



Neural Network for Detecting Anterior Osteophytes

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Abstract: Development of a computer vision system to identify degenerative disorder of the spine is a challenging task. An x ray image shows the features associated with these disorders. Manual analysis from observation of the x rays can be prone to errors due to the low contrast of the x rays images as well as variability in visual judgment from person to person. In this paper a neural network based approach for detection of osteophytes is investigated. Convex hull features of the segmented vertebrae are determined by image processing technique. The network is trained by conjugate gradient descent back propagation algorithm and tested on a set of vertebrae images. After the initial manual assistance in formation of template and the training of the network, the system becomes automated for real time detection of anterior osteophytes.

Keywords: Anterior Osteophyte, x-ray, segmentation, Neural Network, back propagation.

I. INTRODUCTION

Osteophytes are bony protrusion that develops mostly on front side of the vertebrae. Natural aging process, traumatic injury, incorrect postures are the causes for osteophytes. Osteophytes result in pain or neurological symptoms. The cervical spine is mainly at risk to the wearing of the joints and discs. The growth of anterior osteophytes on the front side of the vertebrae is more because the spine's arrangement allows the anterior side to compress more than the posterior side. Hence the development of anterior osteophytes is very common in this region of the spine. The result is that anterior osteophytes are larger than posterior osteophytes and likely to compress a nerve and cause pain. A person showing signs of vertebral degeneration are examined by X rays imaging. The growth of osteophytes, spondylosis, spondylolisthesis and narrowing of the intervertebral space can be observed in x rays. Medical expert generally use vertebral morphometry to evaluate the abnormality of the spine. Osteophytes can be seen as difference in shape at specific location as compared to the normal shape which is rectangular.

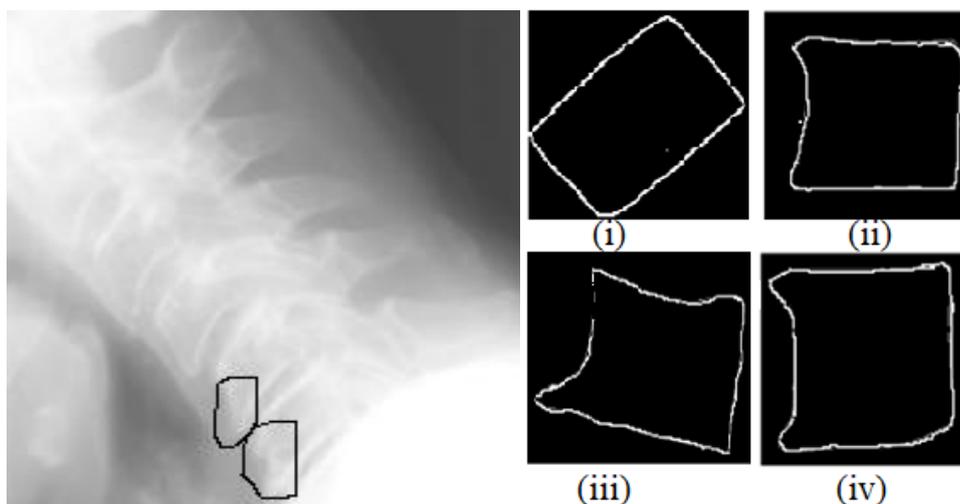


Fig. 1 (a) Osteophytes at vertebra C5 and C6

Fig 1 (b) Normal vertebra shape shown in (i), (ii-iv) show osteophytes at anterior boundary

In the previous work carried by Xu et al [1] dynamic programming aided partial shape matching methods are used to detect osteophytes. Osteophytes are also detected using Macnabs classification by [2] based on radiology and pathology. Image processing methods were implemented for the investigation of four features for osteophytes in



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cervical spine [3]. These features were found to be non adaptable to changes in size of the vertebrae. Maruti Cherukuri et al [4] have used convex hull features based MLP classifier to identify osteophytes in lumbar vertebrae. They have used manual segmentation for determining the vertebra boundary

This paper deals with automatic segmenting the vertebrae by generalized Hough transform. The convex hull size invariant features described for lumbar spine [4] are extracted for cervical spine. A neural network is used to evaluate these features for identification of anterior osteophytes in cervical spine. The paper outline is, section II describes segmentation of vertebra, section III deals with feature extraction followed by experiment set up, result and conclusion.

II. SEGMENTATION

Segmentation is the process of partitioning an image into distinct regions containing pixels with similar attributes. The purpose of segmentation is to simplify and/or change the representation of an image into more relevant and easier to analyze. The Generalized Hough Transform (GHT), introduced by D H. Ballard in 1981[6], is the modification of the Hough Transform to detect arbitrary shape using the principle of template matching. The Hough Transform requires a priori information about the shape that is to be detected in the target image. The Hough Transform can find a match of an earlier defined template in an intended image in spite of changes in orientation and scale and in the presence of noise with the vertebrae occluded with tissues [1]. GHT makes use of an edge image to associate points in a previously formed template and matches them in the target image by means of local gradient information [1]. So the Hough Transform is basically a template matching process, based on a confirmation gathering approach, the confirmation are the votes collected in an array termed as accumulator. The implementation of GHT outlines a mapping from the spatial domain to the accumulator space. This is attained in a computationally efficient manner, related with the attributes of the intended shape. “The Hough transform detects curves by exploiting the duality between points on a curve and parameters of that curve “[4]. GHT methods are even generalized to detect analytical as well as non analytical shapes in grey level images [1]. GHT is a transformation which is used to find arbitrary complex shapes. The GHT can find non-analytical curves [4], by determining an reference origin for shape, and the orientation given by θ and two orthogonal scale factors on the x and y direction. An R-Table is constructed representing the variation of r for the arbitrary shape. The entries in the R-table are formed by selecting a reference point y, for the shape and for every boundary point x, the gradient direction is calculated and r is stored as a function of the gradient direction [4]. The R-table is used to detect occurrence of shapes in an image. All entries into the columns of R table are length, r, and direction, α , from the reference point for each edge point in the shape. The remaining part of segmentation is selecting the best approximation of the reference point. This is done by search process to analyze every edge point in the target image and, based on the local value of θ , find the corresponding (r, α) pairs in the R-table to update the accumulator. The accumulator collects the spatial location of the reference point. The accumulator having the highest value of this peak is selected to be the one that corresponds to the true value of scale and rotation of the vertebrae. Then the location having the highest peak in this accumulator is computed, and this is taken to be the reference point. Thus the pose estimation of the vertebrae is accomplished. The x ray images of the cervical spine are preprocessed using unsharp masking and filtered by an averaging filter. A canny edge detector is used for deriving the edge image. The model for off line training to form an R-table comprises of 20 vertebral templates. The result of segmentation by generalised Hough Transform is shown in fig. 2



Fig. 2 Result of segmentation of vertebrae. Dark points indicate the output of the GHT.



III. EXTRACTION OF VERTEBRAL FEATURES

In this section, four features are described for osteophyte identification in cervical vertebrae. The shape of a normal vertebra is curved and nearly rectangular. The convex hull prepared from its boundary points also has a similar shape. The growth of osteophytes on the anterior side results in departure of its original curved or convex shape. The convex hull features are so enumerated that they will describe the amount of protrusion at the region pertaining to anterior osteophytes. Maruthi Cherukuri et al [4] have developed these features for lumbar spine. The four features used for characterizing of anterior osteophytes in cervical vertebrae are: (1) the ratio areas of the cervical vertebra (AreaV) to the convex hull (AreaC) of that vertebra, (2) Feature F2, the ratio of area of X-ORing (A_{xr}) to the convex hull, (3) the area of X-OR on the vertebra's anterior side (A_x) divided by the vertebra area and (4) the area of the largest connected region on the anterior side (A_{cx}) divided by the vertebra area. The first feature, is denoted as F1, $F1 = \text{AreaV}/\text{AreaC}$. The second as F2, $F2 = A_{xr}/\text{AreaC}$. Fig.3 (a) shows the X-OR for a normal cervical vertebra, and Fig. 3(b) the XOR of an abnormal vertebra with osteophytes on the lower anterior side.

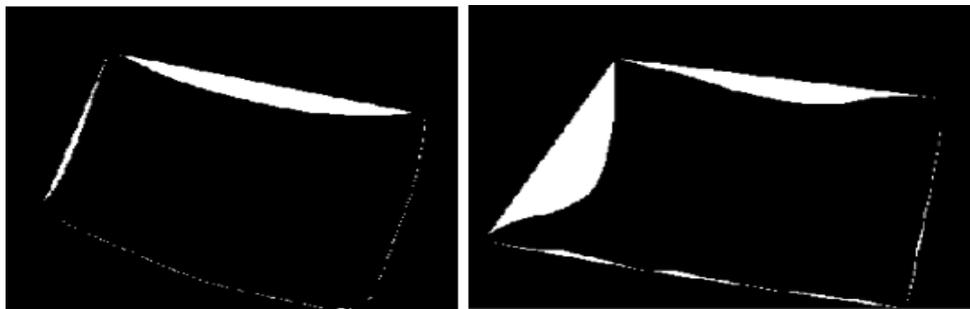


Fig 3(a) X-OR for a normal cervical vertebra Fig.3 (b) X-OR for cervical vertebra with osteophytes on the lower anterior side

The third feature computed is given by the X-OR area on the vertebra's anterior side divided by the vertebral area. All the connected points in the X-OR image on the posterior side are removed. Let Q denote the number of connected components on the anterior side and $R = \{r_1, r_2, \dots, r_Q\}$ be the set of connected components remaining with areas given by A_r , for $1 \leq i \leq Q$, then, the third feature denoted as F3 is, $F3 = \sum_i^Q A_{ri} / A_v$. To calculate the fourth feature, the largest connected part on the anterior side is used. The ratio of the largest connected region from the exclusive-OR regions on the anterior side of the vertebra to the vertebral area is denoted as F4 and is defined as $F4 = \max(A_{roi})/A_v$



Fig.3(c) Fig.3(d) Fig.3(e)
Fig. 3 (c) and Fig.3 (d) show exclusive-OR area after removing the posterior region of the image for normal and abnormal vertebrae. Fig. 3(e) shows largest connected component on anterior side.

IV. EXPERIMENT SET UP

Description of data set: The x ray images of the cervical spine are from the NHANES-II data base. Twenty templates are formed to fully represent the variation in shape and orientation of the cervical vertebrae in the data base. The vertebrae were categorized by a local medical expert into "normal" and "abnormal". Abnormal is having anterior osteophytes. The result of anterior osteophyte classification by neural network is compared with the expert's classification. The algorithms are implemented in matlab.

A neural network is implemented for the classification of vertebra as normal and abnormal. Following is the description of implementation.



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Neural Network Architecture: The Neural Network Architecture used consist of 4 input nodes, 3 nodes in a single hidden layer and one output node (4 - 3 - 1). The activation function for the hidden layer is sigmoid bipolar. The network training is done using scaled conjugate gradient descent back-propagation learning algorithm [10]. In the scaled conjugate gradient algorithm a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. Training occurs according to given training parameters;

Maximum number of epochs = 1000, Minimum performance gradient = 1e-6, Maximum validation failures = 6

Change in weight for second derivative approximation = 5.0e-5

Training is stopped upon meeting any of the criterions given:

- i) Maximum number of epochs reached.
- ii) Performance gradient falls below minimum gradient.
- iii) Cross entropy error for validation starts to increase after having 100percent validation.

The training data consist of features F1-F4 of 144 individual cervical vertebra from C3-C6. The training is carried by randomly selecting 80% samples for training, 5% each for cross validation and testing. The training is automatically stopped when the cross entropy error of the validation samples starts to increase. The training is repeated for ten retraining cycles. After every training cycle, the network is tested for 80 individual vertebrae's.

The test data set consists of 80 individual cervical vertebrae. The testing is carried out after for every training cycle. Four possible outcomes formed during the testing phase are

True positive (TP) – correctly identified Osteophytes

False positive (FP) – incorrectly identified as Osteophytes

True negative (TN) – correctly identified as Normal

False negative (FN) – incorrectly identified as Normal

The accuracy and sensitivity are defined form these outcomes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

V. EXPERIMENTAL RESULTS

The cervical spine vertebrae are segmented by GHT. The result of segmentation of cervical vertebrae C3-C6 is shown in fig2. Individual vertebra is separated and the boundary points are interconnected to form a closed shape. The convex hull of the vertebrae is formed by the convex hull algorithm. The Ex OR operation on these two images is done to obtain size invariant features. The resultant images are shown in fig.5 (a)-5(c).

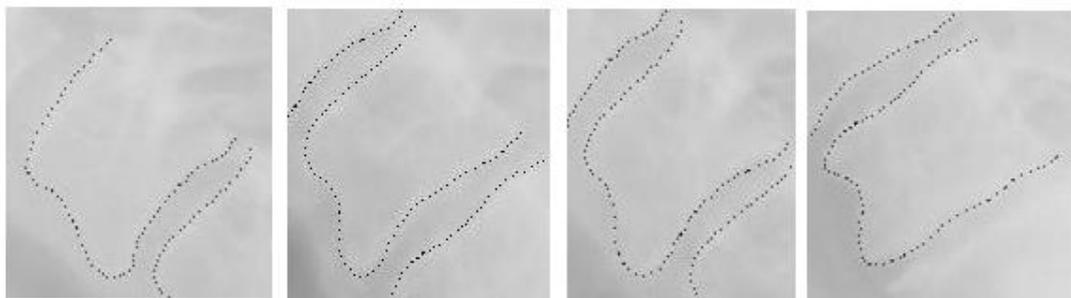


Fig.4 Separated vertebrae C3-C6



Fig 5(a)

Fig 5(b)

Fig 5(c)

Fig 5(a) Filled Vertebra-C4

Fig 5(b) Convex Hull- C4

Fig 5(c) Ex-Or of 5(a) with 5(b)



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Fig 5(d)

Fig 5(e)

Fig 5(d) Posterior side removed Fig 5(e) convex deficiency on anterior side

TABLE 1 Neural network training and testing result

Training cycles	Cross Entropy at 100% Validation	Training Results		Testing Results	
		% Total correct	% Total incorrect	% Correct Normal	% Correct Abnormal
1	0.0447	90.77	9.23	93.75	91.43
2	0.0118	93.08	6.92	95	94.28
3	0.0228	93.86	6.14	93.75	91.42
4	0.0675	89.8	10.2	91.25	91.18
5	0.0859	89.3	10.7	93.75	93.12
6	0.0303	93.08	6.92	95	94.29
7	0.0627	88.78	11.22	90	88.57
8	0.0537	91.84	8.16	92.5	93.94
9	0.0373	92.22	7.78	93.75	91.67
10	0.0811	91.54	8.46	92.5	93.75
Average		91.5	8.5	93.125	92.47

The average accuracy is 92.87% and sensitivity is 90.74%.

VI. CONCLUSION

From the results it can be said that GHT segmentation is an effective method to differentiate for the changes in vertebral shape and pose. Image processing technique on the segmented vertebrae provides four size invariant features. Computation of features F1 and F3 considers the complete vertebrae and are called as global features. Whereas the features F2 and F4 constitute the boundary changes on the anterior side and are termed as local features. The neural network classifier performs with an accuracy of 93.2%. The feature F4 is the most important feature accounting for presence of osteophytes on the anterior side of cervical vertebrae.

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