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Computational methods for quantifying *in vivo* muscle fascicle curvature from ultrasound images

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ABSTRACT

Muscle fascicles curve during contraction, and this has been seen using B-mode ultrasound. Curvature can vary along a fascicle, and amongst the fascicles within a muscle. The purpose of this study was to develop an automated method for quantifying curvature across the entirety of an imaged muscle, to test the accuracy of the method against synthetic images of known curvature and noise, and to test the sensitivity of the method to ultrasound probe placement. Both synthetic and ultrasound images were processed using multiscale vessel enhancement filtering to accentuate the muscle fascicles, wavelet-based methods were used to quantify fascicle orientations and curvature distribution grids were produced by quantifying local curvatures for each point within the image. Ultrasound images of ramped isometric contractions of the human medial gastrocnemius were acquired in a test–retest study.

The methods enabled distinct curvatures to be determined in different regions of the muscle. The methods were sensitive to kernel sizes during image processing, noise within the image and the variability of probe placements during retesting. Across the physiological range of curvatures and noise, curvatures calculated from validation grids were quantified with a typical standard error of less than $0.026\ \mathrm{m}^{-1}$, and this is about 1% of the maximum curvatures observed in fascicles of contracting muscle.

1. Introduction

Muscle fascicles must be curved in order to maintain mechanical equilibrium within pennate muscle (van Leeuwen and Spoor, 1996). During contraction the curvature of the muscle fascicles increases (Hill, 1948; Kawakami et al., 2000; Blazevich et al., 2006; Otten, 1988; van Leeuwen and Spoor, 1992; Maganaris et al., 1998) and these increases have been linked to the internal forces and pressures within the muscle (van Leeuwen and Spoor, 1992). When a muscle fascicle curves, its trajectory changes along its length and displays a longer length than the commonly assumed linear approximation that shares the same origin and insertion (Muramatsu et al., 2002); thus, it is important to quantify fascicle curvature in order to understand details of fascicle strain and pennation angle (Kawakami et al., 1998; Styf et al., 1995).

To date, only a few studies have predicted (van Leeuwen and Spoor, 1992; Sejersted et al., 1984) or quantified curvatures of the muscle fascicles (Kawakami et al., 1998; Muramatsu et al., 2002; Stark and Schilling, 2010; Wang et al., 2009). Previous ultrasound-based studies have used manual digitisation to quantify the path of select fascicles in ultrasound images of muscle. However this process is both time-consuming and can be subjective. Recent developments in the processing of ultrasound images allow the local orientations of all fascicles within a muscle image to be determined (Rana et al., 2009), and these orientation grids provide the information necessary to calculate local curvatures at all points across a muscle image.

The purpose of this study was to (1) develop automated techniques to quantify local fascicle curvatures from the orientation grids of fascicles within a muscle; (2) validate these methods against synthetic test images containing known curvature and noise; and (3) determine the sensitivity of these automated curvature quantification methods to ultrasound placement and contraction level for the medial gastrocnemius muscle.

2. Methods

B-mode ultrasound images were collected (Fig. 1) using a 2D linear ultrasound probe (Echoblaster 128 EXT-1Z, Telemed, Lithuania) at an 8 MHz wave frequency and the images were collected from the medial gastrocnemius of a healthy male subject at a frame rate of 50 Hz. Images of the muscle were 384 pixels wide and extended approximately 150 pixels into the muscle. The subject was seated in a dynamometer (System 3, Biodex, New York, USA) with the right ankle fixed at 75° relative to the tibia. The subject was instructed to perform an isometric contraction

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starting from rest and increasing ankle torque over a three-second ramped contraction until MVC had been reached. The test was conducted on six healthy male subjects (age: 29.2 ± 2.7 years; height: 1.8 ± 0.03 m) and a test/re-test protocol was conducted in which the test was repeated ten times on a single subject. Between tests, the ultrasound probe was removed from the leg, the skin was cleaned and the subject walked back-and-forth along a corridor.

Analogue data for the ankle torque was collected at 1 kHz *via* a National Instruments USB-6229 BNC data acquisition module using a LabView environment. Each ultrasound image was matched to its corresponding torque value. Eleven ultrasound images at torques evenly spaced across the whole torque range were selected for analysis: no images were excluded for analysis. The region of interest within each image was the imaged muscle that occurred between the superficial and deep aponeuroses (that were identified with manual digitisation). The image was then processed using multiscale vessel enhancement filtering and anisotropic wavelet analysis (Rana et al., 2009) from which the local curvatures were quantified using the methods described below (Fig. 2). Local curvatures were determined at every pixel within the muscle image, and so the root-mean-square (RMS) curvature was taken to characterize the general curvature for each image.

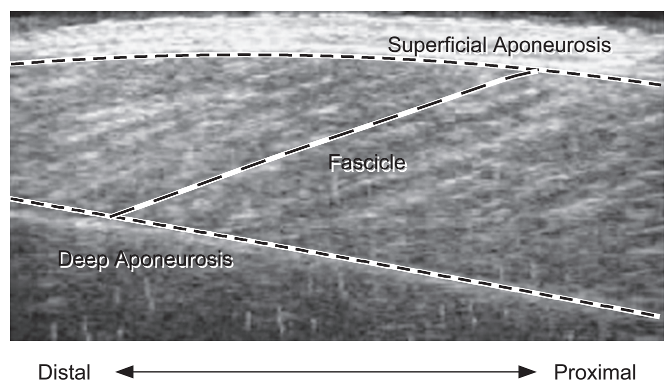

Fig. 1. Two-dimensional ultrasound image from the medial gastrocnemius. The dashed black lines closer to the top and bottom indicate the aponeuroses, and a fascicle is outlined by a thinner dashed line.

2.1. *Multiscale vessel enhancement filtering*

Fascicles in the 2D ultrasound images were accentuated using vessel enhancement filtering (Rana et al., 2009) based on the following equation:

$$V(s) = \begin{cases} 0, & \text{if } \lambda_2 > 0 \\ \exp\left(\frac{-R^2}{2\beta_1{}^2}\right)\left(1-\exp\left(\frac{-s^2}{2\beta_2{}^2}\right)\right), & \text{if } \lambda_2 \le 0 \end{cases}$$

where $V(s)$ is the 2D vesselness response to each scale, s, R is how blob-like the structure is, λ_2 is the eigenvalue that corresponds to the direction of the tubular structure, and β_1 and β_2 are threshold constants that control the line filter sensitivity (Frangi et al., 1998). The vesselness, $V(s)$, was quantified at different scales, s, with the scale being related to the width of the lines being filtered. In this study we used scales of 2, 3, and 4, and the Gaussian grid size was 31×31 pixels. Vessel-enhanced images for a muscle at rest and at MVC are shown in Fig. 3.

2.2. *Image wavelet analysis*

The local orientations at each image pixel were calculated using anisotropic wavelet analysis methods (Rana et al., 2009). The wavelet amplitude, $G(x,y)$, at coordinates (x,y) is given by the following equation:

$$G(x,y) = \exp\left(\frac{x^2+y^2}{-dk}\right)\cos\left(\frac{2\pi(x\cos\alpha - y\sin\alpha)}{\lambda}\right)+o$$

Following previous methods by Rana et al. (2009), this study set the damping of the wavelet to $d=51.243$, the wavelength to $\lambda=7$, the half-width kernel size to $k=20$, and o as the linear offset to satisfy the zero-integral condition. The wavelet kernel was convolved with regions of the multiscale filtered image at different angle orientations spanning $-90^\circ \le \alpha \le +90^\circ$, increasing in one-degree increments. The wavelet with orientation α that yields the highest convolution value for a particular region around a pixel was assigned as the orientation of the fascicle at the pixel. This was repeated for each pixel within the muscle image, and the orientation value was assigned to the corresponding pixel of an orientation grid.

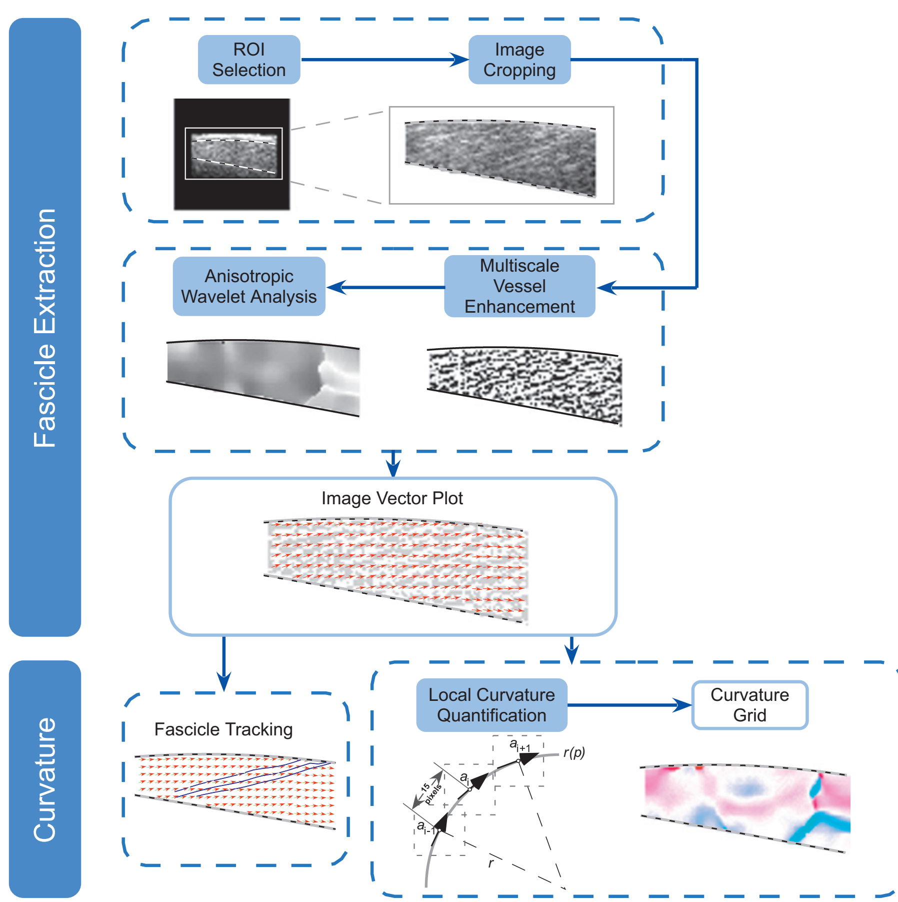

Fig. 2. Graphical representation of the steps in the algorithm for curvature quantification.