Surgical Data Science, An Emerging Field of Medicine

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***Abstract*—Computer Assisted Surgery (CAS) significantly changed the course of interventional medicine. The development of medical imaging opened up the possibility for accurate, patient specific planning, and advanced imaging techniques provided the ground for the development of real-time navigation systems. The advancement of minimally invasive surgical techniques and tools required increasing manuality from the surgeon, which facilitated the development of tele-robotic manipulation. These systems provide a vast amount of objective inta-operative data, thus many believe that the next step could be big data analysis for creating and evaluating surgical process models. This emerging field of medicine, called Surgical Data Science, has the potential to improve intervetional medicine with objective statistical analysis, and therefore to provide better patient outcomes and a reduction in healthcare costs.**

***Index Terms*—Computer Assisted Surgery; Big Data Analysis; Surgical Process Model; Surgical Data Science**

I. Introduction

Traditionally, medicine is considered as a highly hierarchal profession, where decision is mainly based on individual experience, rather than objective measurements. With evidence-based medicine gaining increasing attention in many domains, this approach has already changed several fields of medicine (for example pharmacology and internal medicine) [1].
The same applies to surgery: large scale data from heterogenous sources is becoming available. These include: Electronic Health Record (EHR) systems, digital medical imaging (e.g. Computer Tomography, Ultrasound), computer assisted surgical systems etc. While these data sources are rich in information, they are generally unstructured, therefore they rarely get integrated directly into the surgical workflow. Surgical Data Science (SDS), promises to extract knowledge from these inputs, and provide objective measures, linking treatment decisions to medical evidence. To achieve this goal, SDS aims at creating a framework where data collection, analysis and modelling are linked in a common architecture providing real-time performance feedback to the intervention [2].
Even though many insurance organizations and hospitals require an increasing amount of documentation on medical interventions, patient related data is rarely stored in a structured, processable repository [3]. To overcome this obstacle SDS strongly builds on other data-intensive disciplines, such as data-mining, information theory and statistics, and in general,

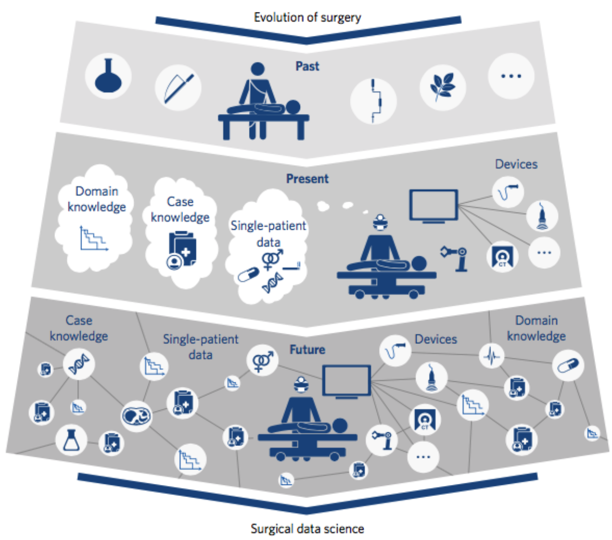

Fig. 1. The development of surgery started with the physician relying on in-situ knowledge, and simple tools. Computer Integrated Surgery means, today the available information and instrumentation vastly improved, however the outcome is still dependent on the surgeon's domain knowledge and experience. As next step forward, surgery will become automated in many areas. Patient specific, objective, optimized care will be delivered using Surgical Data Science techniques [2].

follows suit to the trends of industry eventually creating a collaborative, context sensitive environment based on continuous real-time data enabling Surgery 4.0 [4]. With the gathered information SDS enables technologies like smart ORs (employing context aware systems), surgical robotics, decision support systems, speech recognition for OR manipulation [5]. Eventually, improving the human computer interface during surgery will streamline the surgical procedure reducing the cost and improving the outcome of surgeries.
In this article, we give an overview of SDS and its most promising applications. This review is based on online databases (Google Scholar, Medline, Scopus) searched with the keyword: "Surgical Data Science". The search yielded 33 results, from which 2 hits were discarded due to duplications and 6 hits due to irrelevance to the field of SDS.

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II. Surgical Process Modeling

Surgical Process (SP) is a term, representing the interventional course realising a surgical goal, for example a specific laparoscopic cholecystectomy procedure to remove the gallbladder. The model of this process is called a Surgical Process Model (SPM), where the model is often represented in a formal or semi-formal manner, focusing on predefined interests [6]. The tool of workflow analysis was originally developed for business applications, and only later applied to the surgical field, where it have been shown to increase safety and efficiency [7].

SPMs can originate either from general concepts being applied to the individual pathology (top down approach), or by analyzing measurement data from surgeries, leading to a generalized concept (bottom up approach).

A. Top-down approach

The top down approach, what is considered as the traditional way of surgical procedure planning, is based on clinical guidelines and textbooks describing only the very high level concepts of the procedure. With this method, the surgeon's background knowledge will lead to the patient-specific execution of the surgical plan [8]. In the work presented by Munchenberg et al., a system was developed for the preoperative planning and execution of neurosurgical procedures. They employed a haptic interface to interact directly with the patient data, and robotically execute the planned trajectories, using a neurosurgical manipulator [9]. One of the main advantages to the top-down approach is that it is capable of identifying different granularity levels, and accurately describing the surgery with the required detail [10]. While this method is a natural way of representing general knowledge, and is easily understandable for human readers, as the procedure is usually captured by human observers, this representation rarely provide high-level detail about the individual surgeries.

B. Bottom-up approach

The motivation for examining a bottom-up approach comes from the realization that the above mentioned processes, while capable of representing a reliable surgical plan, the generalized levels are not feasible to be used for quantification. As Neumuth et al. [11] showed, it is possible to create accurate live recordings of surgeries on a detailed, high granularity level. These results showed that the acquired SPM is accurate and reproducible, where the recorded individual SPMs (iSPM) could be used as a basis for process mining techniques. Such techniques were already available, mainly developed for event logs in support of business process model development [12], [13]. Because of several parallel tracks running simultaniously during surgeries, these techniques could not be directly applied to SPMs, and therefore a more generic approach was developed, where the generalized SPM (gSPM) is created using statistical means of the acquired iSPMs [14]. This proved to provide reliable results even when using only 50 iSPMs. In the future, gSPMs could be used as a metric to compare to recorded iSPMs and investigate where and why the iSPM deviated from the gSPM, gaining valuable knowledge on adverse events, surgical skill. It can be used to estimate operational costs and to compare benefits of different surgical approaches.

III. Ontology

While SPMs do organize the acquired data, they do not necessarily build from a machine readable universal dictionary. For many areas of medicine, international healthcare-terminology standards for biomedical data science already exists. These standards are organized into ontologies, such as the Foundational Model of Anatomy [15], Gene Ontology [16] and SNOMED-CT [17]. While these dictionaries do describe the medical background, they do not provide a dictionary for describing interventional medicine. To achieve this goal the OntoSPM international group was formed. The ontology developed by this group (also called OntoSPM) is based on the Basic Formal Ontology (BFO) upper ontology [18], and provides a connection to more specified ontologies, such as LapOntoSPM [19], [20].

IV. SDS in the operating theater

Modern Computer Integrated Surgery (CIS) systems provide detailed measurements on the surgical process, however, the data available from the operating computers—for most cases—is not captured. By providing a framework for recording, storing and annotating such information (e.g. in the form of SPMs built on Ontologies) SDS provides the ground for a wide variety of clinical applications [21].

A. Context-aware automation and assistance

The development of CIS started with the development of digital medical imaging, which provided the basis for preoperative planning. These plans could then be used as a model for task execution on robotic platforms, where the robot uses a variety of sensors to update the model to accurately represent the affected anatomical structures. Results from the surgery could be recorded and could directly feed back into a central database to further improve preoperative planning [22]. This concept provides the basis for CIS and is summarized on Fig. 2. One of the major challenges in CIS is the integration of automated procedures into the surgical workflow. Automated workflow monitoring, would allow the development of automated surgical assist systems, and could streamline the surgical process. Such a system was integrated into to the low-level control architecture of the ROBODOC [23], but today—mostly because of legal issues—newly developed robotic platforms rarely incorporate such level of autonomy. The use of SPMs could provide a platform, where subtask automation—under the supervision of the surgeon—could be integrated into the surgical procedure, freeing up human assistance during the surgery, eventually lowering healthcare costs. Such application needs to observe the surgical scene, and detect the surgical phases autonomously. To facilitate the development of such applications, both robotic challenges and testing datasets have been presented [24], [25]. On these datasets several

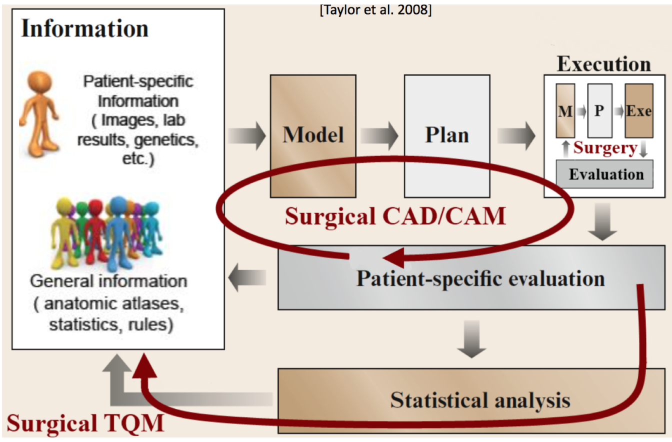

Fig. 2. The concept of Computer Integrated Surgery (CIS) [38] With digital, patient specific data (e.g. X-ray imaging, Ultrasound, MR, CT) available, surgeons can create detailed pre-operative surgical plans. As these devices are becoming more portable, it is possible to integrate them into the OR. Intra-operative imaging then allows for on the fly re-planning of the procedure. After the procedure, the collected data can be used for statistical analysis, providing information on surgical performance. CAD: Computer-Aided Design CAM: Computer-Aided Manufacturing TQM: Total Quality Management

applications have been developed: for organ [26] and tissue classification [27], [28], as well as for tool recognition [29]. Recently several surgical phase detection algorithms have been presented using Random Forests (RF), Hidden Markov Models (HMM) and deep neural networks [30], [31], [32]. Using the da Vinci Research kit [33], [34], it has been shown in a clinical environment that subtask automation is feasible [35], and SPMs were used to integrate automated robotic intraoperative imaging [36]. Another aspect of workflow monitoring is OR workflow scheduling [37]. Since OR time is one of the most expensive resource of the hospital, by monitoring the workflow, it becomes possible to predict the duration of the surgery, as well as optimizing future procedure plans [14].

B. Decision Support Systems

One of the main reasons behind the surgical practice being authority based is that more experienced surgeons have a broader understanding of the importance of individual variations in pathology. While experience probably won't be substituted soon, machine learning can process a large amount of pre-recorded data, providing the operating surgeon with decision support, bridging the experience gap, eventually improving patient outcomes. Such systems could also raise attention on areas of patient care, which are generally outside of the surgeon's focus. SDSs analyzing these "unconventional" correlations, could point out important surgical consequences regarding the full record of the patient-care pathway [39].

C. Surgical Training

Decision support can not only improve in operation results, but trough simulation, it can play an important role in the education as well [40]. For example, theorem-based semantic reasoning have been used to create a simulation system which is flexible, automated and therefore enables patient-specific scenarios for surgery assistance [41], [42]. Another simulation framework used semantic data to implement a cognitive system which autonomously interacts with ontological knowledge bases and creates individual surgical scenarios [43].
During these simulations, monitoring the workflow of training sessions provides important data on surgical skill and on the individual surgeon's technique [44]. On the low-level (gestures) it has been shown that fine-motor skills correlate with indecisiveness of the surgeon [45], while task level assessment can be used for both skill evaluation and for designing individual training curriculas [46], [47], [48].

V. Discussion

Surgical Data Science uses input data from the whole duration of the surgical process and medical care, including the initial symptoms and the long-term outcomes. This approach to surgical interventions require the acquisition and analysis of heterogeneous, multimodal data, which can only be managed if a common framework is developed. This framework can later be used in a multitude of applications including radiation protection planning for interventions [49], analysis software to estimate real-time hypoxemia risk [50], but eventually leads to systems capable of semantically annotating surgical data, performing semantic reasoning and eventually creating context-aware surgical assistance [51]. Ontological knowledge representation shows promising results in this area, however a global framework accepted by professionals and the industry is not available yet. This scale of data collection also raises privacy and confidentiality issues, which requires careful consideration.
SDS is a rapidly developing interdisciplinary field of medicine. While it might seam that development done outside medicine—computer-science and engineering—might solved some of the difficulties in data science, it is challenging to apply those solutions into the surgical field. As this area requires in-depth knowledge of both computer-science and medicine, it seams unavoidable that a new specialty should develop in this field for both academic research and hospital data collection and analysis [52].

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