

Lumbar Spine Classification using Pyramidal Histogram of Oriented Gradients

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Abstract

Objective: To diagnose any injury in the lumbar region of human spine, the classification of each vertebra and Intervertebral Disc (IVD) is the vital task. **Methods:** The classification of the lumbar structure is done using Pyramidal Histogram of Gradients (PHOG). The PHOG technique is applied on the MR Image to select the basic intensity level features. These features are trained with Support Vector Machine (SVM). After building a model with SVM classification algorithm, classify the MR Images for discs and vertebrae separately. **Findings:** The accuracy is calculated to verify the performance of this work. This classification procedure is performed on a lumbar MR image dataset which contains 960 IVDs and 800 vertebrae with T1 and T2 weighted for 80 subjects.

Keywords: Classification, Intervertebral Discs, Lumbar spine, Pyramidal Histogram of Oriented Gradients (PHOG), Support Vector Machine (SVM), Vertebrae

1. Introduction

The human spinal column provides motion and flexibility to the whole body and can handle heavy weight. It consists of 33 vertebrae, the upper 24 are articulating vertebra partitioned by Intervertebral Disc (IVD) and lower 9 are fused, where 5 fused in the sacrum and 4 in the coccyx as shown in Figure 1¹. The upper vertebrae consist of three parts cervical, thoracic and lumbar. The cervical, thoracic and lumbar spine consists of 7, 12 and 5 vertebrae simultaneously. The upper cervical spine has a convex forward curve. The thoracic curve has a concave forward. The cervical spine is numbered from C1 - C7. The thoracic spine is numbered as T1 - T12 and the lumbar spine is numbered as L1 - L5.

Any injury in spine structures are generally examined by X-rays, CT (Computed Tomography), Magnetic Resonance Imaging (MRI) modalities. CT scans which use X-ray, whereas MRI scan uses magnetic fields and radio frequency to produce the images of bones, different organs, soft tissues and other internal body structures. As there is no radiation involved in an MRI scan, it is less

harm to human being. In MRI, the soft tissues in the vertebral column are seen with higher quality than X-ray and CT images.

In the traditional system, the pivotal step in the study, diagnosis, interpretation of the spinal column is to identify where the soft tissues and vertebrae presents. The physician scripts the report following the labeling of the discs and the vertebrae. A system which automatically performs various tasks on human vertebral column needs accurate classification, localization of the vertebral structures. In this paper, the intensity level features from the lumbar spine image are extracted and a model is built to classify the structures of the lumbar spine.

Several works have been done in this area and are discussed.² Introduces an algorithm which has two primary stages. The foremost is the localization of IVD. This is a model-based search approach to select the perfect slice from all the slices and is used to locate all the IVDs of the whole spine. The second step is vertebra detection and segmentation. The midpoint of each vertebra is detected and the primitive borders are extracted in vertebrae

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detection using canny edge detector. The data set contains MR Images of human spine for 5 subjects, and for each subject, there are 7 sagittal slices.

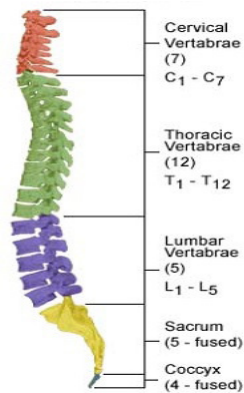


Figure 1. Human Vertebral Column¹.

The backbone anatomical structure's shape, texture, and position estimates are the fundamental information for deformity detection on each IVD and vertebra for the whole spine.³ Comes up with a two-level probabilistic model to localize the soft tissues from MR Image set with both pixel and object features. The authors used Generalized Expectation Maximization (GEM) algorithm for optimizing the IVD label in an effective manner. To improve the efficiency and to maintain the robustness, this two layer process allows the accession of conditional independence at the pixel information. In⁴ the authors developed a new approach for automatically extract the vertebral regions from the spinal MR Images. An automatic segmentation and detection of vertebrae method was discussed. This method consists of three stages. The first is the Ada-Boost based vertebra detection. The authors suggest an improved version of Ada-Boost algorithm. This is the statistical learning approach which produces an efficient vertebrae detector. The next step is detection refinement. The refinement process is based on a curve fitting algorithm. Recovering the missed vertebrae and excluding false detections on the image is the function of this refinement module. The last step is to segment the vertebrae. This segments the vertebra region from the detected vertebral location. The segmentation is done using an iterative normalized cut algorithm.

Digital video fluoroscopy provides a sequence of images with multiple frames. This type of images suffers from noise, enraged by low radiation. Therefore, concluding the position of a vertebra in the image sequence is an ample challenge.

Paper⁵ describes an approach where Hough Transform (HT) is used up to mitigate issues say, occlusion, repeatability, and out-of-plane motion. The feature descriptor to extract the shape of the vertebral body used is Fourier descriptors (FD). This FD is integrated into the hough transform algorithm. By this integration, the Affine Transformation parameters can be obtained. ⁶Describes an automated design to segment and to construct a 3D representation of IVDs from Peripheral Quantitative Computed Tomography (PQCT) image. On certain circumstances such as flexion and extension of IVDs along with the varying heavy load, this method performs the automatic quantitative analysis of increasing disc herniation. Automated segmentation and 3D reconstruction of IVD from PQCT image is the hardest problem mainly due to the noisy image. To view the 3D view of the IVD, Delaunay Triangulation is carried out. This is done on the basis of the points related with the IVD regions. The authors⁷ developed a new algorithm which automatically localize and identifies the bone structures of the human vertebral column on CT scans images. This approach is more computationally efficient and this algorithm uses the regression forest and probabilistic graphical models. Accurate localization and recognizing a single vertebra is attained by taking the spine's texture, appearance and shape. The paper⁸ presented a powerful method using a probabilistic graphical model to localize the human anatomical system and establish a dependent knowledge about the shape of the system. This approach works even when some of the parts are missing while detection process, it allows for robust detection. This is applied in the field of MR Images to detect the spine and label the spine structures.

Feature extraction is the main process in identifying objects. In⁹ they developed the concept of Histograms of Oriented Gradient (HOG) descriptors to detect humans in an image. This is an efficient and widely used feature descriptor for object detection. Initially, it is developed to detect a full human from an image. Later it is used to detect any objects¹⁰⁻¹².

¹³developed a new approach to classify the images with the different variety of objects. The authors introduced a new feature descriptor which represents the local image features like shape and its spatial features, combined as a global pyramid kernel. The global pyramid kernel learns its level weighting parameters to improve the performance. In this work the shape and the appearance kernels are combined together.

¹⁴designed a new way to localize and label the lumbar structures, ie the vertebrae and IVD from the sagittal MR Images. The authors developed a new descriptor called Image Projection Descriptor (IPD). Using IPD and Pyramidal Histogram of Oriented Gradients (PHOG) is applied to the image to extract the intensity features. Support Vector Machine (SVM) is used to built a model with the extracted features. In this approach, the authors have used a linear chain like model, called Markov Chain to design the IVDs and vertebrae as the lumbar structures are always arranged in an order. Dynamic programming is used to find the maximum a posterior solution to localize the IVD and vertebra with Markov Random Field (MRF). Machine learning concept SVM with RBF is also used for Brain Tumor classification¹⁵.

2. System Architecture

The research work done in this paper is represented in Figure 2. Initially for a training image dataset, feature extraction and training is performed. Feature extraction is done by the Pyramidal histogram of Oriented Gradients (PHOG) and a training model is built by SVM classifier. SVM is a supervised learning model that analyzes the data for classification and regression. The supervised learning approach is possible with labeled data. With the model built by SVM and when a test image is given, extract PHOG features and classify it using SVM. Here we used Libsvm¹⁶ as SVM tool. Libsvm is one of the most widely used open source library for machine learning techniques. Libsvm performs classification and regression for kernelized Support Vector Machine.

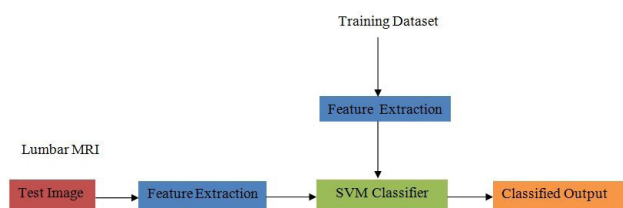


Figure 2. System Architecture.

2.1 Feature Extraction using PHOG

The Pyramidal Histogram of Oriented Gradients (PHOG)¹³ is used for extracting the features. To extract PHOG features, it takes the shape level and spatial features. For each image construct a spatial pyramid. To achieve this, divide the image into small spatial grids similar to a quadtree. Here each small grids models a different layer in

the pyramidal structure of an image. The initial step is to find the Histogram of Oriented Gradients (HOG). Then find HOG for all the spatial levels. By combining all these HOG descriptors we get the PHOG descriptors.

2.2 Training and Testing

SVM is more effective in a higher dimensional space. As SVM's decision function uses the support vectors, SVM utilizes the memory in an efficient way. When the number of sample space is higher than the number of dimensional space, SVM gives the best analysis report. But when the number of features is higher than the sample space, its performance degrades.

The next step in our work is to train the system with the training samples. SVM is used for testing and training. The lumbar IVDs are labeled as T12-L1, L1-L2 ... L5-S1 and the lumbar vertebrae are numbered as L1, L2 ... L5. Each region (IVD or vertebra) is trained separately and a model is built. Based on the model, in the testing phase, the SVM classifies the IVDs and vertebrae.

3. Experimental Setup and Results

3.1 Dataset

We have collected the MR Images from the data set provided by the authors of¹⁴. The positive images and negative images were taken from the dataset. The dataset includes both T1 and T2-weighted mid-sagittal MRIs of the lumbar spine for 80 patients. For each image in the dataset, the ground truth was used to crop the positive images for IVDs and vertebrae. By sliding the window through the images randomly, crop the images to obtain negative dataset. The lumbar MRI which contains the IVDs and vertebrae is shown in Figure 3.



Figure 3. Lumbar MRI.

The dataset for 80 subjects, which contains both T1-weighted and T2-weighted, is in .mat format. Convert the .mat file into .tif format. By the above said procedure, both the positive and negative images were cropped out from the dataset to obtain 960 IVDs and 800 vertebrae as positive images and 1600 images as negative images. Sample positive images of vertebrae are shown in Figure 4.

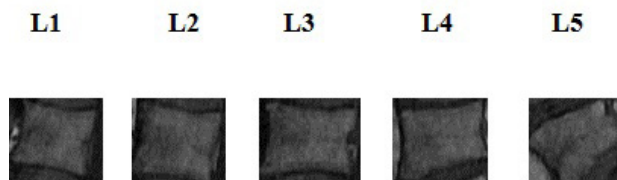


Figure 4. Cropped image of Vertebrae.

3.2 Feature Extraction

Features were extracted using PHOG. The system is tested with the pyramid level with 2 and 3. When the pyramid level is fixed as 2, the number of features extracted was 168. And when the pyramid level is defined as 3, totally 808 features were extracted.

3.3 SVM Classifier

If the dataset has more than two classes, multi-label classification will be preferred. Here multi-label SVM classifier is used. Therefore, totally 11 classes were needed, 6 for IVDs and 5 for the vertebrae. Train the data using kernel functions. The kernel types are linear, polynomial, radial, sigmoid and pre-computed kernel. The Radial Basic Function (RBF) is used in this experimental setup. Set the cost value and the gamma value for training. The probability of classes was obtained in the testing phase. Predict the class with the highest probability and find the accuracy. The output of the test data was a confusion matrix.

In theory, the accuracy of any model is defined as the proportion of true positives and true negatives with the total number of samples. The accuracy is mathematically denoted by the equation (1).

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Number\ of\ Sample} \quad (1)$$

The precision is the total number of IVDs or vertebrae or negative samples which are classified correctly. Precision is defined as in equation (2).

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

The recall is defined as the total number of IVDs or vertebrae that are classified correctly. The recall is also called as Sensitivity. It is calculated as in equation (3).

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

The accuracy, precision and recall of the classification process are calculated for the vertebrae and is shown in Table 1

Table 1. Accuracy, Precision and Recall for Vertebrae using PHOG

Pyramid Levels	Accuracy	Precision	Recall
Level 2	70.83%	79.17%	93.13%
Level 3	70.00%	69.96%	94.15%

Similarly, the accuracy, precision and recall of the classification process are calculated for the IVDs and is depicted in Table 2.

Table 2. Accuracy, Precision and Recall for IVDs using PHOG

Pyramid Levels	Accuracy	Precision	Recall
Level 2	61.81%	62.08%	93.58%
Level 3	61.80%	62.78%	93.63%

4. Conclusion

A classification method to classify the vertebrae and IVDs using Pyramidal Histogram of Oriented Gradients (PHOG) is depicted in this paper. The features were extracted using PHOG. In the training phase, a model is being built using SVM classifier. In the testing phase, based on the model built, testing is performed for the test dataset. The result for this classification process gives an accuracy of 70.83% for vertebrae with pyramid level 2. The accuracy of the classification can be improved by using different feature extraction method other than PHOG. Also, instead of using SVM, other learning methods like Random forest or Ada-Boost can be applied to improve the accuracy.

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