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Abstract. The automatic extraction of the vertebra's shape from dynamic magnetic resonance imaging (MRI) could improve understanding of clinical conditions and their diagnosis. It is hypothesized that the shape of the sacral curve is related to the development of some gynecological conditions such as pelvic organ prolapse (POP). POP is a critical health condition for women and consists of pelvic organs dropping from their normal position. Dynamic MRI is used for assessing POP and to complement clinical examination. Studies have shown some evidence on the association between the shape of the sacral curve and the development of POP. However, the sacral curve is currently extracted manually limiting studies to small datasets and inconclusive evidence. A method composed of an adaptive shortest path algorithm that enhances edge detection and linking, and an improved curve fitting procedure is proposed to automate the identification and segmentation of the sacral curve on MRI. The proposed method uses predetermined pixels surrounding the sacral curve that are found through edge detection to decrease computation time compared to other model-based segmentation algorithms. Moreover, the proposed method is fully automatic and does not require user input or training. Experimental results show that the proposed method can accurately identify sacral curves for nearly 91% of dynamic MRI cases tested in this study. The proposed model is robust and can be used to effectively identify bone structures on MRI. © 2017 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JMI.4.1.014504](https://doi.org/10.1117/1.JMI.4.1.014504)]

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1 Introduction

Pelvic organ prolapse (POP) is a serious health condition that affects about 30% to 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. Current studies have shown some evidence on the association between POP and the shape of the vertebral column. Nguyen et al.² determined that there is a relationship between POP stages and changes in lumbar lordosis and/or pelvic inlet orientation. They found that women with advanced uterovaginal prolapse have less lumbar lordosis and a pelvic inlet that is oriented less vertically than women without prolapse. Mattox et al.³ presented that an abnormal change in spinal curve is a significant risk factor in the development of POP. These studies showed that the shape of the spinal curve can have an impact in the development of POP. Unfortunately, these bone structures are currently segmented manually, through a time-consuming and subjective procedure. This has confined current studies to small datasets limiting conclusive clinical evidence.

Over the past years, various automatic, semiautomatic, and interactive approaches have been proposed for segmenting the vertebra column on MRI and CT scans using two-dimensional (2-D) or three-dimensional approaches. The 2-D approaches

include adaptive-boosting and normalized cuts,⁴ active shape models,⁵ and fuzzy clustering combined with atlas registration.⁶ All these algorithms require intensive learning from a large, manually segmented training set. Although effective in some cases, training-based algorithms may have difficulty in capturing the substantial variations in a clinical context. The ensuing results are often bounded to the choice of a training set and a specific type of imaging data.

As an alternative to learning-based segmentation algorithms, Nieniewski and Seneels⁷ proposed a morphological method for segmentation of the spinal cord on MRI. Semiautomatic methods have been presented for the segmentation of the spinal cord on CT or MRI using multiple-feature boundary classification,^{8,9} top-down knowledge-based techniques,¹⁰ region growing,¹¹ level sets,¹² 2-D snakes,¹³ active surface models,¹⁴ and other techniques.¹⁵

Model-based segmentation algorithms, such as active contours¹⁶ and iterative graph cuts-based algorithms,^{17,18} have also been proposed to identify the vertebral column in spinal MRI. Interactive approaches^{19,20} including live-wire and interactive cut segmentations have been developed as real-time interactive tools for boundary extraction requiring minimum user interaction. However, all of these techniques have been applied to either spine MRI or CT scan, both of which clearly show the anatomy of the vertebrae. Spine MRI is considered the most sensitive image acquisition technique for the spine in routine clinical practice. Nonetheless, dynamic MRI is currently used for assessment of POP as it provides better pelvic floor soft

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Fig. 1 Extraction of ROI for sacral curve: (a) original MRI and (b) extracted ROI for the sacral region.

tissue contrast and movement. To the best of our knowledge, there is no work addressing the automatic extraction of the vertebra on dynamic MRI.

In this paper, a model is presented that combines an adaptive shortest path method with curve fitting algorithms to extract the shape of the sacral curve on MRI as shown in Fig. 1. In our previous work,²¹ a model was presented to automatically extract certain pelvic bone structures on dynamic MRI. In the current work, we address the identification and segmentation of the sacral curve through a new adaptive shortest path method that enhances edge detection and linking, an improved curve fitting procedure, and extensive validation experiments on larger datasets. One of the main contributions of the proposed model is its use of predetermined pixels surrounding the sacral curve that are found through edge detection. This decreases computation time compared to other model-based segmentation algorithms.^{22–24} Moreover, the proposed model is fully automatic and does not require user input or training. The presented model can be used to automatically extract image-based features to improve the diagnosis of gynecological conditions such as POP.

The remainder of this paper is organized as follows: Sec. 2 illustrates the proposed automatic sacral curve segmentation scheme. The results and performance evaluation are presented in Sec. 3. Finally, discussion and conclusions are given in Secs. 4 and 5, respectively.

2 Sacral Curve Segmentation Framework

As shown in Fig. 1, the sacral curve needs to be located automatically from the sacrum structure. Segmenting this structure is challenging due to the lack of image contrast, low signal-to-noise ratio, and reflection along the centerline of the bony structure. The proposed model is divided into three main phases: phase 1—extraction of the region of interest (ROI) from the image; phase 2—preprocessing including image artifacts removal and an enhanced edge detection algorithm on the sacral region; and phase 3—segmentation of the sacral curve through a proposed adaptive shortest path and curve fitting algorithm. The three main phases of the proposed model are discussed in more detail in the following sections.

2.1 Phase 1: Extraction of Region of Interest

The ROI is cropped from the input image as seen in Fig. 1. The starting (sacral promontory) and end (coccyx) points are defined as corner points for which there are two dominant and different edge directions on the local neighborhood of the point. Consequently, these points have been automatically detected

using a corner detector such as Harris corner detection algorithm as presented in our previous work.^{25–28} These points are used to define the ROI that encloses the sacral curve. Based on the analysis of the dataset used in this study, the size of the ROI is defined as 150 pixels by 150 pixels.

2.2 Phase 2: Image Preprocessing—Image Artifacts Removal and Enhanced Edge Detection

2.2.1 Image artifacts removal

The preprocessing phase is necessary to remove noise from the images, and to detect and remove image artifacts from the original dynamic MRI. In addition to the vertebral region, there are some other structures and artifacts shown in dynamic MRI that complicate the detection of the sacral curve. Two artifact removal stages are implemented to clean the image before segmentation. The first stage removes all shadow forming and air-filled structures on MRI such as blood, soft tissues, and dark rims. The second stage removes bright artifacts such as phase-encoded motion artifacts, which are commonly found in MRI.

For the first artifact removal stage, shadow forming and air-filled structures that can mislead sacral curve detection methods are removed based on morphological inpainting, which helps to reconstruct the image. In order to obtain the stage 1 clean image $I_{\text{stage 1}}$, let I_{orig} be the original image, I_{int} be the intermediate image, and γ_B^n and ϕ_B^n represent morphological opening and closing, respectively, of size n with structural element B . In this study, a diamond structuring element of size 4 was used. The intermediate and stage 1 clean images are obtained as follows:²⁹

$$I_{\text{int}} = \gamma_B^{n+1}[\phi_B^n(I_{\text{orig}})] \quad \text{and} \quad I_{\text{template 1}} = I_{\text{orig}} \omega I_{\text{int}}, \quad (1)$$

where ω indicates the supremum operator that finds the least element of the containing set that is greater than or equal to all other elements of the dataset. This template 1 image, $I_{\text{template 1}}$ is used as reference to analyze the minima of the image. Regional minima are connected components of pixels with a constant intensity value, and whose external boundary pixels have a higher value. Therefore, all regional minima of the original image that are lower than the template 1 image, $I_{\text{template 1}}$ are removed. This procedure removes blood, soft tissue, and other dark and small structures from the image and the resulting image is called stage 1 final image, $I_{\text{final}}^{\text{stage 1}}$.

For the second artifact removal stage, bright artifacts are quantified by the weighted sum of the intensity values of all pixels. Let $SH[p(a, b)]$ be the artifact value for pixel p at row a and column b of the image. $SH[p(a, b)]$ can then be calculated as follows:

$$SH[p(a, b)] = \frac{\sum_{j=b}^H G(j-b) I(a, j)}{\sum_{j=b}^H G(j-b)}, \quad (2)$$

where H indicates the number of rows in the image, $G(\cdot)$ and $I(\cdot)$ represent the Gaussian weighting function and pixel intensity, respectively. Then, the template 2 image, $I_{\text{template 2}}$ is obtained by applying the infimum operator as follows:

$$I_{\text{template 2}} = I_{\text{final}}^{\text{stage 1}} \ominus SH[p(a, b)]. \quad (3)$$

Fig. 2 Artifact removal process: (a) original image and (b) reconstructed image.

$I_{\text{template}2}$ is used as reference to analyze the maxima of the image. Regional maxima are connected components of pixels with a constant intensity value, and whose external boundary pixels have a lower value. Therefore, all regional maxima of the stage 1 final image, $I_{\text{final}}^{\text{stage}1}$ that are higher than the template 2 image $I_{\text{template}2}$ are removed to keep the final clean image, I_{final} . Figure 2 shows an example of a reconstructed image after both artifact removal stages.

The preprocessing steps result in a cleaned image that can be subsequently processed for further analysis. In this work, edge detection is used to estimate the location of the sacral curve. An enhanced edge detection algorithm is presented to generate groups of edge pixels. This is followed by edge grouping to assign edge points to edges by considering each point's relationship to neighboring edge points.

2.2.2 Enhanced edge detection

Canny edge detection is a well-known edge detection method because of two main features: nonmaximum suppression and double threshold.³⁰ The principles of the traditional Canny edge detection algorithm are as follows: (1) using Gaussian filtering for noise reduction, (2) calculating the gradients at 4, neighboring and comparing the detected points with its neighbor pixel in each direction. If the gradient value is not maximum, the algorithm considers this pixel as nonedge point (this step is called nonmaximum suppression), (3) checking edge points by comparing the gradient value between the detected point and the high and low threshold values. If the gradient value is greater than the high threshold value, it is marked as a strong edge pixel. If the gradient value is smaller than the high threshold value and larger than the low threshold value, it is marked as a weak edge pixel—considered as an edge pixel only if it is connected to an edge. If the gradient value is smaller than the low threshold value, it is suppressed and considered as nonedge pixel. However, there are two problems that can be observed on the traditional Canny edge detector: (a) the Gaussian filter might also smooth some edges resulting in the loss of edge information and false edges, and (b) the two threshold values are difficult to define. This causes the removal of edges or counting noise as edge pixels.

The proposed method aims to overcome the first problem using anisotropic filtering instead of Gaussian filtering. Anisotropic filtering is considered a feature-preserving image denoising filter that aims to remove noise from the image without removing useful information such as edges, lines, and other

details that can be used to interpret the images. However, the effectiveness of anisotropic diffusion image denoising depends on parameters that include a conductance function, an integration constant for numerical stability, and a gradient modulus threshold. We selected the conductance function as $1/[1 + (x/K)^2]$ because it favors larger regions over smaller ones, where K represents the gradient magnitude threshold that guides the degree of the diffusion. To select a gradient magnitude threshold, we chose a “noise estimator” that uses the absolute value of an image gradient to estimate the threshold.³¹

The second problem can be solved by finding the gradient direction of each pixel and using only one threshold value. We use AverageG, obtained by subtracting the average gradient direction from the normal direction of a center pixel at an eight-neighborhood area. AverageG results in a smaller value if both the gradient and normal directions of the edge pixel have the same direction. Thus, the pixel is considered as an edge pixel if AverageG is smaller than the threshold value determined based on Otsu's method.³² This process is described in Algorithm 1.

2.3 Phase 3: Segmentation—Adaptive Shortest Path and Curve Fitting Algorithms

2.3.1 Adaptive shortest path algorithm

After edge detection and edge grouping, the sacral curve is identified using an adaptive shortest path algorithm, which customizes and improves the traditional Dijkstra's algorithm³³ to connect edge pixels and edge groups that form the sacral curve. In an edge map, the distance between edge pixels in the same group or from different groups is not defined. The traditional Dijkstra's algorithm cannot be applied directly to connect edge pixels and edge groups. The shortest path algorithm developed in this research is adaptive because it dynamically calculates the distance between edge pixels, and hence determines how edge pixels and edge groups are connected to each other and form the structure of interest (the sacral curve in this study). Edge pixels are considered as nodes in an edge map. Each pair of two adjacent nodes in the same edge group along the sacral curve is connected directly via a link. The length of a link, i.e., the distance between two directly connected nodes, is defined using a cost function. The adaptive shortest path algorithm uses the Euclidean distance as the cost function, which is calculated using the coordinates of two adjacent nodes in a group. The distance between two nodes in a group that are not adjacent to each other is the summation of distances for pairs of adjacent nodes on the path that connects the two nodes.

In addition to determining the distance between nodes in the same edge group, the adaptive shortest path algorithm also calculates the distance between nodes from different edge groups so that edge groups may be connected to form the sacral curve. The adaptive shortest path algorithm identifies the sacral curve by connecting edge groups that form the shortest path from the starting node (sacral promontory) to the end node (coccyx) as shown in Fig. 1.

To connect two edge groups, certain nodes in one group must be connected to certain nodes in the other group and their distances must be calculated. There are two steps in determining the distance between two nodes from different edge groups. First, it is necessary to determine the nodes from different edge groups that are connected directly. There are three alternatives: (a) only the two end nodes of an edge group are directly connected to those of the other edge group; (b) the end nodes of

Algorithm 1 Pseudocode for enhanced edge detection algorithm

Input: Edge map of the final clean image.

Output: Edge map that represents the original image.

Step 1: Check the edge map for possible edge pixel $I(i, j)$. Go to the last step if there is no possible edge pixels found.

Step 2: Find the gradient direction to obtain, the value between the average gradient direction and the normal direction of the point $I(i, j)$. If it's smaller than the threshold, go to step (4).

Step 3: Keep checking the pixels that cannot be selected, and calculate AverageG, if AverageG is smaller than the threshold go step (4), otherwise go to the last step.

Step 4: Select the pixel $I(i, j)$ for $\text{AverageG} < T$.

Step 5: If there are any other possible pixels, select them as edge pixels. If there are no possible pixels, go to step (3).

Step 6: Keep checking the edge map for new edge pixels. If a pixel is not selected, go to the first step.

an edge group are directly connected to all nodes in the other edge group; and (c) all nodes in one edge group are directly connected to all nodes in the other edge group. In the second step, the distance between directly connected nodes from different edge groups is calculated.

The distance between two nodes from different edge groups is equal to the Euclidean distance between the nodes times a multiplier. The reasoning and benefit of incorporating a multiplier are multifold. First, it is expected that most nodes in the same edge group either belong to the sacral curve or not. The case in which some nodes in an edge group belong to the sacral curve while others in the same group do not is unlikely because nodes in the same edge group meet the similarity constraint. Based on our experiments, a multiplier that is greater than one helps to ensure that the sacral curve contains most nodes from the same edge group before moving to include nodes from another edge group. Second, nodes from two different edge groups do not meet the similarity constraint because they have different gradients. If both groups are supposed to be part of the sacral curve, the distance between directly connected nodes from the two groups should be greater than the Euclidean distance since there is likely a gradient change from one group to the other. Third, a multiplier should not be too large, e.g., equals or is greater than two. A large multiplier indicates that a large amount of MRI data is missing between the two edge groups that are directly connected in the identified sacral curve. Therefore, it was observed from our experiments that a value between one and two for the multiplier helped in identifying sacral curves that best matched the ground truth.

The adaptive shortest path algorithm identifies the shortest paths from the starting node (sacral promontory) to the end node (coccyx). The distance of the shortest paths is minimal among all paths that connect the starting node and end node. Let $c_{i,j}$ be the distance between node i and node j . $i, j \in V$, where V is the node set in an edge map. Let (i, j) represent an arc that originates from node i and points at node j , $(i, j) \in E$, where E is the set of arcs in the edge map, if i and j are connected directly. $c_{i,j} < \infty$ if $(i, j) \in E$. $c_{i,j} = \infty$ if $(i, j) \notin E$, i.e., if i and j are not connected directly. For the purpose of identifying the sacral curve, a connection (link) between two nodes is bidirectional; $(j, i) \in E$ if $(i, j) \in E$ and vice versa. Also, $c_{j,i} = c_{i,j}$. The adaptive shortest path algorithm is described in Algorithm 2.

2.3.2 Curve fitting algorithm

Once edge groups are determined and connected, curve fitting is necessary to represent the sacral curve mathematically. We use a robust curve fitting procedure to finalize the segmentation. A robust curve fitting solution based on iteratively reweighted least squares (IRLS) is employed to fit a sacral curve because it provides a compact way to represent the curve. Among several available IRLS techniques, Tukey's Biweight³⁴ is adopted to finalize the sacral curve segmentation because it can robustly fit the curve from data containing outliers, which are false detections in this case.

3 Results

3.1 Dataset Description

A representative set of 207 dynamic MRI was used in this study, which were obtained from a 3-T GE system (General Electric Company, GE Healthcare, United Kingdom) using an eight-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 sequence in the midsagittal plane for 23 to 27 s with a temporal resolution of 2 s (FOV 300×300 mm², slice thickness 3 mm, TR/TE 2000/75 ms, 20 image sequences, and in-plane resolution of 1.6×1.6 mm²). Subjects were coached, prior to imaging, on performance of an adequate valsalva maneuver (straining maneuver) to observe the movement of the pelvic organs from rest to maximum strain. The image data have been preprocessed and deidentified. The Institutional Review Board at the University of South Florida considered the study exempt since all protected health information was previously removed from the clinical and MRI data before collected from a database for this study. The presented method was implemented using MATLAB® 2013a on a workstation with 3.40 GHz, Core i7-3770 CPU processor, and 16 GB RAM.

The images were categorized based on the quality of the images as "best case" ($A = 102$ images), "moderate case" ($B = 67$ images), and "worst case" ($C = 38$ images). The "best case" can be described as a case in which the edges of the structure are connected between the starting and end points. The "moderate case" is defined when the edges of the structure are not completely connected between starting and end point,

Algorithm 2 Pseudocode for adaptive shortest path algorithm

Input: Edge map of an image

Output: Edge pixels that represent the sacral curve

Step 1: Connect every pair of adjacent nodes in the same edge group with a bidirectional link.

Step 2: Connect any two end nodes from two different edge groups with a bidirectional link.

Step 3: Assign to every node $i, i \in V$, a value representing the distance between the start node (sacral promontory) and i . For the starting node, set the value to 0. Set the value to ∞ for all other nodes i 's.

Step 4: Mark the starting node visited. Mark all other i 's unvisited. Set the starting node as the current node.

Step 5: Calculate the distance between *each* unvisited neighbor $j, j \in V$, of the current node $i, i \in V$. A node j is a neighbor of i if there is an arc begins at i and points at j , i.e., $(i, j) \in E$. The distance between i and j is the sum of the value set for i and c_{ij} , which is the Euclidean distance if i and j are in the same edge group, or is equal to the Euclidean distance between i and j times a multiplier if i and j are from two different edge groups.

Step 6: For each unvisited neighbor j of the current node i , compare the distance between j and i calculated in step 5 and the value set for j . Set the value for j as the smaller one between the two.

Step 7: Identify the unvisited node with the smallest value. Mark the node visited. Set the node as the current node. If the node is the end node (coccyx), stop. The value set for the end node is the minimum distance between the starting node and end node. Otherwise, go to step 5.

Step 8: Backtrack from the end node to starting node and identify the nodes on the shortest paths from the starting node to end node.

but the gap is reasonably small. For the “worst case,” the gap between the edges of the structure is much bigger and many small edges exist around the sacral structure.

3.2 Extraction of the Sacral Curve

To construct the ground truth, the sacral curves in 207 images were manually segmented using ANALYZE (Mayo Clinic, Rochester, Minnesota). The ground truth set of sacral curves was obtained by averaging the locations established by two experienced gynecologists. This was used to compare the performance of the proposed automatic segmentation method. Figure 3 shows the results of the comparison with two error metrics that characterize the similarity: (1) Hammoude metric, d_{HMD} and (2) average metric, d_{AVR} . Other quality metrics, such as Hausdorff metric, mean sum of squared metric, and mean

absolute distance metric have been tested and similar results were obtained.

- The Hammoude metric, d_{HMD} is based on a comparison of the differences between two curves using an XOR operator. All pixels along the curves have label “1” and all the other pixels have label “0.” Given two binary images, $A = (a_1, \dots, a_n)$ is identified by the proposed model and $B = (b_1, \dots, b_m)$ is the ground truth. It is obtained by

$$d_{HMD} = \frac{\#(A \cup B) - \#(A \cap B)}{\#(A \cup B)}, \quad (4)$$

If d_{HMD} is a low value, it indicates high similarity between both curves.

Fig. 3 Adaptive shortest path process: (a) edge map with different edge groups after edge detection, and (b) edge map after the proposed adaptive shortest path algorithm connects the edge groups resulting in the sacral curve.

- The average metric between two contours, d_{AVR} is defined as the average distance to the closest points, $d(a_i, B)$ as follows:

$$d_{AVR} = \frac{1}{N_A} \sum_{i=1}^{N_A} d(a_i, B), \quad (5)$$

where N_A is the length of A and the average distance is obtained as follows:

$$d(a_i, B) = \min_j \|b_j - a_i\|, \quad (6)$$

which correspond, respectively, to the squared distance's average and to the absolute distance's average between corresponding points in the boundaries.

The proposed model was tested on a total of 207 cases and the performance is evaluated using the average of each of the two error metrics across three different scenarios: (A) traditional Canny edge detection and adaptive shortest path algorithm without preprocessing step, (B) enhanced edge detection and adaptive shortest path algorithm without preprocessing step, and (C) enhanced edge detection and adaptive shortest path algorithm with preprocessing step. To the best of our knowledge, there are no previous algorithms for sacral curve segmentation on dynamic MRI. For this reason, the proposed model cannot be compared with other methods.

Figure 4 shows the segmentation results for three dynamic MRIs corresponding to the best, moderate, and worst cases. White and green lines indicate manual and automatic segmentation, respectively. Figures 4(c) shows the results on the worst case where manual and automatic segmentations differ the most. This is due to the high presence of dark regions around the sacral region, which diminishes the visibility of the sacral region

and results in lower performance accuracy compared to the other two cases. A threshold value for d_{HMD} was determined by the experts for considering an accurately detected sacral curve.

Finally, Fig. 5(a) shows the comparison between traditional Canny edge detection and adaptive shortest path algorithm without preprocessing step (scenario A). It can be observed from the box plot that the combination of these two methods can identify the sacral curve with the lowest accuracy based on both error metrics and compared with the other scenarios. As can be seen from the results, the accuracy differences between the best cases and the worst cases are significantly higher. For instance, the Hamoude metric, d_{HMD} for the best case is 0.21 ± 0.91 (mean $\pm$ standard deviation) while the worst case is 0.46 ± 1.18 .

Figure 5(b) displays error metrics for scenario B where enhanced edge detection and adaptive shortest path algorithm were applied without preprocessing. It can be observed that the edge detection enhancement process improved the accuracy for each case compared to scenario A and using the same image dataset. Even though the preprocessing step was not introduced in this scenario, the accuracy of the moderate cases is almost similar with the best cases obtained from scenario A. This may be due to the use of anisotropic filtering, an edge preserving filtering, on the enhanced edge detection. Similar results are observed for the worst cases where the Hamoude metric, d_{HMD} for the worst case is 0.25 ± 0.72 . These results show that the accuracy for the worst cases has significantly improved. It can be seen that the accuracy difference between the best cases and the worst cases still exist; however, it is less than the previous scenario. The average metric between the two contours, d_{AVR} is 2.1 ± 0.82 and 3.9 ± 0.24 for the best case and worst case, respectively.

Figure 5(c) presents the evaluation test results of the proposed sacral curve segmentation model for the three cases (scenario C) and using the same two error metrics. The proposed

Fig. 4 Segmentation results by the proposed sacral curve segmentation model: (a) best case, (b) moderate case, and (c) worst case. White and green lines indicate manual and automatic segmentation, respectively.

Fig. 5 Error metrics for three scenarios: (a) traditional edge detection and adaptive shortest path algorithm without preprocessing step, (b) enhanced edge detection and adaptive shortest path algorithm without preprocessing step, and (c) proposed enhanced edge detection and adaptive shortest path algorithm with preprocessing step.

model uses the enhanced edge detection and adaptive shortest path algorithm with preprocessing step. As observed from the figure, the proposed model provides the best accuracy for all three cases. The difference in performance between the best cases and the worst cases is much less than the other scenarios presented in Figs. 5(a) and 5(b). These results indicate that the proposed preprocessing step, which eliminates dark and bright structures from the image, improves accuracy for all three cases when combined with the proposed enhanced edge detection and adaptive shortest path algorithms.

4 Discussion

In this paper, an automatic image segmentation framework is proposed that introduces an adaptive shortest path method and combines it with curve fitting algorithms to eliminate the need for user input and training. Although similar techniques have been used in other applications, they have not been considered for image segmentation. The proposed technique aims to enhance the segmentation of structures, particularly bones, from low contrast and nonhomogeneous images while eliminating any user interaction or use of a training set for feature extraction. The presented model is divided into three main phases: extraction of region of interest, preprocessing, and segmentation. In the first phase, the sacral region is cropped from the input image. In the preprocessing phase, noise reduction of the images is performed. Then, the sacral region is first identified using enhanced edge detection algorithm followed by edge grouping. In the last phase, an adaptive shortest path and curve fitting algorithm are performed to finalize the segmentation of the sacral curve. Results demonstrate that the presented method can locate the sacral curve with high accuracy in the test cases, including the best, moderate, and worst cases. Two error metrics were used for performance comparison: (1) Hamoude metric, d_{HMD} and (2) average metric, d_{AVR} . It can be observed that the

proposed model can accurately identify the sacral curve in 91% of the tested cases. Results show that the sacral curve was accurately identified in 100% of the best cases, 94% of the moderate cases, and 57% of the worst cases.

5 Conclusion

A new technique to automatically segment the sacral curve on MRI has been presented. An adaptive shortest path algorithm is presented that improves the traditional Dijkstra's algorithm to find the edges of the sacral curve. This new algorithm determines how edge pixels in the same edge group and from different groups are connected, and which edge groups form the sacral curve. As a final step, a curve fitting based on IRLS using Tukey's Biweight is performed to finalize the segmentation of the sacral curve. Quantitative experiments demonstrate that the proposed automatic segmentation technique can accurately segment the sacral curve from a variety of dynamic MRI cases. Experimental results show that the proposed technique is robust and efficient compared to traditional approaches. This technique can also be applicable to the segmentation of other structures on images. Future work aims to incorporate prior knowledge about the shape of the bony structure into the algorithm. The segmented sacral curves can be used to analyze their correlation with the presence of clinical conditions such as POP on larger datasets and thus potentially improve clinical diagnosis.

Disclosures

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