Coarse X-Ray Lumbar Vertebrae Pose Localization using Triangulation Correspondence

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***Abstract*— Dual-Energy X-ray Absorptiometry Scanner is essential for medical diagnostics and clinical routine. Typically, this type of device generates two radiography images of the human spine, including the Anteroposterior and Lateral sides. However, these two photographs presented distinct perspectives. The suggested method consists of three fundamental phases. The grayscale lumbar input image was initially projected vertically utilizing its vertical pattern for automated cropping. Then, Delaunay triangulation was done out using the SURF features as triangle nodes. Using the edge density of each node, the posture area of the vertebrae was computed. The proposed method provided an automated estimation of the position of the human lumbar vertebrae, hence reducing the radiologist's workload, computing time, and complexity in numerous bone-clinical applications. The outcome of the proposed method can support numerous applications, including segmentation of lumbar vertebrae pose, bone mineral density examination, and vertebral pose deformation. The proposed approach can estimate the vertebral position with an accuracy of 80.32 percent, a recall of 85.37 percent, a precision of 82.36%, and a false negative rate of 15.42 percent.**

Keywords—DXA, vertebrae pose localization, Delaunay triangulation, SURF features

I. Introduction

Digital image segmentation facilitates the automation or ease of the delineation of anatomical features and other regions of interest in a substantial variety of medical imaging applications [1]. In a range of medical applications, image segmentation is used to categorize distinct anatomical features, such as vertebrae, bones, and soft issues. To make an accurate medical diagnosis, it is required to distinguish low-level image characteristics of the object of interest, such as the shape of the vertebra body in the case of spine images, due to the high degree of similarity between images of the same biological class. Medical image indexing is another potential application for this information. The majority of segmentation research in the realm of medical imaging has been conducted on magnetic resonance (MR) [3] or computed tomography (CT) images [2]. The segmentation of x-ray images has been the subject of substantially less research and development. As a result, we present in this paper an x-ray-applicable paradigm for the investigation of vertebral mobility. The framework is built on a novel technique that exclusively employs the recognition of faces and corner vertebrae. We want to develop a computer vision program for use with x-ray images of medical patients that will assess vertebral movement and compare the mobility of each vertebra to that of other vertebrae in the same image.

Traditional image segmentation methods presume that the regions to be segmented contain homogenous characteristics. Under this premise, segmentation algorithms seek to divide the input image into regions depending on homogeneity requirements for feature

features [4]. Unfortunately, these homogeneity criteria cannot be met for large and complex x-ray images. Consequently, segmentation of x-ray images of the spine is typically conducted using a hierarchical method. The distinct section of the image, including the main spine region, is segmented at a coarse level of detail initially. The spine is then subdivided into individual vertebrae [5]. The detection of borders is another method. Moreover, there are some research works which takes account to this problem but they still failed. Numerous studies have introduced techniques for segmenting vertebrae using MRI imaging. [6] automated the identification of discs in clinical lumbar MRI images using machine learning and heuristics. In this study, HOG and SVM are used as classifiers. 53 clinical cases were located with a 99% of precision. [7] presented a method for segmenting the position of vertebrae using GVF snake. This study established a semi-automatic segmentation method in which the region of interest was manually labeled before it could be retrieved automatically.

To increase the accuracy and reduce the number of errors in the extremely difficult human spinal segmentation technique. Presented is an algorithm for locating spinal joints. The remainder of this article is organized as follow: Section II background knowledge of this research work. Section III illustrates the proposed method, which consists of region of interest segmentation, SURF Features extraction, create triangular mesh using Delaunay triangulation, and vertebrae pose region are localized. Section IV Experimental Result, and section V conclusion and discussion is shown. Our main contributions is:

- To localize the Lumbar vertebrae pose area in low contrast environment. Figure 1 illustrated the vertebrae pose which need to be located. From observation, the each pose is traditionally difficult to proceed.

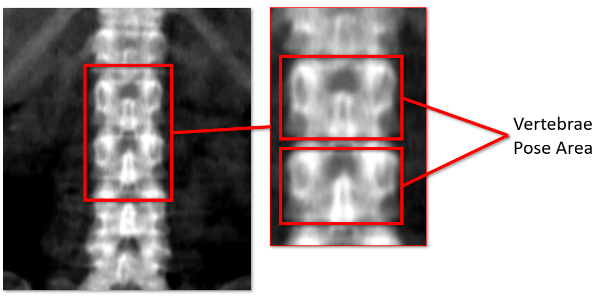

Figure 1 Lumbar vertebrae pose in low contrast condition

II. Background

A. Human Lumbar Spine

The lumbar spine extends from below the twelfth and last thoracic vertebra (T12) to the top of the sacral spine, also known as the sacrum (S1) [8]. The majority of people have five lumbar vertebrae (L1-L5), although it is not unheard of to have six. The levels of the lumbar spine are numbered beginning with L1 and ending with L5 or L6.

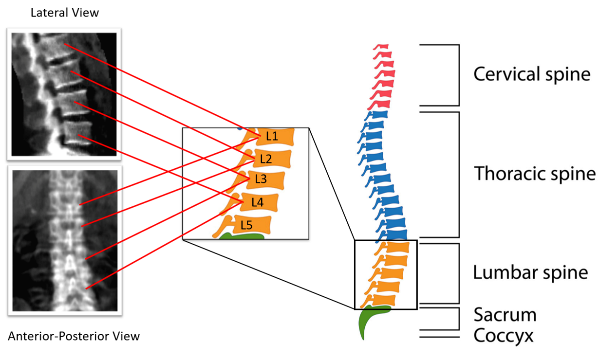

Figure 2 X-Ray image of lumbar (left) and structure of human spine (right)

B. Speeded Up Robust Features (SURF)

In the realm of computer vision, SURF is an acronym for the patented local feature detector and descriptor known as speeded up robust features [9]. Possibile uses include object recognition, image registration, classification, and even the reconstruction of three-dimensional models. The scale-invariant feature transform (SIFT) descriptor partially inspired the development of this descriptor. The baseline version of SURF is significantly faster than SIFT, and SURF's designers feel it is more robust than SIFT when it comes to handling diverse image modifications.

To locate places of interest, SURF uses an integer approximation of the determinant of the Hessian blob detector. This determinant can be calculated using three integer operations and a previously computed integral image. Its feature descriptor is computed utilizing the complete Haar wavelet response from the region surrounding the point of interest. These are also something that may be computed using the integral image. SURF descriptors have enabled the localisation and recognition of objects, people, and faces, as well as the reconstruction of three-dimensional scenes, the tracking of objects, and the extraction of points of interest.

C. Delaunay Triangulation

In mathematics and computational geometry, a Delaunay triangulation, sometimes known as a Delone triangulation, is a form of triangulation. It is defined as a triangulation $DT(P)$ for a set P of discrete points at a general location, and it is constructed so that no point in P lies within the circumcircle of any triangle in $DT\ (P)$. Delaunay triangulations tend to avoid sliver triangles because they optimize the minimum of all angles of the included triangles. Due of Boris Delaunay's contributions to geometry, the triangulation is named after him.

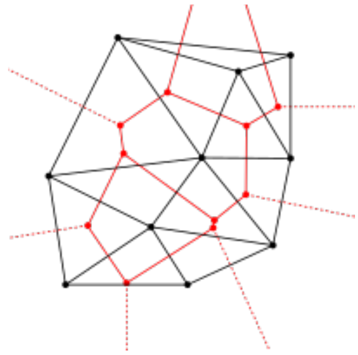

Figure 3 Delaunay triangulation structure

III. Methodology

This paper proposed an automatic segmentation of human Lumbar vertebrae pose area using Delaunay triangulation. Its description is illustrated Figure 4.

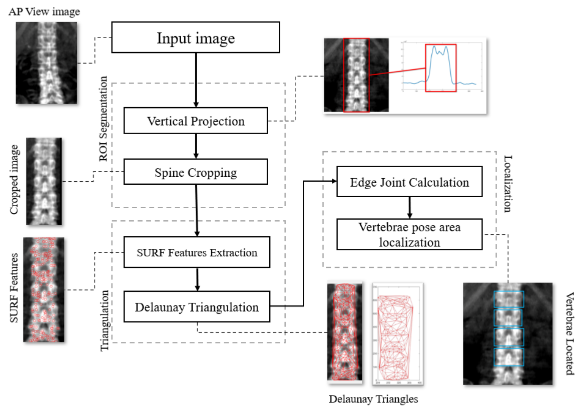

Figure 4 Outline of proposed framework

The proposed algorithm consists of three main phases. Firstly, the grayscale input lumbar image was projected vertically for auto-cropping using its vertical pattern. Secondly, Delaunay triangulation was performed using its SURF features as triangular nodes. Lastly, the vertebrae pose area was determined using node's edge density.

A. Region of Interest Segmentation (ROI)

For eliminating the outer area of X-Ray image, Figure 5 (c) coarsely determination of the spine area is performed using vertical projection in Figure 5 (c). To project the grayscale image, the vertical projection can be expressed as:

$$H_k(X) = \sum_{i=1}^{n} X_{k,i}$$

Where $H_k(X)$ is a vertical projection of each k column of the image, n is the whole number of columns, i is a number of image's row of each k.

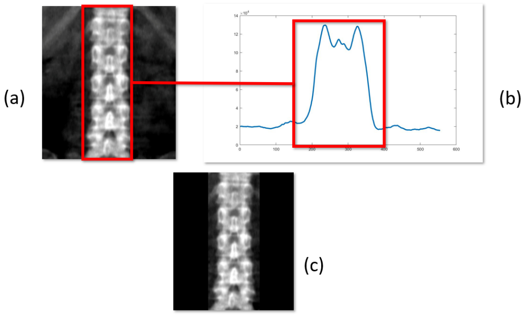

Figure 5 Original Input image (a), vertical projection graph (b), and result of spine cropping (c)

After applying a vertical projection profile to an image, it is possible to observe that the data has a normal distribution pattern. To determine the ROI (Region of Interest) from the graph, the normal distribution equation is utilized. Using normal distribution, the image is subsequently cropped appropriately.

B. Triangulation using Delaunay's approach

To create the Delaunay triangulation mesh, the cropped image is extracted the high significant features as its nodes in Figure 6 (a). The detector is responsible for finding the interest points in an image, while the descriptor is responsible for defining the features of the interest points and building the feature vectors that correspond to the interest points. The SURF attributes are unaffected by shifting, rotating, or scaling transformations, and are slightly impacted by illumination and affine transformations.

$$H(x,\sigma) = \begin{pmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{pmatrix}$$

where $L_{xx}(X,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in point x, and similarly for $L_{xy}(X,\sigma)$ and $L_{yy}(X,\sigma)$.

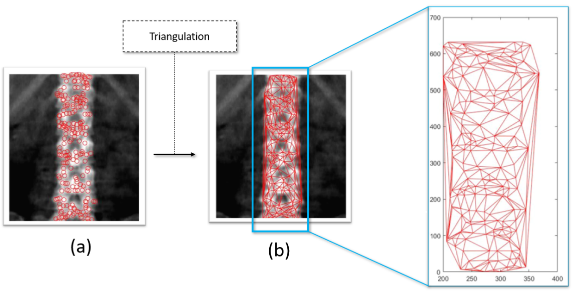

Figure 6 SURF features plot (a), and Delaunay triangulation (b)

The nodes determined by SURF features then triangulated using Delaunay triangulation, Figure 6 (b). The Delaunay triangulation can be formulated in Algorithm I.

Algorithm 1 Delaunay Triangulation

```
Algorithm  Delaunay(P)
    Input  a set P of n point in ℝ²
   Output  DT(P)
compute a triangulation T of P
Initialize a stack containing all the edges of T
While stack is non-empty
 do pop ab from stack and unmark it
   if ab is illegal then
     do flip ab to cd
        for xy ∈ {ac, cb, bd, da}
            do if xy is not marked
              then mark xy and push it on stack
return T
```

The result of Delaunay triangulation mesh is demonstrated in Figure 6 (b). The result structure from this procedure is used to determine in the localization step.

C. Vertebrae Pose Localizaion

In this step, the mesh structure from previous step is accounted to regulate the vertebrae pose area. From the observation, Figure 8 (a) shows the area of vertebrae pose acquire more edge of mesh than the gap between pose's region as appears in Figure 8 (b).

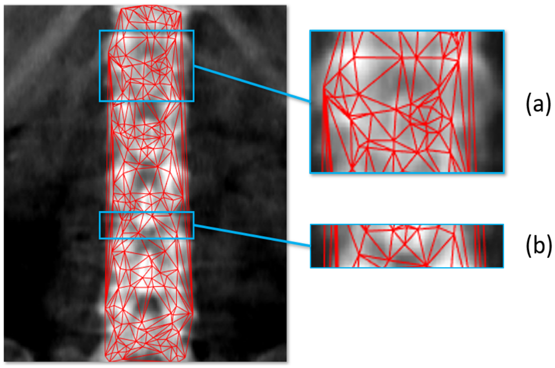

Figure 7 Delaunay triangulation structure of vertebrae pose area (a), and the gap between pose (b)

So that, to determine the area of vertebrae pose can be adjusted by number of edges connected to each node. The approach can be described in Algorithm II

Algorithm 2 Delaunay edge counting

```
Algorithm  Delaunay Edge Counting
    input  directed graph (DT) G = (V,E) with edge lengths λ: E → ℝ>0
     data  priority queue Q with keys dist[·], number of edge v
initialization
while Q not empty do
 extract v ← Q with minimum dist[v]; push v → S
 foreach vertex w such that (v,w) ∈ E do
   path discovery //-shorter path to w?
    if dist[w] > dist[v] + λ(v,w) then
     dist[w] ← dist[v] + λ(v,w)
     Insert/update w → Q with new key; σ[w] ← 0;
     Pred[w] ← empty list
   path counting
    if dist[w] = dist[v] + λ(v,w) then
     σ[w] ← σ[w] + σ[v]
     append v → Pred[w]
```

Finally, the area of lumbar L1 – L4 vertebrae is located.

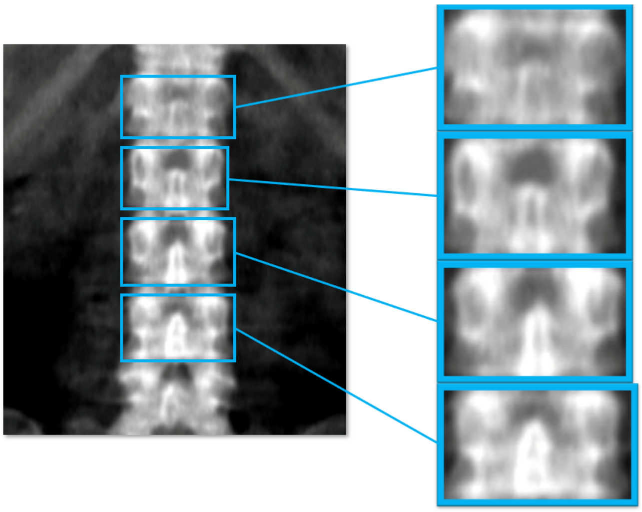

Figure 8 Spine localization result

IV. Experimental Result

The dataset that was utilized in the lab scale experiment was composed of fifty radiography pictures of the lateral human spine. These images were generated by a Dual-Energy X-ray Absorptiometry scanner (DXA Scanner) that was provided by a nearby hospital. There are images of good quality, medium quality, and low quality included in the dataset. These distinctions are due to the varying doses of radiation that were received by each patient. The image that is obtained has a higher quality the more radiation that is employed to create it. During the experiment, the ground-truth photos were analyzed alongside the automatic lumbar segmentation that was performed. Precision and recall are the two metrics that are used to evaluate performance (Confusion Matrix). According to the findings of the trial, the suggested strategy improved accuracy by 80.32%, while also increasing precision by 90.0% and recall by 88.5%.

TABLE I. Experimental Result using confusion matrix

Dataset	Confusion Matrix			
	Accuracy	Recall	Precision	FNR
Good	87.60	88.32	84.24	11.56
Medium	81.38	86.55	83.11	16.20
Low	71.97	81.23	79.73	18.51
Average	**80.32**	**85.37**	**82.36**	**15.42**

Furthermore, the proposed approach was evaluated using the gold-standard matric, consisting of Jaccard Index Measurement (JM), Hausdorff Distance (HD), and Percentage Area Difference (PAD). The experimental result shows that the proposed approach reaches the best performance in the evaluation compared with traditional measurements.

TABLE II. Experimental result comparation

Method	Evaluation		
	JM	*HD*	*PAD*
Proposed Approach	**0.82**	**10.87**	**2.33**
Watershed	0.54	46.28	5.19
DRLSE	0.77	27.98	4.63
Region Growing	0.81	32.89	4.48

V. Conclusion

In this study, a technique employing Delaunay triangulation for lumbar vertebrae localization from low-radiation radiography images generated by Dual-energy X-ray Absorptiometry is proposed. The proposed algorithm involves three primary steps. Initially, the grayscale input lumbar image was projected vertically using its vertical pattern for automatic cropping. Using its SURF features as triangle nodes, Delaunay triangulation was then carried out. The posture area of the vertebrae was estimated using the edge density of each node. The proposed approach can automatically identify the human lumbar spine region. This can assist lessen the radiologists' workload. In general, the proposed method can be employed as a preliminary step in bone structure identification and segmentation study. The segmentation of the lumbar region for particular cases of exostosis and bone collapse will be attempted in future research.

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