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TADAA: Towards Automated Detection of Anaesthetic Activity

Bryan Houliston[a], Dave Parry[a], Alan Merry[b]

[a] *AURA Laboratory, School of Computing + Mathematical Sciences, Auckland University of Technology, Auckland, New Zealand*
[b] *Department of Anaesthesiology, Faculty of Medicine, University of Auckland, Auckland, New Zealand*

Abstract

Task analysis is a valuable research method for better understanding the activity of anaesthetists in the operating room (OR), providing evidence for designing and evaluating improvements to systems and processes. It may also assist in identifying potential error paths to adverse events, ultimately improving patient safety. Human observers are the current 'gold standard' for capturing task data, but they are expensive and have cognitive limitations. Our current research – Towards Automated Detection of Anaesthetic Activity (TADAA) - aims to produce an automated task analysis system, employing Radio Frequency Identification (RFID) technology to capture anaesthetists' location, orientation and stance (LOS), and machine learning techniques to translate that data into low-level and high-level activity labels. In this paper we present details of the system design and promising results from LOS sensing testing in laboratory and high-fidelity OR simulator settings.

Keywords:

Anesthesiology, Task performance and analysis, Automated pattern recognition, Radio

Introduction

Anaesthesia, generally regarded as more complex than aviation [1], seems a suitable and worthwhile field for the application of similar techniques. Numerous studies have found that human factors, such as poor record keeping, ignorance of standards or failure to adhere to them, and lack of communication, are major contributors to preventable adverse events during anaesthesia [2].

Weinger, an authority in anaesthetic task analysis, sums up his motivation: "A scientific description of the anesthesiologist's task patterns and workload would aid in our understanding of the nature of the anesthesiologist's job and provide a more rational basis for improvements" in processes, equipment, OR layout, training and other aspects of anesthesia [3]. Having a 'scientific description' is particularly important in medicine, with its requirement for improvements to be evidence-based [4] . However, existing methods for anaesthetic task analysis are limited in their ability to produce scientific data in a timely, cost-effective way.

This provides the motivation for our current research project, Towards Automated Detection of Anaesthetic Activity (TADAA). In the next section we briefly introduce anaesthesia, review recent literature on anaesthetic task analysis and automated activity detection, and describe our prototype TADAA system. We then present initial results from evaluation of the system in our lab and in simulated anaesthetic procedures. Finally we outline outstanding issues and plans for future development.

In New Zealand hospitals there is always one anaesthetist present during an operation. They are assisted by a technician and possibly a nurse. Additional anaesthetists may be present as supervisors, trainees, or assisting in complex procedures.

Anaesthetic Task Analysis

Anaesthetists currently record some of their own activity in an anaesthetic record completed for each procedure. While this is a clinically important task, treating the patient always takes precedence. Thus parts of the record are often completed from memory, or with normalised activity [5], and its accuracy cannot be guaranteed.

When more rigorous activity recording is required, the gold standard approach is to employ independent observers [3, 6]. The observers, either in the OR or viewing video recordings, classify anaesthetists' activity into a number of *a priori* categories. A typical list of categories is shown in Table 1.

Table 1 - Anaesthetic activity categories used in [3]

Manual - Prepare drugs, Line placement, Give drugs, Mask ventilation, Bag ventilation, Suction, Manipulate airway, Intubation, Laryngoscopy, Adjust anaesthetic machine, Adjust monitors, Adjust IV
Communication - Attending, Nurse, Surgeon, Patient, Teaching, Other
Observing - Anaesthetic machine, Monitors, Patient, Airway, IVs, Surgical field, Other
Other – Anaesthetic record, Position patient, Clean up, Other

But human observers are not the ideal instrument for recording scientific data. They may make errors when fatigued, distracted, or their view is obstructed. Maintaining intra- and inter-observer consistency in classifying activities can be difficult [7].

Automated Activity Detection

Automation in anaesthesia is nothing new. Computerised systems that record patients' vital signs, and raise alarms when certain conditions occur, are widespread [5]. However systems to record anaesthetists' activity are rare, with none seeming to have progressed beyond very limited use [11, 13-15].

Activity recognition systems can be characterised in various ways, including:

- The type of sensor(s) used.
- Whether sensors are part of the environment or worn or carried by the research subject(s).
- Whether sensors detect body motion, location or movement around an environment, or object use.
- Whether sensor data is analysed for activity using *a priori* rules, or machine learning.

These were the four aspects that most informed the design of our TADAA system.

Methods

TADAA System Design

We selected RFID as the most suitable sensor technology. The TADAA system uses RFID to perform location sensing. An RFID-tagged person can be located by readers embedded in the environment, using the received signal strength (RSS) of their tag's transmissions. The RSS varies by the distance between tag and reader, as per the principle of lateration-by-attenuation (LAT) [12]. However, location sensing is complicated by the fact that RSS is affected by many factors other than distance (such as tag orientation, intervening objects or people, interference from other electronic devices, atmospheric conditions) in ways that are difficult to quantify.

Nevertheless, real time location systems (RTLSs), a common RFID application in hospitals, employ this approach to locate tagged people or equipment in wards, floors or entire buildings, generally to within a few metres. Research suggests that more precise location is possible over smaller areas [13, 14].

To support activity recognition, the TADAA system is intended to detect an anaesthetist's orientation and stance in addition to their location. An anaesthetist located next to a patient may be performing a number of activities, but the list of possibilities can be greatly reduced if it is known, for example, that they are facing the anaesthetic machine, or that they are seated rather than standing. The TADAA system therefore has an anaesthetist wear two tags, one front and one back.

Several tags are also placed at 'landmark' locations within the anaesthetic triangle, such as the drug trolley, anaesthetic machine, and the patient.

Finally, a few tags are suspended from the ceiling to act as 'canaries in the coalmine'. Since these tags do not move, change orientation, or get obstructed, their RSSs should remain relatively stable. Any changes would indicate a general environmental effect that may also affect other tags.

RFID Equipment

The TADAA system uses Wavetrend active RFID equipment, operating in the 433MHz radio spectrum. Tags transmit every 1.5 seconds. The readers can process only one tag transmission at a time. So if multiple tags transmit at the same instant, then all but one transmission will be lost. The reader ID, tag ID, date, time, and RSS are captured for each transmission. (RSS is expressed in an arbitrary unit that doesn't appear to correspond to any standard unit of power or signal strength.)

Accurate LAT requires a fine-grained and relatively stable RSS, and a predictable RSS-distance relation [13]. Effective activity recognition requires that the time between tag reads should be less than the shortest activity duration of the activities being performed [13,14].

Tests were performed in the AURA Lab to determine how well the RFID equipment satisfied these requirements:

- Time between reads, for 20 tags with 1 reader.
- RSS-distance relation, over distances from 0.5m to 6m. This was done once with the tag stationary at each 0.5m interval, and then with the tag moving.

No specific tests were performed for RSS granularity and stability, as the existing tests provide the necessary data.

Tests were also performed to gauge the impact on a tag's RSS when an anaesthetist:

- Wears the tag.
- Changes tag-reader orientation, by changing stance.
- Obstructs the tag, by standing between it and the reader.

LOS Sensing

The TADAA system was deployed in a high-fidelity OR simulator. Data was first collected from two dry runs during which one of the authors simply adopted 17 typical LOSs, without performing any activity.

The main data collection was from 40 simulated procedures, performed over 20 days by 20 different anaesthetists. Along with the RFID data, the procedures were also videotaped and recorded by a human observer. Each anaesthetist was asked to rate the distraction caused by the RFID tags, the RFID readers, and the observer on a visual analog scale (VAS).

The videos served as the ground truth, with an LOS determined manually for each second of video. The RFID data was aggregated to produce one record per second, combining the

RSSs for all tags and readers. Missing RSS values (due to the 1.5s transmission rate and lost transmissions) was filled in with the average RSS for the relevant tag, reader and known RSS values.

The RFID data was then clustered using the Self Organizing Maps (SOM) functions in MATLAB's neural network toolbox. Analysis was first performed on the dry run data. SOMs were trained with the data from dry run 1 and tested on the data from dry run 2, using different combinations of SOM size and tag subsets.

SOMs were evaluated using precision, or positive predictive value. Each cluster was assigned to the LOS which contributed the largest number of records. Those records were considered true positives (TP). Any other records in the cluster (from other LOSs) were considered false positives (FP). The SOM's precision was calculated as total TP / (total TP + total FP).

Results from analysis of the dry runs informed further analysis of data from the simulated procedures.

Results

RFID Equipment

The average time between reads was approximately 2.5s, with a standard deviation of 1.7s.

The minimum RSS value recorded during testing was 89 and the maximum 212. RSS granularity, up to distances of 6m, was therefore 123 points. The standard deviation in RSS was approximately 0.8% of the average RSS value.

RSS did vary by distance for all tags, but not in a predictable way. The RSS-distance relations shown in Figure 1 are typical: an overall downward trend, but with peaks and troughs. Different tag-reader combinations exhibited different RSS-distance relations. As Figure 1 illustrates the RSS at a given distance varied by up to 40 points depending on whether the tag was moving away from or towards the reader.

Table 2 shows the maximum effect on RSS of common interactions between anaesthetists and tags.

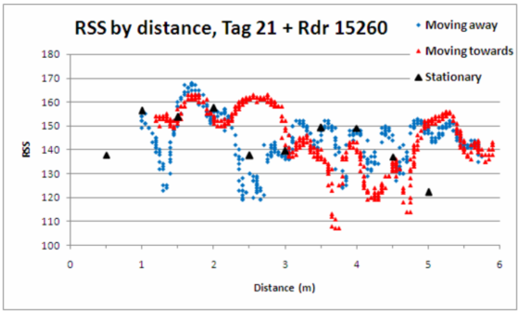

Figure 1 - Example RSS-Distance Relations

Table 2 – RSS effect of anaesthetist-tag interactions

Condition	Maximum Change in RSS
Change tag orientation	+30 points
Wear tag	-20 points
Obstruct tag	-10 points
Wear + obstruct tag	-35 points

LOS Sensing

Table 3 shows the maximum precision achieved by training SOMs on the data from dry run 1. When the most precise SOM was tested on the data from dry run 2, it gave only 39% precision. Similar results were found with SOMs trained on dry run 2 data and tested on dry run 1 data.

Given the results of dry run testing, a few changes were made for the analysis of simulated procedure data :

- Tag subsets were removed as a variable since there was minimal difference between the various combinations at the larger SOM size. All tags were included.
- RFID data cleaning method was added as a variable. Given the variation in RSS values across the two dry runs, we expected there might be differences in SOM precision depending on whether missing RSS values were filled in with averages based on other data for the procedure (as had been done for the dry runs), other data for all procedures on the same day, or other data for all procedures. For the sake of completeness we also tried no data cleaning.
- Larger SOM sizes were tried, since video analysis identified 150-200 LOSs per procedure, rather than the 17 used in the dry runs.

Table 4 shows the maximum precision achieved by training SOMs on the data from one procedure. When the most precise SOM was tested on data from another procedure on the same day, precision decreased to 54%. When the SOM was tested on data from procedures on different days, precision fell within the 40%-50% range. Similar results were found when repeating the SOM analysis starting with different procedures.

The anaesthetists' VASs for distraction were converted to values in the range 0 (No distraction) to 100 (Worst distraction). Table 5 shows a summary of results.

Table 3 - Maximum SOM precision for dry run 1 data

Tags	SOM Size 5	SOM Size 10
Anaes.	84.1%	95.2%
Landmark	98.3%	99.7%
Ceiling	80%	98.9%
An. + Lnd.	98.9%	99.7%
An. + Clg.	80%	99.8%
Lnd. + Clg.	80%	99.9%
All	80%	99.8%

Table 4 - Maximum SOM precision for procedure 39 data

Cleaning	SOM Size 10	SOM Size 20	SOM Size 30
None	17%	40%	77%
Proc.	58%	92%	96%
Day	56%	84%	92%
All	39%	61%	78%

Table 5 - Distraction Ratings (n=20)

Distraction	Min	Max	Average
Tags	0.25	25.5	5.55
Readers	0.75	10.75	3.94
Observer	1.00	70.00	3.94

Discussion

Based on the laboratory test results, the Wavetrend RFID equipment seems suitable for LOS sensing in most respects. The average time between tag reads of 2.5s is significantly better than the 7.5s - 30s reported in [13,14]. Likewise, tag granularity of 123 points is significantly better than the 8 points reported in [13]. The RSS standard deviation is small in relation to the average, indicating that RSS is very stable.

The major challenge presented by the RFID equipment is the RSS-distance relations. While we didn't expect the tags to exhibit ideal inverse square relations [12], we were surprised at so much variation between different tag-reader combinations. This would seem to preclude the use of LANDMARC-style RSS comparisons across tags [14]. But it doesn't disqualify the equipment from use for LOS sensing; the inherent tag-reader differences can be regarded as simply another source of RSS variation, alongside movement, orientation, and so on.

Our assumption that the RSSs of the ceiling tags would remain relatively stable was proven to be true only for the tags closest to each reader. They can continue to serve as 'canaries'. For the ceiling tags directly over the anaesthetic triangle, RSS does appear to be affected by anaesthetists' movement. We were surprised to see that, at larger SOM sizes, the landmark and ceiling tags both seemed to be more useful for LOS sensing than the anaesthetist tags (see Table 3).

The very high precision scores of SOMs trained on the dry run data (see Table 3) was encouraging, albeit achieved in a very 'sensing-friendly' environment with only one person and a small number of LOSs. We expected much lower precision in the more realistic simulated procedures, so 90+% scores were surprisingly high. Such scores clearly won't be possible in a real-time system, since they rely on having all the data for the procedure / day. Having to fill in missing RSS values using data from previous days, or even earlier in the same day, can reduce precision significantly, although is still an improvement over no cleaning at all (see Table 4).

Some decrease in precision when testing SOMs across procedures / days was expected, but such large decreases were surprising. Comparing the RFID data for matching tag-reader-LOS combinations across the two dry runs revealed that the RSS values in dry run 2 were up to 30% higher. The 'canary' tags showed increases of up to 10%, suggesting that some general environmental effect may have accounted for some of the difference. The remainder likely reflects changes in the location and orientation of anaesthetic and landmark tags between procedures. For example, the operating table is frequently moved between procedures so that the floor underneath can be cleaned. If it's not replaced in the same location and orientation, even a small change could result in large differences in RSS (see Figure 1 and Table 2). These differences could possibly be detected, and corrected for, with a calibration process before each procedure or at the start of each day.

Unsurprisingly, the anaesthetists found the RFID tags and readers much less distracting than a human observer (see Table 5). The cost of the TADAA system's hardware is approximately the same as a human observer's tablet PC. The system's ongoing cost, replacing active RFID tags every 5 years, is significantly less than an observer's remuneration.

Future Work

We continue to develop the TADAA system's RFID data cleaning, and SOM analysis approaches, and to prepare Hidden Markov Machine (HMM) algorithms for activity recognition testing.

In the medium term, we intend to complement RFID with additional sensors. RFID is best suited to LOS-specific manual activities (see Table 1). Detecting LOS-independent activities would be better done by other sensors. Communications, for example, might use a microphone suspended above the anaesthetic triangle. We are also considering means of recognising not just when a drug is administered, but which drug and how much. Analysis of patient vital signs may assist this, as in [10].

We ultimately see the TADAA system as a tool for improving patient safety. "In anaesthesia every complication has the potential to cause lasting harm to the patient. Therefore deviations from the norm must be recognised and managed promptly and appropriately" [5]. Activity data collected over time could be mined to produce 'norms' for procedure types, patient conditions, and so on. These would be as detailed as the Hierarchical Task Analysis (HTA) in [15] but based on actual practice. Anaesthetic activity detection in real-time could then compare actual activity with the norm, recognise deviations and raise alarms.

Conclusion

Task analysis has the potential to "provide more rational basis for making improvements" in anaesthesia, and ultimately to improve patient safety. But to do so it must capture scientific data to satisfy the requirements of evidence-based medicine, and not be too intrusive or expensive to implement in practice. Current task analysis methods, based on theory or observation, are unlikely to meet these criteria.

The TADAA system is intended to automate anaesthetic task analysis, through use of active RFID technology, and a combination of SOM and HMM machine learning informed by existing task analysis data. Testing in our lab and in high-fidelity

OR simulations suggest that the TADAA system is less intrusive and expensive than observers. However accurate location sensing, a first step towards activity detection, remains a challenge in the face of a complex interaction of factors affecting RFID's radio signals.

As development of TADAA continues we envisage adding new sensors, and means of storing, mining and visualising activity data. We see the system as potentially a valuable tool to improve patient safety in anaesthesia, and in other medical disciplines.

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Address for correspondence

Bryan Houliston
AURA Laboratory
School of Computing + Mathematical Sciences
Auckland University of Technology
Private Bag 92006
Auckland 1142
New Zealand.
Tel: +64 9921 9999 extn 5206
Email: bryan.houliston@aut.ac.nz