Increasing Visibility through Process Mining

Kalyan S Pasupathy
Mayo Clinic, USA

David A Clark
University of North Carolina Hospitals, USA & University of Missouri, USA

INTRODUCTION

To be able to provide safe, effective, and efficient care in today's competitive environment, hospitals must have process visibility and continuously improve quality (Kemafor, Sheth, Cardoso, Miller, & Kochut, 2003). Process visibility refers to the ability to see and understand all aspects of a process at any point in time (Klotz, Horman, Bi, & Bechtel, 2008). However, the complex nature and the high degree of variability reduce process visibility (Clark & Pasupathy, 2014). Although complete visibility is unrealistic, it can be improved using a variety of tools and techniques. Process mining can aid in the reduction of this gap.

Process mining involves the extraction of data from "event logs" stored in various hospital information systems (Mans, Schonenberg, Song, & van der Aalst, 2008). Following extraction, these events are linked, clustered, and examined for flow patterns. Identifying both patterns and flow can assist in the verification of conventional process maps and improve visibility (W. M. P. van der Aalst, Weijters, & Maruster, 2010). However, process mining has challenges related to mining hidden tasks, mining duplicate tasks, mining loops, dealing with noise, etc. A thorough understanding of the existing information system architecture and work processes is essential. Failure to properly understand and manage system complexities can potentially lead to poor data quality (Watts, Shankaranarayanan, & Even, 2009). Poor quality of data can be harmful to system usability and operational performance, resulting in poor decision making. The strength mining results and the decisions are dependent on the quality of the available data. It has been estimated that approximately five percent of an organization's data is of poor quality. Researchers have identified numerous data quality issues in health care, especially problems with accuracy, completeness, and timeliness (Gray, Orr, & Majeed, 2003; Peabody, Luck, Jain, Betenthal, & Glassman, 2004; Thiru, Hassey, & Sullivan, 2003).

Radio frequency identification (RFID) is an advancement in technology and can collect comprehensive data on events, by tracking patients, providers and equipment and improving efficiency and outcomes (Chien, Yang, Wu, & Lee, 2009; Hsieh et al., 2010; C. Huang et al., 2007; H.-H. Huang & Ku, 2009; Leu & Huang, 2009; Raths, 2008; Stahl, Holt, & Gagliano, 2009; Sun, Wang, & Wu, 2008; Tzeng, Chen, & Pai, 2007; Wicks, Visich, & Li, 2006). Process mapping has been used to improve processes and increase efficiency, for instance to reduce overcrowding (Parks, Klein, Frankel, & Friese, 2008) and streamline workflow in ancillary departments (Nagula, Lander, Rivero, Gomez, & Srihari, 2006). Process mapping provides qualitative information and RFID provides a quantitative perspective (Clark & Pasupathy, 2014). The purpose of this paper is to develop a framework and method to integrate process mining with process mapping and RFID to improve process visibility. This framework supports continual identification and correction of process visibility gaps. The reduction of these gaps should assist in the understanding of complex interactions in

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health care, variability in the process, and support continuous process improvement efforts.

The next section introduces process mining, and various techniques along with its application in healthcare are discussed. Then, the benefits and drawbacks of process mining are identified and those of process mapping and RFID are summarized. Next, the integration framework and method are discussed and finally, future research directions are identified.

BACKGROUND

Process Mining

Process mining is a technique employed to gain an understanding of a process by extracting data from event-logs to develop a process model. There are three classes of process mining techniques – *discovery*, *conformance analysis* and *extension* (W. M. P. van der Aalst & Weijters, 2004). For discovery, there is no *a priori* model, and the model is built solely based on event log data (W. M. Van Der Aalst, Reijers, & Song, 2005). In the case of conformance analysis, there is an *a priori* model, this model is compared against the event log and any discrepancies that arise are studied (Rozinat & van der Aalst, 2006). And finally, extension also has an *a priori* model. This goes one step further beyond conformance analysis, where instead of just comparison, the model is enhanced. To illustrate basic process mining, following is an example. This technique can only be used if the sequence of events is known. A typical event-log includes the following data elements: (1) case ID, (2) patient ID, (3) activity, (4) resource, (5) start time, and (6) end time. Table 1 is a fabricated event log of patients checking into a hospital, having blood drawn, arriving at the surgery waiting area, and entering the holding area to prepare for surgery.

The case ID is a unique identification number that refers to a specific instance of the process. It must be unique to distinguish one instance of

Table 1. Example surgery patient preparation event log

Case ID	Patient ID	Activity	Resource	Start Time	End Time
Case 1	1002894	Patient Registration	Clerk 1	5:00	5:25
Case 2	3941286	Patient Registration	Clerk 2	5:20	6:05
Case 3	1002894	Patient Blood Draw	Technician	5:26	5:40
Case 4	1145563	Patient Registration	Clerk 1	5:30	5:47
Case 5	5876953	Patient Registration	Clerk 3	5:37	5:41
Case 6	1002894	Patient Waiting Area	-	5:41	6:00
Case 7	5876953	Patient Waiting Area	-	5:42	6:10
Case 8	1056327	Patient Registration	Clerk 3	5:43	5:49
Case 9	1145563	Patient Waiting Area	-	5:48	6:00
Case 10	1056327	Patient Waiting Area	-	5:50	6:03
Case 11	1002894	Patient Holding	Nurse 1	6:01	6:45
Case 12	1145563	Patient Holding	Nurse 2	6:01	7:29
Case 13	1056327	Patient Holding	Nurse 3	6:04	7:00
Case 14	3941286	Patient Blood Draw	Technician	6:05	6:20
Case 15	5876953	Patient Holding	Nurse 4	6:11	7:31
Case 16	3941286	Patient Waiting Area	-	6:20	6:45
Case 17	3941286	Patient Holding	Nurse 1	6:45	7:40