A Statistical Approach for Muscle Fascicle Orientation Estimation in Ultrasound Images

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Abstract—**Ultrasound imaging has been widely used to investigate muscle properties. The fascicle orientation is usually measured manually, which is subjective and time consuming In this study, an automatic estimation method based on statistical characteristic of the fascicle region is proposed to detect the fascicle orientation. The performance of the proposed method is compared to manual detection using clinical images from human subject. The experimental results show that the proposed method is robust, and the difference between the two methods is within 1 degree. The proposed method has the potential for widespread application in biology sciences.**

Keywords- Fascicle orientation, Ultrasound image, Automatic estimation

I. INTRODUCTION

Ultrasound imaging has been adopted to investigate human muscle with no radiation and low cost [1]. This method can provide real time images which are capable to view the muscle fiber dynamics during contraction [2]. Recently, ultrasound imaging has been introduced to qualify the muscle changes [3], such as in muscle thickness, pennation angle, fascicle length and other properties [4-8]. Since these morphology parameters have direct relation with the muscle mechanical properties contractions, they could potentially provide a flexible way for revealing the intrinsic muscle characteristic [9]. The traditional method of manual extraction for these parameters are subjective and very time consuming when dealing with large number of ultrasound images.

Hough Transform (HT) [5] has been adopted to estimate fascicle orientation. This method build the Hough space based on the edge map of the ultrasound images, and the global peak is found corresponding to the position of a straight line in the image space [10]. The method greatly relies on the performance of the edge detector that could be compromised by speckle noise [11]. Radon Transform (RT) does not require edge detection and its inherent integration feature is less susceptible to background noise. Recently Radon Transform has been introduced to detect the line features in ultrasound images. Heng [12] proposed to use localized Radon transform to refine the locations and directions into proper range, in which the fascicles are supposed to be found. In their method, revoting strategy is introduced to extract fascicles one by one following the descending order of their integrated pixel intensities.

These methods described above aim to detect fascicle lines, and then estimate the fascicle orientation by identifying the angle between the deep aponeurosis and the muscle fascicle. However, the fascicle segments are usually significantly shorter than the image dimensions, and line detection algorithm often fails, especially when high-level noise is present. The purpose of this study was to develop a robust method using the statistical characteristic of the local region to quantify the fascicle orientation for ultrasound images.

II. METHODS

A. Method overview

Taking into account the fact that fascicles and muscle fibers in ultrasound images have coherent orientation tendencies, we used a multi-stage process to determine fascicle orientation (Fig. 1): region of interest (ROI) definition, Radon transform and orientation estimation using Kurtosis. The raw ultrasound images are manually segmented to obtain the ROI. The subsequent steps are automatic, and the orientation estimation of current frame is based on the information of its previous frame. In-vivo muscle images from human subjects were used to test the proposed methods.

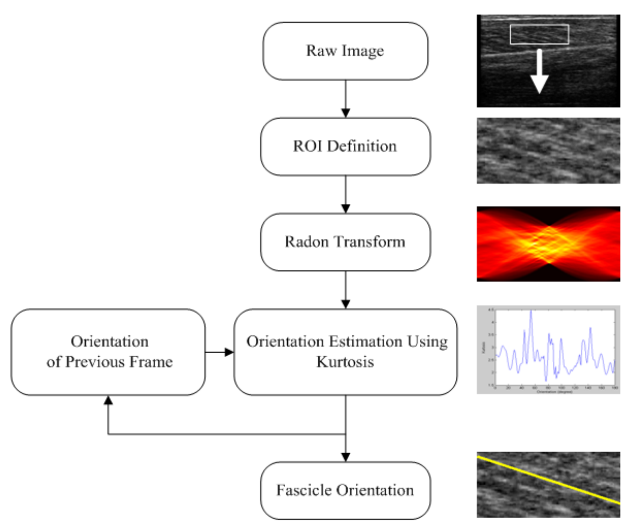


Fig. 1. The diagram of the proposed method

B. Standard Radon Transform

The standard RT over a 2-D Euclidean space is defined as

$$F(\theta,\rho)=\iint_D f(x,y)\,\delta(\rho - x\cos\theta - y\sin\theta)dxdy$$
(1)

Where D is the image grid, $f(x,y)$ is the image intensity at position (x,y), δ is Dirac delta function, ρ is the distance from the center of the image to the line, and θ is the angle between the x axis and the line. As defined by this equation, the peaks in the Radon space denote the features where the straight lines are likely to be found.

Sicne the Radon transform respresents intensity integration over the entire image plane, the fascicle segments which are significantly shorter than the image dimensions are difficult to detect, specially when high-level noise is present. Heng [12] proposed to use localized Radon transform to refine the locations and directions into proper range, in which the fascicles are supposed to be found. In their method, revoting strategy [5] is introduced to extract line features one by one following the descending order of their integrated pixel intensities. In the propose method, instead of detecting line features from the Radon space, we use a statistical approach to estimate the fascicle orientation, and thus improve the robustness of the estimation algorithm.

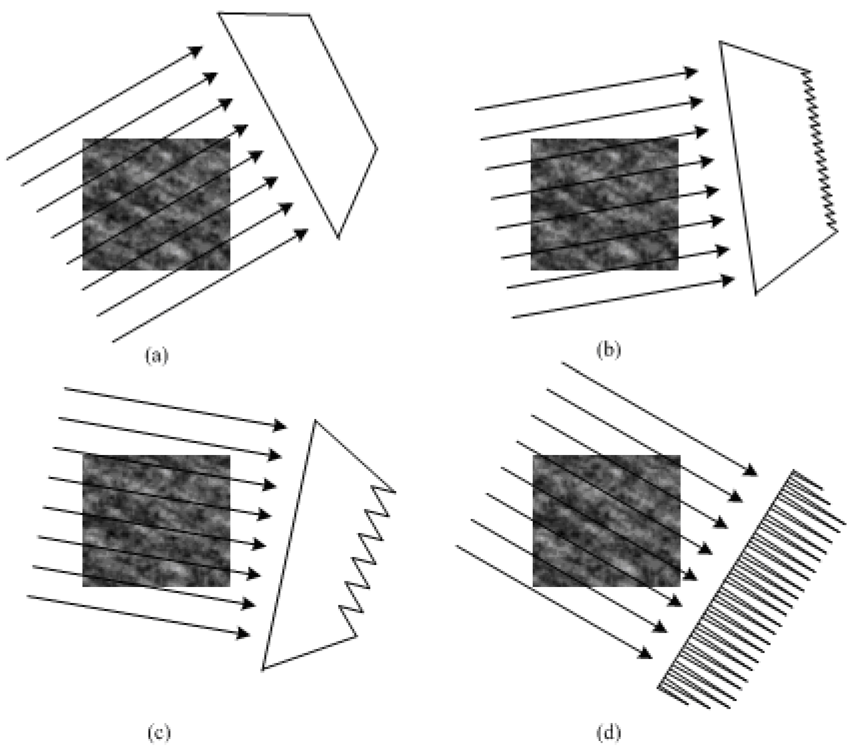


Fig. 2. An illustration of the Radon transform at four different angles (a–d).

C. Fascicle Orientation Estimation Using Kurtosis

Kurtosis is a measure of how outlier-prone a distribution is. In probability theory and statistics, kurtosis is a measure of the shape of the probability distribution of a real-valued random variable. It is closely related to the fourth moment of a distribution. The kurtosis, or peakness of a distribution is defined as

$$k=\frac{E(x-\mu)^4}{\sigma^4} \tag{2}$$

where μ is the mean of x, σ is the standard deviation of x, and $E(t)$ represents the expected value of the quantity t. The Radon transform projects a grid of parallel lines across the image and calculates the integral of the image intensities along each line. When the orientation approaches the dominant orientation of structures within the image, the Radon transform has greatest variability across the image (Fig. 2). In [13], kurtosis has been proved to be sensitive to fascicle orientation in the ultrasound images. In this paper, this variability was quantified by kurtosis.

D. Tracking Strategy

Usually tracking the fascicle orientation continuously over a series of ultrasound images is more robust than detecting the orientation in each frame separately, because results from previous frames could be used as prior knowledge to track the fascicle orientation in the current image. In the proposed method, we estimate the fascicle orientation not only based on the kurtosis in Radon space, but also the estimation results of the previous frame. To be more specific, the Radon transform is performed within relatively limited directions around the orientation detected in the first frame, the peak is searched in the kurtosis of the Radon space to determine the fascicle orientation in the second frame. The same procedure is applied to other frames by constantly updating tracking direction range using the results from the previous frames.

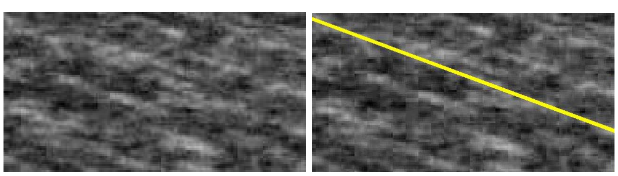
III. RESULTS

A. Experimental Setup

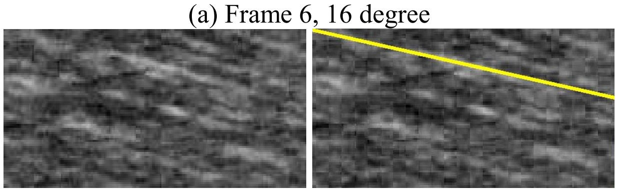
The ultrasound images of the medial gastrocnemius muscle are acquired by a personal computer-based ultrasound system (Echoblaster 128, Telemed, Vilnius, Lithuania) [14]. A 96-element, 7 MHz linear probe is aligned with the fascicle plane. The probe was secured over the skin surface with a compressive bandage to minimize probe movement relative to the skin. A digital output signal from the ultrasound system was used to synchronize data collection. All ultrasound data were recorded to file for subsequent offline analysis. Prior to data collection participants walked at about 4 km/s speed for a minimum of 30 s to facilitate adaptation to the speed, and the ultrasound data were subsequently collected for at least 30s. The muscle region of interest was defined as the area between the superficial and deep aponeuroses of the MG muscle that was visible in the ultrasound image.

B. Results

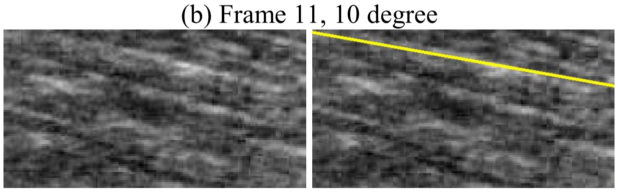
Three original ultrasound images are shown in the left column of Fig.3, and the manual detection results are shown in the right column. The fascicle orientation is manually tracked by marking out one of the significant fascicle line in the continuous frames. The estimation results of the orientation is 16, 10, 8 degree for the fame 6, 11, 16 respectively.



(a) Frame 6, 16 degree



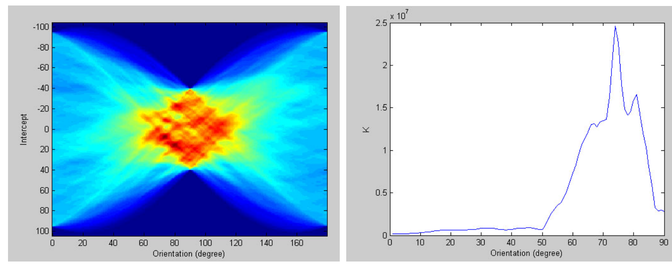
(b) Frame 11, 10 degree



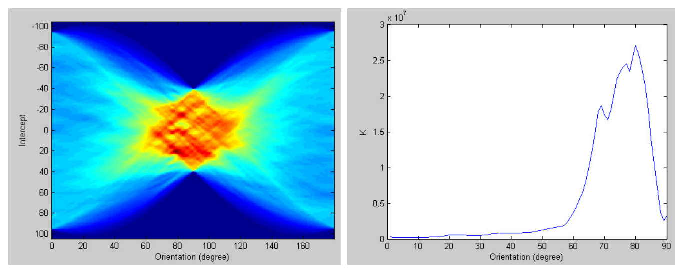
(c) Frame 16, 8 degree

Fig. 3. Original ultrasound images and the manual detection results.

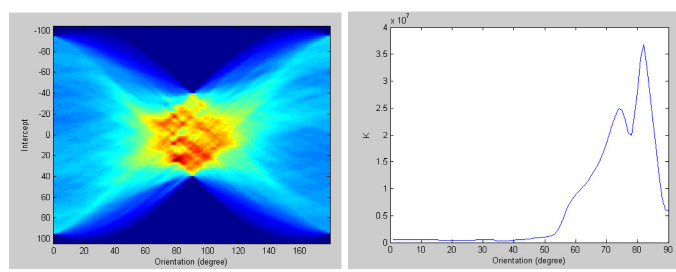
The Radon transform of the three ultrasound frames is shown in the left column of Fig. 4. We use the standard color bar defined in Matlab 2009 to present the distribution of Radon space. For each orientation, we calculate its K value using Equation (2). The peak K values appear at 74, 80, 82 degree for frame 6, 11, 16 respectively, and the corresponding dominant orientations are 16, 10, 8 degree. The estimation results are consistent with manual results. Note that we calculate the Radon space every 1 degree in this experiment, therefore, the estimation accuracy is 1 degree.



(a) Frame 6, peak K value at 74 degree.



(b) Frame 11, peak K value at 80 degree.



(c) Frame 16, peak K value at 82 degree.

Fig. 4. The Radon space and corresponding K values.

A high quality ultrasound video of 60 frames is chosen to further qualify the proposed method. In this experiment, we calculate the Radon space every 0.4 degree to improve the estimation accuracy. The manual detection is accomplished by find the fascicle line in the ultrasound image by one clinical expert, the operation is repeated for three times and the results are averaged to obtain the final results. It can be seen in Fig.5 that the difference between the two methods is within 1 degree, and less than 0.5 degree in most cases. It can be concluded that the proposed method is robust, and the accuracy can be further improved by interpolation on the orientation curve [15]. Certainly, the Radon space construction could be more precise if computational efficiency is not an urgent issue [16].

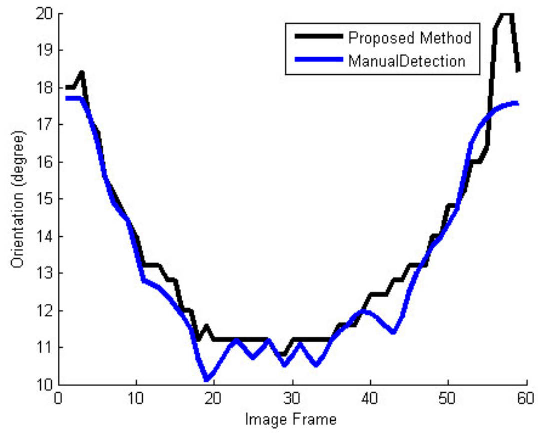


Fig. 5. Tracking result comparison between the proposed method and manual measurement.

IV. CONCLUSIONS

With the increasing amount of ultrasound images, it is difficult to manually detect or measure the muscle architecture parameters. We have presented a statistical, robust method of automatically tracking muscle fascicle orientation. The results obtained using automated tracking are in close agreement with those obtained using manual measurement, which currently represents the "gold standard" of fascicle orientation analysis [17-22]. The automated method presented here provides a viable alternative to the manual approach for estimating fascicle orientation changes during human motion and has the potential for widespread application in biology sciences.

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