Fully Automated Localization of Multiple Pelvic Bone Structures on MRI

Sinan Onal- *IEEE Member*, Susana Lai-Yuen, Paul Bao- *IEEE Senior Member*, Alfredo Weitzenfeld- *IEEE Senior Member*, Stuart Hart

***Abstract*— In this paper, we present a fully automated localization method for multiple pelvic bone structures on magnetic resonance images (MRI). Pelvic bone structures are currently identified manually on MRI to identify reference points for measurement and evaluation of pelvic organ prolapse (POP). Given that this is a time-consuming and subjective procedure, there is a need to localize pelvic bone structures without any user interaction. However, bone structures are not easily differentiable from soft tissue on MRI as their pixel intensities tend to be very similar. In this research, we present a model that automatically identifies the bounding boxes of the bone structures on MRI using support vector machines (SVM) based classification and non-linear regression model that captures global and local information. Based on the relative locations of pelvic bones and organs, and local information such as texture features, the model identifies the location of the pelvic bone structures by establishing the association between their locations. Results show that the proposed method is able to locate the bone structures of interest accurately. The pubic bone, sacral promontory, and coccyx were correctly detected (DSI > 0.75) in 92%, 90%, and 88% of the testing images. This research aims to enable accurate, consistent and fully automated identification of pelvic bone structures on MRI to facilitate and improve the diagnosis of female pelvic organ prolapse.**

I. INTRODUCTION

Pelvic Organ Prolapse (POP) is a serious health condition that affects about 30-50% of women [1]. It occurs when a pelvic organ such as bladder, uterus, small bowel and rectum drops from its normal position and pushes against the vaginal walls. Dynamic magnetic resonance imaging (MRI) is currently being used for assessing POP as it provides global assessment of the movements and interactions of pelvic floor organs while avoiding the use of ionizing radiation [2]. The current practice consists of manually identifying specific reference points on three pelvic bone structures as shown in Fig. 1: pubic bone, sacral promontory, and coccyx.

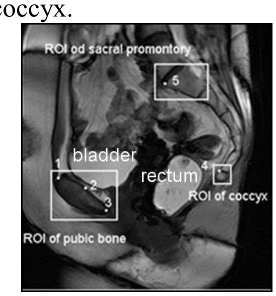

Figure 1. Regions of interest.

Based on these points, reference lines are drawn to measure and define the severity of POP. Unfortunately, the manual identification of these points and measurements is a time-consuming and subjective procedure. For this reason, it is expected that a model that automatically locates the bone structures of interest and extracts image-based predictors from patient specific MRI can facilitate and improve the evaluation of POP. However, bone structure detection is a challenging task on MRI since bones are not easily differentiable from the soft tissue as their pixel intensities tend to be very similar.

Various approaches have been proposed for the automated organ localization in medical images using geometric methods, statistical atlas-based techniques, and supervised methods to find multiple organs such as heart, liver, spleen, lungs, kidneys and bladder [3-10]. Among supervised methods, there has been an increasing interest in regression-based approaches for anatomical structure localization, since organs and tissues in the human body have known relative arrangement. Zhou et al. [11] introduced an approach based on boosting ridge regression to localize the left ventricle in cardiac ultrasound 2D images. Criminisi et al. [12] proposed regression forests to predict the location of multiple anatomical structures in CT scans. Cuingnet et al. [13] presented an improved regression forest to find kidneys in CT scans. Bagci et al. [14] built a hierarchical transfer function from image space to object space to find anatomical structures in CT and MRI. These methods use the difference of mean intensities to locate the bounding boxes of the anatomical structures on the images. Since considering only intensity levels in MRI is not sufficient for the localization of anatomical structures, particularly bone structures, a new approach is needed to automatically detect bone structures on MRI.

In this paper, we present a fully automated model that locates the bounding boxes of multiple bone structures on

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MRI using support vector machines (SVM) based classification and non-linear regression model with global information. The presented method first identifies organs using *k*-means clustering and morphological opening operations. Then, it uses the spatial relationship between the organs and bone structures to estimate the locations of the latter. The pubic bone is located using the relative location between bones and organs, and texture information. Then, a non-linear regression model is used to predict the location of other bone structures whose local information is weak such as sacral promontory and coccyx. The main contribution of this approach is a new parameterization through non-linear regression approach for the multiple bone localization problem on MRI.

II. MULTIPLE BONE LOCALIZATION FRAMEWORK

As shown in Fig. 1, three regions of interest (ROIs) need to be located automatically that correspond to the pubic bone, sacral promontory, and coccyx. However, bones are not easily differentiable from the soft tissue on MRI as their pixel intensities tend to be very similar. This is particularly true for bones located on the vertebra such as sacral promontory and coccyx. On the other hand, both the bladder and the rectum are easily visible as retrograde bladder/ureteral dye is injected during image capturing to improve visualization. Therefore, the regions for both the bladder and the rectum have high intensity values on the MR images and can be used as contextual information to automatically locate the pelvic floor structures of interest. For these reasons, our approach consists of localizing the pubic bone first using both global and local information, and then use global information to localize the sacral promontory and coccyx.

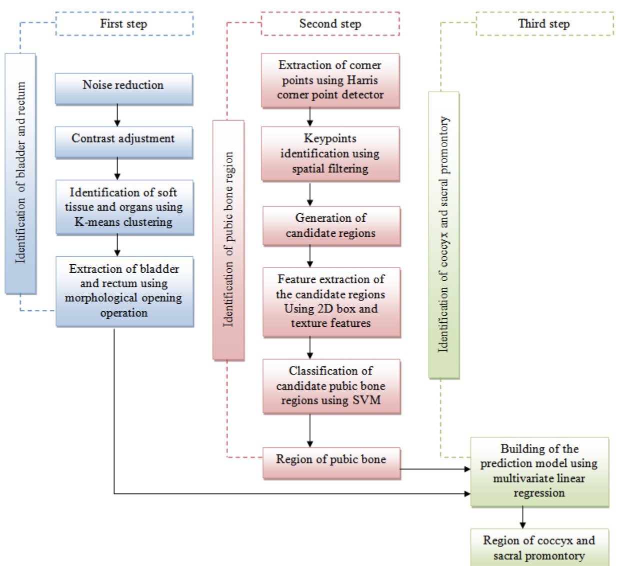

Figure 2. Overview of the proposed method.

The proposed method consists of three main steps: identification of bladder and rectum, identification of pubic bone region, and identification of coccyx and sacral promontory regions (see Fig. 2). The first step starts with noise reduction and contrast adjustment of the images. Then, the bladder and rectum are identified using bisecting *k*-means clustering using pixel intensities and morphological opening operation. In the second step, the pubic bone region is localized based on “key” points, which are corner points on the input image that satisfy certain intensity and location constraints. Based on the identified key points, candidate bounding boxes of the pubic bone can be determined. The best bounding box that describes the pubic area is selected using support vector machines (SVM) with 2D box features. In the third step, the coccyx and sacral promontory regions are localized using the location of the bladder, rectum and pubic bone via a non-linear regression model. Following is the detailed description of the proposed method.

A. Dataset Description

A representative set of 207 dynamic MRI were used in this study. The dataset was divided into a training set of 117 images and a testing set composed of the remaining 90 images. MR images were obtained from a 3-Tesla GE system (General Electric Company, GE Healthcare, UK) using an 8-channel torso phased-array coil with the patient in a modified dorsal lithotomy position. Dynamic MRI of the pelvis is performed using a T2-weighted single-shot turbo spin-echo (SSH-TSE) sequence in the midsagittal plane for 23-27 seconds with a temporal resolution of 2s (FOV 300×300 mm2, slice thickness 3 mm, TR/TE 2,000/75 ms, 20 image sequences, in-plane resolution of 1.6×1.6 mm2).

B. Identification of Bladder and Rectum

The first step of the proposed method is to perform noise reduction by applying a 3 by 3 Gaussian kernel due to its computational efficiency. After noise reduction, contrast adjustment is performed to improve the contrast in the images by stretching the range of intensity values.

Given the clearer visibility of the bladder and the rectum on dynamic MRI due to ureteral dye use, these two organs can be automatically identified to be used as contextual information for the localization of the bone structures. We use a “bisecting *k*-means” algorithm to identify regions on the image and to overcome the initialization susceptibility of the basic *k*-means clustering algorithm. In our study, the value of k is 4 because the region of the pelvic floor is divided into four sub-regions representing the bone, cartilage, soft tissue and organ, and background.

After identifying the four types of regions, the regions with the highest intensity are selected to locate the bladder and rectum regions. However, many regions with similar intensities to the bladder and rectum may be identified. To separate the organs of interest, size, homogeneity, and location constraints were incorporated. For size constraint, connected regions that have less and more than a specified number of pixels were removed using morphological opening operations. The minimum and maximum size for a region to be retained is 1,800 pixels and 10,000 pixels, respectively. These values were obtained based on the image dataset. For homogeneity, it was observed that the bladder and rectum regions on MRI are homogeneous regions without internal holes. Therefore, the euler number, which is a topological descriptor, was used to determine the number of holes inside the regions and to eliminate those regions with internal holes. Finally, as location constraint, the location of the bladder and rectum normally appear close to the middle of the image so the search of these two organs was limited to the center of the image.

C. Identification of Pubic Bone Region

The localization of the pubic bone is achieved through the identification of key points on the image that satisfy specific location and intensity constraints. These key points are generated through the identification of corner points using the Harris corner detector [15]. Although there is no relationship between corner points and the appearance of the pubic bone, corner points can be extracted without any user input and result in fewer points to be analyzed in comparison with using pixels. Then, spatial filtering was used to eliminate corner points that are outside of the vicinity of the pubic bone. The filtering operation includes location and intensity constraints to ensure that corner points that are below and to the left of the bladder and within a specific distance and intensity range are retained.

After spatial filtering, potential pubic bone regions are generated as seen in Fig. 3. These bounding boxes are centered at the keypoints and the size is set to a fixed value to enclose the pubic bone region. This value was determined based on the analysis of the image dataset obtained for this study. Each of these bounding boxes represents a potential bounding box for the pubic bone. However, as shown in Fig. 3, some of these bounding boxes do not completely enclose the pubic bone as the keypoints may fall near the boundaries of the bone. For this reason, the bounding boxes that completely enclose the pubic bone need to be identified. To do this, we propose to analyze each candidate region based on 2D box features and texture features. 2D box features provide the average intensity difference between two displaced boxes. Texture features have shown to enable more reliable results on MRI by providing the relative position information of any two pixels with respect to each other [16, 17]. We used 297 generated 2D box features and six texture features. The texture features in this study are average gray level, average contrast, smoothness, skewness, uniformity, and entropy. Since each feature provides unique information to group the candidate regions, all of them were used in the classification process.

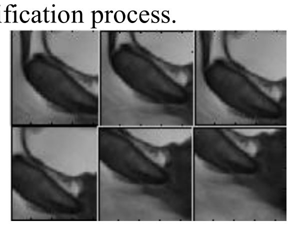

Figure 3. Examples of generated candidate regions for pubic bone.

Since the centered pubic bone is desirable for bounding boxes bone location process, 2D box features provide information on whether the pubic bone is in the center of the bounding box or not. Similarly, texture features calculate six measures of texture from each generated region.

The feature set representing the candidate regions is evaluated using SVM. SVM has been shown to achieve the highest classification accuracy for medical diagnosis compared to other classification techniques [18, 19]. Our study consists of a two-class problem where candidate bounding boxes are classified into bounding boxes of pubic bone or not. The classification of the candidate regions involves two steps: construction of the classifier and prediction. In the first step, a classifier structure is constructed based on the training data set using SVM. We trained SVM using the Gaussian radial basis function kernel to provide a non-linear decision surface. The model was evaluated using 10-fold cross validation. After the regions are trained according to the features, the second step of the segmentation process is to apply the model to test images using the built SVM classifier. The anticipated outcome at the end of this process is a set of two groups of regions that are automatically classified as enclosed pubic bone regions and partially enclosed pubic bone regions.

D. Identification of Coccyx and Sacral Promontory Regions

Given that the locations of the bladder, rectum, and pubic bone are strongly correlated with the locations of the sacral promontory and coccyx, we built a non-linear regression model to predict the location of the coccyx and sacral promontory regions. We parameterize the location of the pelvic floor structures using the bladder, rectum and pubic bone location information. For training, we consider our input as $(\boldsymbol{S_i}, \boldsymbol{P_i})$, where $\boldsymbol{S}_i$ is the input matrix and $\boldsymbol{P}_i$ is the predicted matrix. $\boldsymbol{S_i}$ consists of the locations of the centroids of the structures, and the relative distances between the centroids of the bladder and rectum to the centroid of the pubic bone. $\boldsymbol{P_i}$ consists of the distances between the centroids of sacral promontory and coccyx to the centroid of the pubic bone. The validation of the trained model was checked with 10-fold cross validation.

Once the centroids of the sacral promontory and coccyx are identified, their bounding boxes are determined based on the mean and variation of the bounding boxes from the training dataset. PCA is used to provide the fixed size of the bounding box for each region. For instance, the maximum size for the bounding box of the sacral promontory has been defined as [60p*x* x 60 *px*] based on the training dataset and PCA. For the coccyx, the maximum size for the bounding box was determined to be [30*px* x 30*px*]. These bounding boxes are centered at the centroids of the sacral promontory and coccyx.

III. RESULTS

The validation of the proposed multiple bone localization model was performed on a representative clinical dataset of 207 dynamic MRI. The presented method was implemented using Matlab 2012b on a workstation with 3.00GHz dual processors and 2 GB RAM.

The regions identified through the proposed localization method were compared to the regions identified manually by experts. The Euclidean distance between the centers of the predicted and ground truth bounding boxes was used to assess the accuracy of the bone localization approach. In addition, we quantified the region overlap between the predicted and ground truth regions using the *Dice Similarity Index* (DSI).

Table I provides the average center error in mm for the 90 testing images. The average center error for the pubic bone is 3.2 mm with 1.2 mm standard deviation. For the coccyx, the average center error is 14.5 mm with 4.6 mm standard deviation while the error and standard deviation for the sacral promontory are 8.1 mm and 3.8 mm, respectively. It can be observed that the center error for the pubic bone is the lowest compared to the coccyx and sacral promontory while average center error for the coccyx is the highest. The reason is that both local and global information was used for the localization of the pubic bone whereas only global information was used for the coccyx and sacral promontory. This is due to the lack of local information that could be used to identify these two bones. Moreover, the manual identification of the coccyx on MRI by experts is very difficult and subjective thus explaining the high average center error for the coccyx by the presented model.

TABLE I. AVERAGE CENTER ERROR (MEAN ± STANDARD DEVIATION) FOR PELVIC BONE DETECTION

Average Center error (mm)		
Pubic bone	**Coccyx**	**Sacral Promontory**
3.2±1.2	14.5±4.6	8.1±3.8

TABLE II. PERCENTAGE OF CORRECTLY DETECTED CASES BY THE PROPOSED BONE LOCALIZATION MODEL

	Pubic bone	**Coccyx**	**Sacral Promontory**
DSI > 0.90	90% (82)	81% (79)	86% (81)
DSI > 0.75	92% (82)	88% (79)	90% (81)
DSI > 0.65	98% (82)	93% (79)	96% (81)

Table II provides the percentage of correctly detected cases at different thresholds for DSI. It can be observed that even at very high thresholds for DSI, the proposed method can correctly detect the pubic bone (DSI > 0.90) in 90% of the testing images by the proposed scheme. Similarly, the proposed scheme correctly detected the sacral promontory in 86% of the unknown images and the coccyx in 81% of the images. Once the overlapping percentage between two regions is decreased to 0.75, the proposed scheme correctly detected the pubic bone (DSI > 0.75) in 92% of the testing images. At the same time, the sacral promontory and coccyx were correctly detected in 90% and 88% of the testing images, respectively

IV. CONCLUSION

A model using SVM based classification and non-linear regression model with global and local information is presented to automatically localize multiple pelvic bone structures on MRI. The main contribution of this approach is a new parameterization through non-linear regression approach for the multiple bone localization problem. The model uses the location of pelvic organs to approximate the relative location of the pelvic bones. The best pubic bone region is selected using a SVM classifier based on texture and 2D box features. Then, a non-linear regression model was built to establish the association between the locations of the bladder, rectum, and pubic bone with respect to the location of the sacral promontory and coccyx. Results demonstrate that the presented method can accurately find the location of the bone structures on each image consistently. Additional information might be needed to improve the localization of the sacral promontory and coccyx regions using local information. The presented method can be applicable for the automated localization of bone structures on MRI to facilitate the extraction of measurements for clinical diagnosis.

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