Ultrasonics 72 (2016) 150–157

Contents lists available at ScienceDirect

Ultrasonics

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

Deep learning based classification of breast tumors with shear-wave elastography

Qi Zhang [a,*,1], Yang Xiao [b,1], Wei Dai [a], Jingfeng Suo [a], Congzhi Wang [b], Jun Shi [a], Hairong Zheng [b,*]

[a] School of Communication and Information Engineering, Shanghai University, Shanghai, China
[b] Paul C. Lauterbur Research Center for Biomedical Imaging, Institute of Biomedical and Health Engineering, Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China

ARTICLE INFO

Article history:
Received 22 September 2015
Received in revised form 30 June 2016
Accepted 5 August 2016
Available online 6 August 2016

Keywords:
Deep learning
Shear-wave elastography
Breast tumors
Point-wise gated Boltzmann machine
Computer-aided diagnosis

ABSTRACT

This study aims to build a deep learning (DL) architecture for automated extraction of learned-from-data image features from the shear-wave elastography (SWE), and to evaluate the DL architecture in differentiation between benign and malignant breast tumors. We construct a two-layer DL architecture for SWE feature extraction, comprised of the point-wise gated Boltzmann machine (PGBM) and the restricted Boltzmann machine (RBM). The PGBM contains task-relevant and task-irrelevant hidden units, and the task-relevant units are connected to the RBM. Experimental evaluation was performed with five-fold cross validation on a set of 227 SWE images, 135 of benign tumors and 92 of malignant tumors, from 121 patients. The features learned with our DL architecture were compared with the statistical features quantifying image intensity and texture. Results showed that the DL features achieved better classification performance with an accuracy of 93.4%, a sensitivity of 88.6%, a specificity of 97.1%, and an area under the receiver operating characteristic curve of 0.947. The DL-based method integrates feature learning with feature selection on SWE. It may be potentially used in clinical computer-aided diagnosis of breast cancer.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

In women, breast cancer is the most prevalent life-threatening disease and the second leading cause of cancer death [1]. Researchers have devoted their efforts to diagnosis, prevention, and treatment of breast tumors by using various types of imaging modalities, such as mammography, ultrasound, and magnetic resonance imaging. Breast cancer tissue is harder than normal breast tissue and benign tumor tissue, and it is believed that the hardening process begins in the early stage of cancer [2]. This hardness information has been utilized for breast tumor classification, when the shear-wave elastography (SWE) is developed as a novel, noninvasive, and cost-effective US technique for real-time visualization of breast tissues' elastic properties [2,3]. Compared with standard ultrasound focusing on morphological alterations of breast cancer, SWE provides additional information regarding the biomechanical, functional properties of breast tumors [2,4,5]. Thus, SWE can help differentiate between benign and malignant breast tumors without interventional diagnostic procedures [2,3,6–8].

Examples of SWE images shown in Fig. 1 illustrate high visual variability for diagnosis of breast tumors, caused by the different hardness distributions of breast tissues between benign and malignant tumors. A benign tumor (Fig. 1b) is usually soft and elastically homogeneous and thus presents with even blue on SWE, while the tissues surrounding a malignant tumor (Fig. 1a and c) is often hard and elastically heterogeneous and thus depicted in mixed colors with some foci of red. Apparently, visual diversity can be quantified by computer vision algorithms to guide a computer-aided diagnosis (CAD) system for distinguishing benign and malignant tumors [7,9,10].

Traditionally, CAD of breast tumors on standard ultrasound and SWE uses the statistical features (SFs), also called human-crafted features in research areas of computer vision. The SFs include tumor shape and morphological parameters, intensity statistics, and texture features quantifying tumor heterogeneity [6,7,11–17]. The SFs are often extracted by relying on expert knowledge or human labor, and the choice of particular SFs hugely affects the classification performance [10]. On account of recent advances in machine learning technology, deep learning (DL) has

* Corresponding authors at: Room 803, Xiangying Building, Shanghai University, No. 333, Nanchen Road, Shanghai 200444, China (Q. Zhang). 1068 Xueyuan Ave., SZ University Town, Shenzhen 518055, China (H. Zheng).

E-mail addresses: zhangq@shu.edu.cn (Q. Zhang), hr.zheng@siat.ac.cn (H. Zheng).

[1] Qi Zhang and Yang Xiao contributed equally to this work and are co-first authors.

http://dx.doi.org/10.1016/j.ultras.2016.08.004
0041-624X/© 2016 Elsevier B.V. All rights reserved.

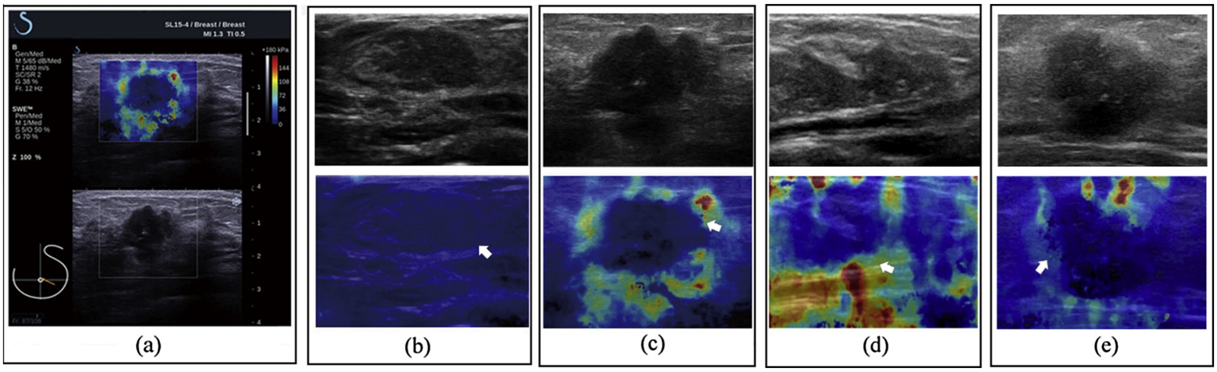

Fig. 1. Examples of breast tumor shear-wave elastography (SWE). (a) A typical image for dual-modality visualization of B-mode ultrasound (bottom, grayscale) and SWE (top, color). The regions of interest (ROIs) are marked with rectangles and the color bar to the right of SWE denotes the elastic modulus (i.e., hardness) of tissues, which decreases from red to blue. (b–e) ROI enlargements of two benign tumors (b, d) and two malignant tumors (c, e). Top: B-mode; bottom: SWE. Here, the malignant tumor depicted in (c) is also the tumor shown in (a). (b) and (c) show SWE of two typical tumors, where red areas in (c) depict very stiff tissues associated with malignancy; (d) and (e) are borderline cases and may be easily misdiagnosed. The black holes absent of color denote areas with invalid measurement of elastic modulus. White arrows point to tumor borders. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

gained a great attention in various fields from speech and image recognition to game playing, drug discovery and genomics [18,19]. DL involves applying multiple processing layers to raw data (such as the pixel values of an image) to learn features (representations) of the data with multiple levels of abstraction [18]. Thus in an image classification scenario, DL allows a computer to be fed with raw pixel values and to automatically discover the learned-from-data features needed for classification [20]. For CAD of breast tumors with SWE, the image features automatically induced from image pixels by DL may have better performance than SFs.

However, breast tumor SWE images contain artifacts, noise, and other irrelevant patterns, such as irregular stiffness distributions [7]. For instance, the neighboring tissues of a benign tumor (Fig. 1d) appear unevenly hard while those of a malignant tumor (Fig. 1e) seem moderately soft, which may easily lead to misdiagnosis. To deal with these irrelevant patterns is an extreme difficulty in building DL architecture that can robustly learn from complex SWE image data. Hence the challenge is how to learn robust representations that can distinguish useful (i.e., task-relevant) patterns from large amounts of distracting (i.e., task-irrelevant) patterns [21,22]. Another challenge is how to understand and utilize the patterns that may be task-relevant but are difficult to interpret by human observers, such as the black holes absent of color on SWE (Fig. 1b–e), i.e., the missing areas with invalid stiffness values.

Popular DL methods including the autoencoder and convolutional neural network are unsuitable for conquering these challenges, because they do not focus on differentiating task-relevant and irrelevant patterns. Instead, a newly proposed DL method, the point-wise gated Boltzmann machine (PGBM), appears to be a promising technique by introducing a gating mechanism to estimate where task-relevant patterns occur. In this paper, a unified DL architecture based on PGBM is presented for robustly learning SWE image representations and discriminating between benign and malignant breast tumors [22]. Therefore, no specific features need to be manually identified by users and the training set is used by the DL network to learn the inherent task-relevant patterns.

2. Methods

2.1. Image acquisition and pre-processing

This retrospective study was approved by a local institutional review board. Informed consent was obtained from all patients. All SWE examinations were performed by experienced radiologists using a Supersonic Aixplorer system (SuperSonic Imagine, Aix en Provence, France). The study population was comprised of 121 female patients. Each patient might have multiple lesions, and for each lesion, one or two images were acquired and stored in DICOM standards. Here, for the lesions difficult to interpret and diagnose, two images were acquired. All lesions underwent excisional biopsy, core needle biopsy or fine-needle aspiration biopsy for pathologic diagnosis, used as the gold standard for evaluation of the CAD. When multiple biopsy results were available, the final diagnosis was determined according to the following priority: excisional biopsy, core needle biopsy and fine-needle aspiration biopsy. There were 227 images in total, consisting of 135 images of benign tumors and 92 of malignant tumors.

All images were deidentified for patient confidentiality. A recorded SWE image was depicted as a composite color image (bottom of Fig. 1b–e) superimposed on the corresponding B-mode grayscale image (top of Fig. 1b–e). A pure SWE image is derived by subtracting the B-mode grayscale image from the composite color image [6,7]. Each pure SWE image was in a size around $360 \times 490 \times 3$, and it was downsampled to a fixed size of $36 \times 49 \times 3$ with a resolution of 12.26 ± 1.62 pixel/cm (Fig. 1b–e) by using the bilinear interpolation. Then it was transformed from a matrix to a vector of pixels, which was directly used as the input of the DL networks.

2.2. Deep learning architectures

DL architectures, originally introduced as the deep belief networks (DBNs) [23,24], are artificial neural networks built by learning feature hierarchies with features from higher levels of the hierarchy formed by the composition of lower level features, with the goal of yielding more abstract and distinct representations [20,25]. DBNs are composed of several layers of restricted Boltzmann machines (RBMs), which model binary data-vectors using binary latent variables [20,23]. However, RBMs cannot be directly used to model complex SWE image data due to the interference caused by irrelevant patterns [21]. The PGBM, as a higher-order Boltzmann machine, is presented as follows to model the above complex image data [22].

2.3. Point-wise gated Boltzmann machines

In CAD of breast tumors with SWE, the image data contains a large amount of irrelevant sensory patterns. Exploring an automatic learning algorithm to distinguish relevant and irrelevant

Download English Version:

https://daneshyari.com/en/article/8130183

Download Persian Version:

https://daneshyari.com/article/8130183

Daneshyari.com