Computerized Medical Imaging and Graphics 56 (2017) 60–73

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

Plantar fascia segmentation and thickness estimation in ultrasound images

Abdelhafid Boussouar[a,*], Farid Meziane[a], Gillian Crofts[b]

[a] School of Computing, Science and Engineering, University of Salford, Salford, Manchester M6 6PU, United Kingdom
[b] School of Health Sciences, University of Salford, Salford, Manchester M5 4WT, United Kingdom

ARTICLE INFO

Article history:
Received 7 September 2016
Received in revised form 9 January 2017
Accepted 13 February 2017

Keywords:
Ultrasound (US)
Speckle noise
Plantar fascia (PF)
Segmentation
Radial Basic Function Neural Network (RBF-NN)
Feature extraction
Classification

ABSTRACT

Ultrasound (US) imaging offers significant potential in diagnosis of plantar fascia (PF) injury and monitoring treatment. In particular US imaging has been shown to be reliable in foot and ankle assessment and offers a real-time effective imaging technique that is able to reliably confirm structural changes, such as thickening, and identify changes in the internal echo structure associated with diseased or damaged tissue. Despite the advantages of US imaging, images are difficult to interpret during medical assessment. This is partly due to the size and position of the PF in relation to the adjacent tissues. It is therefore a requirement to devise a system that allows better and easier interpretation of PF ultrasound images during diagnosis. This study proposes an automatic segmentation approach which for the first time extracts ultrasound data to estimate size across three sections of the PF (rearfoot, midfoot and forefoot). This segmentation method uses artificial neural network module (ANN) in order to classify small overlapping patches as belonging or not-belonging to the region of interest (ROI) of the PF tissue. Features ranking and selection techniques were performed as a post-processing step for features extraction to reduce the dimension and number of the extracted features. The trained ANN classifies the image overlapping patches into PF and non-PF tissue, and then it is used to segment the desired PF region. The PF thickness was calculated using two different methods: distance transformation and area-length calculation algorithms. This new approach is capable of accurately segmenting the PF region, differentiating it from surrounding tissues and estimating its thickness.

1. Introduction

The plantar fascia (PF) or plantar aponeurosis is an aponeurotic thick, fibrous and strong connective tissue that provides stability to the medial longitudinal arch of the foot (Huang et al., 1993). It originates at the medial calcaneal tuberosity and extends toward the digits in three different structural bands: medial, central, and lateral (Chang, 2010) (Fig. 1). The central area is the largest, most affected by disease and most susceptible to deformities (Kwong et al., 1988; Kelikian, 2012). The PF plays an important role in stabilizing the foot during walking and running. However, a commonly encountered condition is foot pain due to overuse. The assessment of foot pain typically involves clinical examination and diagnostic imaging Park et al. (2014). The role of diagnostic imaging is to provide objective information which significantly then informs clinical decisions on treatment options. Ultrasound (US) imaging is a real-time imaging technique used in the diagnosis of the PF, which is readily available, fast, causes no radiation exposure, portable, accurate, and cost-effective (Pope, 1999; Szabo, 2013). Moreover, it is considered highly reliable and favourable in the diagnosis of diabetic foot with plantar fasciitis, ankle infections and damaged soft tissue (Crofts et al., 2014; Angin et al., 2014; Szabo, 2013; Akfirat et al., 2003). Although US imaging offers many advantages in the diagnosis of PF conditions, it is often considered operator dependent when used by non-experts. In addition, the quality of images may be affected by the presence of speckle noise (Ganzalez and Woods, 2002) which may diffuse the image edges, making medical interpretation and biometric measurements challenging, and therefore impacting the accuracy of diagnosis.

Research has reported thickening and hypoechoic deformities of the PF as part of the diagnostic criteria and PF characteristic features (Park et al., 2014). Increased PF thickness of >4 mm and decreased PF echogenicity are considered symptomatic (Fabrikant

* Corresponding author.
E-mail addresses: a.boussouar1@edu.salford.ac.uk (A. Boussouar), f.meziane@salford.ac.uk (F. Meziane), g.crofts@salford.ac.uk (G. Crofts).

http://dx.doi.org/10.1016/j.compmedimag.2017.02.001
0895-6111/

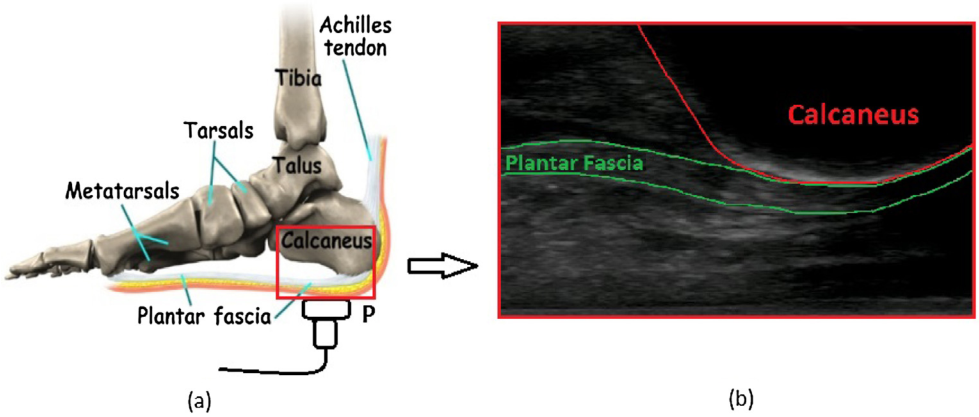

Fig. 1. Plantar fascia region: (a) Anatomical illustration diagram showing the anatomical location of the plantar fascia and positioning of the US probe, P. (b) The longitudinal sonogram of the scanned region related to (a), showing the plantar fascia area and the calcaneus.

Fig. 2. Probe position, longitudinal orientation and sample US images for all PF different structures. (a) Rear PF section; (b) Mid PF section; and (c) Forefoot PF section.

and Park, 2011; Wearing et al., 2007; Saber et al., 2012). Different protocols are used in the literature to manually measure PF thickness: (1) PF measurement has primarily been limited to thickness at the insertion of the calcaneus with either inter- or intra-rater reliability (Cheng et al., 2012); (2) average bias of repeated PF measurements (Wearing et al., 2004); (3) recent work (Crofts et al., 2014) has shown that the PF thickness varies along its length. Therefore, a reliable means of quantifying PF thickness in different sites (rearfoot, midfoot and forefoot) is advantageous (Fig. 2).

Automatic segmentation is one of the most critical tasks in medical image analysis; it is mainly used to locate region of interest (ROI) objects and boundaries in images. It is considered the most challenging task in medical US imaging compared to other imaging modalities, such as CT and MRI due to attenuation, speckles, shadows, signal loss and drop-out.

Furthermore, there is no commonly accepted method for US image segmentation because segmentation techniques vary widely according to the specific problem, application, imaging modality, human interaction, the homogeneity of images, spatial characteristics of images, continuity, texture and image content (Noble and Boukerroui, 2006; Rueda et al., 2014). Although many segmentation methods and techniques of US images exist, there is little literature on the segmentation process of the plantar fascia in US images of the foot. The only previous work found in relation to PF tissue US images is that reported in (Deshpande et al., 2013) using the Chan-Vese active contour segmentation method (Chan and Vese, 2001). The Chan-Vese model is based on the variational information in grayscale intensities of the image. This proposed technique was effective in the detection of bones and in segmenting the soft tissue layers between the bone and the skin in US images of the foot. However, this method is used for segmenting the whole plantar tissue without defining different plantar tissue areas. Most active contour methods used in US images suffer from the following shortcomings that seriously affect the segmentation results (Chang et al., 2010): (1) these methods are sensitive to the edge gradient; (2) they need a clear definition of the initial contour mask; (3) they depend on the number of iterations which may affect segmentation accuracy; and (4) they suffer from a high level of computational complexity. Many researchers have made various improvements to the standard active contour, but the disadvantages of this method are still not fundamentally overcome.

Artificial neural network (ANN) techniques have attracted considerable attention in medical imaging due to its intelligence and learning capabilities of performing complicated tasks such as US segmentation and classification. Previous studies (Chang et al., 2010; Noble and Boukerroui, 2006) have shown that integration of ANN can facilitate and improve the segmentation process. Fig. 3 illustrates how ANNs can be used to segment the ROI of US images. In general, ANNs supervised segmentation approaches consist of following steps: (1) the input images are divided into different overlapping patches; (2) different sets of features are calculated on these image patches and then selected to reduce their redundancy; (3) the selected feature vectors are then presented as input vectors to the trained ANN (trained previously with a set of ground truth segmentation, performed manually by experts) where the image patches are classified as a part of either the background or the ROI; (4) the results of the image patches classification are then combined and merged into a region mask (in black and white colour for background and ROI, respectively); (5) region mask labelling and superposing.

The manual segmentation and analysis of the large PF US datasets is a tedious, time-consuming and complex task for