Process Mining the Trauma Resuscitation

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***Abstract*—We present our process mining system for analyzing the trauma resuscitation process to improve medical team performance and patient outcomes. Our system has four main parts: trauma resuscitation process model discovery, process model enhancement (or repair), process deviation analysis, and process recommendation. We developed novel algorithms to address the technical challenges for each problem. We validated our system on real-world trauma resuscitation data from the Children's National Medical Center (CNMC), a level 1 trauma center. Our results show our system's capability of supporting complex medical processes. Our approaches were also implemented in an interactive visual analytic tool.**

***Index Terms*—Process Mining, Trauma Resuscitation, Medical Process Diagnosis**

I. INTRODUCTION

Trauma is the leading cause of death and acquired disability among children and young adults. Because early trauma evaluation and management strongly impact the injury's outcome, it is critical that severely injured patients receive efficient and error-free treatment in the first several hours of injury. During the trauma resuscitation, multidisciplinary teams rapidly identify and treat potential life-threatening injuries, then develop and execute a short-term management plan. The Advanced Trauma Life Support (ATLS) [1] protocol has been widely adopted as the initial evaluation and management strategy for injured patients worldwide. Although its implementation has been associated with improved outcomes, the application of this protocol has been shown to vary considerably, even with experienced teams. Many deviations from the ATLS protocol, e.g. the omission or delaying of steps, may have minimal impact on the outcome, but have been shown to increase the likelihood of a major uncorrected error that may lead to an adverse outcome.

The objective of this project is to develop a computerized decision support system that can automatically identify deviations during trauma resuscitations and provide real-time alerts of risk conditions to the medical team. We are approaching this goal using four process mining techniques [2] (Figure 1). (1) Process model discovery, extracting workflow models from data. (2) Process model enhancement, repairing the workflow model to mitigate the divergence between data-driven workflow models and expert hand-made models. (3) Process deviation analysis, discovering and analyzing the medical team errors. (4) Process recommendation, building a recommender system that can give treatment suggestions to medical teams.

Key challenges for this study include limited data size, permissible deviations, variable patients, and concurrent teamwork. (1) Limited data: the trauma resuscitation workflow data needs to be coded manually in a labor-intensive way. To our best knowledge, there is no reliable system that can automatically capture trauma resuscitation workflow data. (2) Permissible deviations: it is necessary to distinguish the acceptable deviations (false alarms) from unexpected deviations (true alarms). (3) Variable patients: patients come to the trauma bay with different injuries that need different treatment plans. (4) Concurrent teamwork: trauma resuscitations need concurrent collaborative work within a medical team comprised of examining providers (surveying physicians), bedside nurses (left nurse, right nurse and charge nurse), and other team roles (e.g., surgical coordinator, anesthetist).

In this study, we contributed a comprehensive process mining framework with related techniques. We showed what problem each process mining technique solved and how these techniques worked together to achieve our project goals. We evaluated our process mining framework and techniques on a complex real-world medical case, the trauma resuscitation process. Our results showed the effectiveness of our techniques over existing process mining methods.

II. RELATED WORK

Many medical processes are performed based on domain knowledge and standard protocols. For trauma resuscitations, the ATLS [1] protocol suggests a medical examination flow based on treatment priorities: Airway → Breathing → Circulation → Neurological Disability. Despite the use of standardized evaluation and management protocols, deviations are observed in up to 85% of trauma resuscitations [3]. Although most deviations are variations that result from the flexibility or adaptability needed for managing patients with different injuries, other deviations represent "errors" that can contribute to significant adverse patient outcomes, including death [4][5].

To discover and analyze the process errors, previous research used two different approaches: data-driven and expert-model-based. Data-driven methods rely on process models or patterns discovered from historic data, while expert-model methods rely on process models or rules designed by domain experts. Data-driven methods work by comparing individual process enactments to the discovered average process representation, such as the average process trace [6], the data-driven model [7], or frequently occurring patterns [8]. Expert-model-based approaches locate the deviations by checking the conformance between particular enactments to the expert model [9], or constraints or rules specified by medical experts [10]. In our study, we combined both methods. First, we discovered the data-driven model and designed the expert model based on

Figure 1. Process mining framework with related techniques we used in trauma resuscitation process analysis.

medical domain knowledge. Then, we compared the data-driven and expert-model to uncover the discrepancies between practice and expectation. The discrepancies were evaluated by medical experts to determine if model enhancement is needed. Lastly, we used the enhanced expert model to discover and analyze more process deviations.

To reduce process errors, Clarke et al. [11] and Fitzgerald et al. [5] developed computer-aided decision support systems that recommend treatment steps. These systems, however, rely on hand-made rules specified by medical experts, lack generalizability, and are subject to human bias. We developed an automatic, data-driven, label-free framework for process analysis and recommendation.

III. Data Description And Definitions

Ninety-five resuscitations were coded by medical experts from video recordings collected at trauma bay of CNMC between August 2014 and October 2016. Collection and use of the data was approved by the Institutional Review Board.

The coded **trauma resuscitation cases** $\boldsymbol{c} = [c^{(1)}, \dots, c^{(l)}]^T$ is a vector of elements $c^{(i)}$. Each $c^{(i)} = \{id^{(i)}, \boldsymbol{x}^{(i)}, \boldsymbol{T}^{(i)}\}$ denotes a **resuscitation case** (TABLE I), which is indexed with a unique case id, contains the resuscitation trace $\boldsymbol{T}^{(i)}$, and has a vector $\boldsymbol{x}^{(i)}$ of context attributes. A **resuscitation trace** $\boldsymbol{T}^{(i)} = [a_1^{(i)}, \dots, a_k^{(i)}]^T$ includes k activities that are ordered based on activity occurrence time. **Context attributes** $\boldsymbol{x}^{(i)} = [x_1^{(i)}, \dots, x_g^{(i)}]^T$ is a vector of g recorded patient attributes (e.g., patient age, injury type) and hospital factors (e.g., day vs. night shift, prehospital triage of injury severity).

IV. Methods And Results

Process model discovery, process model enhancement, and process deviation analysis are descriptive analytics, aiming to extract insights and knowledge from historic data. Process recommendation is predictive or prescriptive analytics, aiming to determine the best treatment procedure given observed context attributes (e.g., patient demographics).

TABLE I
Sample Trauma Resuscitation Data

Case ID	Activity	Start Time	End Time
xx1	Pt arrival	0:00:00	0:00:01
xx1	Visual assessment-AA	0:00:45	0:00:52
xx1	Chest Auscultation-BA	0:00:55	0:00:58
xx1	R DP/PT-PC	0:01:04	0:01:05
xx1	Total Verbalized-GCS	0:01:29	0:01:30
xx1	Total Verbalized-GCS	0:01:50	0:01:51
xx1	Right pupil-PU	0:02:12	0:02:18
xx1	Left pupil-PU	0:02:19	0:02:24
xx1	Right pupil-PU	0:02:24	0:02:25
xx1	Visual inspection-H	0:02:33	0:02:34
xx1	Palpation-H	0:02:33	0:02:37

(a) Trauma resuscitation trace

Case ID	xxx1	xxx2
Age category	24-96	24-96
Sex	Male	Female
Night Shift	0	1
Weekend	0	0
Pre-arrival Notification	1	0
Trauma Activation Level	Transfer	Attending
Intubation	0	0
Glasgow Coma Score >13	1	0
Injury Type	Blunt	Penetrating
Injury Severity Score	5	12
Neck Injury Severity Score	3	5

(b) Context attributes

Properties	Stats
Num. Cases (or Patients)	95
Num. Total Activities	10851
Num. Activity Types	132
Num. External Attributes	17
Time Period	2014.08 – 2016.12
Size of Medical Team	[7, 12]
Longest Trace (Num. Acts.)	196
Shortest Trace (Num. Acts.)	60
Avg. Num. Acts. in Traces	114.2

(c) Data statistics

ID	Ext. Attributes	Resus. Traces
$id^{(1)}$	$x_1^{(1)}, \dots, x_g^{(1)}$	$a_1^{(1)}, \dots, a_k^{(1)}$
$id^{(2)}$	$x_1^{(2)}, \dots, x_g^{(2)}$	$a_1^{(2)}, \dots, a_k^{(2)}$
$\vdots$	$\vdots$	$\vdots$
$id^{(n)}$	$x_1^{(n)}, \dots, x_g^{(n)}$	$a_1^{(n)}, \dots, a_k^{(n)}$

(d) Data formalization

A. Process Discovery of Resuscitation Workflow

Existing workflow discovery algorithms (e.g., heuristic miner, genetic miner, alpha miner [2]) have problems in handling duplicate activities. For example, during trauma resuscitation, the medical team checks patient's eyes twice for different reasons. First, during the primary survey, they assess the patient's pupillary response for neurological disability. Second, during the secondary survey, they examine patient's eyes in more detail, looking for injuries to the cornea, sclera and eyelids. An accurate workflow model should be able to distinguish the first eye check from the second one, despite their identical labels. Existing workflow mining algorithms assume that duplicate activities in a process trace are equivalent. We solved this problem using Hidden Markov Models (HMM) to represent the workflow. To induce an HMM, we proposed a novel inference algorithm guided by trace alignment (AGSS) [12]. AGSS (Figure 2) first initializes a general Markov chain λ_0. After initialization, AGSS determines two factors: which states to split and when to stop splitting. AGSS determines the splitting candidates from the alignment matrix and orders them by column frequency. After calculating the splitting candidates, AGSS performs iterative splitting.

AGSS Medical Process Model Discovery:
Given: A set of resuscitation traces $\boldsymbol{T} = [\boldsymbol{T}^{(1)}, \dots, \boldsymbol{T}^{(n)}]$.
Objective: Successively splitting state $s_j \in \boldsymbol{S}$ to find an HMM topology λ_s that maximizes probability $P(\boldsymbol{T}|\lambda)$:

$$\lambda_s(\boldsymbol{T}) = \underset{\lambda}{\operatorname{argmax}}\, P(\boldsymbol{T}|\lambda) = \underset{\lambda}{\operatorname{argmax}} \prod_i P(\boldsymbol{T}^{(i)}|\lambda) \qquad (1)$$

where $P(\boldsymbol{T}^{(i)}|\lambda)$ is observation sequence probability, solved with the Forward algorithm [13]. $\boldsymbol{S}$, the set of states to be split, is calculated using the trace alignment algorithm [14].

We tested AGSS on trauma resuscitation workflow data and compared it to existing state-splitting HMM inference algorithms. Our results show that AGSS is not only more computationally efficient, but also produces more accurate HMMs. Our results also show the workflow model discovered by AGSS is more readable and more representative than models discovered by existing HMM inference and process mining algorithms.

B. *Process Model Enhancement of Resuscitation Workflow*

As required for process deviation analysis, an initial expert model was developed by medical experts. The initial model underwent several revisions until the domain experts reached a consensus about which medical activities to include and in which order. We used two different approaches to enhance the expert model. First, we compared expert model to the data-driven model discovered using our AGSS algorithm. The model induced by AGSS helped discover three discrepancies between the initial expert model and actual practice. These discrepancies were analyzed for repairing the expert model. Afterwards, we performed a more detailed and comprehensive model diagnosis using conformance checking [15] with twenty-four trauma resuscitation cases. We discovered more discrepancies between the model and practice, and came to the conclusion that our initial model could not fully represent the resuscitation process. In our preliminary analysis, we identified 57.3% (630 out of 1099) activities as deviations based on the initial expert model, of which only 24.6% (155 out of 630) were true deviations (i.e., process errors), while the remaining 75.4% deviations were false alarms due to process model incompleteness, coding errors, or inadequate algorithms. We then applied different strategies to address the false alarms, e.g., repairing the expert model, improving the coding procedure, and updating the algorithm. We tested the repaired model on ten unseen resuscitations, achieving 93.1% deviation discovery accuracy.

Process Enhancement:
Given: Historic resuscitation traces $\boldsymbol{T} = [\boldsymbol{T}^{(1)}, \dots, \boldsymbol{T}^{(n)}]$ and a hand-made expert model λ_e.
Objective #1: Discover process deviations $\boldsymbol{\varepsilon}$ from $\boldsymbol{T}$:

$$\boldsymbol{\varepsilon} = \mathcal{C}(\boldsymbol{T}, \lambda_e) \quad (2)$$

where $\mathcal{C}(\boldsymbol{T}, \lambda_e)$ is the conformance checking algorithm [15], taking process traces and expert model as input and outputting the process deviations.

Objective #2: Classify $\boldsymbol{\varepsilon}$ as true alarms (i.e., process errors) and acceptable variations (i.e., false alarms $\boldsymbol{\varepsilon}'$). Repair the expert model λ_e to eliminate $\boldsymbol{\varepsilon}'$.

C. *Process Deviation Analysis of Resuscitation Workflow*

The main goal of process deviation analysis is to test our hypotheses, proving the adverse effects of accumulated deviations on trauma patient outcomes and team's ability to compensate for major errors.

Our previous deviation analyses were performed manually by medical experts and automatically based on the conformance checking algorithms. For manual deviation analysis, we analyzed thirty-nine resuscitations and discovered the number of errors and the number of high-risk errors per resuscitation

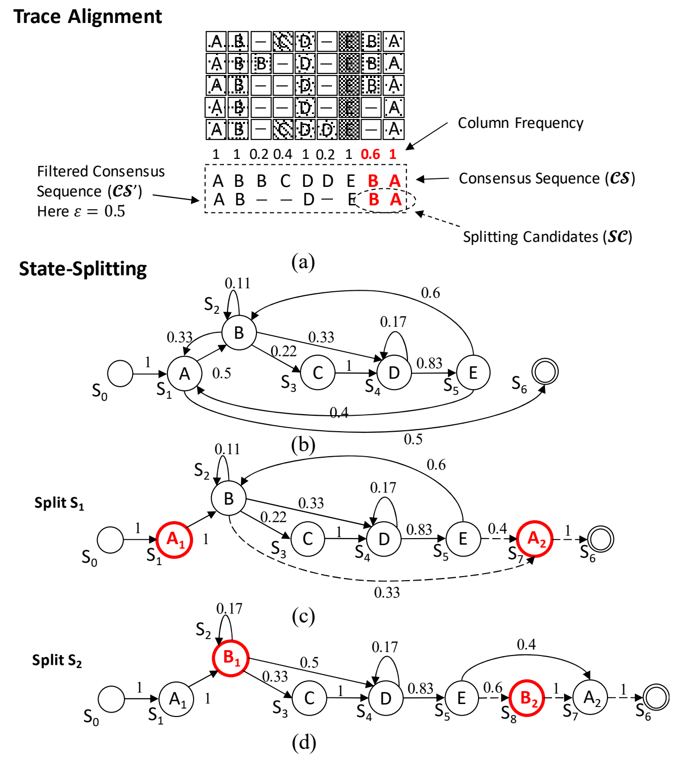

Figure 2. Our Alignment-guided State-splitting algorithm for discovering a more representative data-driven workflow model [12]. (a) Trace alignment algorithm to find splitting candidates. (b)(c)(d) State-splitting HMM inference.

increased with the number of non-error process deviations per resuscitation (correlation-coefficient=0.42, p=0.01 and correlation-coefficient=0.62, p<0.001, respectively) [18]. For automated deviation analysis, we performed conformance checking on the enhanced process model using ninety-five trauma resuscitations. We detected 1,059 process deviations in 5,659 activities of 42 commonly performed assessment activity types (11.1 deviations/case). Our results also show that the resuscitations of patients with no pre-arrival notification (p=0.037) and blunt injury (blunt vs. non-blunt p=0.013) were significantly correlated with more deviations.

D. *Process Recommendation of Resuscitation Workflow*

To help reduce medical team errors, we developed a process recommender system [16][17] (Figure 3) that provides data-driven step-by-step treatment recommendations. Our system was built based on the associations between similar historic process performances and contextual information (e.g., patient demographics). We introduced a novel similarity metric that incorporates temporal information about activity performance, and handles concurrent activities. Our recommender system selects the appropriate prototype performance of the process based on user-provided context attributes. Our approach for determining the prototypes discovers the commonly performed activities and their temporal relationships. We tested our system on the trauma resuscitation and intubation processes, achieving recommendation accuracy of up to 0.77 F1 score (compared to 0.37 F1 score using ZeroR) and having 63.2% of recommended procedures lie within the top-five neighbors of the actual

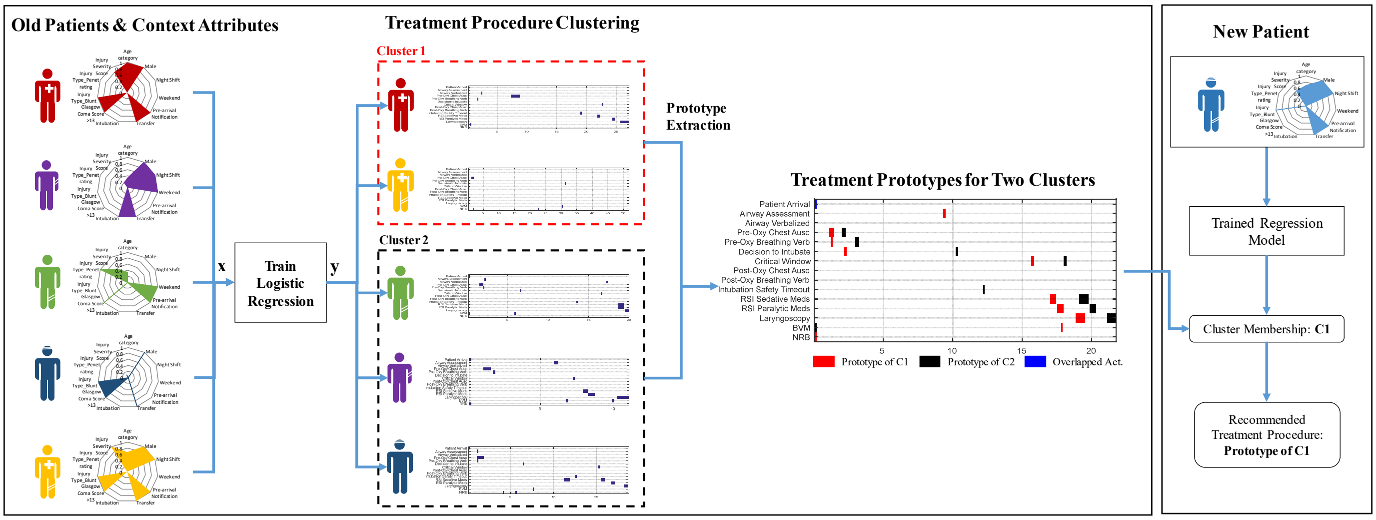

Figure 3. Medical process recommender framework [3]. Treatment procedures were clustered based on similarity (horizontal axis of the matrices represents time and vertical axis represents activity type). A logistic regression model is trained between context attributes and cluster membership. Treatment prototypes were calculated from each cluster. When a new patient comes to the trauma bay, trained regression model takes context attributes as input and outputs the cluster membership (e.g., C1). A treatment prototype is recommended based on the cluster membership (e.g., Prototype of C1).

historic procedures in a set of eighty-seven cases.

Process Recommendation:
Given: A new patient with context attributes $\boldsymbol{x}'$.
Objective: Recommend a treatment plan $\boldsymbol{T}_{\boldsymbol{x}'} = [a_1, \dots, a_k]^T$ to the medical team that maximizes:

$$\boldsymbol{T}_{\boldsymbol{x}'} = \underset{\boldsymbol{T}}{\operatorname{argmax}}\, S(\boldsymbol{T}, \boldsymbol{T}_g) \tag{3}$$

where $\boldsymbol{T}_g$ is the ground-truth treatment procedure and $S(\boldsymbol{T}_x, \boldsymbol{T}_y)$ is the similarity measure of two process traces [16].

V. Conclusion

We presented the framework and associated techniques used in our trauma resuscitation process analysis and diagnosis. Our framework includes four parts: process model discovery, process model enhancement, process deviation analysis, and process recommendation. For each part, we showed the core problems, methods, and results we achieved so far. This paper shows a substantial implementation of process mining techniques on a significant real-world problem.

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