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REVIEW ARTICLE

Surgical process modelling: a review

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Abstract
Purpose Surgery is continuously subject to technological and medical innovations that are transforming daily surgical routines. In order to gain a better understanding and description of surgeries, the field of surgical process modelling (SPM) has recently emerged. The challenge is to support surgery through the quantitative analysis and understanding of operating room activities. Related surgical process models can then be introduced into a new generation of computer-assisted surgery systems.
Methods In this paper, we present a review of the literature dealing with SPM. This methodological review was obtained from a search using Google Scholar on the specific keywords: “surgical process analysis”, “surgical process model” and “surgical workflow analysis”.
Results This paper gives an overview of current approaches in the field that study the procedural aspects of surgery. We propose a classification of the domain that helps to summarise and describe the most important components of each paper we have reviewed, i.e., acquisition, modelling, analysis, application and validation/evaluation. These five aspects are presented independently along with an exhaustive list of their possible instantiations taken from the studied publications.
Conclusion This review allows a greater understanding of the SPM field to be gained and introduces future related prospects.

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Introduction

Context

In recent years, due to progress in Information Technology fields, computer assistance has been developed in healthcare systems. The operating room (OR), in particular, has undergone significant transformations evolving into a highly complex and technologically rich environment. Computer-assisted surgery (CAS) (or computer-assisted intervention (CAI)) systems have now a vital role to play in current surgical performance. For instance, during surgical planning, CAS and image-guided surgical systems provide access to multi-modal imaging technologies, and relevant information about the patient. During surgery, they provide visualisation to pre- and intra-operative information about the patient with respect to the operative field, and also provide passive or active robotic support. New issues and technological challenges related to this complex OR and CAS systems have been discussed by Cleary et al. [1] or Rattner and Park [2].

This first generation of CAS systems mainly focused on providing the surgeon with access to medical information of the patient before and during surgery, and active or semi-active robotic assistance. It was, however, outlined that such assistance would be different according to the surgical task, due to different needs and levels of importance. There was also an increasing need for new tools providing better resource management in the OR. For instance, surgeons need to be freed from technical problems through the automatic handling of software and hardware tools. These requirements illustrate the main motivation for surgical procedures models. The need for dedicated model-based systems for surgical procedures was first outlined for creating surgical simulation systems [3,4]. The idea of describing the surgical procedure as a sequence of tasks was first introduced for analysis purposes in minimally invasive surgeries (MIS) [5], as well as for surgical planning and intra-operative image management [6] and for robotics systems [7].

Following progress in model-based surgical intervention systems, understanding of the surgical scenario was proposed to improve the management of CAS systems. Jannin et al. [8] defined the term *surgical model* as "generic or patient-specific surgical procedures that workflows aim to automate". In their work, they stated that model-based systems of surgical interventions must address behavioural, anatomical and pathological aspects as well as integrate information about surgical instruments that can be used with *a priori* knowledge for the development of the OR of the future. The term *surgical workflow* has been defined as "the automation of a business process in the surgical management of patients, in whole or part, during which documents, information, images or tasks are passed from one participant to another for action, according to a set of procedural rules" [9]. The term surgical process (SP) has been defined as "a set of one or more linked procedures or activities that collectively realise a surgical objective within the context of an organisational structure" [10]. This term is generally used to describe the steps involved in a surgical procedure. A surgical process model (SPM) has been defined as "a simplified pattern of an SP that reflects a predefined subset of interest of the SP in a formal or semi-formal representation" [10]. SPMs were first introduced for supporting surgical intervention using a model of surgical progress. Indeed, the precondition for computer-supported surgical intervention is the specification of the course model describing the operation to be performed. Being able to identify information such as activities, steps or adverse events within a surgical intervention and having the possibility of relying on a surgical model is therefore a powerful tool in helping surgeons. The use of SPMs may prove effective in facilitating the surgical decision-making process as well as surgical teaching and assessment, thereby having a direct impact on patient safety. It could help in anticipating patient positioning, optimising operating time or analysing technical requirements. In light of the growing interest in this field, and for the first time, we propose in this paper to undertake a methodological review of the literature focusing on the creation and the analysis of SPMs.

Search methodology

The review was carried out using Google Scholar to search on the specific keywords: "surgical process model", "surgical process analysis" and "surgical workflow analysis". In addition to the Google Scholar results, we added another list of possible citations that were taken from the references of the first set of selected publications. We included articles published in peer-reviewed journals as well as full papers published in major international conference proceedings that dealt with the use of SPMs. International conference proceedings were included since the field is very recent, resulting in more conference publications than peer-reviewed journals. Only English language publications were selected. The research included was published between 2002 and end of 2012. In order to achieve an overview of the publications related to the creation and analysis of SPMs, we focused on publications which aimed to study the procedural dimension of surgery. The first inclusion criteria used during the selection process was therefore the fact that works have to take into account the sequential aspect of the surgical procedure, i.e., study the duration and sequencing of tasks performed during the surgery. Moreover, we were interested in pieces of work that focused at least one part of their analysis on the act of surgery, beginning when the surgeon performs the first task on the patient and ending when the surgeon makes the suture. It was defined as the second inclusion criteria. The focus was therefore on the surgery, and anaesthesia studies were not included in this review (for detailed explanation of similar works not included into the study, please refer to Sect. 3.). When a project has been published several times with no change in the dedicated elements of the diagram, the journal publication and if none, the most recent conference paper has been used. The entire selection process is shown on Fig. 1. From an initial selection of $N = 272$ publications, a total of $N = 46$ publications were finally selected for full-text review.

Figure 2 shows the Google Scholar results before the selection process only. We can see that the SPM creation and analysis field is very recent. It has evolved in particular from 2007, evidence of the recent evolution of the field.

SPM taxonomy

In order to clarify the review and the discussions, we propose a model for describing and classifying the methods using five components and their corresponding elements (Fig. 3). Each of the five components addresses one major aspect of the SPM methodology, and every element that results can be instantiated with its set of possible values. The first component is the modelling, i.e., what is studied and is modelled, where the goal is to describe and formalise the work domain.

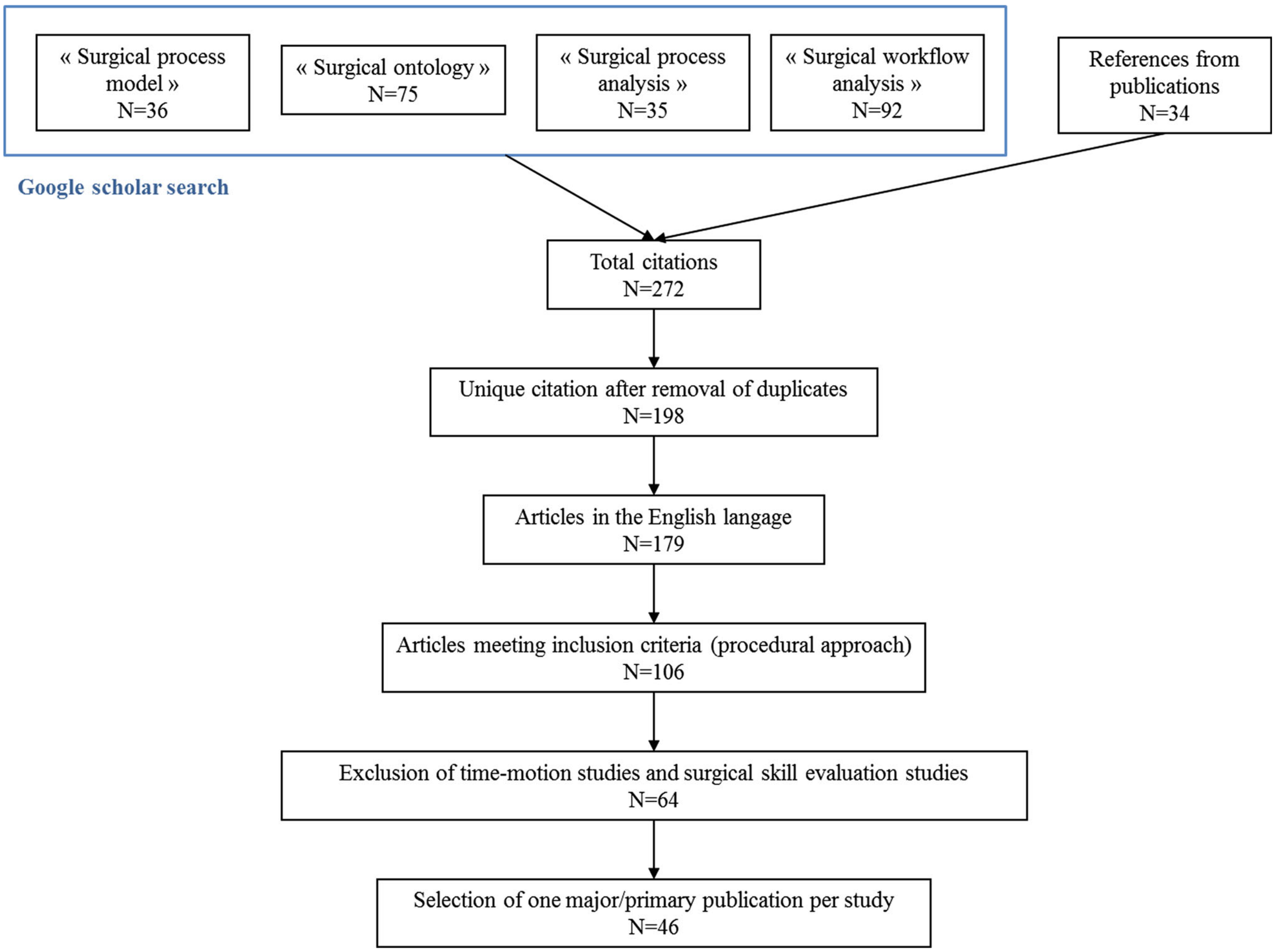

Fig. 1 Process used in the selection of publications for full-text review

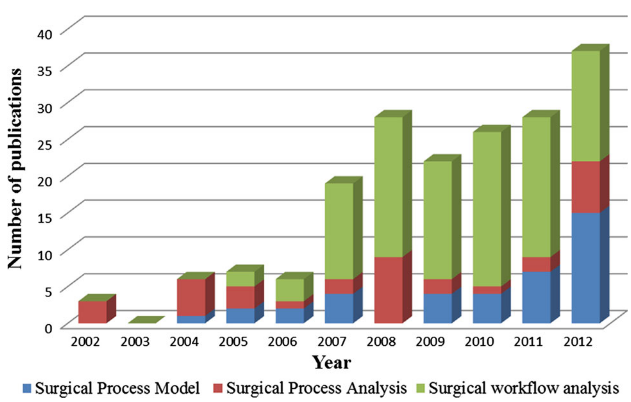

Fig. 2 Evolution of the number of papers in the field from 2002 to December 2012

The second component is the data acquisition performed by human observations or by sensor systems. The third is the analysis that tries to make the link between the acquired data and the information that we want to model. Another component specifies the different applications of the systems based on SPMs and finally, the last component describes the different kind of validation and evaluation studies that were conducted for assessing these systems. The whole review is organised according to diagram of Fig. 3. In the following subsections, each part of the diagram is explained in detail.

Granularity level

The whole SPM methodology, and especially the acquisition and modelling components, is organised around the concept of granularity level. A granularity level is defined as the level of abstraction at which the surgical procedure is described. MacKenzie's group [5,11,12] proposed a model of the surgical procedure that consists of different levels of granularity: the procedure, the step, the substep, the task, the subtask and the motion. Each (sub)task can for instance be broken down into various motions and forces primitives. They then used a hierarchical decomposition to structure the complex environment and the interaction between the surgical team and new technologies. Because of the marked differences in the

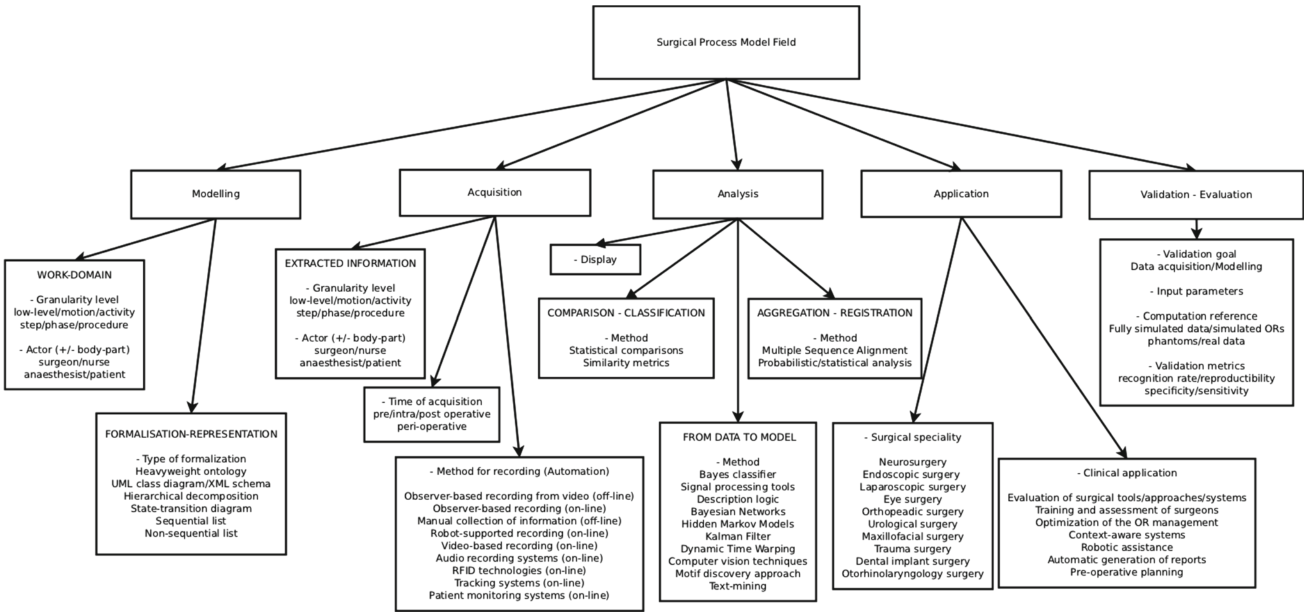

Fig. 3 General overview of the field

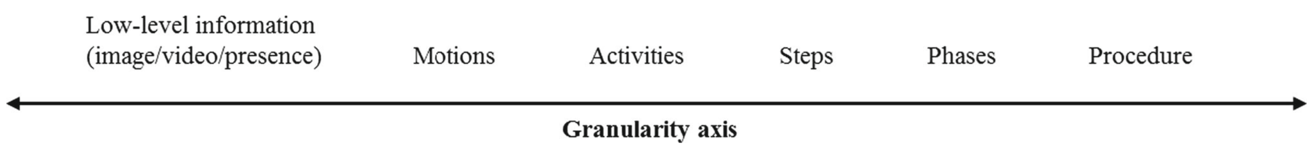

Fig. 4 Different levels of granularity of a surgical procedure

terminology used in the papers studied, in this paper, we will use the following terminology for describing the different granularity levels of surgical procedures (Fig. 4). The highest level is the procedure itself. The procedure is composed of a list of phases. A **phase** is similar to the notion of Lo et al.'s [13] surgical episode, defined as the major types of events occurring during surgery. Each phase is composed of several steps. A **step** is considered to be a sequence of activities used to achieve a surgical objective.

A step has been often called "task" in the literature. An **activity** is defined as a physical task. This level appears to be identical to a surgeme, previously defined as a well-defined surgical motion unit [14]. Each activity is composed of a list of motions. The **motion** can be considered to be a surgical task involving only one hand trajectory but with no semantics. One assumption is that each granularity level describes the surgical procedure as a sequential list of events, except for the surgical procedure itself and for lower levels where information may be continuous.

Modelling

This first component describes and explains the work domain of the modelling, i.e., what is studied and what is modelled. Two elements are crucial for identifying the work domain: (1) the granularity level at which the surgical procedure is studied and (2) the operator(s) involved in the surgical procedure on whom the study will focus. A third element can be added is (3) formalisation. In many cases, a formalisation phase is required for representing the knowledge collected before the analysis process can take place. Knowledge acquisition is part of the underlying methodology of this component. It is the process of extracting, structuring and organising knowledge from human experts.

Granularity level

Information that is studied (i.e. information that is modelled) is laid out on the granularity level axis defined in Fig. 4. Investigations have concentrated on the activity level, but all granularity levels have been studied. At the highest level, the global procedure has been studied [15–18], as well as the phases [13,19–30], the steps [8,9,31–36] and the motions [14,37,38]. Some studies integrated two or more of these granularity levels in their modelling [5,7,12,18,39,40]. No low-level information has been considered here.

Operator

The information that is studied involves one or more of the actors of the surgery: the operator studied may be the surgeon,

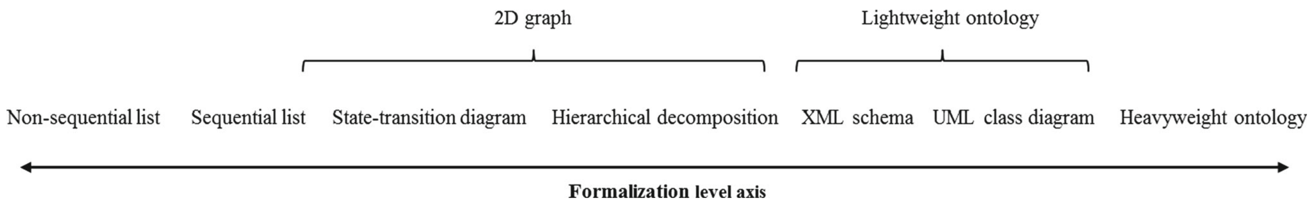

Fig. 5 Different levels of formalisation of the surgery

the nurse, the anaesthetist, the patient or several of these operators.

Formalisation

Formalisation is necessary for allowing automated handling and processing by computers. It is also necessary for bottom-up approaches to have a representation of the sequence of surgery through ontologies or a simple list of phases/steps/activities. At the highest level, we find the heavyweight ontologies, which have been used to represent the detailed context of a SPM study [21,33,36,39,41,42]. A heavyweight ontology is a lightweight ontology, i.e., an ontology based on a hierarchy of concepts and relations, enriched with axioms used to fix the semantic interpretation of concepts and relations. Then, in the category of lightweight ontologies, we find UML class diagrams and/or XML schemas [8,9,43,44]. Both approaches define entities and the relation between these entities. We then find all 2D graph representations, which have been used mostly with hierarchical decompositions, state transition diagrams and non-oriented graphs. Lastly, at the lower level, simple sequential [16–20,22,24,25,29,45] or non-sequential lists [14,37,38] were also used, suggesting a list of words for representing one or many levels of the surgery's granularity (Fig. 5).

Data acquisition

The second component of the diagram, which is also the first step towards the creation of an SPM, is data acquisition, i.e., the collection of data on which the models are built. Four main elements may be distinguished in the acquisition process: (1) the level of granularity of the surgical information that is extracted, (2) the operator(s) on which the information is extracted, (3) the time when the acquisition is performed and (4) the recording method. This section is divided according to these four elements.

Granularity level

Like the Modelling component, the level of granularity of the surgical information that is extracted allows the acquisition to be characterised, as it determines in how much detail the SP is recorded. Studies have focused on the recording of the entire procedure [17], of the phases [28], of the steps [25,33,39], of the activities [43,46–51] and of the motions [52]. But efforts have been made in particular on extracting low-level information from the OR: videos [13,15,22,23,31,41,53,54], audio, position data [21,34,42], hand/tool/surgical staff trajectories [12,14,24,37,38,40,55], information about the presence/absence of surgical tools [19,25,32] or vital signs [18]. Several elements of this low-level information can also be combined [16,20,26,27,29,30,36,45].

Operator

Surgery always directly involves several operators. All staff members can have an impact on surgery and their roles and actions can be studied: the nurse [40,55] for trajectory data extraction and the patient [7–9,16–18,45] for images or vital signs extraction. Overall studies of the entire surgical staff have also been proposed [15–17,24,28,29,33,35,45], where the surgeon, the nurses and possibly the anaesthetist were included. For tracking systems, this notion can be specified by defining, in addition to the operator, parts of the human body involved such as the hand, eye, forehead, wrist, elbow and shoulder.

Time of acquisition

The precise time of the data acquisition is also a vital piece of information for discriminating acquisition techniques. In most of the studies, data are extracted from intra-operative recordings. In some studies, this was done post-operatively (*retrospective*). In the case of the manual collection of information, this is done pre-operatively (*prospective*). Additionally, the term peri-operative generally refers to the three phases of surgery. Some acquisitions include all of these three phases to obtain information about the entire patient hospitalisation process [17,45].

Recording methods

Two main approaches have been proposed: observer-based and sensor-based approaches (Table 1). Observer-based approaches are performed by a human observer. For off-line recording, the observer uses one or multiple videos from the OR to record retrospectively the surgical procedure [5,12,

Table 1 List of possible data acquisition methods

Observer-based approaches			Sensor-based approaches					
Observer-based recording from video (off-line)	Observer-based recording (on-line)	Manual collection of information (off-line)	Robot-supported recording (on-line)	Video-based recording (on-line)	Patient monitoring systems (on-line)	RFID technologies (on-line)	Tracking systems (on-line)	Audio recording systems (on-line)

19,25,32,33,35–37]. For on-line recording, the observer is directly in the OR during the intervention [44,46–48,50,51]. Lemke et al. [35] first highlighted the importance of studying OR processes using on-line observer-based approaches to study both ergonomic and health economic aspects. The principle is to extract information from the OR using one or multiple sensors in an automatic way, and to recognise activities or events based on these signals. Sensors can be of different types, ranging from electrical to optical systems. In the beginning, studies used sensors based on Radio Frequency IDentification (RFID) technologies, directly positioned on instruments or on the surgical staff during the intervention, to detect the presence/absence of the tools or actors [45,56]. Then, efforts were made to use robot-supported recording [7,14,34,52], including surgeon's movements and the use of instruments. Robots have been used as a tool for automatic low-level information recording. Tracking systems [20,21,24,30,37,38,40,42,55] have also been used in various studies; mainly through eye-gaze tracking systems positioned on surgeons or through staff member tracking devices. Other types of methods have also been tested for recording information: patient monitoring systems [16–18,45] and audio recording systems [29,45]. Finally, the use of on-line video-based recording, sometimes combined with other data acquisition techniques, has especially received increased attention [13,15,16,20,22,23,26,29,31,41,54], with either wide-angle video camera recording the entire OR or surgical video camera such as endoscopic or surgical microscope videos.

Analysis

Analysis methods can be divided into three types: methods that go from data to final model, methods that aggregate or fuse information and methods that classify or compare data to extract a specific parameter. The three approaches are presented in the following subsections. Additionally, methods for displaying the analysis results have been studied to obtain a visual representation after the analysis process.

From data to model

The challenge here is to use the data collected during the acquisition process to create an individual model (i.e. iSPM) and to make the link between the acquisition process and the modelling. Top-down approaches are defined as analyses that start from a global overview of the intervention using patient-specific information and a description of high-level tasks (such as phases or steps) to fine-coarse details (such as activities or motions). Conversely, bottom-up approaches use as their input low-level information from sensor devices and try to extract high-level semantic information. The methodology employed for either bridging the semantic gap in the case of bottom-up approaches or to generalise and formalise individual recordings in the case of top-down approaches is based on statistical or data mining concepts. One issue is to determine whether or not the model needs a training step. This step is needed for assigning classes to the training set. In such cases, the creation of the model is not fully automatic and may be entirely manual or a mix between human intervention and automatic computation.

As part of supervised approaches, simple Bayes classifier with Linear Discriminant Analysis [14] and neural networks [38] have been tested in the case of activity/step/phase recognition. Signal processing tools have been used for analysing patient vital signs [16,18] or audio recordings [29]. In the case of *top-down analysis*, description logic has been tested [21,33,35,39,42], as well as model instantiation [8], decision tree [9], inference engine [36] or workflow engine [28]. In the case of *bottom-up analysis*, graphical probabilistic models have often been used to describe dependencies between observations. Bayesian networks (BN) have recently proven to be of great interest for such applications, with an extension in the temporal domain using Dynamic BNs (DBN). Temporal modelling allows the duration of each step and of the entire process during its execution to be evaluated. Many time series models, such as Hidden Markov Models (HMM) or Kalman filter models, are particular examples of DBNs. Indeed, HMM, which are statistical models used for modelling non-stationary vector times series, have been widely used in SPM analysis [15,31,32]. The dynamic time warping (DTW) algorithm has also been often tested with success because of its ability to precisely wrap time series [19,26]. Computer vision techniques have also been used for extracting high-level information before using supervised approaches such as neural networks [20], Support Vector Machines (Support Vector Machines) [22], Bayesian networks [26], HMMs/DTW [23,26,27,54] or Linear Dynamical System, spatio-temporal features and multiple kernel learning (Haro et al. 2012). Computer vision techniques have also been mixed with description logic [41]. SVMs have been employed before the use of time series analysis [15]. Statistical analysis [45], sequential analysis [7,34,52], trajectories data mining [24], times automata [40] or model checking [55] have also been used. Dealing with heterogeneous sources, a multi-objective Bayesian framework has finally been implemented for feature selection, and supervised classifiers were then launched [30].

As part of unsupervised approaches, no extensive work has been undertaken. Only a motif discovery approach has been used [37] that does not need any *a priori* model.

Finally, an SPM whose data acquisition and modelling stay at the same level of granularity is also possible. In such cases, the goal of the analysis is not to create a real model, but to perform either aggregation/fusion or comparison/classification.

Aggregation–fusion

The goal here is to create a global (i.e. generic) model (gSPM) of a specific procedure representing a population of surgical procedures by merging a set of SPMs. One possibility is to merge similar sequences as well as filter infrequent ones to create average SPs in order to obtain a global overview of the surgery. Another is to create gSPMs that represent all possible transitions within SPs. A synchronisation stage may be necessary for both approaches in order to be able to merge all SPs. Generally, probabilistic or statistical analyses have been used for the fusion [5,44], but multiple sequence alignment has also been tested [43] within text mining approaches to automatically analyse post-operative procedure reports as well as patient files.

Comparison–classification

The principle is to use an SPM methodology to highlight a specific parameter (i.e. meta-information) that explains differences between populations of patients, surgeons or systems. Simple statistical comparisons (such as average, number of occurrence or standard deviation) have been used [12,17,51] to compare populations. Similarity metrics have also been proposed by Neumuth et al. [49] to compare different SPs. DTW along with the K-Nearest Neighbour (KNN) algorithm have been tested within unsupervised approaches [46].

Display

Once data are acquired and the model is designed, it is generally useful to have a visual representation of the data to explore them qualitatively and to illustrate the results. However, complex data structures sometimes prevent straightforward visualisation. High-level task recordings of SPMs can be displayed according to two types of visualisations: temporal and sequential aspects [47]. Temporal display focuses on the duration of each action, whereas sequential display focuses on the relation between work steps. Moreover, in the sequential display, one possibility is to create an exhaustive tree of each possible sequence of work steps. Sensor-based recordings are easier to visualise. As it is represented by time series data, an index plot can be used (e.g. in Forestier et al. [46]). The idea of an index plot is to display the sequence by representing an activity as a rectangle of a specific colour for each value, and a width proportional to its duration. An information sequence can be easily visualised, and a quick visual comparison can be performed (Fig. 6).

Clinical applications

The analysis and modelling of surgical procedures cover multiple surgical specialities, issues and challenges. Five major applications in particular have been the focus of increased attention: (1) evaluation of surgical tools/systems/approaches, (2) training and assessment of surgeons (3) optimisation of OR management (4) context-aware systems and (5) robotic assistance. We first present the surgical specialities that have been covered by these systems, and then, the five main applications are detailed. A final subsection presents other potential applications.

Surgical speciality

SPMs have been applied to many surgical specialities, but minimally invasive surgery (MIS), including endoscopic and laparoscopic procedures and neurosurgical procedures have been preferred. Within laparoscopic and endoscopic procedures, Cholecystectomy and Functional Endoscopic Sinus Surgery (FESS) have been widely studied. Works can also be found in eye surgery [23,44,49,50,54], maxillofacial surgery [7], trauma surgery [15,18,45], dental implant surgery [21], urological surgery [43] and otorhinolaryngology (ORL) surgery [44]. In general, systems have been specific to a surgical speciality or even a particular surgical intervention, but a few papers have described more generic surgical systems.

Applications

Evaluation of tools/surgical approach/systems: The evaluation of surgical tools or systems was the first application targeted by research laboratories, at the request of surgeons

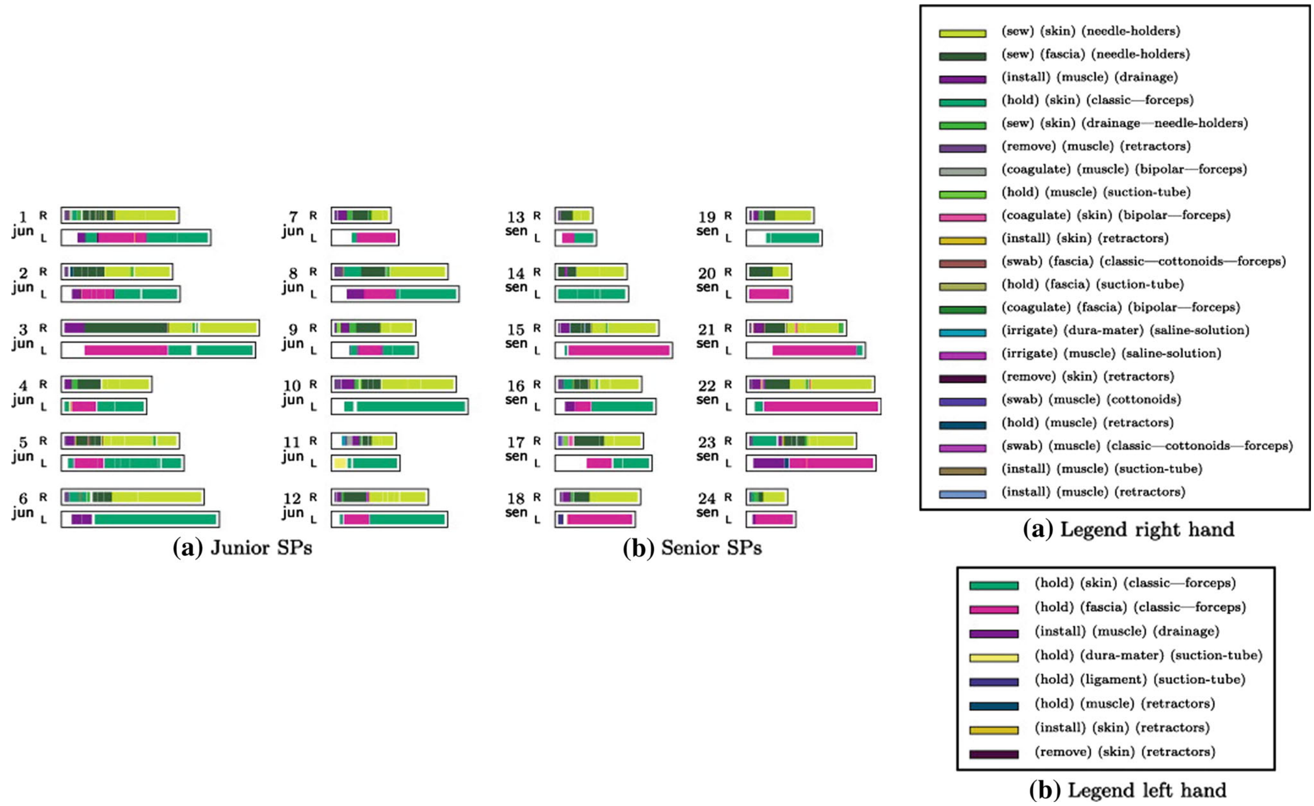

Fig. 6 Index plot used in Forestier et al. [46] representing the activities of the right (R) and left (L) hand for a population of 24 lumbar disc herniation surgeries performed by junior (**a**) and senior (**b**) surgeons

[5,12,35,43,44,48,50,57]. The analysis methods used in such cases were the comparison and classification methods.

Training and assessment of surgeons All junior surgeons currently train with the teaching help of senior surgeons. This is a very time-consuming, interactive and subjective task. The need for new automatic training systems using tools for the evaluation of surgeons has motivated extensive research into the objective assessment of surgical skills [58,59]. Surgical expertise has been widely studied in the literature. It is usual to distinguish technical from non-technical skills [60]. Technical skills include motor skills as well as procedural and conceptual knowledge [61]. Non-technical skills include cognitive skills and interpersonal skills [60]. Surgical process modelling is a methodology which allows some aspects of motor skills (timing or trial-error loops, for instance) and some aspects of procedural knowledge to be assessed. The ability to recognise simple movements, activities, steps or phases precisely is a very powerful tool in automating surgical assessment. Surgical training may also benefit from SPM methodology since it allows access to a formal description of the entire procedure, or a possible surgical scenario inside a population of cases (as represented by gSPM). For a complete discussion on the motivations of objective skill evaluation, one can refer to Reiley et al. [58].

Optimisation of OR management The need for perioperative surgical workflow optimisation has emerged [16,62], especially regarding the specifications of the OR of the future [1]. With the increased number of CAS systems and new technologies, being able to manage and coordinate all these systems correctly is becoming vital. The optimisation of physical and human resources can reduce efforts and therefore improve patient outcomes, reduce hospital's costs and increase efficiency. Moreover, being able to identify different phases within the OR could be useful to know how to assign staff, prepare patients or prioritise OR clean-ups. Better management relying on surgical information can also provide useful communication information [63].

Context-aware systems Many CAS systems, such as augmented reality (AR) systems or new imaging protocols, have been developed recently and integrated in the OR. Some limitations have been outlined. They are mainly used for a short period of time only, and the visualisation of additional information strongly depends on the current state of the intervention. Moreover, surgeons have to deal with adverse events during operations, arising from the patient him/herself but also from the management of the operation. The idea is to be aware of the current surgical situation in order to adapt assistance accordingly (e.g. in Sudra et al. [42]). Additionally, difficulties can be detected and risk situations better handled. For instance, variations of live signals can be used to warn surgical staff in the detection of anomalies.

Robotic assistance Many pieces of research have demonstrated the importance of robots in assisting surgery, and particularly using SPMs [7,34,52,55]. Surgical robots play a vital role in improving accuracy in surgical procedures. Two families of robots have been introduced for intra-operative assistance: semi-active and active robots. Semi-active robots make the link between surgeon and patient. Surgeons perform their tasks outside the OR using the robot which reproduces the surgeon's hand movement on the patient. These types of robots are used for specific tasks only such as biopsies or endoscopies for MIS. Active robots are used directly in the OR to replace the surgeon for certain tasks. Both types of robots could benefit from SPMs in supporting these tasks using predefined models. The use of robotic assistance also aims to compensate for the lack of human resources in many hospitals, and in particular the lack of nurses [40,55]. The new generation of robots that are currently being tested are able to pinpoint the progress of the intervention by automatically acquiring data from the surgical environment and creating SPMs.

Two other applications that have often been implicit in multiple publications are the automatic generation of post-operative reports and the help in pre-operative planning.

Post-operative reports are paper or electronic files that are generated post-operatively by the surgeon for documenting surgical procedures. Procedures are described as a succession of actions and steps that are manually included in a "log-file" for further filing. This step of the procedure is very tedious and time-consuming. The idea behind automating this process is to automatically extract as much information as possible from the surgery with the help of multiple sensors and to create prefilled reports [23,64]. All studies that retrieve information from the OR, regardless of their level of granularity, have potentially the possibility of automatically creating prefilled reports.

For helping pre-operative planning, the goal is to better anticipate adverse events and possible problems during surgery by using formalised knowledge acquired by previous interventions and also by having an idea of all the possibilities offered by SPs. Aggregation and fusion techniques may be helpful in such cases for creating gSPMs.

Validation–evaluation

We distinguish validation, defined as studying whether the system or method is actually doing what it is intended to do, from evaluation, defined as the study of the added value of a system or a method. Each aspect of the SPM methodology is subject to validation. The design of a validation study includes (1) the specification of a validation goal, (2) the definition of input parameters, (3) the computation or estimation of a reference (validation data sets) against which the results of the method to be validated will be compared, (4) the definition of validation metrics that will quantify the comparison and (5) the operator using the system [65].

Two main aspects have been validated by the selected publications: the data acquisition process and the modelling phase. Validation data sets consist of fully simulated data from computers, data provided by simulated ORs, from phantoms or real data directly from surgical interventions and patients. Computer simulations are one way of validating data that are easy to create, process, analyse and control, but are usually far from clinical reality. Similarly, virtual environments (simulated ORs) are also quite far from reality. While both approaches allow real flexibility for validating systems, it remains very difficult to model realistically a surgical environment, such as haptic feedbacks, anaesthesiological constraints or surgeon/patient interaction. Moreover, even if the simulation is close to reality, the human factor is missing and could be an issue for applications that are intended to be used in real OR environments. The third possibility is to use real surgical devices on phantoms instead of humans. Even if the environment is closer to reality than complete virtual environments, it remains a part of the procedure that is not realistic. The validation strategies generally consist of leave-one-out or k-fold cross-validation approaches. The comparison metrics are the recognition rate (accuracy), reproducibility, specificity and sensitivity.

Few evaluation studies have been conducted and reported in the literature [21,34,40]. Some papers indirectly showed the added value of the SPM approach through its use in comparing populations of surgical cases performed with different systems or by surgeons with different surgical expertise. For these few papers that evaluate their systems, the same possible limitations as the validation part can be expressed.

Similar works not included in the corpus

From the beginning of the 90s, many clinical studies were published which used the principle of time-motion analysis. Time was the first information chosen by teams to evaluate surgical systems or to assess surgeons. Publications covering time-motion analysis used off-line observer-based recording from videos (installed in the OR, on the surgeon) for acquiring sequences of phases/steps/activities that are then processed through statistical analysis. The corresponding studies, mainly published in clinical journals, restricted their analysis to statistical computations of time or number of occurrences. They were not included in our corpus. Some major examples of publications are listed here:

Table 2 Classification of time-motion analysis publications, for the data acquisition and the modelling component

	Data acquisition				Modelling		
	Granularity level	Operator +/− body part	Time of acquisition	Method for recording	Granularity level	Operator +/− body part	Formalisation
Time-Motion analysis	Steps/activities/ motions	Surgeon	Intra-operative	Observer-based recording from video (off-line)	Steps/activities/ motions	Surgeon	Hierarchical decomposition

Table 3 Classification of surgical skills evaluation using robot-supported recording publications, for the data acquisition and the modelling component

	Data acquisition				Modelling		
	Granularity level	Operator +/− body part	Time of acquisition	Method for recording	Granularity level	Operator +/− body part	Formalisation
Surgical skill evaluation	Motions	Surgeon	Intra-operative	Robot-supported recording (on-line)	Motions	Surgeon	Sequential list of words

[11,57,66–74]. A classification of their data acquisition techniques and modelling is proposed here in Table 2.

Some papers used robot-supported recording, such as the paper of Hager et al. [75] or Rosen et al. [59]. Fully connected HMMs were used for classifying hand trajectories to assess the level of surgeons' expertise. They were not included in our corpus since they did not incorporate any sequential aspect of the surgical processes. An recent review has already been published on the methods for objective surgical skills' evaluation [58], which includes all papers using trajectory analysis for surgical skills assessment. A non-exhaustive list of these papers is given here: [14,59,75–78]. A classification of their data acquisition techniques and modelling is also proposed in Table 3.

Others studies focused on the preprocessing steps before an SPM analysis. Radrich et al. [79,80] presented a system for synchronising multi-modal information using various signals for surgical workflow analysis. Sielhorst et al. [81] synchronised 3D movements before the comparison of surgeons' activities. Speidel et al. [82] focused on the identification of instruments in MIS, with the goal of improving current intra-operative assistance systems.

With a methodology similar to SPM, some other studies focused on the modelling of the peri-operative process, based on hospital systems [83,84], hospital data [85,86] or on surgical staff activities [87,88]. Other research focused on the modelling of the OR environment (inside and outside) but without looking at the surgery itself [17,89,90]. Their main objective is the improvement of the quality of patient care along with greater medical safety by studying flows or activities. Also, from an anaesthetist's point of view, work has been undertaken which looked at the ergonomics and organisation inside the OR [91–97]. None of these studies focused on the surgical process and were therefore not included in our corpus.

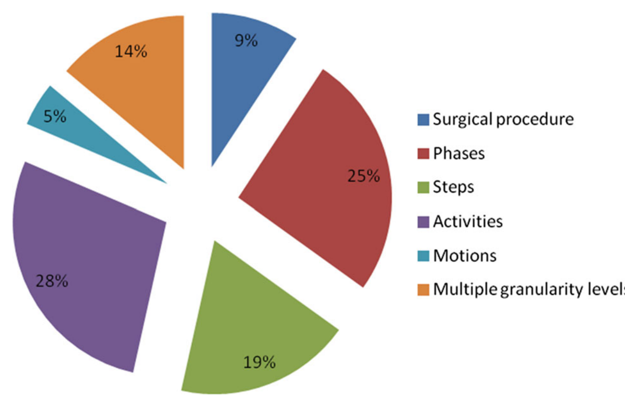

Fig. 7 Repartition (percentage of publications) of granularity levels of the modelling

Discussion

Modelling

As we can see from Fig. 7, all granularity levels have been studied, with a particular focus on steps and activities. Moreover, a consequent number of these studies use multiple granularity levels in their modelling. This type of approach seems to be required for creating global SPMs which integrate all aspects of the surgical procedure.

From the methods used for formalisation, XML schema, which is a lightweight ontology, defines a grammar that characterises the structure of a document or the type of data used. XML schemas can be a solution for describing SPMs at a high level of granularity, but they do not include important concepts such as classes or organisation into a hierarchy. In addition, they do not provide a relevant solution for representing the dynamic aspect of the process. As XML schema, the UML class diagram does not allow unique and uniform entities to be defined. Both approaches seem to be less suited to the formalisation of a surgical context than heavyweight ontologies. These allow two elements corresponding to the same unit to be specified. Unlike taxonomies that define classes and the relations between these classes, ontologies allow inference rules to be defined. Jannin et al. [8] proposed a model based on the pre- and post-operative acquisition of data, including interviews with surgeons. The types of surgical procedure, steps and actions were extracted and allowed the model to be created. Lemke et al. [35] first defined a surgical ontology as a formal terminology for a hierarchy of concepts and their relationship in the specialised clinical context of surgical procedures and actions. Later, Burgert et al. [39] proposed an explicit and formal description of an upper-level-ontology based on General Ontological Language (GOL) for representing surgical interventions. These pieces of work were the first to introduce heavyweight ontologies in the context of surgery.

Formalisation is crucial to be able to compare and share studies between different centres. Even though two centres acquire data about the same surgical procedure using the exact same terminology, a heavyweight ontology is still needed to be able to use both sets of data in a shared study, since this is the only way to ensure that a term has a single meaning in both studies. A heavy and rich formalisation is the key for the future analysis of SPMs to tackle all these issues.

Data acquisition

Both observer-based and sensor-based data acquisition approaches present advantages and drawbacks. Within observer-based approaches, the data acquisition process can be supported by two levels of knowledge: the description relies on *a priori* knowledge available or to fixed protocol created by local experts. In the first case, standard surgical terms are reported for describing surgery, whereas in the second case, the first step consists of building up its own vocabulary. The related models are in most cases not based on ontology, and they are thus not an efficient formal representation of the knowledge and are also not easily sharable between centres. Moreover, the major concern of the on-line observer-based approach is the need for manual labelling. At the same time, it is the best way for recording finer details and capturing a high semantic level, which makes this technique advantageous compared to sensor-based approaches. Finally, observer-based approaches have the capacity to cover high granularity levels for describing surgery, from the lower level (time) to the highest, allowing the observer to take on the responsibility of acquiring semantic information. On the other hand, it is a very time-consuming and costly approach

Sensor-based approaches are now increasingly adopted. For motion detection using tracking systems, the main drawback is that it relies on tools only and rare movements may not be efficiently detected due to the lack of dedicated training. Compared to other data acquisition techniques, analyses of videos would have a source of information that does not have to be controlled by a human. Videos are a very rich source of information, as demonstrated in laparoscopy by Speidel et al. [41]. Using image-based analysis, it is possible to acquire relevant information about surgery without disturbing the flow of the intervention. Unfortunately, current image-based algorithms, even with progress in computer vision, do not allow the well-known semantic gap to be captured in full. For instrument use models, in spite of high detection accuracies, the major concern is that the recording of signals is not automatic when RFID tags are not used. In practice, RFID tags are too intrusive, and some vital information such as the anatomical structures treated are missing. Eye-gaze tracking systems are interesting because they take into account the perceptual behaviour of the surgeon, but it would require large modifications during the intervention course not to alter the clinical routine as it stands. Generally speaking, all type of sensors additionally installed in the OR show promising results for the challenge of workflow recovery, but the main drawback is the modification of the OR set-up and the need to manage such new devices. Also, they do not have this ability to capture information with semantic meanings, but have the advantage of recording live signals automatically or semi-automatically, which is less time-consuming and allows the design of context-aware systems.

Currently, no papers cover multiple levels of granularity, which shows the difficulty of combining different data acquisition methods at different granularity levels. Multiple sensors can be used for instance for both capturing videos and the positions of instruments, but the combination of observer-based and sensor-based approaches turns out to be very difficult to set-up. We see from Fig. 8 that no predominant techniques have been used.

Analysis

The choice of analysis methods that allow one to go from data to model is vital in SPM methodology. Bottom-up

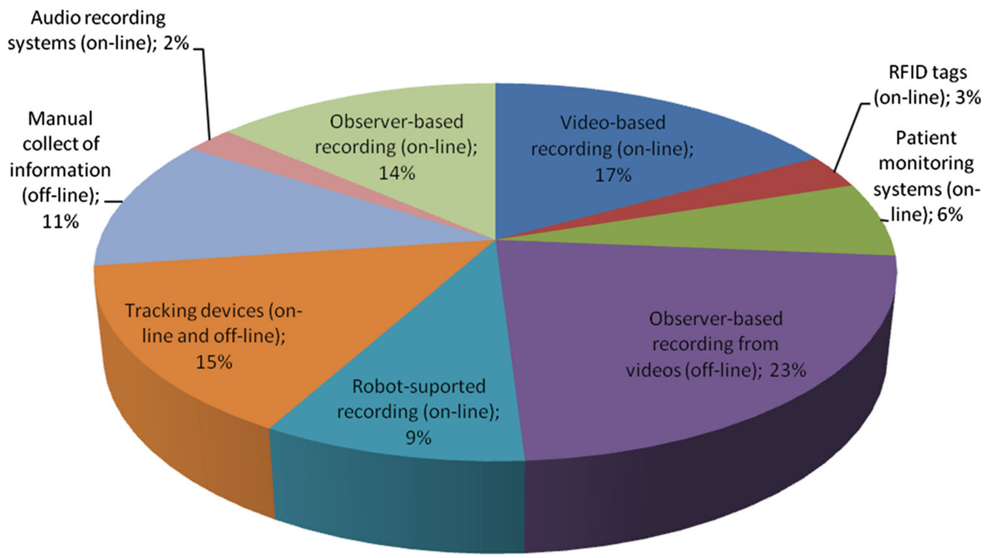

Fig. 8 Repartition (% of publications) of data acquisition techniques

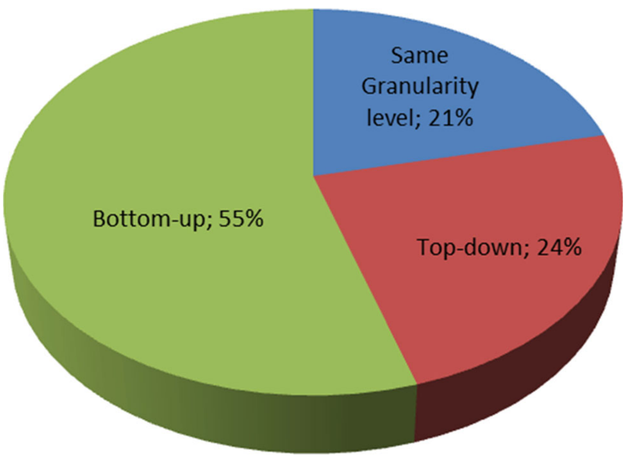

Fig. 9 Repartition (% of publications) of the type of approaches used for "data to model" approaches

approaches are the most current (Fig. 9). They allow a bridging of the semantic gap between numeric and symbolic data. Based on a preliminary formalisation, these methods all use supervised techniques based on a training stage, except for the work of Ahmadi et al. [19]. People report recognition rates of from 70 up to 99 %, but these values are very difficult to compare due to the differences of validation strategies as well as the number and type of data used. The two others approaches (approaches that stay at the same granularity level and top-down approaches), even if they have still not completely demonstrated their interest for the field, are now more and more used.

The category of aggregation/fusion analysis method is important because it is a smart way of creating gSPMs that can be used as a supplementary tool for assisting surgeons. It allows creating procedural knowledge models based on an automated SPM analysis. The problem is that it only represents the SPMs that are studied and may not cover all SP possibilities. No extensive work has been performed while this type of approach suggests good prospects in the future. Efforts must therefore be made here for integrating and automating average models of surgical processes in clinical routines.

Similar to the previous category of the analysis approach, comparison and classification using surgical processes has not yet motivated many studies, but it may be a direction that needs to be considered. Comparisons of tool uses, surgeons or surgery performance using these kinds of methods allow a quantitative validation and assessment of the impacts on the surgical procedure.

Applications

We have restricted in the diagram potential applications to the 5 most common ones cited in the papers. Additionally, when multiple applications were cited in the papers, we only used the main, clearly identified one. Figure 10 shows the repartition of applications as well as the surgical specialities.

Most of the SPM studies were performed in the context of neurosurgery or endoscopy/laparoscopy. This is not surprising, as neurosurgery and MIS have been the most common applications used for computer-assisted surgery research. In the case of endoscopic and laparoscopic procedures, surgical procedures are often highly standardised, they are widely documented and have inter-patient variability which remains very low. Data are also easily available for engineers for this surgical speciality. In neurosurgical procedures, data can also be easily acquired. In the case of eye surgery, new studies are using this surgical speciality because of the very short and standardised procedures.

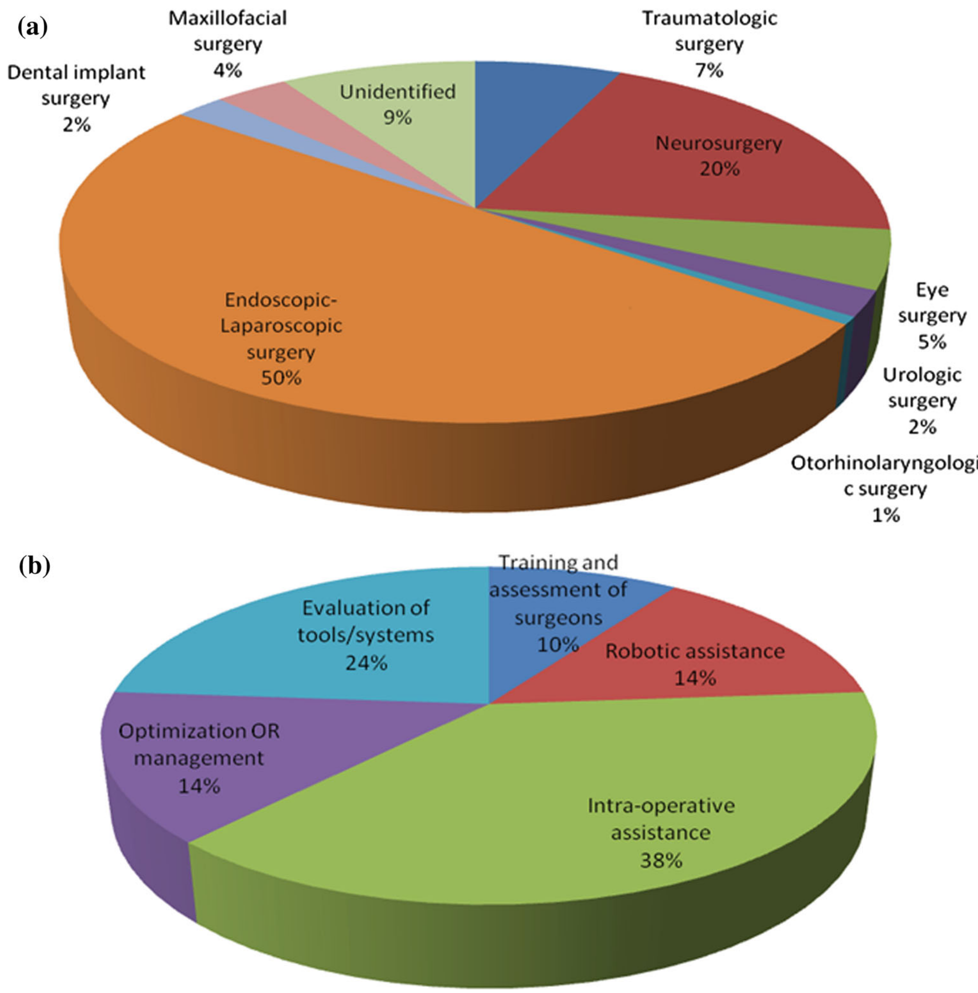

Fig. 10 Repartition (% of publications) of surgical specialities (**a**) and clinical applications (**b**)

The distribution of applications is more uniform than the distribution of surgical specialties. Even if systems aiming at improving intra-operative assistance predominate, the four other applications have been seriously and similarly considered. Ahead of the large number of applications cited in publications, we see that SPMs can be useful along the entire surgery timeline, from pre-operative use to post-operative analysis. They can be used in every medical process and adapted to every surgical speciality, which shows the potential importance of SPMs.

Validation–evaluation

Most of the papers include validation studies (Fig. 11, left) of the analysis part (69 %), while only 4 % of the papers validated the acquisition step; 27 % of the papers do not validate their systems at all. When used, validation studies were performed (Fig. 11, right) using clinical data in most cases (78 %). Few studies use phantoms, simulated OR or computer simulations.

Of the 46 publications that were peer-reviewed, only three of them performed evaluation studies. Table 4 shows the different elements of their evaluation studies. However, no validation combined to evaluation has been conducted at the same time. This shows that research in the field, while being under considerable development, has not yet been introduced into the clinical routine.

Correlations with other information

The correlation of SPMs with other information, such as patient-specific models, is an important prospect in the field. Patient-specific models are constructed from pre- and post-operative patient data such as clinical data or images [98–101]. Being able to correlate patient outcomes and pre-operative data with SPM would allow predictions to be made of the best possible surgical processes.

One other possibility would be to correlate SPMs with surgeons' decision-making processes during the intervention. The decision-making process in surgery can be conceptualised by two steps, the assessment and the diagnosis of the situation that must be used to select a specific action. The major aspect of the decision-making is that the decision

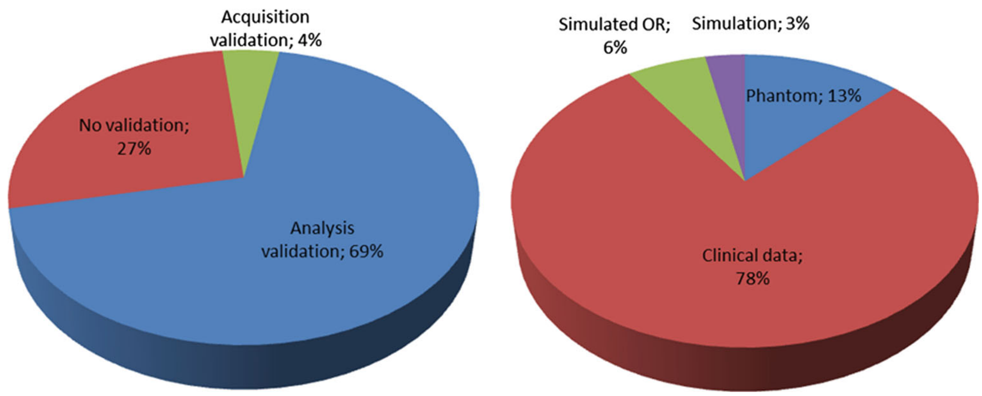

Fig. 11 Repartition (% of publications) of the types of validation (*left*) and types of validation data (*right*)

Table 4 Classification of the 3 publications performing evaluation studies

	Evaluation				
	System evaluated	Validation objective (Medical context)	Data set	Metric	Operator
Katic et al. [21]	Context-aware augmented reality system	Drilling planned implant	Phantom	Medical usability (questionnaire)) Implant position comparison	Surgeon
Ko et al. [34]	System for intelligent interaction scheme with a robot	Porcine cholecystectomy	Clinical data	Number of voice commands	Surgeon
Yoshimitsu et al. [40]	Scrub nurse robot	Endoscopic surgery	Clinical data	Instrument targeting time	Nurse

depends on the level of expertise and tasks demanded. Dedicated models can be designed for surgical decision-making support by including this aspect. Moreover, correlation between pre- and post-operative interviews of surgeons with the intra-operative intervention strategy would allow an analysis of surgeons' decision-making process to be made, especially under the pressure of time and a better understanding and anticipation of further adverse events [102–104].

Future of SPM

Despite the potential impacts of SPM on computer-assisted surgery outlined by the scientific and clinical communities, such methodology still needs to be deployed in clinical environments and applications and to demonstrate its added value. Some deadlocks remain. The first concerns the automatic acquisition and real-time and robust monitoring of SPs. It seems clear that multi-sensor approaches will be needed to reach high recognition rates at different granularity levels. Different points of view need to be used from closed sensors attached to operator's body, views of the operative field, signals from OR devices, patient's intraoperative data to large angle views of the whole operating room. Another issue relies on the computation of generic SPMs as the collection and gathering of possible SPs, as followed within an homogeneous population of surgical cases. Such generic SPMs constitute real procedural knowledge models (ref) and are needed to provide systems with a list of possible scenarios. However, they are limited by the data itself. Being sure that generic SPMs fully cover inter-patient, inter-surgeon, inter-OR variability requires large worldwide data repositories with standardised terminologies and corresponding ontologies. The computation of generic SPMs also faces strong methodological issues in the aggregation/registration aspects, as a complex multiple sequence alignment problem. SPM methodology has the potential of allowing development of relevant comparison/classification approaches and metrics that could help understanding of surgical expertise. Whereas the current developed metrics emphasise differences in practice, there is a need for methods explaining reasons of such differences. Finally, SPM methodology also needs to be seen by the clinicians as a skill augmentation support, a powerful teaching tool, rather than a "big brother" style-watching eye. Without a clear understanding of potential added value of the methodology by the clinicians, as well as a strong ethical awareness and control of the use of such data, such methodology will hardly be accepted by clinicians, increasing time from bench to bedside.

Conclusion

Following the growing need for a new generation of CAS systems, new techniques have emerged based on the modelling of surgical processes. Research studies have been performed towards the development of sophisticated techniques for optimising, understanding and better managing surgeries and the OR environment based on SPMs. In this paper, we have presented a methodological review of the creation and the analysis of SPMs, focusing on works that modelled the procedural dimension. To organise the review, we have introduced a classification based on 5 major aspects of the SPM methodology: acquisition, modelling, analysis, application and validation/evaluation. Using this classification, we have presented the existing literature and discussed the different existing methods and approaches. On the methodological side, we have shown that efforts still remain to be made in integrating the different granularity levels into a global framework. Both bottom-up and top-down approaches need to be combined. Methods are still needed to combine SPM into average generic SPMs. This methodological review has emphasised the possible large impact that SPM methodology may have in future surgical innovations as well as in surgical education, planning or intra-operative purposes. However, the technology is recent and there is still a lot of work to be done to demonstrate quantitatively its ethical added value within concrete clinical applications.

Conflict of interest None.

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