Real-time transverse process detection in ultrasound

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ABSTRACT

PURPOSE: Ultrasound offers a safe radiation-free approach to visualize the spine and measure or assess scoliosis. However, ultrasound assessment also poses major challenges. We propose a real-time algorithm and software implementation to automatically delineate the posterior surface patches of transverse processes in tracked ultrasound; a necessary step toward the ultimate goal of spinal curvature measurement.

METHODS: Following a pre-filtering of each captured ultrasound image, the shadows cast by each transverse process bone is examined and contours which are likely posterior bone surface are kept. From these contours, a three-dimensional volume of the bone surfaces is created in real-time as the operator acquires the images. The processing algorithm was implemented on the PLUS and 3D Slicer open-source software platforms.

RESULTS: The algorithm was tested with images captured using the SonixTouch ultrasound scanner, Ultrasonix C5-2 curvilinear transducer and NDI trakSTAR electromagnetic tracker. Ultrasound data was collected from patients presenting with idiopathic adolescent scoliosis. The system was able to produce posterior surface patches of the transverse process in real-time, as the images were acquired by a non-expert sonographer. The resulting transverse process surface patches were compared with manual segmentation by an expert. The average Hausdorff distance was 3.0 mm when compared to the expert segmentation.

CONCLUSION: The resulting surface patches are expected to be sufficiently accurate for driving a deformable registration between the ultrasound space and a generic spine model, to allow for three-dimensional visualization of the spine and measuring its curvature.

KEYWORDS: Ultrasound, Segmentation, Image guidance, 3D Slicer, SlicerIGT, Open-source

1. PURPOSE

Scoliosis is a condition where an abnormal lateral curve that causes discomfort develops in a patient's spine [1]. Scoliosis develops in 2-3% of school age children, and treatment for severely scoliotic patients involves inserting metal braces to correct the patient's spine. Before the scoliosis treatment begins, a physician must have a clear and reliably correct representation of a patient's spine. Current practice, and the gold standard for obtaining this representation is to use X-ray imaging. Unfortunately repeated exposure to ionizing radiation has shown to increase the probability of a patient developing leukemia, breast or prostate cancer [2]. Since ultrasound is poses no risk of ionizing radiation to patients, and is considered portable when compared to X-ray, it may be a practical alternative for monitoring and diagnosing scoliosis in patients. However, the range and field of view of ultrasound are limited, and the images it produces can be very difficult to interpret. Despite producing limited information, an ultrasound image may still be interpreted by searching for specific landmarks that indicate spine orientation, such as transverse processes [3], or the center of the lamina [4].

However, once the operator identifies a desired landmark in a frame, the image must then be manually segmented, which is tedious and time-consuming due to the high degree of skill and knowledge required to isolate possible landmarks, given the amount of noise which is typically present in ultrasound images. A further difficulty is that even experienced operators may need to repeatedly scan a patient before they obtain a sufficiently complete set of satisfactory quality ultrasound images. This is because immediate interpretation of the image contents in spinal ultrasound is extremely difficult and scans may need to be reviewed before confirmation can be given for a satisfactory series of images.

Several methods have been proposed to aid in segmenting vertebral landmarks. Semi-manually defined image regions undergoing maximum intensity projection on the coronal plane has been shown in scoliosis measurement [4]. These results were obtained using a high-end externally tracked ultrasound machine and significant time (over 5 minutes) was spent on manual marking of each recorded ultrasound sequence. Local filters, such as directional Hadamard features [5], can successfully assist in segmenting spinal landmarks. However, these local filters require the operator to place a filtering window somewhere over the landmark during the scanning process, or once the scans have been completed. Thus the question remains how to guide the operator to the vicinity of a skeletal landmark in real-time as images are captured. Building on our previous work [6] to localize transverse processes in ultrasound images, we propose an algorithm for localizing the posterior contour of transverse processes in real-time as the patient is scanned by a non-expert sonographer.

2. METHODS

The proposed algorithm automatically finds the posterior surface of transverse processes in ultrasound frames. The operator scans a patient using an ultrasound probe. Incoming frames are then processed to automatically identify bone surfaces, as seen in Figure 1. As frames are processed, the collection of 2D bone surfaces extracted from the images are reconstructed into a 3D volume using pose information acquired from a position tracking device, building up the image such as shown in Figure 2.

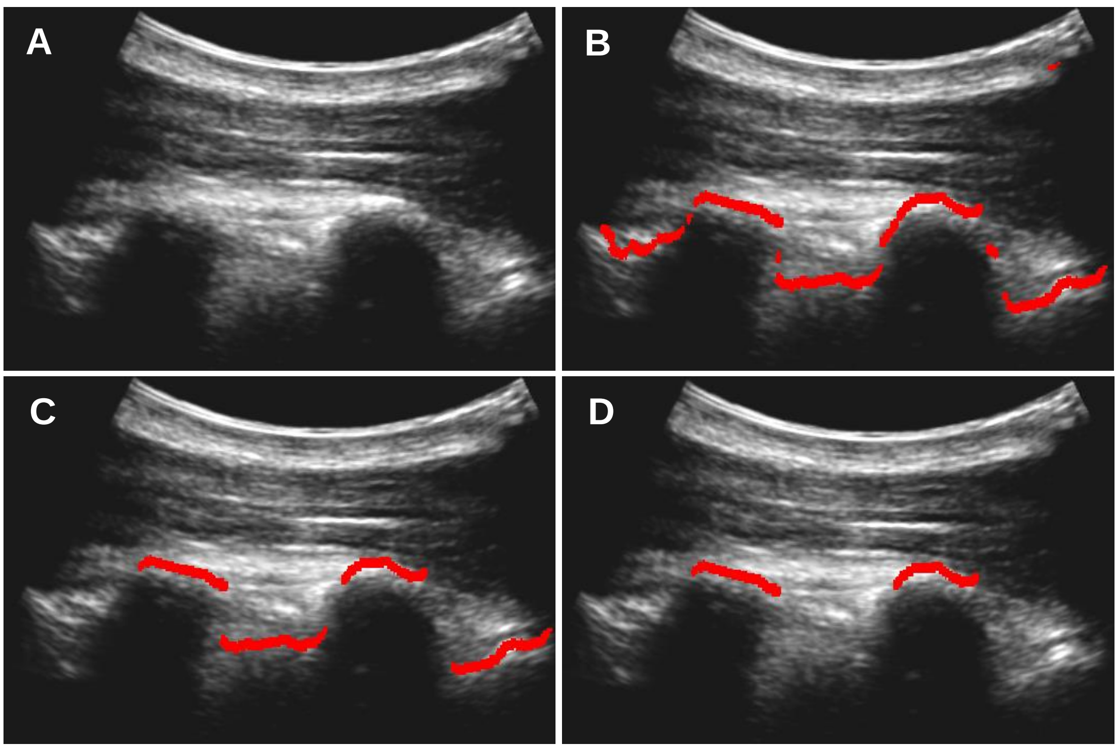

Figure 1. Raw frame produced by an ultrasound scan (A). An outline is drawn on any parts of the frame that give way to darkness to indicate possible bone areas (B). All areas that are too small, located too close to the scanning device, or located on the frame edge are removed (C). Areas that do not block sound are removed (D).

2.1 Transverse process detection algorithm

First, if the algorithm is receiving images from a curvilinear transducer, each frame is converted into a linear image [7]. In order to remove noise from the image, we apply a binary threshold and a Gaussian blur. Then we utilize edge detection, island removal, erosion, and dilation filters – with all pre-processing occurring in this order. Since bones cast shadows in ultrasound, any non-shadow region that has darkness beneath it is initially marked as a possible transverse process by the algorithm. By then checking the size and position of each of the potential bone areas, false bones can be identified and eliminated using the latter pre-processing steps such as island removal and edge detection, as mentioned previously.

The next step taken by the pipeline is to verify if the bone area is genuinely casting a shadow. This is done by looking at the darkness behind a possible bone area and seeing if there is sufficient non-shadow data to either side of it. If the area is not blocking a significant amount of the ultrasound image, it cannot be a transverse process. All bone surfaces that remain are seen as correct locations where a transverse process can be found. If the original frame was taken using a curvilinear transducer, the algorithm will convert the image back into its original format.

The final image is then used to construct a 3D volume (Figure 2). The image is built in real-time, allowing the sonographer to fill in any apparent gaps or missing vertebra.

Figure 2. 3D volume reconstruction from the algorithm's output, showing a qualitatively correct and accurate posterior surface patches of the transverse processes.

2.2 Tracked sonography system

In the setup used in this study, a SonixTouch (Analogic Corp., Peabody, MA, USA) ultrasound device was used to acquire 2D images from the patient's spine. The ultrasound transducer used was an Ultrasonix C5-2 device with curvilinear geometry, and it was equipped with a 3D trakSTAR (NDI, Waterloo, ON, Canada) electromagnetic tracker, so that the 2D images may be reconstructed into a 3D volume.

Once the algorithm has generated an output, we used the volume reconstruction application as part of the PLUS open-source software toolkit [8] to fully render the spine in 3D. The open-source medical image analysis and visualization platform 3D Slicer [9] was used to visualize and evaluate our results. The method has been implemented within the PLUS toolkit as a virtual device C++ class *vtkPlusTransverseProcessEnhancer*.

2.3 Sonography protocol

Subjects had sagittal ultrasound images taken in sweeps from left to right of centerline from their superior thoracic to inferior lumbar region while in a natural standing position. Images were acquired directly from the transducer by an experienced sonographer. No pre-filtering algorithms were applied to any acquired images in the study other than those described in Section 2.1. Standard water-based ultrasound transmission gel was used for acquisition of all images. Images were collected at a frequency of 2.5 MHz, with an imaging depth of 100 mm. Other imaging parameters were set to manufacturer defaults.

2.4 Experimental design and analysis

An experienced operator manually segmented the posterior surface of transverse processes in four ultrasound sweeps; each sweep containing several vertebras. Two regions were marked in each frame: A ground truth that definitely contains bone and a tolerance margin that surrounds the bone. The ground truth region represents what the output should ideally be, and the tolerance margin encompasses all leeway where a landmark could be placed by our method. The algorithm's accuracy was evaluated by comparing the output to the two marked regions (Figure 3). As the algorithm segments the thin surface of the bones, and the baselines correspond to the whole bony area, a margin of 1mm was added to the algorithm's output for comparison with the ground truth's baseline.

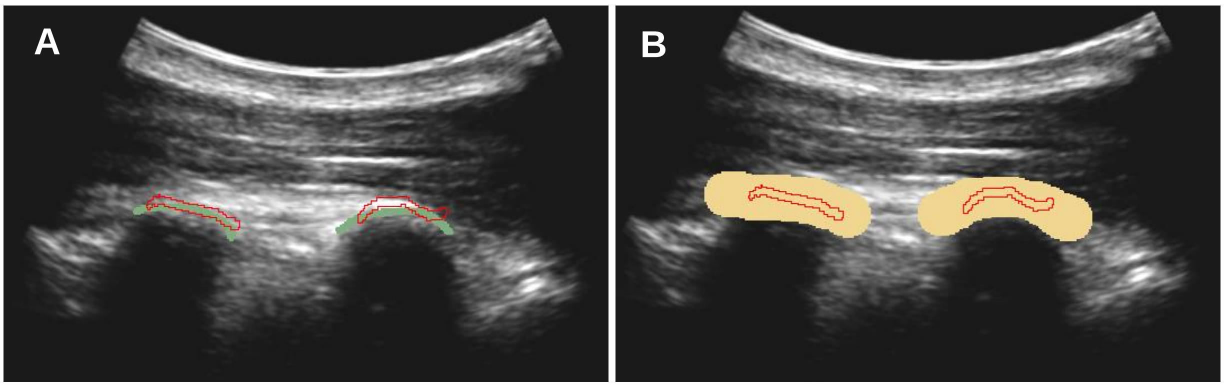

Figure 3. Algorithm output, depicted using a red outline, compared to ground truth, shown in green (A) and tolerance

3. RESULTS

Table 1 and Table 2 give Hausdorff distances of the algorithm's segmentation compared with the tolerance margin and ground truth determined by the expert segmentation. Since the tolerance margin represents the maximum area in which a bone can be found, F+ was included as a metric in Table 1 as it quantifies the percentage of times where the output placed a bone outside of the expert segmentation. Conversely, the ground truth indicates the minimum area in which a bone can be found, so F- was chosen as a metric in Table 2, since it quantifies the areas where the output failed to mark a location that was inside the expert segmentation.

The four scans contained a total of 74 frames, and each scan took on average 0.302 s to pass through the pipeline, with the set having a standard deviation of 0.056 s overall. These results indicate that the pipeline is capable of segmenting one frame in 0.016 s, yielding 62 frames per second, which qualifies for real-time processing.

Tolerance Margin				
	Hausdorff Max. (mm)	**Hausdorff Avg. (mm)**	**Hausdorff 95% (mm)**	**F+ (%)**
Scan A	20.4	4.5	10.1	0.05
Scan B	67.4	5.2	22.1	0.48
Scan C	40.8	3.7	10.5	0.16
Scan D	57.2	7.2	19.2	0.07
Avg.	46.4	5.1	15.5	0.19

Table 1. Comparison of our algorithm's output with the tolerance margin. F+ (False Positive) is the percentage of the total sweep where the output placed a bone outside of the tolerance margin.

Ground Truth				
	Hausdorff Max. (mm)	**Hausdorff Avg. (mm)**	**Hausdorff 95% (mm)**	**F- (%)**
Scan A	13.4	1.6	5.3	0.75
Scan B	65.5	5.8	31.0	1.41
Scan C	21.4	1.6	6.0	0.59
Scan D	32.5	3.2	10.2	2.12
Avg.	33.2	3.0	13.1	1.22

Table 2. Comparison of our algorithm's output with the ground truth. F- (False Negative) is the percentage of the total sweep that was marked as a definite bone, but the algorithm failed to fill in.

4. DISCUSSION

Of the four series of ultrasound sweeps, Series A, B, and C all contained landmarks that ranged from simple to moderately difficult for the method to detect. Series D contained more difficult frames to identify. It is noteworthy that the results for Series D were not as large of an outlier as was expected. Overall, the results indicate that the algorithm was able to detect the areas that contained landmarks well, as it often lined the output correctly with what was marked by the expert.

It is worth noting that all four ultrasound sweeps were obtained using a transducer with curvilinear geometry, however since the segmentation process used by the algorithm is intended for linear images, the method had to take two extra steps. First, prior to the noise reduction, the method converted the images into a linear format, and second, once the image had been segmented, it was converted back into a curvilinear image. Taking these two extra steps for conversion means that the algorithm performed slower in the time trials mentioned above than it would if it was used with a linear transducer.

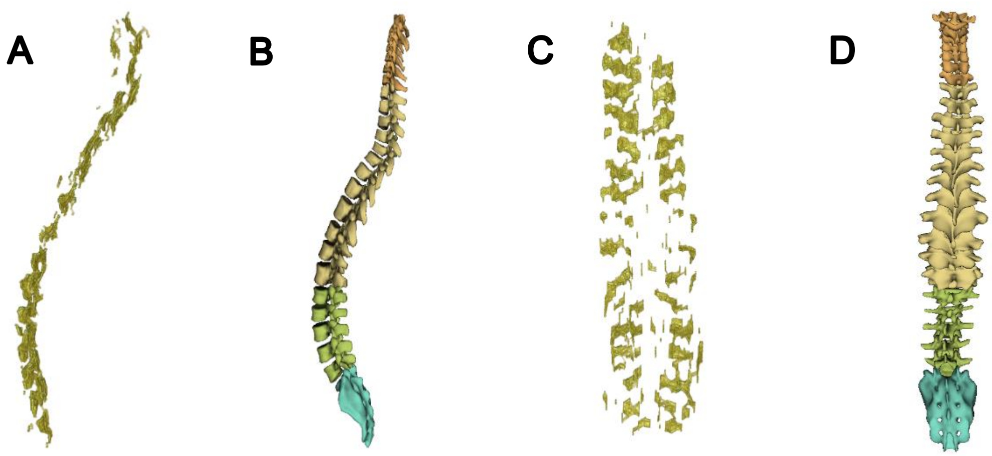

Figure 4. Bone patches (A – left view, C – posterior view) outputted by our system may be registered deformably (B – left view, D – posterior view) with a model of a healthy spine, thus allowing for visualization of patient's spine and eventually for measurement of the curvature.

The outputs, such as those shown in Figure 2, provides a qualitative understanding of the shape of the spine, but it is not sufficient for accurate visualization or, let alone, for accurate measurement of the curvature. To that end, we consider adapting the work of Church *et al*. [10], where segmented anatomical landmarks on the transverse processed are used to deformably register a generic spine model to ultrasound space. Using this method, upon hand-segmentation of the transverse processes in the bone surface patches outputted by our system, an image like in Figure 4 can be obtained, to show a qualitatively good visualization of the patient's spine. However, manually placing landmarks is an error-prone and very tedious process. Instead, in the future we plan to implement a method wherein we down-sample the bone surface patches and use a variant of the iterative closest point registration method to achieve automated and quantitatively accurate deformable registration of the generic spine model to ultrasound space; allowing for accurate measurement of the curvature.

5. CONCLUSION

A software algorithm has been developed that is able to delineate the posterior surface of transverse processes in ultrasound images with acceptable accuracy. The speed of the algorithm allows for real-time processing, facilitating enhanced ultrasound scanning. The individual tracked image frames and delineations can be reconstructed into a 3D volume, also in real-time. Deformable registration of this reconstructed volume to a spine model yields a full model of the specific patient, which is expected to yield clinically accurate measurement of the spinal curvature in three dimensions.

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