Context-Aware System to Create Electronic Medical Encounter Records

TR Number TR-CS-06-05

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July 19, 2006

Abstract

We describe a prototype system to capture and interpret data in a perioperative environment in order to construct an **E**lectronic **M**edical Encounter **R**ecord (EMR). The EMR records and correlates significant medical data and video streams with an inferred higher-level event model of the surgery. Information from Radio Frequency Identification (RFID) tags provides basic context information including the presence of medical staff, devices, instruments and medication in the operating room (OR). Patient monitoring systems and sensors such as pulse oximeters and anesthesia machines provide continuous streams of physiological data. These low level data streams are processed by the TelegraphCQ adaptive dataflow system to generate higher-level primitive events, such as a nurse entering the OR. A hierarchical knowledge-based event detection system correlates primitive events, patient data and workflow data to infer high-level events, such as the onset of anesthesia. The resulting EMR provides medical staff with a permanent record of the surgery that can be used for subsequent evaluation and training.

1 Introduction

In a perioperative setting, hundreds of patients and staff may be fbwing through dozens of operating rooms on a daily basis in a single facility. Typically, one third of the patients are unscheduled and identifi ed only on the day of surgery. The resulting chaos can be overwhelming, even with some form of electronic health record (EHR) system (currently available in 12

In the Pre-Operative period the perioperative system needs to orchestrate and monitor the following activities:

- Patient identifi cation
- Determine staff readiness
- Confi rm operating room readiness
- Assure supplies and equipment availability
- Capture data on incoming medical record, capture vitals, I/Os, pre-operative medications, tests, and scans
- Monitor patient entry into operating room
- Monitor patient readiness

Monitoring patient entry into the operating room and patient readiness for surgery are critical to successful outcomes, particularly with respect to patient safety. Automated monitoring of positioning and timing of the patient can reduce manual data entry, increase accuracy, and provide analytical data essential to planning for process improvement.

Our goal is to develop a *Context-Aware Perioperative Information System* that will automate most of the perioperative support functions such as patient tracking, inventory

management, clinical documentation etc with the help of pervasive computing and semantic web technologies. In this paper we present the prototype for a context-aware system to create electronic medical encounter record to document the events occurring during a surgery.

Clinical record keeping in high velocity healthcare delivery environments like surgery is a necessary and critical task. It is also a time consuming task that detracts from hands on patient care and contributes to extraordinary labor costs associated with collecting, transcribing and re-keying records throughout the perioperative process. The details of the surgery are documented in patient charts called the *Perioperative Record* . This record contains information about the patients vital signs at periodic intervals, medicines administered, complications if any, supplies and tools used etc. Errors in medical documentation cost billions of dollars to the health industry every year [6]. Inaccurate records put not only the patient but also the healthcare provider at risk [4] [20].

The data recorded during the perioperative process become a part of the patients medical history and is used by physicians to give further treatment to the patient. Data collection in the operating room is complicated due to several reasons. Firstly, multiple providers (eg, surgeons, anesthesia care providers, nurses) record data for a single care event (ie, the patient's surgery). Secondly, information collected by one provider is not readily available to another. Thirdly, experienced nurses assess the patients' condition accurately and provide appropriate treatment, sometimes without documenting these procedures; thus, duplication or differences occur in documentation, data gathering can be cumbersome, and not all details are recorded.

An Electronic Medical Record (EMR), has the potential to reduce documentation errors by minimizing data redundancy and providing accurate details of the ongoing surgery [2] [10]. Formally, an EMR is a medical record or any other information relating to the past, present or future physical and mental health, or condition of a patient, that resides in computers which process this data to deliver more effi cient health-related services. The EMR is an essential part of systems like the Traumapod [8] where surgeries are performed by remotely controlled robots and no humans are involved in the process. Only the EMR can provide details of the events occurring during the surgery.

The context-aware EMR records and correlates signifi cant medical data and video streams with an inferred higher-level event model of the surgery. A hierarchical knowledge-based event detection system correlates primitive events, patient data and workfbw data to infer high-level events, such as the onset of anesthesia. The resulting EMR provides medical staff with a permanent record of the surgery that can be used for subsequent evaluation and training.

2 Context-Aware System

The operating room (OR) has several medical devices that provide information about the patients status. In addition to these devices, we can deploy sensors in the OR that

can provide us with better view of the activities occurring in the operating room during a surgery. We define a medically significant event as any event that affects or is a part of the surgical procedure. Many systems [29] [21] [28] have been built that monitor physiological parameters of a patient and signal alarming conditions. Healthcare providers use these alarms as cues as it is not possible to maintain a constant vigil over the patients' health status. The alarms are in the form of an audio alert or a message displayed on the computer screen that can be seen by the healthcare provider.

Most of these alarms are low-level alarms such as tachycardia, apnea or any other abnormal pathological state. Such low level alarms hardly provide any detail about the patients condition. To provide more meaningful information the alarms or medical events need to be interpreted at a higher level and documented. In addition to physiological data we can make use of data streams from sensors that can be deployed in an operating room to capture additional events such as tools and medicines used and identities of the members of the clinical staff. In our research we use the Radio Frequency Identification (RFID) system to detect medical supplies, tools and the staff.

3 Related Work

Analyzing the patients' physiological data to detect alarming conditions has been a subject of research for over a decade. Several patient monitoring systems have been developed that alert the healthcare provider to alarming conditions. InCare [29],is one of the earliest automated systems to detect events in post-cardiac operated patients. InCare had a rule-based system that used multi-variable and trend based analysis of physiological data to detect events. Similarly, Schecke et al [28] designed a knowledge-based decision support system for patient monitoring in cardio anesthesia. The medications used and progress of the surgery was fed into the system manually by one of the members of the surgical staff.

[11] Hewlett Packard Labs has recently developed a framework that allows development of scalable software systems to monitor and analyze continuous streams of data. A prototype system BioStream was implemented to show its use in remote patient monitoring. BioStream is built on top of stream data processing architecture for real time processing of physiological signals. They use a database-oriented approach to analyzes data streams. The streams are subjected to "operators" that belong to a part of a patient plan. The current prototype is capable of identifying simple pathological conditions by monitoring ECG signals.

Bardram et al [12] developed a context-aware infrastructure to build context-aware applications for a hospital environment. The infrastructure includes sensors to detect presence of the nurse in the room, a smart pill container, a smart hospital bed to identify the patient. Radio Frequency Identification (RFID) is used to detect the people and the medications being used. A Context-Aware Electronic Patient Record was designed to present an user interface that adapts based on the current context.

Though the individual components of our system such as the algorithms to analyze

physiological data, stream processing of data have been studied in previous systems, to the best of our knowledge no system has yet been developed to create an EMR in the perioperative environment. We developed a context-aware system that monitors and analyzes the data streams from various medical equipments and create an Electronic Medical Encounter Record, according to the inferences made by analyzing the data streams, in a perioperative environment. The surgical team can see the record being populated in real-time which ensures that everyone is aware of the progress being made and of the patients health status at all times. The system was designed to detect events during trauma care and general anesthesia scenarios.

4 System Architecture

The context-aware system is designed as a 3-tier event detection system. Events at the lower levels are processed to infer high-level events. Data is collected from various sensors in the operating room and this data is processed to reconstruct the surgical context and infer the medically signifi cant events.

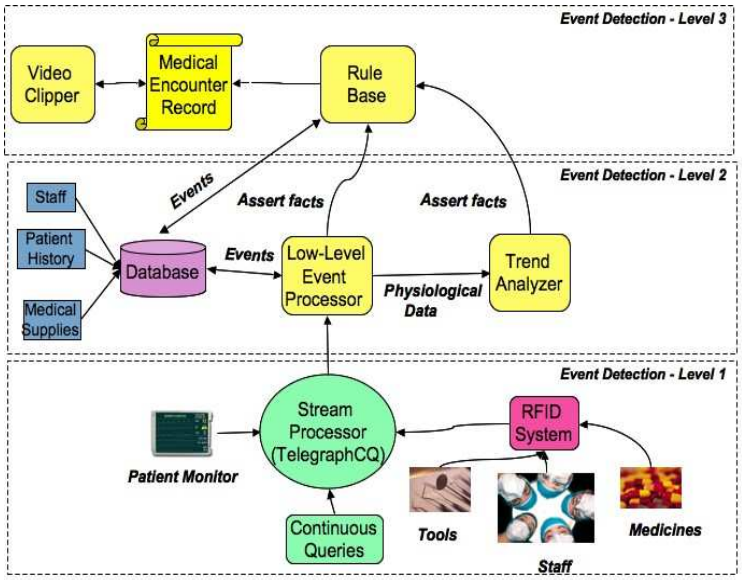

Figure 1: System Architecture

4.1 Data Sources

- **Patient Monitors** The operating room has several patient monitoring systems that track the patients physiological parameters. For example, pulse oximeter monitors blood oxygen saturation levels, vitals signs monitors track heart rate,

blood pressure etc. To monitor the patients condition during the surgery, the surgical team monitors the value and change in physiological parameters. We use data streams from these patient monitors to determine the state of the patient during the surgery.

- **Radio Frequency Identification (RFID)** The medical supplies and tools are tagged with passive RFID tags. RFID is also used to determine the staff present in the OR. Readings from the RFID reader are analyzed to determine the resources used during the surgery and the team performing the surgery. Figure 2 shows the data sources used to acquire contextual information in the OR.

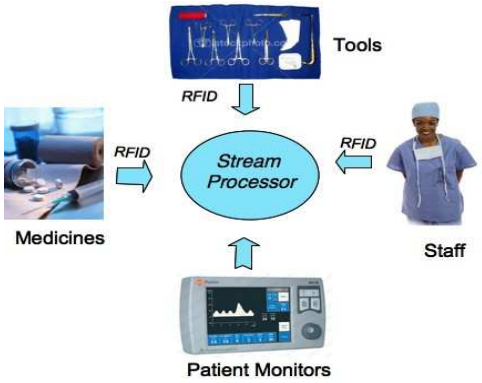

Figure 2: Data Sources in Operating Room

4.2 Data Stream Management System: TelegraphCQ

The patient monitoring systems and the RFID reader produces continuous streams of data that need to be processed and analyzed in real-time to detect events. Traditional database systems have been designed to manage finite data sets where client queries are processed immediately against data stored in tables. In applications that processes continuous data streams, clients require long-running continuous queries that are evaluated as data streams through the application. For example, consider a query in a stock market application that monitors the stock updates. "For the five most recent trading days starting today, select all stocks that closed higher than MSFT on a given day. Keep the query standing for twenty trading days".

We use a data stream management system, TelegraphCQ [13], developed at University of California, Berkeley to process the physiological and RFID data streams. Data from patient monitors and the RFID reader is pushed to the stream engine continuously. Queries over these data streams are specified over a time window. As new data arrives, the queries are evaluated and results are returned to the client. These queries are called "Continuous Queries". We can have several data sources that can connect to the stream-processing engine. Queries can be also be specified across streams of data or streaming

data and data in static tables. In traditional database systems, data is stored/indexed. When queries are received, the queries are processed against data stored in tables and results are returned to the client whereas in a stream management system, queries are stored/indexed and are evaluated as data flows through the system.

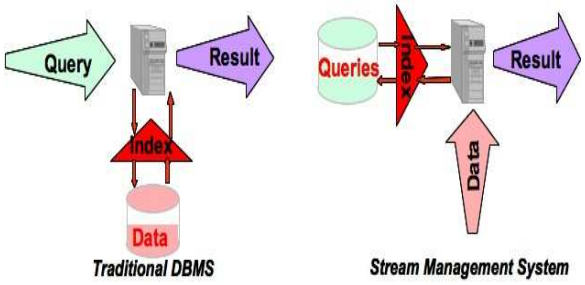

Figure 3: Traditional Database Vs Stream Management System

4.3 Analyzing Physiological Data

Physiological parameters reflect a patients health status. Interpretation of physiological data to infer the patients condition is a challenging problem. Some of the earliest data analysis systems used simple limits on physiological parameters for basic interpretation. The more advanced systems considered dependencies between parameters to provide more meaningful interpretations [29] [21] [28]. The problem with such systems is the high rate of false positive or false negative events. The poor performance was due to the fact that physiological data was interpreted independently of the clinical conditions in which the data was acquired. Physiological parameters not only depend on the physiologic processes but also on factors such as patients current condition, medical history, medicines administered and the sequence of occurrence of other events. Most systems consider only a subset of these factors.

Each parameter has a range of values that can be classified as normal or abnormal. However, given a data value, there is no set threshold that will deterministically classify the value as normal or abnormal. Also as mentioned above the interpretation of a parameter varies with the clinical context. We use the fuzzy set theory to capture this uncertainty in medical data. Fuzzy membership functions are used to classify data values. The value can be ”very low”, ”low”, ”normal”, ”high” or ”very high”. Rate of change is another important factor that is used to determine the health status of the patient. The change can be ”constant”, ”stable” or ”abrupt” and the value can be ”increasing” or ”decreasing”. The value and rate of change of value is used to detect events.

Given a data value, the memberships functions determine the degree to which the value belongs to a particular set. The value of the membership varies between 0 and 1 where 1 implies absolute membership. The set points used to define the range of values varies

with each patient. For example, the range of normal blood pressure for a hypotensive patient will be different than the range for a patient with normal blood pressure. In the current version of the system, the set point for each parameter is preset for a patient. Future versions of the system will set these limits by analyzing the patients medical history and the pre-op diagnosis.

The membership functions used for each parameter were different and partitioning of the range of values was determined by eliciting information through interviews with an anesthesiologist. Some of the functions used were [24] TriangleFuzzySet, Trapezoid-FuzzySet, SFuzzySet etc. To defuzzify the values we use the maximum defuzzifi cation function. In this method the mean of the x values, with maximum membership values over the entire set of FuzzyValues, is calculated.

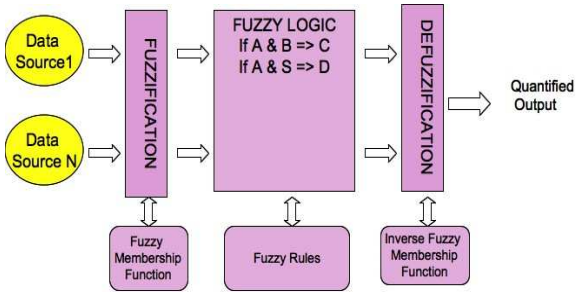

Figure 4: Fuzzy Rule-Based System

4.4 Analyzing RFID Data streams

Figure 5 shows the RFID system we used in our prototype. We used the Symbol AR400 900MHz Reader and passive RFID tags. An RFID tag has a unique 96-bit identifi er called the Electronic Product Code (EPC). The RFID reader returns the list of EPC codes it detects. We implemented the Byte Stream Protocol to interface with the RFID reader. The RFID API we developed provides a layer of abstraction over the low level protocol. The API processes results from the RFID reader.

The RFID module polls the reader periodically to get the list of RFID tags visible. The passive tags use the energy incident from the reader, to return their EPC code. The reader reads the tags at its own internal frequency. Hence the same tag may be reported more than once in the list of tags detected. When many tags are in close proximity, the signals returned by the tag collide and result in loss of data. Thus a single read from the reader is not suffi cient to detect all tags reliably. We use some heuristics that we determined experimentally to determine the visibility of the RFID tags. We aggregate RFID data for a time period of 30 seconds and then count the number of times a tag is seen in this time period. The reader is sampled every 2 seconds.

```
If Number of Times Tag Seen >= 5 then
   Event (Tag Visible)
```

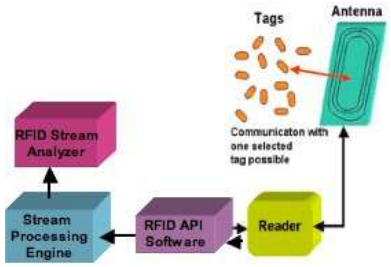

Figure 5: RFID System

```
If tag not seen for >= 120 seconds then
   Event (Tag Invisible)
```

4.5 Techniques to Correlate Low-Level Events

We have a hierarchical event detection system, where events at lower-level are correlated to infer high-level events. A rule-based system, JESS [3] with FuzzyJ library, is used to define the rules to correlate events. The knowledge base was developed by gathering information from an anesthesiologist by interviews and from medical literature [18] [15] [17] [16] [19] [30] [14] which describe methods to analyze and interpret physiological data. The techniques use to correlate the events are:

- **Multi-variable Analysis**

  Monitoring a physiological parameter in isolation does not give much information about the state of the patient. Coleman et al [31] state that "each physiologic state variable is intimately related directly and indirectly to many others by relationships that depend on the condition of the subject". This means that physiologic parameters not only depend on physiologic processes but are also affected by the patients current condition. For example low and decreasing blood pressure, does not give signify too much detail. However, low and decreasing blood pressure with high and increasing heart rate implies potential loss of fluids. Monitoring a physiological parameter along with its relationship with other parameters helps determine more meaningful events.

- **Event History**

  A high level event is a composition of low-level events. The composition can be a conjunction or disjunction of events [22]. In a conjunction, the high level event is signaled only when all the low-level events are detected, whereas in a

disjunction the high level event is signaled when at least one of the low level events is detected.

Example: Event Conjunction

```
If (TensionPneumothorax)
   and (SBP "low" and "increasing")
   and (HR "high" and "decreasing") then
       Event (Decompression)
```

Event history is a set of low-level and high-level events already detected. Low-level events need to be considered in the context of the events that occurred prior to the current event to infer additional events. A surgery can be viewed as a finite state machine where the complex high-level events govern the state transitions.

- **Effect of Medicines**

  The medicines administered during the surgery, may or may not have a significant effect on the patients physiology. Time the medicine was administered, effects expected, duration of effect and time to affect are some of the factors that need to be taken into account to detect their effect in the physiological parameters. The RFID system signals when a medicine is detected in the operating room. Detection of the medicine does not imply if the medicine was actually administered. In the current version of the system we record all the medicines detected by the RFID system. For those medicines whose effect is observed in the physiological parameters, an event is signaled to indicate that the medicine was actually used. However, we do not consider the adverse effect the medicine may have on the patient. Incorporating the information of medications used to detect events is a difficult problem. Firstly, strength and duration of the effect of the medication may vary with each individual. Secondly, it is difficult to estimate the adverse effect a medicine may have on a patient. We have preliminary results to show the utility of such information for event detection.

  Example:

```
If (RR "abrupt decrease"
   and SBP "abrupt decrease"
   and HR "stable")
       If (Time Anesthetic detected < 40 sec)
          then Event (Start Anesthesia)
```

- **Pre-op Diagnosis**

  Before the patient is brought into the surgery, the patients condition is evaluated. The evaluation includes taking note of the vital signs, any medical care provided, a physical examination and any other notable medical condition. The pre-op diagnosis is used to initialize the event history. The actions taken during the surgery also depend on the pre-op diagnosis. We experimented with using

this information in detecting events. For example, if the patient was bleeding excessively prior to the surgery, detecting fluid infusions during the surgery is more accurate. Currently we use pre-op diagnosis to only provide clues about the patients condition before the surgery starts.

5 Electronic Medical Encounter Record

The EMR can be displayed on a computer screen in the operating room. It provides a summary of the patient profile, the pre-op diagnosis and laboratory reports. The vital signs of the patient are updated periodically on the screen during the surgery. The event list gets populated as events are detected. A part of the screen is used to show the medicines and the surgical staff as detected by the RFID system. As members of the surgical team enter and leave the OR, the screen is updated to show only those present in the room. For each event we save the vital signs of the patient at that instant of time. Given the complete video of the surgery, video clips for each of events are created and the corresponding video url is stored in the medical encounter record. When reviewed at any time after the surgery, the surgeon can interact with the record to see the vital signs of the patient at the major points in the surgery. Instead of viewing the entire video footage of the surgery, the surgeon can browse through the key parts of the video by selecting an event from the event list. Figure 6 shows a snap shot of the EMR.

Figure 6: Electronic Medical Encounter Record

6 Results

In this section we describe the test environment we used to evaluate our system. We used physiological data sets from the Human Patient Simulator (HPS) [5] called Stan, manufactured by the METI Inc. It is a complex system that emulates the human body response to medical treatment. The simulator is used to train medical students.

Stan, shown in Figure 7, can be loaded with various patient profiles. For example, the doctor could create an asthmatic patient with chronic heart disease who is taking a handful of certain drugs and is currently experiencing anaphylactic shock, a severe allergic reaction. The medical students in turn have to figure out how to treat the patient. If medication is required, the drugs are ”administered” by scanning a bar code on a syringe. The computer produces in Stan the physiological response that the drug would have produced in a patient with that medical condition.

This system was made available to us by the Air Force Simulation Center at University of Maryland Medical School. In order to evaluate our system we used two custom scenarios. This system was developed as a part of the Traumapod [8] which focuses on trauma care on the battlefield. Hence we chose to use trauma related scenarios to evaluate our system. The HPS remains in each of the states in a given scenario for a fixed period of time after which it transitions to the next state. The changes in the physiological parameters of the simulator are logged constantly and the parameters vary according to the current state of the HPS. In addition to the scenarios mentioned below we created slight variations of these scenarios.

6.1 Scenario 1: Blunt Trauma Multiple Injuries

This scenario consists of a patient who has been wounded in a battlefield. In this scenario the patient is goes through the following states during the course of trauma care:

- Hypovolemia (Excess blood loss)
- Tension pneumothorax
- Decompression
- Fluid Infusions

6.2 Scenario 2: General Anesthesia

In this scenario we subject the simulator to general anesthesia and follow the steps to wake the patient at the end of the procedure. The general steps followed are:

- Intubation
- Pain Relief

- Administer Anesthetic
- Maintain Anesthetic
- Reduce Anesthetic

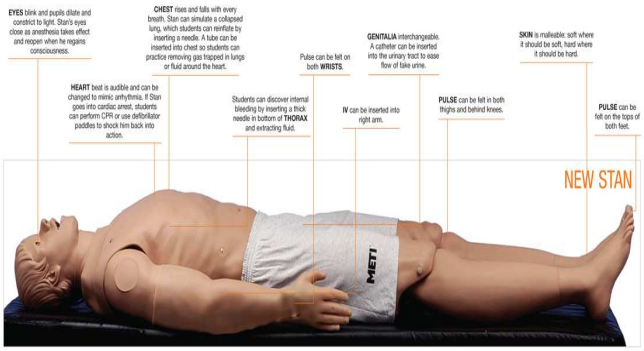

Figure 7: Human Patient Simulator

The above two scenarios are simulated on different patient profiles. Each patient has different medical history and pre-op diagnosis. Each of the scenarios was simulated with five different profiles. Slight variations of the scenarios were simulated to give us more varied data sets. We gathered data sets from 30 simulations on the METI system. The simulations were run over 7 different patient profiles for the two scenarios mentioned above. The key events to be detected from the data sets are

- Tension Pneumothorax
- Decompression
- Hypovolemia
- Fluid Infusion
- Start Anesthesia
- External ventilation
- Paralytic Administered
- Reduce Anesthetic

6.3 Performance Parameters

- **False Event Detection:**
  One of the important performance characteristics of a monitoring algorithm is the number of false positive and false negative events detected. An event is a false negative when the event is inappropriate of the input data. A false negative is

generated when the system signals events that did not occur. For example: Conditions to detect hypovolemia are increasing heart rate and a decreasing blood pressure. But these conditions occur during Tension pneumothorax also. Failure to detect changes in oxygen saturation will result in signaling of hypovolemia. Thus a false negative for tension pneumothorax is detected and a false positive for hypovolemia is generated.

$$Sensitivity = \frac{No.of TruePositives}{(No.of TruePositives + No.of FalseNegatives)}$$

Sensitivity of 100% means that all events were recognized by the system. However, sensitivity of 100% can be achieved trivially by using all positive test cases. Specifi city of the system is also required for complete evaluation.

$$Specificity = \frac{No.of TrueNegatives}{(No.of TrueNegatives + No.of FalsePositives)}$$

- **Latency of detecting events:**
  The latency between the occurrence of an event and its detection by the monitoring algorithm plays an important role in the performance of the system. The event list that the system constructs is timestamped. However, the actual time of occurrence of an event has a signifi cant impact on the way the event is interpreted. Therefore the order of detection of events and the time of detection is essential.

Figure 8 shows the sensitivity for each of the events and Figure 9 shows specifi city.

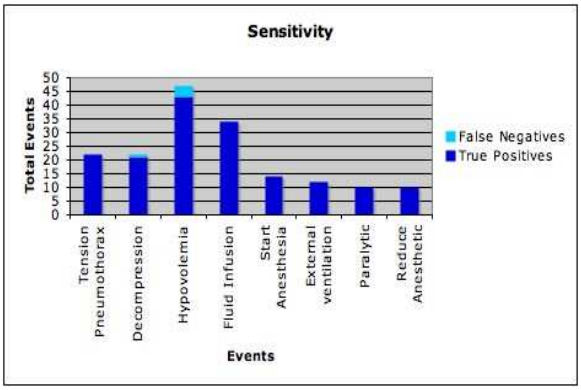

Figure 8: Sensitivity of Events

Hypovolemia and Fluid Infusion are the events with high false positives. These events depend on the blood pressure and heart rate which are affected by number other pathological conditions. However, making use of the pre-op diagnosis reduced the false positives for these events by 30%. The events ”Paralytic Administered” and ”Reducing

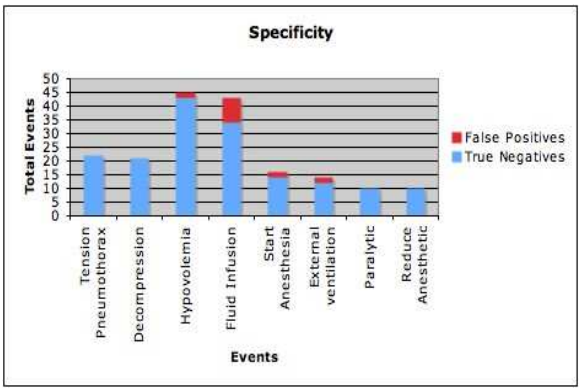

Figure 9: Specifi city of Events

Table 1: Average Latency of Detecting Events with Standard Deviation

Name	Average Latency	Standard Deviation
Tension Pneumothorax	56.3	11.08
Decompression	29.3	5.44
Hypovolemia	36.8	7.12
Fluid Infusion	35.01	7.86
Start Anesthesia	50.12	12.22
External ventilation	32.5	7.07
Paralytic Administered	47.2	13.35
Reducing Anesthetic	9.6	7.3

Anesthetic" show 100% specifi city and sensitivity as they are triggered only when the medicine is detected by the RFID reader. Without RFID, it is diffi cult to detect these events by just monitoring the physiological data.

Our rule base currently has 27 rules. Adding and retracting facts from the knowledge base is an expensive operation. We designed the knowledge base to minimize such operations. As rfi d events are detected facts are either asserted or retracted. For our rule base we start with a knowledge base of 12 initial facts. Given the size of the rule base, Table 1 show the average latency and the standard deviation of detecting each of the key events.

The latency of detecting events has signifi cant variance between events due to the nature of the events. Some events such as Tension Pneumothorax develop over a period of time and hence are not detected immediately, whereas events such as administration of a paralytic produce signifi cant changes in the physiology within a short period of time. Thus latency is interpreted on a per event basis.

6.4 TelegraphCQ

To evaluate the performance and scalability of TelegraphCQ we conducted some preliminary tests. The tests we performed in a local sub network with 100 Mbits/s Ethernet card. The load on the network was zero. Fixed amount of data was streamed to the stream engine at a constant rate. Telegraphcq was deployed on a Pentium 4 machine with 2.4 GHz CPU, 1.00 GB RAM. The aim was to test amount of data loads that Telegraphcq could handle without loss of data.

To determine amount of data handled, we log the data streamed to TelegraphCQ and compare it with the summary presented by tcq when it gets the end of the stream. The amount of data it can handle depends on the queries. We were able to generate .722 Mb/sec which TelegraphCQ could handle without loss of data. The query used was an aggregate query to count the number of distinct tags seen in a window. A study by [27] Plagemann et al showed that TelegraphCQ is capable of handling upto 3.4 Mb/sec of network data for certain types of queries. They used a network traffic generator for their load tests.

In its default configuration, TelegraphCQ is capable of handling 64 input data streams and 32 client connections. Changing the configuration, we could increase the number of client and data connections up to 100. The number of connections could be further increased by additional changes in the configuration. Increasing the data connections required recompilation with the current version of TelegraphCQ. Thus TelegraphCQ can easily handle additional data streams with minimal changes in the configuration.

7 Discussion

The system evaluation showed that the it had 100% sensitivity. However, the data set was small and was obtained from a Human Patient Simulator. The results may vary with real patient data. Also as the knowledge-base grows, addition of new rules to detect more events may increase the number of false positives.

Currently we use simple queries over the data streams to detect low-level events. We maintain a state variable model and use various techniques to correlate these low-level events to infer more meaningful events. Some of the event correlation can be done by using appropriate queries on data streams. The current version of TelegraphCQ does not provide support for sub-queries and access to historical data. With support for sub-queries and access to archived data in the subsequent version we can move some of the event correlation rules to the stream processing level.

We use RFID to detect staff and medicines in the operating room. The use of RFID in healthcare presents a number of critical issue unique healthcare in addition to the basic limitations of the technology.

- **Electromagnetic Interference:** The healthcare environment is already full of safety critical devices that are sensitive to radiation at various frequencies.

- **Tagging Medical Supplies:** We conducted a feasibility study of using RFID to tag medical supplies. The current state of art is not sophisticated enough to allow tagging of all medical supplies. The smallest passive tags available are 1" x 1". With tags of this size it is difficult to tag items like surgical tools, medical supplies like cotton balls, sponges, gauze etc. Tags that are of the size of a grain of rice are also available. But these tags are designed to embed under the skin of cattle or humans. These are not suitable to tag medical supplies.
- **Environment Hazards to Tags:** The healthcare industry presents a unique challenge to the physical integrity of RFID tags because of its pervasive infection control measures. Supplies like sponges, gauze become wet with fluids. Tags attached to clothes may be damaged when they are washed. The RFID tags were originally designed to tag objects for supply chain management and are not capable of withstanding harsh medical environments.

Inspite of the above the limitations, its use is healthcare is expected to rise rapidly. According to a report published by IDTechEx [25] "the market for RFID tags and systems in healthcare will rise from $90 million in 2006 to $2.1 billion in 2016. Primarily, this will be because of item level tagging of drugs and Real Time Locating Systems (RTLS) for staff, patients and assets to improve efficiency, safety and availability and to reduce losses." The technology is expected to evolve to address the requirements of RFID in hospital environments.

Another important aspect to consider is that the EMR documents only those events that are detected by the system. A complete perioperative record has several details such as physical observations of the patients body, devices implanted, exact amounts of fluids infused etc. These are the kind of details that cannot be deduced from the data sources we currently use.

8 Future Work

In this section we describe some of the ongoing extensions we are implementing and enhancements that could improve the system.

8.1 Traumapod

Trauma Pod [8] is a DARPA funded project that whose aim is to develop an automated medical treatment system that does not require onsite medical personnel on the front lines of battle, and is ready to receive, assess, and stabilize wounded soldiers during the critical hours following injury.

The first phase of the program is an effort to develop robotic technology to perform a totally unmanned surgical procedure within a fixed facility. A human surgeon will conduct all the required surgical procedures from a remote location using a system of surgical manipulators. The system's actions are then communicated wirelessly to the

surgery site. Automated robotic systems provide necessary support to the surgeon to conduct all phases of the operation.

In this unmanned system, our system will be used to take surgical notes and create an electronic medical encounter record. This record is more sophisticated and detailed as we can infer several medically significant events by analyzing the messages exchanged between the robotic systems.

8.2 Domain-Based Medical Ontology

A knowledge-based system represents relationships between objects, entities and concepts that exist in a domain of interest. Ontology is a specification of such concepts. The relationship between the objects is specified in a vocabulary that is used by the knowledge systems to represent knowledge [26]. Within health informatics, ontology is a formal description of a health-related domain.

The use of ontologies in medicine is mainly focused on the representation and (re-)organization of medical terminologies. Physicians developed their own specialized languages and lexicons to help them store and communicate general medical knowledge and patient-related information efficiently. Such terminologies, optimized for human processing, are characterized by a significant amount of implicit knowledge. Medical information systems, on the other hand, need to be able to communicate complex and detailed medical concepts (possibly expressed in different languages) unambiguously.

In the perioperative environment, use of a standardized language decreases patients' risk for injury by eliminating inconsistency of language or meaning. This is a difficult task and requires a detailed analysis of the structure and the concepts of medical terminologies. But it can be achieved by constructing medical domain ontologies for representing medical terminology systems.

The benefits of using a medical ontology are:

- Ontologies can help build more powerful and more interoperable information systems in healthcare.
- Ontologies can support the need of the healthcare process to transmit, re-use and share patient data.

Constructing the medical encounter record using a domain-based ontology will make the record usable by other health-informatics systems for further processing. Several groups, such as GALEN [9], CIMIT [1], SNOWMED-CT [7], have developed medical ontologies to represent medical concepts. Most groups focus on a domain within medicine and have their ontology represent concepts relevant to the domain. The Unified Medical Language System (UMLS) [23] is a meta-thesaurus created by the National Library of Medicine (NLM) that integrates the ontologies developed by various groups.

8.3 Supply Tracking with RFID

Supply counting is an important procedure during a surgery. It is the responsibility of the surgical team to ensure that no supply is left within the patients body at the end of the surgery. RFID can be used to perform supply counts provided all supplies can be tagged. Since RFID tags cannot be localized, as an alternate solution we can use low frequency readers to detect tags in a particular zone of the operating room. The ability to divide the operating room in zones will allow us to track the supplies in the operating room and ensure no supply is left within the patients body.

Tracking supplies at this granularity can also be useful in inferring events that are not detectable through physiological data streams. For example, if the surgeon is holding a vascular clamp and the surgery involves placing a shunt, we can estimate the time that the clamp was used to clamp the blood vessels. With the current system, such events are not detectable.

8.4 Video Capture

The physicians use the perioperative and anesthesia records of a surgery performed to gain an insight into the complications produced, if any, and form a diagnosis based on the analysis of these records. A video clip of the surgical site for each key event can help the physician get an accurate picture of the past surgery. In a training environment, the supervising physician or doctor has to watch hours of video footage of surgery performed by residents to evaluate their skills. The medical encounter record; with video clips for the key events can improve the effi ciency and speed of evaluation. We need to work on estimating the time duration of each event to create clips of appropriate length.

9 Conclusion

We presented a prototype of a context-aware system that analyzes data streams in an operating room to detect medically signifi cant events and document them in an electronic encounter record. The system uses technologies like Radio Frequency Identifi cation to acquire contextual information such as resources used and the staff present in the OR. We explored the use of medical history and effect of medicines on physiology and we conclude that such techniques help us detect complex and more meaningful medical events. The system architecture is scalable and can be easily extended to detect events over larger number of scenarios.

10 Acknowledgements

We would like to thank Colonel Grissom at the Air Force Simulation Center, University of Maryland Medical School, for the use of the HPS METI system to evaluate our system. We would also like to thank Dr. Geoffrey Kuzmich for the invaluable clinical advice on developing the medical rule base without which this work would not be possible.

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