Embedding Conformance Checking in a Process Intelligence System in Hospital Environments*

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Abstract. Process intelligence is an effective means to analyze and improve business processes in companies with high degree of automation. Hospitals are also facing high pressure to be profitable with ever decreasing available funds in a stressed healthcare sector, which calls for methods to enable process management and intelligent methods in their daily work. However, traditional process intelligence systems work with logs of execution data that is generated by workflow engines controlling the execution of a process. But the nature of the treatment processes requires the doctors to work with a high freedom of action, rendering workflow engines unusable in this context.
In this paper, we introduce a novel method to conformance checking that computes fitness of individual activities in the setting of sparse process execution information, i.e., not all activities of a patient's treatment are logged. We embed this method into a process intelligence approach for hospitals without workflow engines, enabling process monitoring and analysis.

Keywords: process modeling in healthcare, visualization and monitoring healthcare processes, conformance checking

1 Introduction

Hospitals nowadays have to face several challenges. They have to be cost-effective and efficient while offering high quality service for each patient and they need to adjust to a changing healthcare situation. One established means to tackle these challenges is the management of business processes. Hospitals strive to improve their performance by managing their most important treatment processes, by modeling and standardizing them in the form of clinical pathways.

Clinical pathways are one way of improving the quality of patient service through efficient usage of resources and defining clear responsibilities [22]. A clinical pathway is defined as a structured, multidisciplinary care plan, which defines the steps of a patient

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treatment for a certain disease in a specific hospital [23]. While clinical guidelines provide a generic recommendation for a certain disease, clinical pathways capture details of local structures, systems and time frames to address the guideline recommendations in the concerned hospital. Process modeling allows the domain experts, in particular the doctors, to discuss, refine, and enhance treatment processes in a guided, common, and well documented way.

In the domains that require high flexibility, e.g., healthcare, the business processes are executed rather manually than automated allowing the necessary degree of freedom. However, during manual enactment of the treatment process, there is data produced while performing certain activities, e.g., registering the patient, lab orders, or administering a drug. This data is stored in several locations of the hospital's IT system landscape. But, there are many activities of a treatment process as well that happen without leaving any observable trace in IT systems. Nonetheless, the existing sparse information about treatment execution can be used to bring transparency into the execution of a process to monitor performance, such as progress, runtime, and cost. Further, it enables conformance analysis. However, special techniques are required, as existing approaches for process monitoring and conformance checking assume that all activities are logged in the process execution log. In this paper we present a novel approach to tackle this gap by utilizing well-known techniques, i.e., from process mining, and combining them with process models designed by domain experts.

Domain experts, e.g., doctors, have their own views on the processes they perform. It is crucial to present them the available information that can be inferred from the collected sparse data in their view on their natural abstraction layer. In the process model they are able to grasp the environment of a monitored section as well, e.g., the adjacent activities, assigned roles, attached documents, even if these surroundings are not monitored and exist only in the model. To ensure and improve the quality of the business processes, resp. clinical pathways, the users of such a monitoring system are interested in answers for questions like: What is the progress of my currently running cases? How long does the process take in average? Does the execution of the cases conform to the process model?

This paper describes an approach that brings the process model, holding the context about the performed activities, and the execution data of observable activities together to enable process monitoring and analysis. The approach is aligned to the business process lifecycle [28], cf. Fig. 1. In a first step (i) the process model is designed and event monitoring points (EMPs) are defined as required by the domain experts. During the (ii) configuration step those EMPs are connected with the data located in the broad IT landscape of the organization. During process execution (iii), the data is collected and used in the monitoring system. Once a certain amount of data is available, it is evaluated (iv), whether the model fits the recorded data and whether the EMPs were gathered as intended. In the likely case that the evaluation shows that the model does not reflect the behavior observed at the EMPs, the model can be adjusted by redesigning it, starting another iteration.

The remainder of this paper is structured as follows. Section 2 gives an overview of related work. Section 3 provides a general description of our approach and explains, how a monitoring system is introduced step by step. In Section 4 we discuss an implementation of a process intelligence system in a hospital. We review the presented approach regarding benefits and limitations in Section 5, before we conclude the paper and give a brief outlook on future work in Section 6.

2 Related Work

In the following we discuss related concepts and related work to enabling business process intelligence in hospitals.

2.1 Processes in Hospitals

In the medical sector, clinical pathways are special standardized treatment processes. They describe detailed steps for an ideal patient over all involved disciplines, e.g., surgeons, anesthesiologists, and nurses. By following the pathway step by step, an equally high quality of treatment and better foreseeable length of stay in the hospital can be reached [21].

In practice, a clinical pathway can be supported on several levels [25]. On the first level, clinical pathways describe activities, tasks and responsibilities in a printed form as complement to a patient's medical record. On the second level, the existing documentation is replaced by a special paper form that describes the clinical pathway. At the third level, the paper forms are replaced by clinical information systems that hold all documentation that can be used for analysis and operational guidance. On the forth level, the pathways are optimized and generalized, so that new pathways can easily be developed and connected to existing ones.

Raetzell and Bauer [18] as well as Köth et al. [8] describe a top-down approach for defining clinical pathways. Before the pathway can be modeled it has to be discussed which roles are involved. One member from each role should take part in the process modeling activity, creating the to-be process. Before the roll-out in the hospital, the pathway should be tested and refined in several trial periods.

Ronellenfitsch et al. [21] give an overview about successfully introduced pathways in surgery. While evaluating these pathways and comparing them to the patients' treatment without pathways several advantages of the pathways turned out. Through a clear definition of treatment steps, the whole process gets more transparent for patients as well as for physicians and their new colleagues. Several evaluations (e.g. [23]) showed a shorter length of stay in hospital, a lower mortality rate or cost reduction because double examinations could be avoided and the treatment process could be better planned.

2.2 Business Process Intelligence

The described approach in this paper introduces a business process intelligence (BPI) system in a hospital. Mutschler et al. [16] present a reference architecture, composed of an integration layer, functional layer, and a visualization layer for a BPI system. These systems address "managing process execution quality by providing several features, such as analysis, prediction, monitoring, control, and optimization" [5]. A great deal of work is available about capturing and storing process execution data for process monitoring and analysis, e.g., [5,2,14]. Dahanayake et al. [4] give an overview of Business Activity Monitoring (BAM), define an architecture framework, and classify systems. Bobrik collected requirements for a process monitoring system for system-spanning business processes and derive a framework to visualize business processes execution [3].

However, the majority of these approaches supports automated process execution only, where each activity is transparent to the controlling system. In contrast, we face the challenge of sparse event information where parts of the model are not observable.

2.3 Process Mining and Conformance Checking

Instead of manually modeling the processes of a hospital in an extensive elicitation procedure, one can also use existing traces of the processes in the hospital as an input to process mining algorithms [26]. These algorithms infer the process models that fit the observed real behavior. Process mining has been applied more or less effectively in healthcare, where Mans et al. mined the process models for a dutch hospital based on their accounting information [13,12]. Yet, there are domain specific complications. The procedures in healthcare are quite complex compared to typical business domains with high automation, as the number of different activities is very high [13]. Still, by applying heavy preprocessing steps, like filtering rare and complex traces through clustering techniques, the main processes can be identified quite well.

A methodology describing a mining based information gathering process was presented by Rebuge and Ferreira [19]. They also stress that preprocessing and clustering is necessary for obtaining useful results, but also account for the organizational and performance perspectives of mining.

As the results of process mining are inspiring for many researchers worldwide, by now, a plethora of mining algorithms have been proposed and implemented in the open source platform ProM [27]. The algorithms that are able to abstract from less frequent activities and transitions are particularly useful in complex scenarios like hospitals. The heuristic miner and the fuzzy miner are two example candidates that fall into this category [26].

However, process mining can not construct models containing more information than what is available in the underlying event logs. In our setting, only sparse process execution information is available, which leads to mined process models that do not reflect the treatment processes as perceived by the doctors. Thus, we rely on manually modeled processes.

Doing conformance checking in healthcare most often fails with the absence of complete log information of the treatment processes executed. Montani and Leonardi [15] discuss the similarity of different traces following a clinical workflow by using cost-based trace alignment. They provide a flexible means to define similarity between activities based on a taxonomy and propose the clustering of similar traces for indication whether a certain trace is common (the containing cluster is quite large) or an exception (the containing cluster is rather small). However, they rely on a process execution engine that executes the processes and are focusing on similarity between sequential processes mainly.

3 General Approach

The aim of our work is to establish a process intelligence system in a hospital where no process engine controls the processes. In this setting only some activities of the process models can be made observable and transparent to the system. These are the activities where medical staff interacts with the IT infrastructure during the process. In this setting we embed a conformance checking method to make sure the interactions happen according to the models and detect areas of deviations.

This paper describes a cyclic approach, depicted in Fig. 1 that is divided into four phases:

– Phase 1: (Re-)Designing of the treatment process, resp. clinical pathway, as a process model and definition of event monitoring points (EMPs) of interest, cf. Sect. 3.1.
– Phase 2: Configuring the monitoring system to establish the connection between the EMPs defined in phase 1 and the data located in several sources of the organization's IT system landscape, cf. Sect. 3.2.
– Phase 3: Gathering data based on the configuration, defined in phase 2, and monitoring of the process execution with respect to information about performance, e.g., progress, time, and cost, cf. Sect. 3.3.
– Phase 4: Evaluating the data gathered in phase 3 regarding conformance between recorded data and designed process model, the correctness of the data and whether the monitoring system provides the information needed, cf. Sect. 3.4.

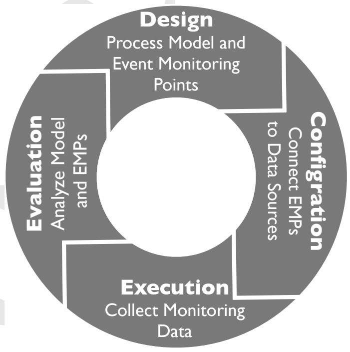


Fig. 1. Lifecycle for running a process intelligence solution

3.1 Design: Process Model and Event Monitoring Points

For the elicitation of process models, an interdisciplinary team has to be created that consists of domain experts, as well as of at least one process designer. The domain experts have to get familiar with the concepts of process modeling, e.g., with the modeling language BPMN [17]. This can be done in a warm-up exercise by modeling a trivial daily process that everybody is familiar with, e.g., the process of getting ready in the morning.

Once the domain experts are aware of the basic modeling concepts, the modeling of the treatment processes can be started. The treatment processes are captured as clinical pathways and are modeled in the mentioned interdisciplinary teams collaboratively using best practices from clinical guidelines [6] and the knowledge and experience of the domain experts to adjust the guidelines to the hospital's environment and requirements. First the main process is designed, which can later be refined into several subprocesses. Note that this process model is designed by the domain experts that are interested in the analysis and monitoring questions mentioned in Sect. 1. Thus, making it the most appropriate view for the users to present monitoring information in.

Based on the resulting model, EMPs have to be defined by the domain experts that can describe when a certain task started or ended [7]. Data for these EMPs can be later retrieved from the information systems and help to analyze and monitor the process.

3.2 Configuration: Connect EMPs to Data Sources

After designing the business processes and defining the EMPs, the EMPs can be bound to an implementation. Example implementations are a call of a web service, reading a certain cell in a spread sheet, or executing an SQL query to gather information about process enactment. We proposed an architecture for this configuration in an earlier work [7]. Setting up event and process instance correlation is part of the implementation. In hospital environments this is possible utilizing unique treatment case IDs and patient IDs that are used consistently across all IT systems. Note that currently this phase requires a high degree of manual effort. We are investigating semi-automatic ways to provide configuration assistance in the future.

3.3 Execution: Collect Monitoring Data

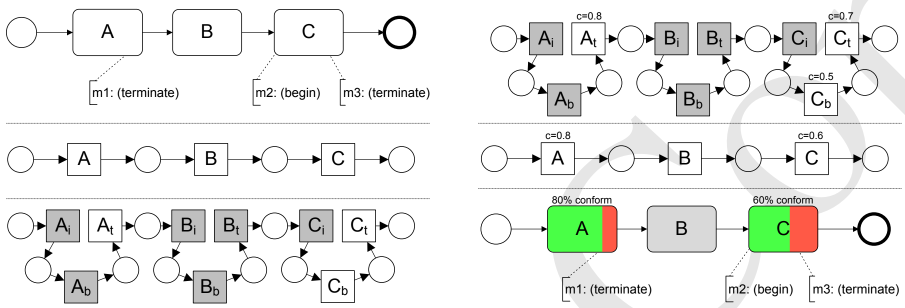
The configured EMPs are used to gather process execution data and discover the occurrence of events. The extracted and correlated events can be used to visualize the enactment performance in a monitoring user interface or to calculate measurements and KPIs to allow an in-depth analysis.

An analysis of process execution data allows answering questions like: How long did an instance need from the start to the end of the process in average? How long did an instance described by certain properties need for a certain process fragment? Which steps were already passed by a certain instance, what are the next process steps? In our earlier work, we addressed the question of identifying the most probable state of a process instance with sparse execution information [20].

3.4 Evaluation: Analyze Model and EMPs

Conformance checking is a technique to quantify the differences between what is specified in a model, and what happens in real life. Conformance checking methods known from process mining replay the logs in the model [24] or map them to the model with a cost-based alignment [1], to detect execution traces that do not conform to the model. These techniques assume that the model and the log use the same set of activities and that models exist in the form of Petri nets.

In the approach presented here, these two assumptions are not fulfilled, and need special attention. First, we need a Petri net representation for the process models, e.g., models in BPMN, which were elicited in Section 3.1. The translation from BPMN and other languages into Petri nets has been addressed for the most relevant workflow patterns [9]. We build on this translation and replace each activity with a basic activity lifecycle in a post processing step. The basic activity lifecycle consists of transitions *init*, *begin*, and *terminate*. States of interest might be the waiting time from *init* to *begin*, or the execution duration between *begin* and *terminate*. Fig. 2(a) sketches this Petri net translation on a simple sequential process. In the resulting Petri net, we mark the unmonitored transitions gray. These are not represented as monitoring points.



(a) Translation of an annotated operational business process in BPMN into a Petri net. The annotations describe monitoring points attached to the model at certain state transitions. First step uses translations as in [9] and the second is a postprocessing step replacing each activity with a simplistic lifecycle of *init*, *begin*, and *terminate*. The observable transitions of the resulting Petri net are white, the unobservable are marked gray.

(b) With the conformance results for each monitoring point for a state transition, we calculate the error rate of the activity by the weighted sum of the error rates of each participating EMP. Further, we can propagate this information to the operational process model in BPMN. In this view, we mark unmonitored activities gray for the user to distinguish between elements that are recorded and those that only exist in the model.

Fig. 2. A two step approach to highlight conformance errors based on EMPs in a process model in BPMN

For conformance analysis, we need to gather the historical events that were recorded manually. Ideally, these are already in electronic form, e.g., spread sheets, databases, or clinical information systems. Otherwise, this information needs first to be digitalized. The event information can then be sequentialized into a list of ordered events to produce an event log that serves as input to the conformance checking algorithms proposed in [24,1].

The work of Adriansyah et al. [1] is based on alignments using a cost-based fitness metric. Costs for insertion—when an expected activity of the model is missing from the trace—and costs for skipping— when an activity is in the trace that is not expected in the model— can be defined for each activity separately. We make use of this flexibility and set the cost for insertion of unobservable activities in the model, i.e., the transitions marked gray in Fig. 2(a) to 0 and leave the remaining transition costs on the default value. With this configuration, a cost-optimal alignment of each trace in the log to the model can be computed. These alignments show for each trace, which operations were necessary for replaying the trace in the model. The three identified categories are: *valid* when an event of a trace could be replayed in the model correctly, *inserted* when an activity in the model is missing from the log, and *skipped* when an event in the log needs to be skipped, as it is not expected in the model. See Fig. 3 for examples with calculated fitness values with example alignment costs, cf. [1]. Note that in the figure, there is a fourth kind of category. These *unobservable* activities are the ones not reflected in the log and assigned costs of 0.

Fig. 3. Different examples of alignments for traces, cf. [1]

The algorithms implemented in ProM provide a detailed view of each trace and the global fitness and cost of alignment. But we want to provide an overview for the domain experts showing which event monitoring points are violating the designed execution in the model. Thus, we need an aggregated information for each EMP and for the monitored activities.

This alignment rate for each EMP is calculated as follows. Let e be an event. Let t be an aligned trace to the model, i.e., a finite sequence of *valid*, *inserted* and *skipped* events. The alignment rate of each event is calculated as the number of traces in which the event e was aligned correctly, i.e., only *valid* occurrences of e in t, divided by the number of traces the event e occurred in, i.e., *valid*, *inserted* or *skipped* occurrences of e in t. This alignment rate is an indicator, how often the event monitoring point was participating in a conformance violation according to the designed process model.

It is natural to present the conformance checking results to the end users in their process models. Since we have the transformation mapping from the process model to the Petri nets as in 2(a), we can visualize the conformance violations in the original process model. Process participants and controllers can then identify conformance violations in their view and abstraction layer. An example visualization of the alignment rate per activity is shown in Fig. 2(b) where the alignment rate for each EMP is averaged and encoded as a green colored fraction of the activity node.

4 Case Study in a Healthcare Scenario

The general approach presented in the above section was used in the implementation of a process intelligence system in a hospital's surgery department. The liver transplantation pathway designed there serves as a case study for a rather complex treatment process which is handled in a multidisciplinary team of medical personal.

In the beginning, an interdisciplinary team of physicians and process experts modeled the special treatment process. Because the participating physicians had no prior knowledge in process modeling, a one-day introduction and course about process modeling, especially about Business Process Model and Notation (BPMN), was given.

For modeling the clinical pathway together with the surgeons, tangible Business Process Modeling (t.BPM) was used [10]. It is a set of plastic tiles that can be used to model processes on a table having the iconography of BPMN. The t.BPM toolkit enables domain experts to actively shape their processes and allows the process expert to act as a facilitator. The process was refined in several steps. First, the main process was modeled. Afterwards, subprocesses were analyzed, interactions and dependencies between subprocesses were defined. The whole pathway was described on three levels of detail.

Based on the resulting model, EMPs, e.g., first admission of patients, or start of the evaluation for transplantation, were defined and assigned. This was done within the surgeons' team. They had to discuss which monitoring points are essential, how these points can be defined exactly and in which clinical information systems these data are located. By configuring the EMPs the surgeons intend to answer concrete question about their treatment processes, e.g.:

- When does the patient, having one out of several liver diseases, arrive at the surgery department for the first time?
- When does the evaluation for the liver transplantation start?
- When does the patient arrive at the operational room? When does she leave?

Afterwards, data from clinical information systems were added to the process steps at selected event monitoring points. Interestingly, it turned out that not all predefined monitoring points could be assigned with data. For example, the monitoring point for the acceptance of a liver for transplantation was defined as a timestamp. In practice, this is an undocumented decision of a surgeon who does a phone call to accept a liver for transplantation leaving no trace in the IT systems of the hospital.

After assigning data, a first analysis of the pathway, based on records from the past, could take place. It turned out that the modeled process did not cover all patient cases. Therefore, the process had to be discussed and modified again together with the surgeons.

The resulting monitoring system is designed for answering questions, such as: How did all of my cases perform? Which activities are performed for running instances at the moment? How does the process execution perform? A screenshot of the system is shown in Fig. 4, where besides the BPMN process model, patient statistics addressing analysis questions are depicted in the upper part as histograms. The system was developed in an iterative procedure following an agile development paradigm, i.e., early prototypes were developed and discussed and tested with the domain experts. Figure 4 shows the latest version of the user interface, where the focus is on simplicity and preset analytics questions, such as *Which cases exist?* or *Where are the cases currently?* Whereas, earlier versions had more advanced filtering options for the cases, which proved to be too complicated for the non-tech-savvy domain experts.

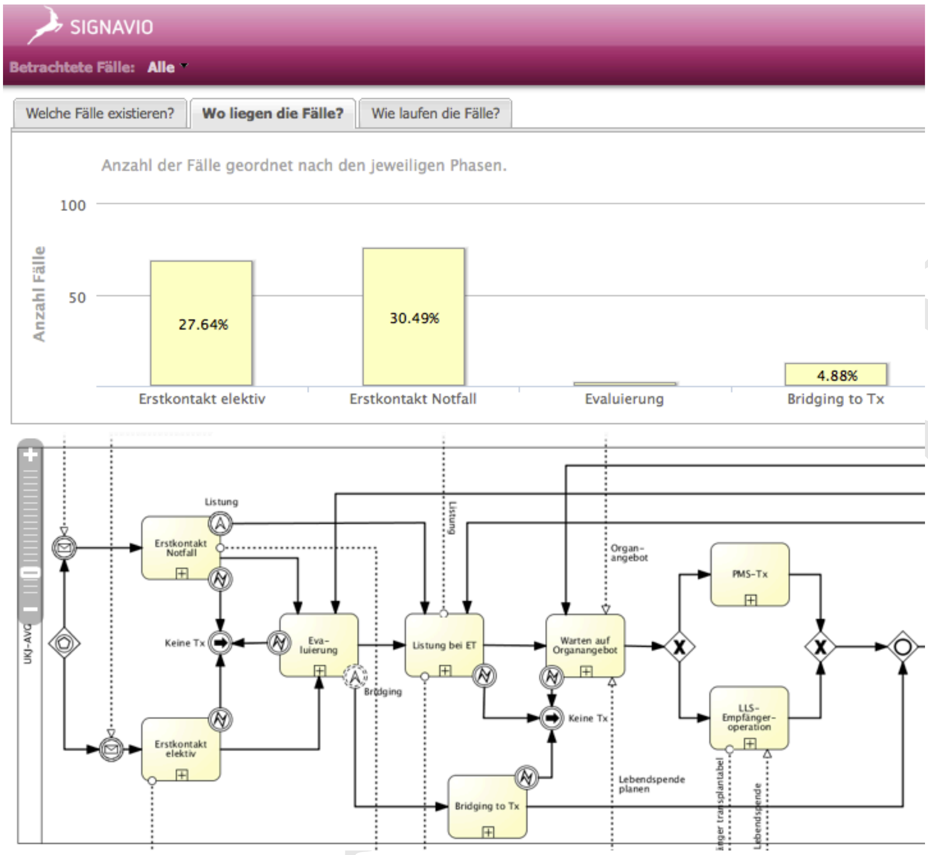


Fig. 4. Liver transplantation process model used in Signavio Process Analyzer for process monitoring and analysis (aperture).

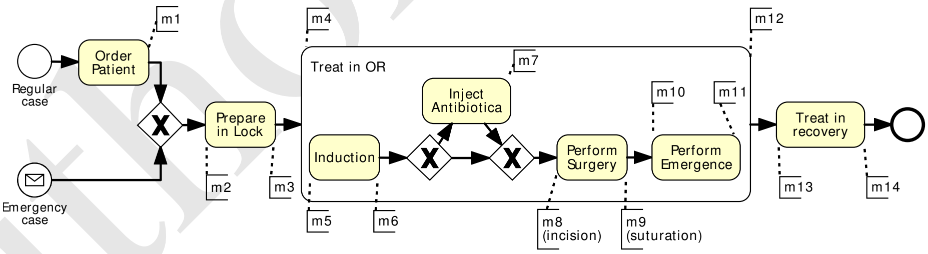


Fig. 5. Process model of a surgery

Fig. 5 shows the surgery part of the process that is densely packed with event monitoring points. Measuring and monitoring this part of the treatment process is important, because the operating room is the most costly asset of a hospital [11], and laws demand a detailed documentation of surgeries.

We performed the conformance checking method introduced in Sect. 3.4 on real data for this surgery process. The results for each EMP are summed up in Table 1. We

EMP	event name	fitting	inserted	other pos.	all	failing	fitness
m_1	Patient ordered	552	0	0	552	0	1.000
m_2	Arrival in Lock	1006	280	9	1295	289	0.777
m_3	Departure of Lock	862	297	136	1295	433	0.666
m_4	Arrival in OR	1270	11	14	1295	25	0.981
m_5	Start of induction	1261	34	0	1295	34	0.974
m_6	End of induction	1253	42	0	1295	42	0.968
m_7	Antibiotics prophylaxis	183	0	112	295	112	0.620
m_8	Incision	1253	42	0	1295	42	0.968
m_9	Suturation	1239	55	1	1295	56	0.957
m_{10}	Start of emergence	1129	88	78	1295	166	0.872
m_{11}	End of emergence	1167	106	22	1295	128	0.901
m_{12}	Departure of OR	1219	62	14	1295	76	0.941
m_{13}	Arrival in recovery	1223	32	40	1295	72	0.944
m_{14}	Departure of recovery	1271	24	0	1295	24	0.981

Table 1. Cost-based alignment of model and log for the surgery process in Fig. 5

analyzed 1315 cases and filtered 19 unfinished traces out that did not end with departure of recovery or departure of OR.

For the alignment we used a cost function with equal weights of 2. This means that if the order of execution between two activities is switched in the log as opposed to the model, the algorithm can pick arbitrarily which of the two was correct, and which one needs to be skipped and inserted for proper alignment. However, we did one adjustment to the main activities in the surgery, being *Incision* (m_8) and *Suturation* (m_9), and set their alignment costs higher to 3. This means that the algorithm tries to align the adjacent activities around the ones with higher costs, resulting in higher conformance values for the activities with higher costs. We argue that as long as the algorithm does not make a fair non-deterministic choice in the decision, we want to have the main activities positioned correctly and the supporting activities around them.

In conformance checking, unfinished traces distort conformance results. Here the set of events is given by the EMPs $m_1, \ldots, m_{14}$, so we did not detect any events that had to be *skipped* in the log for an alignment, as all events in the log have corresponding activities in the model. However, if we encountered an alignment, where an event was skipped at the position assigned by the model and inserted elsewhere, i.e., it happened before preceding activities or after succeeding ones, we counted this as one error indicating *other position*. The two optional events *Patient ordered* and *Antibiotics prophylaxis* were only present in 552 and 295 cases respectively. Note that violations of undocumented optional events cannot be detected, resulting in high conformance values for *Patient ordered*. The *Antibiotics prophylaxis* was often done before the induction or even outside of the OR.

The resulting fitness numbers offer only a high abstraction and identify areas, where the documentation is not conform to the model. Consider the observed change of order of two activities that are in sequence according to the model. The replay algorithm can either decide that the first one is correct and skip and insert the second one to achieve alignment, or vice versa. This decision depends on the costs of the alignment operations of the activity, resulting in less alignment operations and higher fitness scores for costly activities. In this perspective, the proposed conformance check is only fair, if all activities have equal costs and the alignment algorithm makes a balanced choice which activity to skip and insert for the alignment.

5 Discussion

With introducing the process intelligence system in a hospital's prototype environment, cf. Fig. 4, we gained a lot of insights about users' experiences and learned about the requirements and expectations these users have. This iterative evaluation led us to several prototypes for a business process intelligence system during the project. For example, we compared several user interface layouts and filtering techniques for the process execution data. The current prototype provides a quick glance at the most relevant analytics questions that the doctors and nurses are interested in. A gain of transparency of treatment durations with visualization in the process models is achieved. Further, unfinished cases can be identified that are dangling in some activities. Usually, this is due to a lack of documentation, but also treatment errors might cause dangling cases. The outcome of the patient treatment can be measured in the process model by analyzing the percentages of mutually exclusive paths in the process that indicate different outcomes.

Note that the approach also has some limitations. At this stage, the configuration of such a system is quite expensive, time-consuming and needs manual effort. The conformance check of single EMPs and affected activities, as proposed here, serves only as a rough indicator of correct behavior, and it does not contain information about the reasons for deviations. A root cause analysis considering also the adjacent EMPs and activities is necessary to identify the underlying conformance issues. Doctors can then be made aware of these issues, which can be documentation mistakes or other treatment model violations, in order to improve the quality of the clinical pathways. At the current stage, support for *correct* deviations, i.e., proper reactions to unexpected and not modeled exceptions, is missing. If the treatment of the patient proceeds in an unforeseen way that is not captured by event monitoring points, it is treated also as a conformance issue and needs to be distinguished manually.

The technique used for conformance checking is based on a cost based alignment of observed execution with planned treatment. Consider the case of an observed switch in the execution order of two adjacent activities. As long as the underlying alignment algorithm does not make a fair random choice which activity to penalize, an interpretation of the results is difficult. To overcome this issue, the weighting functions can be tuned to pin more important activities to the model and align the supporting activities around them. This has to be done with the knowledge of domain experts, so that they can identify more crucial conformance issues, which are observable if these higher-cost activities have to be skipped and inserted for optimal alignment. However, if this proposed approach is used in fairly standardized clinical settings, e.g., in surgery departments, the majority of cases are still reflected in the analytics interface. Detecting unintentional deviations and reacting properly helps to ensure the positive effects of introducing clinical pathways on economic issues, on the quality of treatment measured through outcomes and patient satisfaction, and on the transparency of treatment for physicians and nurses.

For medical personnel, this conformance checking can already provide support in the clinical pathway. E.g. when patients have to come regularly to investigations, the conformance check can find patients who did not come. With this information, an early warning system can be established that lists such patients so that they can be contacted. Furthermore, missing investigations can be found, and double investigations can be avoided.

6 Conclusion

Clinical pathways describing treatment processes of patients are a useful instrument in routine care in hospital, especially for procedures with a high complexity of treatment in multidisciplinary teams. In this paper, we introduced an approach to enable process intelligence in a hospital. After designing a process model and defining EMPs together with medical personnel, the data captured from information systems can be used for performance monitoring and analysis as well as for conformance checking of standardized treatment procedures. With our approach we gain a higher transparency in the treatment process for medical personnel as well as for patients. But still, the system configuration is time-consuming, costly and needs manual effort.

In the future we will investigate semi-automatic binding of EMPs with process models to tackle the issue of the expensive configuration of such a process intelligence system. We will also work on user guidance for root cause analysis of conformance issues. Temporal constraints in the clinical pathways are not considered yet, because the described process intelligence system operates on a high level of business process model granularity. Thus, the topic of temporal constraints is not an issue at this stage, but needs to be addressed in future work.

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