Context-Aware System to Create Electronic Medical Encounter Records

by

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ABSTRACT

Title of Thesis: A Context-Aware System to Create Electronic Medical Encounter Records

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> An Electronic Health Record (EHR) is a medical record or any other information relating to the past, present or future physical and mental health, or condition of a patient which resides in computers for the primary purpose of providing health care and health-related services.

EHRs improve clinical quality by providing ready access to all relevant clinical information at the time of the patient encounter or phone call, receipt of clinical alerts at the point of care, the ability to easily monitor and analyze patient outcomes. The EHR softwares currently available in the markets are very expensive and require extensive training before physicians can use these systems. Also all these systems require the physician or nurse to enter the data in the record manually.

We have developed a smart context-aware system to semi-automatically build an EHR that records the medically significant events of a surgery. The system analyzes the data streams obtained from various sensors deployed in an Operating Room (OR) in real-time to detect events. We refer to this electronic record as the Electronic

Medical Encounter Record (EMR). This record then becomes a part of the patients medical history. This record will provide the next physician an accurate account of the medical treatment given to the patient. Sensors in the OR include the blood oxygen monitor, the heart rate monitor etc.

Data from these sensor streams is analyzed using a stream processing engine to extract the low level events, such as high blood pressure etc, occurring during the surgery. These events are correlated using techniques such as multi-variable analysis, trend based analysis etc to identify events that become a part of the electronic medical record. Radio Frequency Identification (RFID) is used to acquire contextual information such as presence of medical staff in the operating room and identification of medicines used during the surgery.

Dedicated to My Parents

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TABLE OF CONTENTS

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

The process of performing a surgery involves several important steps that need to be performed before and after the surgery takes place. The perioperative process can be divided into three stages

- Pre-operative process
- Intra-operative process
- Post-operative process

During the perioperative process details such as patients vital signs, medicines administered, complications if any, supplies and tools used etc are documented by more than one member of the nursing staff. The time spent for preparing for the surgery and documenting the process accounts for a large part of the total time required to perform a surgery.

The data recorded in 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 because multiple providers (eg, surgeons, anesthesia care providers, nurses) record data for a single care event (ie,

the patient's surgery). Traditionally, many health care facilities use three separate records with similar or duplicate data collected by different providers throughout the intraoperative phase of care. Information collected by one provider is not readily available to another; thus, duplication or differences occur in documentation, data gathering can be cumbersome, and many of the same data elements exist on all records. Figures 1, 2, 3 and 4 in the Appendix show the records used in the hospitals to record the details of the perioperative process.

Each of the providers during the surgery need an detailed information about the patients health status to perform their part in the surgical process. For example, the anesthesiologist needs to be aware of any patient allergies before the anesthetic is administered. Experienced nurses are able to assess the patients' condition accurately and provide appropriate treatment, sometimes without documenting these procedures. It is essential to capture all the treatment given to the patient for the surgery to proceed efficiently.

Errors in medical documentation cost billions of dollars to the health industry every year [7]. Inaccurate records put not only the patient but also the healthcare provider at risk [5] [27]. An Electronic Medical Record (EMR), has the potential to standardize the documentation in the perioperative environment, minimize data redundancy and provide accurate details of the ongoing surgery [2] [14]. 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 which resides in computers which process this data to deliver more efficient health-related services. EMR records include " patient demographics, progress notes, problems, medications, and vital signs, past medical history, immunizations, laboratory data and radiology reports.""

Data in this form can be easily shared with other physicians and is accessible at the point of care. Clinical quality is improved by having more ready access to

all relevant clinical information at the time of the patient encounter or phone call, receipt of clinical alerts at the point of care (e.g., being reminded of a drug interaction or allergy as you're writing a prescription), the ability to easily monitor and analyze patient outcomes. The EMR is an essential part of the systems like the Traumapod [10] 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.

Several hospitals and healthcare providers have started using systems that allow then to document patient care details in an electronic format. Systems like [36] InCare, [38] PAAT , [15] BioStream monitor the patients health in post-operative phase or in telecare environments. They make use of various algorithms to detect alarming conditions and alert the physician appropriately. 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. In this thesis we present a smart 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.

1.2 Problem Statement

The operating room 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 (OR) during a surgery. We define a medically significant event as any event that affects or is a part of the surgical procedure. Many systems [36] [28] [35] have

been built that monitor physiological parameters of a patient and signal alarming conditions. These alarms are used as cues by healthcare providers 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. We developed a system that analyzes the data streams from various sensors in the operating room to identify medically significant events and create an Electronic Medical Encounter Record at the end of the surgery.

1.3 Thesis Organization

The rest of the thesis is organized as follows: In Chapter 2 we will describe the system architecture and the algorithms used to detect events in the operating room. We discuss the techniques used to analyze physiological and RFID data streams. Chapter 3 provides details of the RFID system deployed and its use in identifying events. It describes the features of RFID and its use and limitation in the healthcare environment. We present experimental results in Chapter 4 followed by related work in Chapter 5. Chapter 6 present conclusions of the thesis study, ongoing research and

ideas for future work.

Chapter 2

Context-Aware Rule-Based System to Detect Medical Events

In this chapter we describe a context-aware system used to detect low events in the operating room and algorithms to correlate these low level events.

2.1 Motivation

An operating room can be thought of a smart space where we have several sensors collecting information about the patients state. Typically during the surgery, the nursing staff monitor these data signals to keep track of the patients condition during the process and take appropriate actions. Interpreting these signals and forming an accurate hypothesis about the patients condition requires years of experience. The patients condition is subject to numerous factors that must be taken into account before making a decision about the patients state. Automating the process of clinical documentation poses significant challenges. The physiological data along with RFID data streams collected from sensors can help us infer the medically significant events that occur during the surgery. For example, increasing heart rate with decreasing blood pressure indicates loss of body fluids. However, just analyzing physiological data cannot capture all events. For example, assessment of physical characteristics

such as dilation of pupils cannot be detected from the physiological data. However, we can infer occurrence of several events by monitoring these data streams. Context-aware applications typically execute in an environment that is changing dynamically and the execution of the computation adapts according to the changes. In a peri-operative environment the context includes the surgical staff present in the room, the surgery being performed, the medical supplies used, patients medical history and physiological data. The electronic medical encounter record can be made more detailed by considering the context of the surgery. Previous work [36] [28] [35] [26] has focused on identifying alarming conditions by analyzing physiological data from patient monitors. Some algorithms adapt to an individual patient by detecting patterns in physiological data over a period of time. None of the current algorithms to detect alarming conditions consider the patients medical history or the knowledge of medications used during the surgery. With a context aware system we can capture a detailed record of the events occurring during the surgery and also reduce the number of false events signaled.

2.2 System Architecture

Our system is divided into three major functional components: Data acquisition, Low Level Data Processing, Database and Data Analysis module.

2.2.1 Data Acquisition

For our research, we assume that our system has noise free data available in the digital form from the medical sensors. Our focus is on data analysis and we leave the problem of data acquisition methods for experts [36] [18] [20].

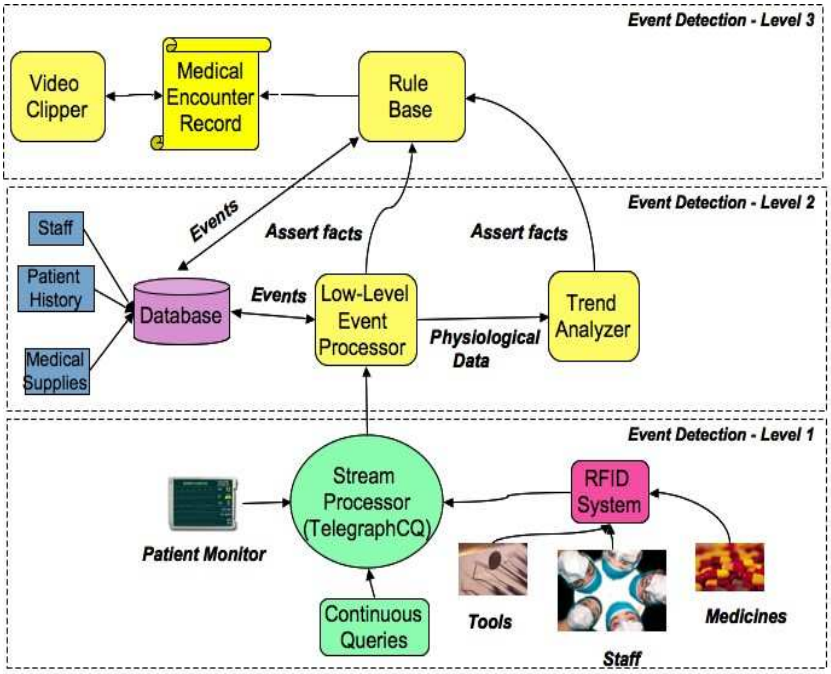


FIG. 2.1. System Architecture

2.2.2 Stream Processing Engine

Analyzing continuous, high-volume data feeds poses a special challenge for applications as varied as automated financial-market trading, security-incident detection and weather forecasting. All these applications use analytically discovered patterns to generate predictions, yet the value of these predictions is degraded by long processing times. Most of the systems developed to analyze medical data use simple methods, where data is buffered for a short period of time and then trends such as increasing, decreasing etc are established based on rate of change. Streaming data arrives when it's ready, irregularly and unpredictably. While point-in-time values matter, the data may contain important patterns that can be discerned only by looking at "time windows" rather than points and only by correlating data from multiple sources. Stream processors allow us to specify advanced queries that join/filter multiple data streams. We used the stream-processing engine developed at University of

Berkeley, TelegraphCQ [17].

In an operating room we get streams of sensor data from the various sensors deployed. The data includes physiological signals and signals from other pervasive devices such as RFID tags, Bluetooth devices etc. Correlating data from these data sources can help us build a clinical context and capture the significant events occurring during the surgery.

Data analysis is done in a hierarchical fashion. At the lowest level we have the data sources, which stream data to the stream-processing engine. The data sources are software modules that emulate the sensors. We assume that the data is error free and noise free. As the data arrives at the stream-processing engine, the stored queries are evaluated and the results are sent to the trend analyzer. The trend analyzer has different modules to process results of queries on different data streams.

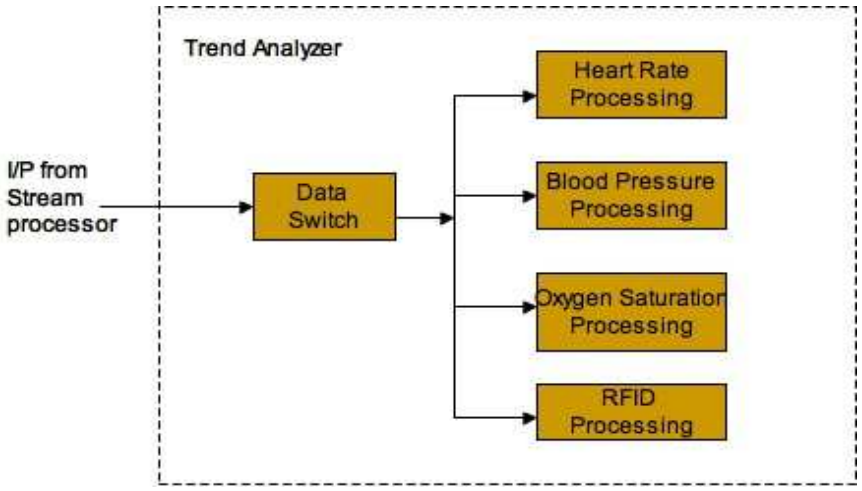


FIG. 2.2. Trend Analyzer

The results from the stream processor are streamed to a data switch, which in turn sends the results to the appropriate processing module. Each of the physiological data processing modules establishes trends in the physiological data.

2.2.3 Event Detection

Previous work [19] [22] [24] on monitoring a patients condition based on physiological data shows that it is a non-trivial task and has a lot of uncertainty in it. Intelligent patient monitoring algorithms have been developed using machine learning techniques.

Sukuvara et al [36] developed a system InCare that would identify specific conditions in post-cardiac patients. Data was collected and analyzed by a signal processor that interfaced with beside monitors. The rate of change of physiological values was used to match against pathological patterns to identify events. Though the system was fairly accurate it did not take into account any other information besides the trends in the physiological data. The system was implemented using technologies that are now obsolete. Now we have sophisticated systems that can handle large amounts of data and have immense computation power.

Krol et al [26] designed algorithms that to detect critical conditions during anesthesia. Zhang [38] created a system that simultaneously collects physiological data and clinical annotations at the bedside, and to develop alarm algorithms in real time based on patient-specific data collected while using this system. The system requires the nursing staff to enter the clinical annotation for each alarm signaled.

Bardram et al [16] developed a prototype context-aware system for a hospital environment. This system consists of a context-aware hospital bed, context-aware pill container and a context-aware electronic patient record. These systems make use of RFID sensors and touch sensors to detect the location of the nurse, the pill container and the patient. Little has been done towards detecting events in the perioperative environment and creating electronic documentation.

2.2.3.1 Classification of Events

Events are classified into two categories:

- Low-level Events
- High-level Events

2.2.3.2 Low-Level Events

Event detected by executing simple queries on the sensor data streams are low-level events. Abnormal values for a physiological parameter, detection of an RFID tag etc are example of low-level events. These events do not always signal a medically significant event. Correlating these events in the context of the environment helps us determine the significance of their occurrence. Analysis of physiological data at the low level involves determining the rate of change of data and the range to which the value belongs.

2.2.3.3 Detecting Low-Level Physiological Events

Changes in physiological data takes place gradually. Therefore using absolute thresholds to determine the range or rate of change is inefficient and leads to signaling false events. For the boundary conditions it is difficult to determine whether the value is normal or not. To capture this uncertainty in modeling data we make use of Fuzzy Set theory. In the current research we use the uncertainty concept to classify the rate of change and the range of the data measured only.

According to fuzzy set theory, a fuzzy concept like normal heart rate is represented by a membership function. This function can have a value between 0 and 1. A membership value of 1 (75 bpm) implies that the value is normal whereas value of 0 (30 bpm) implies that the the value is not normal. For values, between 30-70

bpm, yields a membership function value between 0 and 1 which denotes the degree to which the value is normal. Multiple fuzzy sets can be defined for a range of values. Some values belong to multiple sets with a varying degree of membership. For each physiological variable, we define the following fuzzy parameters:

- **Rate of Change**

  The rate of change of data is determined by comparing consecutive data values. The stream processor aggregates data over a time window and then sends the average values to the trend analyzer. Thus comparing consecutive average values gives us a good estimate of the rate of change of values. Since it is a fuzzy concept its we can represent the rate of change in the following linguistic terms: "Slight increase", "constant increase", "abrupt increase", "slight decrease", "constant decrease" or "abrupt decrease".

- **Range of values**

  For each variable, we set limits for the range of normal, high and low values. Based on these limits we determine the range to which a data value belongs. The limits are patient dependent and are set when the application is initialized. This is discussed in more detail in the next section. The value of the parameter can be: "Very low","Low","Normal","High" or "Very high".

2.2.3.4 Detecting Low Level RFID Events

Figure 2.3 shows the components of the RFID system. The software module interfacing with the reader, constantly polls the reader for the tags detected and streams the Electronic Product Codes (EPC) of the tags detected to the stream-processing engine. The stored queries in the engine are evaluated every time data is pushed to the engine and the results of the query as then pushed to the RFID stream analyzer. An RFID tag can be associated with either medical staff or the

medical supplies. The RFID stream analyzer makes this association and establishes the presence or absence of a tag in the operating room.

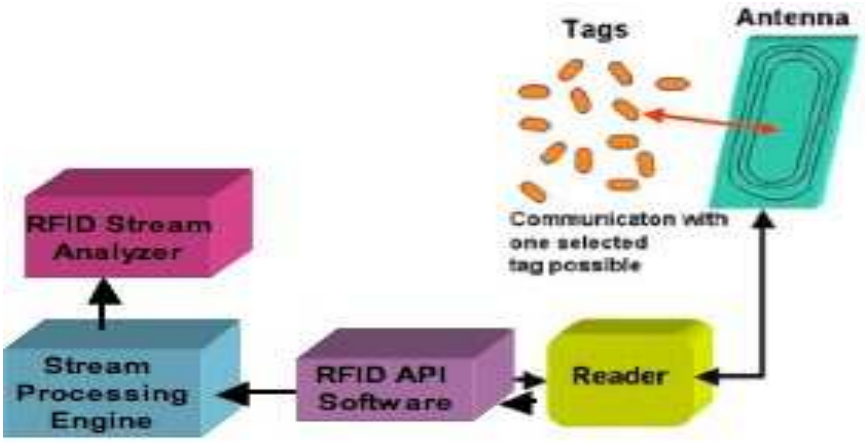


FIG. 2.3. RFID System

2.2.3.5 High-Level Events

Analyzing the physiological data streams in isolation may lead to detection of several false events. Patterns occurring in physiological data are specific to each patient and depend on the current and past medical history. For example, a patient with asthma will have high respiratory rate at the onset of the surgery as opposed to the patient with no such condition.

Medicines administered during the surgery may produce drastic changes in certain physiological parameters. These changes are a normal response to the medicine but may be interpreted as an abnormal condition when the algorithm as no knowledge of the medicines used. Correlating low-level events is the key to determine medically significant events occurring in the operating room. We make use of the following techniques to correlate and identify high-level events in the perioperative environment.

Table 2.1. Commonly Monitored Physiological Parameters

Name	Normal Range	Conditions
Systolic blood pressure	90-110	Hypertension, Hypotension
Diastolic blood pressure	70-80	Hypertension, Hypotension
Respiratory Rate	8-16 breaths/min	Tachypnea, Respiratory Arrest
Blood Temperature	37	Hypothermia
Oxygen Saturation	98-99	Hypoxia

2.2.3.6 Multi-Variable Analysis

A patients physiology consists of several parameters. Table 2.1 lists most frequently monitored parameters along with the range of values for healthy patients and some conditions associated with each parameter. Abnormal readings for a physiological parameter can signal low-level events like hypothermia, hypoxia etc.

Observing these events do not help us infer the goings on in the surgery or what stage the surgery is in. Thus these conditions do not always signify an alarming condition or a significant event. However, simultaneous analysis of these parameters can help us identify more meaningful events.

Example 1: Detecting Hypovolemia

Tachycardia with increasing heart rate and hypotension with decreasing blood pressure may signify loss of excess fluids.

```
If HR > 90 and HrRateOfChange = Increasing
    If SBP < 90 and DBP < 70 and BpRateOfChange = Decreasing
        Then Event (Hypovolemia - Excess Loss of fluids)
```

In order to detect events we need to determine the set of parameters that need to be monitored. Not every parameter needs to be monitored for each event. Interviews of clinicians and literature review [12] [23] helped us identify the parameters to be

monitored for certain conditions. Multi-variable analysis alone is not sufficient to identify events with accuracy. We also need to consider the surgical context before we can signal an event.

2.2.3.7 Context of Surgery

Several parameters together determine the context for the surgery being performed. The surgical context includes the following:

- The surgical staff present
- The patients pre-operative assessment and his medical history
- The medicines used during the surgery

The patients medical history includes details such as known allergies, past medications used, known diseases or medical conditions, laboratory reports, radiology reports etc. Medical history information can be use effectively to detect events. For example:

Example 2: Detecting Tachypnea

From Table 2.1 we know that normal range of value for respiratory rate is 8-16 breaths/min. Therefore a rule such as:

```
If RR < 8 then
    Event Tachypnea
```

However, if the patient has a history of asthma, he or she can have a normal respiratory rate of 20-25 breaths/min. Thus making use of patients medical history can help reduce signaling of false events.

2.2.3.8 Effect of Medicines

Medicines can have a significant effect on the patients physiological output. However, the effect of a medicine is not always observable as a change in physiological data. Therefore, given that a medicine was administered we associate this information with the change in physiology but not vice versa i.e by observing the changes in the physiology we cannot determine whether a medicine was administered. Associating the change in physiology with a medication is tricky and depends on the following:

- The time taken for the medicine to show its effects. Some medicines have an immediate effect while others may take anywhere between a 5-20 minutes.
- Duration for which the medicine is in effect
- Dose of the medicine

We need to associate the time at which the medicine is detected and the time its effect reflects in the physiology. We maintain a knowledge base that classifies medicines into categories, the effects of the medicine; time to take effect, duration of effect and the typical scenarios in which it is used.

Thus rules are based on a class of medicines rather than a specific instance. Consideration of the medications used helps reduce the number of false events dramatically. In our system, we signal an event for medicines whose effect was detected in the physiological parameters. The other medicines detected by the RFID system may or may not have been administered.

Example 3: Effect of an Anesthetic (Propofol)

Administration of an anesthetic results in an abrupt drop in the blood pressure and the respiratory rate, while the heart rate remains stable. Propofol takes effect in 40 seconds Thus if we detect propofol followed by an drop of more than 25% in the blood

pressure and a drop in respiratory rate we can determine that an anesthetic has been administered.

2.2.4 User Interface

We designed the user interface for the medical encounter record in Java. This interface 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 an when events are detected. A part of the screen is used to show the medicines and the surgical staff as detected by the RFID system. 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.

2.2.5 Performance Parameters

1. **False Event Detection:**

   One of the important performance characteristics of a monitoring algorithm is the number if false events detected. An event is false when it is inappropriate for the input data. For example: Conditions to detect hypovolemia are increasing heart rate and a decreasing blood pressure. But these conditions occur during Tension pneumothorax also. Thus failure to detect changes in oxygen saturation will result in signaling of hypovolemia. The methods used to detect high-level events help minimize the detection of false events.

2. **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

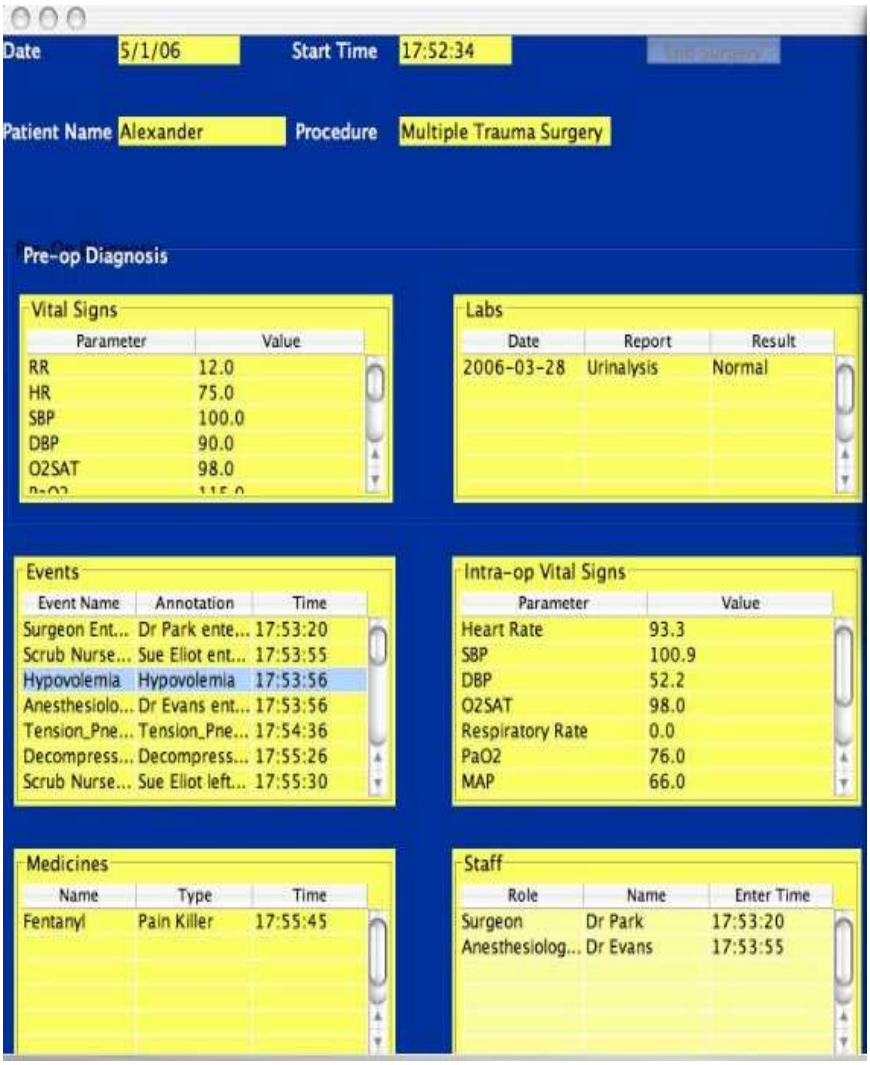


FIG. 2.4. User Interface

time of occurrence of an event has a significant impact on the way the event is interpreted. Therefore the order of detection of events and the time of detection is essential.

Chapter 3

Radio Frequency Identification System

3.1 Introduction

Radio Frequency Identification (RFID) systems allow automatic capturing of data using contact less radio frequency identification. These systems are mainly used to identify and track object. In this chapter we shall see how RFID can be used in healthcare and in acquiring context information in a per-operative environment.

An RFID system has three major components:

- **RFID tag or transponder** This is a microchip that stores data and a coupling element (coiled antenna). It is located on the object to be identified. It can be active or passive depending on whether it has its own power supply or not.
- **RFID reader or transceiver** This device is responsible for reading from and even writing data onto a RFID tag. The passive tag derives its power from the signal transmitted by the reader. A reader consists of a RF module, a control unit, and a coupling element and also an interface to the data processing subsystem.
- **Data processing subsystem** This is the system, which makes use of the data obtained from the tag by a reader. The communication signal incident upon

them by the tag-reader powers passive tags up. The mechanism could either be inductive coupling(near field) or far-field energy harvesting. Near-field extends up to a distance $1/(2\ f)$ meters from the signal source.

3.1.1 Classification of RFID Tags

RFID tags can be active, passive or semi-passive. Depending on the application requirements the appropriate tags are used.

- **Active RFID Tags**

  These tags are battery powered in order to transmit a signal to a reader, and are generally used for high-value goods that need to be tracked over long ranges (100 feet or more). Active tags are usually more expensive than passive tags, typically priced as much as $20 apiece. The high cost of active tags make them suitable to tag objects that are of high value and need to be tracked constantly.

- **Passive RFID Tags** These tags are not battery powered, and instead draw power from electromagnetic waves given off by an RFID reader. The read range for passive tags is usually less than two meters, and these tags can be priced at less than a dollar.

  Passive tags require no maintenance, and are primarily intended to track items at the pallet, case, and individual levels. These low-cost tags are the focus of the Auto-ID Center, and are being used in its field trials. These tags are suitable to track supplies and personnel in an operating room.

- **Semi-Passive RFID Tags** These are similar to active tags because they have batteries, but the battery is used only to run the microchips circuitry, not to power communications with the reader. These tags are typically priced above

a dollar and are generally used for tracking high-value goods, with longer read ranges.

3.1.2 Types of RFID Chips

The microchips contained within RFID tags can be identified as read-write or read only.

- **Read-Write RFID Chips**

  New information can be added to these chips, or existing information on these chips can be written over when the chip is within range of a reader. These chips are generally more expensive than read-only chips and are typically used to track high-priced, valuable items.

- **Read-Only RFID Chips:** Generally less expensive than read-write chips, these chips store information that can never be changed unless the chip is re-programmed electronically. We note that read-only RFID chips can also use electrically erasable programmable read-only memory (EEPPROM), in which case the data stored on the chip during the manufacturing process can be over-written through an electronic process that is able to erase and reprogram the data on the chip.

3.1.3 RFID Frequency Ranges

RFID tags and readers operate at various frequencies, and at the moment there is no universal set of global frequencies (although we note that the 13.56 MHz band is considered global). Although some vendors claim to have created a universal, or agile reader (capable of reading tags operating at multiple frequencies),

RFID tags generally operate at the low-frequency, high-frequency, ultra-high-frequency, or microwave levels. Each frequency has advantages and disadvantages

that make it more suitable for certain applications. Typically, the lower the frequency, the slower the data read rate, and the better the ability to read on (or near) wet or metal surfaces, which typically interfere with radio waves and tend to short radio waves. We summarize some information about the different frequencies of passive RFID tags in Fig 3.1

Frequency Range ›	LF (Low) 125 KHz	HF (High) 13.56 MHz	UHF (Ultra High) 868-915 MHz
Read Range (Passive Tags)	< 2ft	~3ft	~15-30ft
Data Rate	Slower ----------Faster		
Passive Tag Size	Larger----------Smaller		

FIG. 3.1. RFID Frequency Ranges

3.2 RFID in Perioperative Environment

In addition to the medically significant events, a complete medical encounter record consists of nursing documentation. This documentation includes details such as the names of the members of the surgical staff, medicines and tools used during the surgery. Also in chapter 2 we saw that just analyzing physiological data is not adequate to detect high-level medical events. Knowledge of the medicines administered can help us identify events more accurately and reduce the number of false events signaled. We chose RFID to detect the presence of surgical staff and the patient in the operating room and the medicines used.

For use in the perioperative environment, we used a 900MHz system that would detect RFID tags in the range of one to two meters. The reader would be deployed near the operating table. This gives enough range to detect the staff and the medicines being administered. The surgical staff and the medicines were tagged with passive

RFID Tags.

3.2.1 RFID System Components

1. **Reader:** There are several RFID readers available in the Market with different capabilities. Each of the readers has custom protocols and apis used to communicate with the RFID reader. Our system is customized to communicate with the Symbol AR400 900MHz reader [9].

2. **Tags:** Passive RFID tags were used to detect personnel and medical supplies. These tags are cost effective and work well for the application requirements.

3. **RFID API Software:** The AR400 system did not come with any application-programming interface. We implemented the protocol to communicate with the AR400 RFID reader and created a custom application programmer interface.

4. **Stream Processing Engine:** The stream engine retrieves data about tags detected from the RFID reader periodically. This list of tags returned by the reader consists of duplicate tag reads also. This list is processed by the api functions to return only unique tag ids. The stream engine further processes this data by executing queries over a time window on the data stream. The results of the queries are then sent to RFID stream analyzer. Details of the stream-processing engine are covered in Chapter 2.

5. **RFID Stream Analyzer:** Each RFID tag is associated with a medical supply or a member of the staff. Based on the results of the queries sent by the stream engine, the analyzer determines the presence or absence of tags and signals appropriate events.

3.2.2 RFID API Software

In this section we will describe in brief the *Byte Stream Protocol* [13] we implemented to communicate with the reader. The reader is always waiting in passive mode for this protocol. The Host system initiates all communication sequences. The packet sent from the Host system is as a request and the reply from a reader is a response. It is a synchronous protocol, which means that the Host must wait to receive the response for last request before issuing a new request. The maximum length of a request packets data section is 64 bytes; the maximum length of a response packets buffer space is 256 bytes. We connect to the reader using a TCP/IP connection. Figure 3.2 show the packet format for the request and response respectively. Table 3.3 defines the fields of the packet.

General Communication Sequence Figure 3.4 shows the general communication sequence for the byte stream protocol. For a TCP/IP socket connection, the Host system needs to establish connection to the reader before any message exchange. An established TCP/IP socket connection will be kept open until the Host system closes it or error occurs.For each request sent by the Host system to a reader, there could be multiple response packets back. The progress bit in a response packets status field serves as an indicator. Being zero means this is the last packet; otherwise, it means the command execution is still in progress and more packets are going to come until the last one with this bit set to zero.

3.2.3 Limitations of RFID Technology

3.2.3.1 Tag Collisions

Current RFID systems are limited in their accuracy to detect presence of RFID tags. The reader may detect tags that are not present in the vicinity or may not

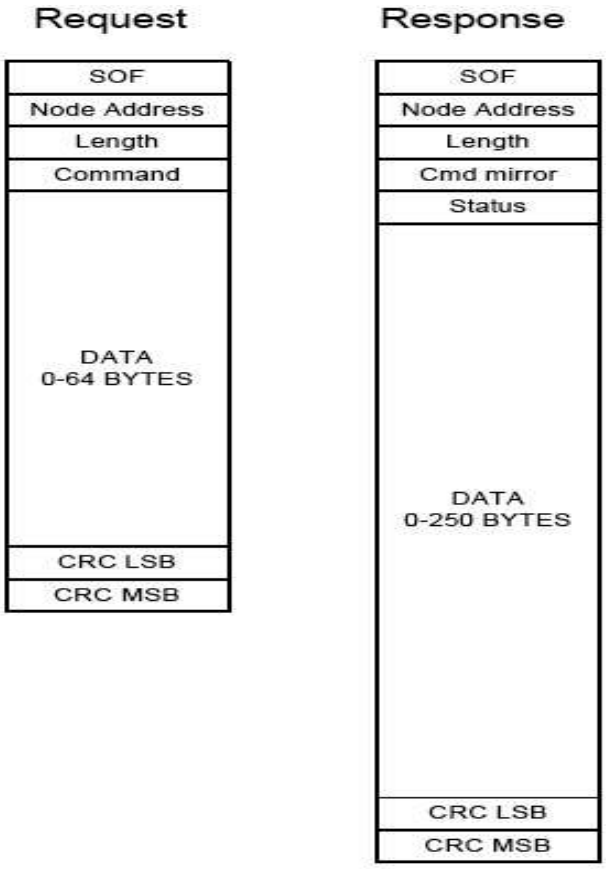


FIG. 3.2. Byte Stream Protocol Packet Format

detect all the tags that are within its range. This problem is related to the concept of tag collisions. When the reader emits a signal, all tags that receive the signal respond by sending their tag ids. When there are several tags close to each other or overlapping, the reader may not receive all the tag ids.

The signals sent by the tags collide and results in loss of data. Thus a single read from the reader is not enough to decide the presence or absence of a tag. Repeated reads are required to make such assertions. Our algorithm uses the following criteria to determine the presence of a tag. Count the number of times a tag id is present in the RFID data stream over a window of 60 seconds.

`If the` $Count > 5$ `then`

Field	Size(Byte)	Value	Description
SOF	1	0x01	Start of Frame
Node Address	1	0~0x1F	RS485 network node address of the recipient or responding reader.
Packet Length	1	Dependent	The length of the packet including CRC, but excluding SOF
Command	1	Various	The action to be taken by a reader
Cmd Mirror	1	Dependent	Mirror the original command in the response packet
Status	1	Various	The result or status of a command execution
Data	Various	Dependent	The parameters or data for the command or response
CRC	2	Dependent	Bitwise inversion of the 16-bit CCITT-CRC of the packet excluding SOF, with the LSB (Least Significant Byte) first

FIG. 3.3. Byte Stream Protocol Packet Field Definitions

`Tag is present in the vicinity`

A tag is considered to be missing when its visibility count becomes zero.

3.2.3.2 Interference:

The 900 MHz systems are advertised to have a read range of 3 meters. However this range is valid for scenarios where there are no major obstructions between the antenna and the RFID tag. Presence of metallic objects and fluids between the tag and the antenna result in loss of signals and the tag cannot be detected.

3.2.4 Issues in Healthcare

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.

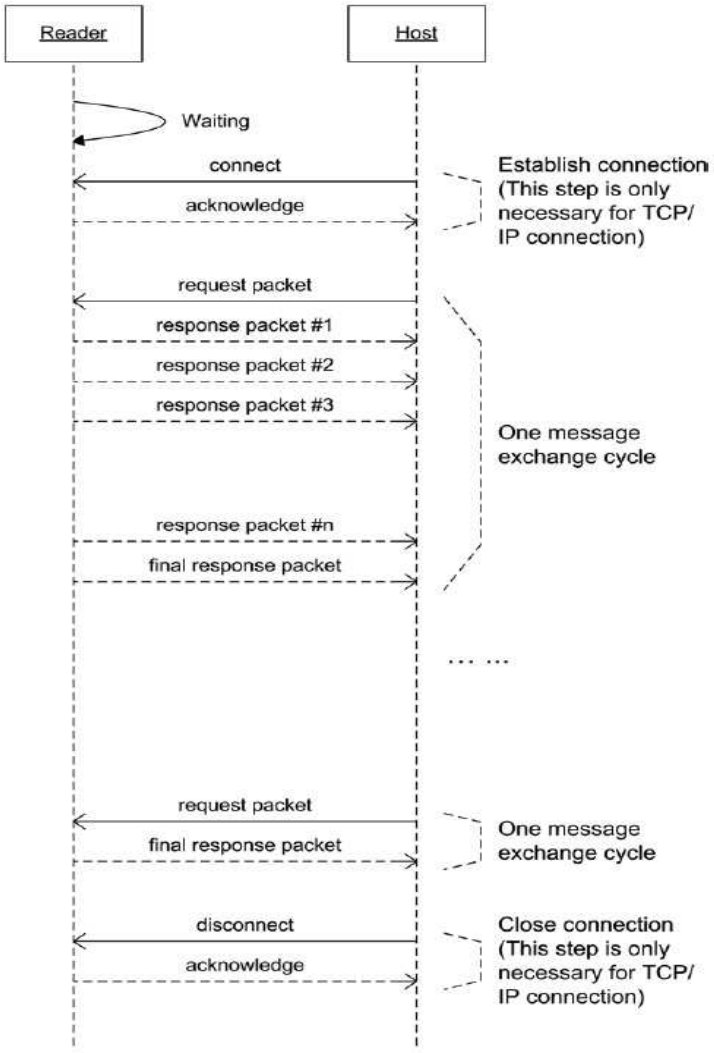


FIG. 3.4. General Byte Stream Protocol Communication Sequence

- **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 inches. 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.

3.2.5 Discussion

In spite of the limitations of the current state of art RFID has immense potential for use in healthcare.

- **State Information On Tag** RFID tags have a small amount of on chip memory. This memory can be exploited to store state information of the object on the tag itself. For medicines, the expiration date can be stored on tag. Tools can have information such as number of times it has been used, date when it was last sharpened etc. With this information on the tag itself, the state information can be obtained by reading the tag and it obviates the necessity of storing this information in a database. Currently, this information is stored in the database.

- **Updating Information on Tags** In order to maintain state information on tags, we need to write this data to the tag. The range at which a tag can be written is usually shorter than the read range. Laboratory test results show that the operation of writing to the tag seldom succeeds in the first attempt. As the distance from the antenna increases the number of write failures increase. Thus updating information on tags in real-time is subject to a lot of inaccuracy.

- **Supply Counts** One of the important tasks of a scrub nurse is to ensure that no supplies are left within the patient at the end of the surgery. The numbers

of supplies used are counted and should either end up in the waste bin or in the storage. With RFID we can only determine a range in which a tag is detected. Partitioning an operating room with high frequency RFID systems does not help us determine the exact zone/location of the tags. Low frequency RFID systems work at a very short range.

For such systems the tag must be very close to the antenna before it can be read. These systems do not offer any advantage over the bar-code systems. Localization in RFID systems is a subject of research. When this becomes possible, supply count can be possible with RFID.

Chapter 4

Results

To evaluate the performance of our system we used physiological data sets from a human patient simulator.

4.1 Human Patient Simulator

The Human Patient Simulator (HPS) is a product of Medical Education Technologies Inc (METI). The HPS is called Stan for Standard Man. "The system consists of electrical, mechanical, hydraulic and pneumatic devices that accurately control bodily functions. His eyes blink, his pupils dilate, his pulse can be felt in the same spots a doctor would check on a humanat the wrist, neck, crook of the arm, thigh and foot. His circulatory system is a series of hoses laid out like veins and arteries and can contain water or fake blood. Air bags in the chest pneumatically rise and fall to simulate breathing, while external mechanical "lungs" replicate the flow of oxygen and carbon dioxide." All these systems connect through a series of wires and are controlled by an Apple Mac G4.

Stan is controlled by a software interface. When an instructor logs on to the Patient Editor software, the first thing he or she will see is a screen with a medical history template. The teacher chooses the name, age, and gender of the patient–

FIG. 4.1. Human Patient Simulator [6]

thanks to interchangeable genitalia Stan can become Sue– and fills out a brief medical history, including current complaints.

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:

4.1.1 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:

- Excess blood loss
- Tension pneumothorax
- Decompression
- Fluid Infusions

4.1.2 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

The HPS remains in each of these states 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 above we created slight variations of these scenarios.

The above two scenarios are simulated on different patient profiles. Each patient has different medical history and pre-op diagnosis. Figure 4.2 shows a sample patient profile.

Each of the scenarios was simulated with five different profiles. Slight variations of the scenarios were simulated to give us more varied data sets.

Standard Man Narcotized

Name, Age, and Gender:

Stan D. Ardman ("Standard Man", "Stan"), 33-year old, male

History of Present Illness:

Otherwise healthy adult with compound ankle fracture requiring ORIF.

Past Medical History:

None
NKDA
Denies tobacco, alcohol, and IV drug use
Runs 2 miles several times a week

Past Surgical/Anesthetic History:

Tonsillectomy at age 6, general anesthesia without complications
No family history of anesthetic problems

Review of Systems:

CNS:	Negative for stroke
Cardiovascular:	Negative for hypertension, angina, DOE
Pulmonary:	Negative for COPD, asthma, recent URI
Renal/Hepatic:	Negative for renal failure, jaundice
Endocrine:	Negative for diabetes, thyroid disease
Heme/Coag:	Negative for anemia, bruising

Current Medications:

None

Physical Examination:

General:	Healthy adult male, average build, in no distress
Weight, Height:	70 kg, 6'0"
Vital Signs:	HR 73 bpm, BP 113/52 mmHg, RR 13 br/min, SpO2 97%
Airway:	Full dentition, no loose teeth FROM neck & TMJ, wide oral opening, 4 fb mandible, MC 1
Lungs:	Relaxed respiration, with clear bilateral breath sounds
Heart:	RRR. Normal S1, S2; no S3, S4, murmur, or rub

Laboratory, Radiology, and other relevant studies:

HCT:	42.3%

Narrative:

This patient profile is identical to Standard Man, except that the patient has received 500 µg of fentanyl. This causes respiratory depression and blunting of physiologic control mechanisms such as the baroreflex and the ventilator response to carbon dioxide. This patient profile is useful for scenarios in which you do not want the patient to breathe spontaneously during mechanical ventilation, but do want some ventilatory response (though blunted as compared to the awake baseline) to hypoxemia and hypercapnia.

FIG. 4.2. Patient Profile

4.1.3 Limitations of The HPS

During our simulations we discovered certain limitations of the HPS system.

- The physiological responses produced by the HPS under certain conditions are not as would be expected in a human.
- The rate at which the parameters change in response to a pathological condition is not as quick as would be observed in a human patient

- When subjected to a complicated scenario, such as a combination of scenario 1 and 2, the HPS fails to produce the desired response. It works well for small relatively simple scenarios.

Due to the above limitations the data sets produced by the HPS are not very accurate. Hence the rule engine triggers some false positives and false negatives.

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
- Reduce Anesthetic

Figure 4.3 shows the sensitivity for each of the events and Figure 4.4 shows specificity.

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 Anesthetic" show 100% specificity and sensitivity as they are triggered

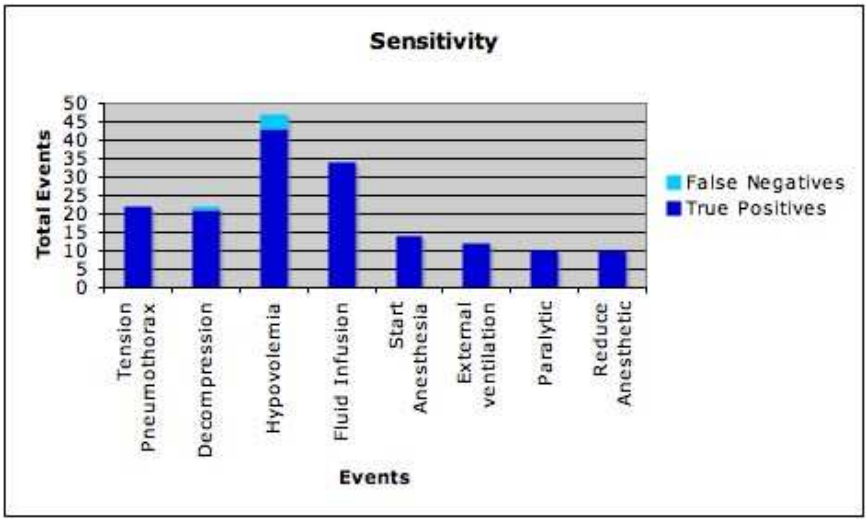


FIG. 4.3. Sensitivity of Events

only when the medicine is detected by the RFID reader. Without RFID, it is difficult 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 rfid 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 4.1 show the average latency and the standard deviation of detecting each of the key events. The high standard deviation implies that event detection is highly subjective to an individual patient as the change in physiology is affected by the patients medical history. For example, it is difficult to detect Hypovolemia in a hypotensive patient and the change in blood pressure is gradual as compared to a patient with normal blood pressure who blood pressure will drop rapidly with loss of fluids.

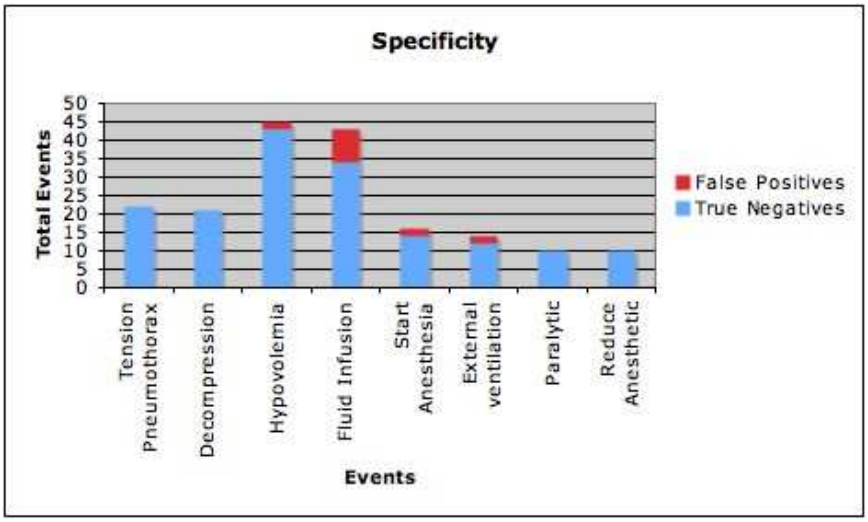


FIG. 4.4. Specificity of Events

4.1.4 Discussion

In this section we shall discuss the scalability of the system architecture. We have developed a context aware system that is capable of analyzing physiological data streams and detecting medically significant events. We also make use of radio frequency identification technology to detect medicines administered and the surgical staff present in the Operating room. A stream-processing engine that executes low-

Table 4.1. 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

level queries on the data streams processes the data streams. The trend analyzers further process the results of these queries.

Scalability of our system depends on the capabilities of the stream engine TelegraphCQ, the trend analyzers and the Jess Rule Base.

4.1.4.1 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 will 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 [34] 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.

Currently we use simple aggregate queries over the data streams to get average data values over a time window. To analyze or determine the rate of change of values we have trend analyzers that determine the change for each parameter. Current version of telegraphcq does not support subqueries. It allows only a single pass over data in a time window. When the subquery support is added, the determination of rate of change can be done using simple queries instead of having a trend analyzer for each parameter.

As the number of physiological parameters to be monitored increases, the number of trend analyzers will also increase linearly. This is because the same rules for rate of change do not apply to all parameters.

4.1.4.2 JESS: Rule Base

The Jess rule base is an expert system that has a set of if-then rules and a working memory. The rules are evaluated against the contents of the working memory, which changes over the course of time. Jess uses an efficient approach to evaluate rules called the Rete Algorithm. Jess is faster than some popular rule engines written in C. Computational complexity of Rete is linear in the size of the working memory [4]. Also, Rete is an algorithm that explicitly trades space for speed, so Jess' memory usage is not inconsiderable.

However, Jess does contain some commands, which will allows us to sacrifice some performance to decrease memory usage. In our system, size of the working memory changes slowly, once the initial set of facts has been added. As the physiological parameters change their values, the existing facts are updated to reflect the change. We avoid adding and retracting facts frequently as this affects the performance of the

system. The working memory will increase linearly as the number of parameters to be monitored increases with the current system design. Thus the rule base is scalable as new rules can be added without significantly degrading the performance of the rule base.

4.1.4.3 RFID API

In addition to reading RFID tags, the API provides support for writing tags, writing tags within view of a specific antenna, killing a tag etc. The system can be easily extended to make to use of these functions as required. Some of the scenarios where this can be done are described in the future work section.

Chapter 5

Related Work

5.1 Alarm Algorithms

Automated patient monitoring systems and algorithms has been a subject of research since over a decade. Several prototype systems and alarm algorithms have been created. As mentioned previously, the focus of these systems was to detect alarming conditions. In our research we presented a system that captures any medically significant event. Our algorithms and techniques are based on the previous work done.

One of the major limitations of the previous systems is the high false alarm rate. These systems determined an alarming condition by observing each physiological parameter individually. Each parameter had an absolute threshold. When the value crossed this threshold an alarm would be signaled. This is a very inefficient way to monitor the patients state for several reasons. Firstly, as reported by Koski et al [19] changes in a single parameter is not sufficient to determine an alarm. Secondly, in the overall context of the patients state, the alarm may be meaningless. During anesthesia, sudden drop in respiratory rate is an expected response. But this can be inferred only from the context of the surgery. Therefore conventional alarm algorithms do not provide sufficient information about a patients state.

One of the techniques suggested by Koski et al [19], to reduce false alarms was multi-variable analysis. Simultaneous monitoring of more than one parameter can help determine alarms with more accuracy. Navabi et al [28] developed an integrated anesthesia monitor that could detect intubations with high accuracy. The algorithm monitored the end-tidal carbon-di-oxide, oxygen saturation and airway pressure. With this method the false et-co2 alarms were reduced by 70% and false heart rate alarms reduced by 68%.

[26] Krol et al developed similar computer algorithms to detect conditions like Light Anesthesia by analyzing hemodynamic data. Schecke et al [35] designed a knowledge-based decision support system for patient monitoring in cardio anesthesia and Sukuvaara et al [36] developed system to monitors the state of post-cardiac surgery patients. Both used multi-variable analysis to detect alarms. Fuzzy set theory was used to model uncertainties in the decision-making process.

While monitoring more than one variable at a time helped reduce false alarm rates, not all parameters are monitored for each condition. Mylrea et al [31] showed that monitoring a smaller number resulted in better output.

The thresholds set for various parameters is another source of false alarms. In Chapter 2 we saw some examples showing that absolute thresholds are not efficient to detect alarming conditions. A limit that is alarming for one patient may not be harmful for another patient. A study by Makivirta and Koski et al [29] shows that actual range of values indicating an alarming condition does not vary significantly from the limits decided by a physician. However, there are outliers in the data values that cause false alarms. Thus setting limits according to individual patient state reduces number of false alarms and produce more meaningful alarms.

Thresholds for parameters are dynamic based on the patients medical condition. Changing the threshold to adapt to the patients condition will help reduce the number

of false alarms. Algorithms to detect alarming conditions make use of a small subset of data that a clinician would otherwise use to determine the patients condition. [24] Bloom s study showed that interpretation of signals varied with the context of the patients state.

[37] Tsien studied four algorithms that filter output signals of a bedside monitor: moving average, moving median, delay, and sampling rate. Moving average algorithms and delay algorithms decreased false alarms up to a particular window size. Moving median algorithms seemed more likely to eliminate true alarms than false alarms. The sampling rate algorithm showed no consistent effect on the positive predictive value of the alarms.

[24] Bloom et al represented a cluster based algorithm to analyze physiologic data. The aim is to group patient measurements that resemble each other in subgroups. Each group represents a possible distinct state that the patient can be in. Weights are assigned to each measurement and discriminant analysis is used to estimate the patients state. Cluster analysis was used on one hundred and twenty three averaged EEG spectra of dogs subjected to severe, hypoxia and hypoxic states. Cluster analysis distinguished four different states though only three were defined. They concluded that even though their technique suffers from some weaknesses, clustering can approximate the number of distinct states of the patient.

[22] Hunter et al developed a Time series workbench to help clinicians detect events in data collected from patient monitors. The approach used is to segment the time series data into intervals and feed the data segments to a pattern matcher that could detect events. The example used here is to detect the re-siting of transcutaneous CO2/O2 probe on a baby in the NICU. The algorithm used to segment time series data is to find an interval of set of points that satisfy a relative error threshold. This is called is the best-fit algorithm. These intervals are then merged to create a

super-interval. A test on 45 samples resulted in an accuracy of 89%. As the relative threshold error increased the accuracy decreased significantly.

In this thesis we have assumed the physiological data available to be noise free and valid. But this is another area of research. Horn et al [21]developed a knowledge-based system that used time-point, time-interval and trend-based methods to eliminate and repair faulty data received from physiological monitors. Data validation resulted in reduced false positive alarms rate.

5.2 Decision Support and Patient Monitoring Systems

Research in the area of patient monitoring has resulted in a number of systems making use of artificial intelligence techniques to improve the quality of patient monitoring systems. In this section we will see case studies of some of the systems.

One of the earliest rule-based alarm systems was developed by Sukuvaara et al [36] to detect a set of conditions in post-cardiac operated patients. The conditions included hypovolemia, hypertension etc. The system consisted of a data acquisition module Datalog, which collected signals from patient monitors, and InCare, a rule-based system that consisted of the rules to detect events by combining the measured signals and estimated trends. The system was capable of detecting events even when the data available was incomplete. Data values and trends over a time window were used to detect events. Evaluation of the system on 35 post-cardiac operated patients resulted in a specificity of 71% and sensitivity of 100%.

Machine learning algorithms are typically used to learn patterns or trends in a data set. These algorithms adapt over a period of time and detect patterns with increasing accuracy. Zang et al developed two intelligent alarm algorithms for patient monitoring based on Classification Tree and Neural Networks. These algorithms aim to create models that are specific to a patient. Classification tree learning is

a method for inductive inference that takes on continuous-valued, discrete-valued, and/or Boolean inputs and generates a discrete-valued output, and the learned function is represented by a classification tree or a set of if-then rules. It classifies each instance by sorting it down a tree from the root, through branching nodes that depend on the values of the instances attributes, to a leaf node, which represents the instances class. Neural Networks learning is among the most effective methods for learning complex sensor data. Both these methods are shown to be effective in identifying whether or not an alarm is a true alarm or not.

[15] 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 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. Operators can be simple database operators like it filter and join to specific algorithms to analyze medical data. A set of operators is defined for each patient constituting a patient plan. The system is still in the development stages and the initial prototype is capable of identifying simple pathological conditions by monitoring ECG signals. This is the only system we found in the literature that tries to make use of stream processing of data.

5.3 Fuzzy Logic in Medicine

Physiological data streams are continuous valued data streams and the changes in parameters are gradual. In classical set theory, given a data value, it is assigned to a distinct set based on the rules to classify data values. There is no ambiguity in the process. The gradual changes occurring in physiological data make it difficult to

make such unambiguous classification. [33] According to Freidmann

> Fuzzy sets resolve the mismatch between the discreteness of symbolic systems and continuity of medical reality. For clear-cut cases a fuzzy system produces the same results as its underlying symbolic skeleton. For borderline cases, however it determines the degrees of fit of what is actually present and its internal descriptions and propagates these degrees through the system to its output, where they serve to qualify the results of the reasoning process.

[30] Martin et al give an introduction to fuzzy control systems and argue how the use of such systems is useful in healthcare: specifically in detecting conditions during anesthesia. [25] Becker et al designed an intelligent patient monitoring system to detect conditions during anesthesia using fuzzy logic process model. Validation of this system on 641 state variable evaluations showed sensitivity of alarm recognition is 99.3%, specificity is 66% and predictability is 45%.

Chapter 6

Conclusion and Future Work

In this thesis we presented the design, implementation and evaluation of a context-aware system to create an electronic medical encounter record in the perioperative environment. We will conclude with a summary of our studies and findings and scope for future research.

6.1 Summary

We began in Chapter 2, by describing the architecture for the system to detect events. The main components of this system are the stream processing engine - Telegraphcq, the trend analyzer and the Rule based engine. We also described the techniques used to correlate low level events to infer medically significant events. The chapter also discussed the concept of fuzzy logic that we used to capture uncertainty in interpreting the physiological parameters.

In Chapter 3 we discussed how Radio Frequency Identification has been used to build a context in the operating room by tagging medical supplies and surgical staff. We described the details of the RFID system used and the API we developed. We also outlined the issues with current state of art and the potential of RFID in the perioperative environment. RFID can enable use to detect events that are not

possible by monitoring and analyzing the physiological data streams only.

Chapter 4 presents results of the system evaluation. We presented Human Patient Simulator which we used to evaluate the performance of our system. The system has average sensitivity 98% and specificity of 93.47%. The events which were supported by RFID had 100% sensitivity and specificity.

6.2 Ongoing and Future Research

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

6.2.1 Traumapod

Trauma Pod [10] 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.

6.2.2 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 [32]. 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 [3], CIMIT [1], SNOWMED-CT [8], 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) [11] is a meta-thesaurus created by the National Library of Medicine (NLM) that integrates the ontologies developed by various groups.

6.2.3 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 tie the blood vessels. With the current system, such events are not detectable.

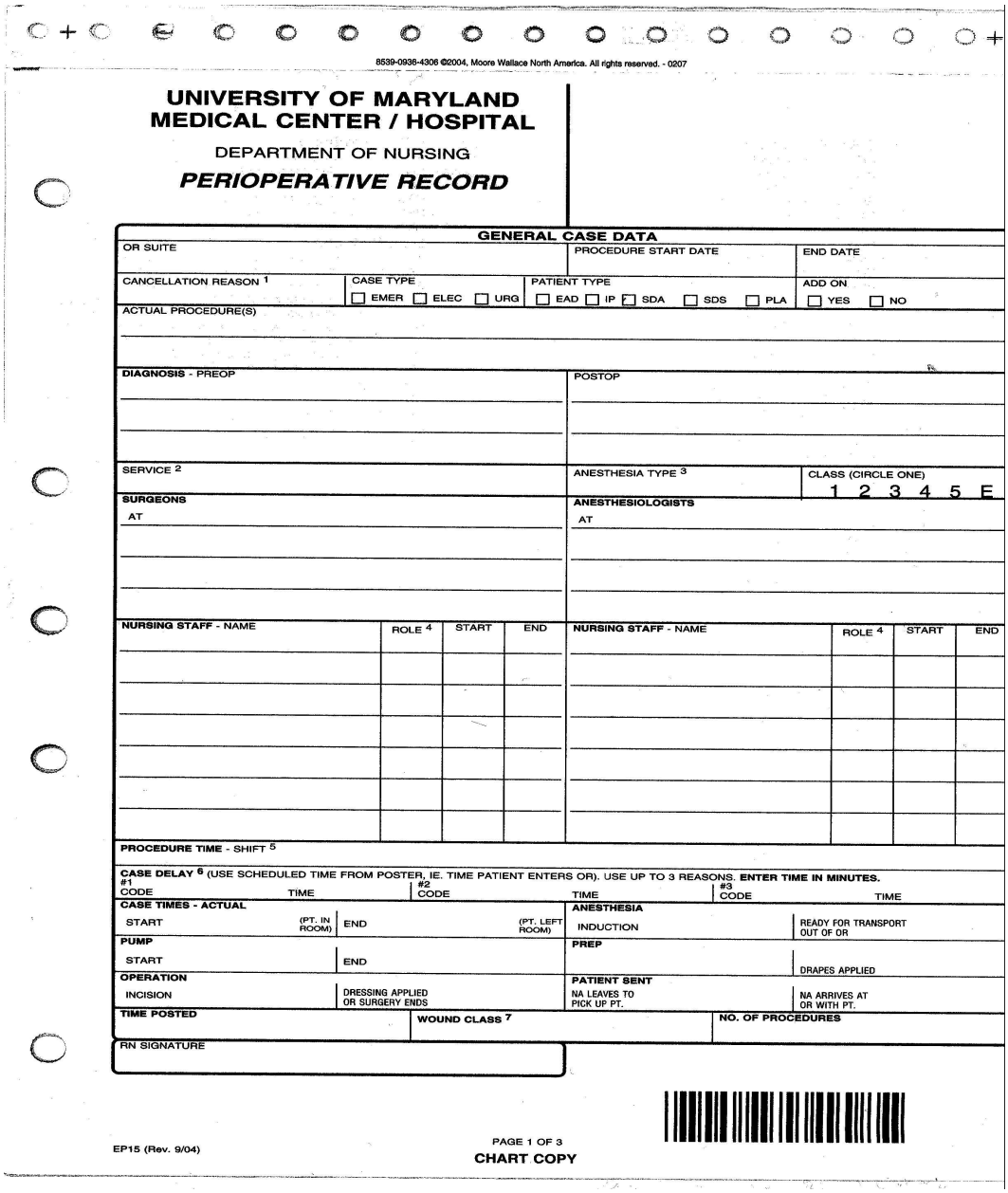
6.2.4 Video Capture

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 efficiency and speed of evaluation.heyy We need to work on estimating the time duration of each event to create clips of appropriate length.

Appendix



UNIVERSITY OF MARYLAND MEDICAL CENTER / HOSPITAL

DEPARTMENT OF NURSING

PERIOPERATIVE RECORD

GENERAL CASE DATA

OR SUITE | PROCEDURE START DATE | END DATE

CANCELLATION REASON [1] | CASE TYPE ☐ EMER ☐ ELEC ☐ URG | PATIENT TYPE ☐ EAD ☐ IP ☐ SDA ☐ SDS ☐ PLA | ADD ON ☐ YES ☐ NO

ACTUAL PROCEDURE(S)

DIAGNOSIS - PREOP | POSTOP

SERVICE [2] | ANESTHESIA TYPE [3] | CLASS (CIRCLE ONE) 1 2 3 4 5 E

SURGEONS AT | **ANESTHESIOLOGISTS** AT

NURSING STAFF - NAME	ROLE [4]	START	END	**NURSING STAFF** - NAME	ROLE [4]	START	END

PROCEDURE TIME - SHIFT [5]

CASE DELAY [6] (USE SCHEDULED TIME FROM POSTER, IE. TIME PATIENT ENTERS OR). USE UP TO 3 REASONS. **ENTER TIME IN MINUTES.**

#1 CODE | TIME | #2 CODE | TIME | #3 CODE | TIME

CASE TIMES - ACTUAL

START (PT. IN ROOM) | END (PT. LEFT ROOM) | **ANESTHESIA** INDUCTION | READY FOR TRANSPORT OUT OF OR

PUMP START | END | **PREP** | DRAPES APPLIED

OPERATION INCISION | DRESSING APPLIED OR SURGERY ENDS | **PATIENT SENT** NA LEAVES TO PICK UP PT. | NA ARRIVES AT OR WITH PT.

TIME POSTED | **WOUND CLASS** [7] | **NO. OF PROCEDURES**

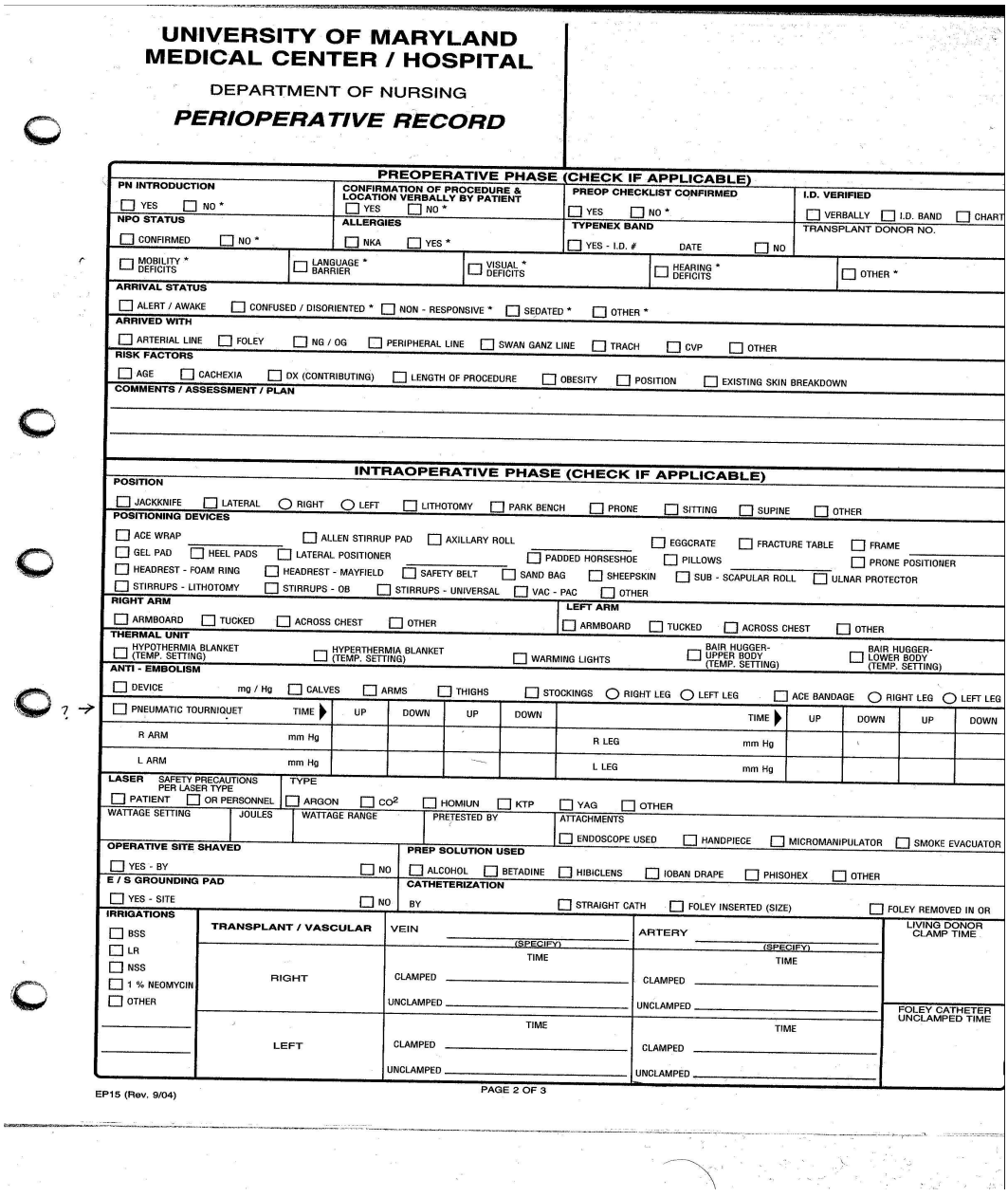
RN SIGNATURE

EP15 (Rev. 9/04)

PAGE 1 OF 3

CHART COPY

FIG. 1. Perioperative Record Page 1



UNIVERSITY OF MARYLAND MEDICAL CENTER / HOSPITAL

DEPARTMENT OF NURSING

PERIOPERATIVE RECORD

PREOPERATIVE PHASE (CHECK IF APPLICABLE)

PN INTRODUCTION ☐ YES ☐ NO *

CONFIRMATION OF PROCEDURE & LOCATION VERBALLY BY PATIENT ☐ YES ☐ NO *

PREOP CHECKLIST CONFIRMED ☐ YES ☐ NO *

I.D. VERIFIED ☐ VERBALLY ☐ I.D. BAND ☐ CHART

NPO STATUS ☐ CONFIRMED ☐ NO *

ALLERGIES ☐ NKA ☐ YES *

TYPENEX BAND ☐ YES - I.D. # DATE ☐ NO

TRANSPLANT DONOR NO.

☐ MOBILITY * DEFICITS ☐ LANGUAGE * BARRIER ☐ VISUAL * DEFICITS ☐ HEARING * DEFICITS ☐ OTHER *

ARRIVAL STATUS ☐ ALERT / AWAKE ☐ CONFUSED / DISORIENTED * ☐ NON - RESPONSIVE * ☐ SEDATED * ☐ OTHER *

ARRIVED WITH ☐ ARTERIAL LINE ☐ FOLEY ☐ NG / OG ☐ PERIPHERAL LINE ☐ SWAN GANZ LINE ☐ TRACH ☐ CVP ☐ OTHER

RISK FACTORS ☐ AGE ☐ CACHEXIA ☐ DX (CONTRIBUTING) ☐ LENGTH OF PROCEDURE ☐ OBESITY ☐ POSITION ☐ EXISTING SKIN BREAKDOWN

COMMENTS / ASSESSMENT / PLAN

INTRAOPERATIVE PHASE (CHECK IF APPLICABLE)

POSITION ☐ JACKKNIFE ☐ LATERAL ◯ RIGHT ◯ LEFT ☐ LITHOTOMY ☐ PARK BENCH ☐ PRONE ☐ SITTING ☐ SUPINE ☐ OTHER

POSITIONING DEVICES

☐ ACE WRAP ☐ ALLEN STIRRUP PAD ☐ AXILLARY ROLL ☐ EGGCRATE ☐ FRACTURE TABLE ☐ FRAME

☐ GEL PAD ☐ HEEL PADS ☐ LATERAL POSITIONER ☐ PADDED HORSESHOE ☐ PILLOWS ☐ PRONE POSITIONER

☐ HEADREST - FOAM RING ☐ HEADREST - MAYFIELD ☐ SAFETY BELT ☐ SAND BAG ☐ SHEEPSKIN ☐ SUB - SCAPULAR ROLL ☐ ULNAR PROTECTOR

☐ STIRRUPS - LITHOTOMY ☐ STIRRUPS - OB ☐ STIRRUPS - UNIVERSAL ☐ VAC - PAC ☐ OTHER

RIGHT ARM ☐ ARMBOARD ☐ TUCKED ☐ ACROSS CHEST ☐ OTHER

LEFT ARM ☐ ARMBOARD ☐ TUCKED ☐ ACROSS CHEST ☐ OTHER

THERMAL UNIT ☐ HYPOTHERMIA BLANKET (TEMP. SETTING) ☐ HYPERTHERMIA BLANKET (TEMP. SETTING) ☐ WARMING LIGHTS ☐ BAIR HUGGER- UPPER BODY (TEMP. SETTING) ☐ BAIR HUGGER- LOWER BODY (TEMP. SETTING)

ANTI - EMBOLISM ☐ DEVICE mg / Hg ☐ CALVES ☐ ARMS ☐ THIGHS ☐ STOCKINGS ◯ RIGHT LEG ◯ LEFT LEG ☐ ACE BANDAGE ◯ RIGHT LEG ◯ LEFT LEG

☐ PNEUMATIC TOURNIQUET	TIME ▶	UP	DOWN	UP	DOWN	TIME ▶	UP	DOWN	UP	DOWN
R ARM	mm Hg					R LEG	mm Hg				
L ARM	mm Hg					L LEG	mm Hg				

LASER SAFETY PRECAUTIONS PER LASER TYPE ☐ PATIENT ☐ OR PERSONNEL TYPE ☐ ARGON ☐ CO^2 ☐ HOMIUN ☐ KTP ☐ YAG ☐ OTHER

WATTAGE SETTING	JOULES	WATTAGE RANGE	PRETESTED BY	ATTACHMENTS ☐ ENDOSCOPE USED ☐ HANDPIECE ☐ MICROMANIPULATOR ☐ SMOKE EVACUATOR

OPERATIVE SITE SHAVED ☐ YES - BY ☐ NO

PREP SOLUTION USED ☐ ALCOHOL ☐ BETADINE ☐ HIBICLENS ☐ IOBAN DRAPE ☐ PHISOHEX ☐ OTHER

E / S GROUNDING PAD ☐ YES - SITE ☐ NO

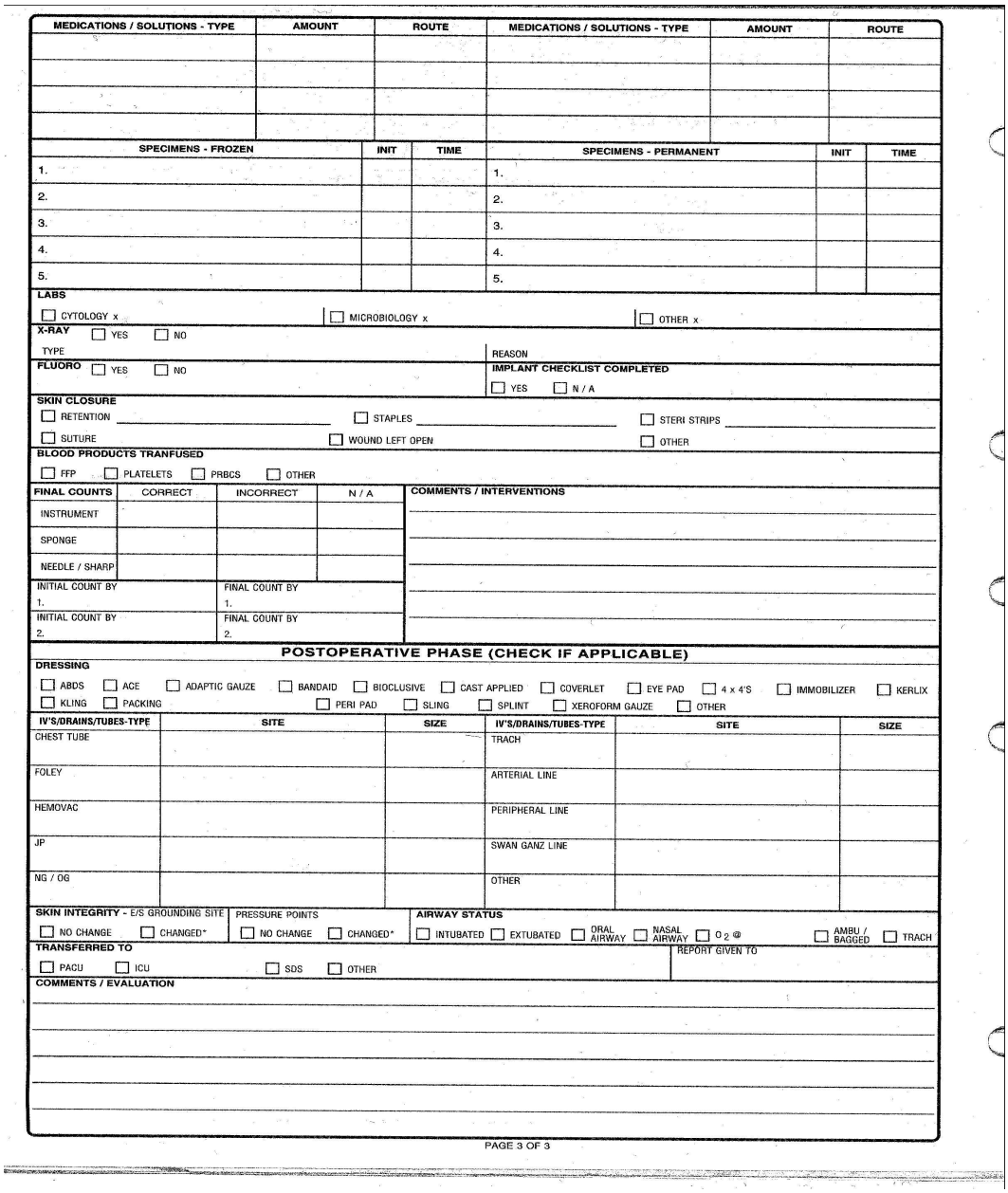
CATHETERIZATION BY ☐ STRAIGHT CATH ☐ FOLEY INSERTED (SIZE) ☐ FOLEY REMOVED IN OR

IRRIGATIONS ☐ BSS ☐ LR ☐ NSS ☐ 1 % NEOMYCIN ☐ OTHER

TRANSPLANT / VASCULAR	VEIN (SPECIFY)	ARTERY (SPECIFY)	LIVING DONOR CLAMP TIME
RIGHT	TIME CLAMPED / UNCLAMPED	TIME CLAMPED / UNCLAMPED	
LEFT	TIME CLAMPED / UNCLAMPED	TIME CLAMPED / UNCLAMPED	FOLEY CATHETER UNCLAMPED TIME

EP15 (Rev. 9/04) PAGE 2 OF 3

FIG. 2. Perioperative Record Page 2



MEDICATIONS / SOLUTIONS - TYPE	AMOUNT	ROUTE	MEDICATIONS / SOLUTIONS - TYPE	AMOUNT	ROUTE

SPECIMENS - FROZEN	INIT	TIME	SPECIMENS - PERMANENT	INIT	TIME
1.			1.		
2.			2.		
3.			3.		
4.			4.		
5.			5.		

LABS

☐ CYTOLOGY x ☐ MICROBIOLOGY x ☐ OTHER x

X-RAY ☐ YES ☐ NO

TYPE REASON

FLUORO ☐ YES ☐ NO **IMPLANT CHECKLIST COMPLETED** ☐ YES ☐ N / A

SKIN CLOSURE

☐ RETENTION _____ ☐ STAPLES _____ ☐ STERI STRIPS _____

☐ SUTURE ☐ WOUND LEFT OPEN ☐ OTHER

BLOOD PRODUCTS TRANFUSED

☐ FFP ☐ PLATELETS ☐ PRBCS ☐ OTHER

FINAL COUNTS	CORRECT	INCORRECT	N / A
INSTRUMENT			
SPONGE			
NEEDLE / SHARP			

INITIAL COUNT BY	FINAL COUNT BY
1.	1.
2.	2.

COMMENTS / INTERVENTIONS

POSTOPERATIVE PHASE (CHECK IF APPLICABLE)

DRESSING

☐ ABDS ☐ ACE ☐ ADAPTIC GAUZE ☐ BANDAID ☐ BIOCLUSIVE ☐ CAST APPLIED ☐ COVERLET ☐ EYE PAD ☐ 4 x 4'S ☐ IMMOBILIZER ☐ KERLIX

☐ KLING ☐ PACKING ☐ PERI PAD ☐ SLING ☐ SPLINT ☐ XEROFORM GAUZE ☐ OTHER

IV'S/DRAINS/TUBES-TYPE	SITE	SIZE	IV'S/DRAINS/TUBES-TYPE	SITE	SIZE
CHEST TUBE			TRACH		
FOLEY			ARTERIAL LINE		
HEMOVAC			PERIPHERAL LINE		
JP			SWAN GANZ LINE		
NG / OG			OTHER		

SKIN INTEGRITY - E/S GROUNDING SITE ☐ NO CHANGE ☐ CHANGED* PRESSURE POINTS ☐ NO CHANGE ☐ CHANGED*

AIRWAY STATUS ☐ INTUBATED ☐ EXTUBATED ☐ ORAL AIRWAY ☐ NASAL AIRWAY ☐ O_2 @ ☐ AMBU / BAGGED ☐ TRACH

TRANSFERRED TO REPORT GIVEN TO

☐ PACU ☐ ICU ☐ SDS ☐ OTHER

COMMENTS / EVALUATION

PAGE 3 OF 3

FIG. 3. Perioperative Record Page 3

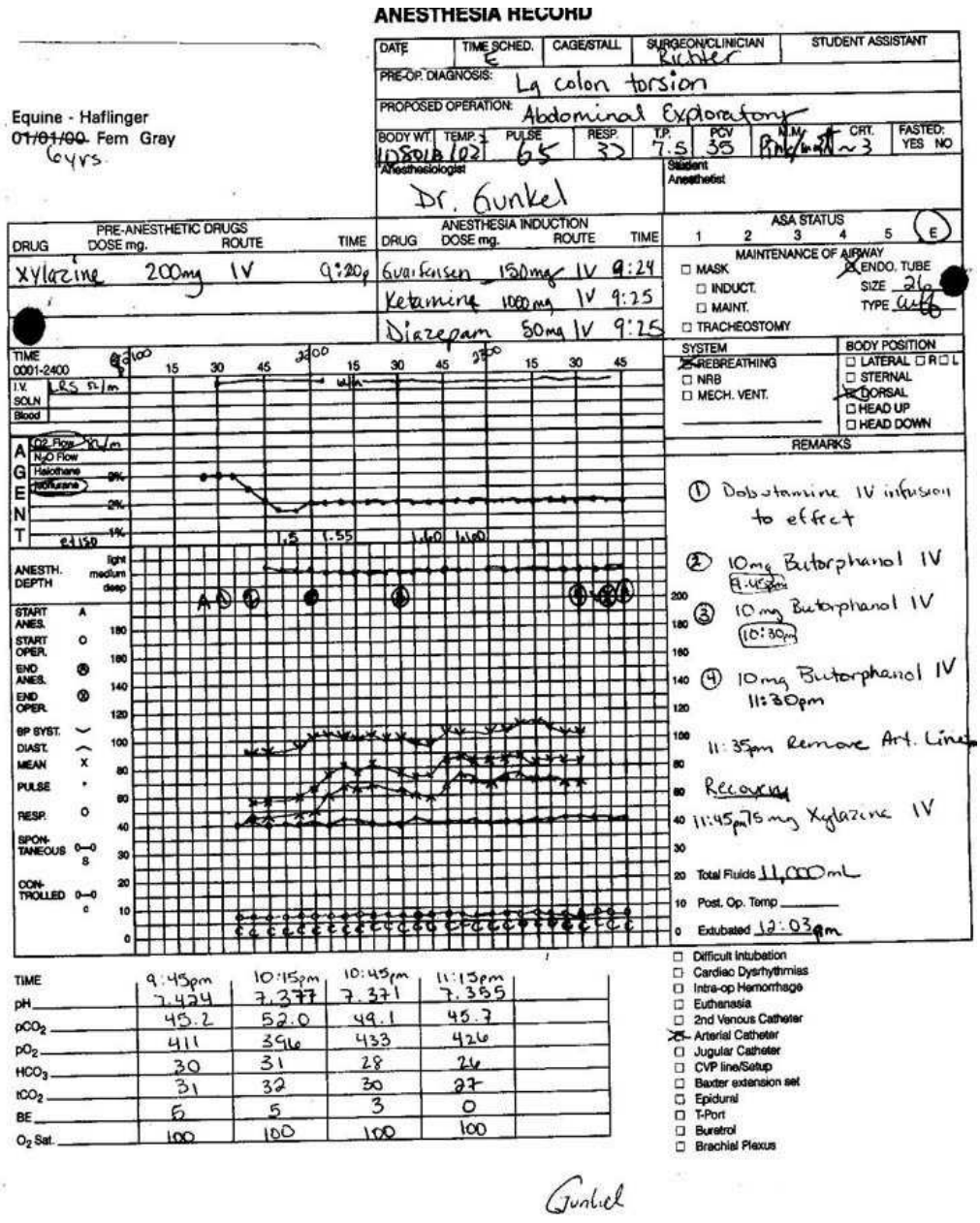


FIG. 4. Anesthesia Record

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