Patient Records Retrieval System for Integrated Care in Treatment of Cervical Spine Defect

Yihan Deng[1,2] and Kerstin Denecke[2](✉)

[1] Innovation Center Computer Assisted Surgery, University of Leipzig, Leipzig, Germany
[2] Department of Medical Informatics, Bern University of Applied Sciences, Biel, Switzerland
{yihan.deng,kerstin.denecke}@bfh.ch

Abstract. In clinical decision making, information on the treatment of patients that show similar medical conditions and symptoms to the current case, is one of most relevant information sources to create a good, evidence-based treatment plan. However, the retrieval of similar cases is still challenging and automatic support is missing. The reasons are two-fold: First, the query formulation is difficult since multiple criteria need to be selected and specified in short query phrases. Second, the discrete storage of multimedia patient records makes the retrieval and summary of a patient history extremely difficult. In this paper, we present a retrieval system for electronic health records (EHR). More specifically, a retrieval platform for EHRs for supporting clinical decision making in treatment of cervical spine defects with the information extracted from textual data of patient records is implemented as prototype. The patient cases are classified according to cervical spine defect classes, while the classification relies upon rules obtained from the corresponding defect classification schema and guidelines. In a retrospective study, the classifier is applied to clinical documents and the classification results are evaluated.

Keywords: Information retrieval · Electronic health record · Patient cases retrieval · Cervical spine defect · Case based decision support

1 Introduction

The degenerative changes of the cervical spine are reflected in multiple aspects of observations such as area of the defect, position of the defect and additional pathology. For this reason, treatment decision making in the context of medical conditions involving the cervical spine requires evidences from all the relevant data sources (medical history, radiology, admission note) since the relevant information is distributed among these sources. The most direct way of determining and classifying these defects is to peruse the information from patient records, which is quite laborious. In clinical practice, the complete process of document selection, skimming, information extraction and aggregation is conducted manually due to missing automatic support. An efficient data collection method and

F. Wang et al. (Eds.): DMAH 2016, LNCS 10186, pp. 10–25, 2017.
DOI: 10.1007/978-3-319-57741-8_2

an automatic retrieval approach are urgently required in clinical practice. An automatic classification and retrieval approach can support in:

1. Improving interoperability and increasing the efficiency of information exchange and the coverage of the defect description,
2. Increasing the accessibility of different information sources during the decision making process,
3. Facilitating the evidence based therapy and patient cohort identification.

Currently, most of the available schemas for cervical spine classification focus on the pathological changes in the spinal canal or rely upon an analysis based on the cross-sectional area [1]. They employ the investigation outcome in axial direction to grade the stages. However, the reasons of these changes and the concrete position of a lesion at the corresponding cervical vertebrae are not considered. Relying upon the graded stages only is insufficient for an effective decision making, especially in the surgical domain, since surgeons are more interested in the anatomical position and pathological changes in the target area. A more practical classification schema was required to cover the pathological changes in cervical spine. In order to provide a solution for surgical practice usage, such a defect oriented classification for the treatment of the spinal canal stenosis has been developed by Meixenberger and Leimert [2]. It is a relatively new perspective in pathological classification of cervical spine defects, since more important aspects are described in the classification schema, which can be directly applied to the further surgical decision making. More specifically, it covers the amount of the affected cervical segments, position of the defect and additional pathologies. With this schema, Daenzer et al. [3] have proposed a decision support model based on MRI image analysis. In evaluations of that model, it turned out that a classification of the defect requires sometimes additional information on the degree or location of pain and previous comparable diagnosis. Such information is captured in clinical documents of the electronic health record. However, there is no method available that supports a text-based classification of defects. In this paper, a concept for text-based defect classification will be introduced relying upon feature extraction and rule-based classification. The main challenges in this context are:

1. Gathering defect related vocabulary
2. Extracting text-based defect features
3. Classifying the defect stages using features extracted from texts
4. Indexing the corresponding aspects of defect
5. Realization of the retrieval based on extracted aspects

The classification method will be evaluated and integrated into a prototype for retrieving information on similar cases of cervical spine treatment. As is illustrated in Fig. 1, the entire system can be divided into two components: the defect classification and its knowledge base and the retrieval work flow based on classification knowledge. The two components will be described in the following sections separately.

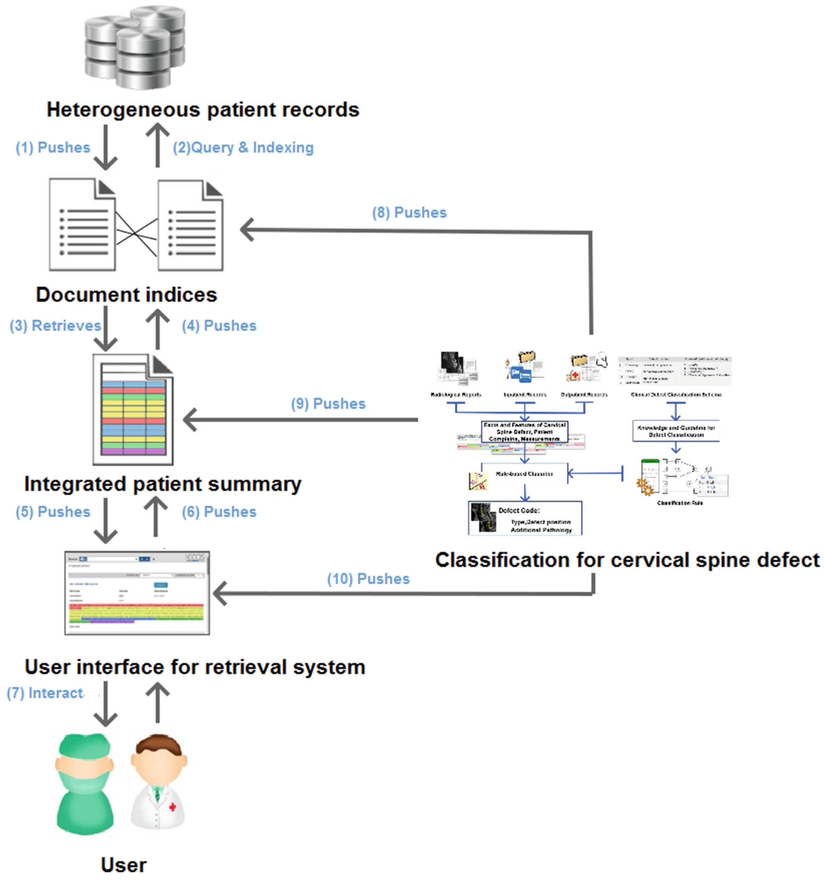

Fig. 1. Flowchart for the retrieval system

2 Knowledge Base for Cervical Spine Classification

2.1 Defect-Based Classification Schema

In this section, we are describing the classification schema underlying our rule-based approach [2]. As an interdisciplinary approach, the schema depicted in Fig. 3 was developed by neurosurgeons and radiologists to assess the disorders and pathologies in cervical spine. The experts from anatomy and medical informatics have also provided their suggestions for the definition of defect grading. In comparison to other schemas, the focus of this new grading method lies on the anatomic landmarks and direct topographical descriptions. It provides a straight access to the actual pathology. The classification schema considers three aspects: type, defect position and grade of additional pathology. The type refers to the number of affected segments and their relations to one another, for example, single, several subsequent or skip lesions. According to different clinical findings

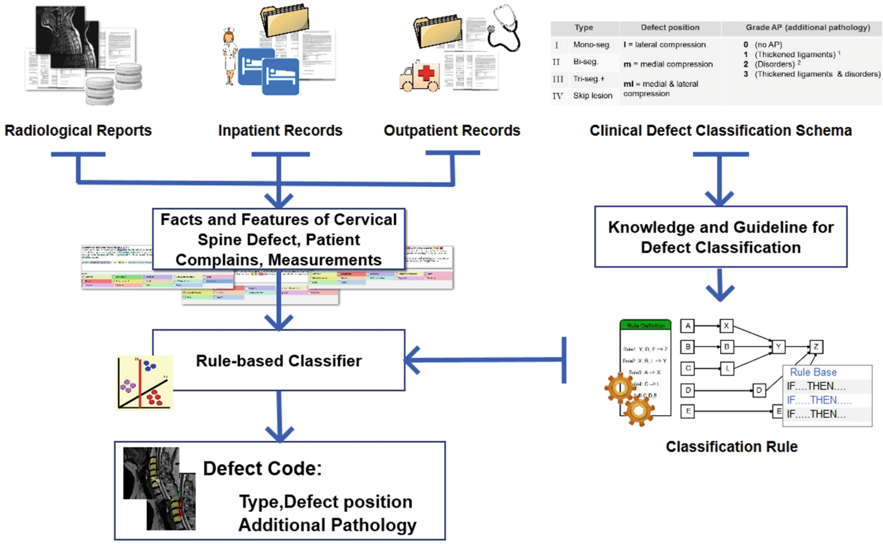

Fig. 2. Schematic graph of the defect classification process

depending on the position of intraspinal pathology, the second point of differentiation is the defect position, i.e. lateral or medial affection of nerval tissue. These two positions may also co-occur at the same time.

The third characteristic in the schema pays special attention to anatomic and functional disorders that have not been taken into account in the existing classifications: besides compression caused by prolapse of the nucleus pulposus and osseous humps, thickening of ligaments like the yellow ligaments and the posterior longitudinal ligament as well as structural disorders (listhesis, kyphosis, hyper lordosis or rotation) may also affect viability in a surgical relevant way. This defect classification schema enables a very detailed description of a defect by using only three characters, for example bi-m2 referring to a bi-segmental stenosis with medial compression of the spinal cord with additional listhesis.

As there are several classification schemas regarding different clinical usage, a brief comparison can point out the differences and advantages of the defect classification schema used in this work (see Fig. 3). For comparison, we consider the classification system based on kinematic magnetic resonance imaging in cervical spondylotic myelopathy [1] and the qualitative grading of severity of lumbar spinal stenosis based on the morphology of the dural sac on magnetic resonance images [4].

In comparison with the aforementioned schema, our defect classification schema is specially designed for surgical practice. It covers more defect information and categorizes additional pathological information. Besides these advantages, a much more direct description of the locoregionary and anatomical causes facilitates the planning and the feasibility of surgical treatment, whereas focusing on consequences like impression of the dural sac leaves several variables regarding the direct interaction between different kinds of tissues. In addition to technical and theoretical feasibility, a precursor of this schema already underwent practical testing, in which ten anonymized patient cases were introduced to more than 100 experienced surgeons, who in majority approved the practicability of that schema.

In summary, the classification proposed by Meixensberger et al. [2] enables direct access to surgical decision/planning by stressing the anatomical/morphological abnormalities. Mentions or occurrences of such abnormalities are easily detectable in patient records both in image and text. In this work, we focus on their detection and classification in textual parts of patient records.

2.2 Text-Based Defect Classification

Hitherto, surgeons have based their decisions on the manual interpretation of radiology images showing the location and degree of defects (see Fig. 3). However, studies have found that this classification is often not reproducible and far from standardized. The patient records contain supplementary documents with additional important evidence which is currently not considered or available at the time of decision-making. Nevertheless, the defect situation and patient status described in the radiology report, anamnesis and admission note are crucial for classification and follow-up therapy planning. To improve the existing defect classification process, we have augmented the image-based classification with an approach relying on information extraction for defect classification from the clinical narratives. The following steps need to be performed:

1. The relevant pieces of information need to be identified in the text.
2. Contexts in which information occurs need to be determined.
3. Rules for mapping extracted information into a defect category mapping need to be defined and the automatic categorization needs to be realized.

More specifically, the classification task is as follows: For each of the three aspects of the underlying classification schema (type, defect position, additional pathology), one out of three or four category needs to be assigned (see classification schema for the number of categories). Only documents with mentions of all three defect-related features will be considered in our pipeline. Defect types, defect position, and additional pathology are identified and classified by the extraction pipeline and by applying classification rules.

We are addressing these issues by developing the following components (see Fig. 2): First, we establish a defect terminology. The defect-related terms are initially gathered from clinical narratives. They are manually classified into categories such as disease, or anatomical concepts at the area of cervical spine. Second, the extraction pipeline is configured. The concepts relevant for defect classification are extracted by a concept mapper that identifies mentions of defect terms. Terms that describe diagnoses and anatomical concepts are mapped to concepts of corresponding standardized medical terminologies and classification

Type		Defect position	Grade AP (additional pathology)
I	Mono-seg.	**l** = lateral compression	**0** (no AP)
II	Bi-seg.	**m** = medial compression	**1** (Thickened ligaments) [1]
III	Tri-seg.+	**ml** = medial & lateral compression	**2** (Disorders) [2]
IV	Skip lesion		**3** (Thickened ligaments & disorders)

Fig. 3. Defect classification schema

systems. Then, regular expressions are used to detect acronyms, conventional expressions and special word combinations.

Third, classification rules are defined. The rules regulate the mapping between extracted features and defect categories. The aforementioned defect classification schema is transformed into corresponding classification rules considering the three main types: defect type (the amount of defect segments), position (medial, lateral or medial lateral) and additional pathology (thickened ligaments, disorders). In the final system, a clinical data interface connected with the hospital information system (HIS) and Picture Archiving and Communication System (PACS) needs to be designed to get the automatic import of patient records while employing the corresponding authentication and authorization process to protect patient data privacy. In this paper, we will focus on the rule-based classification using textual features and the evaluation of extraction results. The performances of these two steps will be evaluated. In the following, the single steps and components are described in more detail.

2.3 Defect Terminology

For detecting defect specific features in clinical texts, a list comprising defect terms in German was generated. At a first step, a clinical expert has annotated the defect relevant terms in patient records. Then, the terms were categorized into several subcategories such as anatomy, symptom, pathology and positions. Meanwhile, the relevant terms in the terminology list were directly linked to the concepts of existing terminologies that are Radlex (German), ICD 10 (German) and MeSH 2010 (German) as expansion to increase the recognition rate of the concept mapping. In total, 311 defect specific terms were included into the concept dictionary.

2.4 Extraction Pipeline

The extraction pipeline is established based on an adapted version of UIMA (https://uima.apache.org/) provided by Averbis GmbH (https://averbis.com/). Two types of concept mapping are implemented in the framework: the exact mapping and the segment mapping. They have been configured to our task by including the cervical spine vocabulary (defect terminology, see section above).

Exact mapping searches only for fully matched terms in the corresponding semantic scope, whereas the segment mapping performs a fuzzy matching considering morphological variations of terms. Further, the contiguous match strategy is employed to obtain the longest match of contiguous tokens within a sentence. Besides, a German negation list is additionally exploited by the concept mapper. Three main types of negations in German were defined, namely post negation (nicht vorhanden (non-existent)), pre negation (frei (free)) and pseudo negation (nicht sicher, ob (not sure whether)).

Moreover, regular expressions were defined to recognize dates, measurements and doses expressed in text. Addressing domain- or task-specific vocabulary, the concept mapper was complemented by additional regular expressions, for example to identify location descriptions expressed as coordination structures. Consider the following example text *HWK 3 und 4* (vertebral body 3 and 4 of cervical spine). The coordination structure needs to be recognized by a regular expression. The first part of the phrase, *HWK-3*, has been captured by the concept mapper, the second part *und 4* needs to be recognized by regular expressions and transformed into standard form of *hwk3/4*. In summary, the anatomical concepts regarding intervertebral disc and positions as well as the additional pathologies are extracted through the aforementioned pipeline.

2.5 Classification Rules Definition

Classification rules are developed to formalize the defect classification schema. The efficiency and effectiveness are main concerns for rule formalization [5]. Therefore, we choose a declarative way to model a rule, which can avoid the complexity of procedure description. Additionally, an easy modification and high reusability are important for the maintenance of knowledge rules. Several methods for rule formalization are available [6]. Among them, the logic programming language Prolog is normally used to transform the knowledge rules. However, our extraction pipeline is implemented in Java. The rules are formalized and hard-coded in Java program code. According to the defect classification schema, three levels of knowledge can be defined. We are organizing it from generic to specific:

1. Common sense includes the temporal comparison, input and output logic.
2. General medical domain knowledge such as anatomical structure and position.
3. Defect specific knowledge indicates the category specification based on the classification schema and the implicit connections between symptoms and categories according to practical surgical experience.

Since the classification foresees only a limited number of defect types, the possible lexical variations of describing defect types are listed explicitly in the rules. For example, a fact can be defined with Java like if(defect("hwk3/4") == true&&no negation) defecttype++;. The input is the normalized form of intervertebral disc, which is mapped with the amount of defect segments. 15 linguistic variations of description of defect types and defect combinations from mono to tri+ have been summarized in the rules. Besides, the incontinuous serials of input will therefore be classified into type skip. In this classification schema, defect stands for the spinal canal stenosis, i.e. low degree of compression will not be classified as defect.

The position should be handled in two types: The first type is the explicit description. It can be directly mapped with position determination functions. For deciding of defect at both medial and lateral position, we have added several specific rules with clinical salience. In addition, the anantomical concept has provided implicit hint for the position. For example, Facettengelenk (intervebral joint or facet joint), uncovertebral (uncovertebral joints), foramina (intervertebral foramina), Nervenwurzel (spinal nerve root) indicate also the defect at the position of lateral.

The additional pathology contains four stages: namely, no additional pathology (0), thickened ligaments (1), disorders (2) or both thickended ligaments and disorders (3). Disorders represent listhesis, rotation, kyphosis, hyper lordosis and steep. Since these concepts are distinct and unique, they are simply summarized in the knowledge base and provide the mapping between extracted features and grading. For example, if (pathologyCheck(object).equals(Ligamental flava) pathology = '1' has defined the pathology in Ligamenta flava as grading one.

3 Retrieval Architecture

3.1 Patient Record Indexing

Based on the automatic extraction and rule-based classification for the cervical spine defect, the important aspects about the defect pathology has been extracted. For indexing the patient records, we are using the method of inverted indices which is a relatively mature technologies in the field of information retrieval [7]. As is illustrated in Fig. 4, the weighting value is:

$$W_{i,d} = tf_{i,d} * log(n/df_i)$$

where

$$d = tf_{i,d} * log(n/df_i)$$

$$tf_{i,d} = frequency\,of\,term\,i\,in\,document\,j$$

$$n = total\,number\,of\,documents$$

$$df_i = the\,number\,of\,documents\,that\,contain\,term\,i$$

The ranking value of one patient record is the sum of all the terms weighting values. The high ranking value indicates the high relevance. For example (see *example* in Fig. 4), if one keyword has a term frequency of 2, an inverse document frequency of 1.9 (10 appearances in 800 documents) a, the W value is 3.8 (achieved by applying the formula). The sum value in Fig. 4(a) example is the sum of all W values of queried terms in one document, the large sum value indicates the high similarity between the query and documents. Besides the sum value, similarity measures such as cosine similarity or structural similarity are also be applied to obtain the relevant electronic health records.

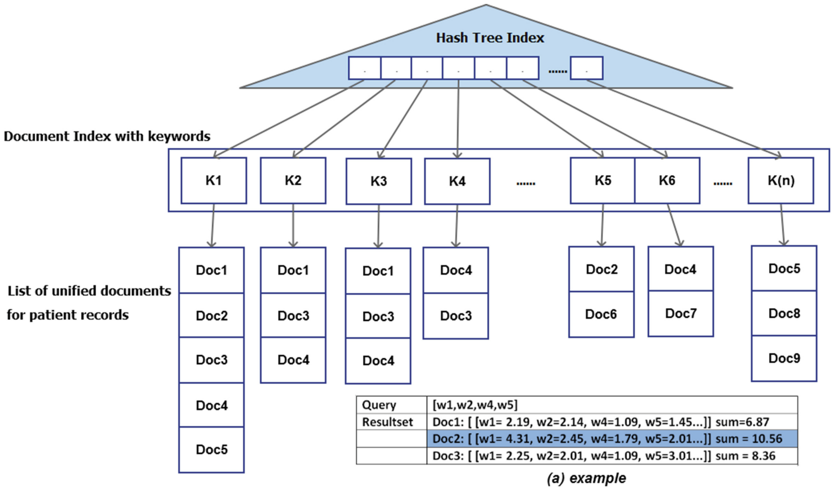

Fig. 4. Index structure of the retrieval system

3.2 Retrieval Interface

The ambition of the retrieval interface is to provide an integrated access to the defect relevant patient information in the treatment of cervical spine stenosis, which bridges the heterogeneous clinical information system and fill the gap of data storage in the clinical work flow. Physicians can therefore use the retrieval interface to find the desired patient record in all different clinical information systems. Meanwhile, the corresponding patient cohort for the cervical spine and the quality studies as well as the communication between attended care providers can be eased. Additionally, the similarity between different patients can be compared not only at term level but also through the metrics derived from the defect classification schema. The current retrieval system can present patient records regarding extracted aspects and also provide the full text search. As it can be seen in Fig. 5, five aspects are shown in the retrieval interface to support the user in navigating through the patient records. The first three aspects shown in the navigation bar on the left are the three dimensions from the classification schema (defect type, position and additional pathology). The other two search aspects are the defect relevant terms and ICD-10 codes. Physicians can get a fast access to any subcategory of the these five aspects. Besides this faceted search, the clinical user can also search for patient records using the query input field. Besides the full text search in the search field, the user can also constitute the query through the query builder, see Fig. 6. The query referring to corresponding aspects can be combined together. With the application of query builder, the desired query can be saved as default search setting.

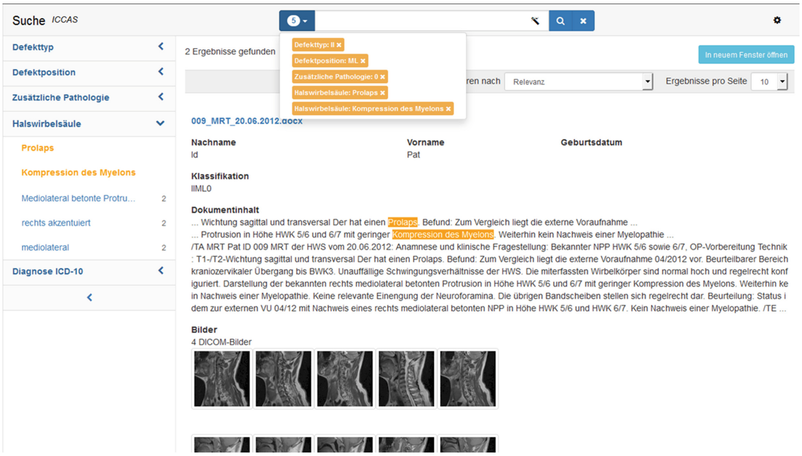

Fig. 5. Screenshot of the clinical retrieval platform: *The platform combines the aspect search (left) and full text search field (middle search field) and patient comparison (blue button). The paired patient record with textual records and images is presented in below. The patient information and defect codes are listed in the middle.* (Color figure online)

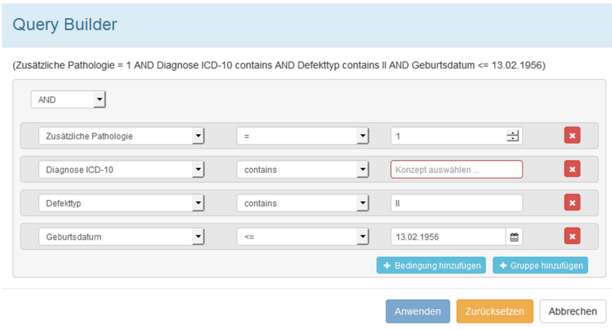

Fig. 6. Query builder of the retrieval platform: *The relevant aspects can be connected with predefined value through Boolean operators, For example, the ICD 10 terminology (stenose) and defect type (mono defect) as well as the additional pathology (rotation) can be saved as default search setting*

The textual reports and the corresponding images are presented in text and image pairs through the interface. Physicians will also have the possibility to send their feedback to the system regarding the classification (see Fig. 7), i.e. they can hand-code the defect category if the suggested automatic one seems to be incorrect. The feedback will be stored as additional classification labels together with patient records and can be used later on in adapting the classification rules.

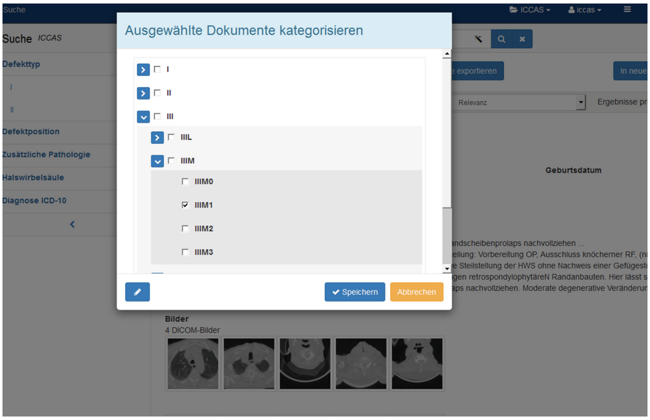

Fig. 7. User Interaction Box. *A manually updated classification of the defect category can be added through the cascading radio buttons by the clinical user.*

4 Evaluation

The cervical spine defect feature extraction and classification will be evaluated based on anonymized patient records (radiology records, discharge summary, outpatient cards). As a preliminary feasibility experiment, 100 samples of patient records in German were annotated manually by a physician with their defect features and defect codes as benchmarks. The performance of the feature extraction and of the rule-based classification was measured in terms of precision, recall and accuracy. More specifically, the experiment evaluated the extraction part of the pipeline, i.e. precision and recall of extracting the features on cervical spine segment, position and additional pathology was determined. In a second experiment, the classification accuracy was assessed. The quality of the retrieval remained so far unconsidered.

5 Results

5.1 Performance of the Extraction

The annotated corpus comprises 100 anonymized patient records. Four records have been detected as unusable for the text-based classification due to the incomplete description of the three required classification categories. For example, the main finding is related to intramedullary spinal cord tumor while the spinal canal stenosis has only been briefly mentioned with few words as secondary finding.

It can be seen in Table 1, that the precision of the extraction for the three feature categories already achieves optimal results. However, the recall needs still to be improved. The detection of cervical spine segments has the highest miss rate due to the non-uniformed notation and abbreviations of these concepts.

Table 1. Extraction results

Extracted element	Precision	Recall	F1
Cervical spine segment	100%	85%	91%
Position	100%	99%	99%
Additional pathology	100%	97%	98%

Table 2. Classification results

Defect category	Accuracy
Type Mono	90%
Typo Bi	95%
Type tri+	94%
Position medial (m)	91%
Position lateral (l)	98%
Position m & l	94%
AP 0	99%
AP 1	97%
AP 2	100%
AP 3	98%

5.2 Performance of the Rule-Based Classification

With the same annotated corpus, the performance of the rule based classification is evaluated. The classification accuracies were calculated for each classification category separately, since all types are assumed to be independent events. No defect falling into the category skip was contained in our data set, hence, in this experiment, we will firstly focus on the evaluation of the three common types of defects (mono, bi and tri+). The accuracy is the proportion of true results in each category. As is illustrated in Table 2, the classification of the feature "additional pathology" has generally a high accuracy, while the classification of type (bi) has shown better performance than the classification of the other two types (mono and tri+).

In summary, the extraction pipeline provides defect features with high precision. At first, the classification of position resulted in a relatively high error rate by the first rule definition and the classification of type (number of defect) has shown deviations in various degrees. After several rule extension and updating, new term features have been considered and added to the rule base. The classification has in this way reached a clearly better accuracy. The detailed analysis and possible improvements will be discussed in an error analysis in the next section.

6 Discussion

6.1 Error Analysis

The feasibility study showed that the current extraction method based on concept mapping and regular expressions achieves optimal precision and good recall. The recall can be improved through the extension of the terminology dictionary and additional regular expressions. Based on the current knowledge base and rules, the explicit description for type and position can be detected with good performance. However, the implicit position reflected in anatomical concepts and different severities of protrusion at cervical spine segments still needs to be extracted for a better category determination. Moreover, modifiers around the mentions of the defect segment in one semantic scope (sentence) should be considered besides negation, since the defect segment and its position are closely related to each other, whereas the analysis at document level cannot guarantee an accurate mapping between a subject and its modifiers.

The main source or extraction errors lies mainly in the identification of the cervical spine segment. After manually inspection, it became clear that a varying vocabulary leads to a high miss rate. The regular expressions regarding three variations defined in our extraction pipeline are clearly insufficient to deal with the various notations used by different physicians. As one possible improvement, possible terms and abbreviations will be collected from the current corpus and will be summarized in regular expressions to increase the recall. Additionally, basic natural language processing methods could be applied to abstract from lexical variations.

According to the current knowledge obtained from guidelines, only the explicit description of medial position using adjectives is mapped, while the position implied by anatomical concept has only partly been summarized. Furthermore, the writing style and conventions of the defect position show a large lingustic variety. Therefore, the rule description of medial position needs to be extended under the help of our clinical experts. Referring to the classification error by the recognition of type (number of defect segments), the reasons are twofold: first, disc protrusion may not always lead to a spinal canal stenosis. If the segment has only been described as protrusion, further information related to severity and the final judgment of this symptom should be extracted to decide whether it is really a spinal canal stenosis. Second, the semantic scope for negations in German is obviously larger than in texts written in English. Especially in clinical narratives, a larger context length need to be considered to determine the negation. Plenty of false positives by type classification in our experiment were caused by an incorrect extraction of negations in those complex sentences with several clauses.

6.2 Limitation of the Study and Approach

The limitation of the experiment is its small data amount and simple evaluation method. More specifically, the correlation between the three defect categories has not been evaluated. For example, it would be interesting to see the co-occurrence between additional pathology and defect numbers, which can also facilitate the generation of rules for defect number determination. In addition, the utilities of rules and length of the decision paths for each classification can be evaluated to test the efficiency of rules, so that the irrelative and inefficient rules can be eliminated. In addition, for our experiment, we considered texts from one department of one hospital. Through inspections of texts of other clinics, we learned already, that terminology usage differs. Thus, adaption needs to be conducted either in rules or in the terminology list to reduce the errors due to linguistic variations. The hard coding of rules has the benefit of a fast calculation and a wrapper for interpreting a rule base is unnecessary. Another possibility would have been to create an external rule base that could be more easily adapted also by layman. Given the limited number of rules and the Java infrastructure that we used (Averbis pipeline), we decided for the hard coding of classification rules.

Besides a rule-based method, machine-learning is a frequently used method for classification tasks. For example, Zhou et al. applied a dynamic language model and a Naïve Bayesian classifier to classify radiology records based on expert annotation [8]. Claster et al. employed the self organizing map (SOM) to learn the correlation between clinical events regarding overuse of radiological diagnosis for children in an unsupervised manner [9]. However, applying machine learning requires a comprehensive annotated data set for learning classification rules or classifier respectively, which was unavailable for the specific use case we were considering. Beyond, automatically trained rules are often not understandable or reproducible by humans. In contrast, our rule base has the benefit of making these rules easy adaptable and re-traceable.

6.3 Extension of Ranking Method

The retrieval platform based on keyword ranking and hash tree has been implemented through Apache Solr framework[1]. The system has received a first clinical evaluation in practice. A physician from an inpatient department has used the system to reduce the treatment duration, while the surgeons in the neurosurgical department applied the system to do the retrieval of the similar cases and planed for the surgical operation. They confirmed the usefulness of the system. However, we still need to perform a structured evaluation of the entire retrieval system and its usability. Further, a more treatment oriented ranking method of the retrieval results need to be developed.

A ranking method underlying that bases on clinically relevant aspects is still not well studied. A possible approach for ranking would be by employing the prior probability so that the weighting considering the classification schema can be used to adjust the ranking schema. More specifically, the ranking formulation can be extended with the probability P from classification schema, which indicates the user preferences.

[1] http://lucene.apache.org/solr/.

$$W_{i,d} = tf_{i,d} * log(n/df_i) * P_d$$

where

$$P = defect\, weight\, for\, document\, d$$

so that the defect classification and user predefined profile can be used to represent the severity of the patient whereas the patient records with significant defect and desired pathology will be ranked higher than other general defect combinations.

7 Conclusion

Due to the frequent occurrences of pathological changes of the cervical spine as well as the numerous possibilities of degenerative changes, the clinical demand for an easy to use and reliable tool for direct classification and for retrieving documents referring to pathological changes of various origins is obvious and urgent. We suggested an approach using information extraction and rules for defect classification. As a pilot study, preliminary experiments have been conducted with the support of surgeons. The usefulness of the automatic classification was confirmed by clinical experts. Our study revealed several concrete challenges of the textual based classification: (1) The diversity of notation, abbreviation and writing style is the main obstacle of an automatic defect classification. Improved mapping methods should be applied to close the gap between expressions in clinical narratives and in standard knowledge bases. (2) The interpretation of implicit features from clinical narratives needs to be considered, e.g. anatomical concept that implies the position. More empirical knowledge should be summarized to overcome the difficulties by the mapping between implicit features and standardized classification rules. (3) The utility of context information is still not well exploited. More contexts should be considered to reduce the ambiguities by the recognition of the classification condition, e.g. the certainty of the physician, the severity of the protrusion should also be considered.

In future, a fine-grained hierarchy will be created for the current terminology dictionary instead of the flat structure, so that the semantic distance between different terms can be compared. More features such as severity, certainty are planned to be extracted. The analysis will be conducted at sentence level instead of document level to increase the mapping rate between subjects and modifiers. Further, an additional clinical study will be organized for collecting more rule definitions from empirical evidence. The final objective of the automatic classification is to determine therapy recommendations. For this purpose, for each defect class and associated features, therapy options need to be made available. Then, the system will be able to provide a therapy recommendation and undermine the decision with relevant cases of previously treated patients.

References

1. Muhle, C., Metzner, J., Weinert, D., Falliner, A., Brinkmann, G., Mehdorn, M.H., Heller, M., Resnick, D.: Classification system based on kinematic MR imaging in cervical spondylitic myelopathy. Am. J. Neuroradiol. **19**(9), 1763–1771 (1998)
2. von Sachsen S.: Computer aided defect classification for model-based therapy of cervical spinal stenosis. In: International Conference on Biomedical Engineering and Systems (ICBES), Prague, Czech Republic (2014)
3. Daenzer, S., Freitag, S., von Sachsen, S., Steinke, H., Groll, M., Meixensberger, J., Leimert, M.: Volhog: a volumetric object recognition approach based on bivariate histograms of oriented gradients for vertebra detection in cervical spine MRI. Med. Phys. **41**(8), 082305 (2014)
4. Schizas, C., Theumann, N., Burn, A., Tansey, R., Wardlaw, D., Smith, FW., Kulik, G.: Qualitative grading of severity of lumbar spinal stenosis based on the morphology of the dural sac on magnetic resonance images. Spine (Phila Pa 1976) **35**(21, 9), 1919–1924 (2010)
5. Samwald, M., Fehre, K., de Bruin, J., Adlassnig, K.-P.: The arden syntax standard for clinical decision support. J. Biomed. Inform. **45**(4), 711–718 (2012)
6. Huang, Z., Teije, A., Harmelen, F.: Rule-based formalization of eligibility criteria for clinical trials. In: Peek, N., Marín Morales, R., Peleg, M. (eds.) AIME 2013. LNCS (LNAI), vol. 7885, pp. 38–47. Springer, Heidelberg (2013). doi:10.1007/978-3-642-38326-7_7
7. Kelly, D., Sugimoto, C.R.: A systematic review of interactive information retrieval evaluation studies, 1967–2006. J. Am. Soc. Inform. Sci. Technol. **64**(4), 745–770 (2013)
8. Zhou, Y., Amundson, P.K., Fang, Y., Kessler, M.M., Benzinger, T.L.S., Wippold, F.J.: Automated classification of radiology reports to facilitate retrospective study in radiology. J. Digital Imaging **27**(6), 730–736 (2014)
9. Claster, W., Shanmuganathan, S., Ghotbi, N.: Text mining in radiological data records: an unsupervised neural network approach. In: First Asia International Conference on Modelling Simulation, AMS 2007, pp. 329–333, March 2007

Springer

http://www.springer.com/978-3-319-57740-1

Data Management and Analytics for Medicine and Healthcare
Second International Workshop, DMAH 2016, Held at VLDB 2016, New Delhi, India, September 9, 2016, Revised Selected Papers
Wang, F.; Yao, L.; Luo, G. (Eds.)

2017, XVIII, 155 p. 63 illus., Softcover
ISBN: 978-3-319-57740-1