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Computer Aided Defect Classification for Model-based Therapy of Cervical Spinal Stenosis

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Abstract The purpose of the presented work is to provide a basis for the development of a therapy model which supports defect specific treatment of cervical spinal stenosis. This contains the definition of a defect classification based on a retrospective study using MRI data sets of 182 patients. The introduced encryption key enables an integration of explicit and reproducible defect descriptions into the therapy model. Furthermore a meta-structure was defined which classify intervention relevant model data and thus provides an important basis for the development of model components. With the aim to facilitate the identification of defect specific characteristics in the MRI data set an approach for a fully automated identification of a stenosis was developed. This makes a contribution to the desired uniform treatment of cervical spinal stenosis.

Keywords**:** Computer Aided Diagnosis, Model-based therapy, Cervical spinal stenosis, Defect classification.

1. Introduction

The model-based therapy is an approach to assist the physician in interpreting important intervention relevant data (Lemke et al., 2008). The model describes linkages between information entities and their weighting for a clinical decision process (e.g. diagnosis or treatment planning). A model-based decision support system contains components for situation assessment and therapy proposal or prognosis (Denecke et al., 2013). For this purpose a structural model has to be defined which is instantiated in the situation assessment, with measured data. The aim of the present work is to apply the model-based approach for assisting the treatment of cervical spinal stenosis. This disease is a narrowing of the spinal canal which is clearly visible in a Magnetic Resonance Imaging (MRI) data set which is used to identify the affected segment and defect characteristics. To classify the cervical spinal stenosis there exist the Muhle Cervical Spondylotic Myelopathy Classification System (Muhle et al., 1998) which can be used to identify the severity grade. However, this classification doesn´t provide information on the number of affected segments or if there are additional pathologies which can influence the treatment strategy. Regarding the treatment itself, there exist no consent which operation technique has to be preferred (Khit et al., 2012; Alvin et al. 2014). To make some sort of progress in this field a therapy model has to be defined which considers a detailed defect classification which can be used to develop

defect specific treatment strategies. First approaches for digital patient and therapy models to assist the clinician are known, for example in the field of head tumor treatment and radiology (Meier et al., 2013; Stivaros et al., 2013). Also, there has been presented isolated applications to assist the diagnosis of spine diseases using algorithms for the detection and segmentation of vertebrae, spinal disc and spinal cord to provide 3D geometry for further disease analysis (de Leener et al., 2014; Larhmam et al., 2013; Law et al. 2013; Neubert et al. 2012; Huang et al., 2009). So far, there can´t be found neither a therapy model for assisting the treatment of cervical spinal stenosis by connecting and weighting intervention relevant data nor methods for automatic stenosis identification. This paper presents first results for the development of a spinal stenosis therapy model. This contains a coding scheme for radiographic defect classification, a meta-structure to classify model data and an approach for an automated recognition of stenosis in an MRI data set.

2. Methods

2.1. Retrospective Study for Definition of Defect Characteristics

The analysis of MRI data sets of 182 patients was performed using the following key features which can be used to describe a spinal stenosis and additional pathologies: stenosis dimension, modification of ligament structures, vertebrae malposition. The investigations of the MRI data sets enabled the determination of key feature frequency and possible joint appearance.

2.2. Codification of Defects and Meta-Structure Definition

Beside the defect classification further information entities for the therapy model could be determined during five work sessions with three neurosurgeons. The first step for a formal model representation is the definition of a meta-structure. This was done on the basis of a meta-structure of Strauß et al. which was used for a patient-model of the ear-nose-throat medicine (Strauß et al., 2008). In that, data classification was performed using the categories *class*, *sub-class* and *type*. It is possible to assign each element a further element or a sub-list with elements. The classes (*static, dynamic)* and sub-classes *(morphologic, functional, Atlas)* used from Strauß et al. so far are not sufficient to structure a patient model for cervical spinal stenosis which assists the diagnosis, treatment process and evaluation of therapy result. Therefore five new classes and four new subclasses are introduced. For the codification of defects main characters, numbers and special characters are used in a defined order.

2.3. Histogram of Oriented Gradients for Recognition of Defect Key Features

For computer-based identification of stenosis in an MRI data set a novel method for bivariate gradient orientation histogram generation from 3D raster image data in combination with an already known linear support vector machine (SVM) (Chang et al., 2011) is used. The stenosis is classified referring to the grading system proposed by Muhle et al. (1998). The stenosis classification is done performing the following steps:

1. Calculate the center point between two vertebrae centers.
2. Perform orthogonal translation in direction of the spinal canal.
3. Generate a box with predefined size at this position.
4. Resample this area of the image to a predefined resolution.
5. Generate gradient orientation features.
6. Classify if a stenosis is present using a SVM.

3. Results

3.1. Defect Classification

According to the observed occurence the *stenosis dimension* is breaked down into the four states *mono-, bi-, tri-segmental and skip lesion* (see figure 1). The first three states indicate how many segments are affected behind each other. The latter state describes multiple segments joint together which contains between two stenosed segments a segment without a stenosis. The key feature ligament modification is

subdivided into *thickening of yellow ligament* and *thickening of the posterior longitudinal ligament*. *Scoliosis*, *Kyphosis* and *Listhesis* are identified as vertebrae malposition. Table 1 gives an overview to the incidence of the mentioned key features which could be determined during the retrospective study.

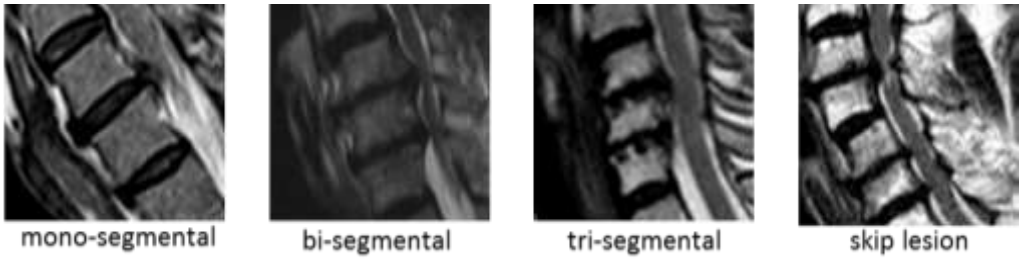

Fig. 1. Defined defect characteristics.

Cervical spinal stenosis is to be very common. The radiographic finding of this disease should therefore be correlated with the clinical presentation prior to decision-making regarding treatment. The sagittal diameter of the cervical spinal canal is of clinical importance in traumatic, degenerative, and inflammatory conditions. A small canal diameter has been associated with an increased risk of injury; however, there is a lack of reliable normative data on spinal canal diameters. The ability to compare various results that measure clinical deficits and outcome after operations is a necessity for successful worldwide discussion of degenerative changes of the cervical spine and its treatment. There is hardly any information in literature how to value and compare outcome assessed by MRI findings. The new created defect classification considers all relevant anatomical structures to define the degree of stenosis and the responsible structures in order to define the best approach to treat the degenerative changes. The encoding of additional pathologies, like thickening of ligaments, is a totally new approach on this way and may change the surgical anticipation of MRI findings and lead to patient specific surgery. The bi- and tri-segmental stenosis with medial compression, usually C5-C7 and C4-C7, are the most frequent pathologies (see table 1). An additional thickening of the yellow ligament and posterior longitudinal ligament should be considered as an extra pathology.

Table 1. Incidence for defined key features.

Stenosis dimension		**Additional pathologies**	
mono-segmental:	48	Thickening of yellow ligament:	54
bi-segmental:	56	Thickening of posterior longitudinal ligament:	51
tri-segmental:	68	Vertebrae rotation (scoliosis):	14
Skip-lesion:	10	Kyphosis:	48
		Listhesis	19

3.2. Machine-readable Defect Description

In the following there is an example for a textual defect description using the defined key features: *Monosegmental stenosis affecting cervical vertebraes 3/4 with a medial compression. As additional pathology there exists a thickening of the yellow ligament and a listhesis.* A more practical and reproducible format is provided with the use of codes for each key feature (see table 2). The suggested codes are placed behind each other regarding a defined order and using dots to separate the single codes.

Table 2. Encryption key for cervical spinal canal stenosis.

Code	Description
Dimension[D]	
M	Mono-segmental
B	Bi- segmental
T	Tri-segmental
S	Skip-lesion
Segment [S]	
[C2...TH1]	Identifier / Position
Location [L]	
m	Medial compression
l	Lateral compression
Additional pathologies [AP]	
*	Thickening yellow ligament
#	Thickening posterior long. lig.
K	Kyphosis
L	Listhesis
R	Vertebrae rotation

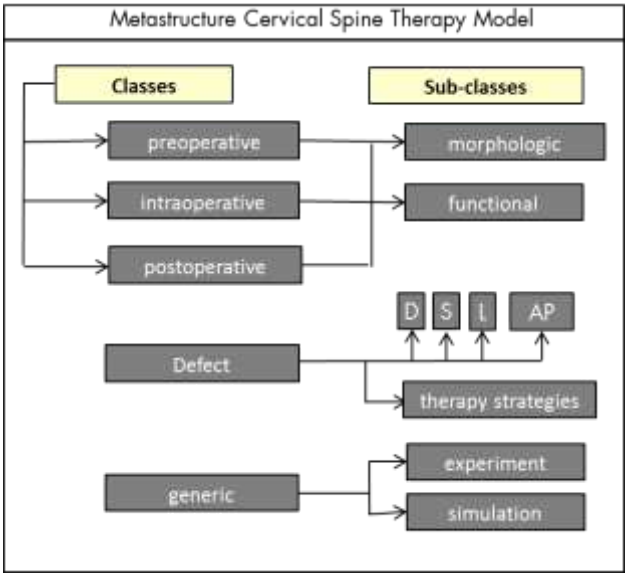

Fig. 2. Meta-structure of the cervical spine therapy model.

Regarding to this the defect described in textual form above can be described explicitly using the following code sequence: **M.[C3/C4].m.*.L**

3.3. Meta-structure for Cervical Spine Therapy Model

The first classification of model data is done using the three intervention phases *preoperative, intraoperative and postoperative* (see figure 2). In each of the phases there are data which describes *morphological* features of the disease (e.g in intraoperative phase: CT data) and which give information about the physiology of the patient (e.g. in preoperative phase: nerve conduction velocity) which can be classified as functional data. To integrate the defect classification into the therapy model an extra class is introduced. Belonging sub-classes are the *defect code* and the *defect specific treatment strategy*. This sub-classes can contain further elements. For example the first element *D* of sub-class *defect code* can contain a link to the automated identification of stenosis dimension. Regarding to the use of a class *Atlas* in the meta-structure of Strauß et al. (2008) it seems to be of interest to get details of the anatomy. To consider this in the therapy model available findings gained from experiments or numerical simulation are integrated as generic information introducing two new subclasses (see figure 2).

Table 3. Validation results for automated stenosis identification in MRI data sets.

Classification Performance measure	Number datasets	Rate
True Positives	53	66.25%
False Positives	10	12.5%
True Negatives	13	16.25%
False Negatives	4	5%
Cross-Validation Accuracy	**66/80**	**82.5%**

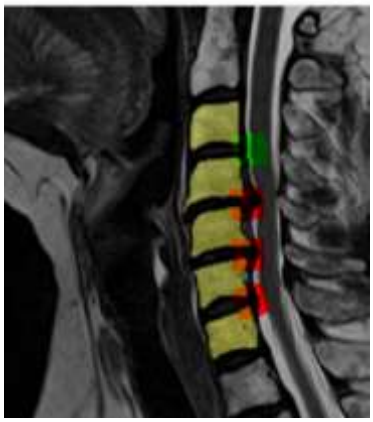

Fig. 3. Color-coded stenosis classification (green = no stenosis, red = stenosis).

3.4. Fully Automated Stenosis Identification

A detailed performance evaluation on 20 T2-weighted MR images of the cervical spine area is given. In a leave-one-out study on our MR image dataset, the proposed algorithm achieves a classification accuracy of 82.5 percent. More detailed results are given in table 3. An exemplary result on a patient MR image is shown in figure 3.

4. Conclusion

The presented meta-structure for a therapy model which aims to assist the neurosurgeon in a defect specific treatment of spinal stenosis is essential to work out intervention relevant model elements. The introduced defect classification with belonging codes enables a reproducible description of radiographic

disease characteristics. This is an important basis to develop defect specific treatment strategies. Against the background that determination of stenosis dimension is currently dependent on the impression and experience of the neurosurgeon the developed approach for fully automated stenosis identification in MRI data can make a contribution to a more uniform treatment of spinal stenosis. The automatic detection of stenosis in combination with the new classification will change the surgical strategy.

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