DYNAMIC MANAGEMENT OF PERIOPERATIVE PROCESSES: A PARADIGM THROUGH MODELING AND VISUALIZATION

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Abstract: Managing workflows for surgical services in large multi-speciality hospitals is a challenging task in part due to intrinsic as well as exogenous uncertainties and disturbances. Models and historical data are used to project utilizations and resource requirements for managing operating rooms (OR) over weeks and months. Such projection methods may be adapted in management decision making on the day of surgery if real-time event data can be obtained. Unaided performance in such dynamic tasks may be enhanced by decision and awareness support systems composed of statistic modelling, real-time sensor data, and visualization, communal and mobile display technologies. We developed a paradigm to combine modelling, simulation, real-time sensor data processing, and visualization to assist in the coordination of the activities associated with perioperative processes. *Copyright © 2006 IFAC*

Keywords: Workflow, perioperative processes, surgical processes, real-time data, scheduling, coordination, visualization, process modelling, uncertainty, computer supported cooperative work.

1. PERIOPERATIVE PROCESSES AND COORDINATION

Information technology is transforming the delivery of healthcare, a significant and growing sector in the economy. It is projected that by 2010, healthcare will occupy 17% of the Gross Domestic Product of the US (Heffler et al., 2002). The imperative of safe and efficient healthcare demands wide use of information technology to improve the process of care in every aspect. Wide application of simulation, modelling, and other industrial and manufacturing methodologies may be one key direction in that regard. In hospital settings, surgical services are often at the centre of therapeutic interventions, having a leading impact on the financial performance of a hospital. Perioperative processes (from decision of surgery to recovery) are a combination of pre-planning and scheduling with *ad hoc* mutual adjustment during execution on the day of surgery. Just like in industrial processes, many people are involved at different times and locations in delivering care. Coordination of their activities directly impacts on patient safety and smooth workflow. A number of coordination mechanisms, such as standardization are used in improving coordination among workers across time and space. A key challenge in perioperative processes is the inherent uncertainties and disturbances, which make schedules and standardization less effective and mutual adjustment more important. As a result, one would expect the need for collaborators to be aware of workflow status around them, including upstream care (e.g., in pre-operative holding areas), downstream care (e.g., in post-operative care units), and concurrent activities (e.g., use of diagnostic imaging by non-surgical services). Such awareness may enable care providers to work pro-actively to improve safety and efficiency.

In recent years research in OR management has produced a number of statistical models, both for tactical planning (e.g., Mulholland et al, 2005; Dexter et al, 2002) as well as for day of surgery decision making (e.g., Dexter et al, 2004). Combined with real-time event data from special sensors or algorithm processed monitoring data (Xiao et al, 2005), these models lay a foundation for supporting dynamic management of peri-operative processes. We anticipate rapid adoption of information and communication technology in healthcare that will provide the infrastructure for data-driven decision making. We developed a paradigm, ORViS (which stands for OR Visualization), for research in a number of areas to support decision making in dynamic management of perioperative processes. In this paper, we will present an overview of ORViS, and describe an application of the paradigm to predication of case finishing time using historical event data as well as real-time sensor data.

2. MODELING AND SIMULATION FOR REAL-TIME DECISION SUPPORT

Real-time event data, such as those captured through passive sensors and abstracted from networked databases, can be mined and used in combination with historical data to provide awareness information to collaborators, wherever they may be. Ranges of possible future states may be predicted based on simulation of models driven by real-time data. Decision makers are not only advised of current status, but also the current status in the context of planned activities and what has happened, plus what the future might be and what are the implications of different options. These elements for supporting decision making and awareness were incorporated into a research paradigm to link modelling, simulation, and visualization, as illustrated in Figure 1 below.

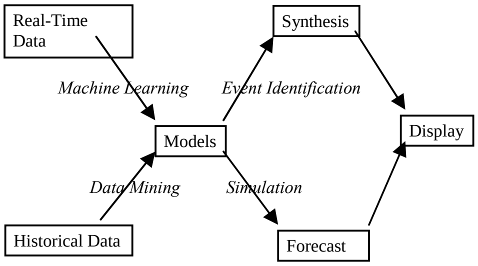

Figure 1. *ORViS: a research paradigm to integrate advances in real-time data collection, machine learning, data mining, and display technology for the purpose of supporting dynamic management of perioperative processes.*

2.1 ORViS: Leveraging simulation, modelling and visualization techniques in support of joint dynamic decision making.

ORViS as a paradigm provides a useful framework to incorporate advances in several areas of data processing and modelling for application domains where work is highly collaborative with high level of input fluctuation, such as dynamic management of peri-operative processes.

Visualization for joint decision making. In contrast to automation of workflows (as what workflow systems are typically designed for), ORViS emphasizes on visualization of work processes to assist decision makers through passive data collection and automated event abstraction. The complexity of perioperative processes in typical large hospitals often prevents accurate modelling of all important parameters and consistent rapid data update. Decision and awareness support systems should be considered as an information source among many available to and used by decision makers. Output displays are to inform rather than dictate options.

Historical data and knowledge distilled through simulation. To coordinate, workers along surgical flow frequently predict future events based on experiences. Historical data and knowledge, although theoretically available in various formats, are difficult to rapidly absorb and incorporate in real-time decision making. Increasingly, availability of computation resources and simulation techniques means that the historical data and knowledge, as captured by models, can be made available to decision makers in the form of forecasts which are continuously updated. Forecast of future events based on models are thus a way to distil potentially large amounts of historical data.

Process visualization with real-time simulation input. Simulation has historically been used in capacity planning (tactical decision making, e.g., Dexter et al, 2005), shorter-term service-specific staffing (e.g., Dexter et al., 2003), and case scheduling (Dexter et al., 2002). With increased ability to acquire real-time event data through passive sensors and database middleware, available computation power makes it possible to simulate perioperative processes in real time and in parallel with the actual processes. Users could assess implications of what-if scenarios based on the real-time data input. Sensitivity analysis of different decision options could be conducted to allow decision makers to balance different priorities.

Automation of data acquisition and visualization of key parameters. Workers in perioperative processes are usually highly experienced and trained. Barriers to optimal decisions for these workers are lack of information about the current status, schedules and plans, and contingencies. Part of the burden in managing dynamic work processes is to obtaining and communicating status information (e.g., Moss & Xiao, 2002). Automating data acquisition through passive means (i.e., not required of active user data input) and synthesizing identified events into meaningful information to users would be more likely viewed as useful. This is in contrast to decision support in the form of automatic scheduling. In addition, complexity in many organizations often leads to significant amount of efforts in balancing different priorities and resolving conflicts (e.g., Xiao et al, 2005). Based on the concept of situation awareness, design of displays should be guided by providing users with the ability to perceive what has happened, to comprehend what the situation is, and to project what will likely happen. Visualization of key parameters should be guided by providing users with information in a format so that choices are visually obvious to the users.

2.2 *Opportunities of data mining, machine learning and ORViS: Leveraging simulation, modelling and visualization techniques in support of joint dynamic decision making*.

The ORViS paradigm provides specific suggestions for areas where several fields could contribute, as illustrated in Figure 1.

Real-time data and machine learning. Indoor positioning technology (e.g., radio frequency identification) and other process tracking sensors will over time enable automatic capture of more complete picture of dynamic processes for the purpose of assisting process managers in real-time. In the context of perioperative processes, real-time data may include positions of clinicians and supporting personnel, patients, and key instrument. Other real-time data sources include status videos, patient monitors and network accessible status sensors (e.g., instrument settings). Statistical modelling and machine learning techniques can be applied to identify interesting events. Algorithms have been developed to process real-time data streams and video images for similar purposes.

Data mining and historical data.
Automatic data collection over time produces large amount of historical data. Historical data provide a basis for structural modelling and other data mining procedures to establish models and key statistical parameters for predictive purposes. These parameters include means and standard deviations, stratified to a number of independent variables or predictors.

Simulation and forecasting.
With models and real-time data, estimates of systems future states may be established through simulation. Simulation may be continuously updated with real-time data. Aggregates of individual parameters about future states, in different time horizons, may be obtained and constantly updated through simulation (e.g., discrete event algorithms) to provide data to decision makers in a format compatible to their information needs and easy for them to incorporate into their decision making. Sensitivity analysis can be performed on different options. Contingency analysis can be performed to assess potential risks due to uncertain events, such as a request of an emergency surgery.

Event identification and Synthesis.
To support decision makers, streams of real-time data need to be synthesized with other types of data, such as scheduled activities (e.g., from surgical information systems) and resource availabilities (e.g., from staff schedules). Simulation results for prediction and sensitivity analysis can be synthesized together with display of current status and plans.

Visualization and display.
It is important to present dynamic data in highly synthesized, graphical formats, so that decision makers can obtain information quickly. Many advances have been made recently to visualize various types of information. New methods may still be needed to present dynamic real-time data along with projected future states, which are uncertain. Additionally, passively acquired process data may have to be combined with human input data, the reliability of which may be highly variable. Schedules in healthcare frequently reflect intentions, requests, and commitments, as opposed to events scheduled to happen. The heterogeneity of reliabilities of different data sources and uncertainties in forecasted states may require development of new techniques of visualization.

4. VISUALIZATION FOR DYNAMIC MANAGEMENT

Communicating simulation results has been considered a critical link in supporting decision makers [Davis et al 1993]. Day of surgery decision making is under the context of rapid changes and unforeseen events with conflicting stakeholders. Coordinators and clinicians are mobile. They are under constant interruptions and time pressure. They may not be able to manipulate user interfaces in any significant ways. These challenges thus demand the displays of decision support information to be intuitive, providing at-a-glance view of multiple options, consequences of different options (sensitivity analysis), opportunities for optimizing schedules, potential conflicts, contingencies to be concerned, and threats to plans and schedules. The potential multitude of information may be difficult to display in condensed, intuitive manner. To promote proactive actions, information to support dynamic management of perioperative processes should combine real-time status information, scheduled events, and available resources.

Additionally, in contrast to tactical, long-term decision making, decision support for day of surgery decision making tasks needs to be robust against delays in updating status, errors, and/or incomplete information. For example, in order to predict over-utilized OR time, a decision support system should have access to most current schedules, which at many facilities are not revised sufficiently often as a day progresses. Automated data acquisition methods should be fully exploited. However, human decision makers have to be assumed to have objectives and information not part of computerized information systems.

Visualization for supporting day of surgery decision making is further challenged by users' environments. Charge nurses, for example, are highly mobile. It is impractical for them to carry large, bulky display units. The dynamic management of perioperative processes is highly distributed among workers. Visualization displays need to accommodate the information needs of multiple people. Concepts such as communal displays may be useful, so that information is widely disseminated.

3. PREDICTING CASE FINISHING TIME

We illustrate the application of the ORViS paradigm through the example of supporting day of surgery decision making. In particular, the paradigm is used to provide prediction of key parameters of ORs through forecasting case finishing times.

Typically at the start of the day, a surgical suite has a posted surgical schedule: a list of cases with surgeon and procedural names, requested OR times, and room assignment. Additional information may be included in the list, such as diagnosis, patient information (age, sex, medical record number, etc), special requirement (isolation precaution, instruments, etc), pre- and post-procedure locations, assistant surgeons, and anesthesia care providers. The posted schedule is usually amended by a list of add-on and emergency cases. Coordinators (nurses and anesthesiologists) also have a staffing plan for the day, which includes the list of care providers for different shifts (e.g., 7a-3p, 7a-7p, 7a-5p, 11a-7p, 11a-11p, 3p-11p, 7p-7a, 11p-7a).

The day of surgery decisions differ from the tactical and longer-term operational decisions which determine staffing patterns and OR time allocations several months in advance (Dexter et al., 2003, 2005). To execute the posted surgical schedule with the staff available on a particular day, the coordinators along with staff make decisions over a number of choices. These decisions may be classified into three types: a) case and room assignment, b) staff assignment, and c) monitoring and prodding workflow. In this section, we focus on visualization of forecasted OR parameters that are dependent on case finishing time. These parameters include the time when an OR becomes available for the next patient, the number of ORs running at a given time, the number of patients coming out of the ORs, and the time when a patient comes out ORs.

Day of surgery decisions are needed for a number of reasons, such as uncertainties and contingencies in perioperative processes.

For example, OR times may turn out to be much longer or shorter than scheduled, primarily due to inherent uncertainties of procedures (Dexter & Ledolter, 2005). The surgeons may encounter difficulties during surgery. They may add or delete a procedure during surgery.

As another example, patient conditions may warrant urgent surgery not scheduled at the beginning of the day. Conversely the patient conditions may have changed that the patient is no longer a candidate for the planned surgery, and the posted case has to be cancelled as a result.

Another type of contingencies are those associated with staffing. Surgeons may be occupied due to other responsibilities and not available to perform the surgery. There may be a temporary shortage of nursing staff with the skills to perform an urgent case due to a variety of reasons.

Day of surgery decisions are needed for resolving remaining degrees of freedom in activity priorities when choices exist among activities, such as which rooms to clean first, which patients to transport first, and which room to start first.

Case and room assignment. Occasionally multiple options exist for which case should be performed next in a given room, and for in which room a case is to be performed. Opportunities for such decision points occur when urgent cases are requested, cases are cancelled or finished much earlier than anticipated. They tend to occur towards the end of the day when add-on cases are to be scheduled.

Staff assignment. Options for staff assignment may exist independent of case and room assignment. Generally two types of staff assignment occur. One is for providing staff breaks. In such situations, coordinators may decide to assess the desired break times against possible case finishing time. Another type of staff assignment occurs towards the end of the day when the planned OR times come to an end (e.g., at 3pm). At hospitals with many (> 12) ORs, OR times may end at staggered stages (e.g., at 3pm and 7pm), perhaps maintaining rooms staffed throughout the night. Coordinators may decide in advance how to arrange staff for those ORs still open at a given time (e.g., at 3pm), and perhaps ask staff to stay after their shifts end.

Monitoring and prodding: Coordination under uncertainties and contingencies frequently requires anticipatory behaviour since scripted activities may be ineffective. For surgical suites where events are less predictable, coordinators and staff may spend much effort in monitoring and prodding. Examples of anticipatory behaviours may include deciding when to call next patients and to get next patients ready, when to page surgeons for their presence in ORs, when to check readiness for the next case, and when to prepare for the arrival of patients out of ORs.

Coordinators and staff may monitor perioperative processes to detect potential delays so they can react quickly. Delays may be in the form of prolonged cases or turnovers. Similarly, coordinators may be interested in shortened cases (early finish) for opportunities of scheduling add-on cases.

Extensive work exists for modelling case finishing time that may be used for supporting day of surgery decisions making (e.g., Strum et al, 2000). These models may be combined with real-time sensors to provide automated forecasts that are updated continuously throughout of the day. The forecasted parameters, in addition to predicted case finishing times, can include predicted tardiness/earliness of case starting times and over-/under-utilization for either a whole OR suite or individual ORs.

For example, the remaining time b for an on-going case that has started d hr ago can be estimated accurately based on the model (Dexter et al, 2004):

$$b = \exp\left\{\overline{T} + s\sqrt{1+1/N} * T^{-1}\left[N-1, \tau + (1+\tau) * T(N-1, \frac{\ln(d) - \overline{T}}{s\sqrt{1+1/N}})\right]\right\} - d$$

where N is the number of cases from which historical data are derived, $\overline{T}$ the mean of the natural logarithm of historical mean durations, s the standard deviation of the natural logarithm of historical OR times, $T^{-1}(N-1,\alpha)$ the α^{th} percentile of the cumulative Student's t distribution function with $N-1$ degrees of freedom, and $T(N-1,\beta)$ the cumulative probability of the Student's t distribution function with $N-1$ degrees of freedom when the value of the t-statistic is equal to β.

Instead of providing decision makers point estimates of case finishing time, ranges may be estimated based on the model. For example, based on 121 historical cases that were scheduled for 2.5 hrs in one hospital, the 10%-90% prediction interval for the time remaining in an on-going case that was scheduled to last 2.5 hrs can be estimated as in Figure 2. For example, after 1 hr into the case (i.e., hours of the case elapsed = 1 hr), the estimated range of time remaining will be [0.4 - 3.3] hrs.

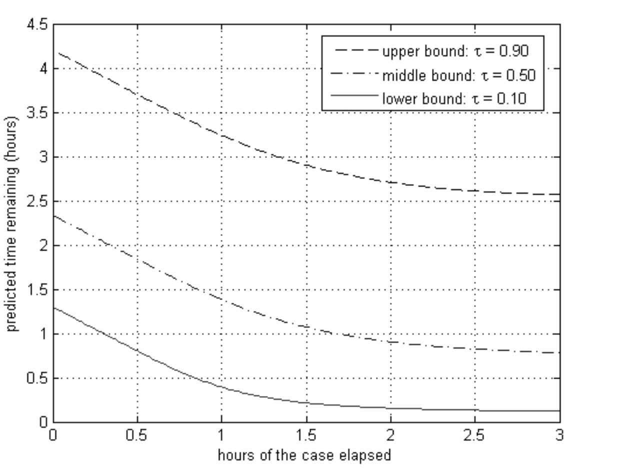

Figure 2. *The upper and lower prediction bounds of case time remaining for cases scheduled for 2.5 hrs, based on 121 historic cases that were scheduled for 2.5 hrs. τ: probability.*

Automated systems may be developed to detect case starting time (as opposed to reliant on human input, for example) (Xiao et al, 2005).

Figure 2 also illustrates the wide ranges of estimated case finishing time due to inherent uncertainty of surgical cases. Sensors may be used to provide estimates of case finishing time based on detected surgery progress. These sensors may include automated activity analysis of OR video images, processing of patient monitor signals, and other electrical or electronic signals.

For example, we analyzed the distribution of the lead times of temperature probe removal before cases ended. Figure 3 illustrated the distribution of lead times for 201 cases that occurred in 10 ORs with actual OR times equal or shorter than 2.5 hrs. Statistical models are being established to allow narrowed ranges of estimated finishing time after the event of temperature probe removal is detected.

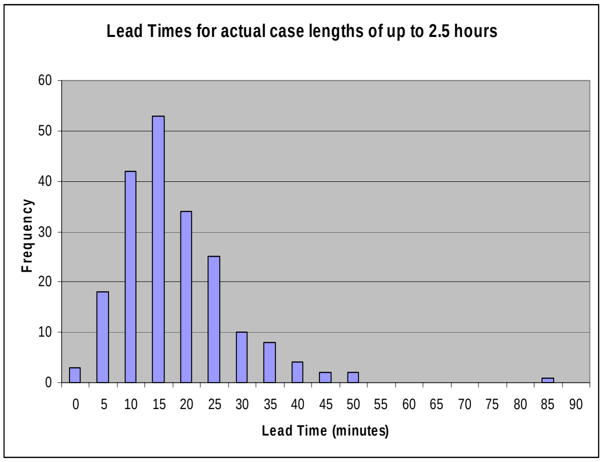

Figure 3. *Histogram of lead times (time differences between temperature probe removal and case ending time) for 201 cases in 10 ORs that lasted up to 2.5 hrs.*

We believe that ORViS provides a useful framework for leveraging new techniques in machine learning and other computational advances to automatically extract event timing data and to provide forecasted ranges of estimated case finishing times.

5. DISCUSSIONS AND CONCLUSIONS

Healthcare processes in hospital settings are a combination of pre-planning and scheduling with ad hoc mutual adjustment during execution. In contrast to industrial processes, most hospital care processes are highly variable. Coordinators rely on real-time information and their experiences to make decisions. Simulation and modelling tools have been extensively used for tactical decision making, such as capacity planning, OR time allocation, and staffing requirement. With advances of real-time data processing and display technology, decision makers may be aided by simulation and modelling tools. The ORViS is a paradigm that may guide the development of systems to improve decision making.

Case finishing time is an interesting example of leveraging the power of computation, real-time sensors, and human decision makers. Clinicians projected case finishing times based on the requested time on the posted schedules, along with their experiences about particular procedures and surgeons involved. For example, certain procedures may have wider ranges of OR times than others. However, case starting times are often not registered and not easily available. Predicting case finishing time becomes difficult. Consequently, workers have little to base on their decisions that may impact on utilizations and timeliness of case starting times.

The ORViS paradigm, when applied to forecasting case finishing time, essentially suggests a way to supplement human decision makers with historical data as well as passive event registration mechanism.

The ORViS also suggests several areas for modelling and technological development. For example, sensors may provide passive means to timestamp intraoperative events (e.g., incision and closure). Systematic data collection may enable statistical modelling that provides superior forecast of case finishing time. Sensitivity analysis techniques, perhaps through simulation methodologies, may be developed to provide outcome information on different options of staffing and scheduling. Visualization techniques are needed to display scheduling and staffing information in integrated ways. User interfaces may be designed with new concepts in displays, such as visualization of uncertainty, risks, constraints, and event evolution based on data feed from automatic and manual sources.

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