Semi-Automatic Detection of Cervical Vertebrae in X-ray Images Using Generalized Hough Transform

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Abstract—Vertebra detection presents the first step of any automatic spinal column diagnosis. This task becomes more difficult in the case of the cervical X-ray images characterized by their low contrasts and noise due to skull bones. In this paper, we describe an efficient modified template matching method for detecting cervical vertebrae using Generalized Hough Transform (GHT). The proposed method consists of three main steps toward vertebrae detection: 1) Offline training to obtain a robust average model of cervical vertebra. 2) Detecting the potential vertebra centers. 3) Adaptive Post-processing filter.

X-ray Image data of 40 healthy cases were used to validate our approach by using a total of 200 cervical vertebrae. We obtained an accuracy of 89%.

Keywords—Medical imaging, Vertebrae detection, X-ray image, Hough Transform, Template matching

I. INTRODUCTION

Recent statistics [1] show that over 80% of adults will have back pain at least once in their lives. Vertebrae abnormalities is one of back pain causes. Different imaging modalities (X-Ray, CT, MRI, etc.) are used by specialists for clinical diagnosis. Indeed, automatic and semi-automatic analysis bears a major aid to doctors and will save considerable time.

Accurate vertebra detection is a necessary step to efficient spinal column diagnosis. It gives valuable information about vertebrae localization, which is a difficult task to perform manually. Actually, several segmentation methods have been investigated in the literature such as Active Shape Model (ASM) [2] and Generalized Hough Transform (GHT) [3], etc. These contributions focused on three medical imaging modalities: the conventional radiography (X-Ray), the Computed Tomography (CT) and Magnetic Resonance (MR).

Alomari et al. [4] proposed a two level probabilistic model for the localization of inter-vertebral discs in MRI. They achieve an accuracy ranging from 87% to 89.1% using two testing experiments of 50 and 55 MRI cases respectively. Klinder et al. [5] developed an automated model-based vertebra detection, identification and segmentation in the case of CT images. They used GHT for the detection step, and announce a detection accuracy of 92 %.

Benjelloun et al. [6] proposed a framework of two segmentation approaches applied to X-ray images. They developed a semi-automatic tool to estimate and analyze vertebral mobility. Long et al. [7] proposed to use the active shape model (ASM) theory toward segmentation of C2 and C3 cervical vertebrae. They indexed a large collection of digitized X-Rays images from the National Health and Nutrition Examination Surveys (NHANES). Recently Lecron et al. [8] proposed a heterogeneous implementation based on ASM segmentation enabling to locate vertebrae in X-ray images. This method allowed to reduce the computing time thanks to the simultaneous exploitation of multiple CPUs and GPUs (Graphic Processing Unit).

Our contribution focuses on the development of an efficient method of vertebrae detection in X-ray cervical spine images. Indeed, our proposed approach enables a high accuracy (89%) of detection thanks to the effective exploitation of a modified Generalized Hough Transform. This method is based on a template matching technique used to recognize arbitrary shapes. This paper is organized as follows. Section II describes the proposed vertebrae detection approach that consists of three main steps: modeling, potential centers detection and post-processing. Experimental results are presented in section III using a set of 40 X-ray images (200 vertebrae). Finally, section IV concludes and describes future works.

II. METHOD OVERVIEW

The proposed approach is a new cervical vertebra detection method using a modified template matching approach based on the Generalized Hough Transform [2]. This method presents an edge-based recognition process known by its robustness to extract arbitrary shapes and its invariance to scale change, rotation and translation. The success of this method relies mainly on the quality of the pattern used. Our approach is based on three main steps:

A. Modelling.
B. Potential centers detection.
C. Post-processing

The three segmentation framework steps proposed in this paper are presented on Fig. 2.

A. Modeling

The modeling process is an offline task wish aims to make a template of the vertebrae. It is composed of three steps:

1) Geometric model construction: In this step, we build a vertebra mean model representing the average shape corresponding to a set of 25 vertebrae. The contour used to create this mean shape was extracted manually. the resulting model is shown in fig. 1
Fig. 2. The steps of the proposed approach.

2) **Gradient computation and edge detection:** After creating the mean shape, we apply the Canny edge detector [9] to our model. Within this operator, the image is first smoothed to reduce the noise. This step is realized by convolving the image with the kernel of Gaussian equation (1):

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x^2+y^2)/2\sigma^2}$$

The gradient is next computed by applying the Sobel-operator. The approximation is performed in horizontal and vertical directions by applying two masks.

The direction of the edges is determined by the equation (3).

$$\varphi = \arctan \left( \frac{G_x}{G_y} \right)$$

The next step is non-maximum suppression. Only the local maxima in the gradient image are preserved. Finally, an edge tracking by hysteresis is used, where high and low threshold are defined to make a filter for pixels of the last image.

3) **GHT:** The generalized Hough transform [2] method is used to detect non-analytic curves. This method take edges direction \( \varphi \) into account to reduce the number of false positive and makes the algorithm faster. The offline phase of the GHT consists of calculating the template shape called the R-table. It is a discrete lookup table, constructed using information about position and direction of edge points of the vertebra model.

Let \( N \) be the number of the model edge points \( p_i(x_i, y_i) \) \((i = 1 \ldots N)\) and \( \varphi_i \) its corresponding gradient. The first step is to determine a reference point \( \bar{t}c = (y_c, x_c) \). In our case this point represent the center of the vertebra, it is calculated by the equation (4):

$$c = \frac{1}{N} \sum p_i \quad (4)$$

The R-table is then constructed by analysing all the boundary points of the model shape. For each point \( p_i \), we compute the distance \( r_i \) (5) and \( \beta_i \) (6) the angle between the horizontal direction and the reference point \( c \). Then we store the two parameters \((r_i, \beta_i)\) as a function of the orientation \( \varphi \).

$$r_i = c - p_i \quad (5)$$

$$\beta_i = \arctan \left( \frac{y_c - y_i}{x_c - x_i} \right) \quad (6)$$

Therefore, the R-table, (Fig. 3), allows to recompute the center point position, using edge points and the gradient information, equation (7).

$$x_c = x + r\cos(\beta) \quad , \quad y_c = y + r\sin(\beta) \quad (7)$$

![Fig. 3. The general R-table form.](image)

The \((r, \beta)\) parameters and the orientation \( \beta \) used in the modified Hough transform in case of a single edge point of the vertebra are presented in Fig. 4.

![Fig. 4. The GHT parameters corresponding to an edge point from vertebra model.](image)
The R-table construction algorithm can be expressed as follow (Listing 1):

1. Create the R-table.
2. For each edge point $p_n$ do
   a- Compute the gradient direction $\varphi$
   b- Calculate $r_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$
   c- Calculate $\beta_i = \arctan\left(\frac{x_i - x_c}{y_i - y_c}\right)$
3. Increment $r_i$ and $\beta_i$ as a function of $\varphi$
4. End

Listing 1. Pre-processing steps used to create the R-table.

B. Potential vertebrae centers detection

For the potential vertebrae centers detection, we propose a semi-automatic process based on a manual selection of the regions of interest (ROI). Two points are placed to cover the area of cervical vertebrae. We make a preliminary pre-processing step based on histogram equalization to enhance X-ray images. Next, we use the Canny and Sobel operators for edge detection. Then, we perform the online GHT process based on the R-table calculated at the training. These steps are detailed below:

1) Contrast-Limited Adaptive Histogram Equalization: This step aims to prepare the X-ray images to edge detection by using the Contrast-Limited Adaptive Histogram Equalization (CLAHE) [10] technique used to improve the image contrast. It computes first different local histograms corresponding at each part of the image, and uses them to change the contrast of distinct regions of the image. This method is well known by limiting noise amplification. The result of this step is shown in Fig. 5(b).

2) Gradient computation and edge detection: In this step, we repeat the same process described in the model construction. Therefore, edge detection with Canny filter is applied to the improved image, and sobel operator is performed in $-x$ and $-y$ directions. The result of the edge detection is shown in Fig. 5(c).

3) GHT accumulator construction: This step represents the core of the Generalized Hough Transform detection. It aims to determine the position of the center points of vertebrae in the target X-ray image by using the information stored in the R-table.

In practice, for each edge point $p$ in the edge detection result (Fig. 5(c)), we compute the gradient direction $\varphi$. Then, we vote for all possible positions $\vec{r}$ of the reference point in the accumulator array, where $\vec{r}$ are the positions $(r_i, \beta_i)$ indexed under $\varphi_i = \varphi$ in the R-Table. The candidate centers are indicated by finding local maxima in the voting scheme.

The size of the vertebrae change slightly in the images, so the proposed model may be not easily matched, for this reason, we add a new parameter $S$ to make a range of scale for to enhance the detection process. Therefore, a single point $p(x_i,y_i)$ in the image votes for candidate centers $(a_p,b_p)$ computed as shown in equation (8)

$$
\begin{bmatrix}
a_p \\
b_p
\end{bmatrix} = \begin{bmatrix}
x_i \\
y_i
\end{bmatrix} + S \cdot \begin{bmatrix}
\beta_{\varphi_p} \\
\cos(\beta_{\varphi_p})
\end{bmatrix}
$$

(8)

Where $s$ is the scale, $(r_{\varphi_p}, \beta_{\varphi_p})$ the parameters obtained in (5) and (6) corresponding to $\varphi$ value in the R-table.

Listing 2 summarize the detection algorithm used to create the GHT accumulator. The result of this step is shown in Fig. 6.

1- Find all edge detection points
2- For each feature point $(x_i, y_i)$
   a- Compute the gradient direction $\varphi$
   b- For each $(r_{\varphi_p}, \beta_{\varphi_p})$ indexed under $\varphi$ in the R-table
      - For each scale $s$, compute the candidate center $(a, b)$
      - Increment $(a, b)$ in the accumulator
3- Potential centers are given by local maxima in the accumulator

C. Post-processing analysis:

For the post processing analysis we propose an approach composed of two steps:

1) **Linear regression fitting**: we apply a simple linear regression based on a processing selection of top voted point from the accumulator.

The objective of this step is to select the effectively voted points \((x, y)\) based on the straight line equation (9).

\[
\begin{align*}
    y &= ax + b \\
    a &= \frac{\sum xy}{\sum x^2}, \text{ Where } \sum x = \sum (x_i - \bar{x})(y_i - \bar{y}) \\
    b &= \bar{y} - a\bar{x}
\end{align*}
\] (9)

2) **Adaptive distance filter**: An adaptive filter is finally applied to the result of the linear regression fitting step. This task aims to check the distance between selected points. Based on these distance, we compute the average distance between vertebrae centers. This enables us to eliminate false centers (with a distance higher or smaller than the average distance).

III. EXPERIMENTS AND RESULTS

Experimentations have been conducted using a set of 40 digitized X-ray films. These images presenting cervical spine region (Fig. 5(a)) are obtained from the National Health and Nutrition Examination Surveys database NHANES II.

These experimentations are focused on the detection of the cervical vertebrae C3 to C7 (Fig. 7). Indeed, our input images contain a total of 200 (40x5) vertebrae. We notice that the mean model was build using a set of 25 cervical vertebrae (Fig. 2).

Fig. 8 shows the obtained detection results of the cervical vertebrae C3 to C7 by using the proposed approach in case of four X-ray images. These results enabled a global accuracy of 89% on the 200 vertebrae investigated as shown in Table 1. Notice that the C7 vertebra is detected with a rate of 60% which is lower than the mean accuracy. This is due to the edge detection step which does not detect efficiently this vertebra. The noise surrounding this cervical area makes this detection more difficult.

![Fig. 7 Cervical vertebra C1 to C7](image_url)

We note also that edge detection and gradient computation steps depend on the contrast level of the input images. The use of CLAHE method allowed to achieve an efficient gradient computation, and hence enhanced the edge extraction.

![Fig. 6 Candidates vertebrae centers that totalise more than T votes: (a) T= 15 (b) T= 18 (c) T= 22](image_url)

Table 1. Accuracy recognition.

<table>
<thead>
<tr>
<th>Vertebrae type</th>
<th>Detection rate</th>
<th>Global accuracy</th>
<th>With C7</th>
<th>without C7</th>
</tr>
</thead>
<tbody>
<tr>
<td>C3</td>
<td>97.5%</td>
<td>89.0%</td>
<td>96.3%</td>
<td></td>
</tr>
<tr>
<td>C4</td>
<td>95.0%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C5</td>
<td>95.0%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C6</td>
<td>97.5%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C7</td>
<td>60.0%</td>
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</table>

Table 2 presents a comparison of vertebrae detection rate of the proposed method with other methods. We focus on methods where the rate of detection is announced. The table 2 shows two methods in case of lumbar vertebrae.

![Table 2. Comparison of vertebrae detection rate with other methods.](image_url)

<table>
<thead>
<tr>
<th>Method</th>
<th>Detection rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alomari et al. [4]</td>
<td>89.1%</td>
</tr>
<tr>
<td>Klinder et al. [5]</td>
<td>92.0%</td>
</tr>
<tr>
<td>Proposed method (without C7)</td>
<td>96.3%</td>
</tr>
</tbody>
</table>
IV. CONCLUSION

In this paper, we presented a new semi-automatic approach used to detect cervical vertebrae in X-ray images. Our contribution is based on the Generalized Hough Transform. The objective was to localize the cervical spine centers. Thus, we have proposed an offline process for vertebrae mean shape modeling and data construction. Thereafter, we conducted a robust template matching analysis to find potential vertebrae centers. Finally, we proceeded by an adaptive filter exploiting linear regression fitting to achieve vertebrae centers detection. As result, the proposed method gives promising detection rate for a large set of X-ray images.

For our future works we plan to develop a fully automated segmentation method based on our contribution. We plan also to make an optimization of the GHT transform to increase the vertebrae detection accuracy.

Fig. 8. Final results detection of C3 to C7 vertebrae for 4 cases.
REFERENCES


