Process Mining: Towards Comparability of Healthcare Processes

Emmanuel Helm[1(✉)] and Josef Küng[2]

[1] Research Department of e-Health, Integrated Care,
University of Applied Sciences Upper Austria, 4232 Hagenberg, Austria
emmanuel.helm@fh-hagenberg.at
[2] Institute for Applied Knowledge Processing,
Johannes Kepler University, 4040 Linz, Austria
jkueng@faw.jku.at
https://www.fh-ooe.at/
http://www.jku.at/

Abstract. With the technology emerging more and more possible applications of process mining in healthcare become apparent. In most cases the goal of applying process mining to the healthcare domain is to find out what actually happened and to deliver a concise assessment of the organizational reality by mining the event logs of health information systems. To develop medical guidelines or patient pathways considering economic aspects and quality of care, a comparative analysis of different existing approaches is useful (e.g. how different hospitals execute the same process in different ways). This work discusses how to use existing process mining techniques for comparative analysis of healthcare processes and presents an approach based on the L* life-cycle model.

Keywords: Process mining · Data mining · Process quality

1 Motivation

One reason for the lack of Business Process Management (BPM) technologies in healthcare is the complexity of the processes, where unforeseen events in the course of a disease or during the treatment are to some degree a "normal" phenomenon [1].

Process mining provides an a-posteriori empirical method to *discover* processes in observed system behavior (i.e. event logs) [2]. A goal of applying process mining techniques to the healthcare domain is to understand the complex interactions between multiple actors, both human and machine, and the underlying, partially implicit processes [3].

To develop medical guidelines or patient pathways considering economic aspects and quality of care, a comparative analysis of different existing approaches is useful. Partington et al. propose the application of process mining as *an evidence-based business process analysis method* to investigate variations in clinical practice and delivery of care across different hospital settings [4].

M.E. Renda et al. (Eds.): ITBAM 2016, LNCS 9832, pp. 249–252, 2016.
DOI: 10.1007/978-3-319-43949-5_20

2 Problem

The characteristics of healthcare processes make it impossible to apply rigorous BPM, Workflow Management (WFM) and Business Process Reengineering (BPR) techniques. Mans et al. make it clear that *a hospital is not a factory and patients cannot be cured using a conveyor belt system* [5]. However, the authors of [3,5,6] (among others) agree that process mining has the potential to improve healthcare processes by increasing compliance and performance while reducing costs.

The comparison of mined healthcare processes aims to show the (dis)similarity of practices across different healthcare providers and to identify potential improvements. In addition to the general challenges of applying process mining techniques to the healthcare domain, comparative analysis also has to deal with the *gaps* between different healthcare providers. These gaps mostly originate from the fact that different organizations are essentially executing the same process without following a strict process model [7].

To enable the comparability of two mined process models, shared semantics are necessary (i.e. using the same terms for the same activities and characteristics). The precondition for semantic interoperability is a formal representation of data within the healthcare information systems. Since healthcare systems are often heterogeneous and autonomous IT systems, the formal representation varies strongly [6].

Only two approaches that compare the processes of different healthcare providers were found in the literature. While Partington et al. [4] actually compared data from different sources (i.e. different information systems), for Mans et al. [8] the basis was a shared database, filled by different hospitals.

3 Approach

The presented approach extends the *L* life-cycle model* for process mining to support comparative analysis and cross-organizational mining [7]. It is based on a case study comparing four hospitals (cf. [4]) and on the experience gathered during a process mining project comparing eight Austrian hospitals.

The critical stages of *extraction* (1), *control-flow model creation* (2) and *model enhancement* (3) [7] are extended to allow for parallel execution, thus enabling interaction between the different mining activities (i.e. between the mining of processes from different hospitals).

4 Results

Figure 1 shows the extended L* life-cycle model for comparative analysis. It comprises all stages of the original model but spares the steps between the stages for better readability (e.g. inclusion of historical data and handmade models). Previous research aimed at *Stage 1* to prepare the logs of different information systems for further analysis [9,10].

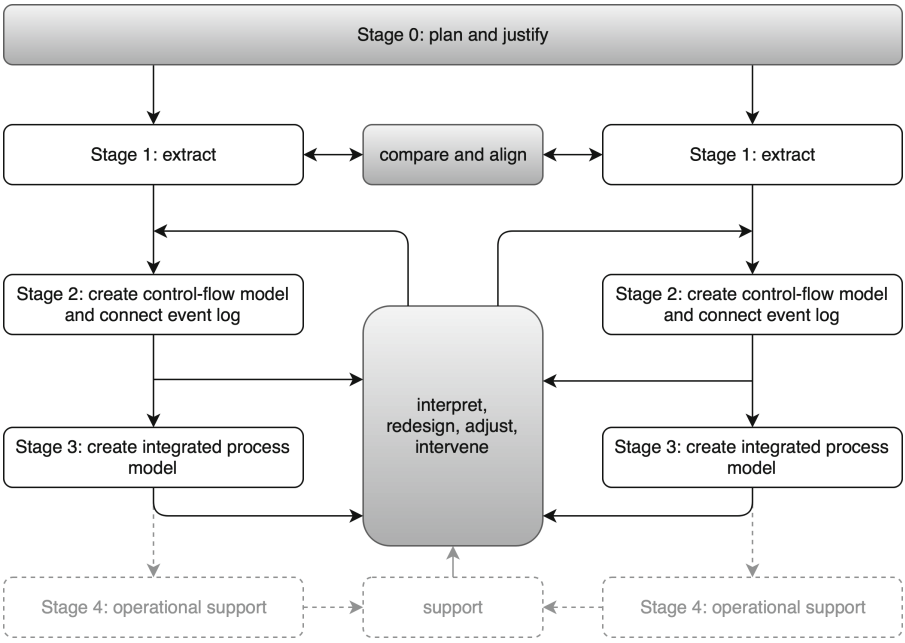

Fig. 1. The extended *L* life-cycle model* for comparative analysis, based on the original model in [7] and the adoption in [4]. Continuous alignment between the parallel stages is necessary to minimize the number of necessary iterations.

On the left and right side in Fig. 1 the two parallel mining processes comprising the respective stages are depicted. Extending the original L* life-cycle model, the *interpretation*, *intervention*, *adjustment* and *redesign* steps are conducted with both models together. Additionally a new step during the *extraction* stage was added, to *compare and align* the logs before applying automated process discovery techniques.

Currently methods are developed to show possible gaps at all stages. After identifying a gap, key figures indicate if hospitals either do fundamentally different things or they record the same things differently (e.g. using different coding systems). The mining activities can then be adopted accordingly, leading for example to further preprocessing of the logs.

The first approaches are based on statistical analysis of the base logs (e.g. t-tests based on the frequency of specific events). Further approaches will include graph similarity measurements and conformance checking techniques (cf. for example the works of Dijkman et al. [11] and Van der Aalst [12]).

5 Conclusions

By coordinating multiple mining activities it is possible to identify the gaps in early stages, thus reducing the number of iterations necessary to present meaningful,

comparable process models. However, room for further improvement was identified since the early stages involving the comparison and semantic alignment of different data sources lack automation and tool support.

References

1. Reichert, M.: What BPM technology can do for healthcare process support. In: Peleg, M., Lavrač, N., Combi, C. (eds.) AIME 2011. LNCS, vol. 6747, pp. 2–13. Springer, Heidelberg (2011)
2. Van der Aalst, W.: Process Mining: Discovery, Conformance and Enhancement of Business Processes. Springer, Heidelberg (2011)
3. Kaymak, U., Mans, R., van de Steeg, T., Dierks, M.: On process mining in health care. In: IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 1859–1864. IEEE (2012)
4. Partington, A., Wynn, M., Suriadi, S., Ouyang, C.: Process mining for clinical processes: a comparative analysis of four Australian hospitals. ACM Trans. Manage. Inf. Syst. (TMIS) **5**(4), 19 (2015)
5. Mans, R.S., van der Aalst, W.M., Vanwersch, R.J.: Process Mining in Healthcare: Evaluating and Exploiting Operational Healthcare Processes, pp. 17–26. Springer, Heidelberg (2015)
6. Lenz, R., Peleg, M., Reichert, M.: Healthcare process support: achievements, challenges, current research. Int. J. Knowl. Based Organ. (IJKBO) **2**(4), 1–16 (2012)
7. Van der Aalst, W., et al.: Process mining manifesto. In: Daniel, F., Barkaoui, K., Dustdar, S. (eds.) BPM Workshops 2011, Part I. LNBIP, vol. 99, pp. 169–194. Springer, Heidelberg (2012)
8. Mans, R., Schonenberg, H., Leonardi, G., Panzarasa, S., Cavallini, A., Quaglini, S., van der Aalst, W.: Process mining techniques: an application to stroke care. Stud. Health Technol. Inf. **136**, 573 (2008)
9. Paster, F., Helm, E.: From IHE audit trails to XES event logs facilitating process mining. In: Digital Healthcare Empowering Europeans: Proceedings of MIE2015, vol. 210, p. 40 (2015)
10. Helm, E., Paster, F.: First steps towards process mining in distributed health information systems. Int. J. Electron. Telecommun. **61**(2), 137–142 (2015)
11. Dijkman, R., Dumas, M., García-Bañuelos, L.: Graph matching algorithms for business process model similarity search. In: Dayal, U., Eder, J., Koehler, J., Reijers, H.A. (eds.) BPM 2009. LNCS, vol. 5701, pp. 48–63. Springer, Heidelberg (2009)
12. Van der Aalst, W.M.: Business alignment: using process mining as a tool for Delta analysis and conformance testing. Requirements Eng. **10**(3), 198–211 (2005)