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A Study of Automated Fetal Head Detection by Pre-processing based on Ultrasound Image Gray Feature and Iterative Randomized Hough Transform

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1. Introduction

Fetal head detection in ultrasound images is an important primary step for many clinical applications. However, owing to the discontinuity and irregularity of fetal skulls and the low resolution and signal-to-noise ratio of ultrasound images, it is challenging for surgeons to recognize it manually and manual analysis is always time-consuming. Therefore, automated or semi-automated medical image processing [1-5] should be used to ensure a better effective, precise and consistent measurement.

Hough transform (HT) [6], Randomized Hough Transform (RHT) [7] and Random Sample Consensus (RANSAC) [8] are several techniques for ellipse detection, but they may fail when the strong noise can corrupt the curve peaks in the parameter space. An improved method named iterative randomized Hough transform (IRHT) [4] was proposed for detection of incomplete ellipses under strong noise conditions.

In this study, we discuss an automated detection of fetal head by pre-processing based on ultrasound image gray feature and iterative randomized Hough transform (IRHT). Firstly, fetal ultrasound images are segmented by k-means clustering method, and the fetal skull is skeletonized by distance transform. After that, the ellipse of fetal head in skeleton image will be detected automatically by IRHT.

The rest of this paper is organized as follows: Section 2 describes pre-processing steps from raw image to skeleton image. Section 3 presents iterative randomized Hough transform algorithm. Section 4 gives the experimental results for fetal head detection. Section 5 concludes this paper.

2. Pre-processing

For fetal head detection in ultrasound images, the skeletons of fetal skulls should be extracted in pre-processing. Because speckle noise is often superimposed into ultrasound images, a bilateral filter [9] with a 5×5 window was 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 was operated to increase the contrast through a 11×11 structuring element.

After that, K-means clustering algorithm [10] is applied to distinguish the bright object from gray object and background. It aims to segment all image pixels into k (here, k = 3) clusters in which 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, we only need to extract the basic skeletons of fetal head. 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 made 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 for fetal head detection.

$$T = \mu_{k-1} - 0.75 \times \sigma_{k-1} \quad (1)$$

where, μ_{k-1} is mean value of the bright object, σ_{k-1} is standard deviation of the bright object (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 was used to remove small bright objects. Morphologic dilation with a 1×1 structuring element and closing with a 2×2 structuring element were used to smooth the boundaries of large bright objects. After a series of pre-processing, the skeletons of the bright object were extracted from distance transform [11].

3. Iterative randomized Hough transform

In ultrasound images, fetal head often appears as bright object with some gaps, because fetal 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 in ultrasound images. Consequently, a useful head-detection algorithm must effectively deal with these disturbances.

An iterative randomized Hough transform (IRHT) [4] was recently developed for the detection of ellipse with large gaps and strong noise, derived from randomized Hough transform (RHT) [7] method. The following parts make a brief description of the RHT and IRHT.

3.1 Randomized Hough transform (RHT)

In a binary image, the curve to be detected can be modeled by $f(c, z) = 0$, where $c = [\alpha_1, \dots, \alpha_2]^t$ 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, $z_i = (x_i, y_i), i = 1, \dots, n$, 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 count at c is increased by one in the parameter space and stored in its corresponding accumulators. This process is repeated until a predefined number of valid samples (K) are processed. The location of the count 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 [12] :

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

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

3.2 Iterative randomized Hough transform

Region of interest (ROI), as a new technique was imported in IRHT with the purpose of reducing noise interference from whole image. In RHT, 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, ROI shrinks into a smaller rectangular region enclosing detected

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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.

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 $x_0, y_0, a\ and\ b$.

4. Experiments

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 reported by Hadlock et al. [13]. This priori knowledge could be used to construct a constraint as $\mu_e - 3\sigma_e \le e \le \mu_e + 3\sigma_e$, namely, $0.651 \le e \le 0.915$, to improve the IRHT performance. About 99.7% of fetal heads would have an eccentricity in this range.

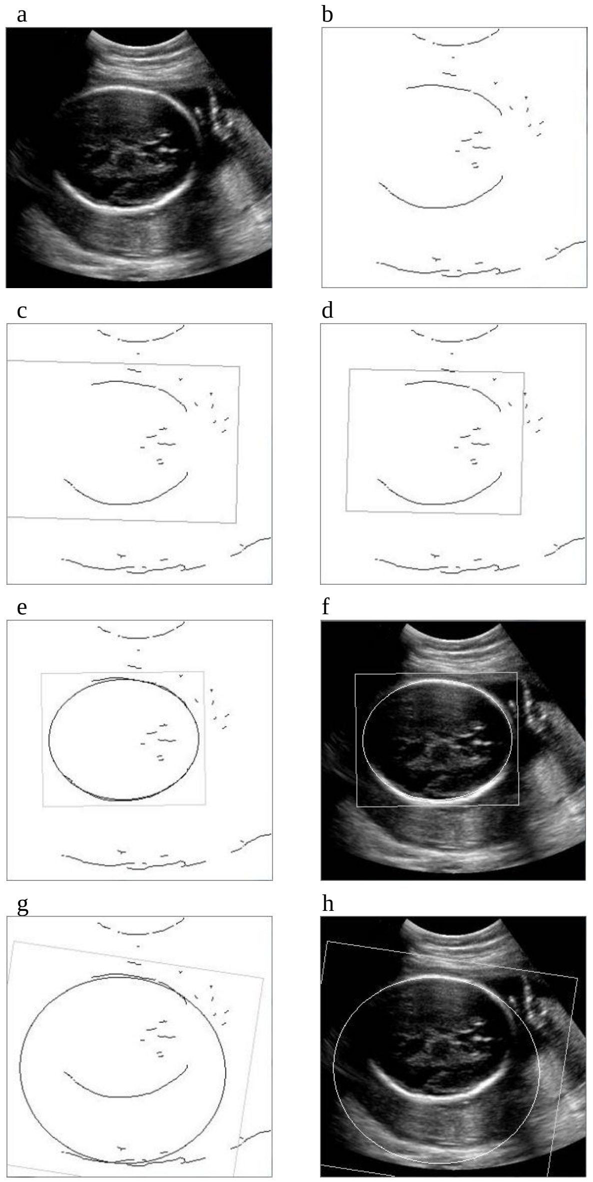

Fig. 1. Skeletonization and detection of fetal head in US images. (a) A clinical US fetal head image. (b) Skeletons of bright object used as input to IRHT. (c) After 1st iteration. (d) After 2nd iteration. (e) After the 6th iteration, IRHT has converged and the skeleton image with the detected ellipse. (f) The detected ellipse in (e) superimposed on (a). (g) The detected ellipse by RHT (K = 20,000). (h) The detected ellipse in (g) superimposed on (a).

Fig.1 illustrates the procedure of skeletonization and detection for fetal head ultrasound images. The IRHT algorithm correctly converged to the head after six iterations. However, the standard RHT failed to detect any of the head objects even after 20,000 samples were processed under the same eccentricity constraint.

5. Conclusions

In this paper, we have proposed a method for an automated detection of fetal head in US images. Through the pre-processing based on ultrasound image gray feature, we could extract the basic skeleton of fetal skull and remove the noise maximally at the same time. The iterative randomized Hough transform has been proved to be an effective method for the detection of incomplete ellipses in an image with strong noise. The results demonstrated that the proposed method is robust and effective for automatic fetal head detection in clinical ultrasound images.

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