Automatic Workflow Capture and Analysis for Improving Trauma Resuscitation Outcomes

Sen Yang
Department of Electrical and Computer Engineering, Rutgers University, Piscataway, NJ

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. The Advanced Trauma Life Support (ATLS) 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 resuscitation and provide real-time alerts of risk conditions to the medical team. To achieve this objective, my dissertation addresses three research questions:

1. How to automatically identify deviations from the trauma resuscitation process using manually coded data.
2. Whether high process variability is independently associated with the occurrence of major errors.
3. How to predict the errors in real time.

Currently, we have 48 trauma resuscitation cases manually coded at the Children's National Medical Center, which includes 7983 events total. Medical experts on our research team have developed a workflow model of 58 required tasks and 70+ acceptable additional tasks. Previously with ProM (www.promtools.org), an open-source process mining tool that can identify deviant practices through conformance analysis, we evaluated 39 (out of 49) resuscitations based on the expert model. In total, 1030 events were identified as deviations, of which there were 651 deviations of commission (unnecessary or repeated evaluations of treatment steps [e.g., intubation without indication]), 312 deviations of omission (omission of necessary steps [e.g., failure to measure end-tidal CO_2 after intubation]), and 104 scheduling errors (steps out of order [e.g., assessment of neurological status after administration of paralytic agents]). After being checked manually by our medical experts, the deviations were classified based on cause. 261 were classified as errors (practices that risked adverse outcomes [e.g., omission of airway assessment]), 511 were acceptable (e.g. acceptable repetition of visual inspection on Chest), 105 were coding problems (i.e., disagreements between different data coders), 108 were model problems (i.e., biases in expert model), and 82 were algorithm issues. Actions were taken to address each problem. For example, issues with the model were addressed by repairing the expert model based on insights from the deviation analysis. Coding problems were addressed by updating the data coding dictionary and adding inter-rater reliability analysis into the coding scheme.

Currently, we are working on question #2, trying to verify the association between process variability and occurrence of major errors. To define the process variability, we have two different approaches. The first approach is to count the deviations from the analysis in question #1. The second approach is purely data-driven: defining the process variability as the distance between a single process procedure and the average. My current work tries to discover the average procedure using the Trace Alignment algorithm or Hidden Markov Model (HMM). Although finding an accurate, unbiased measurement of variability is difficult, the even greater challenge is question #3. To provide real-time alerts of risk conditions, we must build prediction models. However, human error is elusive and qualitative, influenced by environmental, mental, emotional, and attentional factors. In practice, these factors are hard to quantify and record. Provided with only the workflow data, we must center our strategy on statistical prediction, finding underlying associations between the occurrence of errors and their preceding activities or procedures. Our medical experts have successfully identified 7 different tasks that may be associated with the error "Lapse in In-line Stabilization" (failure to maintain the immobilization of injured spine) using a dataset of 45 instances. However, the challenge still exists for two reasons. Firstly, no existing techniques can record the resuscitation data automatically, and so the amount of data is limited by manual coding speed. Secondly, we lack a suitable prediction model capable of both working with small datasets and making real-time error predictions.

Our research is an application of computing-oriented health informatics in an emergency medical setting. This research has the potential to advance the use of information technologies (especially workflow/process analysis) in healthcare and other medical fields. Our study can also help improve the medical team's ability to manage human errors during trauma resuscitations or other critical medical care processes with similar tasks and workflow procedures. In addition, this research can provide valuable feedback for the improvement of existing techniques and inspire novel technical ideas in health informatics.