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AN ACCURATE AND ROBUST FETAL HEAD DETECTION ALGORITHM INTEGRATING A VOTING SCHEME AND AN IMPROVED IRHT METHOD

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ABSTRACT

To achieve accurate and robust detection of fetal heads in US (ultrasound) images, this paper proposes a method that integrates a voting scheme and an improved iterative randomized Hough transform (IRHT) method. First, a skeleton image is extracted from the input US image by pre-processing. Next, the voting scheme, which applies the improved IRHT method to detect ellipses from the skeleton image, is repeated P times, in each of which, if the difference between each detected ellipse's parameter values and each parameter values saved in the list is small, the accumulator of the nearest values in the list is incremented by one (voting); otherwise, the detected parameter values are appended to the list. Finally, the ellipse with the most voted values in the list is outputted as the final detection result. As a result of experiments that use 24 US images captured under different conditions, it turns out that the proposed method achieves a very high ellipse detection rate of 95.3%±6.86%, which is much higher than IRHT and improved IRHT.

1. INTRODUCTION

In recent years, thanks to safety, low cost and noninvasiveness, ultrasound (US) images are frequently applied in prenatal clinic examination for fetal growth evaluation [1], gestational age estimation [2], and fetal weight estimation [3], etc. To evaluate fetal growth, head circumference (HC) is one of the important biometric measurements. However, due to the discontinuity and irregularity of fetal head skulls, low resolution and signal-to-noise ratio of US images, the procedure of fetal head detection could be experience dependent and time consuming for medical doctors.

To solve the above-mentioned problem, a number of automatic or semi-automatic methods have been developed for ensuring a better effective, accurate and consistent HC measurement. Randomized Hough Transform (RHT) [4], Random Sample Consensus (RANSAC) [5], Iterative Randomized Hough Transform (IRHT) [6] are typical techniques for fetal head measurement by ellipse detection, but they may fail when strong noises corrupt the peaks in the parameter space, which results in a poor consistent measurement. Though some learning based methods [7, 8] are proposed to detect fetal heads for a better performance by introducing learning architectures, they often applied IRHT or Hough Transform for ellipse detection and inevitably lead to the same problems of those methods. In addition, the authors have proposed an improved IRHT method [9] for achieving more robust and accurate results by introducing the number (N) of pixels on the ellipse, but it can achieve only an unsatisfied detection rate due to noise curves on which there are quite many pixels.

In order to acquire a consistent measurement and a high detection rate despite the noise curves, we propose an effective voting scheme based on the improved IRHT method [9] for detecting fetal heads in US images contaminated by strong noises. First, pre-processing extracts a skeleton image from the input US image. Next, the improved IRHT method detects ellipses from the skeleton image, which is repeated P times. Meanwhile, an ellipse list is created and a voting for each detected result saved in the ellipse list is executed. Finally, the peak (with the most votes) in the ellipse list is outputted as the final detection result.

2. ALGORITHM

2.1. Overview

Figure 1 illustrates the proposed method, which exploits a voting scheme based on the improved IRHT [9]. First, a skeleton image is extracted from the input US image by pre-processing (Sec. 2.2). Next, the voting scheme (Sec.

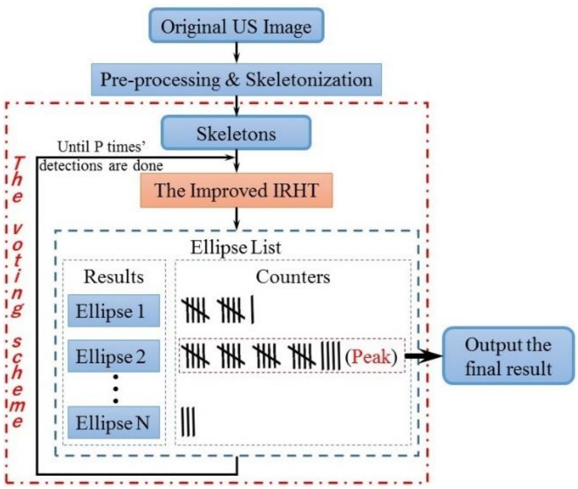


Figure 1. Overview of the propose method.

2.4) is carried out as follows. The improved IRHT method is applied to detect ellipses from the skeleton image (Sec. 2.3). This process is repeated P times, in each of which, if the difference between each detected ellipse's parameter values and each parameter values saved in the list is small, the accumulator of the nearest values in the list is incremented by one (voting); otherwise, the detected parameter values are appended to the list. Finally, the peak (with the most votes) in the list is outputted as the final ellipse detection result.

2.2. Pre-processing

For detecting the fetal head in the US image, the skeletons of the fetal head skull should be extracted as (a) bright region(s) by pre-processing. Since speckle noise is often superimposed into US images, a bilateral filter [10] with a 5×5 window is utilized to reduce the speckle noise and preserve the edge, where the standard deviations both in the color space and coordinate space are set to 50 in the experiments. Subsequently, a white top-hat transform in mathematical morphology is operated to increase the contrast with an 11×11 window.

After that, the K-means clustering algorithm [11] is applied to distinguish the bright region(s) from the other regions in the fetal US image. The mean value μ_i and the standard deviation σ_i $(i = 1, \ldots, k)$ of cluster (region) i can be calculated from the segmentation results. The class number of K-means is three, because US images of the fetal head are segmented into three components, i.e., head skull, soft tissue, and background. Since the K-means method is sensitive to noise, the bright region(s) obtained from the segmentation results could be corrupted by much noise. We need to extract the skulls' skeletons without noise as the input to the original or improved IRHT method.

In order to suppress the noise impact in the K-means method, a global thresholding is used to convert the intensity image into a binary image; then, the bright region(s) can be extracted from the background by a threshold value T. The following threshold value T obtained by preliminary experimental studies, is adopted to extract (a) bright region(s),

$$T = \mu_b - 0.75 \times \sigma_b \tag{1}$$

where μ_b is the mean value of the bright region, σ_b is the standard deviation of the bright region (Here, we suppose the bright region is classified into b-th cluster).

As for binary image, a binary morphologic opening operation with a 2×2 window is used to remove some small bright regions. Morphologic dilation with a 1×1 window and closure with a 2×2 window are used to smooth the boundaries of the large bright regions. After the pre-processing, the skeletons of the bright region are extracted by distance transform [12].

Figure 2 shows an example of the procedure of the pre-processing and skeletonization in US images: (a) original fetal US image, (b) result of applying a bilateral filter to image (a), (c) result of applying a white top-hat transform to image (b), (d) segmentation result of applying the K-means clustering method to image (c), (e) result of applying a global thresholding with a threshold value T defined in Eq. (1) to image (d), and (f) skeletons of the bright region extracted by applying distance transform to image (e). Then the procedure of fetal head detection, which is detailed in Sections 2.3 and 2.4, is performed for image (f).

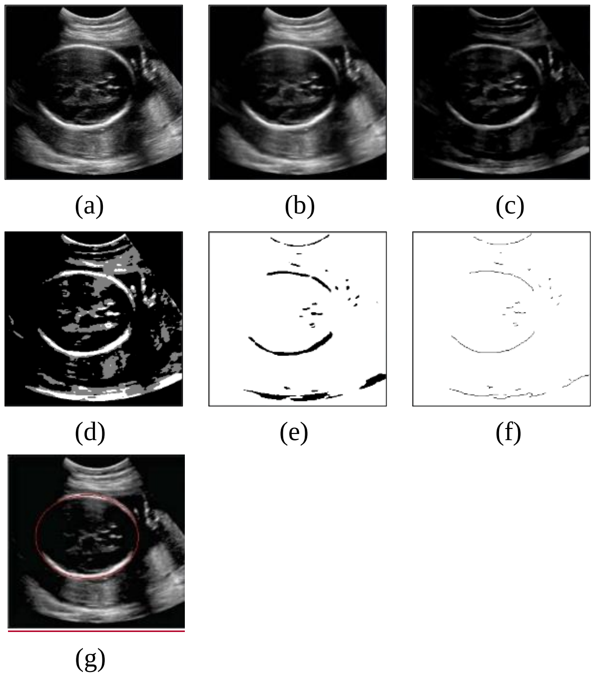


Figure 2. Pre-processing and skeletonization.

2.3. Improved Iterative Randomized Hough Transform

In US images, fetal head skulls often appear as the bright region with some discontinuities, because fetal head skulls are not completely closed. In addition, some other structures also may generate bright spots in US images. Furthermore, various artifacts and noise are usually present in US images. Accordingly, a useful head detection algorithm must effectively deal with these problems. To solve these problems, the authors developed an improved IRHT method [9] for detecting ellipses in US images despite the large discontinuities and strong noise for achieving more robust and accurate results, where the improved IRHT method is based on the original IRHT method [6]. In the following, the original and improved IRHT algorithms are overviewed.

2.3.1. Iterative randomized Hough transform

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 method [4] 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 (fits to) an 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 is outputted as the final detection result. For ellipse detection ($n = 5$), the following equation is utilized [12, 13] :

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

where the five parameters, $[U, V, R, S, T]^t$, can be converted into the standard ellipse parameters $c = [x_0, y_0, a, b, \phi]^t$: (x_0, y_0) are the coordinates of the center 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 $e = b/a$.

The IRTH method employs a randomized Hough transform (RHT) to a region of interest (ROI) in the image space by iterative parameter adjustment and reciprocal use of the image space and parameter space. The region of interest of RHT method is always the whole image, and it does not change during the whole process. However, the region of interest of the IRHT method is updated based on the latest estimates of the parameters during the iteration process. Meanwhile, noise pixels are gradually excluded from the region of interest, and the estimation progressively gets accurate.

2.3.2. Improved iterative randomized Hough transform

On the basis of the principle of the IRHT method, we further introduce the number (N) of pixels on the detected ellipse as a goodness of the detected ellipse. In each iteration, K valid samples are detected by RHT method, and top-M peaks (Herein, M is experimentally selected as 10) in the accumulators of the K valid samples are selected. Then, the number of pixels on the ellipse is calculated for the selected top-M peaks. Subsequently, the result with the maximal number of pixels on the ellipse is accepted as the result in each iteration, and used to update the region of interest for the next iteration. This iterative process continues until the size difference of the ROI between successive two iterations is very small, and the detected ellipse in the final iteration is the final result. Herein, the convergence conditions which is the same conditions used by IRHT method are: 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 [9].

2.4. Voting Scheme

As shown in Fig. 3, the method proposed by this paper includes the improved IRHT method. The original IRHT method uses random sampling of five points, but the random sampling does not always give accurate results. On the other hand, the improved IRHT method can make a better detection accuracy because of counting the number of pixels on the detected ellipse to reduce the impact of sparse noise pixels. However, it may fail when the skeleton image extracted from the input US image are occupied by some noise curves. Nevertheless, the curves of fetal head skull should be the most dominant components of the skeleton images, compared with the noise curves. Thus, misdetection of the skull curves by the improved IRHT method should occur at a small probability. By considering these, multiple attempts by a voting scheme should be able to further reduce the probability that the misdetection, which is a small probability event, occurs.

Based on the results of P detections ($P = 100$ in this paper) by the improved IRHT method [9], the proposed method makes a list for saving all the detected results and their accumulators. For each detection, a voting is made for the results in the list. More specifically, the difference between the current detection result and each of the results saved in the list is compared: i.e., if the difference is within a pre-defined small range, then the accumulator of that result in the list is incremented by 1; otherwise, the current detection result is appended to the list as a new one. This process is repeated P times. Consequently, the final result is determined by detecting the highest peak (with the most votes) in the accumulators from the list.

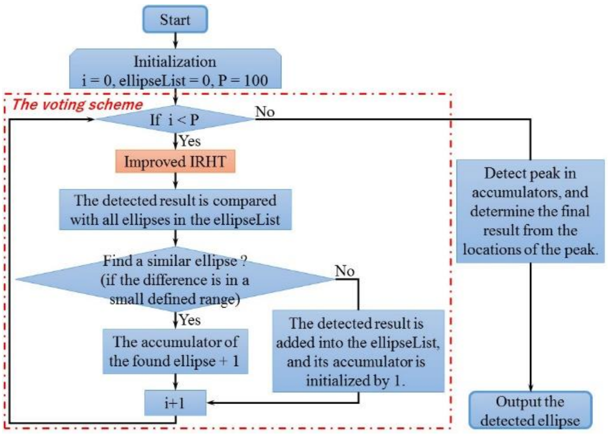


Figure 3. Flow chart of the propose method.

3. EXPERIMENTS

US images containing fetal heads at about 20-32 weeks' gestational age are used for the experiments, where the US images are consolidated impossible anonymous. To heighten the performance of the algorithm, a priori information, reported by Hadlock et al. [2] is applied to the experiments: i.e., 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 $\mu_e - 3\sigma_e \le e \le \mu_e + 3\sigma_e$, namely, $0.651 \le e \le 0.915$, and about 99.7% of fetal heads would have an eccentricity in this range. Therefore, only the result whose parameter e is within this range is accepted.

Although a strict convergence condition is used in the iterative process of the original and improved IRHT methods, as introduced in Sec. 2.3.2, a relatively relaxed range is experimentally defined for the proposed voting scheme (the processing marked by a red doubly dotted line rectangle in Fig. 1) by less than 8.5° in ϕ; less than 5 pixels in each of x_0 and y_0; less than 6 pixels in each of a and b; and less than 19 pixels total in x_0, y_0, a and b. Namely, if the difference between the detected result and the ground truth made by experienced physicians is within such a relatively relaxed range, it is considered as a correct result; otherwise, it is a wrong result.

3.1. Experiment on the Effect of Noise

Two US images, each of which is contaminated by weak nose (Fig. 4 (a): Image 1) and strong noise (Fig. 4 (b): Image 2), respectively, are used to evaluate the original IRHT method [6], the improved IRHT method (i-IRHT) [9] and the proposed method. Each of the three methods is performed 50 times for each US image, and detection rates of each method in Table 1 are obtained. The detection rate is calculated by the number of correct detection results divided by the total number of the detections (i.e., 50 times).

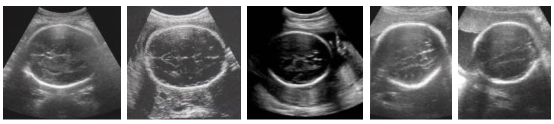
Table 1 Detection rates of each method on two images

	IRHT	i-IRHT	Proposed method
Image 1	88%	94%	100%
Image 2	30%	78%	93%

In Table 1, a comparison of the results for the three methods is listed. We can observe that for Image 1 with weak noise the three methods achieve high detection rates; in particular, the proposed method achieves the best rate of a 100%. However, for Image 2 with strong noise only the proposed method can achieve a high detection rate of 93%, which is much higher than those of the other two methods. On the other hand, the result of the i-IRHT method is much better than that of the original IRHT method since the i-IRHT method considered the number of pixels on the ellipse. Consequently, the results in Table 1 indicate that the proposed method can achieve the best detection rate among the three methods, and a robust performance especially for images with strong noise. An example of the detection result is superimposed to the original image, as shown in Fig. 2 (g).

3.2. Experiment on Different US Images

24 US images (Fig. 4), which have variations in terms of noise, the discontinuity and irregularity of fetal head skulls, are used to evaluate the three methods, where each method is performed 50 times for each image.



(a) (b) (c) (d) (e)

Figure 4. Some examples of the used 24 US images.

In Table 2, the mean and standard deviation of the detection rates for the 24 US images are listed for each method. Table 2 demonstrates that the proposed method achieves much higher detection rate than the other two methods. It also indicates that the standard deviation of the detection rate by the proposed method is much smaller than the other two. This emphasizes that the proposed method is robust against wide variations in the noise, which are often contained in US images, such as, speckle noise, electronic noise and thermal noise.

Table 2 Mean and standard deviation of the detection rate of each method for 24 US images

IRHT	i-IRHT	Proposed method
46.0%±49.6%	74.0%±26.2%	95.3%±6.86%

In addition, the program of ellipse detection is performed by a CPU E3-1240 v3 @ 3.40GHz, and the mean time of executions is about 2.43 seconds for 100. Since any optimization is not been considered currently, the efficiency of the algorithm should be able to be improved by 10-20 times based on parallel computation and GPGPU technology.

4. CONCLUSION

To achieve robust and accurate detection of fetal heads in US images, this paper has proposed a method that integrates an improved IRHT with a voting scheme. The proposed method votes the ellipse estimation result obtained by the improved IRHT to the parameter space and obtains the final detection result by finding the peak in the parameter space.

Experimental results for comparing the proposed method with IRHT and improved IRHT using 24 US images demonstrate that the proposed method can achieve much higher detection rate mean (95.3%) and smaller standard deviation (6.86%).

Remaining issues include further improvement of the accuracy and efficiency of the algorithm by optimizing parameters used in the algorithm.

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