Lymph Node Detection Using Robot Assisted Electrical Impedance Scanning and an Artificial Neural Network

Årsvold, Alex Tinggaard; Zeltner, Andreas Sørensen; Cheng, Zhuoqi; Schwaner, Kim Lindberg; Jensen, Pernille Tine; Savarimuthu, Thiusius Rajeeth

Published in:
2021 International Symposium on Medical Robotics (ISMR)

DOI:
10.1109/ISMR48346.2021.9661502

Publication date:
2021

Document version:
Accepted manuscript

Citation for published version (APA):

Go to publication entry in University of Southern Denmark's Research Portal

Terms of use
This work is brought to you by the University of Southern Denmark. Unless otherwise specified it has been shared according to the terms for self-archiving. If no other license is stated, these terms apply:
• You may download this work for personal use only.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying this open access version

If you believe that this document breaches copyright please contact us providing details and we will investigate your claim. Please direct all enquiries to puresupport@bib.sdu.dk
Lymph Node Detection Using Robot Assisted Electrical Impedance Scanning and an Artificial Neural Network

Alex Tinggaard Årsvold∗,‡, Andreas Sørensen Zeltner∗,‡, Zhuoqi Cheng∗,§
Kim Lindberg Schwaner∗, Pernille Tine Jensen†, Thiusius Rajeeth Savarimuthu∗

Abstract

Lymphadenectomy, also known as lymph node dissection, is frequently performed as a surgical treatment for cancer. Lymph nodes grow inside fat and have similar color as fat, making them difficult to detect. In Robotic Assisted Minimally Invasive Surgery (RAMIS), it can be even more challenging due to the lack of haptic feedback. This study proposes a novel method to measure the electrical property of a target tissue site and determine whether a lymph node is present underneath through an Artificial Neural Network classifier. The proposed system and method are built, analyzed, and evaluated based on simulation and ex vivo tissue phantom experiments. The experimental results show a very high accuracy (93.49%) in detecting a lymph node that is embedded deep inside fat. Given the promising results and the portability of the proposed system, we believe it has great potential to improve the quality of related surgical procedures.

1 Introduction

According to the World Health Organisation, 10 million people are estimated to have died of cancer in 2020, making it the second leading cause of death globally [1]. Approximately 39.5% of men and women are diagnosed with cancer at some point during their lifetime [2]. Cancer cells normally loosely grow on the other healthy tissues, and they often break from the primary tumor and travel to a new area of the body. This process is known as metastasis, and the spread is often through the lymph system or bloodstream.

Lymphadenectomy, also known as lymph node dissection, is frequently carried out to remove lymph nodes from a target area. This process is required generally for two purposes [3]. The first of these is diagnosis of metastasis, where one or more lymph nodes are extracted and evaluated under a microscope for traces of cancerous tissue. Second, lymphadenectomy is also performed to remove some or all nodes in the cancer area to prevent further metastasis.

The ideal lymphadenectomy procedure removes all the pathological lymph nodes, keeping the healthy nodes and surrounding tissues undamaged. This procedure requires an accurate location of the lymph node [4]. However, lymph nodes are surrounded by fat tissue, which is visually similar, making visual detection difficult.

The modern medical system has been promoting the use of Robot Assisted Minimally Invasive Surgery (RAMIS) for lymphadenectomy. However, due to the lack of tactile sensing for most current surgical robotic systems, surgeons cannot estimate the lymph nodes’ location through palpation as they commonly do in open surgery. Nevertheless, the integrated near-infrared (NIR) fluorescence imaging in the robotic systems has been found to ease this difficulty [5]. By injecting indocyanine green solution in the patient before the surgery, NIR imaging can expand the visible spectrum to overlay on normal color images during the operation and highlight the indocyanine dyed tissues. This method works well for superficial lymph nodes but may have problems for the case when lymph nodes are deeper inside fat [6]. In addition, indocyanine lights up both the blood vessels and lymph nodes. Areas with a higher concentration of blood vessels and lymph channels, may be mistaken for lymph nodes, which may lead to the accidental removal of a so called “empty package” [7]. This kind of malpractice has a clear negative effect on the surgery, and reoperation may be needed. In addition, diagnostic ultrasound is a non-invasive technique used to image inside the body, and it can help to detect lymph nodes. However, it requires to introduce an additional instrument to the operational site.

In our previous study, we proposed and developed a Robot Assisted Electrical Impedance Scanning (RAEIS) system which can measure the electrical property of soft tissue directly, using established electrosurgical instruments such as forceps or scissors [8]. Utilizing a tripolar configuration, an enhanced sensing capability for detecting subsurface tissue structures with different electrical conductivity is achieved. In this paper, we propose to apply the RAEIS system to measure the Electrical Bio-Impedance (EBI) of the suspected tissue surface, and predict the presence of a lymph node based on the measured data, using an artificial neural network (ANN). The proposed system and method require little hardware modification to the existing surgical system, and it can provide the surgeons with high flexibility to inspect a tissue region of interest. Experiments demonstrate that this process is very accurate
and fast. Given the above advantages, we believe this system will improve the lymph nodes searching process significantly during RAMIS.

The rest of the paper is organized as follows: Section 2 describes methods including modeling, simulation, system setup, and calibration. In Section 3, we present a series of experiments for the system evaluation. The experimental results are provided in Section 4, and discussed in Section 5. Section 6 concludes this study.

2 Method

2.1 Robot Assisted Electrical Impedance Scanning

Compared to the bipolar configuration which has concentrated sensitivity on tissue superficial layer [9, 10], the tri-polar sensing configuration of the RAEIS system can achieve a more stable impedance measurement thanks to the integrated controlled current source and high input impedance for signal pickup [8]. Please refer to [11] for more discussions regarding the comparison between bipolar and tri-polar sensing. Given the impedance measurement and the corresponding measurement pattern, the electrical property of tissue can be derived. Since different tissues have significantly different electrical properties, the sensed information can be used for identifying different tissues and detecting pathological tissues [12, 13, 14, 15].

The EBI sensing of biological tissues treats the material under test (MUT) as a complex electrical component in the measurement circuit. The tri-polar sensing configuration consists of three electrodes: one current-source electrode (CSE), one voltage-measurement electrode (VME), and one ground electrode (GND). The GND should be attached to a distal region of the MUT and have a bigger size compared to the other two electrodes. To measure the electrical properties of the MUT, the CSE injects excitation current into the object, and the electric potential is measured from a series of different locations on the MUT through the VME.

In Fig. 1(A), electrode A is the CSE and an excitation current I passes through it to the tissue. Electrode B is the GND for the current return. For the case that the MUT is homogeneous, the current flow through A disperses radially into the material. In this case, the current density at point M, which is at a distance d from A, can be calculated as

$$J_M = \frac{I}{2\pi d^2}$$  \hspace{1cm} (1)

We assume that the conductivity of the MUT is \(\sigma\). The electric potential at point M can be computed by integrating (1) according to Maxwell’s equation

$$V_M = -\int_{r_0}^{d} \frac{I\sigma}{2\pi d^2} \, dr = \frac{I}{2\pi \sigma} \left( \frac{1}{d} - \frac{1}{r_0} \right)$$  \hspace{1cm} (2)

where \(r_0\) represents the equivalent radius of the CSE electrode.

For the case where there is a subsurface layer of different material \(\sigma_2\), as shown in Fig. 1(B), the potential measured at point M is contributed by two parts, namely the direct current through the superficial material \(\sigma_1\) and the reflected current from the interface between \(\sigma_1\) and \(\sigma_2\) [16]. When the current propagation hits the interface at depth \(h\), a part of current continues in \(\sigma_2\) while the rest is reflected. The intensity of the reflected current is reduced by a factor \(k\) which is defined as

$$k = \frac{\sigma_1 - \sigma_2}{\sigma_1 + \sigma_2}$$  \hspace{1cm} (3)

This reflection also occurs at the interface between the air and \(\sigma_1\), where a total reflection is presumed. The above reflection during the current propagation generates an infinite series of virtual images of the source that contribute to the electric potential at point M (the summation part in (4)).

$$V_M = \frac{I}{2\pi \sigma_1} \left( \frac{1}{d} + 2 \sum_{n=1}^{\infty} \frac{k^n}{\sqrt{d^2 + (2nh)^2}} - \frac{1}{r_0} \right)$$  \hspace{1cm} (4)

The value of \(r_0\) is generally difficult to obtain, and thus we propose to use the potential difference to remove its impact. This is done by taking the potentials at two positions on the MUT surface, M and N, and calculating their difference: \(V_{MN} = V_M - V_N\).

Since an impedance spectroscope is used in this study, the measured value is presented as an impedance module. As the injected current is controlled, the difference of the measured impedance \(\Delta Z\) between point M and point N has the following relationship with the apparent conductivity \(\sigma\) of the MUT according to (2).

$$\Delta Z = \frac{V_{MN}}{I} = \frac{1}{2\pi \sigma} \left( \frac{1}{d} - \frac{1}{d + \Delta d} \right)$$  \hspace{1cm} (5)

The above equation can be used to derive the conductivity of the MUT as follows.

$$\sigma(d) = \frac{1}{2\pi \Delta Z} \left( \frac{1}{d} - \frac{1}{d + \Delta d} \right)$$  \hspace{1cm} (6)

The value of \(\sigma\) is constant against the measurement distance \(d\) if the MUT is homogeneous. However, if different material exists in the subsurface region, \(\sigma(d)\) will show an increasing or decreasing trend due to the reflection current.

To detect the presence of a subsurface lymph node, a series of \(\sigma(d)\) can be measured at different distances \(d\), which can
then be passed through a machine learning classifier for determination. To ensure the magnitude of $V_{MN}$ is big enough, the scanning distance setting is designed by making $\frac{1}{d} - \frac{1}{d+\Delta d}$ relatively big. Table 1 shows the setting of $d$ and $\Delta d$. This setting requires the VME to measure 6 positions (6, 7, 9, 11, 15 and 21 mm) in total, which results in 5 values of $\sigma(d)$.

It is commonly known that the electrical characteristics of biological tissue are frequency-dependent [17]. Cell membranes are composed primarily of lipids that do not readily allow current to pass through. This barrier can be overcome by using alternating current at relatively high frequencies. In this study, multiple frequencies are applied during the EBI measurement to obtain more sensing information.

### 2.2 Machine Learning for Detection

Given the sensing information, an ANN is used to estimate the likelihood that a lymph node is present at a given location in the $x$-$y$ plane. An ANN model is well suited to this task, as they are typically able to learn non-linear and complex relations between data. Although the model training can be time-consuming and require large amounts of data, prediction based on ANN is generally fast.

As shown in Fig. 2, the ANN structure takes a list of conductivity values as input and outputs a single value representing the confidence to claim the presence of lymph node. The input is formatted as a vector of multiple $\sigma_i, \omega_j$ values. The subscript $i$ represents the data measured at the $i$th location (Table 1), and $\omega_j$ represents the used excitation frequency. The ANN is constructed as a binary classifier which outputs 1 if a lymph node is detected and 0 if no lymph node is detected. To scale the confidence of the lymph node detection, the sigmoid function, which has an output range between 0 and 1, is used as the activation function for the output neuron.

Binary cross-entropy is chosen as the loss function to train the ANN. This function is a log loss function, where the loss decreases as the confidence in the correct label increases. This makes the training process efficient. The optimization of the ANN requires tuning of multiple hyper-parameters including the size of hidden layers, the number of neurons on each hidden layer, the activation function on each layer, the learning rate, the choice of the optimizer, the number of training epochs, and the batch size. The above parameters are determined through trials and errors based on the data collected from simulations and experiments.

This eventually results in an ANN consisting of a single hidden layer of 256 neurons. A sigmoid activation function is used in the output layer. The network is trained with a learning rate of 0.001, which, together with the Root Mean Squared Propagation (RMSProp) optimizer, is found to be efficient without trapping in local minima. To balance between training time and performance, 50 training epochs and a batch size of 16 are used. TensorFlow for Python is used during the development of this framework.

### 2.3 System Setup and Calibration

In this study, the system is proposed to be a user-controlled inspection at a point of interest. The user controls the CSE forceps to a position of interest, and the VME forceps is controlled by a robot to perform the voltage measurement on the tissue surface in different preset $d$ automatically. Subsequently, the conductivity $\sigma(d)$ is computed and input to the ANN for prediction.

The scanning motion for the VME is illustrated in Fig. 3(B). After the user controls the CSE to a target site, a contact-lift-move scanning pattern is implemented for the VME. This motion pattern allows good contact with the tissue and avoids causing tissue damage. As described in Table 1, the VME is required to measure the electrical potentials at 6 points on the tissue surface.

The setup used for data collection and proof-of-concept study is shown in Fig. 3(A). Two Universal Robots UR3 (Universal Robots A/S, Denmark) robots are used. Each robotic arm is equipped with monopolar curved scissors (Intuitive Surgical Inc., U.S.). Two 3D printed adapters are used to fix the scissors onto the end-effectors of the robots. Each forceps is intended only for use as one electrode: the left forceps are used as the CSE, and the right forceps are used as the VME. The GND electrode is placed in the sample at the opposite end from the measurement site.

An Eliko Quadra Impedance Spectroscopy ¹ is used to provide the excitation current and measure the voltage. This sensor can measure 15 different frequencies from 1 kHz to 349 kHz with a 1 kHz sampling rate, and a 99.9% accuracy is reported.

---

¹ [https://www.eliko.ee/products/quadra-impedance-spectroscopy](https://www.eliko.ee/products/quadra-impedance-spectroscopy)
The robot control is developed and executed on a networked laptop computer using the ur_rtde Python library. Data collection is performed in MATLAB on Windows, while robot control and data processing take place in a Python script running on Ubuntu.

After the system is established, calibration values for the $x$, $y$, and $z$ coordinates are applied, which can be used to make minor adjustments to ensure the correct placement of each forceps.

### 3 Experimental Evaluations

Two experiments were designed to evaluate the proposed system. The first experiment was carried out using Finite Element Simulation as a proof-of-concept study, and the second experiment was designed to evaluate the system in a realistic environment made of ex vivo tissues.

#### 3.1 Finite Element Simulation

The simulations were done using COMSOL Multiphysics 5.5. In the simulation environment, we first modeled the fat tissue using a 100×100×80 mm block. As shown in Fig. 4, two electrodes of similar shape to the tip of the robotic scissors were placed on the tissue block. The electrodes were inserted with 1 mm depth into the tissue to simulate the slight pressing on the tissue which causes the soft tissue to deform and surround the tip of the scissors. Also, a lymph node was embedded inside the fat tissue. Considering that a lymph node has a shape approximating a spheroid and its size varies from a few millimeters to 25 mm, the simulated lymph node had a short axis of 10 mm and a long axis of 20 mm. Different depths from the lymph node top to the fat surface were set during the test including 2, 3, 4, 5, 7 and 15 mm.

Both the fat tissue and lymph node tissue were configured with electrical properties according to [18]. The simulation used only the electrical properties of two frequencies as can be seen in Table 2. The material of the electrodes was set to be steel which has much higher conductivity compared to the tissues.

The data collection was performed using the parameter sweep function of COMSOL. During the simulation, two frequencies were implemented: 1 kHz, and 349 kHz, which are the minimal and maximal frequency for the ELIKO Quadra. During the data collection, the left electrode was used to inject current and the right electrode measured the voltage. Data was sampled based on a grid on the surface of the tissue. The CSE was moved on the fat surface on each vertex of the grid, and the VME moved to a series of corresponding positions (Table 1) in the +x direction for voltage measurement. The range of the grid was set to be 40×16 mm and the region was centered on top of the lymph node. Different intervals of the grid (between 3 and 11) were set, resulting in different datasets for ANN training and testing.

The Matthews correlation coefficient (MCC) [19] was used here to evaluate the performance of the trained ANN model. We chose MCC for the evaluation because it achieves a balanced measure, taking all the elements of a confusion matrix, false positives (FP), false negatives (FN), true positives (TP),

<table>
<thead>
<tr>
<th></th>
<th>1 kHz</th>
<th>349 kHz</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_{\text{Fat}}$</td>
<td>0.022404</td>
<td>0.24731</td>
</tr>
<tr>
<td>$\sigma_{\text{Lymph Node}}$</td>
<td>0.52427</td>
<td>0.55384</td>
</tr>
</tbody>
</table>

Table 2: Electric properties for the used tissues.
and true negatives (TN), into consideration. The true label was given if the lymph node was present and a false label was given if no lymph node was under the scanning region.

\[
MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}},
\]

(7)

### 3.2 Experiments on ex vivo tissue phantom

The second experiment was designed to evaluate the system based on a realistic tissue phantom. Specifically, we aimed to test the efficacy of the ANN detection of lymph nodes which were embedded in a mass of ex vivo fat.

The experimental setup is shown in Fig. 5(A), including the proposed system and an artificial phantom. Fig. 5(B) shows the phantom made of fat tissue with real lymph nodes from pigs. We first put a layer of fat on the bottom of a container. Then a lymph node was placed on it, and another layer of fat was placed on the top of the phantom, covering the lymph node. The lymph node was measured at a size of 15×12 mm in x and y dimensions respectively. It was placed at \(x = 17\) mm, \(y = -8\) mm with respect to the global frame (center of the container bottom). The depth of the lymph node was estimated to be about 6 mm.

Experimental data was collected in two groups. The Control group contained data measured on the area of pure fat, and the data measured with a lymph node under the scan was put in the Experimental group. The scanning positions for the Experimental group are presented as the black line which is 8 mm to the left of the lymph node center and ranges from 20 mm to \(-12\) mm in y direction as shown in Fig. 5. Evenly spaced positions on this line were set as the CSE position, and the VME scanned the voltages along the +x direction.

Each input data was a vector of 75 conductivity values which were acquired in different positions (Table 1) and in 15 frequencies. Data in different conditions were fed to the ANN model, and the evaluation of performance was done using 5-fold cross-validation.

---

**Figure 6:** The calculated conductivity distribution based on the 11×11 grid setting results before and after offset compensation.

**Figure 7:** Illustration of the offset between the measured conductivity distribution map and the ground truth. The amount of reflected current that can be measured depends on the relative position among the CSE, the VME and the subsurface lymph node.

### 4 Results

#### 4.1 Simulation Results

The conductivity based voltage measured in simulation on a 11×11 grid setting is computed and plotted in Fig. 6(Top). The ground truth, which is the projection of the lymph node to the x-y plane, is also plotted. According to the conductivity distribution, an offset between the center of the contour plot and the ground truth is observed. This has been explained in [8]. As illustrated in Fig. 7, the relative position of the VME is in the x+ direction with respect to the CSE. In position 1, although the CSE is not above the lymph node, the measured conductivity can still reflect the existence of a hidden lymph node because the reflected current can reach the VME. In contrast, for the measurement condition of Position 2, only very little reflected current can travel to the VME. In this case, the reflecting current can be too weak to be detected. The above analysis indicates that an offset is essential to be introduced when marking the ground truth.

The center distance between the ground truth and the contour plot is computed, and the offset is found to be 8 mm. The compensated plot is shown in Fig. 6(Bottom).
Moreover, the computed conductivity values are used to train and test the proposed ANN model. The ANN manages to get a loss of 0.4327 and an accuracy of 0.8061 on the training set. Also, a loss of 0.4687 and an accuracy of 0.7928 are found on the validation set. The output of the ANN, which is the confidence ranging from 0 to 1, is plotted in Fig. 8. The MCC score is computed and found to be 0.667, demonstrating the effectiveness of lymph node detection based on the proposed method.

4.2 Experimental Results on Tissue Phantom

In the ex vivo tissue experiment, we collect 261 data points including 115 data in the Control group and 146 data in the Experimental group. A new ANN model is trained on the collected data using the same structure as previously. The training batch size is reduced to 4, and the number of training epochs is raised to 250 to account for the limited number of data points available.

5-fold cross-validation is used for evaluating the system performance. Metrics including loss and accuracy are stored for each fold, and processed. The experimental results show that the accuracy of the model is 93.49 ± 2.60%. The loss values during the ANN training also indicate a good convergence of the model (0.17 ± 0.04). In this study, we set a relatively low speed for the scanning due to safety considerations, and thus it takes about 12 s to measure at one CSE position. This process can be greatly improved by increasing the robot speed in the future. The time for ANN to provide a prediction on input is 40 ms, which is plausible for the real-time intra-operative sensing requirement.

5 Discussion

According to the experimental results both of the simulation and tissue phantom, a very high detection accuracy is obtained. Specifically, the confidence map plotted in Fig. 8 indicates the system’s prediction of the presence of a lymph node. The confidence increases towards the middle of the region. This is due to the spheroid shape of the lymph node. The region closer to the lymph node center has a smaller distance from the tissue surface to the lymph node. In addition, due to the imaging nature of electrical impedance, the shape of the detecting object is generally diffused. This feature suggests that the proposed method can be suitable for object detection instead of shape reconstruction.

In the ex vivo experiment, we did not implement a grid scanning on the tissue surface. This is because the system is designed for the surgeon to inspect a site of interest flexibly instead of scanning a region with a dense grid. Especially for lymphadenectomy, we believe the location of the lymph node can be more interesting for surgeons than the reconstructed shape of the lymph node. One limitation of this technology is the need of avoiding sensing on blood spot by either forceps since blood is conductive.

Our future study will investigate the possibility to train an ANN on simulation data and test it on ex vivo tissues, which is believed to simplify and accelerate the training process.

6 Conclusion

This study presents the concept and development of integrating an ANN classifier into a RAEIS system for the detection of subsurface lymph nodes. This process is achieved by non-invasive measurement of electrical impedance on the tissue surface using two already installed electrosurgical tools. The obtained conductivity feeds to an ANN binary classifier to estimate the presence of lymph nodes. An average accuracy of 93.49% is obtained in the experimental study, demonstrating the effectiveness of the proposed method. This system can be a standalone sensing modality or can be used to supplement the existing fluorescence to improve the lymph node detection efficiency during RAMIS.

References


