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● *Original Contribution*

LUMBAR ULTRASOUND IMAGE FEATURE EXTRACTION AND CLASSIFICATION WITH SUPPORT VECTOR MACHINE

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Abstract—Needle entry site localization remains a challenge for procedures that involve lumbar puncture, for example, epidural anesthesia. To solve the problem, we have developed an image classification algorithm that can automatically identify the bone/interspinous region for ultrasound images obtained from lumbar spine of pregnant patients in the transverse plane. The proposed algorithm consists of feature extraction, feature selection and machine learning procedures. A set of features, including matching values, positions and the appearance of black pixels within pre-defined windows along the midline, were extracted from the ultrasound images using template matching and midline detection methods. A support vector machine was then used to classify the bone images and interspinous images. The support vector machine model was trained with 1,040 images from 26 pregnant subjects and tested on 800 images from a separate set of 20 pregnant patients. A success rate of 95.0% on training set and 93.2% on test set was achieved with the proposed method. The trained support vector machine model was further tested on 46 off-line collected videos, and successfully identified the proper needle insertion site (interspinous region) in 45 of the cases. Therefore, the proposed method is able to process the ultrasound images of lumbar spine in an automatic manner, so as to facilitate the anesthetists' work of identifying the needle entry site. (E-mail: yushuang@nus.edu.sg) © 2015 World Federation for Ultrasound in Medicine & Biology.

Key Words: **Epidural anesthesia, Feature extraction, Feature selection, Video processing, Support vector machine, Machine learning, Medical image processing.**

INTRODUCTION

Epidural/spinal anesthesia (EA) is widely used in surgery for pain relief. A properly performed epidural procedure is the "gold standard" treatment to reduce pain during childbirth (Collis and Morgan 1995; Rawal 2012; Riley 2003). Around 50%–90% of women in labor in developed countries choose EA for pain relief (Osterman and Martin 2008). However, EA is rated as one of the most difficult procedures to perform in anesthesiology (Konrad et al. 1998). One of the key challenges for EA is identification of the needle entry site, which is traditionally identified by palpating the patients' lumbar spine (Whitty et al. 2008). This blind technique may lead to difficulties in needle insertion or require multiple insertion attempts if the entry site is not properly chosen, leading to complications in the process (Arzola et al. 2007; Paech et al. 1998). The case is worse for individuals with obesity, the landmarks for whom are much more difficult to palpate (Ellinas et al. 2009; Øberg and Poulsen 1996).

Ultrasound imaging, as a non-radioactive, convenient and inexpensive medical imaging modality, has been introduced to EA to assist epidural needle insertion since the 1950s (La Grange et al. 1978). Previous research has confirmed the effectiveness of ultrasound imaging compared with the traditional palpation method (Grau et al. 2002, 2003; Shaikh et al. 2013; Whitty et al. 2008). However, despite the benefits of ultrasound, the effective interpretation of ultrasound images remains a challenge, especially for anesthetists who received limited training in reading ultrasound images (Ecimovic and Loughrey 2010). The low spatial resolution and inherent speckle noise of ultrasound images cause the subtle anatomical features to be indiscernible from the surrounding background (Noble et al. 2011). Full interpretation of ultrasound images requires professional training, and the learning curve is steep (Chin and Perlas 2011). Therefore,

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a large proportion of anesthetists are reluctant to adopt ultrasound imaging in common practice.

To ease ultrasound image interpretation and facilitate the applicability of ultrasound in epidural needle insertion, automatic interpretation of lumbar ultrasound images has been investigated by researchers. Tran and Rohling (2010) used phase symmetry and template matching to extract the spinous process and ligamentum flavum in paramedian images. Kerby et al. (2008) proposed labeling the lumbar level automatically with panorama images obtained from the paramedian view. In addition, an augmented reality system that projects the identified lumbar vertebra levels on a patient's back was developed so as to assist spinal needle insertion (Al-Deen Ashab et al. 2013).

Although automatic interpretation of lumbar ultrasound images has been explored, the related literature focuses mainly on the longitudinal view. Ultrasound images in the transverse view, which reveal important anatomic information and have frequently been used by anesthetists for precise pre-puncture localization of needle entry site, were less researched from the automatic image interpretation perspective (Arzola et al. 2007; Balki et al. 2009). In our previous research, we developed an image processing and identification procedure for the automatic interpretation of ultrasound images in the transverse view (Yu et al. 2014b). A four-layer cascading classifier was developed to classify the interspinous images and bone images. Success rates of 94.8% on training sets and 93.23% on test sets were achieved on images obtained from pregnant participants. However, because four tunable parameters were involved in the cascading model, the robustness of the algorithm might be influenced by minor modification of the free parameters.

This article further extends the research of automatic identification for transverse lumbar ultrasound images by proposing a machine learning-based approach to further increase the classification accuracy and make the classification algorithm more intelligent and robust. We developed an intelligent image identification procedure including feature extraction, feature selection and a classification algorithm based on a support vector machine (SVM).

METHODS

Materials and image acquisition

The ultrasound video streams used in this research were collected from KK Women's and Children's Hospital (Singapore), with institutional review board approval and individual participants' consent. Pregnant women scheduled for caesarean delivery gave consent to ultrasound of their lumbar spine prior to EA. For data collection, an ultrasound system (Model U660, Canyearn Medical, Chengdu, China) and a 3.5-MHz curvilinear ultrasound probe (C3.5MHzR60, Canyearn Medical) were employed, with the scanning depth set to 8–10 cm. Contrast and gain were set as default, −10 and 80, respectively. The attenuation compensation was set with the time gain compensation (TGC) function, which allowed for a stepwise increase in gain to compensate for greater attenuation of ultrasound waves returning from deeper structures. TGC was set as proportional to the depth and remained unchanged for all of the cases collected. The ultrasound video streams were collected from the lumbar spine in the transverse view (L3–L4 or L2–L3) at a constant speed of 15 frames/s (FPS) and then saved as Windows Media Video (*.WMV) format for processing.

During the study, 46 ultrasound video streams were collected from 46 different subjects. After video streams were collected, the image database was obtained by extracting still images from the video streams. Forty images were randomly extracted from each of the video streams, resulting in a total of 1,840 ultrasound images in the training and test database. To reduce label noise, the extracted images were labeled by two experienced sonographers independently: '1' for interspinous images, '−1' for bone images and other images not proper for needle insertion. As two experts were involved in the labeling of the image database, it was inevitable that they may have different opinions on certain images, especially for images located near the junction of the interspinous and bone regions. The labels assigned with unanimous categorization by the two experts were treated as "gold standard" and used for SVM training and testing. On the contrary, the images with adversarial labels indicate that the two experts did not agree on the particular categorization of the image. The adversarial labels were regarded as label noise and removed from the database, so as to decrease the negative influence of faulty labels on supervised learning.

The feature extraction, feature selection and SVM training algorithms were implemented with MATLAB (Version R2012a, The MathWorks, Natick, MA, USA) and run on a personal computer (3.3GHz Core i5-3550 CPU and 8GB installed memory). Sector images were cropped and downsampled by a factor of 2, so as to improve the computation speed.

Ultrasound image features of lumbar spine

The ultrasound images scanned from different regions of the lumbar spine have different features, determined by the region where the probe is placed. When the probe is placed above the spinous process (not proper for needle insertion), the ultrasound wave is impeded by bones, creating a long triangular hypo-echoic acoustic shadow (Fig. 1a). The ultrasound image is dark with a triangular dark window along the midline, which is the main feature of bony images. When the probe is moved