# Feature Extraction and Classification for Ultrasound Images of Lumbar Spine with Support Vector Machine

Shuang Yu[1], Kok Kiong Tan[2], Ban Leong Sng[3], Shengjin Li[4] and Alex Tiong Heng Sia[3]

*Abstract*— **In this paper, we proposed a feature extraction and machine learning method for the classification of ultrasound images obtained from lumbar spine of pregnant patients in the transverse plane. A group of features, including matching values and positions, appearance of black pixels within predefined windows along the midline, are extracted from the ultrasound images using template matching and midline detection. Support vector machine (SVM) with Gaussian kernel is utilized to classify the bone images and interspinous images with optimal separation hyperplane. The SVM is trained with 800 images from 20 pregnant subjects and tested with 640 images from a separate set of 16 pregnant patients. A high success rate (97.25% on training set and 95.00% on test set) is achieved with the proposed method. The trained SVM model is further tested on 36 videos collected from 36 pregnant subjects and successfully identified the proper needle insertion site (interspinous region) on all of the cases. Therefore, the proposed method is able to identify the ultrasound images of lumbar spine in an automatic manner, so as to facilitate the anesthetists' work to identify the needle insertion point precisely and effectively.**

## I. INTRODUCTION

Epidural/spinal anesthesia (EA) widely used in surgery and for post-surgical pain relief. A properly performed epidural procedure is the 'gold standard' of treatment to reduce pain during childbirth [1], [2] . Around 50-90% of women in labour in developed countries choose EA for pain relief [3]. However, the failure rate of EA has been reported to be as high as 20% [4], [5]. One of the key challenges for EA is the identification of needle insertion site, which is traditionally identified by palpating on the patients' lumbar spine [6]. This blind technique may requires multiple needle insertion attempts, leading to the complications for patients. The case is worse for patients with obesity problems, which is increasingly common for pregnant population.

Ultrasound imaging, as a non-ionizing, convenient and inexpensive medical imaging modality, has been introduced to EA to assist epidural needle insertion since the 1950s [7]. Previous researches have confirmed the effectiveness of ultrasound imaging compared with traditional palpation method [8]–[10]. However, despite the benefit of ultrasound, the effective interpretation of ultrasound images remains a challenge, especially for anesthetists who received limited training in reading ultrasound images [11]. The low spatial resolution and severe speckle noises of ultrasound images results in the subtle anatomical features to be indiscernible from the surrounding background [12]. It requires professional training to fully interpret the ultrasound images with deep learning curve. Therefore, anesthetists are reluctant to adopt ultrasound imaging in the common practice.

In order to ease the ultrasound image interpretation and facilitate the applicability of ultrasound in epidural needle insertion, automatic interpretation of lumbar ultrasound images has been investigated by researchers. Train et al. utilized phase symmetry and template matching to extract the lamina and ligamentum flavum in the paramedian images [13]. Kerby et. al proposed to label the lumbar level automatically with panorama images obtained from the paramedian view [14]. Furthermore, an augmented reality system (AREA) which projected the identified lumbar vertebra levels on the patients back was developed so as to assist spinal needle insertion [15].

Although automatic interpretation of lumbar ultrasound images has been explored, it is mainly focused on the paramedian view. Ultrasound images in the transverse view, which reveal important anatomical information and frequently been used by anesthetists for precise pre-puncture localization of needle insertion site, are less researched into from the automatic image interpretation perspective. In our previous research, an image processing and identification procedure was developed for the automatic interpretation of ultrasound images in the transverse view [16]. Template matching combined with position correlator (PC) was proposed to identify the interspinous images and achieved a success rate of 100% on ultrasound images obtained from lumbar spine of healthy volunteers. However, since the clarity of anatomical feature of lumbar spine might degrade during pregnancy [17], the original position correlator designed for healthy volunteer is not effectively applicable to the pregnant patient.

In order to improve the identification accuracy for pregnant patients and make the classification algorithm more general applicable, a feature extraction, feature selection and classification algorithm based on support vector machine (SVM) is developed. Three contributions are achieved with this paper. Firstly, a set of features, which are composed of important parameters, are extracted from the lumbar ultrasound images with template matching and midline detection methods. Secondly, a SVM model with Gaussian kernel is trained using the extracted feature sets, so as to generate the maximal margin for the classification. A high success rate is achieved with the proposed feature extraction and

[1]Shuang Yu is with the NUS Graduate School for Integrative Sciences and Engineering, attached to Department of Electrical and Computer Engineering, National University of Singapore(e-mail: yushuang@nus.edu.sg).

[2]Kok Kiong Tan is with the Department of Electrical and Computer Engineering, National University of Singapore (e-mail: kktan@nus.edu.sg).

[3]Alex Tiong Heng Sia and Ban Leong Sng are with the Department of Women's Anaesthesia, KK Women's and Children's Hospital (e-mail: Alex.Sia.TH@kkh.com.sg, sng.ban.leong@kkh.com.sg)

[4]Shengjin Li is with Duke-NUS Graduate Medical School (e-mail: lishengjin@nus.edu.sg)

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

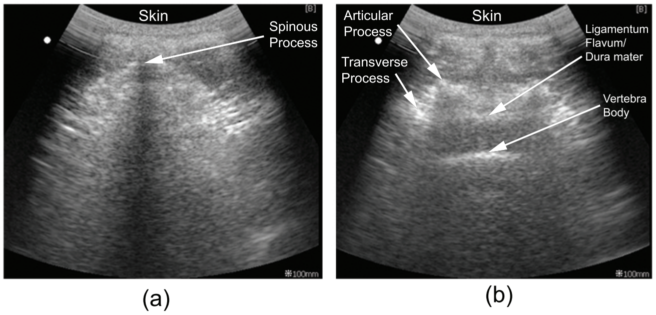


Fig. 1. Ultrasound Image of Lumbar Spine. (a) typical ultrasound image when the probe is placed above spinous process, featured by the triangular anechoic window; (b) ultrasound image when probe is placed on interspinous space, where the articular processes, epidural space and vertebra body are visible.

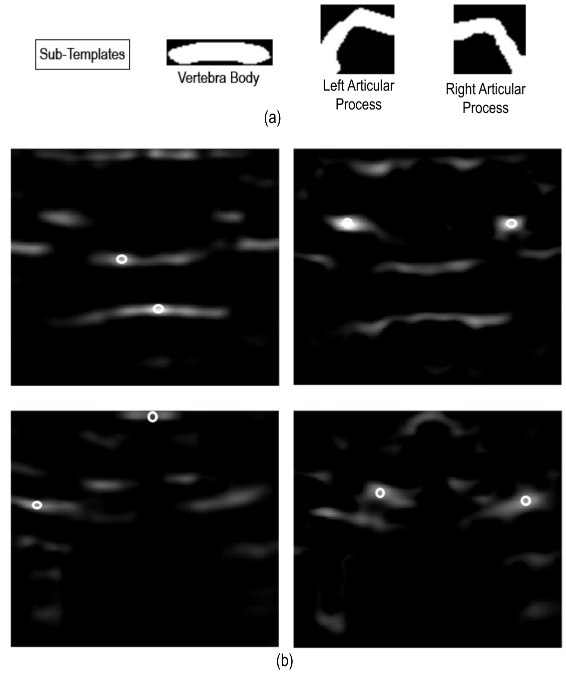


Fig. 2. Feature Extraction with Template Matching. (a) Sub-templates for anatomical features, from left to right: Vertebra body and epidural space, left articular process and right articular process; (b) Matching result of key anatomical features: The left column: matching result of vertebra body sub-template; the right column: matching result for articular process sub-templates; the upper row: interspinous image; the lower row: bone image. The optimal matching position is marked by a circle.

SVM classification algorithm on images collected from the pregnant patients. Last but not least, the trained SVM model is also tested on 36 videos and it successfully identify the interspinous region and bone region on all of the cases collected, with a computational speed fast enough for real-time processing.

## II. Materials and METHODS

### A. Ultrasound Image Feature of Lumbar Spine

The ultrasound images taken at different region of the lumbar spine have different features, determined by the region where the probe is placed. When the probe is placed directly on the spinous process (not proper for needle insertion), the ultrasound wave will be impeded by bones, creating a long triangular hypo-echoic acoustic shadow Fig 1(a)). The the ultrasound image will be dark with a triangular dark window along the midline, which is the main feature of bony images. When the probe is moved to the interspinous region (proper for needle insertion), more details beneath the skin can be noted, as shown in Fig 1(b). The 'flying bat' alike shape on the ultrasound image indicates that the location of the probe is a suitable site for needle insertion [18].

### B. Feature Extraction

Before feature extraction, raw ultrasound images are pre-processed with difference of Gaussian enhanced local normalization, so as to remove the speckle noises and extract the anatomical structure. After pre-processing, local intensity variance induced by uneven ultrasound wave reflection rate are also eliminated. Therefore, a potential element which might deteriorate the image classification is removed.

In this paper, image features are extracted with two approaches, the template matching method to detect the key anatomical features and midline detection approached to obtain image features along midline.

*1) Template Matching:* The visibility of 'flying bat' shape is the criterion adopted by anesthetists to recognize interspinous images [18]. However, in computer vision, due to the variation and distribution extent of the 'flying bat' shape in the image, the recognition of the entire shape is not a easy task. In our previous research, we proposed to decompose the 'flying bat' shape into three sub-features: the 'bat ear' (articular process), epidural space and vertebra body. The decomposed sub-features recognized the articular process and vertebra body with high accuracy on images obtained from volunteers.

In this paper, similar decomposition is employed. Template matching is used to obtain the matching position and matching value between the sub-features and the images. Among the three sub-features, the appearance of the epidural space and the vertebra body both resemble a line. Thus, the same linear sub-template (as shown on Fig 2(a)) is employed for the recognition of both vertebra body and epidural space. Of the two maximum matching regions, the one that locates lower in the image is vertebra body and the superior one is epidural space, which follows the anatomical structure of the lumbar spine. In the interspinous images, the visibility of vertebra body and epidural space is clear and both of them can be correctly recognized. While in the bone images, the maximum matching of the sub-template will occur at different regions in the image; and the matching values for both epidural space and vertebra body are low, as indicated by Fig 2(b). The situation is the same for the matching of articular processes, except that the maximum matching of articular processes should appear on the left and right side of the midline. Therefore, based on the matching position and matching value, it is possible to partly discriminate the interspinous images and bone images.

The parameters obtained with template matching can be utilized to constitute part of the feature vector for the purpose of image classification, including the retrospective depth measurement of epidural space ($\mathcal{D}_1$) and vertebra body ($\mathcal{D}_2$), their matching values ($\mathcal{V}_1$ and $\mathcal{V}_2$), matching position of two articular processes ($\mathcal{P}_3$, $\mathcal{D}_3$ for left articular process and $\mathcal{P}_4$, $\mathcal{D}_4$ for right articular process) and their matching values ($\mathcal{V}_3$ and $\mathcal{V}_4$).

*2) Midline Detection:* The image features along the midline of the ultrasound image is different for interspinous images and bone images. For the bone images, ultrasound image is impeded by the spinous process, resulting in an anechoic region along the midline; while for interspinous images, the epidural space and vertebra body along the midline will be visible. Therefore, the appearance of black pixels along the midline serve as an important feature for the classification of interspinous / bone images.

For the detection of midline, a cost function $J(\vartheta, x_0)$ based on the summation of white pixels within a predefined scanning window is formulated. The window scanned though the entire image within [-45, +45] degrees. The position and degree that gives the minimum cost function value will locate the midline. In order to increase the accuracy of midline detection for interspinous images, a penalty which decreases its weight as a function of depth is imposed on the cost function, so as to allow the appearance of epidural space and vertebra body to be less penalized in the cost function. The cost function is formulated as the in Equation 1.

$$\begin{aligned} J(\vartheta, x_0) = \sum_{i=1}^{n} \sum_{j=-C}^{C} [0.5 + exp(-0.05i)] \times \\ f(i, itan\vartheta + x_0 + j) \times \sqrt{(1 + 0.3|\vartheta||x_0 - n/2|)}; \end{aligned} \tag{1}$$

The first part of the Equation 1 is the penalty term for the appearance of white pixels at different depths. And the third part is the penalty term if the detected midline is not near the middle of the ultrasound image or that it is not vertical. In equation 1, $f(i, j)$ denotes the binary image of the pre-processed ultrasound image with a dimension of $m \times n$; C represents half size of the predefined window, which can be optimally set between 5 - 10.

After optimal $\vartheta'$ and $x_0'$ is obtained and midline is located, the rate of black pixels within the predefined scanning window can be calculated using the following equation:

$$\mathcal{R}_b = 1 - \frac{\sum_{i=1}^{n} \sum_{j=-C}^{C} f(i, itan\vartheta' + x_0' + j)}{2Cn} \tag{2}$$

The depth of epidural space is reported to range from 3-8 cm, indicating that the epidural space and vertebra body appear deeper than 3cm in the image. Thus, the rate of potential epidural space and vertebra body within the scanning window can be calculated with:

$$\mathcal{R}_w = \frac{\sum_{i>=3cm}^{n} \sum_{j=-C}^{C} f(i, itan\vartheta' + x_0' + j)}{2Cn} \tag{3}$$

$\mathcal{R}_b$ and $\mathcal{R}_w$ adds another two parameters for the feature vector. Therefore, combining the 10 parameters obtained from template matching and 2 parameters from midline detection, a feature vector of length 12 is formulated.

### C. Support Vector Machine

After the feature vector has been obtained and normalized, support vector machine (SVM) is employed to optimally classify the interspinous images and bone images. SVM is a supervised learning algorithm which seeks a decision boundary (or separating hyperplane) with maximal margin for the training set. For cases where the data is non-linearly separable, a nonlinear kernel function can be used to enhance the separability of training data.

For the given training samples, $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$, the optimization problem is formulated as:

$$\begin{aligned} min_{w,b} \quad & \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{N}\xi_i \\ s.t. \quad & y_i g(\mathbf{x}_i) = y_i(\mathbf{w}^T\psi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad \forall i \\ & \xi_i \geq 0, \quad \forall i \end{aligned} \tag{4}$$

In the equation 4, $\xi_i$ is slack variable and measures the degree of misclassification of training data $\mathbf{x}_i$. Training data which are misclassified will have their corresponding $\xi_i >$ 1. The parameter $C$ is a regularization term that controls the relative weighting between the two goals of achieving larger margin and decreasing classification error. A larger C corresponds to assigning a higher penalty to errors. $\psi(\mathbf{x})$ is the nonlinear transformation which maps the original feature vector into a higher dimension space.

The dual form of the optimization in equation 4 is:

$$\begin{aligned} max_{\boldsymbol{\alpha}} \quad & Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j \psi^T(\mathbf{x}_i)\psi(\mathbf{x}_j) \\ s.t. \quad & 0 \leq \alpha_i \leq C, \quad \forall i \\ & \sum_{i=1}^{N}\alpha_i y_i = 0 \end{aligned} \tag{5}$$

In this paper, the Gaussian kernel (radial basis function) is used, with the format as equation 6 indicates:

$$\begin{aligned} K(x_1, x_2) &= \psi^T(\mathbf{x}_i)\psi(\mathbf{x}_j) \\ &= exp(-\frac{||x_1 - x_2||^2}{2\sigma^2}) \end{aligned} \tag{6}$$

Quadratic programming can be employed to calculate $\boldsymbol{\alpha}$. Then the optimal hyperplane parameter can be obtained by:

$$\begin{aligned} g(\mathbf{x}) &= \sum_{i=1}^{N}\alpha_{o,i} y_i K(\mathbf{x}, \mathbf{x}_i) \\ y &= sgn(g(\mathbf{x})) \end{aligned} \tag{7}$$

### D. Materials and Image Acquisition

The ultrasound video streams utilized in this research were collected from KK Women's and Children's Hospital, with institutional review board (IRB) approved and patients'

TABLE I

STATISTICS OF TRAINING SET AND TEST SET.

| | Training Set | Test Set |
|---|---|---|
| Subject Number | 20 | 16 |
| Image Number | 800 | 640 |
| Interspinous | 426 | 374 |
| Bone Images | 374 | 266 |

TABLE II

PERFORMANCE OF SVM CLASSIFICATION .

| | Training Set (%) | Test Set (%) |
|---|---|---|
| Accuracy | 97.25 | 95.00 |
| Precision | 97.64 | 96.22 |
| Recall | 97.18 | 95.19 |
| F0.5 | 97.55 | 96.01 |

consent obtained. Pregnant women scheduled for a caesarean procedure were recruited before they were sent to the operation theater. 36 ultrasound video streams are collected from 36 different subjects. After video streams are collected, the image database is obtained by extracting still images from the video streams. 40 images are randomly extracted from each of the video streams, constituting 1440 ultrasound images in the training and test database in total. The extracted images are then labelled by an experienced sonographer: '1' for interspinous images and '-1' for bone images.

## III. RESULTS AND DISCUSSION

Of the 36 videos collected, 20 of them are randomly selected as training set and the remaining 16 are used as test set. Since 40 images are extracted from each video, thus there are in total 800 images in the training set and 640 images in the test set. The detailed statistical information of the images is listed in Table I.

Based on the training set, the SVM model is trained to get the optimal hyperplane with maximal margin. The trained model are then validated on the test set. The best performance is achieved when setting $C = 1$ and $\sigma = 1.5$. The performance of the SVM model on both training set and test set is displayed on Table II.

The trained SVM model is further tested on the ultrasound video streams collected to identify the interspinous region and bone region. In the video processing, the interspinous region is defined by the continuous appearance of more than 5 interspinous images; while for the negative detections, if it is in the interspinous region, no more than 2 bone images shall be detected by the image; vice versa for bone region. According to the definition above, the trained SVM model is able to identify the interspinous region and bone region correctly on all of the 36/36 video streams collected. The computation time cost for each single frame is 57.0ms. Since the video is collected at the frame rate of 15 FPS, thus the computation speed is fast enough for real-time processing.

## IV. CONCLUSIONS

In this paper, we proposed a feature extraction and classification procedure for the ultrasound image collected from lumbar spine. The important anatomical features, including epidural space, vertebra body and articular processes are extracted from the ultrasound images. Moreover, the rate of black pixels along with midline are also extracted after midline is detected. Based on the features extracted from training samples and test samples, SVM is used to classify the interspinous/ bone images with maximal margin. The trained SVM model is also tested on the 36 ultrasound video streams collected from pregnant patients, and successfully identified the interspinous region / bone region on all of the videos collected.

## REFERENCES


[1] Riley ET. Regional anesthesia for cesarean section. Techniques in Regional Anesthesia and Pain Management, Volume 7, Issue 4, October 2003, Pages 204-212

[2] Rawal N. Reg Anesth Pain Med. 2012 May-Jun;37(3):310-7

[3] Osterman MJK, Martin JA. Epidural and Spinal Anesthesia Use During Labor: 27-State Reporting Area, Centers for Disease Control and Preventnion, 2008

[4] Lewis MP, Thomas P, Wilson LF, Mulholland RC. The 'whoosh' test. A clinical test to confirm correct needle placement in caudal epidural injections. Anaesthesia. 1992 Jan;47(1):57-8.

[5] Le Coq G, Ducot B, Benhamou D. Risk factors of inadequate pain relief during epidural analgesia for labour and delivery. Can J Anaesth. 1998 Aug;45(8):719-23.

[6] Paech MJ, Godkin R, Webster S. Complications of obstetric epidural analgesia and anaesthesia: a prospective analysis of 10,995 cases. Int J Obstet Anesth. 1998 Jan;7(1):5-11.

[7] La Grange P, Foster PA, Pretorius LK. Application of the Doppler ultrasound bloodflow detector in supraclavicular brachial plexus block. Br J Anaesth. 1978 Sep;50(9):965-7.

[8] Grau T, Bartusseck E, Conradi R, Martin E, Motsch J. Ultrasound imaging improves learning curves in obstetric epidural anesthesia: a preliminary study. Can J Anaesth. 2003 Dec;50(10):1047-50.

[9] Grau T, Leipold RW, Conradi R, Martin E, Motsch J. Efficacy of ultrasound imaging in obstetric epidural anesthesia. J Clin Anesth. 2002 May;14(3):169-75.

[10] Whitty R, Moore M, Macarthur A. Identification of the lumbar interspinous spaces: palpation versus ultrasound. Anesth Analg. 2008 Feb;106(2):538-40

[11] Ecimovic P, Loughrey JP. Ultrasound in obstetric anaesthesia: a review of current applications. Int J Obstet Anesth. 2010 Jul;19(3):320-6.

[12] Noble JA, Navab N, Becher H. Ultrasonic image analysis and image-guided interventions. Interface Focus. 2011 Aug 6;1(4):673-85.

[13] Tran D, Rohling RN. Automatic detection of lumbar anatomy in ultrasound images of human subjects. IEEE Trans Biomed Eng. 2010 Sep;57(9):2248-56.

[14] Kerby B, Rohling R, Nair V, Abolmaesumi P. Automatic identification of lumbar level with ultrasound. Conf Proc IEEE Eng Med Biol Soc. 2008;2008:2980-3

[15] Al-Deen Ashab H, Lessoway VA, Khallaghi S, Cheng A, Rohling R, Abolmaesumi P. An augmented reality system for epidural anesthesia (AREA): prepuncture identification of vertebrae. IEEE Trans Biomed Eng. 2013 Sep;60(9):2636-44.

[16] Yu S, Tan KK, Shen CY, Sia ATH. Ultrasound Guided Automatic Localization of Needle Insertion Site for Epidural Anesthesia. Proceeding of IEEE International Conference on Mechatronics and Automation, Aug 4-7, Takamatsu, Japan, 2013: 985-990.

[17] Lee Y, Tanaka M, Carvalho JC. Sonoanatomy of the lumbar spine in patients with previous unintentional dural punctures during labour epidurals. Reg Anesth Pain Med 2008; 33(3):266-70.

[18] Carvalho JC. Ultrasound-facilitated epidurals and spinals in obstetrics. Anesthesiol Clin. 2008 Mar;26(1):145-58