Vertebra Localization Using Shape Based Analysis and Unsupervised Clustering from X-ray Images

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Abstract

Accurate vertebral detection in X-ray images is a challenging task mainly due to low contrast and noisy set of image data. For the diagnosis of spinal disorders such as cervical spine trauma and whiplash, the detection and segmentation of vertebra are the fundamental tasks. The first step in detection process is the vertebra localization. In this paper, we propose a new method for the cervical vertebra localization problem. The proposed method contributes a novel composition of a mean model matching using the Generalized Hough Transform (GHT) and unsupervised clustering technique. To detect edges and enhance image contrast, preprocessing is performed on the input X-ray images. After manually selecting region of the interest (ROI), we use a separately generated geometric mean model as a template. A modified GHT is then used for the localization of vertebra followed by Fuzzy c-Means (FCM) clustering technique to obtain centroids of targeted five vertebras ($C3 - C7$). The proposed method secured localization accuracy of 96.88% when tested on 50 X-ray images of publically available database 'NHANESII'.

Keywords: Generalized Hough transform, Fuzzy c-Means, Vertebra localization, Shape based analysis, Unsupervised clustering.

INTRODUCTION

During the past few years, medical imaging has become one of the most useful technology for diagnosis of different diseases such as brain tumor, lung cancer, liver and kidney problems, etc. [1] . This revolution has also helped to obtain information which is useful in many clinical applications and diagnoses of disorders such as osteoporosis, spinal ruptures and cervical spine trauma [2]. The spinal column, along with sacral region and coccyx, consists of seven 'cervical', twelve 'thoracic', and five 'lumbar' vertebrae [3] . The radiographic anatomy of cervical spine is shown in Figure 1.

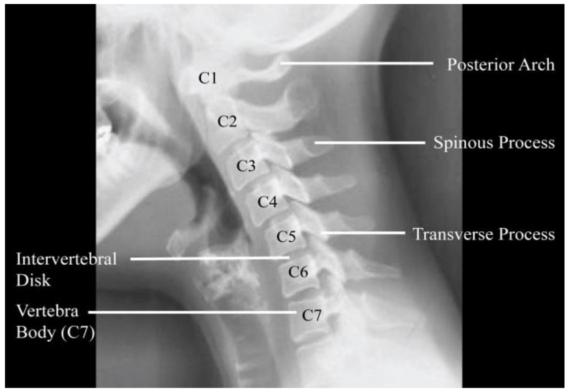

Figure 1.Radiographic anatomy - cervical spine lateral

Each vertebra has the vertebral body for load-bearing, the vertebra larch to protect the spinal cord, and transverse processes for ligament attachment. The inter vertebral discs separate the individual bones providing additional weight-bearing support to these discs and function like shock absorbing springs. The cervical injuries may affect arms, legs, and middle parts of the body [4] . The vertebrae column serves as a support to the other organs of a human body. The localization of vertebra performed accurately can play an important role in the detection of cervical spine disorders. It is of great significance in many orthopedics and neurological applications that the right vertebra be treated. In low contrast X-ray images, the localization of vertebra is quite challenging and a tiring task. Therefore, accurate vertebra localization with high accuracy would be of great interest to the radiologists' community.

Many techniques for vertebra localization and segmentation have been proposed such as active shape model [5] , GHT [6] , etc. The medical imaging modalities such as computed tomography (CT) and magnetic resonance imaging (MRI) are greatly benefited from these contributions.

A model based on two phases for targeting inter-vertebral discs using MRI was proposed by Alomari *et al.* [7] . Their work (i.e., two experiments using 50 and 55 MRI cases) led them attain an accuracy of 87% and 89.1% respectively. Larhmam *et al.* [8] built a mean model of the vertebra intended for template matching. They used GHT for vertebra localization and k-means clustering to obtain targeted vertebra's clusters. Klinder *et al.* [9] proposed a computerized model for the vertebra localization and segmentation using CT scans. The GHT-based detection by employing adapted triangulation shape to localize and segment different vertebrae reports around 70% identification accuracy. Benjelloun *et al.* [10] presented a comparative study of two algorithms for segmentation of X-ray images in their semiautomatic implementation for analysis and estimation of vertebra. Based on ASM segmentation, Lecron *et al.* [11] developed an implementation which enables the localization of vertebrae using X-ray images. The authors have reported reduced computing time through synchronized manipulation of more than one CPUs and GPUs. Larhman *et al.* [12] presented three step automatic diagnosis of spinal column based on off-line training of cervical vertebra and vertebra centroids localization using GHT and adaptive filter post-processing. They have reported accuracy of 89% using 200 cervical vertebrae. Yao *et al.* [13] developed a methodology for extracting and partitioning of the spinal cord using watershed algorithm on CT scan images. Benjelloun *et al.* [14] developed a method for the identification of vertebra boundaries by the use of segmentation along with polygonal regions. This technique was applied for the analysis of vertebra mobility. Recently, they have introduced method based on active shape model for vertebra identification and segmentation [15].

A graphical-model based solution was presented by Dong *et al.* [16] reporting an automatic calculation of the visible vertebrae in images using radiographs. Casciaro *et al.* [17] used local phase measure for the detection of vertebra and obtained 83% accuracy. Lecron *et al.* [18] proposed method based on multiclass SVM. They trained SVM model using SIFT descriptor and 81.6% localization accuracy was reported using 50 X-ray images.

We have focused on development of a method for detection of cervical vertebrae in cervical spine X-rays. This method is used to recognize arbitrary shapes using generalized Hough transform and fuzzy c-means clustering. This paper is organized as follows. First of all different existing techniques are reviewed, followed by our proposed methodology. The next section presents results and a discussion. The last section concludes our work.

Existing Techniques

A. *Generalized Hough Transform(GHT)*

The Hough transform is a widely used technique in many image processing and computer vision related applications. It was originally proposed for the detection of lines, parabolas, circles, etc. but Ballard [6] generalized it to detect arbitrary shapes as well. Therefore, the generalized Hough transform (GHT) became a technique capable to be utilized for pattern recognition. The modification in scale, orientation and translation has no impact on the process of detection. The GHT uses a voting scheme which basically locates the area of candidate X-ray image matching with the mean model, also named as template. The process of detection using GHT comprises two phases: R-table and Accumulator.

The R-table basically represents the template image. It holds the information about the 'position' and 'orientation' of reference image. During training phase, R-table is constructed, as follows. Firstly edges are detected then we find a reference point $c = (c_x , c_y)$ in the candidate X-ray image by using a mean model of required shape. Then the 'distance' and 'angle' are computed using the borderline and reference point of the image. For every landmark point find 'orientation' Φ and the 'relative position' $r = (r_x, r_y)$. We then keep this info in R-table as $f(\Phi)$. The R-table utilizes few parameters representing the template. The voting scheme known as Accumulator is built as follows: For each landmark point p finds the 'gradient direction Φp'. Then, for all the entries representing the location '$p - r_i$' in the accumulator, voting is carried out. Here r_i shows the location (r_i, β_i) in index $\Phi = \Phi_p$ in the R-table. In this process of voting, local maxima is worked out which helps in shape detection.

B. Fuzzy C Clustering

The fuzzy c-means (FCM) is a technique which permits one sample of data to fit in to two or more clusters. This algorithm has widely been used and is a popular technique of clustering introduced by Dunn in 1973 which was later improved by Bezdek [19, 20] . The FCM partitions a set of vectors Xi, $i = 1, 2, 3...n$ into 'C' divisions and defines the center of cluster in every group in such a way that dissimilarity cost parameter is reduced. The technique performs grouping such that an input data can be part of multiple groups with specific degree of membership indicated by values from 0 to 1. It is an iterative algorithm. In a group operation, the algorithm finds out the centers'$C_j'$and the matrix of belongingness 'M_b'making use of the phases.

METHODOLOGY

The proposed method is based on offline training of vertebra mean image. The vertebra localization is performed using generalized Hough transform (GHT) and after candidate vertebra localization fuzzy c-means clustering is applied to get centroids of the targeted vertebras ($C_3 - C_7$). Figure 2 shows an overview of our proposed method.

1) Training

The reference image of GHT stages are used to build a mean image representation of the vertebra. Therefore, in order to reduce the work overload of the

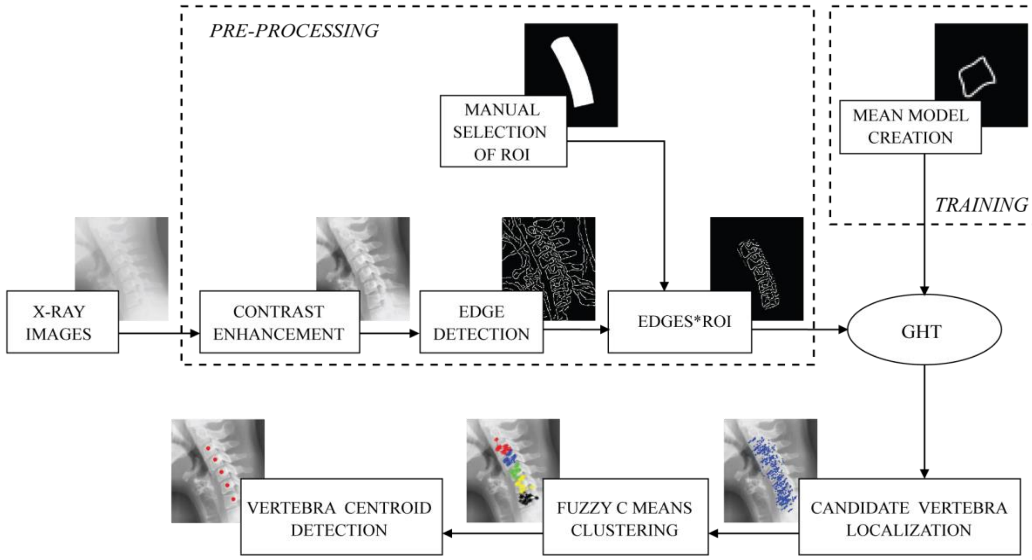

Figure 2: Flow diagram of the proposed system

template matching, a mean shape of the vertebra body is constructed. This mean model is constructed using a set of 50 vertebrae to represent the average shape. The average shape is generated through manual contour selection. The mean model of vertebra body is constructed using the Eq (1) where '*N*' shows the total number of vertebra used for the mean model (N = 50) and '*I*' represents one vertebra body image.

$$Mean_m = \frac{1}{N}\sum_{i=0}^{N} I_i \qquad (1)$$

2) ***Vertebra Localization***

For the accurate localization of vertebra following steps are to be performed on input X-ray image:

1) *Pre-processing:* The input X-ray images are of low contrast and need to be enhanced for vertebra detection. For this purpose the adaptive histogram equalization can be applied. It changes the contrast of X-ray image areas by computing the local histogram of that specific area. This technique reduces the noise amplification of the input image. The canny edge detector gives the edge points of the enhanced image. Next, the region of interest (ROI) is manually selected to decide feasible vertebra candidate in the input X-ray. The ROI covers an area of cervical vertebrae including C_3 to C_7.

2) *Generalized Hough Transform (GHT):* After preprocessing of input X-ray image which includes contrast enhancement, edge detection and selection of ROI, GHT is applied on the resultant image. In GHT training phase, R-table (Table 1) is built which basically represents the vertebra mean model. It involves 'position' and 'direction' of landmark points which we get in pre-processing step. R-table is built by following steps:

- Find out the edges of the input X-ray images using canny edge detector.
- Select a point of reference say (x_r, y_r).
- Join the point of reference & boundary with a straight line.
- Calculate Φ
- In R-table, enter the point of reference (x_r, y_r) as $f(\Phi)$.

Containing edge points $p_e(x_e, y_e)$, e = 1, 2, ., n where n represents the total number of points and Φ_i gives gradient w.r.t.i. An angle formed by the reference point $c=(x_r, y_r)$ with horizontal direction is measured by Equation (2).

$$c = \frac{1}{n}\sum p_e \tag{2}$$

Table 1: General R-Table Form

Orientation Φ	Position (r,β)
0	$(r_x,\beta_x)/\Phi_X = 0$
Φ	$(r_x,\beta_x)/\Phi_X = \Delta\Phi$
$2\Delta\Phi$	$(r_x,\beta_x)/\Phi_X = 2\Delta\Phi$
$3\Delta\Phi$	$(r_x,\beta_x)/\Phi_X = 3\Delta\Phi$
...	...

The distance r_x and β_x are calculated using Equation 3 and Equation 4.

$$r_x = \sqrt{(x_r - x_e)^2 + (y_r - y_e)^2} \tag{3}$$

$$\beta_x = \tan^{-1}\frac{y_e - y_r}{x_e - x_r} \tag{4}$$

Table 1 [6] represents the general ‘R-table’ In second half of GHT, accumulator is constructed in which for each edge point p, Φp is calculated representing the gradient direction. Then voting is performed for all the positions. In the voting technique of GHT, a local maximum is calculated for the identification of the vertebra shape. After voting procedure, we get the final output of GHT as shown in Figure 3 associated with ‘Candidate Vertebra Localization’ in which there are points covering the area of vertebra ($C3-C7$).

3) *Fuzzy C Means clustering:* Next, Fuzzy C Mean algorithm is applied on the points we get as candidate vertebra localization from GHT. Total five clusters ($C3 - C7$) are formed with final centroids after several iterations of Fuzzy C Means. After each iteration membership of data points change and the process continue still we get same membership results in consecutive two iterations, making algorithm converge. As a result, five clusters are formed representing targeted $C3$ to $C7$ vertebrae.

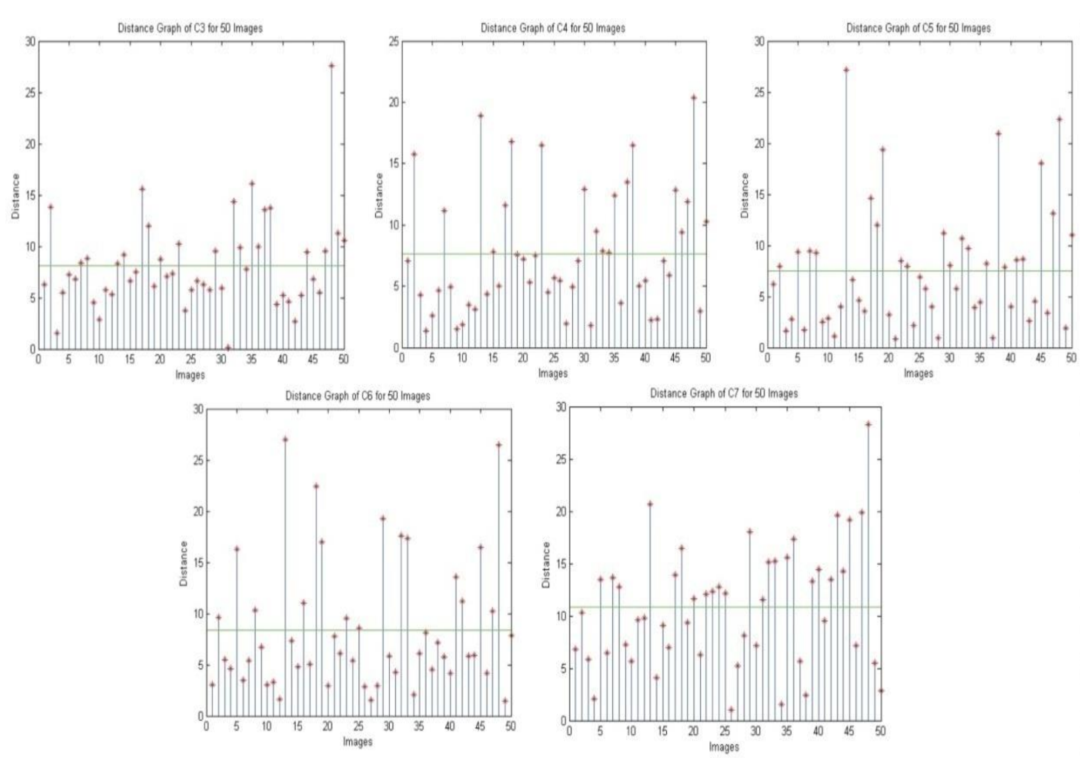

Figure 3: Pixel wise distance between annotated and automated calculated centers for each vertebra along with mean pixel distance (Green Horizontal Line)

Experimental Evaluation

The publically available database 'NHANES II' containing 17000 X-ray images [21] has been selected for evaluation of our proposed method. It includes both cervical and lumbar X-ray images of different patients under several conditions and orientation. In literature, experiments are performed using different number of images of same dataset but none of them has mentioned on which bases they have selected specific image or number of images. We have used 50 randomly selected cervical spine images for testing of our proposed methodology. The mean model is created manually using 50 vertebra body images of NHANES II dataset. All the images are visualized and center points for each vertebra from $C_3$to C_7 are manually annotated. These annotated centroids are used as a ground truth for vertebra localization validation. Figure 3 shows the distance calculated between these annotated centers and the centroids we obtained as a final FCM output. Each graph show the distance of each cervical vertebra for all the 50 images. Further, this distance helps to calculate mean and standard deviation, using which we can draw mean error bar for each cervical vertebra.

Experimental evaluation is performed on two levels using 50 testing images (Figure 4). In visual examination, we analyze the resultant images individually and count the correct results. If the centroid obtained is within the body of vertebra, we would consider it as correctly localized center. We get localization accuracies of 100% for C_3, 98% for C_4, 98% for C_5, 92% for C_6 and 92% for C_7 with overall accuracy of 96%. Our results are shown in Figure 4a. The mean error values of C_3, C_4, C_5, C_6 and C_7 are 8.1378, 7.6241, 7.5284, 8.4043 and 10.8478, respectively as shown by green horizontal line in Figure 3. In second level, Receiver Operating Characteristics (ROC) curves are generated using pixel distance as shown in Figure 4b. The ROC curves [22] curves basically illustrates the performance of the system by varying threshold. They are used to evaluate the response of system in different conditions. These curves show that proposed system achieved 96.88% accuracy at a threshold of 14 pixels. This threshold is selected after analyzing the average size of vertebra in the dataset. Figure 5 shows visual results of the proposed vertebra localization system for some randomly selected X-ray images. The first, second, third and fourth columns show original radiograph, GHT, clustering, and centroid of each cluster representing C_3C_7 results, respectively. It is observed that C_6 and C_7 is not located accurately in many cases as compared to other vertebrae due to the misleading results of edge detection. The detection becomes more problematic task due to the noise covering the cervical area. Moreover, contrast enhancement of the input images has a significant importance in edge detection. Therefore, adaptive histogram equalization is used to enhance the detection of edges and efficient computation of gradient. Table II gives a comparison between different techniques. Results are shown for selected images taken from the same NHANES II dataset as used by other researchers. The algorithm proposed by Larhman *et al.* [8] achieved an accuracy of 97.5% which is a bit higher than accuracy achieved by our proposed technique i.e. 96.88%. This is mainly due to our testing of proposed method on randomly selected subset of images.

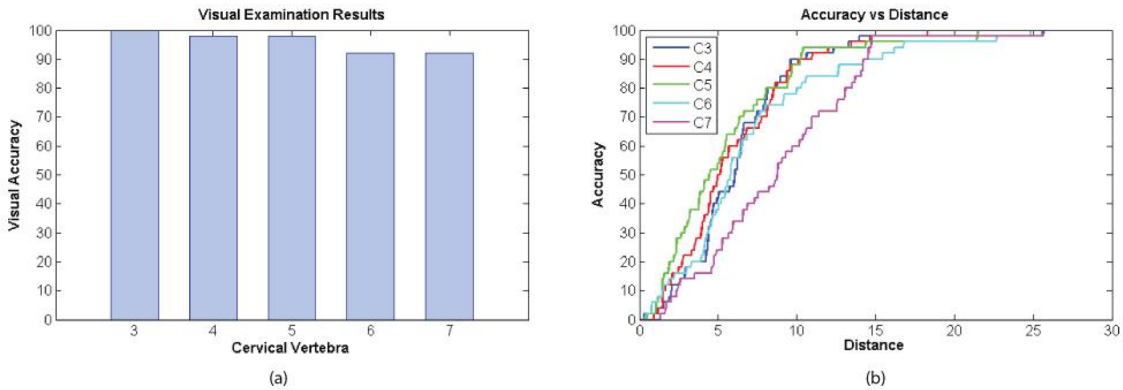

Figure 4. Vertebra localization accuracies a) Visual Examination based accuracies b) ROC curves for each vertebra using pixels distances

Table 2: Comparison of different Vertebra Localization Techniques

Paper	Year	No. of Images	No. of vertebrae	Accuracy %
Larhman [12]	2012	40	200	89
Benjelloun [23]	2012	40	200	Automatic: 64.5 Semi-Automatic: 89
Lecron [18]	2012	50	250	81.60
Larhman [8]	2013	66	330	97.5
Proposed Method	2016	50	250	96.88

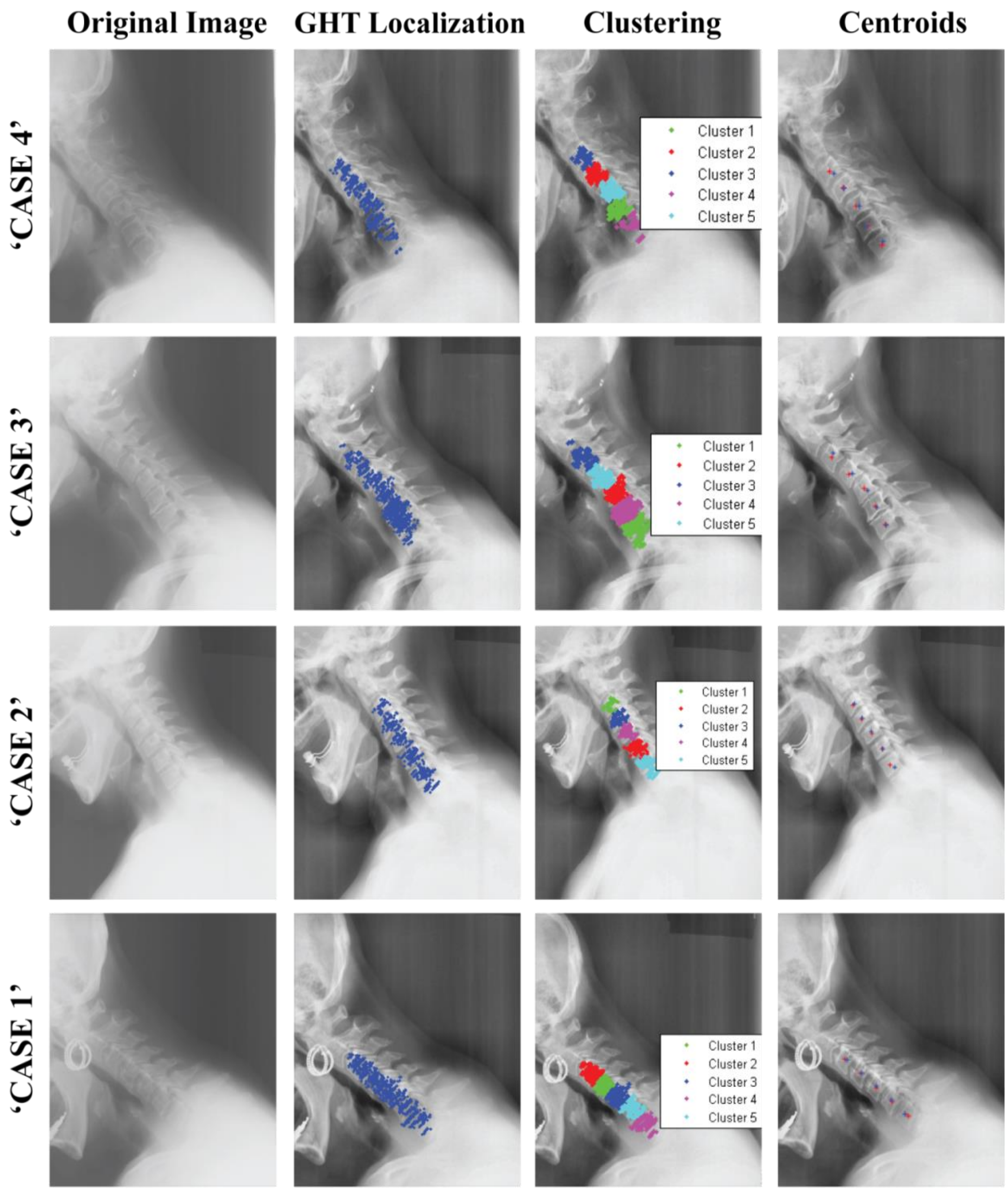

Figure 5.Visual results of the proposed vertebra localization system using randomly selected X-ray images.

CONCLUSION

This work has proposed a novel combination of mean model matching using generalized Hough transform and unsupervised clustering technique to locate five cervical vertebrae from C3 to C7. The performance of the proposed method has been tested using the cervical X-ray images of publically available database 'NHANES II'. The proposed method has been shown to give satisfactory results with a prediction accuracy of 96.88% on 50 cervical radiographs. The future work is focused towards use of localized centroids for automatic segmentation of vertebra.

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