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Analysis of Surgical Intervention Populations Using Generic Surgical Process Models

Authors

Thomas Neumuth[1], PhD, MEng

Pierre Jannin[2,3,4], PhD

Juliane Schlomberg[5]

Jürgen Meixensberger[1,6], MD, PhD

Peter Wiedemann[5], MD, PhD

Oliver Burgert[1], PhD

Departments

[1] Universität Leipzig, Innovation Center Computer Assisted Surgery (ICCAS), Leipzig, Germany

[2] INSERM, U746, Faculty of Medicine, Rennes, France

[3] INRIA, VisAGeS Unit/Project, Rennes, France

[4] University of Rennes I, CNRS, UMR 6074, IRISA, Rennes, France

[5] University Hospital Leipzig, Department of Eye Surgery, Leipzig, Germany

[6] Univeristy Hospital Leipzig, Department of Neurosurgery, Leipzig, Germany

Contact

Thomas Neumuth

Universität Leipzig

Innovation Center Computer Assisted Surgery (ICCAS)

Semmelweisstr. 14

D-04103 Leipzig

Germany

thomas.neumuth@iccas.de

Phone: +49-341-97-12010

Fax: +49-341-97-12009

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Abstract

Purpose: No methods for the generation and comparison of statistical 'mean' surgical patient treatments are available. Such models might be beneficial for the advanced assessment and evaluation of surgical strategies, surgical instruments, devices and assist systems, optimization protocols, and for educational purposes. The availability of 'mean' surgical intervention courses of a patient population would also offer a new methodological quality. This may be applicable in more technical research fields, as well, such as the development of surgical workflow management systems for the operating room of the future.

Methods: Based on several measurements of individual patient surgical treatments, we calculated a 'mean' intervention model, called generic Surgical Process Model (gSPM), for a population of interventions with certain characteristics. Methods for the acquisition, registration of individual patient intervention descriptions, and the calculation of 'mean' treatment models are presented in this article.

Example application: The approach was applied to an example application from eye surgery. Protocols of 102 cataract interventions were divided into two populations: ambulatory and inpatient treatments. For each of the populations it was shown, how differences of gSPMs were assessed and quantified. Additionally, it was possible to identify a statistically most probable intervention course by using the presented methods.

Conclusions: This article introduces the computation and use of statistical 'mean' surgical interventions, termed generic Surgical Process Models (gSPMs). It will show, that differences over larger intervention populations might be identified and quantified. This gives the opportunity to increase evidence for clinical, technical, and

administrative decision making, e.g. for the application of alternative surgical strategies or investments for surgical assist systems.

1 Introduction

Surgical Process Models (SPMs) are models of surgical patient treatments. In a previous work, we have drawn attention to the fact that there exists no explicit methodology that can be used to objectively model surgical strategies at a detailed level [1].

SPMs make the knowledge about Surgical Processes explicit that was previously inaccessible. It facilitates, for example, evaluation studies or requirements studies, and may encourage discussions among clinicians and technicians.

Recently, the work on SPMs has resulted in a new layer of interest: since the previous generation of SPMs was able to represent only a single individual surgical intervention course, what new or additional possibilities would a generic SPM provide? A more comprehensive model could include and combine multiple individual courses into a statistically ‘mean’ model that exhibits a more generic character. Such a generic model could be valuable for the quantification, statistical assessment, and visualization of surgical knowledge and techniques.

Specific application cases could include a comparison of two generic Surgical Process Models to elucidate differences in surgical strategies or to clarify the use of certain instruments or devices. The approach may be useful to assess skill levels, or it could serve as the basis of a detailed extrapolation of intervention costs. Further application cases, e.g. the comparison of patient individual Surgical Process Models (iSPMs) with generic Surgical Process Models (gSPMs), may include an investigation of the reasons why a single surgical intervention course may have deviated from the mean procedure course.

Currently, very few approaches have been proposed to evaluate individual patient or generic models of surgical processes. Recently, the use of SPMs in Medical Engineering and Medical Informatics has been discussed by several authors.

Jannin et al. [2, 3] introduced a method for acquiring patient-individual SPMs using an ontological approach. They applied data mining-based methods to a database of 159 iSPMs, describing surgical procedures on the brain in order to predict certain features of these procedures (called *predicted variables*) from characteristics of the patient and the associated pathology (called *predictive variables*). They used the same methods to classify the data into main families based on the predictive variables and they manually allocated the values of the predicted variables to each family. Although computing gSPMs was one objective of their work, they failed to compute such models.

Other authors have modeled surgical processes in the context of medical engineering for several purposes, such as the automatic identification of interventional phases [4, 5], control of surgical robots [6], and instrument assessments [7]. Clinical work has also focused on surgical processes for reengineering [8], assessing human reliability [9], comparing substitutive surgical strategies [10], and analyzing requirements for Surgical Assist Systems [11].

However, all of these approaches either do not deal with the generation of a generic SPM or provide information only at the level of interventional phases rather than at the level of stepwise work elements.

Some authors have presented approaches for computing gSPMs [12, 13, 14]. These methods, however, do not consider variations of several relevant procedures [12], they were applied only at the conceptual level of intervention modeling without quantification of measurement parameters [13], or they featured a less detailed level of granularity [14, 15].

The notion of *Workflow Mining* in business informatics is closely related to our presented approach. In 1995, Cook et al. [16] published the first algorithms to determine process models from software event logs. The preparatory work, namely the use of process mining to explore business process models, was initiated by Agrawal et al. [17]. The process mining community has been actively working over the past five years to formalize the discovery of process models based on event logs, e.g. [18,19]. For a survey of this area, see van der Aalst et al. [20]. Methods described herein are not applicable to the computation of gSPMs and comparisons between intervention populations, because they do not include multiple perspectives or concurrencies, such as parallel left- and right-handed surgical work steps.

Furthermore, existing sources of information related to surgical procedures, such as clinical guidelines [21, 22] or surgical textbooks, describe surgeries at a very general level; their goals are not to describe interventions in detail, but rather to give treatment recommendations. However, this general level cannot be used for quantification. With the methods utilized in the present work, it becomes possible to base such measurement parameters, such as most probable intervention courses, on real clinical data.

In this paper, we introduce methods for computing *generic Surgical Process Models (gSPMs)*. It is shown, that it is feasible to use gSPMs to quantify differences in surgical workflows of two intervention populations retrospectively. Clinical-use case data from 102 cataract interventions were divided into two populations, according to the application of different treatment strategies. gSPMs were then calculated as 'mean' treatments for each of the populations and the results were subsequently compared across the entire data set.

The research questions addressed in this article include: *How can generic Surgical Process Models be generated from a population of individual Surgical Process Models?* and *How can two gSPMs be utilized to compare two different intervention populations?*

2 Methods

This section introduces methods for generating generic Surgical Process Models (gSPMs) from a population of individual Surgical Process Models (iSPMs). Pertinent terms will be introduced, and an overview of the model development process will be given.

To compute a generic SPM, several stages must be processed (cf. Figure 1). Mandatory stages include: data acquisition for iSPMs, Inter-iSPM registration, and computation of the gSPM. Optionally, additional stages involving feature selection, segmentation, and filtering can be employed to decrease the visual complexity of the resulting models.

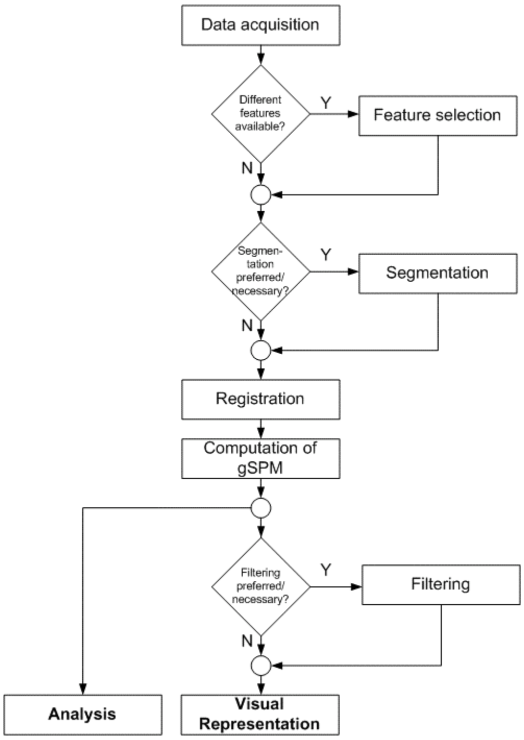

Figure 1: Overview of the model development process for gSPMs

Terms

Essential in this context is the definitions of terms and concepts related to this approach (cf. [1]): the surgical treatment performed on one specific patient is denoted a *Surgical*

Process (SP), and a model of the Surgical Process, e.g. in an information system, is called a *Surgical Process Model* (SPM). SPMs appear in two forms: *patient individual SPMs* and *generic SPMs*. The term *patient individual SPM* (iSPM) is used to refer to an SPM of a Surgical Process that was performed on one patient and thus represents one surgical case. The term *generic SPM* (gSPM) is used to represent the 'mean' surgical treatment of a theoretical patient. Generic SPMs are computed from different populations of iSPMs.

Data Acquisition for iSPMs

Data acquisition deals with the mapping of the surgical procedure from a Surgical Process (SP) to a Surgical Process Model (SPM). To store and process iSPMs, an appropriate data model is required. This data model describes, how entities of the Surgical Process are structured and presented within a given information system.

In this study, surgical work steps during the SP are represented as *activities*. Each iSPM consisted of a number of activities that corresponds to the surgical work steps performed on the patient. Each activity is comprised of information about the work steps, termed *perspectives*. Examples of perspectives include: actions performed (e.g. *suctioning*, *cutting*); the surgical tool used (e. g. *scalpel*, *hook*); anatomical regions treated during the current work step; and start/stop times. An activity, therefore, describes *who* is doing *what*, with what *instrument*, *where*, and *when* during the surgical intervention. Activity examples are shown in Table V.

States symbolize status information and define the context in which activities were performed. Examples of states might be the different intervention phases of a procedure. A system of states acquired concurrently to activities implicitly relates activities to the interventional phases. An example that associates activities A, B, and C with intervention phase #1 is shown in Figure 2.

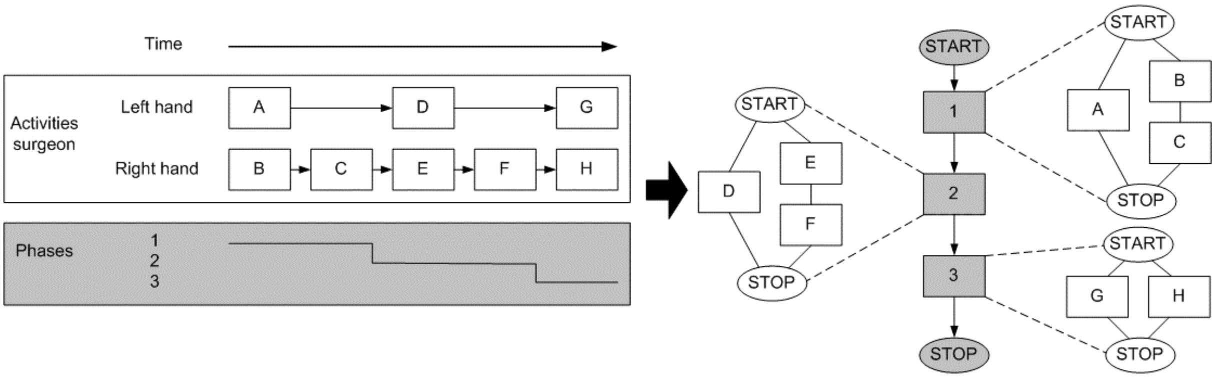

Figure 2: Segmentation of the iSPM according to the relations of activities and states

Before gathering iSPM data, we had to define our terminology, especially for interventional phases or work steps. The former is crucial to segment the intervention into parts and thereby reduce the complexity of the resulting gSPM. The latter ensures a consistent naming of information entities across all relevant surgical cases. Table III and Table IV show examples of the interventional phases, surgical instruments, actions, and treated structures as used for the clinical case example in the next section.

During the live observation sessions, iSPMs were recorded by trained medical observers, who were physically present in the operating room and recorded the performed surgical work steps of the intervention in the iSPM protocol. Data acquisition relied on a specially developed observation support software package, the Surgical Workflow Editor (cf. Figure 3, [23]). The software, running on a conventional tablet PC, presented terminology lists to the observer and asked for a description of the current surgical work step. Temporal information was added automatically. After each observation, the observer saved the protocol in eXtensible Markup Language (XML) format. The protocols that represented the iSPMs were then transferred to a database where further calculations were performed.

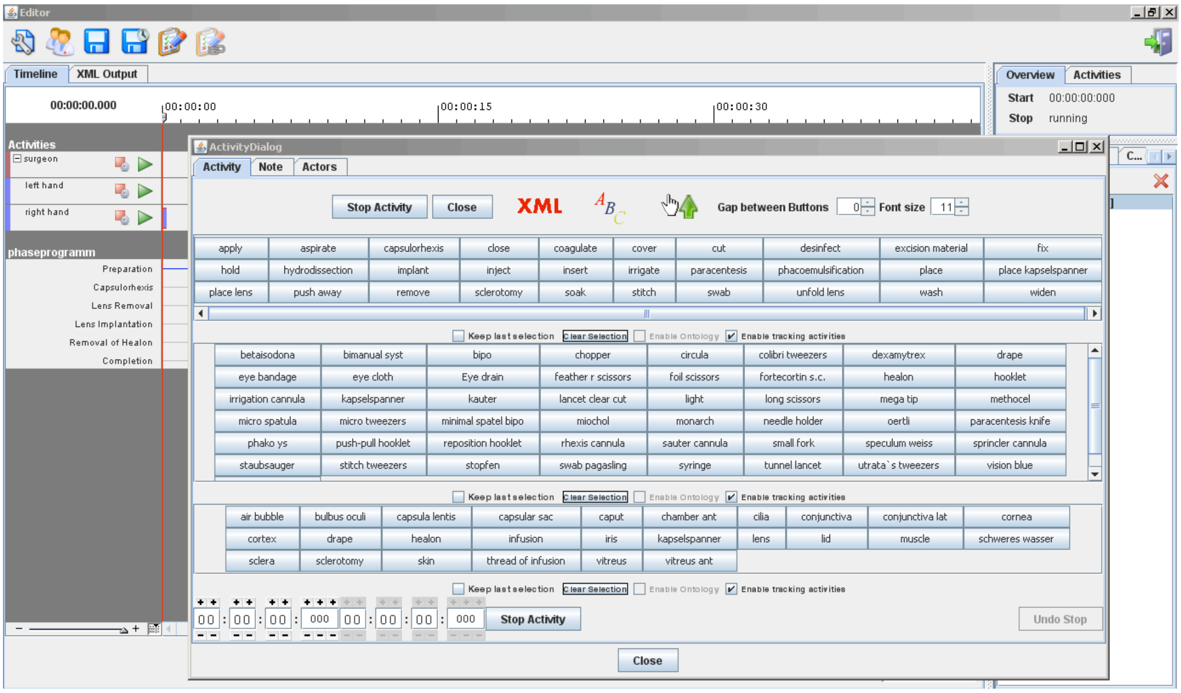

Figure 3: Screenshot of the Surgical Workflow Editor user interface

Feature Selection

Data structures in iSPMs are comprised of various perspectives [1]: organization, function, operation, and space. Each of these perspectives can be used to generate a gSPM with a different focus. The choice of perspective is termed *feature selection*. As features, perspectives can be chosen either exclusively or concurrently. An exclusive perspective choice results in a gSPM that is dedicated to the perspective in question, e.g. performed surgical actions, while a combination of perspectives results in a gSPM that has relevance for all chosen perspectives, e.g. the combination of actions performed and surgical instruments used. The more features that are included in building a gSPM, the more complex the resulting gSPM will be.

Segmentation

Splitting the iSPM into interventional phases is referred to as segmentation. The segmentation step was performed automatically according to the time stamps of the activities and the interventional phases. Consequently, all activities allocated to one interventional phase were selected across all iSPMs within a population.

Inter-iSPM Registration

The objective of the registration step was to associate reference points between iSPMs. In preparation of the generation of the gSPM, the iSPMs of the selected population were registered to each other automatically, based on selected features from subsequent activities (cf. Figure 4). This registration step was performed for each interventional phase. Sequential activities represented transitions, expressed as predecessor-successor relationships. To include defined start and end nodes, artificial *START* and *END* features were added to each iSPM. *START* and *END* were included before the first predecessor and after the last iSPM successor respectively.

Computation of gSPMs

Computation of the gSPM structure: The transitions identified in the registration step were of relevance to the structural representation of the gSPM. For each interventional phase, all acquired transitions were registered based on the literals and were merged into one transition based on equal predecessor and successor activities. The result of this merging step was the gSPM structure.

Computation of the gSPM: The gSPM was subsequently annotated with global transition probabilities. The calculation was performed for all outgoing activity transitions in the iSPMs. The basis for the calculation was the number of sequential activities that each had the same predecessor. Subsequently, the local transition probability was calculated by normalizing the means of the global transition probabilities. The results quantify the transitions in the structural gSPM in terms of percentages (cf. Figure 4). Table I shows how to compute the gSPMs.

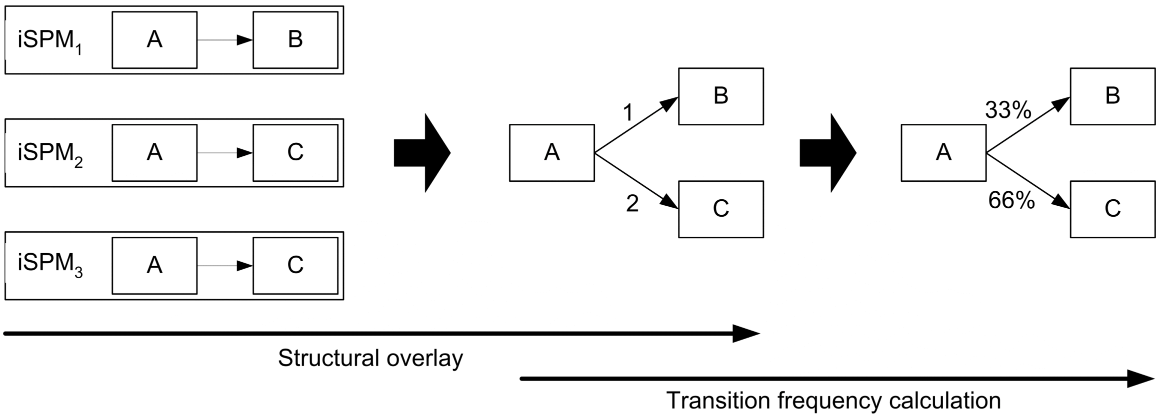

Figure 4: gSPM generation procedure example

Table I: Computational algorithm for gSPM

1. Calculation of activity values
    a. Grouping of all activities according to iSPM population, interventional phase, and selected perspectives
    b. For the duration of each combination, the mean and the standard deviation is calculated
2. Calculation of activity transitions
    a. Grouping of all activities according to protocol-ID, interventional phases, and selected perspectives
    b. Computing the global transition probability for each selected transition in each protocol from the predecessor transition
    c. Calculating mean and standard deviations across all protocols of one iSPM population
3. Joining activity durations with global transition probabilities, calculation of local transition probabilities, and creating the visualization

Filtering for Visual Representation of gSPM

The resulting statistical gSPM can result in complex models that are not amenable to visual representation. For this reason, the optional step of filtering was included for the example data sets to improve visual accessibility. The filtering consisted of masking all transitions whose values were lower than a threshold defined by the user. Filtering did not affect the gSPM, but rather aimed to increase the clarity of the visual representation.

3 Results of the application example

Objective of the Example Study

Cataract surgeries were chosen as a clinical example for the application of our methods. Based on clinical necessity, two treatment strategies are available for treating patients suffering from cataracts: ambulatory or inpatient treatments.

The objective of the example study was the retrospective assessment of the ambulatory and inpatient treatment strategies – our goal was to investigate differences in the gSPMs of both approaches. In addition to the assessment of more ‘trivial’ measures, such as total intervention times or durations of surgical phases, the example study showed how two gSPMs can be utilized to compare intervention populations.

iSPM-Populations

All cataract interventions were performed between March and September 2006 at the Eye Clinic of the University Hospital in Leipzig (Germany). The assignment of the patients to their respective treatment strategy was performed according to clinical necessity and expected complications.

The ambulatory, as well as the inpatient interventions, were conducted by three different, experienced surgeons: one surgeon performed inpatient treatments and two performed the ambulatory treatments.

Only patients with a cataract diagnosis were included in the study. The beginning of the first paracentesis and the end of the Healon removal were chosen as unique criteria for defining the start and end of the interventional record (cf. Table III).

In total, 102 iSPMs of cataract surgery treatments were analyzed, 49 of which were performed as ambulatory and 53 as inpatient surgeries. The patient characteristics are presented in Table II.

Table II: Patient Characteristics for the Example Study

	Ambulatory	Inpatient
Number of cases	49	53
Age	73.7±7.8	68.0±11.2
Sex (m/f)	20/29	22/31
Treated eye (right/left)	27/22	23/30

Cut-suture times were recorded from the Hospital Information System (HIS). One trained medical student was present in the operating room during the surgical procedures and acquired the data for the iSPMs through live observation with the aid of the Surgical Workflow Editor [23]. The validation of the accuracy of iSPM data acquisition has been published in a previous in-depth study [1]. In the latter publication, observers were shown to acquire iSPMs accurately, robustly, and repeatable in both live and video observations, with a content accuracy of 92% and a temporal accuracy of <2 s. Examples of the terminologies used for the interventional phases and for describing perspective content are shown in Table III to Table V.

For statistical analyses, Student's t-test was used with a significance level of α=0.05. Segmentation, registration, and gSPM calculation were performed in a PostgreSQL 8.3 database, and statistics were computed using SPSS.

Table III: Interventional phases for the Cataract surgeries example

Phase	Definition
Capsulorhexis	First paracentesis until end of material excision
Lens Removal	Hydrodissection until end of irrigation/aspiration of lens
Lens Implantation	Cut widening until beginning of irrigation/aspiration of Healon
Removal of Healon	Irrigation/aspiration of Healon

Table IV: Terminology list examples for the use case

WHO	WHAT	WHEREBY	WHERE
surgeon with left hand, surgeon with right hand	apply, aspirate, capsulorhexis, close, coagulate, cut, disinfect, hydrodissection, implant, inject, insert, irrigate, place, remove, widen, …	bipo, chopper, circula, colibri tweezers, drape, eye drain, foil scissors, hooklet, lancet clear cut, monarch, …	bulbus oculi, capsula lentis, capsular sac, caput, chamber ant, cilia, conjunctiva, cornea, cortex, …

Table V: Activity examples recorded by observation

	Example Activity 1	Example Activity 2	Example Activity 3
WHO	surgeon with right hand	surgeon with right hand	surgeon with left hand
WHAT	hydrodissection	wash	hold
WITH WHICH TOOL	sauter cannula	sprinkler cannula	colibri tweezers
WHERE	cortex	conjunctiva	bulbus oculi
WHEN	00:05:30 – 00:06:10	00:02:30 – 00:02:40	00:03:35 – 00:05:05

Analysis and Visualization of gSPMs

This section will compare the ambulatory and the inpatient gSPMs, focusing on the durations of interventional phases and quantifying one interventional phase as an example with regard to the surgical workflow.

Cut-suture times measure the overall duration of the surgical interventions. The general assessment of the cut-suture times showed a significant difference ($p<0.001$) between ambulatory and inpatient cataract procedures. Mean cut-suture times were 00:16:01±00:04:39 for ambulatory interventions and 00:25:16±00:15:34 for inpatient interventions (cf. Table VI).

The interventional phases of *Capsulorhexis*, *Lens removal*, *Lens implantation*, and *Removal of Healon* constitute the surgical core of the intervention. In a second step, the total duration of these core phases was examined for both populations. The total duration for the interventional core phases was significantly different ($p<0.001$) and was 00:09:50±00:03:22 for ambulatory and 00:17:32±00:16:09 for inpatient interventions.

An investigation of the durations of the phases *Capsulorhexis*, *Lens removal*, *Lens implantation*, and *Removal of Healon* showed significant differences in the mean durations as compared to those of the phases *Capsulorhexis* ($p<0.001$; cf. Table VI) and *Lens Removal* ($p=0.002$).

Table VI: Phase durations

	Ambulatory cataract interventions	Inpatient cataract interventions	Significance
Cut-suture time	00:16:01±00:04:39	00:25:16±00:15:34	$t(61.91)=-4.13$, $\mathbf{p<0.001}$
Begin Capsulorhexis until end Removal of Healon	00:09:50±00:03:22	00:17:32±00:16:09	$t(56.90)=-3.39$, $\mathbf{p=0.001}$
Capsulorhexis	00:01:28±00:00:28	00:02:48±00:01:11	$t(68.79)=-7.56$, $\mathbf{p<0.001}$
Lens Removal	00:05:42±00:02:24	00:10:18±00:09:55	$t(58.61)=-3.28$, $\mathbf{p=0.002}$
Lens Implantation	00:00:42±00:00:58	00:00:58±00:01:05	$t(98)=-1.56$, $p=0.12$
Removal of Healon	00:01:37±00:01:18	00:01:41±00:02:20	$t(100)=-0.14$, $p=0.89$

Example results are presented for the *Capsulorhexis* phase in Table VII. The analysis revealed that during this phase in inpatient cataract interventions all activity performances took significantly longer than did the same activities in ambulatory interventions. Except for the activity *Left hand holding Bulbus oculi with colibri tweezers*, the number of occurrences of the respective activities was not significantly different.

The surgeons' left hand used several different instruments. The micro spatula was not used at all in inpatient interventions.

Table VII: Example durations of activities of the Capsulorhexis phase (in seconds, right hand activities shaded)

Activity	No. of occurrences in ambulatory population	No. of occurrences in inpatient population	No. of occurrences per intervention in ambulant interventions	No. of occurrences per intervention in inpatient interventions	Significance No. of occurrences per intervention	Average performance time ambulant cataract interventions in seconds	Average performance time inpatient cataract interventions in seconds	Significance Average performance time per activity
surgeon right hand paracentesis paracentesis knife cornea	49	34	1.00±0.00	1.00±0.00	-	6.06±1.92	14.56±23.47	t(33)=-2.11, **p=0.04**
surgeon right hand inject healon chamber ant	47	52	1.09±0.28	1.27±0.6	**p>0.05**	4.38±1.24	6.15±1.26	t(97)=-7.03, **p<0.001**
surgeon right hand capsulorhexis rhexis cannula capsula lentis	48	51	1.04±0.2	1.18±0.56	**p>0.05**	33.94±8.96	64.37±23.43	t(65.09)=-8.63, **p<0.001**
surgeon right hand cut lancet clear cut cornea	48	53	1.04±0.2	1.02±0.14	**p>0.05**	3.54±0.99	4.75±1.25	t(97.20)=-5.42, **p<0.001**
surgeon right hand excision material utrata`s tweezers capsula lentis	48	53	1.21±0.41	1.11±0.32	**p>0.05**	4.38±1.92	6.02±3.07	t(88.43)=-3.26, **p=0.002**
surgeon left hand hold colibri tweezers bulbus oculi	13	53	1.08±0.28	1.49±0.75	t(53.75)=-3.22, **p=0.002**	33.92±14.73	78.02±27.74	t(35.73)=-7.89, **p<0.001**
surgeon left hand hold micro spatula bulbus oculi	38	0	1.16±0.37	-	-	44.5±16.56	-	-

Assessing the gSPMs for activity sequences revealed the most frequent transitions consistent with the surgical work sequences. The generic SPMs computed for the *Capsulorhexis* phase, using the example data, are shown for both populations in Figure 5. Both gSPMs were filtered with a threshold of 5%, and all transitions with a global probability of less than this threshold were deleted from the gSPM visualizations. Furthermore, the most probable paths were highlighted in each of the gSPMs (grey shaded activities). Due to the concurrent behavior of the surgeons' left and right hands, there are two main paths for each population. As a simple criterion, all transitions connected to the main path that appeared in more than 50% of the respective iSPM population were highlighted using bold lines. Solid lines symbolize the work flow of the surgeons' right hand, while dotted lines symbolize the work flow of the surgeon's left hand.

In Table VIII, the significance of transitions between activities during the *Capsulorhexis* interventional phase is shown. Sample results are presented for all highlighted transitions along the main path of each hand. Both strategies were significantly different for the path of the surgeon's right hand for the *paracentesis* → *Healon injection* transition. This results from the existence of the alternative *paracentesis* → *Vision blue injection* → *irrigation* → *healon injection* path that did not occur in ambulatory interventions. Additionally, the use of a different surgical instrument for left-handed *holding* is reflected in the gSPMs.

Table VIII: Differences in Capsulorhexis activity transitions (for activities on the 'mean' path)

Start activity	Stop activity	global transition probability in ambulatory interventions	global transition probability in inpatient interventions	significance
start	surgeon right hand paracentesis paracentesis knife cornea	1.00±0.00	0.64±0.48	t(52)=5.39, **p<0.001**
surgeon right hand paracentesis paracentesis knife cornea	surgeon right hand inject healon chamber ant	0.94±0.24	0.49±0.50	t(76)=5.78, **p<0.001**
surgeon right hand inject healon chamber ant	surgeon right hand capsulorhexis rhexis cannula capsula lentis	0.81±0.38	0.83±0.35	p>0.05
surgeon right hand capsulorhexis rhexis cannula capsula lentis	surgeon right hand cut lancet clear cut cornea	0.92±0.26	0.84±0.33	p>0.05
surgeon right hand cut lancet clear cut cornea	surgeon right hand excision material utrata`s tweezers capsula lentis	0.94±0.22	0.99±0.07	p>0.05
surgeon right hand excision material utrata`s tweezers capsula lentis	end	0.86±0.27	0.94±0.16	p>0.05
start	surgeon left hand hold colibri tweezers bulbus oculi	0.24±0.43	0.58±0.50	t(99.689)=-3.68, **p<0.001**
surgeon left hand hold colibri tweezers bulbus oculi	end	0.23±0.42	0.80±0.28	t(81.514)=-7.944, **p<0.001**
start	surgeon left hand hold micro spatula bulbus oculi	0.65±0.48	0.00±0.00	t(48)=9.51, **p<0.001**
surgeon left hand hold	end	0.69±0.43	0.00±0.00	t(48)=11.28, **p<0.001**

micro spatula bulbus oculi				

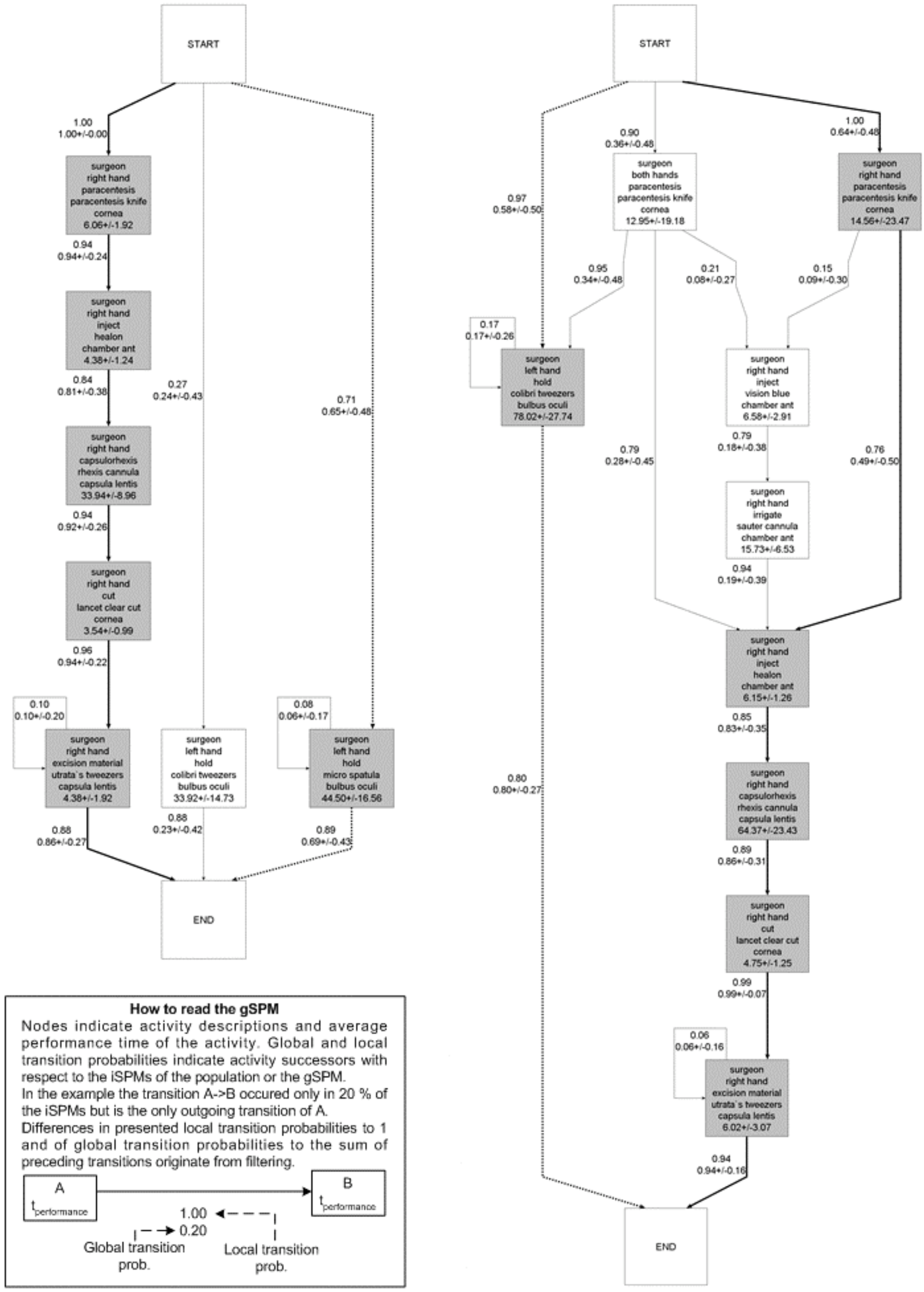

Figure 5: gSPMs for Capsulorhexis phase in ambulatory (left) and inpatient (right) Cataract interventions ('mean' path of right hand: solid line style; 'mean' path of left hand: dotted line style)

4 Discussion

To the best of our knowledge, this is the first approach that presents the computation of a generic Surgical Process Model – a statistical 'mean' surgical treatment based on large populations of real clinical data. As this work has shown, it is possible to create realistic gSPMs from real clinical data. The method presented in this paper showed the essential steps for building gSPMs and using them to assess the surgical work flow of intervention populations.

The example use case compared real clinical data from ambulatory and inpatient cataract interventions and demonstrated that differences between two 'mean' treatments can be assessed and analyzed in detail. For the clinical example data, reasons for differences in procedure times of both surgical treatment strategies could be traced back to individual work steps in both populations.

Our calculated gSPMs for the clinical use case data demonstrated several differences in treatment strategies, which could be expressed in terms of temporal information, as well as by workflow transition disparities. Our example use case showed, that these transitional disparities can be clearly identified, quantified, and analyzed with the help of gSPMs. However, the presented methods work for other intervention types as well, provided they have been recorded using the same methods as described here.

We have considered the application of the overall method from the technical point of view and neglected possible biases from the clinical point of view, such as the complexity of the surgical cases and therefore the allocation of the patients to the impatient group, to show the feasibility of the approach. Furthermore, the cataract interventions in this article have not yet been interpreted from a clinical viewpoint. The differences between ambulatory and inpatient cataract interventions have been used only to provide a clinical example use case to present the idea of gSPMs and to illustrate the application of our methods.

It was possible to recover gSPMs that corresponded to recommended surgical treatments for both strategies. The output of the gSPMs can be adapted to meet a given user's needs. Perspectives and activities can be chosen freely, resulting in models of higher or lower complexity. The more perspectives are concurrently selected, the greater the complexity of the resulting gSPM, and vice versa. Furthermore, a decrease in complexity, resulting in improved lucidity and a higher granularity, can be achieved by segmenting the iSPMs into local parts, e.g. based on interventional phases.

Calculating the transitions between activities also had a side effect: the bottom-up identification of a 'mean' procedure course from the data. By following the transitions with the highest probabilities from the artificial START to the END, a statistical 'mean' procedure course was identified. Clinical experts checked the resulting mean intervention courses to ensure they corresponded with the recommended cataract treatments.

The registration step between iSPMs in this study was based on the literal similarity of the features. This was appropriate in the context of gSPM calculations from the technical point of view, but it does not consider semantic similarities between work step descriptions. Computing the structural gSPM generated a purely logic-oriented model that only presents sequences of work steps.

To assess the transition probabilities between activities, only binary relations based on predecessor-successor relations were considered. Here, several other approaches could also be considered, such as data mining strategies [14, 19, 20]. Examining the sequence of transitions before the current predecessor might lead to a shift of probabilities. However, binary relations were chosen so that the models could be calculated with less complexity.

The objective of this work was to present a method to calculate gSPMs. However, further research is needed to investigate appropriate models from the clinical point of view, with a focus on the clinically relevant granularity of the gSPMs, the inclusion of several perspectives as features, and consideration of the 'history.' The models can also be improved by explicit indication of concurrent activities, a step that was neglected in our example use cases so as not to overload the visual representations.

Several clinical application cases emerge from the new methods. Besides comparing surgical strategies, we could also quantify the use of different surgical technologies to achieve the same surgical goal . This makes an assessment of the influence of Surgical Assist Systems possible. Using gSPMs to train residents allows for an assessment of their progress. Furthermore, intervention costs may be calculated in more detail to improve the hospital's billing efficiency or other financial issues. For instance, operating rooms in hospitals command a vast amount of human resources, device resources, and materials. For this reason, they represent one of the most cost-intensive sectors in hospitals [24, 25]. The use of these resources for individual patient treatments is usually estimated by measurement parameters such as cut-suture times or by derived parameters such as turnover rates [26]. However, cut-suture times do not provide the level of detail of information about the statistical 'mean' treatment of an intervention population as generic Surgical Process Models. This can be put to a multitude of possible uses such as the estimation of resource needs for surgical interventions or an examination of differences in surgical work flow, which may ultimately support administrative billing.

Consequently, the bottom-up identification of the 'mean' intervention course allows for a further application case: the comparison of an individual Surgical Process Models (iSPMs) and generic Surgical Process Models (gSPMs) that could be advantageous to investigate the reasons why a single surgical intervention course deviates from the mean procedure course.

In the future, detailed and rigorous analysis of gSPMs may serve as a powerful tool for surgeons to improve their work, for medical engineers to design support systems, for both to have a common, validated and standardized discussion base, and even for managing personnel to design better corporate structures, as illustrated in this article. Preclinical requirements analysis, retrospective analyses, or post-development evaluations of surgical strategies, surgical skill levels, or the use of new surgical instruments or devices are all use cases that could rely on models obtained from valid gSPMs. From the technical point of view, gSPMs can be also used as a pre-stage in developing workflow management support for the digital operating room of the future.

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