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Original Research

Ontology-based surgical workflow recognition and prediction

Juliane Neumann [a,*], Alexandr Uciteli [b], Tim Meschke [a], Richard Bieck [a], Stefan Franke [a], Heinrich Herre [b], Thomas Neumuth [a]

[a] Innovation Center Computer Assisted Surgery (ICCAS), Faculty of Medicine, Leipzig University, Semmelweisstraße 14, 04103 Leipzig, Germany

[b] Institute for Medical Informatics, Statistics and Epidemiology (IMISE), Faculty of Medicine, Leipzig University, Härtelstraße 16-18, 04107 Leipzig, Germany

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ABSTRACT

Background: Surgical context-aware systems can adapt to the current situation in the operating room and thus provide computer-aided assistance functionalities and intraoperative decision-support. To interact with the surgical team perceptively and assist the surgical process, the system needs to monitor the intraoperative activities, understand the current situation in the operating room at any time, and anticipate the following possible situations.

Methods: A structured representation of surgical process knowledge is a prerequisite for any applications in the intelligent operating room. For this purpose, a surgical process ontology, which is formally based on standard medical terminology (SNOMED CT) and an upper-level ontology (GFO), was developed and instantiated for a neurosurgical use case. A new ontology-based surgical workflow recognition and a novel prediction method are presented utilizing ontological reasoning, abstraction, and explication. This way, a surgical situation representation with combined phase, high-level task, and low-level task recognition and prediction was realized based on the currently used instrument as the only input information.

Results: The ontology-based approach performed efficiently, and decent accuracy was achieved for situation recognition and prediction. Especially during situation recognition, the missing sensor information were reasoned based on the situation representation provided by the process ontology, which resulted in improved recognition results compared to the state-of-the-art.

Conclusions: In this work, a reference ontology was developed, which provides workflow support and a knowledge base for further applications in the intelligent operating room, for instance, context-aware medical device orchestration, (semi-) automatic documentation, and surgical simulation, education, and training.

1. Introduction

Recent technological advances in computer-aided surgical assistance and integrated medical devices contribute to the design and development of intelligent operating rooms (OR) [1,2]. Especially computer vision, machine perception, and learning, as well as surgical workflow management, are enabling technologies for new applications in surgical decision support and situation-aware assistance [3]. Such *surgical context-aware systems* (SCAS) are able to interact with the surgical team perceptively and provide adequate perioperative support. For this purpose, SCAS need to monitor the surgical activities, understand the current situation in the OR at any time, and anticipate the following possible situations. Therefore, the development of SCAS targets two main objectives. The first goal is the *recognition* of the actual situation and the implication to the current surgical process. Based on this workflow recognition, the second goal is the *prediction* of subsequent surgical activities, which the surgical team will perform in the near future. Suppose a SCAS knows about the actual and upcoming activities. In that case, specific context-sensitive assistance functionalities could be provided, e.g. an automatic, situation-aware parameterization of medical devices or the visualization of relevant information [4]. The central challenge in the domain of workflow recognition is the continuous transformation of raw data from various information sources (e.g., medical devices, IT systems, or sensors) into structured information.

Abbreviations: ABox, Assertion Box; AS, Answer Set; gAS, Generalized Answer Set; GFO, General Formal Ontology; gSPM, generalized Surgical Process Model; HLT, High-Level Task; iSPM, individual Surgical Process Model; LLT, Low-Level Task; OR, Operating Room; SCAS, Surgical Context-Aware Systems; SCT, SNOMED CT; SDS, Surgical Data Science; SIO, Surgical Intervention Ontology; SPM, Surgical Process Model; TBox, Terminological Box.

* Corresponding author.
E-mail address: Juliane.Neumann@iccas.de (J. Neumann).

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Subsequently, the gathered information needs to be analyzed to deduce the actual situation in the OR [5]. The data acquisition and subsequent situation interpretation aim to extract a knowledge base that gives the raw data a semantic meaning [6]. In this process, the workflow recognition focuses on handling various data and different interpretation possibilities, subsequently coping with a high level of uncertainty.

The recognition and prediction of processes in the operating room is an integral part of an emerging scientific field in medicine, called Surgical Data Science (SDS) [3]. SDS aims to improve the quality of healthcare and provides better patient outcome through the structural acquisition, organization, analysis, and modeling of procedural data [7]. This work contributes to the field by providing structured knowledge about the actual and upcoming surgical situation combined with a high granular workflow recognition. A robust situation recognition and interpretation is a prerequisite for any applications in context-aware surgical decision support, workflow management, or process automation. Several workflow modeling techniques have been used to represent such knowledge bases, which consist of information entities about the surgical procedure (e.g., performed activities, used surgical instruments, and treated anatomical structures) [8]. In the domain of knowledge engineering, especially ontologies have been utilized to model knowledge bases, enabling the reuse of formal data and information. Ontologies can also provide logical formalisms and a standardized vocabulary for describing surgical procedures [9]. Additionally, ontologies support the usage of methods from the domain of knowledge engineering, such as reasoning and inference-making for complex problem-solving.

This work aims to provide a semantically enriched knowledge base of surgical situations to leverage context-aware assistance functionalities in modern intelligent ORs. For this purpose, a surgical process ontology, which is formally based on a standard medical ontology (SNOMED CT [10]) and an upper-level ontology (GFO [11]), was developed and instantiated for a neurosurgical use case. In addition, a new method for ontology-based surgical workflow recognition and prediction is presented. Therefore, the recognition and prediction of surgical low-level activities, as well as the extraction of the knowledge about the corresponding high-level tasks and the surgical phase, is performed on an abstract instrument recognition as the only input sensor. The information about the currently used instrument is the most accessible information sensor in the OR and can be acquired in minimal-invasive and open-approach surgical settings ([12,13]).

1.1. State of the art

Surgeries are described with different levels of granularity. The surgical procedure consists of phases, which are composed of several steps or goal-oriented *high-level tasks (HLT)* [14,15]. A HLT describes a context-sensitive sequence of *activities or low-level tasks (LLT)*, which, however, can be represented as a 5-tuple containing the *actuator* and the actuators *body part*, the *surgical action*, the treated *anatomical structure*, and the used *instruments/resources* (e.g., the *surgeon* uses the *right hand* to *coagulate* the *muscle* with a *bipolar*) [16]. Intraoperative workflows can be modeled as *surgical process models (SPM)* in form of a statistical mean *or generic SPM (gSPM)* of an intervention [17]. A gSPM is a merged set of *individual process models (iSPM)* and consists of all possible transitions and their global transition probabilities to create an average process.

For surgical *workflow modeling*, there are different approaches presented in the literature [8], including statistical and machine-learning methods (e.g. [18,19]), graphical representations (e.g. [20]), and also ontology-based approaches. In comparison to the workflow prediction based on statistical methods, ontology-based approaches aim to provide additional knowledge and therefore a deeper understanding of the surgical context to improve surgical workflow recognition and prediction. In [9], a general surgical process ontology (OntoSPM) for different applications, such as robotic surgery, training, and SCAS, is described. Katić et al. extended this ontology for laparoscopic surgeries and applied it to recognizing surgical phases for SCAS [21] and context-aware augmented reality systems [22]. Nakawala et al. presented an ontology-based SCAS for surgical training in thoracentesis procedures [23]. In [24,25] an ontology-based situation recognition system for endoscopic navigation was developed, which uses a marker-less localization method.

In the domain of *workflow recognition*, the described approaches are based on different information sources as single sensors or a combination of sensors, to achieve information about the actual surgical workflow. Especially, workflow recognition from data sources, which are already available in the clinical routine, such as endoscopic and microscopic video data (e.g. [26,27]), has gained more importance in recent years. For workflow recognition based on instrument/device detection, there are approaches using instrument sensor data (e.g. [28,29]) medical device data (e.g. [30]) and OR sensors (e.g. [31]). There are also workflow recognition methods based on the detection of surgical actions and gestures (e.g.[32,33,34]). However, the recognition of the anatomical structure for workflow recognition is still sparse and highly specialized to the analyzed use case [35]. To achieve a complete low-level representation of a surgical activity, intraoperative workflow recordings of a human observer [16] or video annotations are used. For the situation recognition and interpretation, the input data must be classified to deduce the implication of the current surgical situation. In most recognition approaches, machine learning techniques, like Hidden Markov Models (e.g. [36]) or Convolutional Neuronal Networks (e.g. [30,37]) are utilized. But also ontology-based approaches for the recognition of surgical processes were presented (e.g. [21,13,38]). Most approaches target the detection of the current surgical phase ([39,40]), however, HLT ([15,31]) and LLT recognition ([30,41]) are also existing. For efficient context-aware support of the surgeon in terms of, e.g., visualization of context-related information at the right time or the context-sensitive parameterization of medical devices, the recognition of the actual phase is not sufficient. The information about the HLT and LLT, which are currently performed by the OR team, is essential and needs to be put into the surgical high-level context.

Context-aware and intelligent systems require both the recognition of the actual situation as well as the prediction of the forthcoming surgical phase, HLTs and especially LLTs for the integration of surgical assistance functionalities and process automation in the surgical workflow. The key challenge is dealing with the high complexity of surgical processes with an immense inter-process variability and numerous ad-hoc processes due to unexpected events, ad-hoc decisions, unpredictable and patient-specific influences, and constantly changing conditions in the OR environment. Applications for surgical workflow prediction have already been shown for the intervention time prediction (e.g. [42,43]), intraoperative resource management [44], prediction of medical device usage [36], and minimal-invasive navigation [45].

2. Methods

In this work, a new method for automatic recognition and prediction of the current and subsequent LLT and also the corresponding HLT, as well as the surgical phase, is presented to provide a semantically enriched knowledge base for SCAS. For this purpose, a surgical process ontology was developed and instantiated for the neurosurgical use case of lumbar discectomies utilizing observer-based low-level recordings of 41 surgical procedures [46].

An abstract instrument recognition is used as the only input sensor for workflow recognition. Hence, the recognition of anatomical structures and surgical actions is not needed in the presented approach. An overview of possible realizations of instrument recognition for endoscopic and microscopic surgery is presented in [12]. For open surgeries, instrument recognition systems such as [13,47], or [48] could be utilized. In addition, medical device usage data can be analyzed for instrument identification and subsequent workflow recognition and prediction [49]. Dergachyova et al. [41] and Liebmann et al. [50] evaluated the selection of input sensors for workflow recognition and identified the used instrument as the essential information. Since sensors for recording anatomical structures and surgical actions are not prevalent in the actual research, the missing sensor information are reasoned with the help of a surgical process ontology. To recognize the current and predict the upcoming surgical situation, the process ontology is queried what activities are possible next, based on the currently recognized situation and the history of the ongoing procedure. To the best of our knowledge, this is the first ontology-based approach of a combined phase, HLT and LLT recognition solely based on the information about the currently used instrument. In addition, a situation prediction based on ontological reasoning, abstraction, and explication is a new contribution to the research field.

2.1. Workflow data set

The data set consists of 41 individual neurosurgical procedures of lumbar disc herniation removal [51]. 21 interventions were recorded at the Department of Neurosurgery, University Hospital Leipzig (Germany), and 20 at the Department of Neurosurgery, Rennes University Hospital (France), between 2008 and 2010. All the patients are newly diagnosed with lumbar disc herniation and had not undergone previous spine surgery. During the microsurgical intervention, the herniated disc was removed via a posterior lumbar spinal approach [51]. The lumbar discectomy procedures are mostly standardized and well-structured, which enables cross-country and cross-clinical process analysis and workflow support.

The recordings of the surgical processes were acquired during live observations by a senior neurosurgeon with a software-based Surgical Workflow Editor [52]. During live observation, the operating time, surgical activities, which contain the actor, used body part, anatomical structure, action, used instrument, and the duration of the activity, as well as the surgical phases, were recorded. The intervention workflows consist of, on average, 119 (±46) activities with a mean intervention duration of 57 min (±27 min). A segmentation of the surgical procedure into 4 phases was realized: *Opening of intervertebral disc* (from skin incision to the removal of disc), *Primary lumbar microdiscectomy* (disc removal), *Control of wound hemorrhage* (optional step for control of hemorrhage), and *Layer closure procedure* (from the end of disc removal or control of hemorrhage until the end of surgery) [51]. All activities were performed either with the surgeon's right or left hand and recorded separately. The workflows contain 10 different actions, 8 different anatomical structures, and 23 different instruments/resources. In total, the data set contains 159 activity combinations. Note that, not every possible combination constitutes a valid LLT.

2.2. Surgical intervention ontology (SIO)

To represent operating room processes as data, information, and knowledge in a systematic, machine-readable, and reusable form, ontologies could be utilized. For this purpose, the generic approach for ontological process modeling was developed and implemented in the Surgical Intervention Ontology (SIO). In Fig. 1, an excerpt of the basic SIO concepts and relations is presented. The representation includes concepts of surgical phases, high-level tasks, and low-level tasks (SIO: Activity). SIO has also been embedded into the General Formal Ontology (GFO) top-level ontology [11,53]. For the representation of surgical situations, the notion of a situation as presented in GFO and explicated in the papers [23,24], was used.

SIO is based on the widely used and clinically validated SNOMED CT (SCT) terminology [10] and utilizes the SNOMED CT concepts as a terminological foundation, and the appropriate concept model attributes as relations [54]. SCT was identified as a suitable nomenclature for the semantic representation of surgical knowledge [55]. It includes over 800.000 terms, which describe 300.000 concepts and about 1 million relationships between those concepts. The description of concepts and their relations are clinically validated. This ensures that a term has a single meaning and allows the exchange of surgical knowledge between different stakeholders and scientific communities. In Fig. 2 the SNOMED CT concept model attributes and relations are depicted that are relevant for surgical situation representation. The root element is the SCT concept "situation with explicit context", which has an associated procedure to describe the surgical intervention. The SIO classes "Surgical Intervention", "Surgical phase", "High-level-task" and "Activity" are associated procedures of the explicit situation. The relevant subconcepts of the SCT high-level concept "Procedure" are mapped to the mentioned core SIO classes (Fig. 3). The concepts may then be described in more detail. For instance, different properties characterize the surgical intervention, e.g., a start time, completion time, or duration, as well as concepts that describe which morphological structure is treated or which approach is used during the intervention. When mapping the process concepts and their relations to SCT attributes, the inherent "domain" and "range" constraints according to the SNOMED CT concept

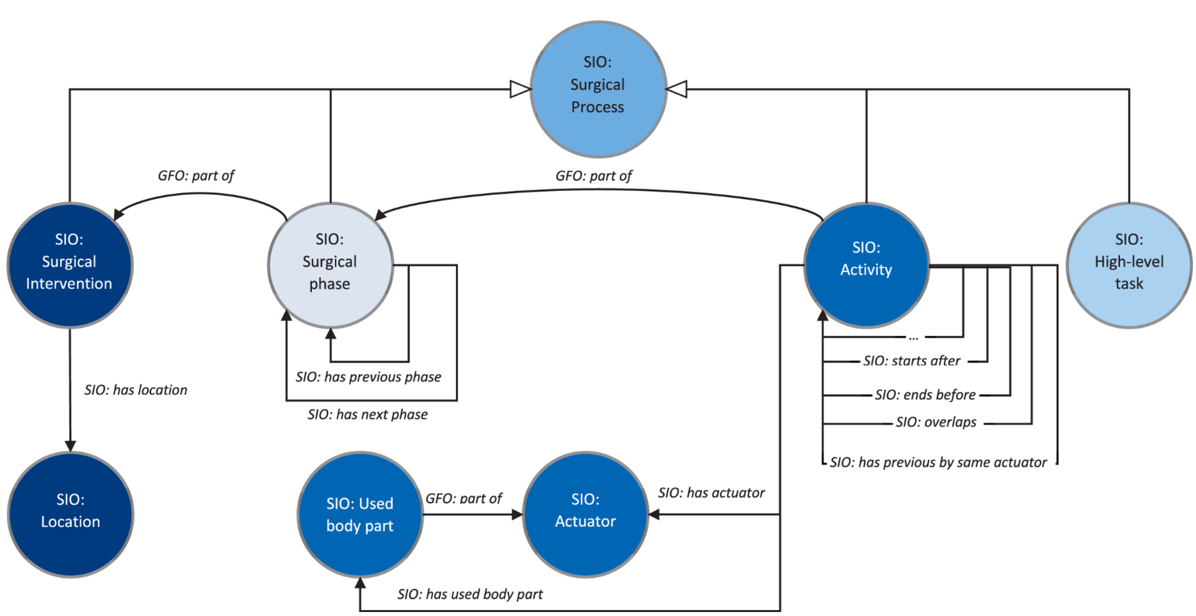

Fig. 1. Excerpt of the basic SIO structure with core concepts and relations for the representation of a surgical situation.

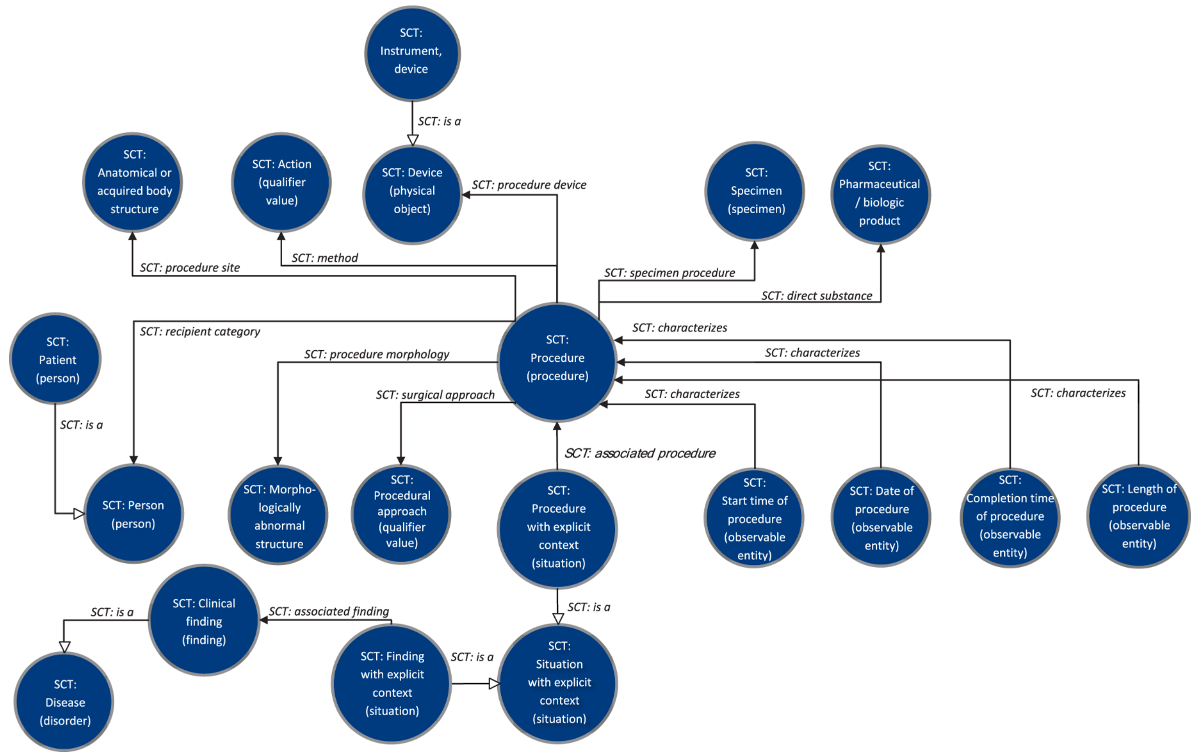

Fig. 2. SNOMED CT concept model attributes and relations used in SIO.

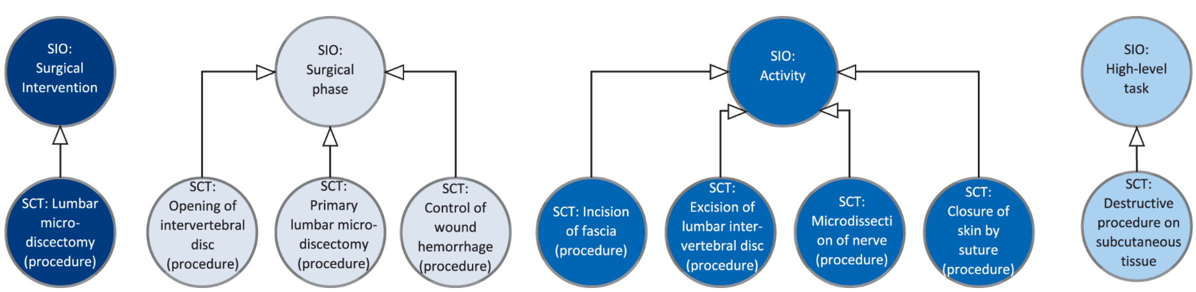

Fig. 3. Example mapping of SNOMED CT concepts to SIO classes.

model have to be considered [56]. For instance, "SCT: Procedure" has the possible attribute "SCT: Procedure device" for the linkage with the concept "SCT: Instrument, device". The domain of "Procedure device" is defined as the concept "Procedure" and the range as "Device" and all its hierarchically descendants.

SIO is a reference ontology that includes only high-level concepts of surgical interventions, general process relations, and generic translation rules for the SCT mapping (Fig. 3). The translation rules define how the process elements are mapped to SCT top-level hierarchy to utilize their descendants for a representation of a specific surgical intervention type. Therefore, SIO describes how a specific intervention ontology is created from workflow data using SCT hierarchy concepts and relations. Based on the generic concept and the SIO, a standardized and reusable representation of surgical processes and process knowledge with an adequate number of terms and consistent terminology could be achieved [54]. Therefore, different surgical interventions could be modeled using the SIO. Most process concepts are represented in SCT, so it is usually not necessary to develop common concepts for processes and activity representations, including actions, resources, or anatomical structures.

2.3. *SIO4Discectomy*

Based on the lumbar discectomy data set, the *SIO4Discectomy* domain ontology was implemented. According to the SIO structure, the process elements of the workflow dataset were transferred into ontological classes and relations between those classes. The terms describe process entities, such as LLT, including actions, instruments, anatomical structures, as well as HLTs, and surgical phases. The terms are defined in the terminological component (TBox), which describes a set of concepts as well as their properties and relations [57]. In contrast, the assertion component (ABox) consists of TBox compliant statements for the representation of individual surgical procedures based on the real-world data of intraoperative workflow recordings. An example of an individual intervention including parameters of the specific surgery, surgical phases, HLT, and one complete activity representation is depicted in Fig. 4.

Firstly, the TBox was developed. For this purpose, an extraction and subsequent analysis of process elements from the workflow data set were performed. The identified process elements were then mapped to SCT concepts according to the structure and restrictions of the SIO core ontology. The mapping of process entities to SCT concepts was done manually using the SNOMED CT Browser [58] and was clinically

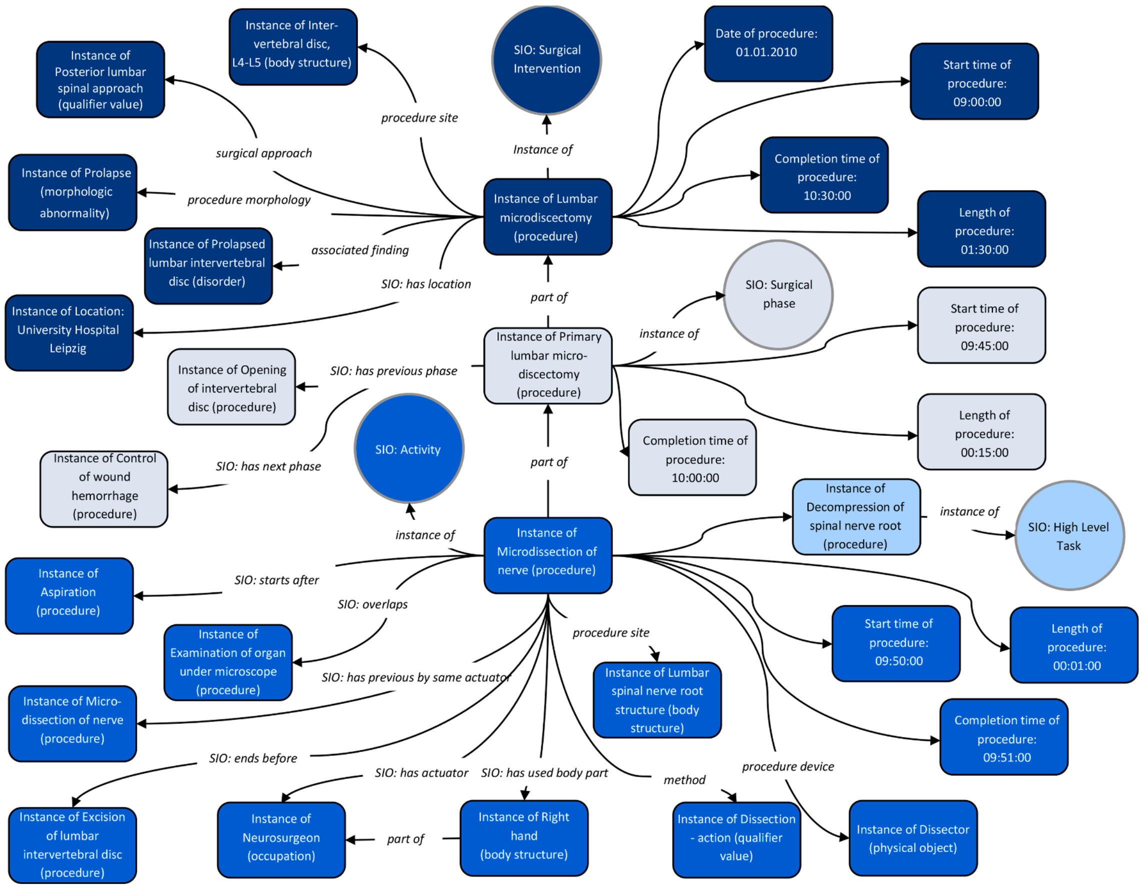

Fig. 4. Simplified example of an ontological description of a lumbar discectomy including parameters of the intervention, surgical phases, HLT, and one complete activity representation with additional relations to previous, parallel, and subsequent activities.

verified by an experienced neurosurgeon afterward. The elements of the surgical workflow records have been designed with a low level of detail due to their maximal reusability during the workflow recording. By translating the entities in SCT terms, a semantical representation with a higher level of detail was achieved [55], e.g., the instrument "hook" was translated to "Nerve/vessel hook" when it was used on the nerve root structure. Otherwise, it was translated to "Skin/tissue hook" when it was used to manipulate skin or tissue.

Additionally, the instruments and resources were classified according to their instrument function [59]. Another example is the action "cut", which was divided into SCT terms "Incision" and "Excision" according to the activity context. In contrast, the anatomical structures were described in the same level of detail since there is no further information about the treated structures, which allows a refinement of the representation without the error susceptibility of retrospective data modifications. All original process elements could be mapped to SCT terms, either with the same level of detail or a higher level of detail of the semantic representation. In the mapping process, the SCT concept hierarchy was used to model the hierarchical ordering of the granularity level of process elements. The highest ordering has the intervention, then in descending order of SCT concepts, the surgical phase, HLT, and LLT were mapped. Another advantage of utilizing SCT for surgical process modeling is the possible use of existing relations, which are already defined in SCT.

The description of the LLT was also added to the SIO4Discectomy ontology. According to the LLT-triplet (instrument, anatomical structure, and action), a representation of the whole activity was defined. For example, the action element "cut" on "skin" or "muscle" has been translated into the separate SCT concepts "Incision of skin of trunk" or "Incision of muscle". This way, the 159 possible activity combinations were defined by 36 SCT procedure terms. According to the context of the HLT and the surgical phase, the semantic descriptions for LLT consisting of the same triplet could be different. In the last step, the LLT representations were allocated to one of 16 HLT representations.

For the implementation of the ABox, the elements of the workflow protocols, such as process entities and their relations as well as logical and temporal aspects of the LLTs, were transferred into SIO4Discectomy as instances, of the implemented classes of the TBox. Since the ontological representation of instances in Fig. 4 is simplified, an example of the instantiated SIO classes is depicted in detail in Fig. 5. For the representation of procedural and sequential relations of LLTs, SIO implements specific object properties (e.g., ends_after, ends_simultaneously, has_next_phase, has_previous_by_same_actor, starts_before). Temporal

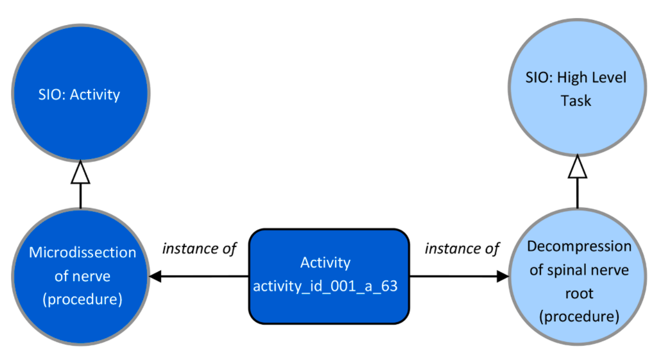

Fig. 5. Example of instantiated SIO classes. A specific activity (with id: 001_a_63) is an instance of the classes "SCT: Microdissection of nerve (procedure)" (is-a/subclass-of "SIO: Activity") and "SCT: Decompression of spinal nerve root (procedure)" (is-a/subclass-of "SIO: High-level-task").

aspects were defined as data properties and SCT terms (e.g., Start time of procedure). The ontology file was generated with OWL API [60], queried, and reasoned with SPARQL [61] within the Apache Jena framework [62].

2.4. Situation prediction

During surgery, an alternation of situation recognition and the prediction of the subsequent activities is performed. In the prediction step, a set of possible activities is determined, while the correct successor of the current situation should be part of the prediction answer set. The prediction result is used to perform a recognition step, which will then be the result for the next situation prediction. A new prediction-recognition cycle is triggered for every recorded LLT activity. Both phases for prediction and recognition are run through again until the last activity of the surgery has been reached. For the evaluation of the recognition and prediction algorithms, in this study, the correct follow-up of the recognition is passed on for the next prediction, regardless of the result of the actual recognition. A Leave-One-Out-Cross-Validation is performed for the evaluation of the situation recognition and prediction.

The situation prediction algorithm is presented in Fig. 6. In the first step, all start activities are queried from the SIO with SPARQL expressions. Since all workflows start with the same activity, this activity is the first recognized activity. For a recognized activity, all possible successors are determined from the surgical process ontology to execute the prediction cycle. All activities with predecessors with the same instrument, the same anatomy, and the same action as the current activity are extracted from the SIO. These possible successors are stored in an answer set AS, from which all duplicates are removed. In the next step, a generalization step is performed, which is depicted in Fig. 8 in more detail. This step results in a new answer set (gAS) with generalized anatomical structures, which will increase the chances that the correct follow-up activity is in the answer set for the recognition.

The prediction is evaluated based on the generalized answer set. For this purpose, two approaches, soft and hard predictions, are used. The soft prediction is considered successful as soon as the correct activity is included in the prediction output answer set. Thus, a high recall but a low precision is expected.

To determine a definite prediction output for the hard prediction, a generalized surgical process model (gSPM) is generated from the SIO and the gAS. It includes the completed predecessors of the actual base activity (process history), all possible successors as well as their transition probabilities [17]. The successor activity with the highest transition probability is identified in the answer set and defined as the prediction output (Fig. 7**, A**). Additionally, a ranking of possible follow-up candidates according to their transition probability is created. To define the prediction output more precisely, the predecessors of the current activity may be included in the probability calculation by forming sequences of 2 or more activities and determining the transition probabilities of their successors (Fig. 7**, B**).

For situation prediction, the next LLT, in combination with its HLT and surgical phase, should be identified. The surgical phase is calculated by querying the answer set gAS for the LLTs phases and determining the most frequent phase. The output of the HLT prediction consists of the most likely successor activity, which is queried for its respective HLT.

2.4.1. Anatomy generalization

During prediction, a generalization step is performed to extend the answer set of subsequent activities, which will increase the chances that the correct follow-up activity is in the answer set for the subsequent

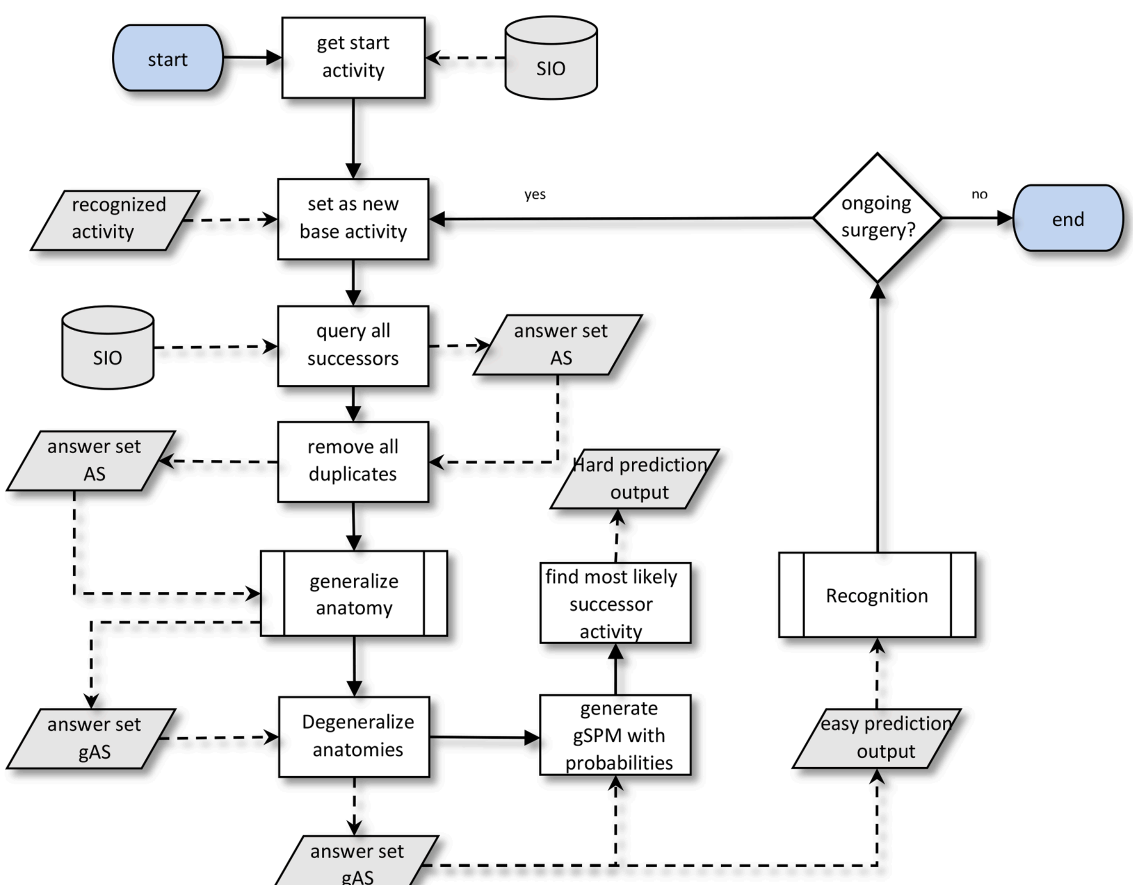

Fig. 6. Algorithm for situation prediction.

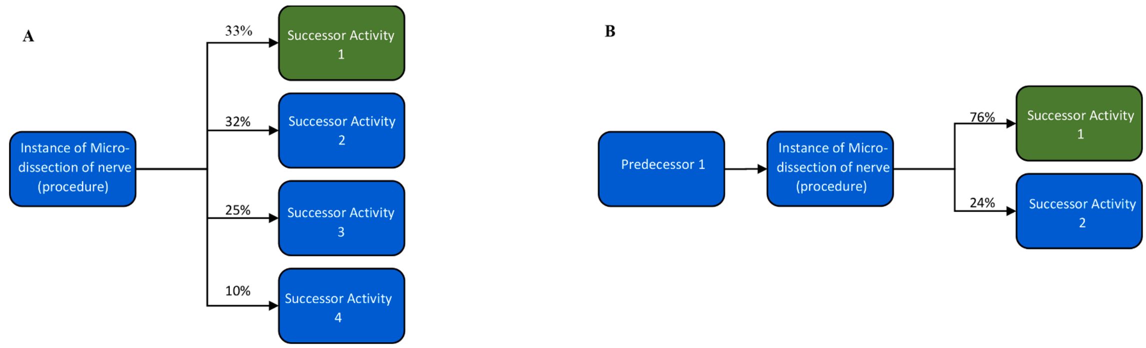

Fig. 7. An example gSPM representing the base activity with predecessor-successor relationships and transition probabilities.

situation recognition. For this purpose, the anatomical structures of the possible successor activities in the actual answer set are generalized. For example, the current answer set contains two activities describing "incision by a scalpel on the skin" and "incision by a scalpel on the fascia". With the help of the hierarchical ordering system of the SNOMED CT ontology, it is possible to describe both anatomical structures with a lower level of detail, e.g., "incision by a scalpel on soft tissue". A single activity is obtained by this generalization of the two anatomical structures. Thus, the correct instrument and action can be inferred more successfully, while the anatomical structure is not distorted. This way, a higher level of abstraction could be determined, which will be specified to the original high-level representation of the activity during the recognition step. During this degeneralization step, the activity "incision by a scalpel on soft tissue" can be also described as "incision by a scalpel on ligament" in addition to the original activity representation in the answer set. The degeneralization step increases the answer set size of gAS for the following situation recognition.

In Fig. 8, the algorithm of this anatomy generalization is presented.

The generalization is performed for all activities in the current answer set AS, which are initially clustered according to their HLT. Then every activity in each HLT cluster is grouped according to its anatomical structures. The parent anatomy is determined for each activity using SNOMED CT and a tree-matching algorithm. The parent anatomy is the semantic nearest superset to the existing anatomical structures in the cluster. Suppose a parent anatomy has been found, which represents all anatomical structures in the cluster. In that case, this anatomy is set as the new generalized anatomy for all activities in the HLT cluster. If no general anatomy can be found after processing all possible parent levels, the most abstract anatomy in SNOMED CT ("Body structure" with SNOMED CT-ID 123037004) is assigned to all activities in the cluster. In the next step, a new answer set gAS is generated, which size should be reduced compared to the original AS while including all activities that can be considered as potential successors. The gAS is returned as prediction/recognition output.

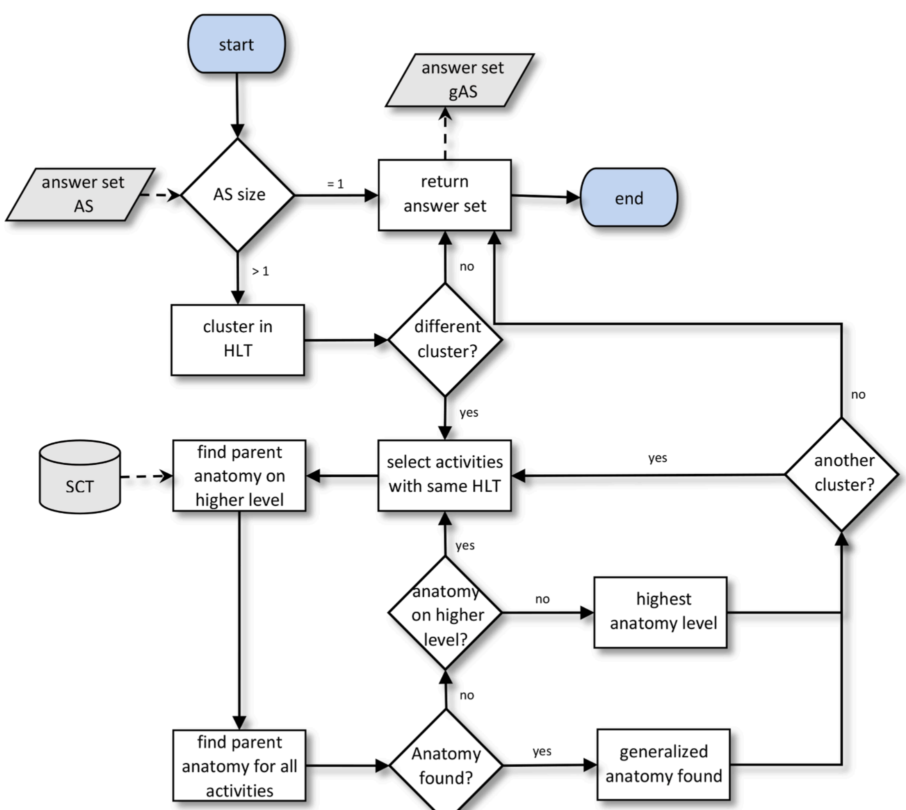

Fig. 8. Generalization step of the predicted/recognized activity (based on the LLT anatomy).

2.5. Situation recognition

The recognition algorithm is presented in Fig. 9. The situation recognition is performed based on the prediction answer set gAS and an abstract instrument recognition, which could be derived offline from annotated workflow data or online from intraoperative sensors. In this study, the next used instrument is queried from the workflow records in the process ontology. In the next step, all activities are determined from the answer set gAS, in which the actual instrument is used. If gAS contains only one LLT, this would be the result of the situation recognition. If the answer set gAS is empty for the currently used instrument, the instrument element of the activity is abstracted. The SIO classifies the instruments according to their functions on the base of SNOMED CT [59]. If the answer set is empty, the SIO is queried for activities with instruments from the same functionality class and builds a new answer set based on the query results. In the best case, the result of this subprocess has exactly-one element, which would be the result of the recognition. In the worst case, it still has no element, which leads to incorrect empty recognition output. If the answer set has more than one element, the recognition output is determined by calculating the activity with the highest transition probability in the gSPM. A recognition output is considered correct if the LLT with degeneralized instrument and anatomical structure element was identified correctly. For phase and HLT identification, the recognized LLT element is queried for its surgical phase and associated HLT.

3. Results

In the workflow data set, 4906 activities were detected in 41 surgical lumbar discectomy interventions. Prediction and recognition were performed for 4862 activities. The remaining 44 activities are parallel end activities, which were excluded from situation interpretation.

3.1. Phase prediction

Based on the LLT soft prediction, the most frequent phase was calculated in the answer set gAS. The resulting normalized confusion matrix of this phase prediction is depicted in Fig. 10. Most correct predicted activities could be classified in the phases “Opening of intervertebral disc (Approach) and “Primary lumbar microdiscectomy (Discectomy)” with high precision and recall (Table 1). Hemostasis activities could occur during every phase of the intervention, which results in low precision and recall of the classification for “Control of wound hemorrhage” (Hemostasis). Except for the activities of sewing, most of the surgical activities in the “Layer closure procedure (Closure)” phase could also be found in the “Approach” phase, which resulted in a low precision, but a high recall of the prediction.

A phase prediction was made for all 4862 surgical activities. 3823 phases could be predicted correctly, which resulted in an overall accuracy of 78.63% of the presented phase prediction.

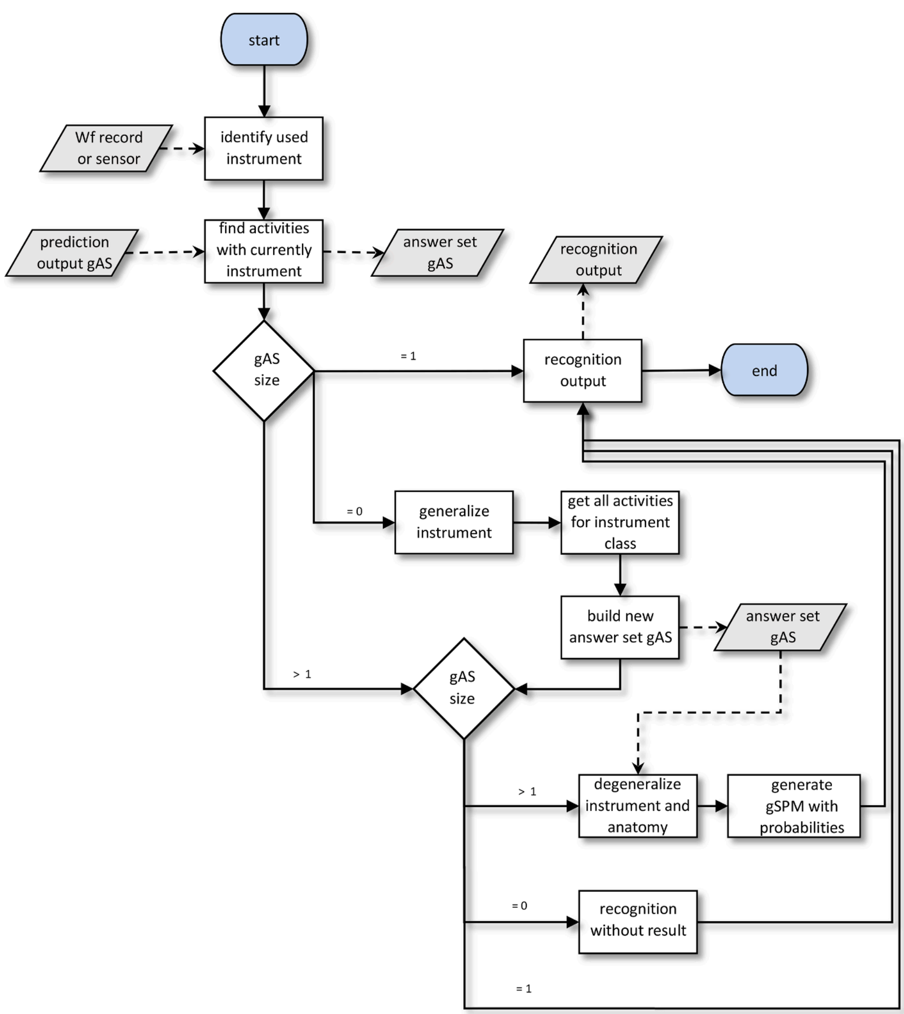

Fig. 9. Algorithm for situation recognition.

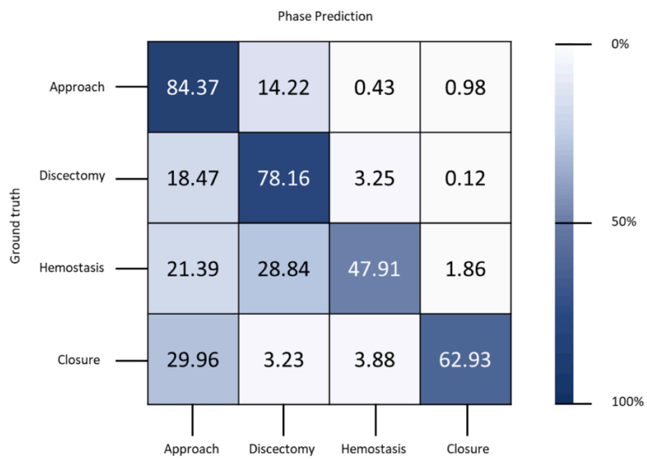

Fig. 10. Normalized confusion matrix of the surgical phase prediction.

Table 1
Results of the surgical phase prediction.

		Correct	All/ Relevant	Precision	Recall	F-measure
Phases	Approach	2154	2553	0.844	0.816	0.830
	Discectomy	1274	1630	0.782	0.743	0.762
	Hemostasis	103	215	0.479	0.557	0.515
	Closure	292	464	0.629	0.904	0.742

3.2. High-Level task prediction

Based on the LLT hard prediction, the most likely activity is queried for its according HLT. The results of this prediction are presented in the normalized confusion matrix in Fig. 11. 16 different HLTs were identified in the workflow data set, which are described with SCT terms (Table 2). A prediction with high precision and recall could be achieved for the most common HLTs 2, 4, and 6 as well as for the HLTs 12 and 14. Low precision and recall were achieved for uncommon activities (e.g., HLTs 1 and 3) or HLT 8, which is related to surgical complications. HLTs that are related to activities with long durations (e.g., HLT 11) and tasks which occur irregularly and are only performed when necessary (e.g., irrigation in case of bleeding (HLT 15)), achieved low prediction outcomes.

A HLT prediction was made for all 4862 activities. 2487 HLTs could be correctly classified, and for 253 activities, no HLT prediction could be made. This resulted in an overall accuracy of the HLT prediction of 51.15%.

3.3. Low-Level task prediction

For the evaluation of the LLT prediction, two approaches, the soft and hard prediction, are performed. The results are presented in Table 3. The soft prediction is considered successful as soon as the correct next activity could be found in the prediction output answer set gAS. Since the soft LLT prediction is the basis for the following recognition step, the goal was to increase the answer set size to maximize the recognition chance. As a result, a high recall but a low precision was achieved. In total, 137.838 predictions were made with an overall accuracy of 3.17%.

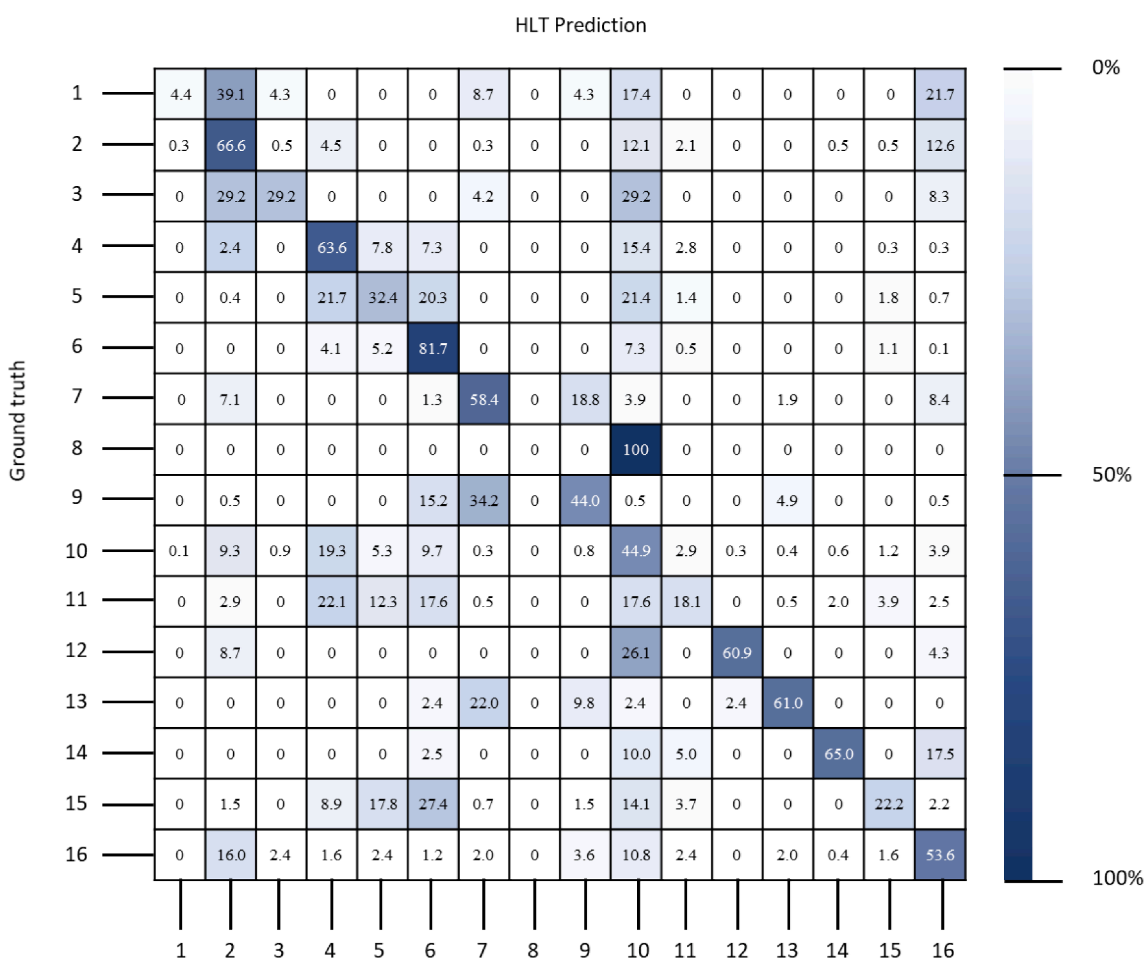

Fig. 11. Normalized confusion matrix of the HLT prediction.

Table 2
Results of the HLT prediction.

ID	SCT ID	SCT Term	Correct	All/Relevant	Precision	Recall	F- measure
1	41447009	Incision of skin (procedure)	1	23	0.043	0.333	0.077
2	363069007	Destructive procedure on subcutaneous tissue (procedure)	253	380	0.666	0.574	0.617
3	699498007	Destruction of tissue of skin (procedure)	7	24	0.292	0.292	0.292
4	239565007	Excision of posterior elements of vertebra (procedure)	572	900	0.636	0.582	0.608
5	231045009	Decompression of spinal nerve root (procedure)	185	571	0.324	0.465	0.382
6	3418002	Discectomy for intervertebral herniated disc. nucleus pulposus (procedure)	617	755	0.817	0.619	0.704
7	363309004	Soft tissue closure (procedure)	90	154	0.584	0.511	0.545
8	112695004	Reparative closure (procedure)	0	1	0.0	0.0	0.0
9	446355000	Suturing of skin and/or subcutaneous tissue (procedure)	81	184	0.440	0.609	0.511
10	51241000	Control of hemorrhage (procedure)	415	924	0.449	0.467	0.458
11	117259009	Microscopy (procedure)	37	204	0.181	0.303	0.227
12	386335003	Infection protection (procedure)	14	23	0.609	0.778	0.683
13	122462000	Drainage procedure (procedure)	25	41	0.610	0.532	0568
14	44491008	Fluoroscopy (procedure)	26	40	0.650	0.667	0.658
15	67889009	Irrigation (procedure)	30	135	0.222	0.395	0.284
16	122546009	Stretching procedure (procedure)	134	250	0.536	0.510	0.522

Table 3
Results of the LLT prediction.

	Correct	All	Relevant	Accuracy	Precision	Recall	F-measure	mean AS size
LLT Soft Prediction	4372	137,838	4935	3.17%	0.031	0.885	0.060	28
LLT Hard Prediction without predecessor	1226	4862	4862	25.22%	0.252	0.252	0.252	1
LLT Hard Prediction with 1 predecessor	1850	4862	4862	38.05%	0.381	0.381	0.380	1

For 33 activities, an empty answer set was retrieved; therefore, no soft prediction could be provided. Each prediction output answer set consists of 28 elements on average.

To determine a definite LLT prediction (hard prediction), the statistical most probable successor of the currently performed activity is calculated. Since only one element was selected and only one element is correct, recall and prediction do not differ. This approach can be improved by including the history of the ongoing procedure. In this case, one predecessor is taken into account. Therefore, pairs of sequences of successive activities are formed to determine the successors and their probabilities. Without considering a predecessor for LLT hard prediction, an accuracy of 25.22% was achieved. The accuracy could be increased by 12.8% using one predecessor for probability calculation, which indicates further optimization potentials by using more complex statistical models (e.g. [18]) in combination with the presented ontology-based LLT prediction. For 252 activities, no hard prediction could be provided.

3.4. Phase recognition

During the situation recognition, a LLT is recognized based on the currently used instrument. The identified LLT element is then queried for its current surgical phase and the associated HLT. The normalized confusion matrix is shown in Fig. 12. The most correctly recognized activities are classified in the “Closure” phase. Comparable to the phase prediction, the phases “Approach” and “Discectomy were also classified with high precision and recall (Table 4). Although the “Hemostasis” phase was classified with lower precision and recall, a sufficient phase recognition could be performed for all phases.

The recognition was completed for all 4862 LLTs, and for 3880 activities, the correct phase was classified. This results in an overall accuracy of the phase recognition approach of 79.80%.

3.5. High-Level task recognition

For every recognized LLT, the according HLT is queried. The results of this recognition are presented in the normalized confusion matrix in Fig. 13. Activities, which are mainly characterized by their used medical device, e.g., HLT 11 (Microscopy (procedure)), 14 (Fluoroscopy

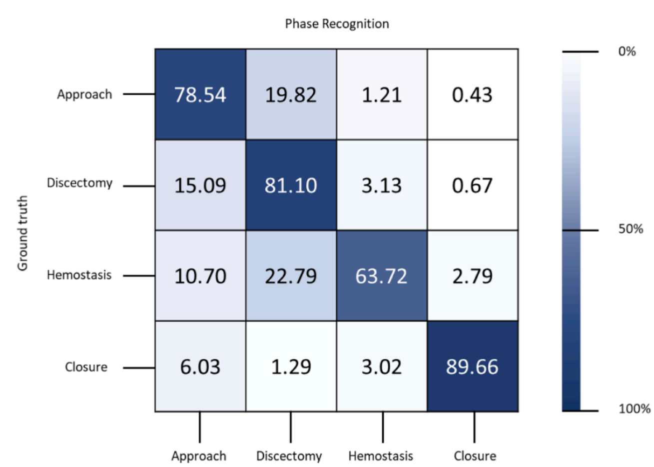

Fig. 12. Normalized confusion matrix of the surgical phase recognition.

Table 4
Results of the surgical phase recognition.

		Correct	All/ Relevant	Precision	Recall	F- measure
Phases	Approach	2005	2553	0.785	0.871	0.826
	Discectomy	1322	1630	0.811	0.702	0.753
	Hemostasis	137	215	0.637	0.588	0.612
	Closure	416	464	0.897	0.937	0.916

(procedure)) and 15 (Irrigation (procedure)), a perfect recognition could be achieved. The classification of HLT 1, 2 and 3 is confused mainly by the treated anatomic structure, which was not part of the recognition input. Due to the same used instruments in the recognized activities, HLT 12 was often confused with HLT 10 (forceps and cotton swab), and HLT 13 was confused with HLT 9 (forceps and needles). HLT 8 represents a surgical complication and was performed only once, while the dura mater has been ruptured. Due to the gSPM transition probability-based recognition, the HLT 8 was not recognized. Except for HLTs 1, 3

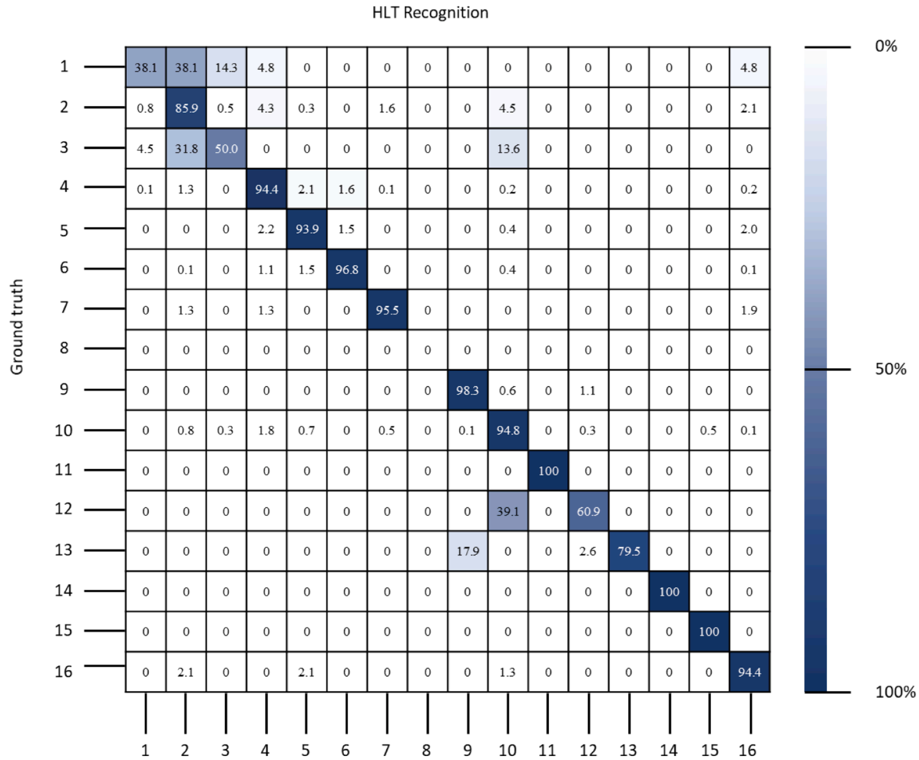

Fig. 13. Normalized confusion matrix of the HLT recognition.

and 8, high precision and recall were achieved for all HLTs (Table 5).

A HLT recognition was made for all 4862 activities from which 4241 could be correctly classified. For 351 LLTs, no recognition was made, resulting in an overall HLT recognition accuracy of 87.23%.

3.6. Low-Level task recognition

The results of the LLT recognition are presented in Table 6. Firstly, the LLT recognition was performed without including the intervention history. With this method, 3378 activities could be correctly recognized based on the currently used instrument. For 252 activities, no recognition was done, which leads to an accuracy of 71.37%. By including one predecessor in the probability calculation, 3512 activities could be correctly classified. For 351 activities, which include start and parallel end activities, no recognition could be made. This method could achieve improved overall accuracy of 74.20%.

4. Discussion

Surgeries of the same intervention type can vary significantly, depending on the skill and experience of the surgeon, patient-specific characteristics, or the occurrence of unexpected events and complications. Although the prediction of forthcoming LLTs is valuable information for implementing context awareness, it is also determined with high uncertainty. Therefore, the main goal of the situation prediction is to reduce this uncertainty by providing a wide range of possible next LLTs (soft prediction) to keep track of the surgical procedure. The achieved recall of 0.886 for LLT soft prediction is considered sufficient for this purpose and the subsequent situation recognition.

In addition, the most probable follow-up activity (hard prediction) is needed for context-aware assistance. The results of the presented prediction approach are sufficient for further developments and applications in the intelligent OR, e.g. for enhanced intervention time prediction or the parameterization of a medical device for a specific

Table 5
Results of the HLT recognition.

ID	SCT ID	SCT Term	Correct	All/Relevant	Precision	Recall	F- measure
1	41447009	Incision of skin (procedure)	8	21	0.381	0.615	0.471
2	363069007	Destructive procedure on subcutaneous tissue (procedure)	323	376	0.859	0.887	0.873
3	699498007	Destruction of tissue of skin (procedure)	11	22	0.500	0.579	0.537
4	239565007	Excision of posterior elements of vertebra (procedure)	825	874	0.944	0.938	0.941
5	231045009	Decompression of spinal nerve root (procedure)	512	545	0.939	0.926	0.933
6	3418002	Discectomy for intervertebral herniated disc. nucleus pulposus (procedure)	727	751	0.968	0.971	0.969
7	363309004	Soft tissue closure (procedure)	147	154	0.955	0.925	0.939
8	112695004	Reparative closure (procedure)	0	0	0.000	0.000	0.000
9	446355000	Suturing of skin and/or subcutaneous tissue (procedure)	173	176	0.983	0.956	0.969
10	51241000	Control of hemorrhage (procedure)	865	912	0.948	0.956	0.952
11	117259009	Microscopy (procedure)	211	211	1.000	1.000	1.000
12	386335003	Infection protection (procedure)	14	23	0.609	0.700	0.651
13	122462000	Drainage procedure (procedure)	31	39	0.795	1.000	0.886
14	44491008	Fluoroscopy (procedure)	36	36	1.000	1.000	1.000
15	67889009	Irrigation (procedure)	137	137	1.000	0.965	0.982
16	122546009	Stretching procedure (procedure)	221	234	0.944	0.891	0.917

Table 6
Results of the LLT recognition.

	Correct	All	Relevant	Accuracy	Precision	Recall	F-measure
LLT Recognition without predecessor	3378	4733	4862	71.37%	0.714	0.695	0.704
LLT Recognition with 1 predecessor	3512	4733	4862	74.20%	0.742	0.722	0.728

upcoming surgical work step. For instance, during lumbar discectomies, the preparation of the fluoroscopic system after the disc removal or the context-sensitive parameterization of the bipolar could be automatically triggered.

The results of the ontology-based situation interpretation performed quite well for these applications in the intelligent OR. To evaluate the required robustness of the presented approach for the application in the real operating room, the recognized activity was used as input instead of the perfect recognition input from workflow data to predict the next LLT, HLT, and phase. Thus, the prediction received a 29% distorted input from the recognition system. It could be shown that the prediction system reacts very robustly to erroneous inputs. A minor decrease in prediction accuracy was found for LLT easy prediction (−0.12%), LLT hard prediction (−0.47%), HLT prediction (−0.93%), and phase prediction (–3.11%) compared to the perfect recognition input.

4.1. Comparison with the state of the art

For *phase recognition***,** Forestier et al. used a decision tree algorithm, which considers the local context of the ongoing surgery [40]. The analysis is based on 21 lumbar discectomy workflow recordings from Leipzig University Hospital. A comparison of the results is shown in Table 7.

In contrast to the ontology-based method, this approach presented by Forestier et al. uses all elements as input sensors (action, instrument, and anatomical structure), which leads to a good F-measure for the approach discectomy, and closure phase. Although only one input sensor is used in the actual study, the results of the phase recognition are comparable with the decision tree approach.

Dergachyova et al. performed a *LLT recognition* analysis with different combinations of input sensors [41]. The LLT recognition based on the instrument as the only input sensor achieved 59.69% accuracy for discectomies performed in Leipzig and 74.89% performed in Rennes. With the presented ontology-based approach, an overall accuracy of 74.20% for both intervention sites was achieved, indicating the reliable performance of the ontological reasoning of missing sensor information. In [41], the best LLT recognition was performed with a sensor combination of instrument and anatomical structure. The actual presented ontological approach could also be improved accordingly if both elements were considered as input sensors for LLT recognition (LLT recognition accuracy of 87.83%).

Franke et al. performed a *LLT prediction* for the same dataset ([63], p. 72) and determined the best estimation hit rate for the next LLT using three different statistical approaches. The best result was obtained with the Adaptive Trace model, which realizes a best prediction rate of 39.45%. This is an improvement of 1.45% compared to the LLT hard prediction with one predecessor performed in this work. The Adaptive Trace Model uses complete sensor information (action, instrument, anatomical structure) and considers the complete surgery history by including all predecessors of the current activity.

Table 7
Phase Recognition in comparison with Forestier et al. [40].

		F-measure (Forestier et al. [40])	F-measure (Neumann et al.)
Phases	Approach	0.896	0.830
	Discectomy	0.810	0.762
	Hemostasis	0.314	0.515
	Closure	0.915	0.742

Compared with the state-of-the-art, the ontology-based approach performed efficiently and achieved adequate results. Although the comparison is limited since different input parameters (all process elements vs only instrument as well as process history vs only one predecessor) were used in the different studies. Nevertheless, equivalent results regarding phase recognition and LLT prediction accuracy could be achieved. Mainly during situation recognition, the missing sensor information (anatomy, action) could be reasoned based on the activity representation provided by the process ontology, which resulted in good recognition results. Thereby, the anatomy information has been abstracted to a higher level if the queried answer set was empty. The ontology's inherent knowledge about anatomies and their hierarchical modeling allows an abstraction of the anatomy (e.g., soft tissue instead of skin or fascia), which leads after a subsequent refinement to a more extensive answer set with valid activity representations. The same applies to the modeled instrument knowledge. If no activity was found in the answer set, which matches the actual input instrument, other instruments with the same functional class (e.g., all cutting instruments) were queried to enlarge the recognition answer set. This approach also enables the easy integration of new instruments into the process representation.

In the presented LLT and HLT prediction, the uncommon tasks are often confused due to the simple underlying statistical model for probability calculation. For the calculation, one predecessor is considered in this study. Increasing the number of predecessors would not necessarily improve the prediction results since activities that have been performed further in the past have an increasingly smaller influence on the current surgical situation [18]. However, a more complex statistical model (e.g., State-Transition-Models, Hidden Markov Chains, Adaptive Trace Models [18]) combined with the presented ontology-based approach could improve the LLT and HLT prediction.

SIO is a reference ontology in which translation rules define how process elements are mapped to SNOMED CT top-level hierarchy to utilize their descendants to represent a specific surgical intervention type (e.g., SIO4Discectomy). In this way, the effort to create large core ontologies and domain ontologies for specific surgical interventions could be reduced. SNOMED CT provides a validated terminology with the additional concepts, relations, and a hierarchical ordering. Since every entity of the workflow data set has a SNOMED CT concept equivalent, the terminology was well suited for the situation recognition and prediction application. In this study, the mapping was performed manually and validated clinically afterward. For future applications and other intervention types, automapping tools such as Snapper:Map [64] could be utilized to reduce the manual effort of the mapping. However, clinical validation is still needed to assess the systems' mapping suggestions.

5. Conclusion

In this work, a surgical process ontology (SIO) was developed to provide a knowledge base for context-aware assistance in the intelligent OR. The knowledge base was applied to a neurosurgical use case (lumbar discectomies) and evaluated for intraoperative situation recognition and prediction. Therefore, a new method for surgical workflow recognition and prediction was presented utilizing ontological reasoning, abstraction, and explication. To the best of our knowledge, this is the first ontological approach of a combined phase, HLT and LLT recognition, based on the information about the currently used instrument as the only input sensor.

Compared with the state-of-the-art, the presented approach performed efficiently, and adequate results were achieved for situation recognition and prediction. Especially, the recognition of phases (79.80%), high-level tasks (87.23%), and low-level tasks (74.20%) achieved sufficient accuracy. Although the prediction accuracy for the surgical phase (76.63%) and high-level tasks (51.15%) is adequate for the intended use case, the low-level task prediction algorithm achieved 25.22% accuracy. The accuracy could be increased by 12.8% (total of 38.05%) using one predecessor activity for probability calculation, which indicates further optimization potentials by applying more complex statistical models in combination with the presented ontology-based prediction.

Integrating SIO into a standardized terminology (SNOMED CT) and an upper-level ontology (GFO) allows formalization and the reuse of the presented concepts. Therefore, the presented reference ontology can be instantiated for different surgical disciplines and intervention types in future applications. In addition, a robust and consistent surgical workflow recognition and prediction were developed, which provides the workflow support and a knowledge base for further applications in the intelligent OR, for instance, context-aware medical device orchestration, (semi-) automatic OR documentation as well as surgical simulation, education, and training.

Statement of Significance

Problem	Well-founded knowledge of the current and upcoming surgical situation is a prerequisite for all intelligent applications and context-aware assistance systems in the intelligent OR.
What is already known	Although different approaches for surgical workflow recognition and prediction have been presented in the literature, the current state-of-the-art is still limited to the availability of the full sensor information (instrument, anatomy, and action).
What this paper adds	In this paper, a new surgical workflow knowledge base was developed, which aims to provide additional knowledge and therefore a deeper understanding of the surgical context. In addition, a first ontology-based approach of a combined phase, high-level task and low-level task recognition solely using the information about the surgical instrument, is presented. A situation prediction based on ontological reasoning, abstraction, and explication is also a new contribution to the research field.

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Availability of data and materials

The SIO4Discectomy ontology and the datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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