a standard deviation (σ_e) of 0.044. It could be used to construct a constraint as $\mu_e - 3\sigma_e \leq e \leq \mu_e + 3\sigma_e$, namely, $0.651 \leq e \leq 0.915$, and about 99.7% of fetal heads would have an eccentricity in this range.



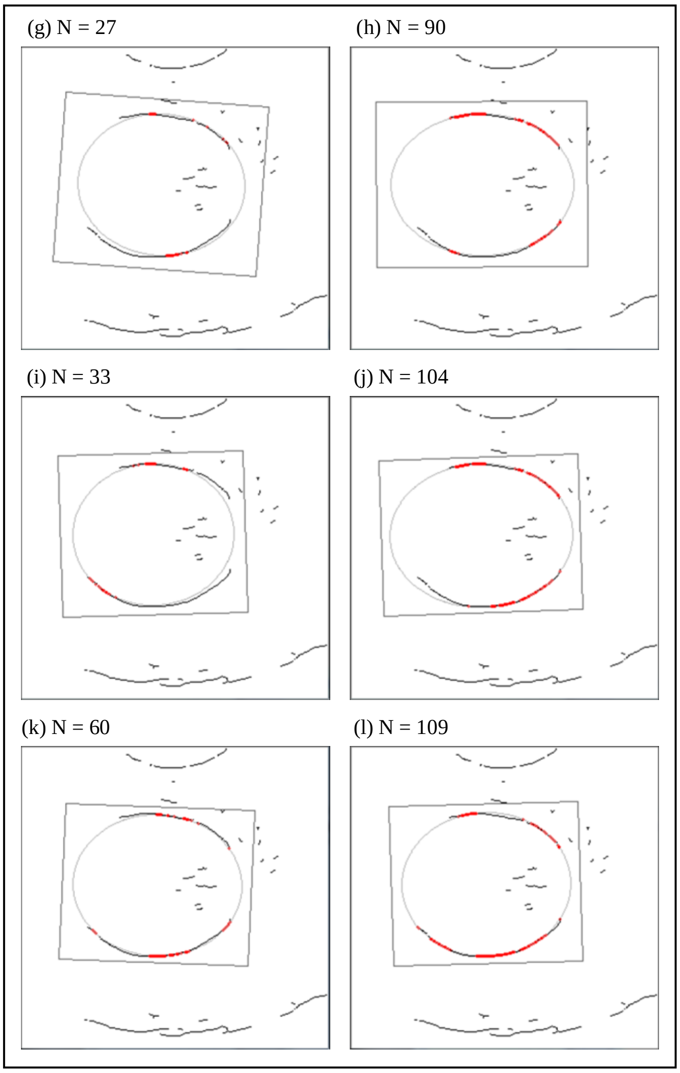


Figure 1. The Skeletonization and detection of fetal head skulls on ultrasound images. (a) a clinical fetal ultrasound image; (b) the result of a bilateral filter with a 5×5 window on (a); (c) the result of a white top-hat transform with a 11×11 structuring element on (b); (d) the segmentation result of K-means clustering method on (c); (e) the restult of a global thresholding with a threshold valut T defined in (1) on (a); (f) the skeletons of bright object extracted by distance transform from (e); (g) the detected ellipse and ROI of IRHT method after 1st iteration (N = 27); (h) the detected ellipse and ROI of improved IRHT method after 1st iteration (N = 90); (i) the detected ellipse and ROI of IRHT method after 2nd iteration (N = 33); (j) the detected ellipse and ROI of improved IRHT method after 2nd iteration (N = 104); (k) the final detected ellipse and ROI of IRHT method after 13th iteration (N = 60); (l) the final detected ellipse and ROI of improved IRHT method after 6th iteration (N = 109).

Fig. 1 describes the procedure of skeletonization and fetal head detection on fetal ultrasound images. (a) depicts a clinical fetal ultrasound image. (b) depicts the result of a bilateral filter with a 5×5 window on image (a). (c) depicts the result of a white top-hat transform with a 11×11 structuring element on image (b). (d) depicts the segmentation result of K-means clustering method on image (c). (e) depicts the result of a global thresholding with a threshold value T defined in (1) on image (a). (f) depicts the skeletons of bright object extracted by distance transform from image (e). (g), (i) and (k) depict detected ellipses and ROIs (region of interest) after 1st, 2nd, and

13th iteration by IRHT method (the detected ellipse after 13th iteration is the final result of IRHT method), and their numbers of points on detected ellipses are N = 27, N = 33, and N = 60. (h), (j), and (l) depict detected ellipses and ROIs after 1st, 2nd, and 6th iteration through our improved IRHT method (the detected ellipse after 6th iteration is the final result of our method), and their numbers of points on detected ellipses are N = 90, N = 104, N = 109. Compared with the results of IRHT method, the numbers of points on detected ellipses of our method on each iteration are much larger, and at the same time the iterative time is also much smaller. Therefore, the results of our improved IRHT method are quite closer to ground truth, and the efficiency is quite better than that of IRHT method.

Table 1. Comparison of the parameters on estimated ellipses by IRHT and Improved IRHT method for 10 times

Num	IRHT						
	x_0	y_0	a	b	ϕ	T	N
1	135	138	83	71	4.71	8	99
2	134	140	84	69	2.64	7	56
3	133	140	83	70	1.00	28	51
4	132	137	86	70	-1.59	6	34
5	137	138	85	70	-3.04	36	41
6	131	138	86	72	4.23	19	41
7	135	138	80	71	4.08	10	107
8	131	138	82	71	2.56	5	56
9	135	139	88	71	4.39	3	68
10	136	138	85	71	-2.33	7	60
$\boldsymbol{\mu}$	134	138	84	71	1.67	**13**	**61**
$\boldsymbol{\sigma}$	*2.08*	*0.97*	*2.30*	*0.84*	*2.98*	*11.10*	*24.24*

Num	Improved IRHT						
	x_0	y_0	a	b	ϕ	T	N
1	135	137	86	72	1.04	4	115
2	131	137	90	72	-1.18	18	91
3	135	137	87	72	-1.16	9	110
4	133	137	89	72	0.22	4	91
5	135	137	85	72	1.78	7	109
6	133	137	86	72	-1.15	3	84
7	135	138	87	71	1.16	6	109
8	132	138	90	71	0.33	2	94
9	134	137	88	72	1.16	3	92
10	131	137	90	72	0.00	3	90
$\boldsymbol{\mu}$	133	137	88	72	0.22	**6**	**99**
$\boldsymbol{\sigma}$	*1.65*	*0.42*	*1.87*	*0.42*	*1.09*	*4.77*	*10.97*

Table 1 illustrates the comparison of the parameters on detected ellipses by IRHT and improved IRHT method for 10 times, and the last two lines list the mean value μ and the standard deviation σ averaged by the estimated parameters of 10 groups. Among these data, we find out the standard deviations σ of each estimated parameter by our improved IRHT method are all less than those of IRHT method, which means the results of our method are more robust and consistent than the results of IRHT method. Furthermore, T denotes the iterative time of the algorithm, and its mean value of our method is less than half of that value of IRHT method, which means the efficiency of our method is greatly improved. N denotes the number of points on detected ellipse, and its mean value of our method is nearly 1.5 times than that of IRHT method, which also means the results of our method are more accurate than the results of IRHT method.

IV. Conclusion

In this paper, we have proposed an improved iterative randomized Hough transform (IRHT) method for automatic fetal head detection on ultrasound images. Through the pre-processing based on the gray feature of ultrasound images, we could extract the basic skeletons of fetal head skulls and remove the noise maximally at the same time. To improve the efficiency and stability of IRHT algorithm for the detection of incomplete ellipses with strong noise, we introduce the number of pixels on ellipse and select the ellipse with the maximal number of pixels on detected ellipse as the result on each iteration. The experiments on fetal ultrasound images demonstrate that the proposed method achieves more robust and accurate results, and has a better performance for fetal head detection than IRHT method.

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