Bringing data-driven process analysis into surgical practice – the surgical process analyzer

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Abstract. The growing number of connected medical devices in the operating room, as well as electronic health records, provide valuable data to analyze surgical processes. In this area of surgical data science, i.e. surgical process analysis, is the challenge to combine methods from computer science and statistics with surgical knowledge about processes and data, such as standard operating procedures, surgical guidelines, uncertainty and data quality. We propose to develop a framework, that integrates handling of data, knowledge models and data analysis with an intuitive user interface for data visualization, process analytics and knowledge capturing, which is usable by domain experts such as surgeons. The aim of this so-called "Surgical Process Analyzer" is to bring surgical process analysis into surgical practice, to provide benefit for patients and advance research in surgical data science by addressing real-world use-cases with collaboration of surgeons and data scientists.

Keywords: Surgery, Process Analysis, Knowledge Modeling,

1 Background

Surgical process modeling is an established field of research. Modeling and subsequent analysis mainly focus on the surgical procedure itself and e.g. objective measurements of surgical skills [1], surgical approaches in different centers [2] and the optimal integration of assistance systems [3]. Furthermore, data from connected medical devices in the operating room has been proven to provide insights into surgical phases [4] that can be used to optimize logistics in the operating room by predicting the duration of a surgical procedure [5]. Another field is clinical pathways, in which computer interpretable guidelines lay the foundation for context-aware decision support [6] and data from electronic health records can be used to perform process mining on treatment procedures [7].

adfa, p. 1, 2011.

However, existing approaches on process analysis in surgery are mostly limited to fundamental research on algorithms for specific methodological challenges. The adoption of successfully developed methods for process analysis by surgeons is limited by their usability for non-data-scientists. On the other hand, the models of procedures, data, guidelines etc. used by data scientists are often developed within specific research projects by single surgeons and are not the result of a discussion in the surgical community about standards in surgical processes.

2 Surgical Process Analyzer

2.1 Aim & Overview

The aim of our work is to develop a surgical process analyzer (SPA), to bring surgical process analysis into surgical practice and thereby advance research in this area of surgical data science into the surgical research community.
SPA is a framework in which surgeons can easily capture their knowledge about processes in meaningful models, handle their data, analyze their processes and visualize the results. The framework should allow data scientist to develop new methods for surgical process analysis that can quickly be adopted by surgeons analyzing their processes. Figure 1 illustrates an overview of the required components.
The following sections describe the requirements for these components and propose a first draft that tackles identified issues. The proposed draft is open for discussion and comments by experts from multiple domains during the surgical data science workshop.

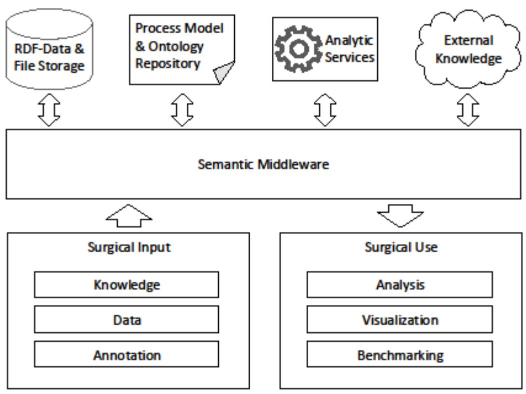

Figure 1- Surgical Process Analyzer: Overview of the components

2.2 Semantic Middleware

The SPA requires a semantic middleware as its core component. Its purpose is a seamless collection, exchange, access and distribution of knowledge and data between surgeons and surgical data scientists. The integration of novel components, like e.g. analytic modules, can be performed without changing user interface or data handling.
For this component we use Semantic MediaMiki (SMW) [8]. SMW is a semantic extension for MediaWiki. It is a web-based knowledge management system and thus allows a distributed and collaborative work. Moreover, it can easily be extended to incorporate new ontologies and analytic services.

2.3 Surgical Input

The surgical input to the SPA comprises knowledge, data and annotations. Knowledge about surgical processes can be obtained from textbooks, publications or surgical practice. Data about processes can be taken from surgical sensors in the operating room, such as light, table or electric sealing devices. Electronic health records of patients can provide information about surgical events along the treatment process (operation, diagnostics, hospital stay etc.). Annotations use the models stored in the SPA (sf. Process model & ontology repository) to provide descriptions to non-machine-interpretable data, like e.g. surgical process steps to sensor data or endoscopic video streams.
Besides providing a database connection by the SPA, we also suggest an interface for common known formats like spreadsheet format. As a result, the SPA allows among others uploading structured spreadsheet data and (semi-) automatically mapping it to the existing data model of the SPA.

2.4 RDF-Data & File Storage

The SPA enables to store structured and unstructured data. Whereas medical devices and electronic health records mainly offer structured data, there is also unstructured data available such as surgical videos and operation reports.
To tackle this heterogeneity, we propose to use a RDF-triplestore for the structured data and annotations of the unstructured data. Thus the former unstructured data can be used for analyzing purposes. Therefore, the RDF-triplestore stores interlinks and semantic enrichments of structured and unstructured data. We will follow the LinkedData principles[1] to avoid of having an unbounded web and provide useful data by looking up the URIs.

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[1] https://www.w3.org/DesignIssues/LinkedData.html

2.5 Process Model & Ontology Repository

One advantage of the SPA is the incorporation of surgical knowledge into process analysis. To use this knowledge, formal descriptions of processes have to be stored in a machine-interpretable way that also adheres modeling standards such as the Business Process Model and Notation (BPMN) [9]. Thereby, we will integrate modeling standards such as BPMN with ontologies which allows to infer new knowledge. Thus, the formally entered knowledge and inferred knowledge is available for advanced process analytics.

To model BPMN in SMW, we integrated a graphical BPMN-editor into SMW. Besides this editor, SMW provides light-weight semantics to model ontologies and the possibility to import existing ontologies. Thus, SMW can be used for collaborative process modeling and semantic annotations of process models in conjunction with ontologies available in the SPA. Therefore, we can import and use existing ontologies, developed by the Semantic Web community and use this knowledge in describing processes [10].

2.6 Analytic Services

Powerful analytic services are the main benefit of the SPA. Numerous algorithms already exist for different applications within surgery such as process compliance for quality assessment [11], prediction of treatment process steps [12] and process similarity [13].

Hence, we will determine existing and important analytic algorithms and provide them as cognitive and reusable services, which can be used by the users to analyze the data. [14]

Furthermore, we argue that surgeons should be able to choose whether the analysis is performed via the web or locally to ensure data privacy. For this purpose, we enable the use of locally deployed machine learning tools like e.g. weka. [15].

2.7 External Knowledge

SPA should be able to integrate external knowledge sources. This does include standards, ontologies etc. Moreover, if surgical process analysis will be adopted by the surgical community, it can be used for external benchmarking by comparing own process analysis results to other surgeons or centers all over the world. However, data security and privacy remains an important issue.

2.8 Surgical Use

We are convinced that surgical data science in general, and surgical process analysis in particular, need a commitment from data scientists and surgeons alike. Patients benefit if new methods and tools are applied to real world surgical use cases. Therefore, the use of the SPA by the surgical community is of utmost importance. On this platform, surgeons will not only be able to analyze their processes, but also demand advanced visualizations of data for interpretation. Moreover, if external knowledge from other surgeons can be incorporated, SPA can become a valuable tool for benchmarking in everyday surgical practice.

3 Conclusion

We described our aim of developing a surgical process analyzer, which brings surgical process analysis into surgical practice. The abovementioned components are separate fields of research, but have to be combined to powerful tools that can be used by surgeons. Major challenges include the widespread agreement on a shared middleware to exchange components, work on standardizations of ontology and process models and building a surgical user base that contributes domain knowledge, data and use-cases.

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