Mining Process Execution and Outcomes – Position Paper

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Abstract. Organizational processes in general and patient-care processes in particular, change over time. This may be in response to situations unpredicted by a predefined business process model (or clinical guideline), or as a result of new knowledge which has not yet been incorporated into the model. Process mining techniques enable capturing process changes, evaluating the gaps between the predefined model and the practiced process, and modifying the model accordingly. This position paper motivates the extension of process mining in order to capture not only deviations from the process model, but also the outcomes associated with them (e.g., patient improving or deteriorating). These should be taken into account when modifications to the process are made.

Keywords: Process mining, business process modeling, Clinical guidelines

1. Introduction

Organizations often try to improve the quality of services provided to their clients by specifying a business process model (BPM) that captures the desired workflow in the organization and how exceptional situations should be handled. The aim is that if these process models would be implemented, the quality of services would increase and costs would be saved. In the healthcare domain, special attention has been given to creating evidence-based clinical guidelines that recommend care processes for patients with defined clinical conditions. Research has been carried out in developing methodologies and tools for specifying guidelines as computer-interpretable algorithms [1], linking them to clinical databases, executing them, and evaluating the impact of these systems [2].

However, organizational processes in general, and patient-care processes in particular, change over time. In real life, we often encounter situations that we neglected to consider in our BPM (e.g., guideline model). These situations could require process paths that were not specified in the BPM. In addition, expanding medical (or in general, organizational) knowledge on new procedures, available treatment options, and evidence for their effectiveness, may push users and organizations into changing their process implementations, often before updating the BPM. Thus, we may find that the actors participating in the business processes (patient-care processes) often do not follow the BPM exactly and may act differently than the model specifies, which may or may not be justified or helpful.

Deviations of the actual performed process from its model have been studied both in the BPM community and in the Medical Informatics community. In the BPM community, process mining has been used to capture process changes, evaluate the gaps between the predefined BPM and the practiced process, and modify the BPM accordingly [3, 4].

In the Medical Informatics community, critiquing approaches [5-7] have been used to compare the actual processes executed to their specified model. Advani et al. [7] describe a model and algorithm for deriving structured quality indicators and auditing protocols from formalized specifications of guidelines used in decision support systems. This critiquing approach can be used to determine whether the deviations followed the intentions of the original model and thus were justified. Traum-AID [6] is a rule-based system combined with a planner. Its critiquing interface examines actions the physician intends to carry out, identifies errors and calculates their significance, and produces a critique in response to those intentions. In the 1980's, Miller [5] developed several critiquing systems in which the physician inputs medical information describing a patient, a current set of test results, and current actions (e.g., ventilator settings), and a proposed set of new actions. The system assesses appropriate treatment goals, and uses those goals for critiquing.

Similar analysis can be used to offer decision-support to physicians only when they deviated from these intentions. Quaglini et al. [8] developed computerized guideline implementations that allow users not to follow al the actions specified in the model, justify the deviation, and select alternative activities out of a wide range of activities that were not planned by the guideline authors but that are related to the original alternative via hierarchies taken from standard clinical vocabularies. Similarly, many computerized guideline formalisms have tools that allow the user to deviate from the normal sequence of activities [9], as flexibility is often needed when the modeled guideline is to handle emergency situations in patients or when the model is out of date and does not convey the latest medical knowledge. Peleg and Kantor [10] used process mining to automatically analyze differences between two versions of process models that were created due to the expansion of medical knowledge, in order to find differences in particular medical knowledge concepts (e.g., new drug) or in concept relationships (e.g., pathogen is not longer believed to cause a disease).

As we strive to improve our BPMs (patient-care models), we must not only track deviations from the process model, but also the outcomes associated with them (e.g., patient improving or deteriorating) so that these could be taken into account when modifications to the process are made.

2. Background

In order to follow process outcomes and relate them to changes in the process, we need a formal process model that can represent goals and outcomes. We rely on the Generic Process Model (GPM) proposed by Soffer and Wand [11].

2.1 The Generic Process Model (GPM)

GPM is a state-based view of a process including the concept of goals. Briefly, GPM offers a process model which is composed of a quadruple <S, L, I, G>, where S is a set of states representing the domain of the process. Each state in an enacted process holds the values of all the properties (or state variables) of the process domain at a moment in time. The law L specifies possible state transitions as mapping between subsets of states, defined by conditions over values of the domain state variables; I is a subset of unstable states, which are the initial states of the process after a triggering external event has occurred; G is a subset of stable states on which the process terminates, termed the goal of the process.

The process goal as addressed by GPM is a state meeting the conditions that should be achieved by the process. GPM distinguishes process goals from soft-goals, which are defined as an order relation on goal states [12]. In other words, soft-goals relate to the *desirability* of possible states in the goal set (all meeting the condition that terminates the process) according to defined business objectives. For example, the goal of a process may be a state where some treatment has been given to a patient, but a state where the treatment does not incur side effects is considered as “better” than a state where side effects are observed. Finally, GPM entails criteria for assessing the validity of a process, namely, its ability to achieve its goal [11]. It enables the analysis of a process to identify causes for invalidity, and suggests appropriate redesign actions to eliminate these causes.

For operational and representational purposes, GPM’s law can be mapped to Petri Nets [13]; states correspond to sets of places of the Petri Net and laws correspond to transitions (including transition guards). Complementing this representation, GPM’s clear distinction of goals and soft-goals can form a basis for improving a practiced process, where improvement can be related to attained soft-goal values and to fewer situations where the goals of the process are not met.

3. Research Objectives

Objective 1: Develop a method for establishing process data on which outcome and goal analysis will be based. This includes patient-specific data referred to by the process model (e.g., age), data about activities that were started and completed, and data regarding outcomes, judged by relevant soft-goal attainment.

Objective 2: Develop methods and tools for analyzing process data to identify relationships between patient-specific data, execution paths, process goals, and outcomes.

4. Demonstration of Our Approach

To demonstrate and motivate our approach, we use a process model based on a guideline for treatment of ear infections (acute otitis media, AOM) [14]. Figure 1 shows a Petri Net of the process model adapted from that guideline. Such a Petri Net can be automatically converted from a GLIF algorithm [15].

In order to have a measure of process attainment of soft and hard goals, and also of exceptions, where goals are not met, we need to analyze and mine the execution log of the actual process, or their reflection in electronic medical records (EMRs), to document for each work item (i.e., an activity performed by an actor on a given case). In addition to the existing process mining ability to identify that an activity has been performed by an actor at a certain time, we also need to mine changes to state variables (e.g., a patient's temperature or his adverse response to a drug) that were not predicted by the process model, and their timestamp. These data could help us in relating activities (both those that followed the process model and those that represent changes) to outcomes. Table 1 presents a potential EMR of a 2.4 year-old patient reflecting the ear-infection process instance as well as outcomes. As can be seen, the physician first followed the guideline, prescribing Amoxycillin for 5 days, as the patient was over 2 years old. But, when AOM was not resolved and the goal state was not reached, he decided to prescribe a 10-day Amoxycillin, which was not according to the guideline. This time, the goal state was reached. Analysis of EMR data of other patients showed that in many of the 2-3 year old patients, AOM was not resolved after 5-day treatment. These relationships between goals and outcomes could suggest ways to improve the clinical process. For example, change the laws L3 and L5 such that patient under 3 (not under 2) would receive a 10-day treatment (Figure 1).

5. Future Work

While the above ear infection scenario demonstrates the potential contribution of process execution and outcome analysis, a systematic method for such analysis is still under development. We are currently working on a hypothetical case study, taken from the clinical guideline domain of vaccinations, which examines actual execution or processes (as determined from synthetic EMR records). We will study how we can automatically deduce from the EMR records whether instances of the process have attained the process model's soft and hard goals, and when and how to characterize exceptional situations. We would like to use data about real process execution and outcomes (log files) along with the preconceived process models to test whether our approach could be used to automatically assess soft and attainment of hard goals as well as assess the occurrence of an exception (i.e., the invalidation of the process due to an unexpected event), resulting in processes that do not meet their goals and remain in intermediate states. We would then like to combine outcomes analysis with delta analysis for populations of patient with similar characteristics to suggest a linkage between process changes and process outcomes.

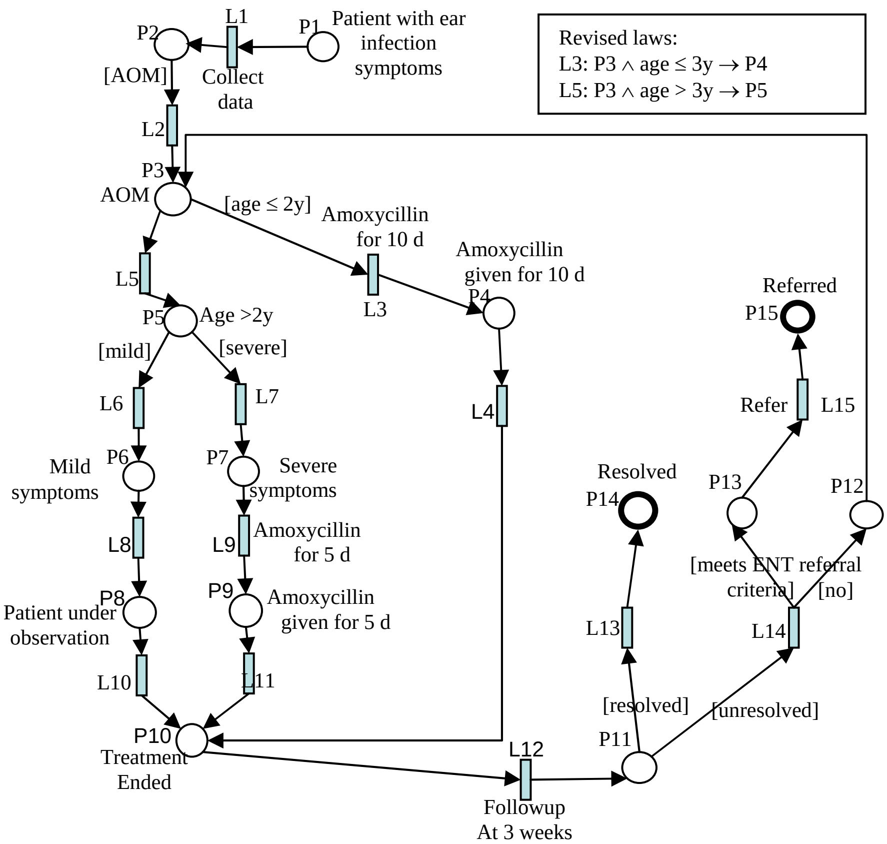

Figure 1. A Petri Net representation of an ear infection clinical algorithm. Places, corresponding to GPM states, are marked as Pi. Transitions, corresponding to GPM laws, are marked as Li. P14 is the desired goal state, P15 is the undesired goal state, and P1 is the initial state.

Table 1. EMR reflecting an ear-infection treatment process and outcomes

Time-Date	State variable	Value	Petri Net place
07-01-01:08:00	AOM	mild	P6
07-01-01:08:10	Medication	5-day Amoxycillin	P9
07-01-21:08:00	AOM	mild	P6
07-01-21:08:10	Medication	10-day Amoxycillin	P4
07-02-12:08:00	AOM	false	P14

The main challenge we are facing is how to establish a causal relationship between the execution data (or delta analysis) and the obtained outcomes. The outcomes of clinical processes are determined not only by the actions taken, but also by pre-existing patient properties, such as age in the ear infection example. The analysis should take these properties into account as affecting variables, and provide recommendations with respect to specific patient properties.

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