READ-TV: Research and Exploratory Analysis Driven Time-data Visualization

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What will the attendee be able to do after being in your session?

The background information on importance of workflow disruptions (FD) in surgical quality will precede formal presentation of a tool that allows for visual and interactive analysis of disruption data. The learner will understand the application of the Poisson stochastic processes in analysis of FD data and how gained insights may lead to development of team interventions aimed at improving performance and ultimately safety.

Description of the Problem or Gap

Surgical technology continues to improve patient outcomes, at the cost of increasing complexity. This increasing complexity of surgical technology may lead to increases in deviations from the expected operation progression, or flow disruptions (FD) (1-3). FDs indicate mismatches between work demands and the configuration of the supporting work system, and have the potential to negatively impact surgical outcomes, such as patient mortality, procedure duration, and surgical errors. FDs also result in negative effects on operating room teams, such as member stress (4) and increased perceived workload (5). In some situations, they may concatenate to trigger safety incidents.

Understanding of longitudinal patterns in FDs, in order to inform system improvements, requires application of quantitative tools to carefully collected data. Such datasets are being accrued by the surgical quality community; however, gaps still exist in our ability to visualize and analyze these. Surprisingly, even though timed event data is common in medical applications, a general-purpose open-source tool for visualization of such data is not available. Moreover, quantitative frameworks for data analysis are also relatively underdeveloped for this application. Therefore, we believe that an open-source visualization and interactive analysis software for FD data is an important missing component for minimizing surgical risk and will have utility in many other applications within the clinical community.

Methods: What did you do to address the problem or gap?

Building of a quantitative framework for FD data analysis starts with the application of homogeneous Poisson processes, which relate the times of occurrence of FD events in terms of an underlying rate. To understand the changes in this underlying rate, changepoint analysis is used to model the rate as a function of time using piecewise constant approximations. The changepoint analysis allows us to identify the specific periods of time where the rate of FD is increased relative to a baseline or a desired operating range.

To visualize the data, we use R/Shiny framework to develop an application for visualization of time stamped data. The Research and Exploratory Analysis Driven Time-data Visualization (READ-TV) application allows for user-friendly mining for longitudinal patterns in data. READ-TV is built specifically for FD analysis, but is easily adaptable to other clinical use cases, as we allow for the use of general metadata on events and cases.

Results: What was the outcome(s) of what you did to address the problem or gap?

READ-TV application allows for import of time stamped event data from multiple cases. Event and case metadata are supported to facilitate filtering and mining of interesting subsets of data. Stem plots are used for visualization of selected event timelines in chosen cases (Figure 1, left). This visualization is accompanied with summary of the number and estimates of rates of occurrence of specific event types (e.g. types of FD).

Change-point analysis is implemented using the `changepoint` R library (6). These analyses allow the users to quickly understand whether the rates of events (FD) is changing across the case timeline and where exactly these changes are occurring (Figure 1, right).

Discussion of Results

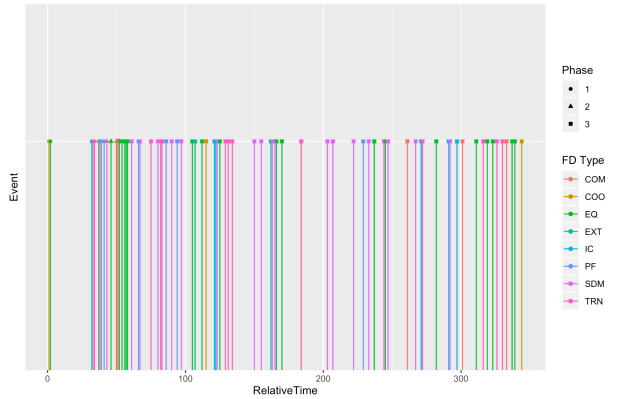
We have demonstrated the READ-TV application to the team of the AHRQ-funded Human Factors and Systems Integration in High Technology Surgery (HF-SIgHTS) study. The ability to visualize and perform quantitative

analysis of the study data was received with unanimous positive feedback and enthusiasm. We continue READ-TV development focusing on (1) increased user-friendliness using the HF-SIgHTS as our focus group, (2) increased functionality, and (3) use of more general localization terminology to allow for other applications.

Conclusion

The ability to visualize FD data will allow the HF-SIgHTS study team to incorporate the corresponding visualizations in developing interventions and training for surgical teams to increase their awareness and understand the sources of disruptions that affect surgical quality and team efficiency.

Attendee's Take-away Tool



	Disruption Type	Count	Rate
1	COM	3	0.008746356
2	COO	7	0.020408163
3	EQ	24	0.069970845
4	EXT	3	0.008746356
5	IC	6	0.017492711
6	PF	7	0.020408163
7	SDM	18	0.052478134
8	TRN	19	0.055393586
9	Combined	87	0.253644315

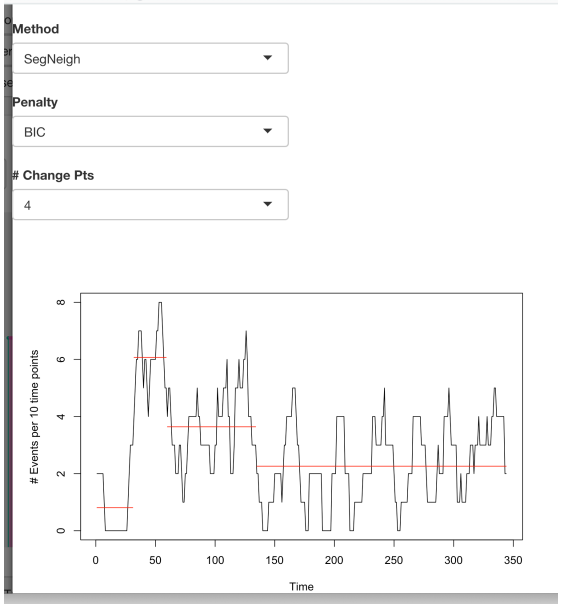


Figure 1. Screenshots of READ-TV demonstrate the event and event rate view (left) and interactive changepoint analysis (right) capabilities.

Use of Knowledge Acquired at Previous AMIA Events

AMIA frequently covers visual analytics tools for timeseries data at the Visual Analytics Working Group sponsored workshops and business meetings.

References

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