AUTOMATED CLASSIFICATION OF ELECTROSURGICAL CAUTERY STATE.

By

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Abstract

Introduction: In computer assisted surgery, it is sometimes necessary to detect when an activated electrosurgical tool comes into contact with a patient, known as the energy event. By continuously tracking the electrosurgical tools’ location using a navigation system, these energy events can help determine locations of sensor-classified tissues of interest. Our objective is to detect the energy event and settings of a cautery robustly and automatically with a technique that does not disrupt the surgical workflow. This study aims to demonstrate the feasibility of detecting the cautery state during surgical incisions. Methods: I detected changes in the current in the cautery cables using a current sensor and an oscilloscope. I implemented a custom 3D Slicer module that uses machine learning to automatically detect energy events, the cautery’s mode, and cautery settings with no change to the surgical workflow. Results: The model was robust in classifying each cautery state with high accuracy, regardless of the different tissue types and power level parameters altered by users during an operation. The model was also able to detect the power level of the cautery. Conclusion: The results demonstrate the feasibility to automatically identify when surgeons make incisions during their operation.
Co-Authorship

The work presented in this thesis was completed under the supervision of Dr. Gabor Fichtinger and Dr. Tamas Ungi.

This work also appears in the following publication:

- Josh Ehrlich, Amoon Jamzad, Mark Asselin, Jessica Robin Rodgers, Martin Kaufmann, John Rudan, Parvin Mousavi, Gabor Fichtinger, and Tamas Ungi.
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Chapter 1

Introduction

1.1 Problem statement

Offering benefits to both patients and clinicians, robotic and computer assisted surgeries are becoming increasingly prevalent in the surgical suite [1]–[3]. These technology-driven procedures feature electrosurgical and power tools, which can require real-time location data to guide and assist the surgeon. Specifically in computer assisted surgery, it may be necessary to detect when an activated electrosurgical tool comes into contact with the patient, known as the energy event [4]. For electrosurgical cautery, placing an accurate timestamp on the energy event is necessary when locating tissue classifications from a sensor that characterizes tissue properties. By continuously tracking the electrosurgical tools’ location using a navigation system, these energy events can help determine crucial locations of sensor-classified tissues of interest [4]. One such tissue classification method is Rapid Evaporative Ionization Mass Spectrometry (REIMS), which can be attached to a surgeon’s electrosurgical cautery. REIMS shows promise because it has high sensitivity and specificity scores in metabolomic tissue identification [5]–[9]. To locate the origin of REIMS classifications, it is necessary to identify the energy events of the cautery itself [10].

In computer assisted surgery procedures, cautery tools are powered by an electrosurgical generator unit (ESU), which outputs a high frequency alternating current transferred into thermal energy upon tissue contact [11], [12]. During a procedure, an
ESU has both “cut” and “coagulate” modes, where the former creates incisions through rapid heating, and the latter seals vessels and tissue with gradual heating.

Beyond cautery tools, it may be possible and necessary to detect energy events in other devices, such as those used in radiofrequency (RF) ablation, robotic surgery, and telesurgery. In RF ablation, tissue surrounding the ablator may become dry or charred, causing a loss of contact with the tool [13]. By tracking the ablator’s energy level throughout the procedure, this loss of contact may be detected more rapidly. In robotic surgery and telesurgery, surgeons do not receive tactile feedback from their tools, as they interact solely with a robot. By detecting energy events, surgeons could be immediately notified when their power tool is activated and touching a patient. Robots that detect energy events may also be able to limit rapid and accidental surgical movements by performing motion scaling, motion compensation, and tremor compensation.

However, there are a few requirements which must be met in order to identify the energy event of surgical power tools. First surgeons often activate the cautery prior to touching a patient. On a similar note, surgeons often touch tissue without activated the cautery. This requires the system to differentiate between an activated cautery and the energy event. This requires detection of activation and tissue contact. Second, any solution must be easily incorporated into the surgical workflow and cannot interfere with clinically approved devices. Finally, many surgical power tools lack the interface to connect to a computer and communicate the mode or activation status. This requires them to be modified before they can be connected to a computer.

In previous work by Asselin et al. and Carter et al., they demonstrated the feasibility of using relative current signals to detect the energy event of a surgical
cautery. To do this, they collected relative current signals and clustered the data based on the cautery mode [4], [14]. However, to implement this system in the operating room, the energy event must be detected automatically. It is also essential to identify any of the cautery’s settings which may cause interference, such as energy level and mode. The cautery mode may cause slight changes in the mass spectra in REIMS tissue detection, interfering with the classification model.

1.2 Thesis Objectives

Our objective is to detect the energy event and settings of a cautery robustly and automatically with a technique that does not disrupt the surgical workflow. This will provide us with the identification of the start and end of surgical incisions and the cautery’s mode (cut versus coagulate), and the cautery’s energy level. Doing so will demonstrate the feasibility of using the cautery state to identify surgical incisions in the operating room.

Energy event detection needs to be implemented and integrated in a software platform to be used in clinical research with REIMS and other tissue classification sensors.

1.3 Thesis Contributions

The following contributions were made in addressing the objectives of my thesis:

1. Designed and developed a method to detect the cautery state by sensing the current from the cautery and using machine learning to automatically classify the signal.
2. Experimentally validated and tested the solution with 20 different tests designed to address the necessary clinical factors.

3. Implemented the solution in a free open-source module and integrated the solution into a surgical navigation system for breast conserving surgery used in clinical research. This will allow clinicians and researchers to use the system and make any modifications they deem necessary to fit their research criteria.

1.4 Thesis Outline

Chapter 2: Background

This chapter will provide an overview of breast conserving surgery and its challenges, and a literature review on key technical details related to my thesis. Finally, it will describe the challenges that provide motivation for my work.

Chapter 3: Detection of electrosurgical cauterity states.

This chapter describes the detection of the cautery state using machine learning. I outline the methodology used including the hardware and machine learning software.

Chapter 4: Translation to clinical research

This chapter is a description of how the cautery state classification is implemented in an open-source application. Additionally, it outlines the integration of this solution into a clinically active surgical navigation system used in breast conserving surgery.

Chapter 5: Conclusion

This chapter summarizes results and provides an overview of the future aims of this project.
Chapter 2

Background

2.1 Breast conserving surgery

The reason for energy event detection is to improve breast cancer surgery. Using a REIMS device, tissues can be classified with the energy event. This may improve outcomes of breast cancer surgery because surgeons could be notified if they cut into tumor tissue.

Breast cancer is the second most common cancer in women to require surgery [15]. There are two surgical procedures used to treat breast cancer: breast conserving surgery (BCS), and total radical mastectomy. BCS, also known as lumpectomy, is performed in early-stage breast cancer and is the preferred treatment option because it provides better cosmetic outcome and less psychological trauma for patients [16]. This procedure seeks to maximize the remaining healthy breast tissue while excising as much tumor as possible. A total radical mastectomy, however, is often used in late-stage breast cancer and involves the complete removal of the breast [17]–[19]. Most breast cancer cases are caught early and as a result, approximately 75% of surgeries are done as lumpectomies [18], [19]. When lumpectomy is performed in conjunction with radiotherapy its survival rates are equal to those of mastectomy [20].

To ensure no cancer is left behind following a lumpectomy, a healthy tissue margin should surround the resected tumor. The narrowest possible healthy tissue margin around the tumor is enough to maximize the chance of survival, as outlined in the joint statement of The Society of Surgical Oncology and American Society for Radio
Oncology [21]. Unfortunately, a cancer-free margin is difficult to achieve because tumors are not directly visible or palpable, and the breast deforms during surgery making intraoperative spatial tracking difficult [22]. In current clinical practice, 20-30% of patients require revision surgery [23]. This is because the lumpectomy specimen contained tumor cells on the excision margin, called a positive margin, and excess tumor tissue may have been left behind [23]. A high rate of revision surgery places a burden on the health care system due to high cost, poor physical and psychological patient health, and decreased efficiency for clinicians [23]. Therefore, decreasing the rates of revision surgery is one of the critical challenges in breast cancer management today.

2.2 Electrosurgical Cautery

In breast cancer surgery, to excise tissue and make incisions, the surgeon uses an electrosurgical cautery (Figure 1). The cautery is a hand-held device and used during surgery to cut tissue and coagulate the surgical site. The energy a cautery uses is provided by an electrosurgical generator unit (ESU). ESU’s output a high frequency alternating current which is transferred into thermal energy upon contact with the patient.
Figure 1. Electrosurgical generator unit, monopolar cautery, and grounding pad.

An ESU has two different modes: “coagulate” and “cut.” Coagulate mode gradually heats tissue resulting in cellular dehydration and shrinkage, reaching temperatures higher than 100 °C. On the other hand, cut mode rapidly heats tissue causing water to boil and cells to rupture, reaching a final temperature between 70 °C – 100 °C. ESU’s can be attached to either a monopolar or bipolar device. In monopolar devices, like those used in breast cancer surgery, the electric current flows from the ESU to the active electrode (the tip of the cautery), to the target tissue on the patient, and then to a neutral electrode, known as the grounding pad [11], [12]. The grounding pad is usually attached to the buttocks, thigh, calf, abdomen, upper arm, or midback [25]. In a bipolar device, like those used in brain cancer surgery, the active and neutral electrodes are located at the tip of a single hand-held device which causes tissue vaporization.
between to the two electrodes. A monopolar cautery is used in BCS. A bipolar cautery differs from a monopolar cautery because it does not use a grounding pad. Instead, the second polar tip is used as the return electrode. A bipolar cautery is used in other procedures like brain cancer surgery. While my thesis focuses on the use of a monopolar cautery, the intended application of this system can be other applications outside of this.

When the cautery is turned on in either cut or coagulate mode, the tip of the cautery can be in the air or touching patient tissue (energy event). The cautery can be in 5 different states: off, cut mode in air, cut mode touching tissue (energy event), coagulate mode in air, and coagulate mode touching tissue (energy event) (Figure 2). The start of a surgical incision is defined as the cautery state transition from off, cut-in-air, or coagulate-in-air to being in cut-touching-tissue or coagulate-touching-tissue. The end of an incision is the reverse transition. We need to detect all five cautery states.

![Cautery states](image)

**Figure 2. Cautery states (excluding off)**

The 3 ESU power levels most commonly used in surgery will be automatically detected. We will detect these power levels across two different cautery machines: a
ConMed and Valley Lab device. We need to detect the power levels when the cautery is in the air state because a surgeon can turn on the cautery prior to tissue contact.

2.3 Signal Processing and Machine Learning Classification

The relative voltage signals from the current sensors on the surgical cautery wire were used to detect the power level and energy event of the cautery. Signal processing was required to analyze the current signal and create features to train a classification model. Signal processing is a discipline that focuses on analyzing and synthesizing signals such as sound, images, or other scientific measures. Signal processing can be used to detect features, components, or other valuable information of interest in a wide variety of use cases [26]. One such function under the domain of signal processing is the Fourier Transform. Fourier transforms can be applied to signal changes through either time or space. This thesis will focus on the use of Fourier transform in a time series. The Fourier transform decomposes a signal into a series of sinusoids that make up the original waveform [27]. The resulting Fourier transform output is a series of frequencies with a corresponding amplitude or magnitude. These frequencies and amplitudes represent the sinusoids that build up into the original signal [27]. In my figures, the y-axis of Fourier transform output represents the magnitude of the signal, and the x-axis represents the corresponding frequency. Using the frequencies and magnitudes in the Fourier transform output, one can compose the original signal [28]. The Fourier Transform reveals fundamental information that is contained the original signal. The resulting features from the Fourier transform can be applied to a variety of signal processing problems.

Using features from the Fourier transform, I classified the data using machine learning methods and predicted the cautery mode. In machine learning, classification is
defined as a problem where the machine learning model or algorithm is tasked with assigning class labels to a series of data points [29]. In the context of my thesis, I used machine learning to assign labels on current signals from cautery wire.

2.4 Rapid evaporative ionization mass spectrometry tissue classification (REIMS)

Multiple solutions have been proposed to locate cancerous tissue intraoperatively. One promising method is mass spectrometry. Mass spectrometry has been used to differentiate tumor from healthy tissue in various surgical procedures with high sensitivity and specificity [5], [7], [9], [30], [31]. Mass spectrometry is a technique that can determine mass-to-charge ratio (m/z) of molecules. This ratio is determined by ionizing particles into charged molecules. The sample to be processed is ionized and sucked into an inlet that acts as the entrance to the mass spectrometer. The sample is vaporized and the particles are accelerated. A magnetic field is often used to stabilize the stream of particles and orient them in the proper direction. The particles strike a detector that determines the relative m/z and number/second (intensity) of each particle. The output of a mass spectrometer is a mass spectrum, or spectra. The spectra are graphs with the x-axis representing different m/z ratios and the y-axis representing intensity. Mass spectrometer systems can vary considerably which impacts when and where systems can be used. For example, some mass spectrometer systems can perform real-time analysis, while others are better in retrospective conditions.

A rapid evaporative ionization mass spectrometer (REIMS) can characterize tissue by analyzing the aerosol produced from ionized tissue. REIMS can be attached to a cautery which can ionize tissue and produce aerosol. The aerosol is collected and sent into a mass spectrometer for analysis. REIMS collects data over a time series and has a
sampling rate of 1 Hz. This means it collects data samples over 1 second intervals and analyzes each sample. One of the challenges with REIMS is that it is destructive, and analysis cannot be made in identical locations because the tissue was vaporized. Intraoperatively, this means surgeons cannot double check the identical location of a tissue incision. However, depending on the width of the cautery blade, it may be possible to cross reference a location within a few millimeters of the incision in question. Various studies have validated this method in-vivo and ex-vivo. In Balog et al (2013), they were highly accurate at classifying malignant and non-malignant tissues from intraoperative incisions. They used principle component analysis and linear discrimination analysis [5]. REIMS has been used in other clinical settings including tissue detection in ex-vivo breast and gastrointestinal cancer [32], ex-vivo colon cancer [9], and ex-vivo endometrial cancer [33].

REIMS fits the requirements for intra-operative margin detection in breast conserving surgery. REIMS shows promise in clinical settings because it can provide near real-time classification and can be attached to cautery devices. This system requires few surgical workflow modifications and is an ideal candidate for margin detection in breast cancer surgery. In short, REIMS has accurate classification results, real-time analysis, and does not modify the surgical workflow [5], [7], [9], [30], [31], [34]. However, REIMS does not contain any spatial information about the location of the tissue incision. The data received from REIMS is the vapor produced from tissues after ionization. The output from REIMS is the mass spectra and associated tissue classification. REIMS requires an additional system that can determine the position of tissue classifications.
We seek to combine the REIMS mass spectra with spatial information relative to the patient. When we combine a REIMS device with a navigation system, such as Electromagnetic (EM) tracking, it is called the NaviKnife (Figure 3). The NaviKnife records two separate data streams, the location of the cautery during surgery and the mass spectra from tissue incisions.

![Diagram of NaviKnife workflow](image)

**Figure 3.** Overview of the NaviKnife workflow during a surgical operation. The electromagnetic tracker (right) provides location information on the tissue classification data by mass spectrometry (left).

A surgical system using the NaviKnife for real-time tissue detection and classification, and real-time position tracking would directly address the problems surrounding breast-conserving surgery. This is because we would be able to spatially locate the type of tissue cut by surgeons and detect positive margins in real-time.
Fusing the position tracking and REIMS classification data streams is computationally challenging. The vapor produced by the cautery must travel from the site of the incision to REIMS through a tube. This results in a temporal delay proportional to the tube’s length and suction of the fume hood. Additionally, tissue vapor mixes with air in the tube which blurs the start and end points of the data stream. Blurring further delays processing because more vapor is required to differentiate between tissue types. Therefore, REIMS has a variable time-delay dependent on a series of factors individualized to the surgical set-up. In contrast, position tracking has a high temporal resolution and minimal temporal delay. By updating the time accurate spatial position data with the time-delayed tissue data, we will be able to localize the tissue classification stream. To locate the position of tissue classifications the start and end times of a surgical incision need to be automatically detected. This means we need to detect the energy event during surgical operations.

However, identifying the energy event of surgical power tools is challenging. The first challenge is that surgeons activate the power tool before touching a patient. Therefore, it is insufficient to only detect when the cautery is powered on. Surgeons also touch tissue with cautery when it is not activated. This means we cannot use the navigation system alone to detect when the cautery is activated and touching tissue. To be highly accurate when identifying surgical incisions, we need to determine when the cautery is both activated and touching a patient. Second, any solution must be easily incorporated into the surgical workflow and cannot interfere with clinically approved devices. Another challenge is that many power tools are sold as closed systems. They cannot connect to a computer and communicate the mode or activation status. If we can
identify the energy event, then we can detect when their tool is touching a patient while activated. If we can identify when surgeons are making incisions, then we can use this information to match NaviKnife classifications to surgical incisions.

Chapter 3

Detection of the electrosurgical cautery state.

3.1 Methodology

To identify the energy event and parameters of the cautery, we attached an SCT-013 current sensor (YHDC, Madrid, Spain) to both the live and return electrodes of the cautery [4], [14]. These two sensors were connected to a PicoScope P2204A USB oscilloscope (Pico Technologies, St Neots, UK) that digitized the electrical signal. I developed software that reads the cautery’s electrical signal from the oscilloscope, records data, and builds a machine learning classifier that identifies the energy event based on the electrical signal (Figure 4 and Figure 5).
Figure 4. Experimental set-up in the operating room.

Figure 5. Schematic of experimental set-up.
3.1.1 Training the Machine Learning Classifiers

Data samples were collected in packets every 50 milliseconds (ms). Data samples were streamed into 3D Slicer at a rate of 20 Hz. Each data sample contained 3900 data points of the cautery’s current resulting in a sampling rate of 78 kHz. The final dataset contained a total of 69,532 data samples from the cautery’s states. A Fast Fourier Transform (FFT) is applied to the time series data. Using SciPy’s Signal library, I used the resample function to down sample the resulting frequency spectrum data down to 200 frequency bands [35]. The resampled signal begins at the same value as original signal. The spacing in the resulting sample is increased and the number of data points is reduced to 400 data points. This reduces the output of the FFT to 200 frequency bands. This was done to simplify the amount of data points needed for analysis, save memory, and reduce analysis time. I then clustered using Principal Component Analysis (PCA). Features from the frequency spectrum were used to train a Support Vector Machine (SVM) and Random Forest Classifier (RFC) from SciKit-Learn. The SVM uses parameters including a regularization parameter of 1.0, linear kernel, shrinking heuristic, and hinge loss function. The RFC uses 100 estimators (trees within forest), Gini to measure the quality of each split, no max depth, a minimum of 2 samples to split an internal node, and a minimum of 1 sample to split a leaf node [36].

Input into the SVM and RFC, are features from the FFT of the electrical signal, the dominant frequencies, and their relative intensities. The FFT displays the intensity versus frequency of each sample of the cautery’s electrical current. These features in addition to 3 PCA components were used to train the SVM and RFC for cautery state detection (Figure 6). See appendix A for more images of FFT of cautery states across tissue types and energy levels.
Figure 6. FFTs (relative intensive versus frequency) when Valley Lab cautery is on.

3.1.2 Experimental Validation

Set-Up:

Two ESU were tested for this experiment: a Valley Lab Force FX C (Avante Health Solutions, Illinois, USA) and ConMed System 5000 (ConMed Corporation, New York, USA). The ConMed cautery device is used during in-vivo BCS surgical operations, while the Valley Lab is used during in-vitro REIMS testing. Each cautery device was tested at three different levels of wattage (W): 30 W, 35 W and 40 W, for both cut and coagulate modes. These power levels were selected because they are standard practice in-vitro and during surgical operations. We tested three different tissues for each cautery
device and wattage including chicken, porcine, and bovine. Varying the tissue type was meant to parallel the changes in tissue types between patients.

3.1.3 Data Acquisition

Energy events were identified by collecting data for each of the 5 cautery states (Figure 7). This requires sampling the waveform of the cautery’s current for clinically viable variables that will change over the surgical procedures. This results in collecting data over 18 different test set-ups: two cautery devices, three power settings, and three tissue types (Figure 8). See appendix A for additional cautery current signal graphs across different tissue types and energy levels. Power level detecting was done using the air states for 3 power levels (30 W, 35 W, and 40 W) for each cautery device (ConMed or Valley Lab). Current sampling was conducted for these parameters in cut-tissue and coagulate-tissue states only. For cautery states off, cut-air, and coagulate-air, the tissue sample did not change the waveform, thus the current was not sampled in these states. Each tissue test contained 120 incisions for both cut and coagulate modes. Each incision was approximately 1s in length. For cautery state detection, validation was done with 8-fold cross-validation. Each fold leaving out all data from one testing variable: either tissue (chicken, porcine, or bovine), or power (30 W, 35 W, or 40W), or machine (ConMed or Valley Lab). The training and validation data sets contained distinct tissue samples to ensure no overlap in model training.
Figure 7. Current samples from the live cautery wire for each cautery state on the Valley Lab ESU.
3.1.4 Testing protocol

To train classifiers that automatically detect the cautery state, we used a leave-1-out 8-fold cross validation for each clinically relevant variable: tissue (chicken, porcine, or bovine), power (30 W, 35 W, or 40 W), and ESU (ConMed or Valley Lab) (Figure 9). To detect the cautery’s power level, we used cautery mode (cut versus coagulate) in air and power level (30 W, 35 W, and 40 W).

<table>
<thead>
<tr>
<th>Chicken</th>
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<th>35 W</th>
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<td>30 W</td>
<td>35 W</td>
<td>40 W</td>
<td>ConMed</td>
<td>Valley Lab</td>
</tr>
<tr>
<td>Liver</td>
<td>Pork</td>
<td>30 W</td>
<td>35 W</td>
<td>40 W</td>
<td>ConMed</td>
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</tr>
<tr>
<td>Liver</td>
<td>Pork</td>
<td>30 W</td>
<td>35 W</td>
<td>40 W</td>
<td>ConMed</td>
<td>Valley Lab</td>
</tr>
</tbody>
</table>

Figure 8. Data acquisition chart for the cautery states for each of the 18 tests set-ups.

Figure 9. Testing protocol using leave-1-out validation (white = training set, red = validation set)
3.2 Results

The average SVM and RFC validation classification accuracy for detecting cautery states is seen in Figure 11. The average accuracy scores for detecting the power level are seen in Figure 12. An example correlation matrix for the leave-out 30 W fold can be seen in Figure 8. Fourier transforms for each cautery state are displayed in Figure 9. Principle Component Analysis on the frequency bins of each sample is seen in Figure 10. FFT features used to train the SVM and RFC are seen in Figure 11. A comparison between cautery devices in the coagulate air cautery state can be seen in Figure 16.
Figure 11. Average accuracy from 8-fold cross-validation detecting cautery state.

The RFC and SVM performed comparably on the leave out tissue and power level sets. On average, the top performing classifier was the RFC for the leave out sets on tissue (98.64%, 98.91%, and 99.24%, respectively) and power (97.03%, 97.75%, and 96.89%). There was no improvement in accuracy when 3 PCA components were included, and they were neglected from the model. For the cautery device leave out set, the top performing model was the SVM (68.77% and 45.29%, respectively). The models performed the best on the leave out tissue set. On the leave out power set, the models performed very well. On the cautery device leave out set, the models did not perform well.

<table>
<thead>
<tr>
<th>Leave out</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tissue</td>
<td></td>
</tr>
</tbody>
</table>
|           | **Chicken:**  
|           | SVM = 98.34%  
|           | RFC = 98.64%  
|           | **Porcine:**  
|           | SVM = 98.74%  
|           | RFC = 98.91%  
|           | **Bovine:**  
|           | SVM = 99.33%  
|           | RFC = 99.24%  
| Power     |           |
|           | **30 W:**  
|           | SVM = 95.31%  
|           | RFC = 97.03%  
|           | **35 W:**  
|           | SVM = 92.98%  
|           | RFC = 97.75%  
|           | **40 W:**  
|           | SVM = 96.88%  
|           | RFC = 96.89%  
| Cautery Device |           |
|           | **ConMed:**  
|           | SVM = 68.77%  
|           | RFC = 29.83%  
|           | **Valley Lab:**  
|           | SVM = 45.29%  
|           | RFC = 27.19%  

Figure 12. Average accuracy detecting the power level for each cautery.

<table>
<thead>
<tr>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cautery Device</strong></td>
</tr>
</tbody>
</table>
|           | **ConMed:**  
|           | SVM = 70.08%  
|           | RFC = 99.05%  
|           | **Valley Lab:**  
|           | SVM = 75.74%  
|           | RFC = 99.93%  |
The top performing model was the RFC for both cautery devices. The SVM still had good accuracy. The results for each machine performed similarly.

Figure 13. Confusion matrix for leave-out 30 W for RFC (left) and SVM (right).

One of the 18 confusion matrixes is displayed in Figure 12 for the leave-out 30 W power set. Both models performed well. As seen above, the model struggled the most separating the cut air and cut-tissue cautery states (classes 1 and 3, respectively). See appendix A for examples of misclassified cautery signals.
The FFTs for each of the cauter y states in the on position are seen in Figure 13. There are clear differences between each of the classes in the frequency domain. Most notably, the difference of intensity can be seen. In the cut tissue and coagulate tissue FFT output, the intensity is approximately 30% and 20%, respectively, of the cut air and coagulate air cauter y states. Differences and frequency characteristics can also be seen for the coagulate states. See appendix A for more FFTs of cauter y signals, in addition to examples of misclassified cauter y signals.
Figure 15. Principal Component Analysis of 5 cautery states for collection with Valley Lab cautery device set to 40 W power excising bovine tissue.

Figure 14 displays a PCA plot for the Valley Lab-40W-bovine. There is separation between each of the cautery states. The smallest separation in states is between cut air and cut tissue. This aligns with the results seen in the confusion matrix and is consistent across all models, confusion matrixes, and PCAs for each of the leave-out-sets.
Figure 16. SVM features used to separate cautery signal for collection with Valley Lab cautery device set to 40 W power excising bovine tissue.

Figure 16 visualizes the frequency features used for training the SVM and RFC models. The maximal intensity and corresponding frequency were plotted against each other and annotated based on the cautery state. For each feature, there is clear separation for each cautery state. Some overlap in feature space occurs between cut air and cut tissue states. This is representative of the confusion matrixes and PCA plots for each model.
Differences between the Valley Lab and ConMed cautery device signal can be seen in Figure 17. Both the frequency and intensity of the signal is different across the devices.

3.3 Discussion

Our model was robust in classifying each cautery state with high accuracy regardless of the different tissue types and power level parameters altered by surgeons during an operation. The model was also able to detect the power level of the cautery. I developed a solution for cautery state classification that is low cost, easy to implement, and does not interfere with the surgical workflow. The method is implemented as open-source software to allow anyone to collect data, train and test a model, and implement the model. Our study demonstrates the feasibility of using the cautery state to automatically identify when surgeons make incisions during their operation.

Consistent across each model was lower classification accuracy when identifying cut-air versus cut-tissue. This is because the differences in electrical signals are less
pronounced. As seen in the PCA plot (Figure 15) and FFT features (Figure 16), the cut-air and cut-tissue data points have less separation. This provides an explanation for the confusion matrix results seen in Figure 12. One solution in the future would be to use alternative features to detect the cut air and cut tissue states. For example, modeling the noise of the cautery signal may provide a valuable alternative and improve the separation of cut air and cut tissue cautery states.

The models performed poorly for the leave out ESU model sets as seen in Figure 10. This was expected by our research team. This is because each ESU has different frequencies associated with each cautery state (Figure 17). By training our models on only a single ESU, with a unique frequency and intensity, the model would not be able to identify the same cautery state from an alternative machine if it had different frequency and intensities. To overcome this, I developed models individualized for a specific ESU. In the future, we will be implementing each classifier model specific to the cautery machine.

Each patient will have different tissue characteristics. To account for this variation in patient, we decided to test a variety of tissues. The top performing models were in the tissue leave out sets. This is an important finding as patient tissue characteristics vary during the operation. The models performed well when classifying cautery state regardless of the power level. I thought that the models may struggle to classify the different power levels. One of the parameters is intensity, which changes depending on the power level of the cautery. However, our model was robust when classifying the energy event regardless of the power level.
The trained model also performed well when identifying the power level of the cautery. This was expected because when modifying the power level of cautery, clear visual differences in intensity can be seen in the waveform. The rationale behind this objective is to demonstrate proof of principle for other surgical power tools. Additionally, to identify the power level, we do not need to identify incisions. Therefore, we only required the detection in the air state because the utility of this feature can be completed prior to make a surgical incision.

Machine learning provided a rapid and effective method to classify cautery signal data. Simpler classification methods, such as hardware electrical solutions may be used in future solutions. The model performed poorly when the cautery device was left out, an expected result based on the different frequencies and waveforms between the cautery machines (Figure 17). To overcome this, separate models were built for each cautery machine.

This study provides a key step toward fully navigated intra-operative mass spectrometry tissue analysis for breast conserving surgeries. By combining the timepoints of a surgeon’s incisions with position tracking, we can locate tumor classifications detected by REIMS. Implementing our method will allow us to classify the cautery state multiple times during each REIMS classification, since REIMS has a sampling rate of 1 Hz, and the cautery state classifier samples at 20 Hz. Using majority voting on the cautery state classifier may improve the accuracy of our model. We can then combine 20 cautery state classifications to improve our detection method. Detecting the cautery state also allows us to analyze differences in mass spectra signatures because the cautery’s mode changes the mass spectra of REIMS [10]. By identifying variation in mass spectra,
we can improve the accuracy of REIMS models. The presented experimental set-up can be implemented on a wide variety of devices. Some devices that may require detecting the energy event include RF ablators and vessel sealers. In ablation, tissue contact is essential to destroy dysfunctional tissue [37], [38]. Maintaining effective and stable tissue contact during ablation would minimize complication risk resulting from delivery of energy to nearby tissue structures [13]. There is a need for a system that monitors an ablator’s energy which would inform clinicians when their ablator loses contact with surrounding tissue to reduce damage to surrounding tissue [39]–[42]. Identifying the cautery state can also improve surgical workflow analysis, mass spectra analysis, and tissue characterization. It is important to identify the proper location of incisions – a key step in an operation - in relation to anatomy and blood supply [43]. Automatically locating surgical incisions may be especially important when incisions must be made in obstructed views, when there is shifting in tissues during the operation, and to ensure minimal destruction to surrounding anatomical structures. Since inflammation and immune responses are correlated with the length of surgical incisions [44], patient infection rates may decrease by providing surgeons with more incision length and location information.

We are limited in this study by a small sample size, which may limit our ability to detect changes in the current signal due to variation in patient tissue. Each patient has slightly different levels of cellular resistance and the location of the grounding pad varies, both of which may affect the cautery’s current. These unidentified changes may impact the model’s ability to effectively classify the cautery state. A next step includes
evaluating the model with an EM tracking system. By pairing the navigation system with
the model, we can determine the accuracy of locating surgical incisions.
Chapter 4
Translation to clinical research

4.1 Implementation

To identify the energy event and settings of the cautery, we made incisions on biological tissue samples and detected the changes in the current of the cautery using a current sensor and oscilloscope (Figure 4 and Figure 5). We implemented this solution in an open-source module in the 3D Slicer application. 3D Slicer is a software for medical computing, commonly used in medical data analysis and computer assisted surgery [25]. 3D Slicer was chosen for implementation because it has a large user base and range of internal modules which will allow a wide variety of researchers to use. I developed the 3D Slicer module that reads the cautery’s electrical signal from the oscilloscope, records data, and builds a machine learning classifier that identifies the energy event based on the electrical signal. My implementation uses the machine learning models to classify the cautery state and a 3D Slicer module to display surgical incisions, the cautery’s mode, and cautery settings with no change to the surgical workflow. The open-source 3D-Slicer module for real-time analysis is called Cautery Classification and can be found at: https://github.com/SlicerIGT/LumpNav.git. This repository contains raw data for validation of our methodology.

The modularity of my application and this system is an important and valuable contribution of my thesis. This system allows any individual to incorporate their own current sensors, oscilloscope, and machine learning methodology into the application. Depending on the use case and the research question, different parameters may be needed
both from a hardware and software perspective. From a hardware perspective, my application allows researchers change the devices to fit their own needs. For example, this enables researchers to investigate other questions that require a more sophisticated current sensor. From the software perspective, my module enables researchers to modify the current ML models and perform further investigation in the various aspect of the ML protocol used in my thesis.

To do this, researchers can download my software from https://github.com/SlicerIGT/LumpNav.git. They will then be able to interact with the user interface through 3D Slicer. Researchers have the additional option to modify the current code design to integrate different classified, training parameters, and hardware tools.

The module enables the user to record the cautery’s electrical signal during each of the cautery states. The recorded states are completed through the module’s graphical user interface. The data is saved via the module in 3D Slicer called Sequences. We can then replay these data streams for further analysis. For example, after a surgical operation, we can review all the data nodes. Each cautery state is recorded through the module. After the cautery states are recorded, model classifiers can be trained within the module. This enables researchers to change the model during surgical operations. It also allows researchers to adjust to changes that may occur intraoperatively.

To implement this system within 3D Slicer, I attached a current sensor to cautery and the oscilloscope digitized the signal. Data samples were collected in packets every 50 milliseconds (ms). Data samples were streamed into 3D Slicer at a rate of 20 Hz. Each data sample contained 3900 data points of the cautery’s current resulting in a sampling
rate of 78 kHz. The final dataset contained a total of 69,532 data samples from the cautery’s states. For tissue testing, we recorded currents (Figure 7) and ran the classifier on each cautery state. These devices were chosen because the oscilloscope and current sensors do not interfere with the surgical workflow and can be attached to a wide variety of surgical power tools. Relative voltage data from the oscilloscope is streamed into 3D Slicer via the PLUS toolkit. PLUS is an open-source software that enables applications to communicate effectively with hardware. PLUS underpins a wide variety of medical devices research [45]. The 3D Slicer module called Cautery Classification transforms the image into an array. Cautery Classification then displays the array as a graph of current versus time.

4.2 Integration

All of our module’s functionality can be accessed through the NaviKnife system. We integrated the cautery state detection system into in the NaviKnife because we wanted it to be utilized during breast conserving surgery. This is a key component of my project because I wanted to ensure that my solution was used to the clinical research application. NaviKnife receives data from three different pieces of hardware (Figure 20 and Figure 19) The REIMS and oscilloscope signal is sent into the NaviKnife via OpenIGTLink. OpenIGTLink acts as the communication protocol between PLUS and 3D Slicer. The EM tracking system and oscilloscope connect to the PLUS toolkit, which sends data to NaviKnife. NaviKnife can then analyze and display the relevant information. This will allow our system to be used in conjunction with the current surgical navigation system.
Figure 18. Oscilloscope signal streamed through LumpNav2.

Figure 19. NaviKnife and cautery state detection architecture
Chapter 5

Conclusions

5.1 Conclusions

To my knowledge, this is the first study that automatically detects the energy events and settings of a cautery, including the cautery’s mode (cut versus coagulate), air versus tissue contact, and power level. The above procedure describes a robust and automatic method to make these detections in two cautery devices, which classifies cautery states with high accuracy. I detected changes in the current in the cautery cables using a current sensor and an oscilloscope. I implemented a custom 3D Slicer module that uses machine learning to automatically detect energy events, the cautery’s mode, and cautery settings with no change to the surgical workflow. The models were robust in classifying each cautery state with high accuracy, regardless of the different tissue types and power level parameters altered by users during an operation. My results demonstrate the feasibility of implementing a low-cost solution, which is easy to implement and does not disrupt the surgical workflow. The model was also able to detect the power level of the cautery. This was completed using an open-source software to allow reuse of the implementation in other projects. The solution is also integrated into a clinically active surgical navigation research system. By combining the time of a surgeon’s incisions with position tracking, we can locate tumor signals detected by the REIMS. This study provides a key step toward fully navigated intra-operative mass spectrometry tissue analysis for breast conserving surgeries.
The long-term objective of the Navigated iKnife is to provide surgeons with the location and relative accuracy of iKnife classifications for surgical incisions in real-time. This will hopefully update surgeons as to the location of potential positive margins in real-time. There are many next steps and future directions to take my thesis in order to accomplish this goal. The next step for automated detection of surgical incisions is to detect the energy event throughout an entire surgical procedure. Collecting further clinical data will improve the generalizability of the system. It will be important to collect data with different cautery devices, a large patient population, and each power level used by surgeons in the operating room. This will ensure that the system can classify cautery states regardless of the system parameters.

The current 3D Slicer module enables data collection, model training and testing, and implementation of the system automatically. The modularity of this system enables users and researchers to change the system to fit their own specifications. Implementing this in the operating room requires collecting in-vivo data. The benefit to having the system within an open-source module is that future users can begin the collection process using my module. Additionally, they can use my module to train their models in the operating room.

After collection sufficient data, real time analysis and classification of the cautery state will be possible. This requires importing the data into the 3D slicer module and a classifier will automatically be generated. Afterwards, the classifier can run in real-time as the researcher makes incisions.

The final step for cautery state detecting is to design experiments that compare cautery state classification with the spatial location of surgical incisions. We need to compare the
time from the surgical navigation system with the cautery detection system. To do this, we need to specify locations within the navigation system and test our cautery detection system by going back over those locations. This will enable us to compare our method to the ground truth of surgical incisions, the actual location of the incision.
Chapter 6

References


11781187, 2013.


2015.


Appendix A

Examples of cautery signal and corresponding Fourier transforms

Figure 20. Off ConMed Fourier transform

Figure 21. Off ConMed cautery current signal
Figure 22 Cut air ConMed Fourier transform

Figure 23 Cut air ConMed cautery current signal
Figure 24 Cut tissue ConMed Fourier transform

Figure 25 Cut tissue ConMed cautery current signal
Figure 26 Coagulate air ConMed Fourier transform

Figure 27 Coagulate air ConMed cautery current signal
Figure 28 Coagulate tissue ConMed Fourier transform

Figure 29 Coagulate tissue ConMed cautery current signal
Figure 30 Cut air Valley Lab 30 W power level

Figure 31 Cut air Valley Lab 35 W power level
Figure 32 Cut air Valley Lab 40 W power level

Figure 33 Coagulate air Valley Lab 30 W power level
Figure 34 Coagulate air Valley Lab 35 W power level
Figure 35 Coagulate air Valley Lab 40 W power level

Figure 36 Misclassified cut tissue incision as cut air
Figure 37 Fourier transform of misclassified cut tissue incision as cut air

Figure 38 Misclassified coagulate tissue incision as coagulate air
Figure 39 Fourier transform of misclassified coagulate tissue incision as coagulate air