

# Bridging Medical Robotics and Electrical Bio-Impedance

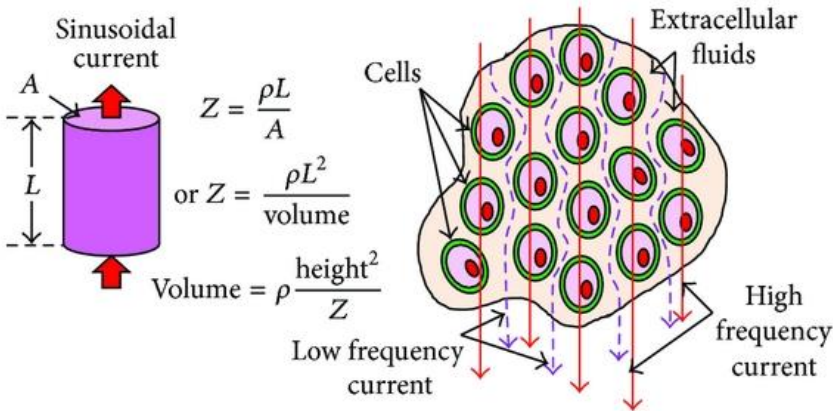
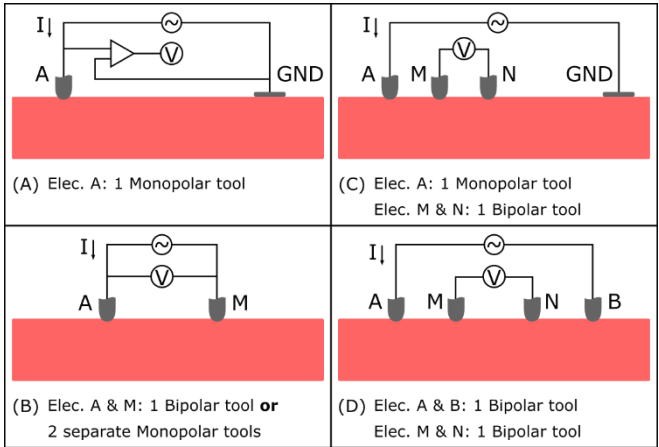
**Cheng Zhuoqi**

Email: [zch@mmmi.sdu.dk](mailto:zch@mmmi.sdu.dk)

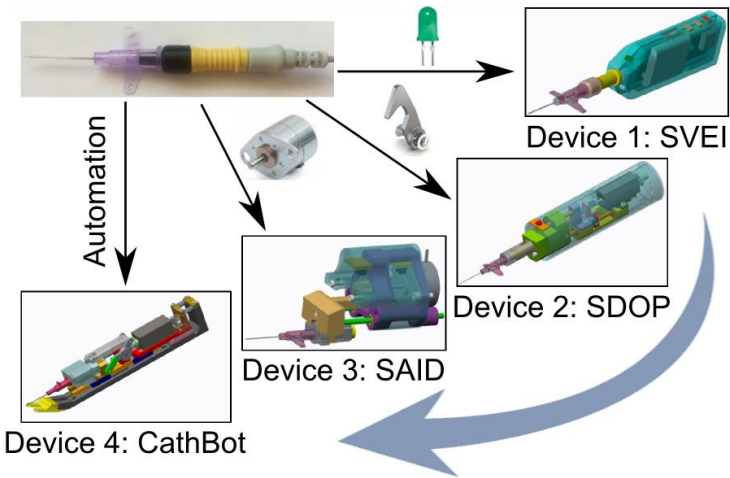
# Index

## Sensing configurations

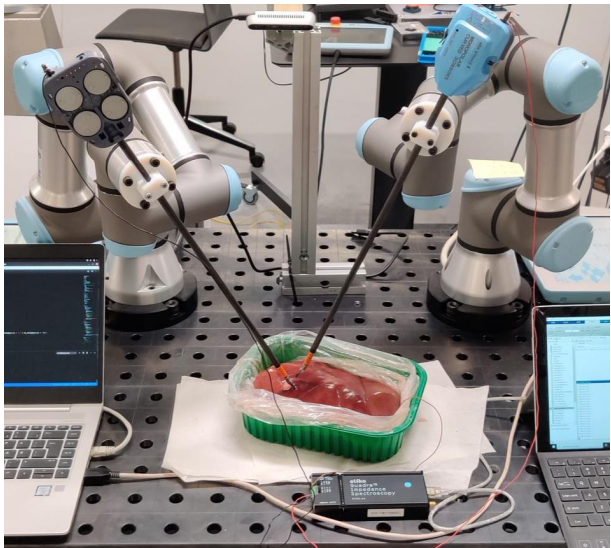
- Monopolar
- Bipolar
- Tripolar
- Tetrapolar



Electrical Bio-Impedance (EBI)

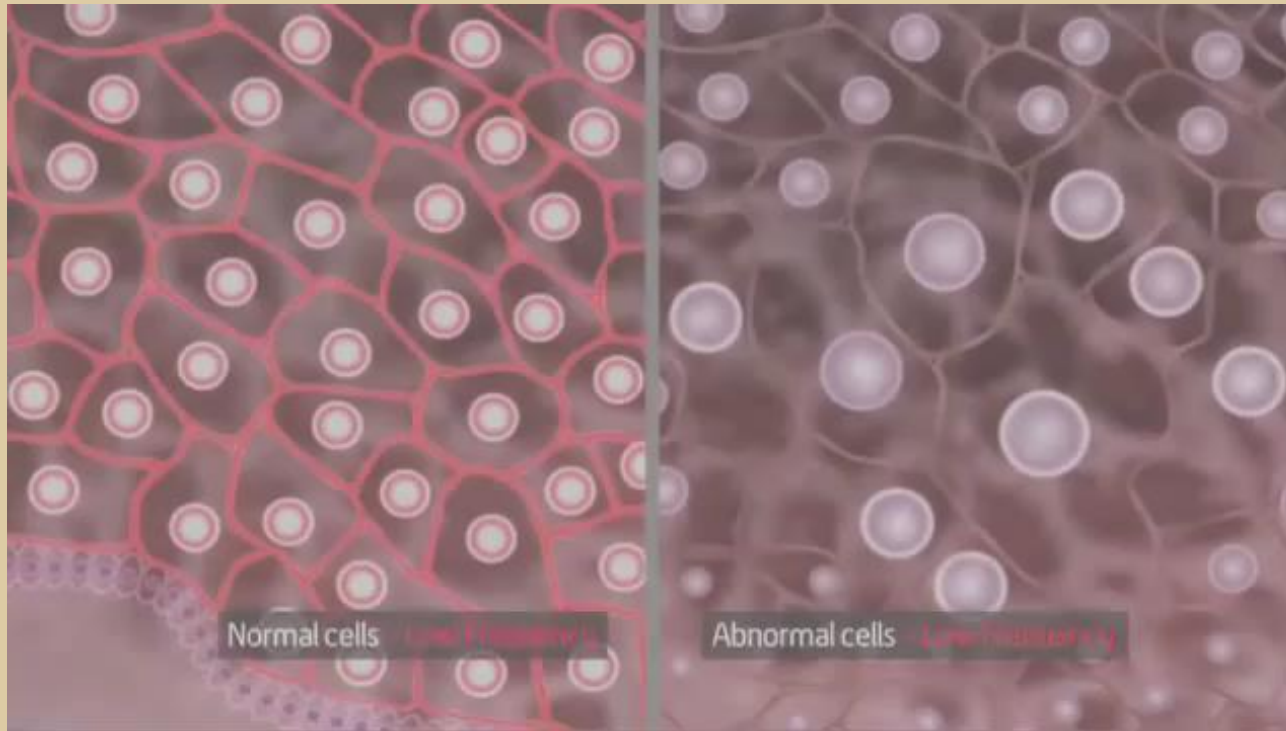


Handheld Robotic Device for Peripheral Intravenous Catheterization



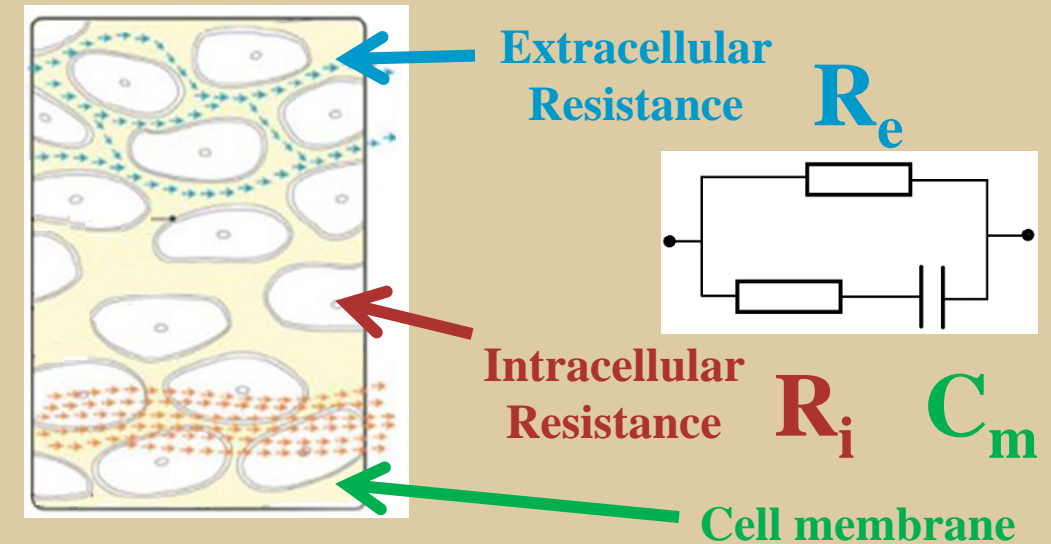
Robot Assisted Electrical Impedance Sensing (RAEIS)

# Electrical Bio-Impedance (EBI)



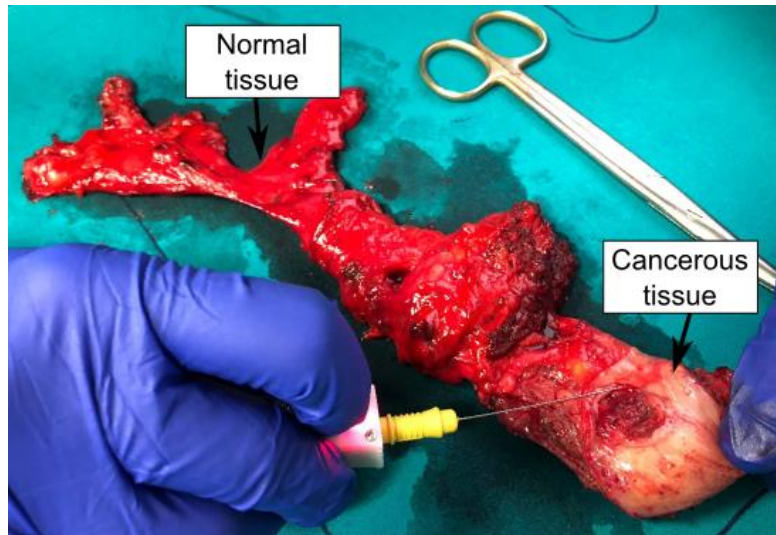
Cell composition and organization are different:

- among different tissue types;
- between normal and abnormal status.



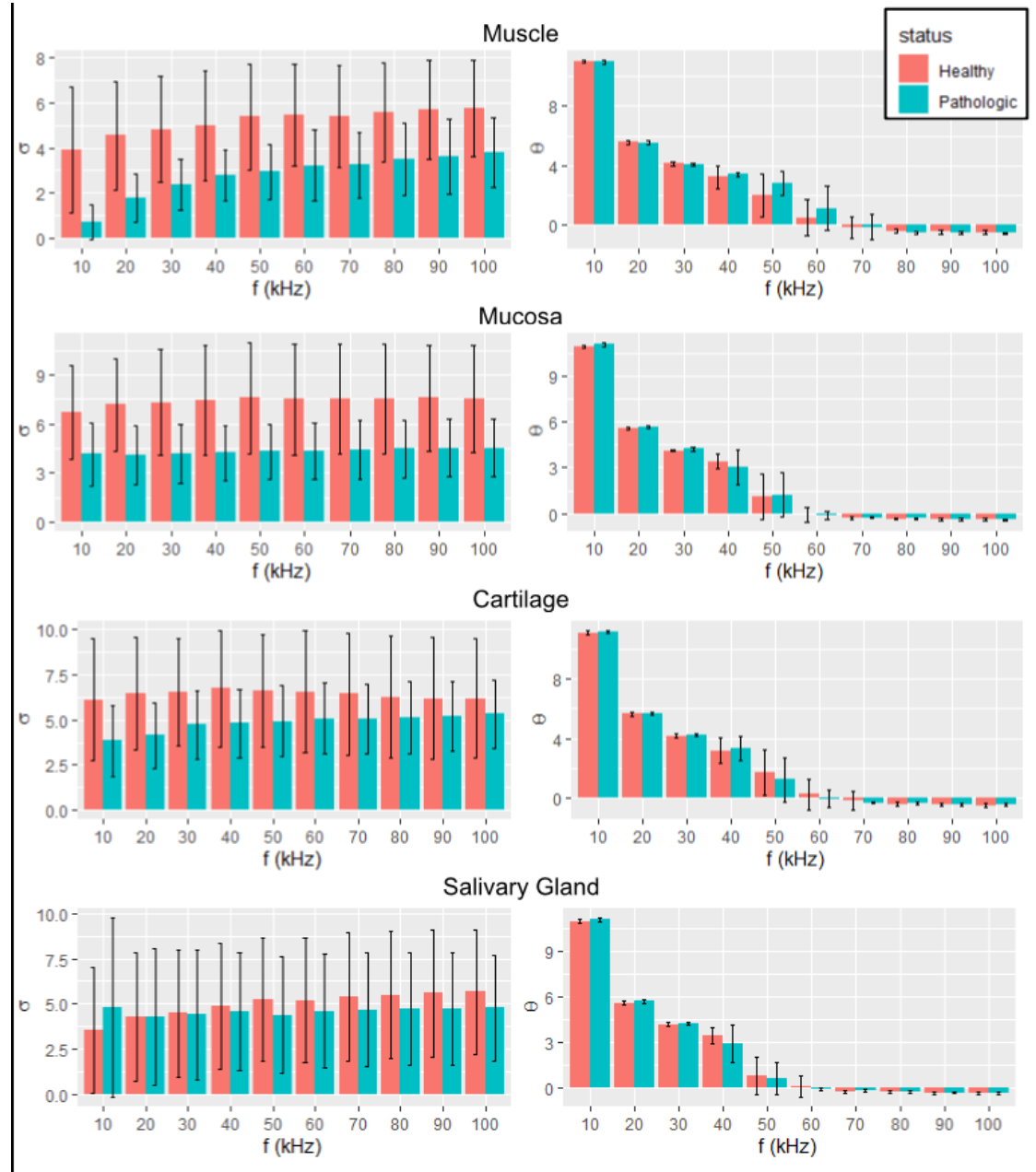
## Cole Model

# Clinical study



586 data collected from 10 patients:

- Muscle
- Mucosa
- Cartilage
- Salivary Gland



# Monopolar & Bipolar

## Monopolar configuration

→ Current density:  $J_{mono} = \frac{I}{2\pi r^2}$

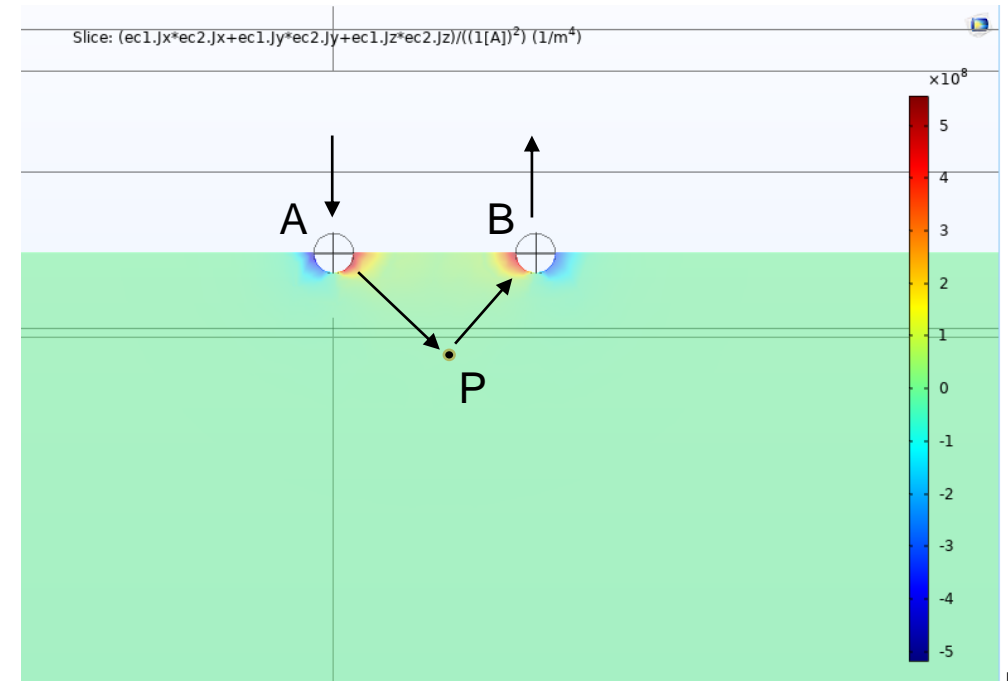
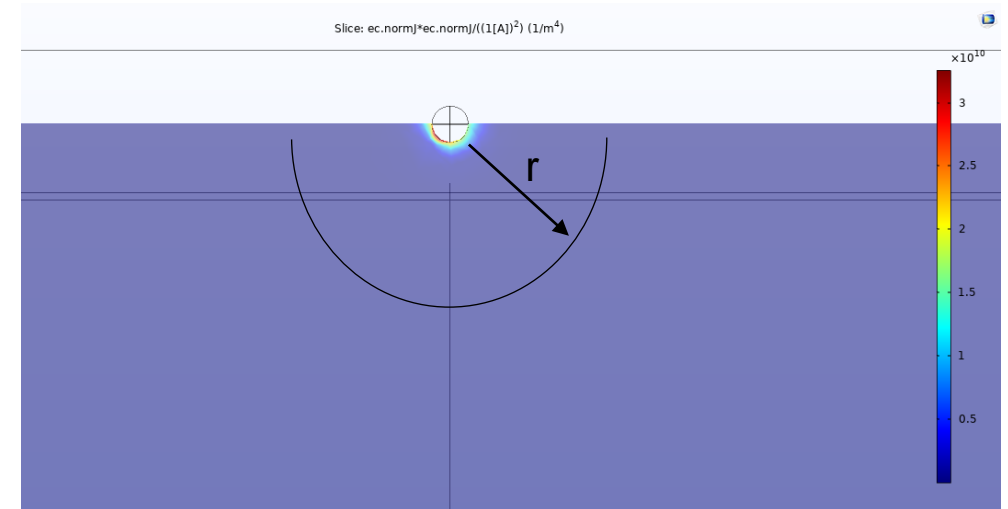
→  $Z_{mono} = \int_{\Omega} \left( \frac{J_{mono}}{\hat{o}} \right) d\Omega = \frac{1}{2\pi\hat{o}} \left( \frac{1}{r_0} - \frac{1}{r} \right), \quad r \rightarrow \infty$

## Bipolar configuration

→  $J_{bi} = \frac{I\overrightarrow{AP}}{2\pi|AP|^2} + \frac{I\overrightarrow{BP}}{2\pi|BP|^2}$

→  $Z_{bi} \approx Z_A + Z_B$

Electric field can be distorted!



# Problems and solutions

$$\rightarrow Z_{mono} = \int_{\Omega} \left( \frac{J_{mono}}{\hat{\sigma}} \right) d\Omega = \frac{1}{2\pi\hat{\sigma}} \left( \frac{1}{r_0} \right)$$

→  $r_0$ : the electrode emersed depth matters!

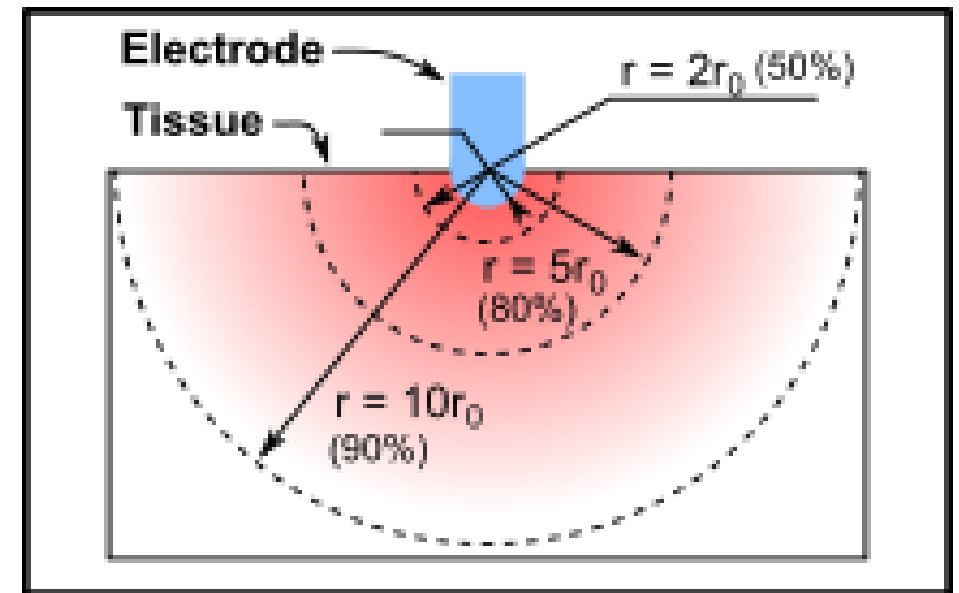
→ Solution:

→ (Robot) Control the electrode emersed depth

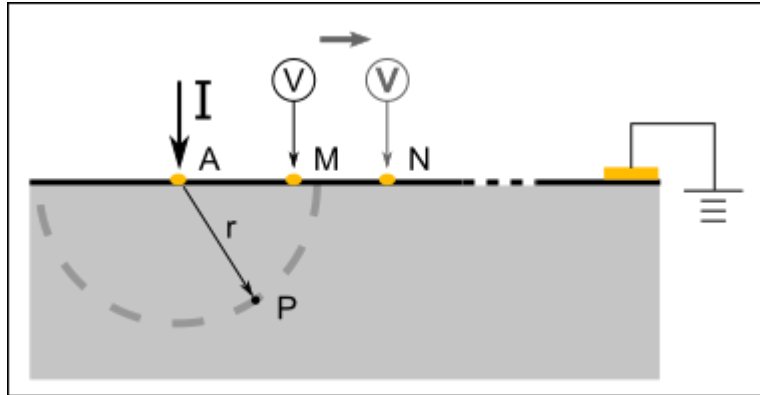
→ What if the electrode has an irregular shape:

→ Calibration using standard saline solutions

Monopolar configuration as an example



# Tripolar configuration



Current density at P: 
$$J_p = \frac{I}{2\pi r^2}$$

Electric potential at P: 
$$V_p = \frac{I}{2\pi\sigma} \left( \frac{1}{r_0} - \frac{1}{r} \right)$$

We measure the electric potential at M & N:

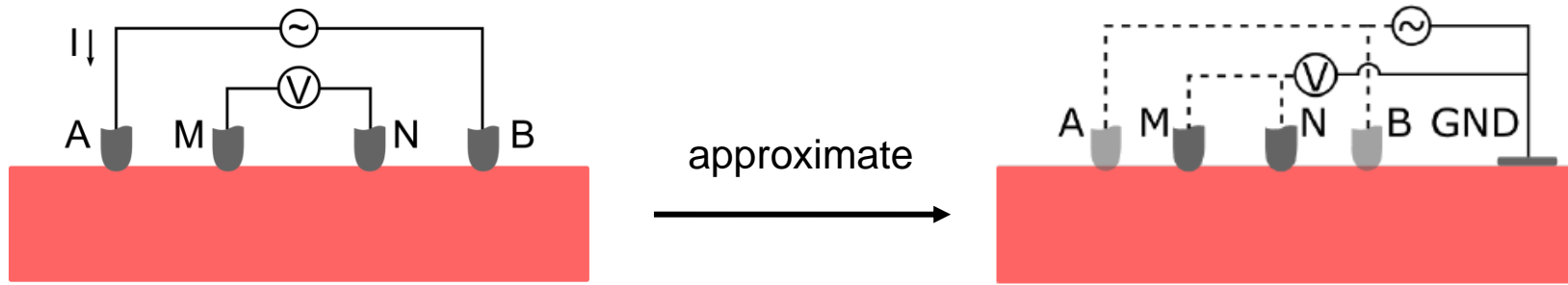
$$V_{MN} = \frac{I}{2\pi\sigma} \left( \frac{1}{|AM|} - \frac{1}{|AN|} \right)$$

Apparent conductivity:

$$\sigma_a = \frac{I}{2\pi V_{MN}} \left( \frac{1}{|AM|} - \frac{1}{|AN|} \right)$$



# Pseudo-tetrapolar configuration

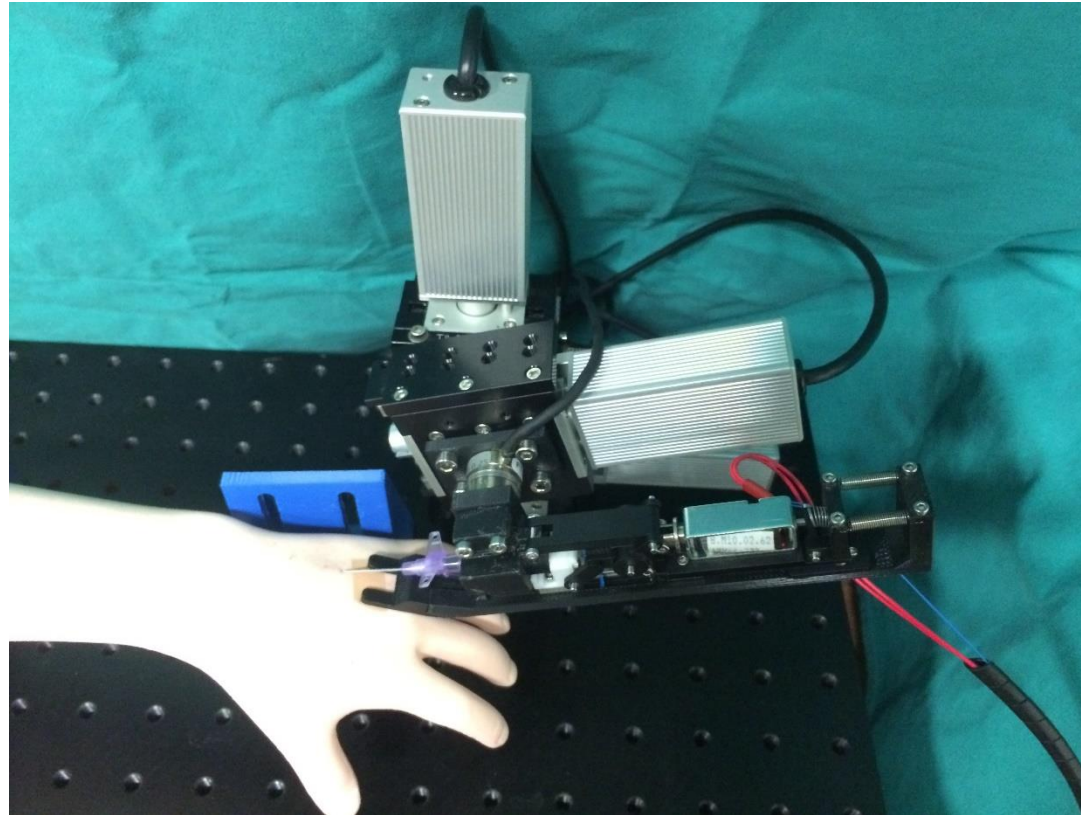


$$Z_{tetra} = Z_{AM} - Z_{AN} - Z_{BM} + Z_{BN} = \frac{1}{2\pi\hat{\sigma}} \left( \frac{1}{|AM|} - \frac{1}{|AN|} - \frac{1}{|BM|} + \frac{1}{|BN|} \right)$$

**Useful in robotic surgery due to the limited number of trocars!**



# Application Example 1: Robotic peripheral intravenous catheterization

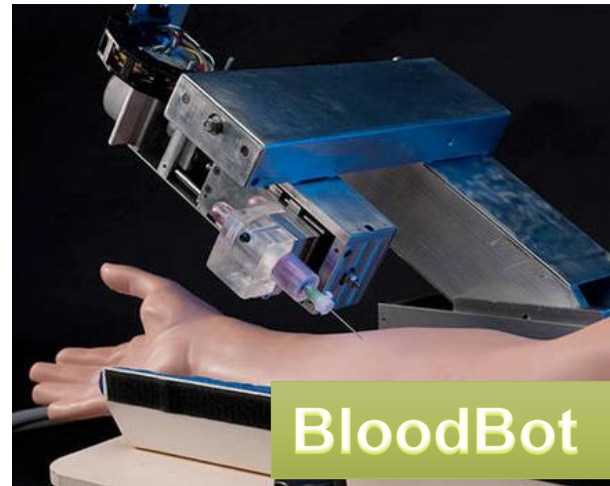
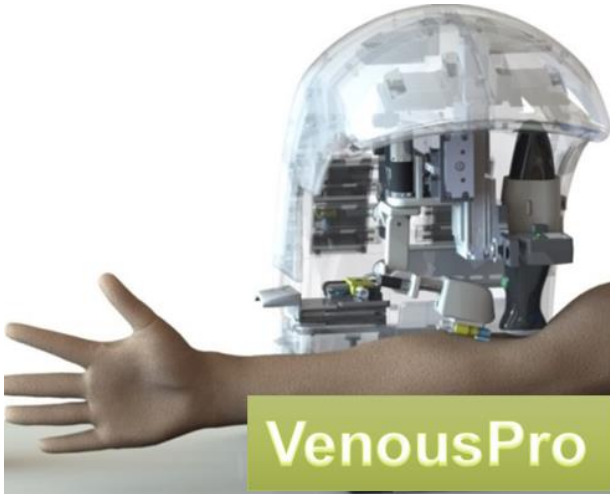
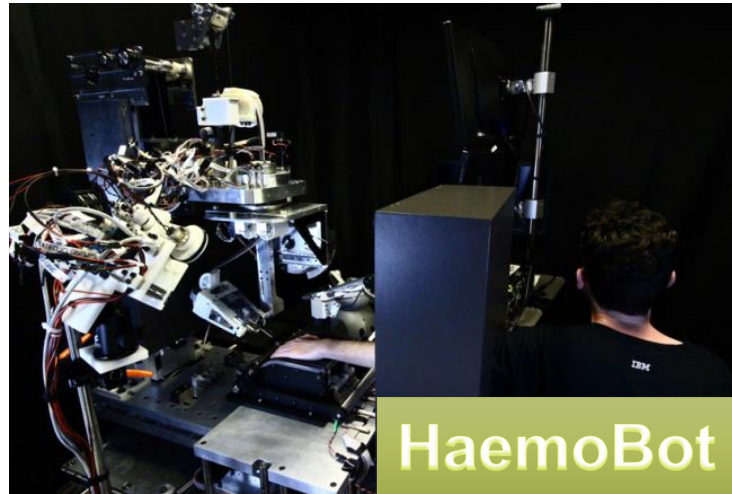


# Medical background

The success rates of Peripheral IntraVenous Catheterization (PIVC) are low:

Patient	1 attempt	2 attempts
Adults <sup>[11]</sup>	72%	
Pediatrics <sup>[12]</sup>	53%	67%





**Not suitable for pediatric patients!**



## Hand-held robotic device for PIVC on pediatric patients

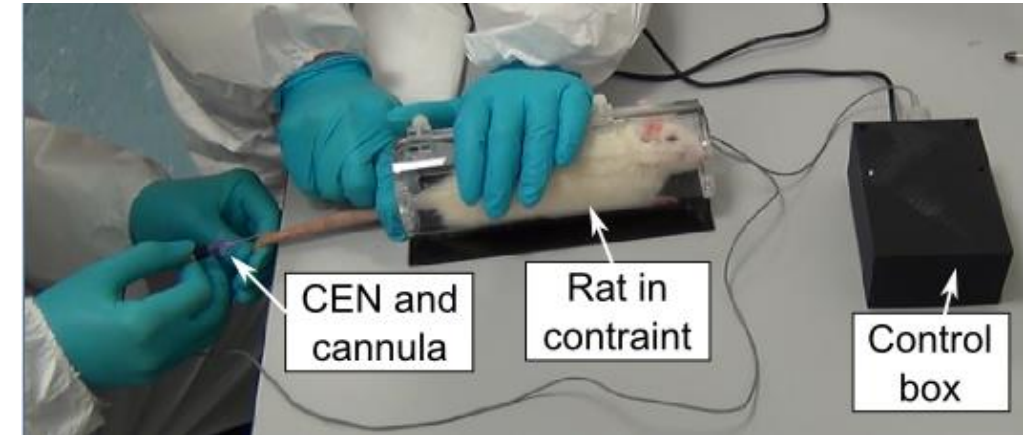
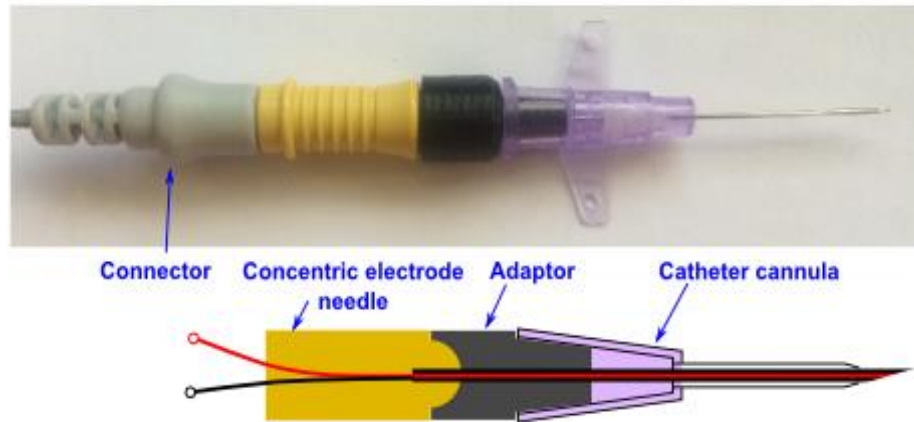
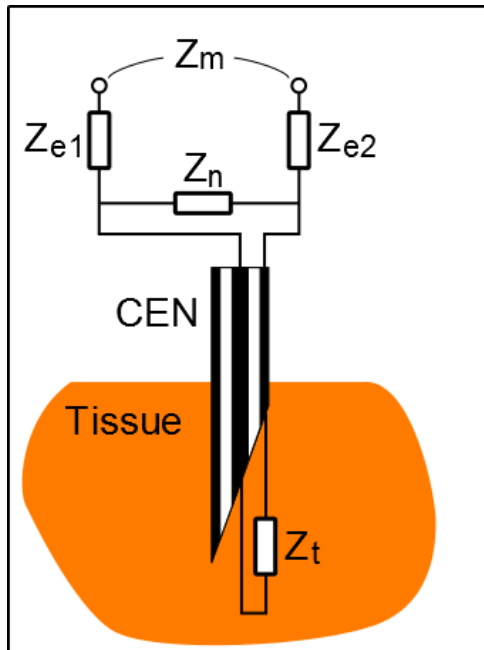
### Advantages:

- Keeping surgeons in control;
- Flexible insertion sites;
- High acceptance rate;
- Low cost and complexity.



# Detect venipuncture using EBI

## Bipolar configuration



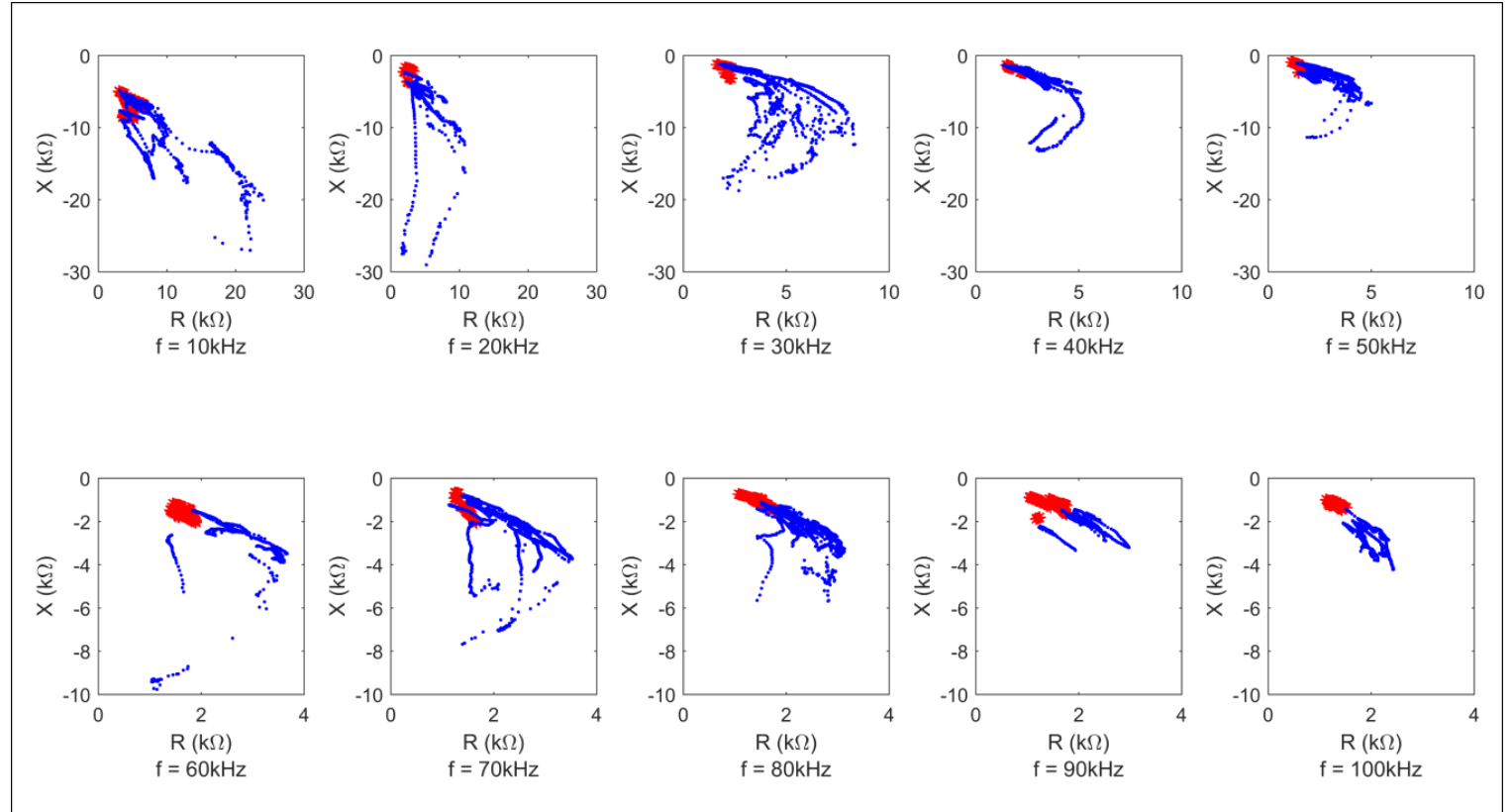
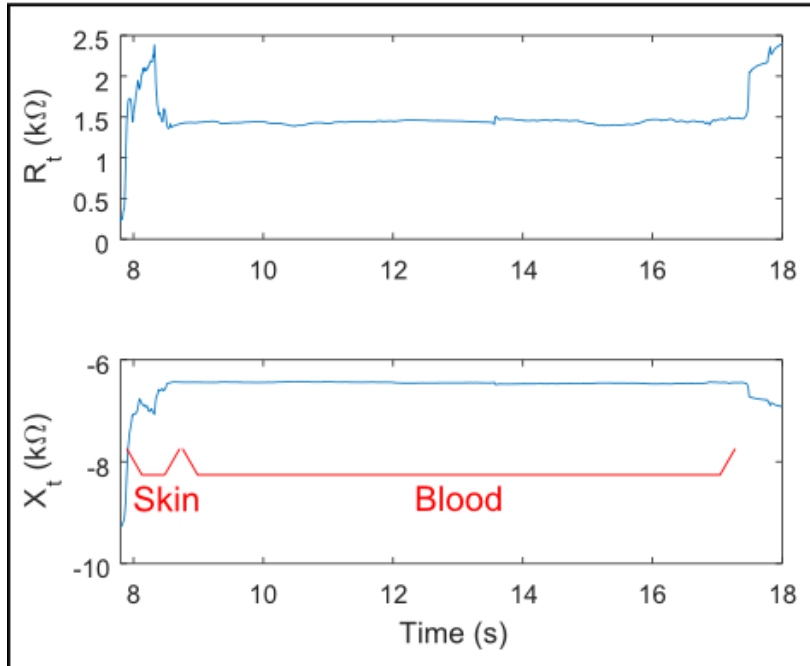
$Z_{e1}$  and  $Z_{e2}$ : the impedance of the electrodes;  
 $Z_n$ : the electrical impedance due to the capacitance effect between the electrodes.  
 $Z_t$ : the electrical impedance of bio-tissue.  
 $Z_m$ : the measured electrical impedance of the equivalent circuit.

The electrical impedance values are interpreted in a format of a real part R (resistance) and an imaginary part X (reactance).

$$Z_t = R_t + jX_t$$

$$\begin{cases} R_t = \frac{R_m(R_n^2 + X_n^2) - R_n(R_m^2 + X_m^2)}{(R_n - R_m)^2 + (X_n - X_m)^2} \\ X_t = \frac{X_m(R_n^2 + X_n^2) - X_n(R_m^2 + X_m^2)}{(R_n - R_m)^2 + (X_n - X_m)^2} \end{cases}$$

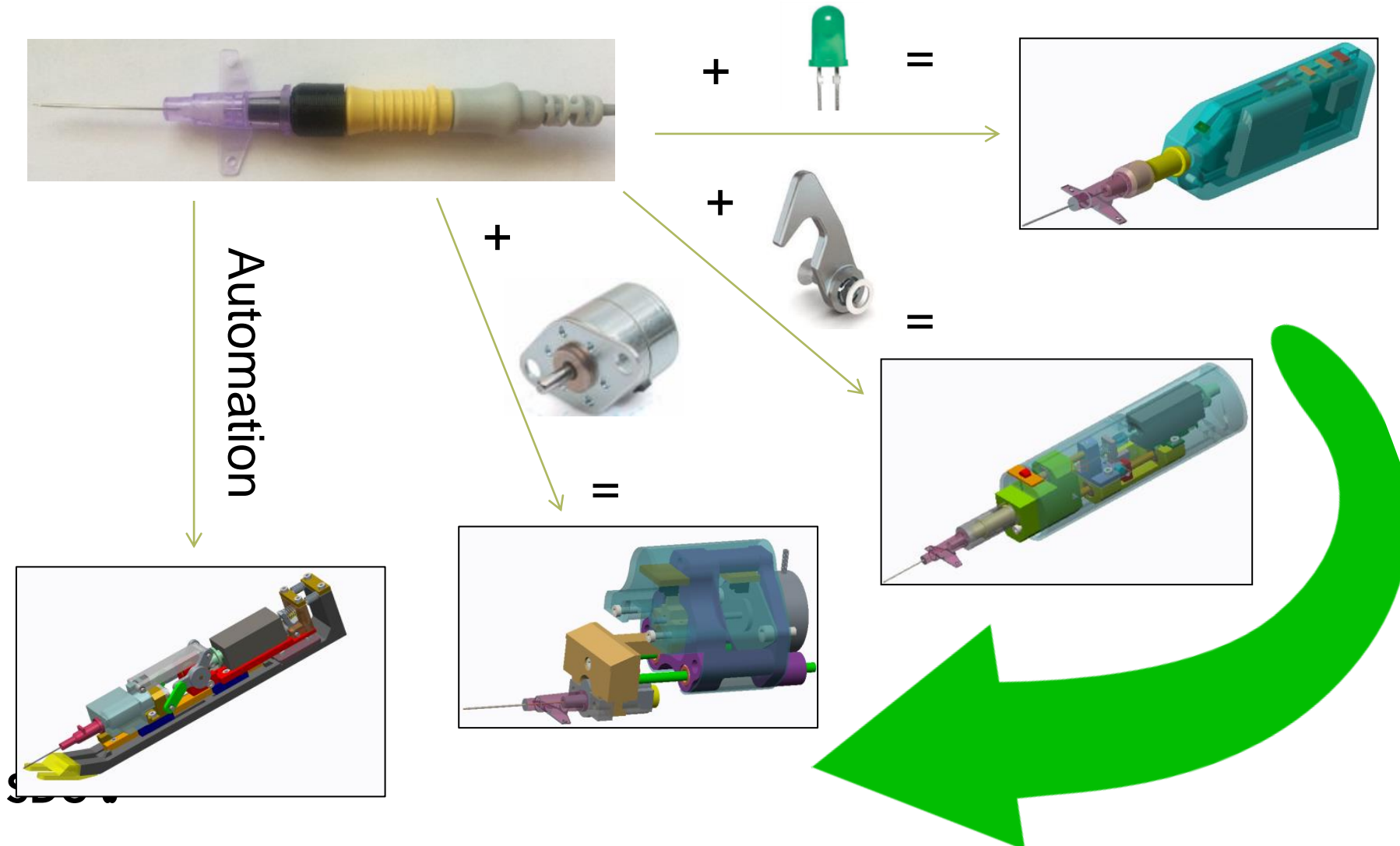
# Data processing and analysis



$f$ (kHz)	10	20	30	40	50	60	70	80	90	100
DT	87.5%	98.3%	92.8%	95.1%	95.1%	100%	89.4%	97.7%	99.4%	100%
LD	74.5%	88.3%	83.8%	88.7%	88.5%	95.9%	78.7%	84.9%	98.2%	99.3%
SVM	74.7%	95.5%	88.2%	89.3%	89.6%	98.2%	82.8%	92.1%	98.6%	100%

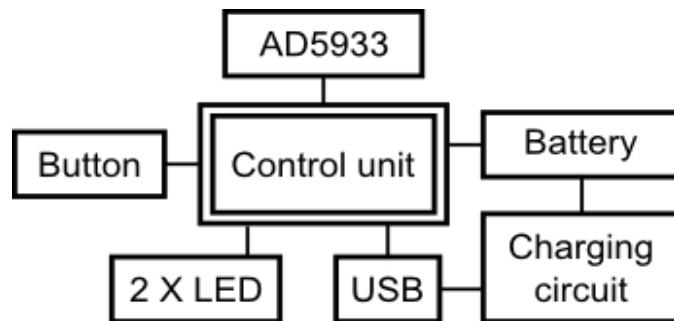
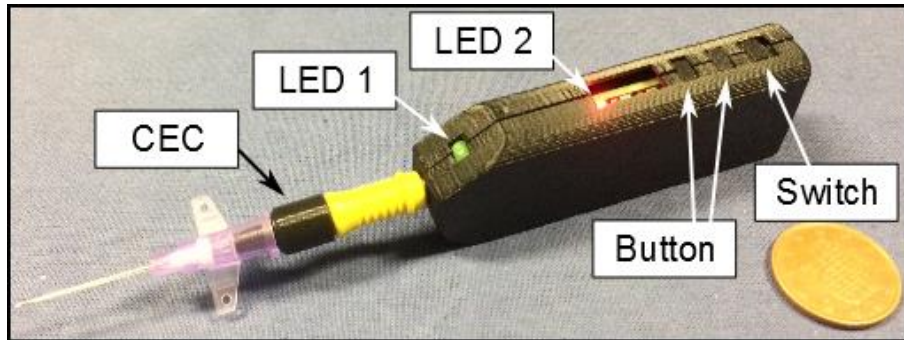
DT: Decision tree; LD: Linear discriminant; SVM: Support Vector Machine.

# Handheld robotic devices



# Device 1: sensor only device

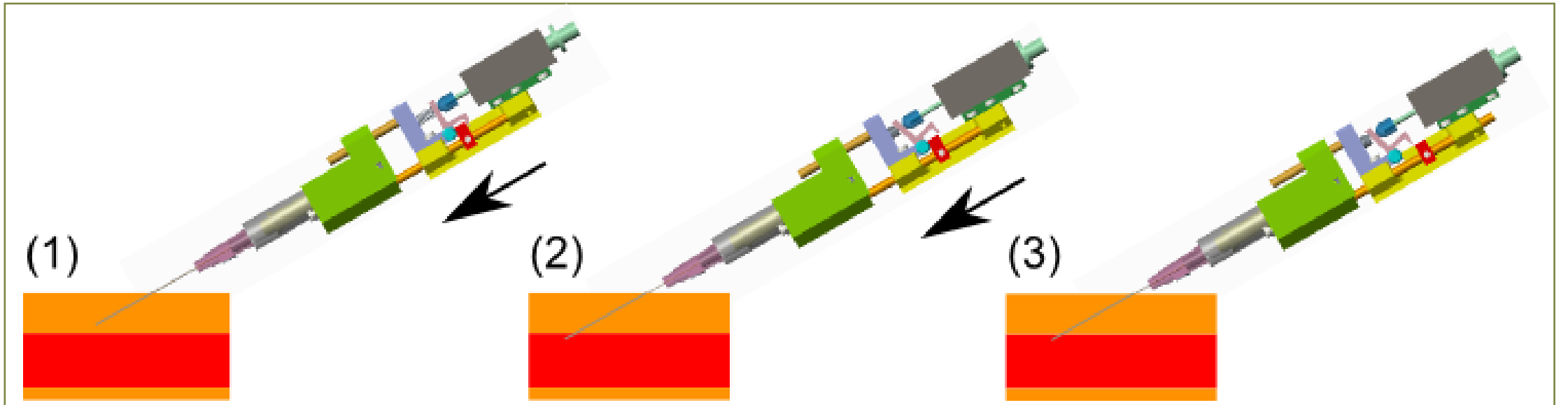
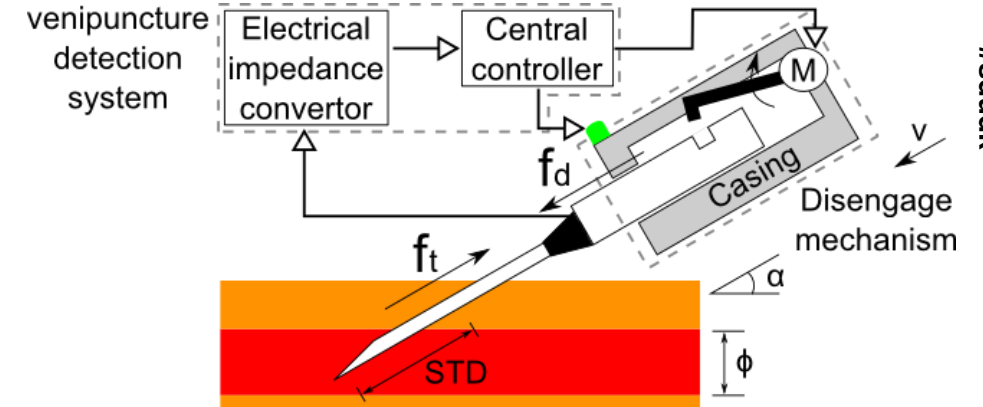
SVEI: Smart Venous Entry Indicator





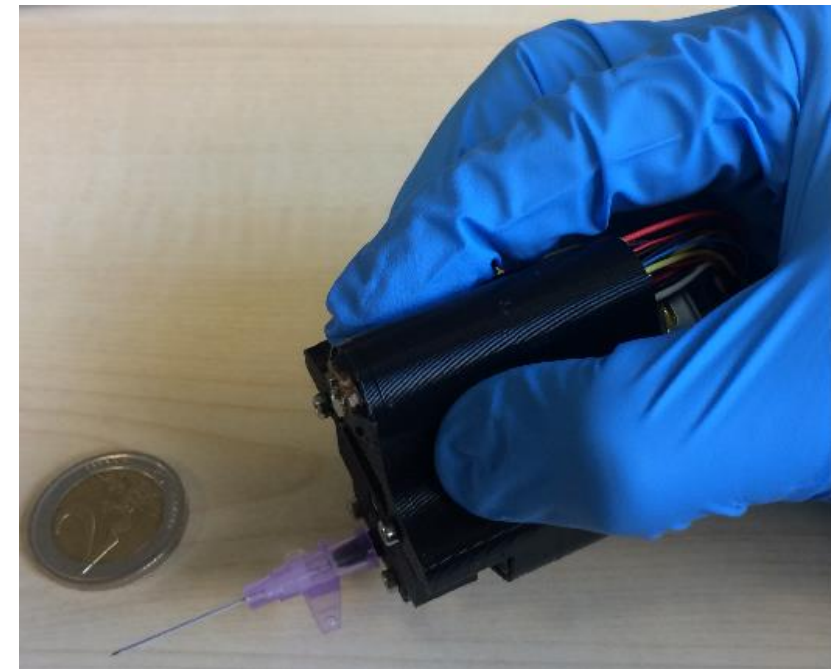
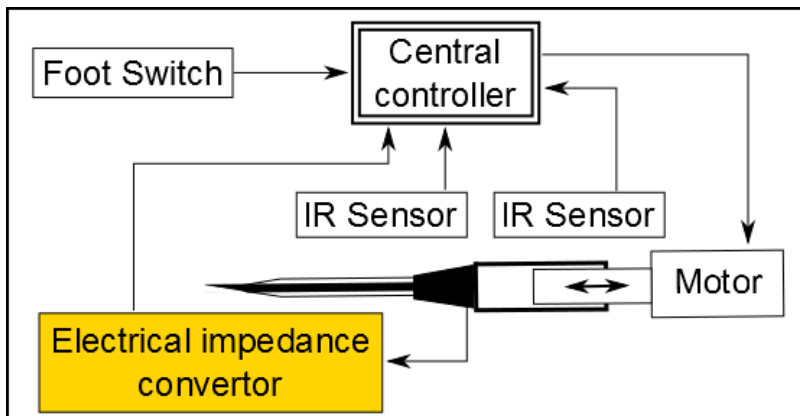
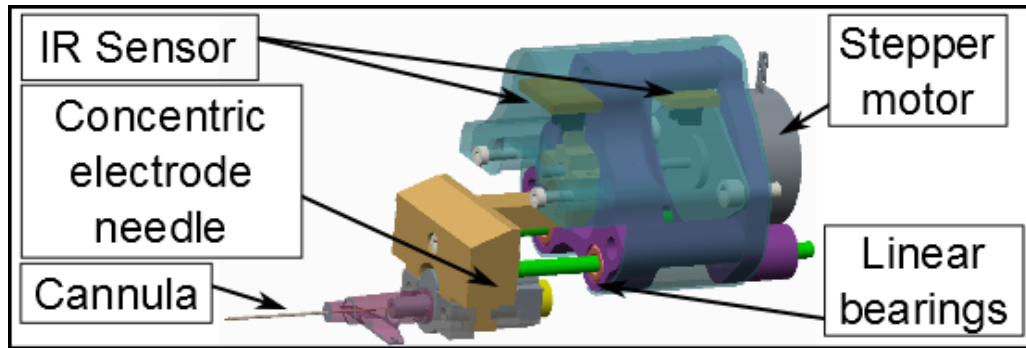
# Device 2: Disengage device

SDOP: Smart Device for Over puncture Prevention



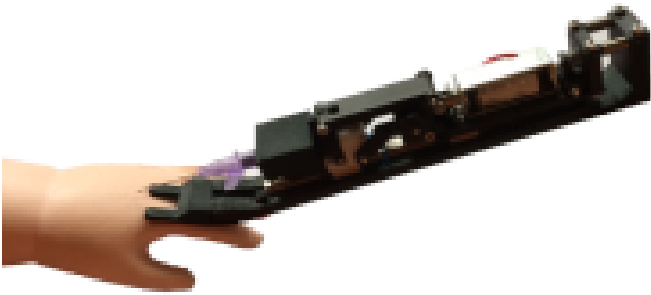
# Device 3: Motorized insertion

SAID: Semi-Autonomous Intravenous access Device



# Device 4: Handheld automation solution

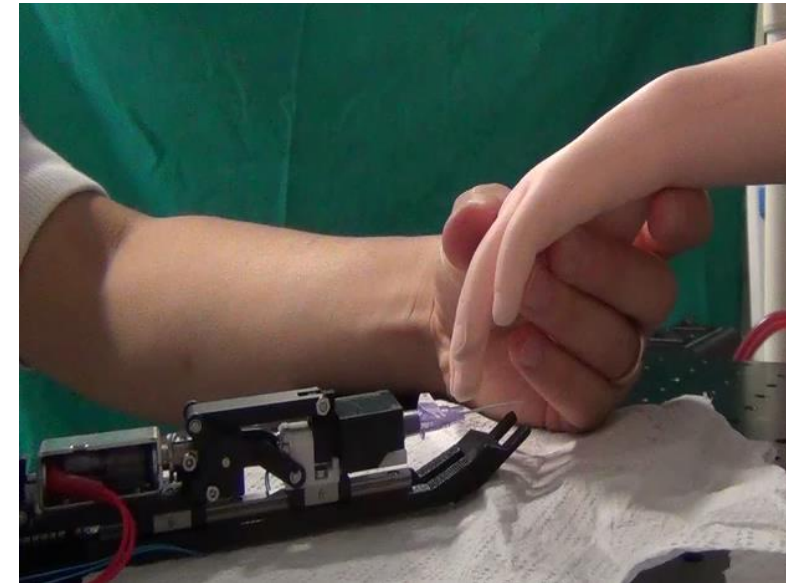
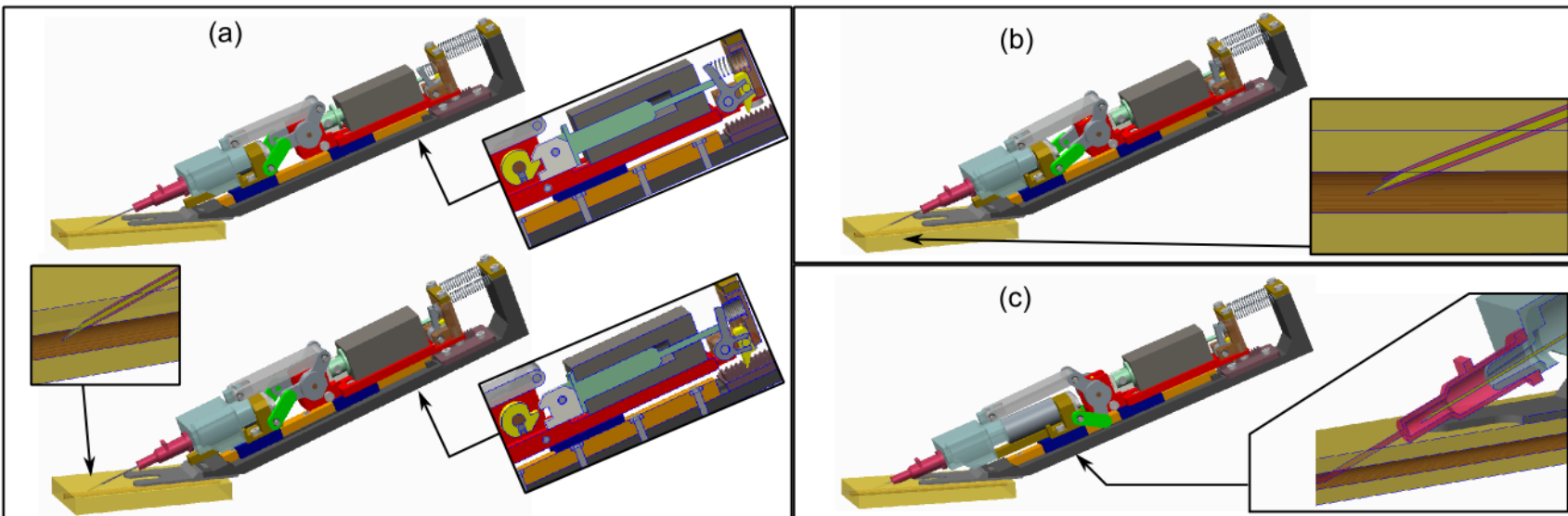
## CathBot



The user only needs to push the handle forwards.

The device:

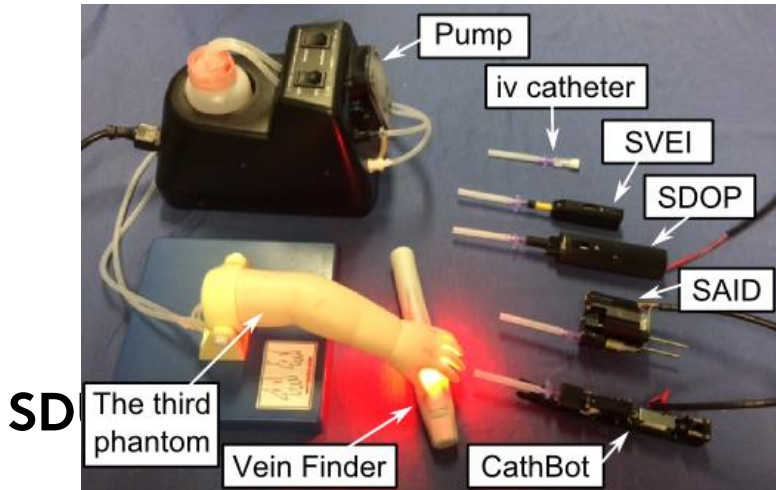
1. Insert the catheter;
2. Stop the insertion after venipuncture;
3. Advance the catheter 1 mm further;
4. Advance the cannula but retract the needle.

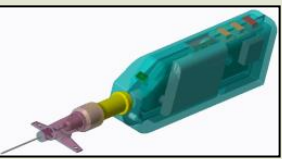
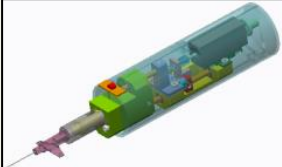
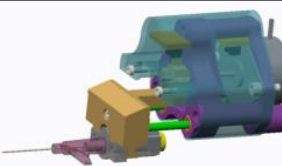
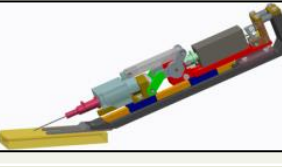



# Experimental results comparing 5 methods

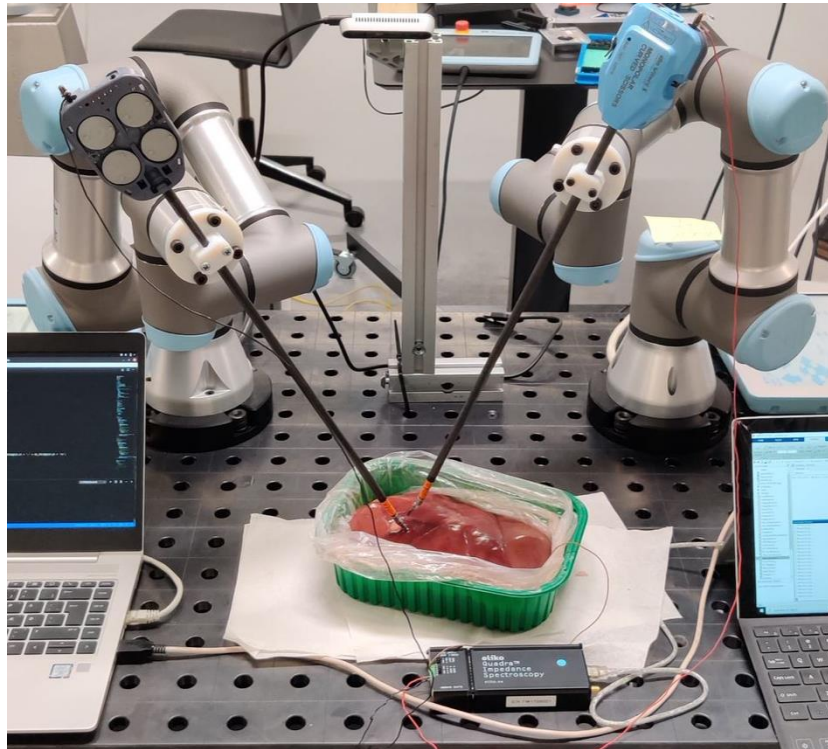
## Compare 5 devices:

- ▶ Evaluates the handheld device with the realistic baby arm phantom.
- ▶ 25 naïve subjects (no experiences of PIVC or needle insertion) were invited to the experiment.
- ▶ Each subject did 10 attempts on the phantom using one of the devices.



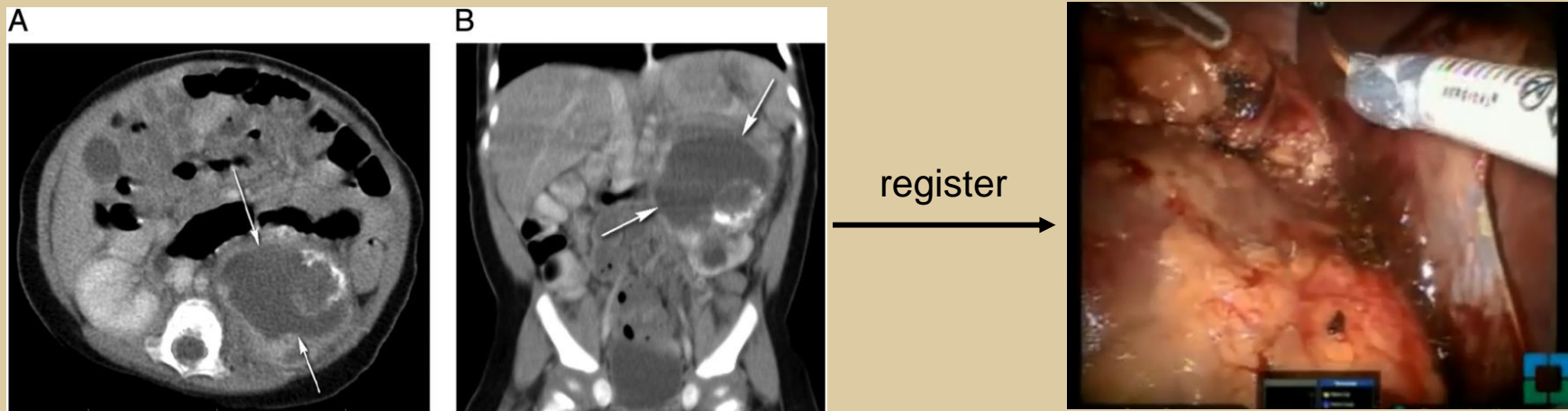
Device	Name	Ave. success rat	1st stick accuracy	Whole operation time	SUS score
	SVEI	86%±15%	5/5	23,9 s	77,8
	SDOP	78%±14,7%	2/5	18,8 s	81,5
	SAID	80%±17%	3/5	19 s	75,8
	CathBot	84%±8%	4/5	16,9 s	72,8
	Conventional	12%±16%	0/5	36,2 s	NA

# Application Example 2: Robot Assisted Electrical Impedance Sensing (**RAEIS**)





# Tissue recognition in Robot Assisted Minimally Invasive Surgery (RAMIS)



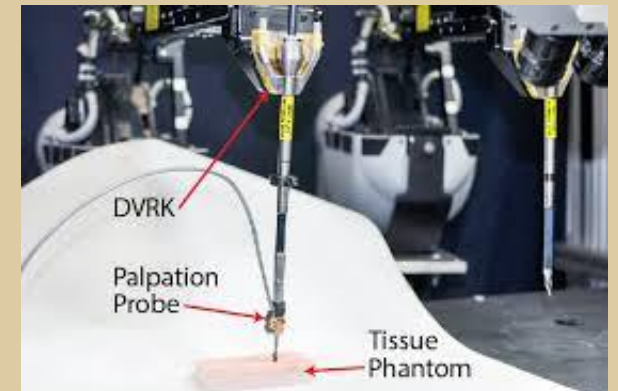
Higher level of perception & recognition for autonomous surgery tomorrow!

# Constraints in RAMIS:

- Number of trocars
- Small workspace
- Robotic maneuverability
- Surgical workflow



**Sensing system built upon the existing surgical robotic instruments & system**



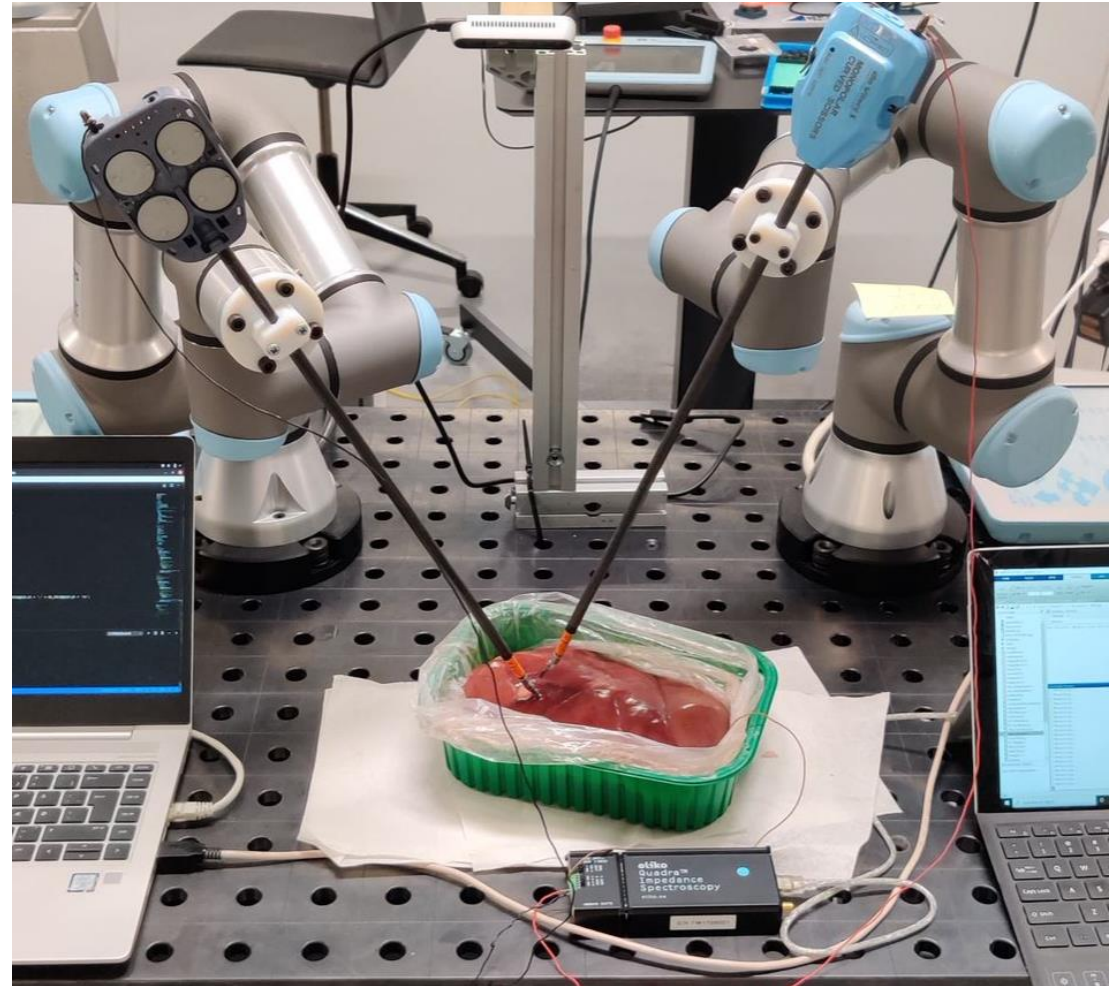


# Robot-Assisted Electrical Impedance Sensing (RAEIS)

**Mobile electrodes controlled by robots to multiple positions for impedance sensing.**

## Advantages:

- No external devices involved to the surgical site
- Flexible and autonomous sensing
- Fast and accurate tissue identification

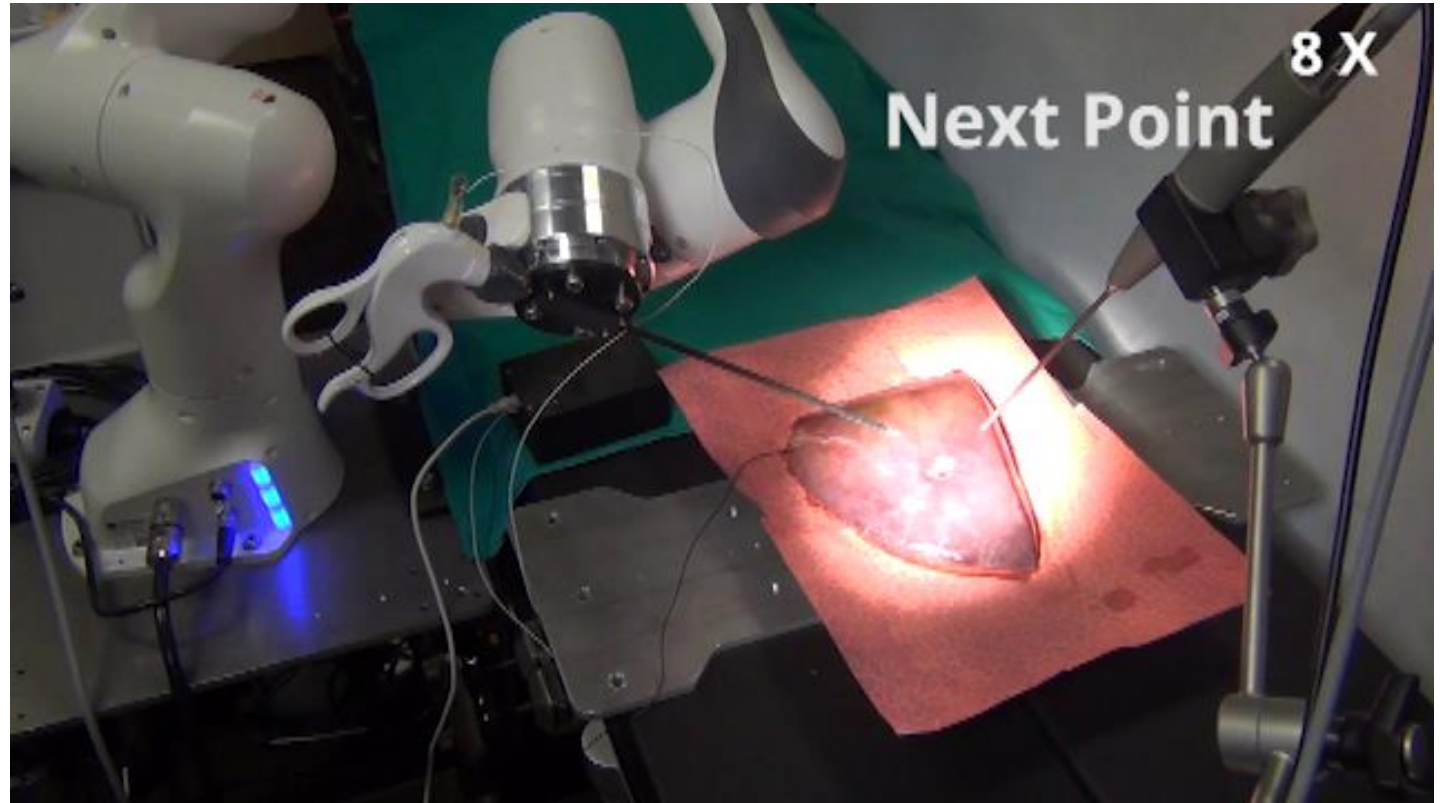
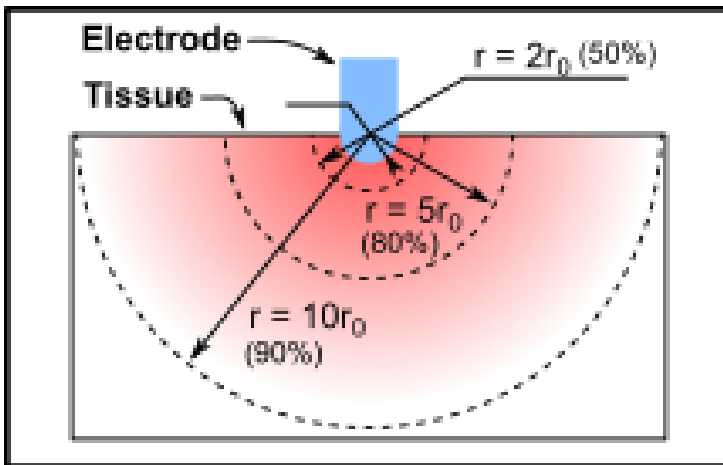


# Monopolar configuration

→ The key is the electrode's pressing depth

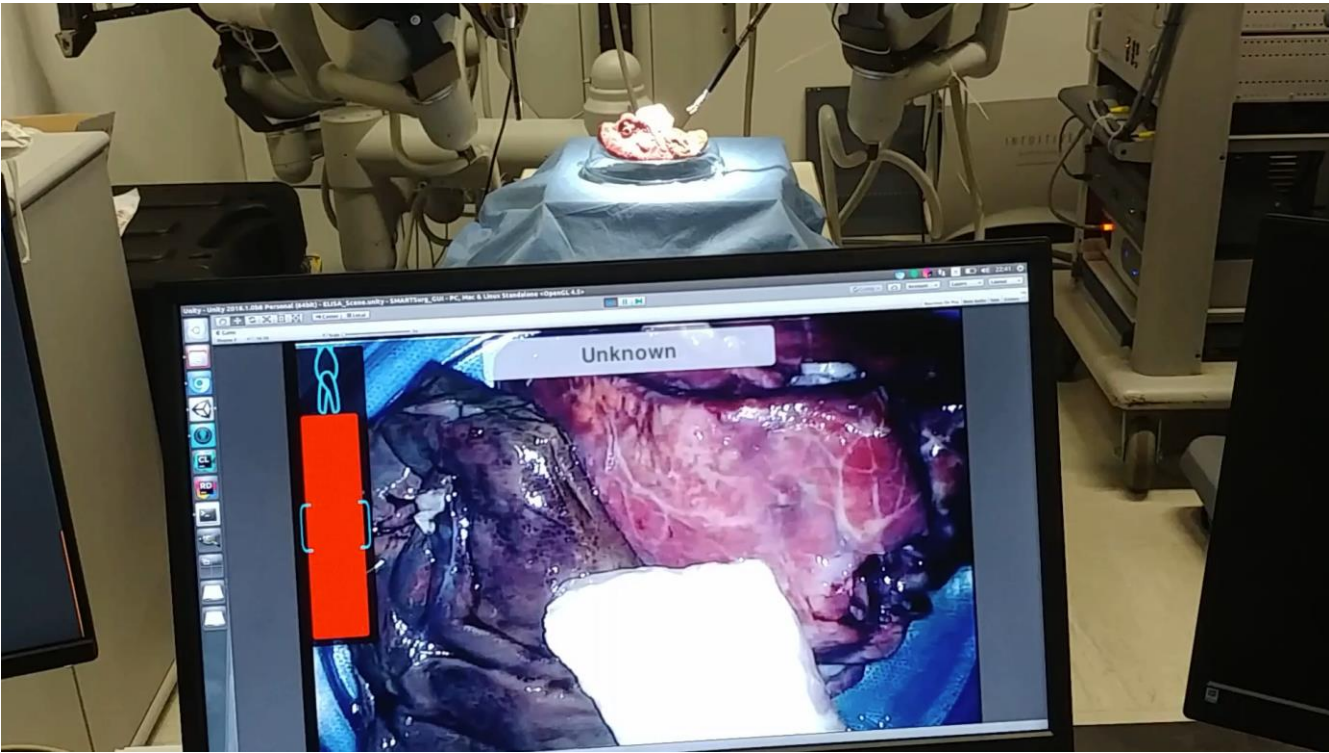
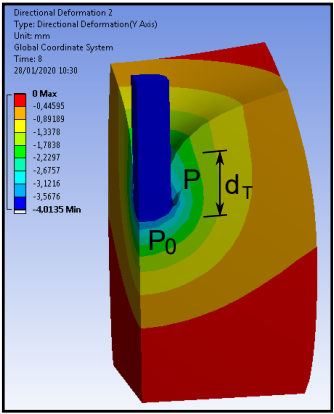
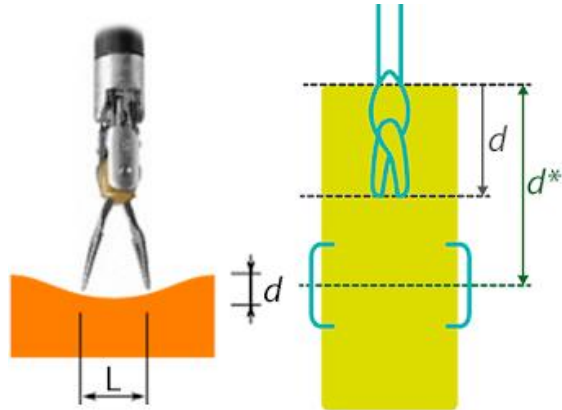
→ Impedance:

$$Z_{mono} = \int_{\Omega} \left( \frac{J_{mono}}{\hat{\sigma}} \right) d\Omega = \frac{1}{2\pi\hat{\sigma}} \left( \frac{1}{r} - \frac{1}{r_0} \right)$$



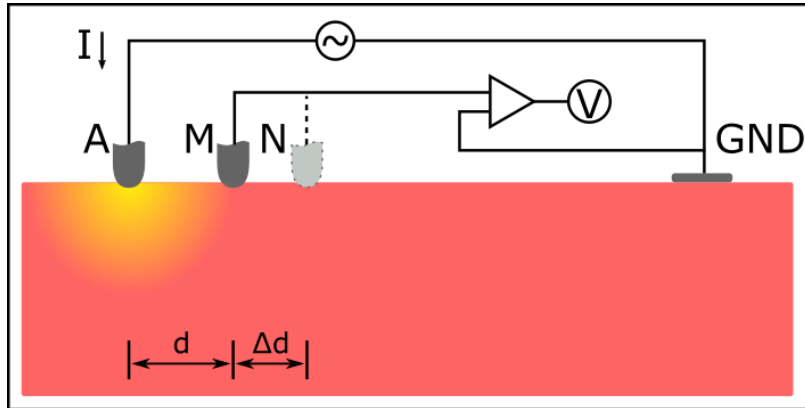
# Bipolar configuration

→ Assuming that bipolar is achieved by 2 jaws: A and B



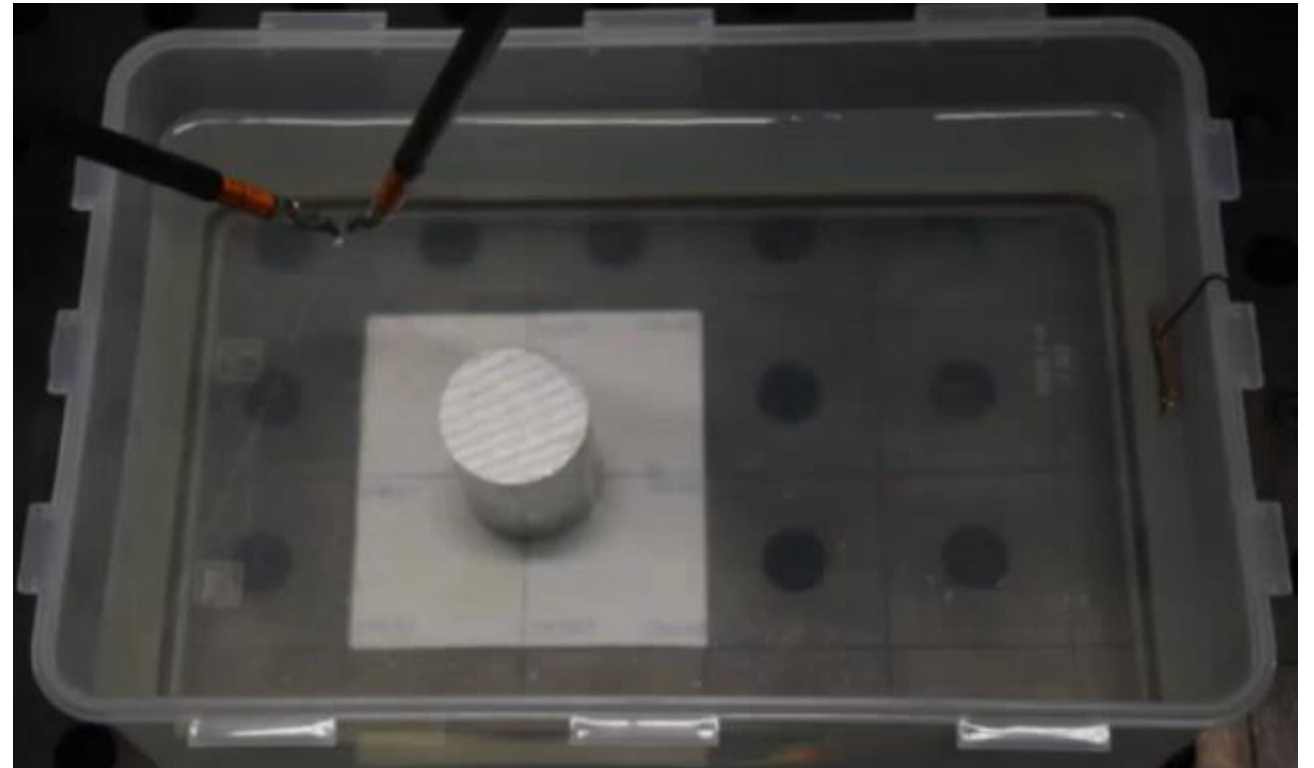


# Tripolar sensing configuration



## Advantages compared to mono/bipolar:

- Insensitive to electrode emerged depth
- Measured material conductivity accurately
- Detect subsurface region

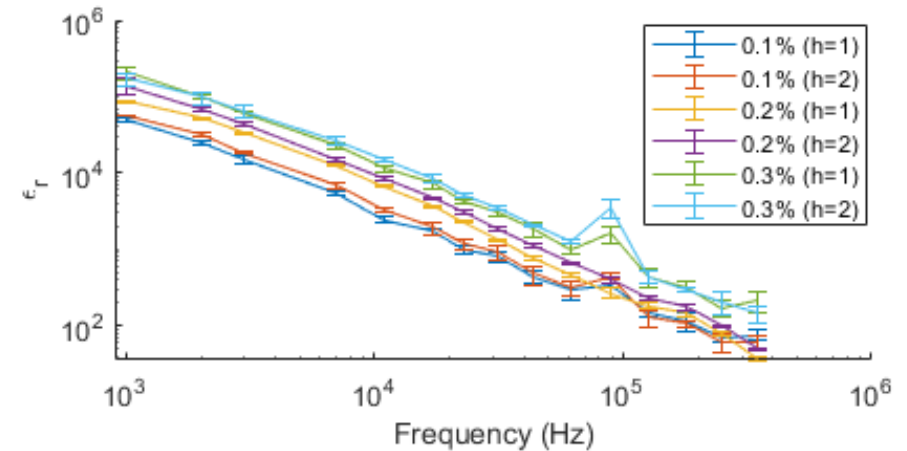
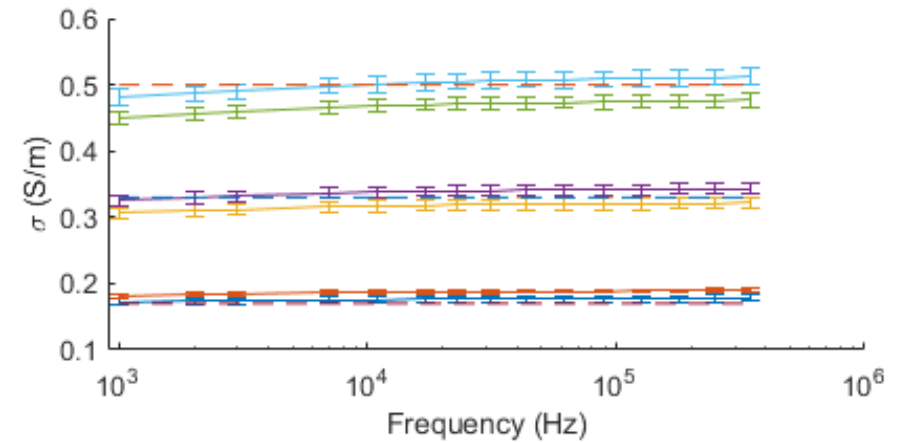
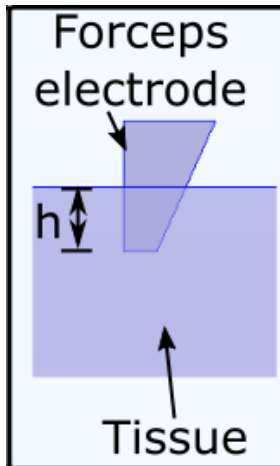


# System characterization

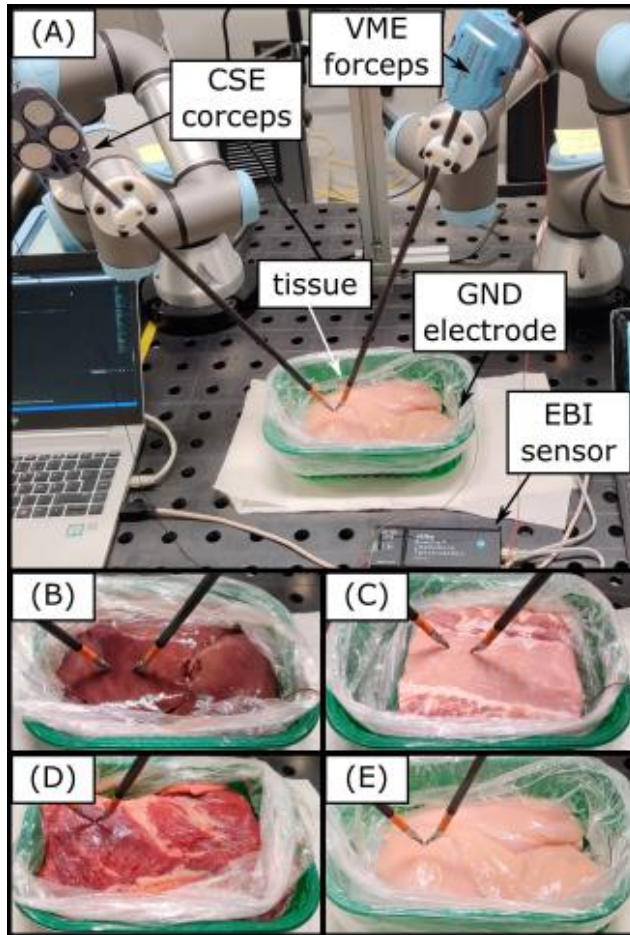
The system was tested using different saline solutions (0.1%, 0.2%, and 0.3%)

Emersed depths of electrodes (h=1mm and 2mm)

$$\begin{cases} \sigma = \frac{1}{2\pi} \frac{Re_{MN}}{Re_{MN}^2 + Im_{MN}^2} \left( \frac{1}{AM} - \frac{1}{AN} \right) \\ \epsilon_r = \frac{1}{4\pi^2 f \epsilon_0} \frac{Im_{MN}}{Re_{MN}^2 + Im_{MN}^2} \left( \frac{1}{AM} - \frac{1}{AN} \right) \end{cases}$$

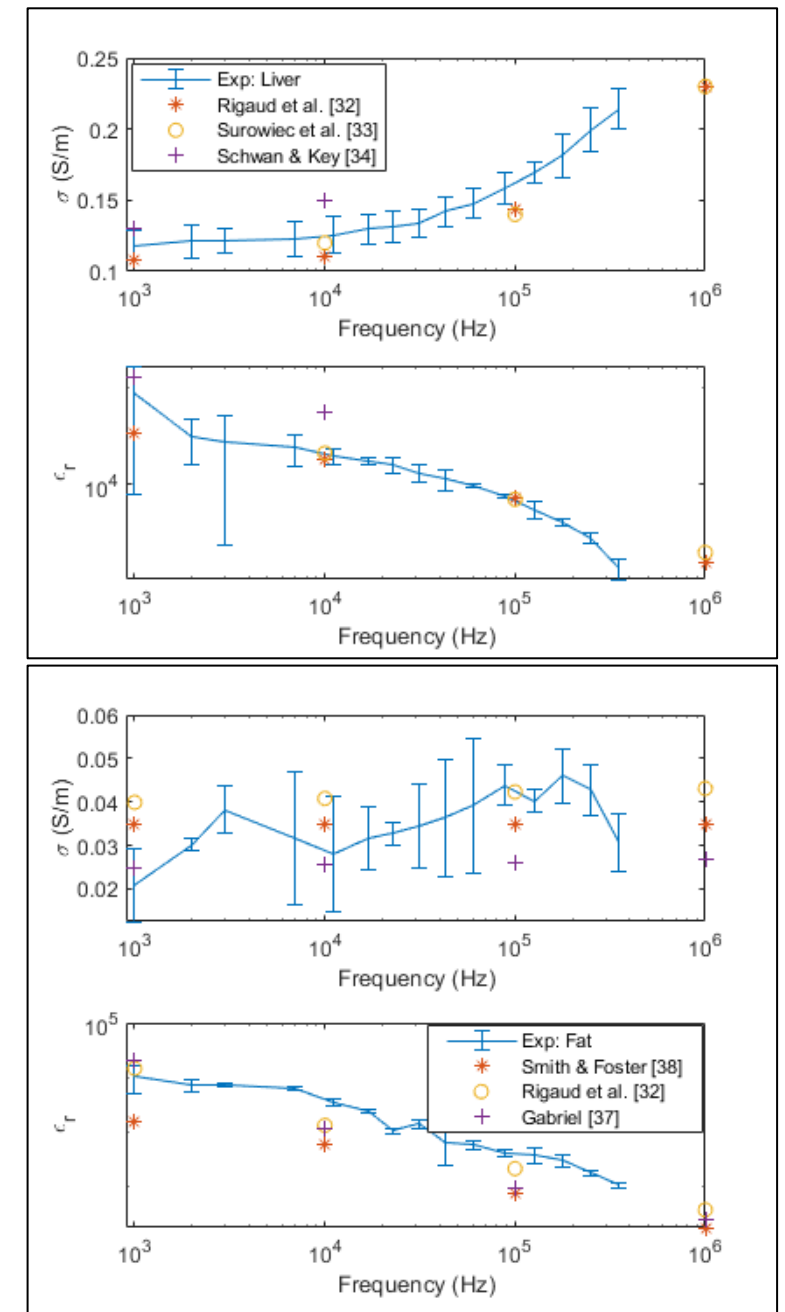
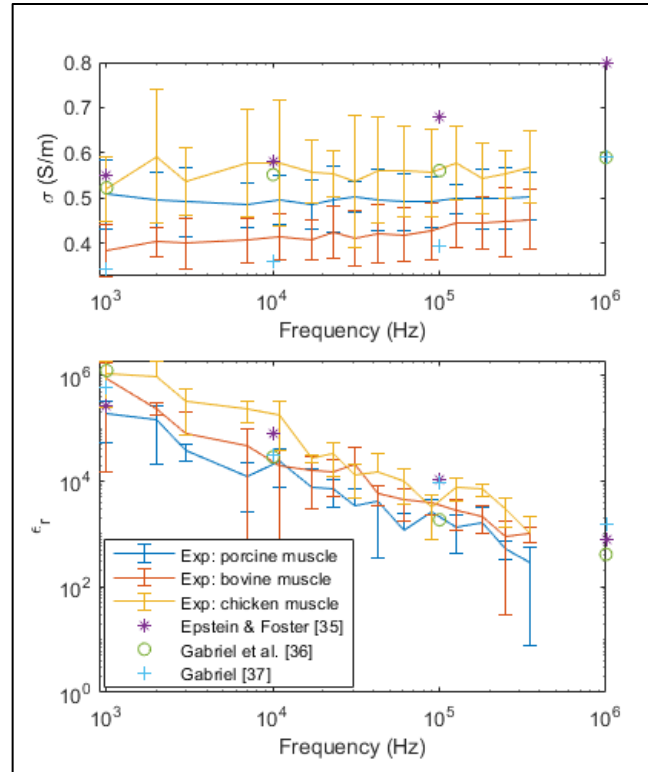


# System characterization

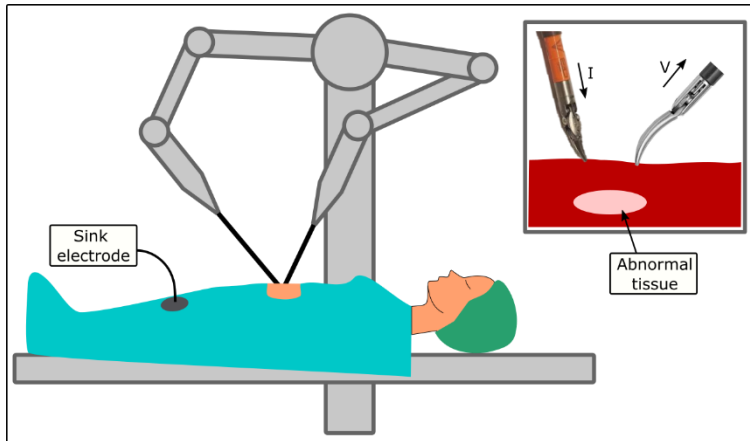


Different ex vivo tissues:

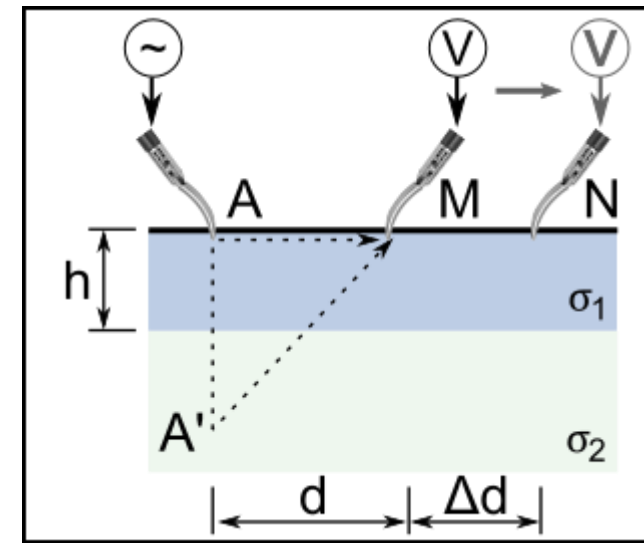
- Porcine liver
- Porcine fat
- Porcine muscle
- Chicken muscle
- Bovine muscle



# Subsurface object detection



- Early stage cancer
- Lymph nodes
- Blood vessels
- Edema
- etc



If the object is constructed by 2 layers:  $\rho_1$  and  $\rho_2$

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

flow from A to M

reflected from the interface

Reflection coefficient  $\kappa$ :  $\kappa = \frac{\sigma_1 - \sigma_2}{\sigma_1 + \sigma_2}$

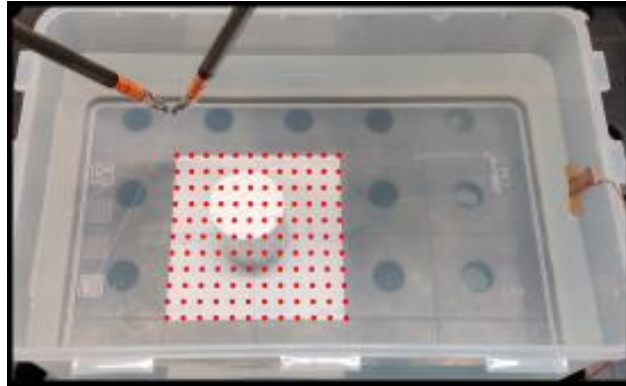
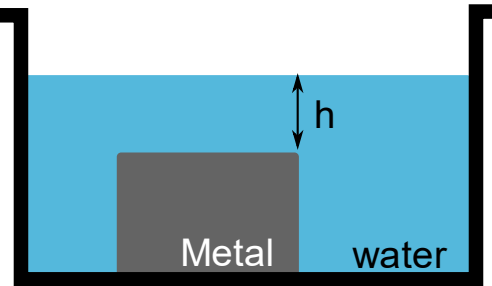
Updated voltage calculation:

$$V_{MN}^* = \frac{I}{2\pi\sigma_1} \left( \frac{\Delta d}{d(d + \Delta d)} + 2 \sum_{n=1}^{\infty} \left( \frac{k^n}{\sqrt{d^2 + (2nh)^2}} - \frac{k^n}{\sqrt{(d + \Delta d)^2 + (2nh)^2}} \right) \right)$$

=0 if there is no subsurface object



# Subsurface object imaging



Scanning area: (100mm\*100mm)

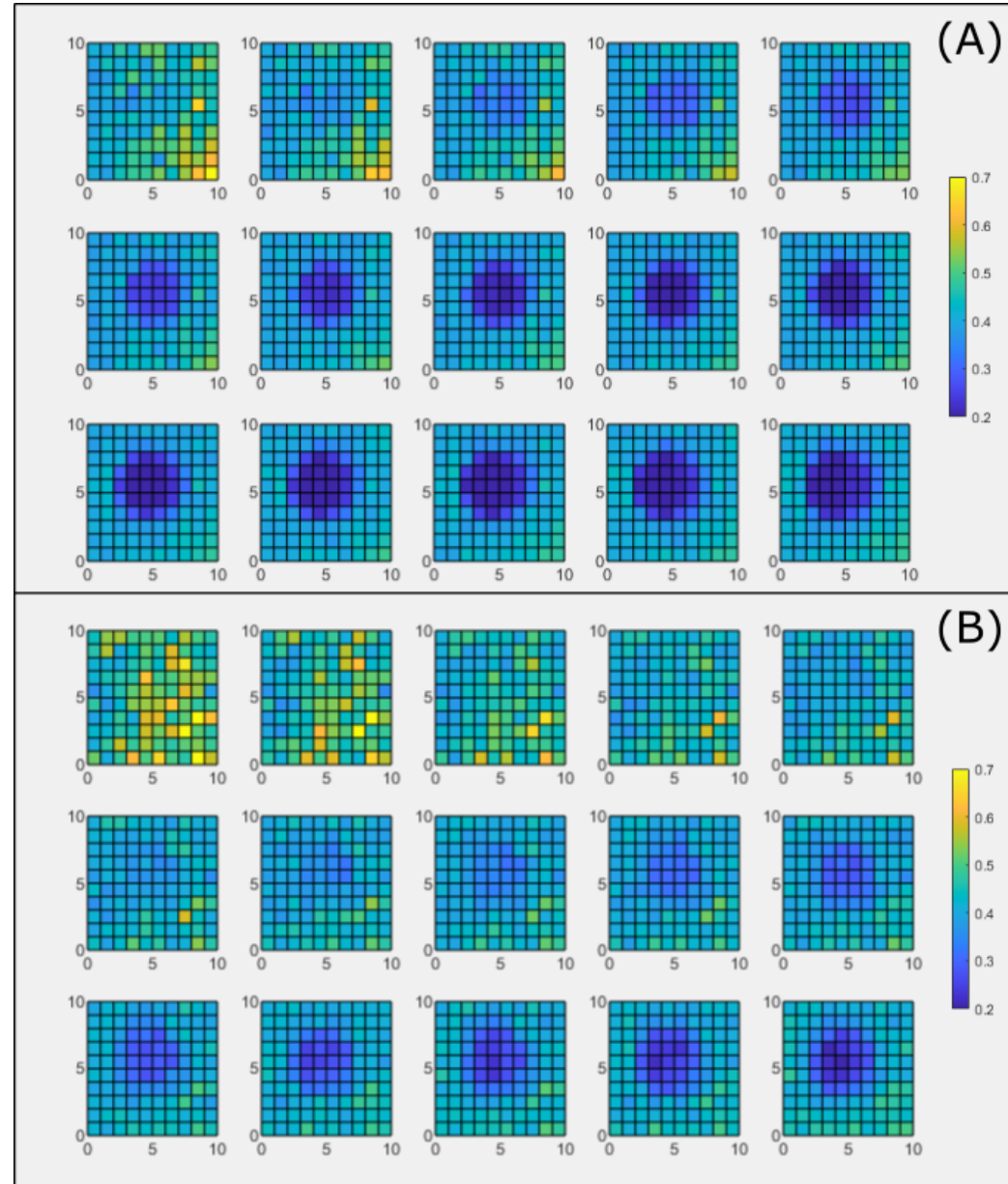
Scanning resolution: 11\*11

metal cylinder diameter: 40mm

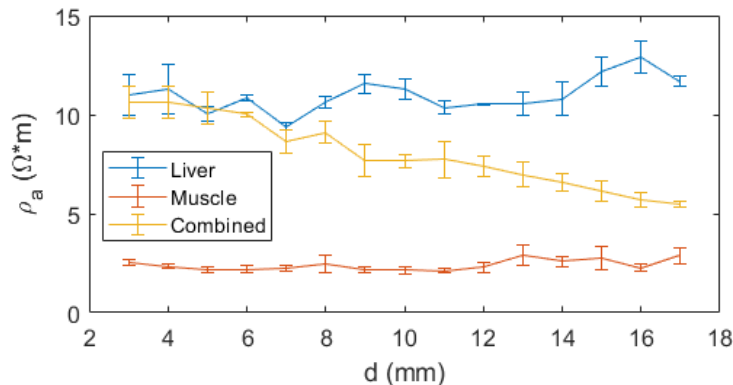
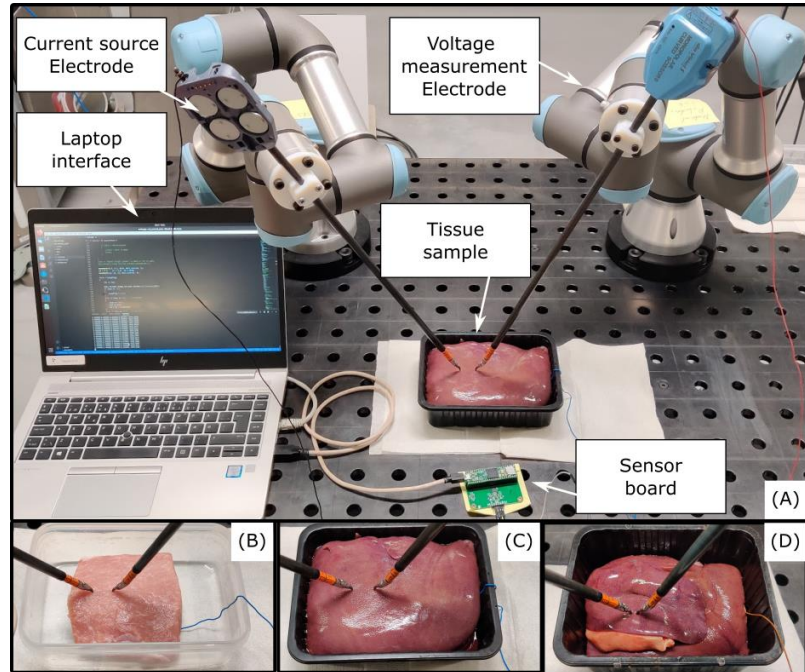
Two conditions (Immersed depth of the metal object:

1)  $h=5\text{mm}$

2)  $h=10\text{mm}$



# Parameter estimation



$$V_{MN}^* = \frac{I}{2\pi\sigma_1} \left( \frac{\Delta d}{d(d + \Delta d)} + 2 \sum_{n=1}^{\infty} \left( \frac{k^n}{\sqrt{d^2 + (2nh)^2}} - \frac{k^n}{\sqrt{(d + \Delta d)^2 + (2nh)^2}} \right) \right)$$

$$\rho_a(d) = \rho_1 \left[ 1 + 2 \frac{d(d + \Delta d)}{\Delta d} \sum_{n=1}^{\infty} \left( \frac{k^n}{\sqrt{d^2 + (2nh)^2}} - \frac{k^n}{\sqrt{(d + \Delta d)^2 + (2nh)^2}} \right) \right] = \underline{\rho_1(1 + \alpha)}$$

## Algorithm 1 Pool of candidates generation

```

if  $\rho_a(d_1) > \rho_a(d_0)$  then
     $k^* = 1$ 
else
     $k^* = -1$ 
end if
for  $k = 0$  to  $k^*$  do
    for  $\alpha = 0$  to  $2k/(1 - k)$  do
         $\rho_1 = \rho_a(d_0)/(1 - \alpha)$ 
        for  $h = 0$  to  $d_1$  do
            for  $d = d_0$  to  $d_1$  do
                calculate  $\tilde{\rho}_a(d)$  using Eq. (8)
            end for
        end for
    end for
end for

```

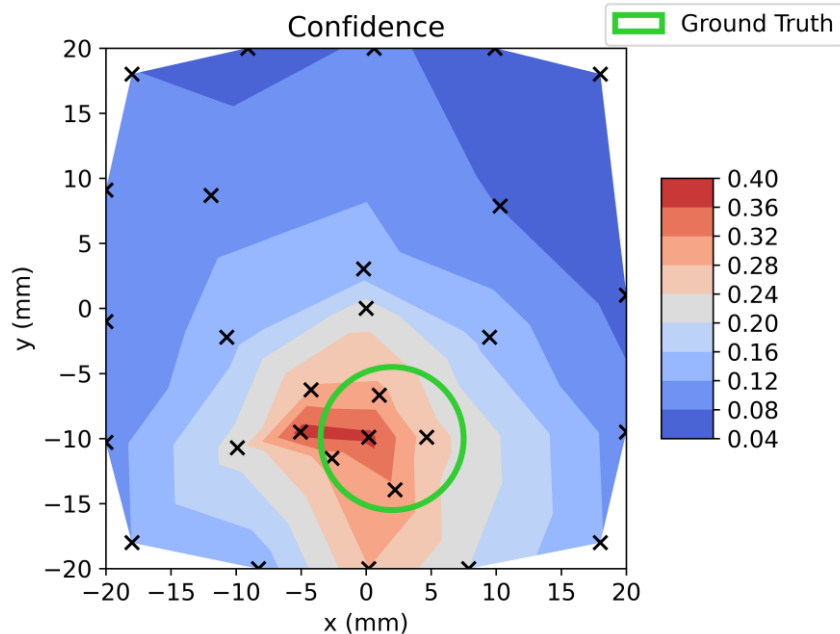
Search algorithm: Nearest Neighbour

## Parameters estimation:

$\rho_1 = 10.99\Omega\text{m}$ ,  $\rho_2 = 3.66\Omega\text{m}$ ,  $h = 6\text{mm}$ .

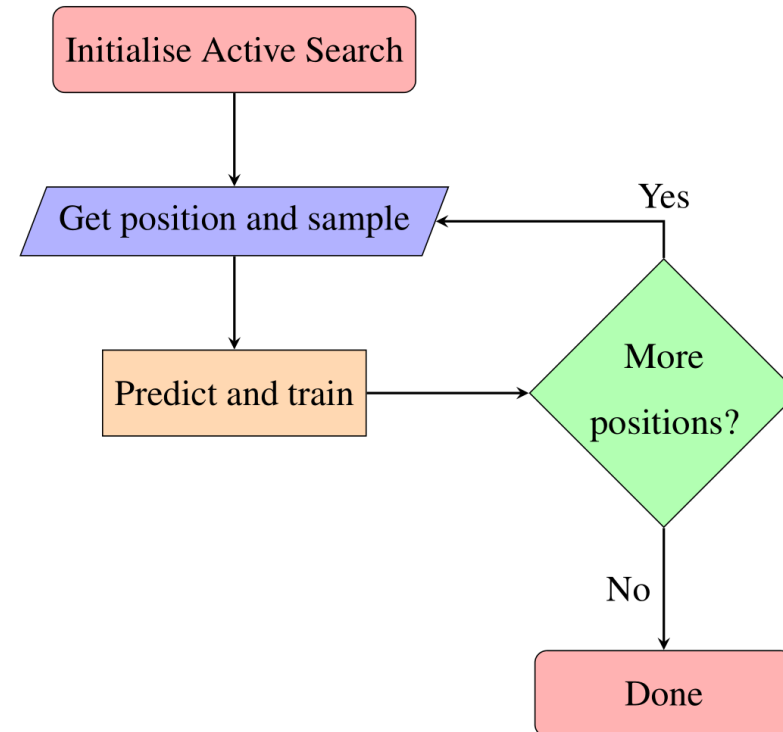
Fitting error Err=0.016  $\Omega\text{m}$ .

The post processing time is 0.13s.  
For each vertex, it takes 8s for VME to scan.  
In total, it takes 16 min to complete the scanning of a 11\*11 grid mesh.



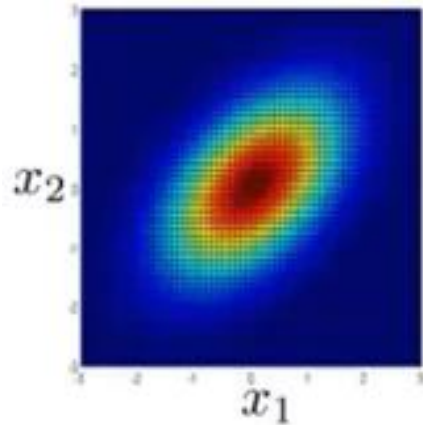
# Active search =

Use **Gaussian Process** to estimate the conductivity distribution;  
Use **Bayesian Optimization** to determine the next sensing point.

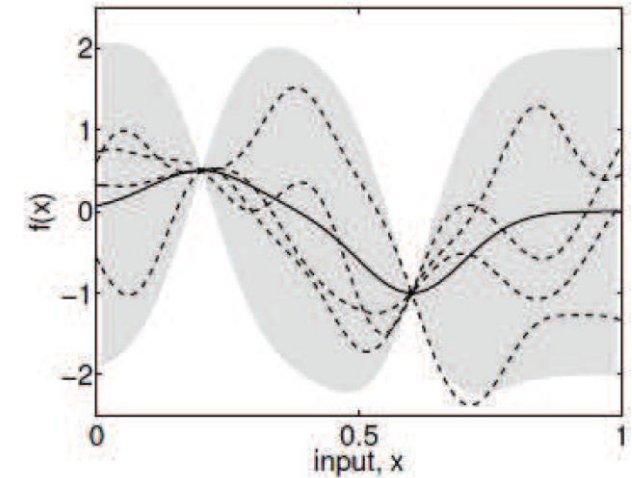
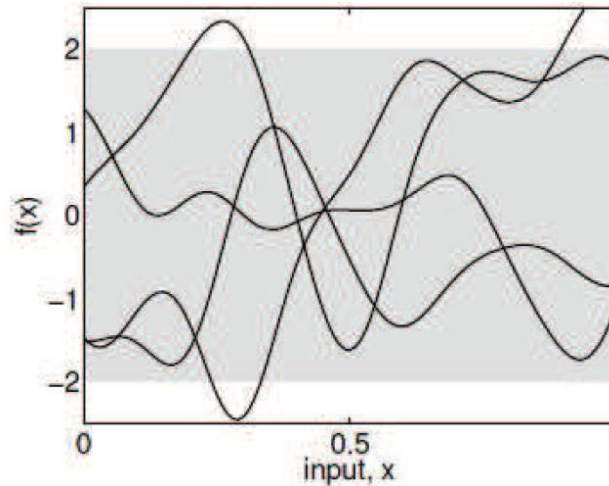


# Gaussian process regression

**Multivariate Gaussian distributions**  
 $N(\mu, \Sigma)$



**Gaussian processes**  
 $GP(\mu(x), K(x, x_*))$



we observe a training set  $\mathcal{D} = \{(\mathbf{x}_i, f_i), i = 1 : N\}$ , where  $f_i = f(\mathbf{x}_i)$

Given a test set  $\mathbf{X}_*$  of size  $N_* \times D$ , we want to predict the function outputs  $\mathbf{f}_*$ .

# A Gaussian Process is a Gaussian distribution over functions:

Assumption:

$$\begin{bmatrix} f \\ f_* \end{bmatrix} \sim N \left( \begin{pmatrix} \mu \\ \mu_* \end{pmatrix}, \begin{bmatrix} K & K_* \\ K_*^T & K_{**} \end{bmatrix} \right)$$

Mean function:  $\mu(x)$

Covariance function:  $K(x, x')$

$$K(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2\ell^2}(x - x')^2\right)$$

$K(x, x')$  is the kernel.

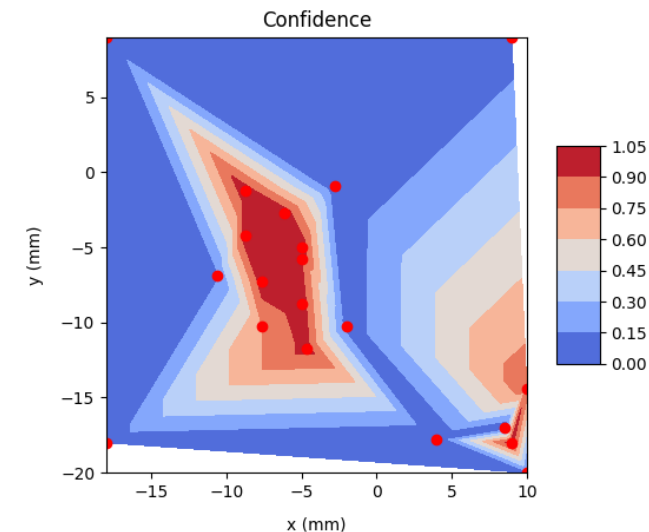
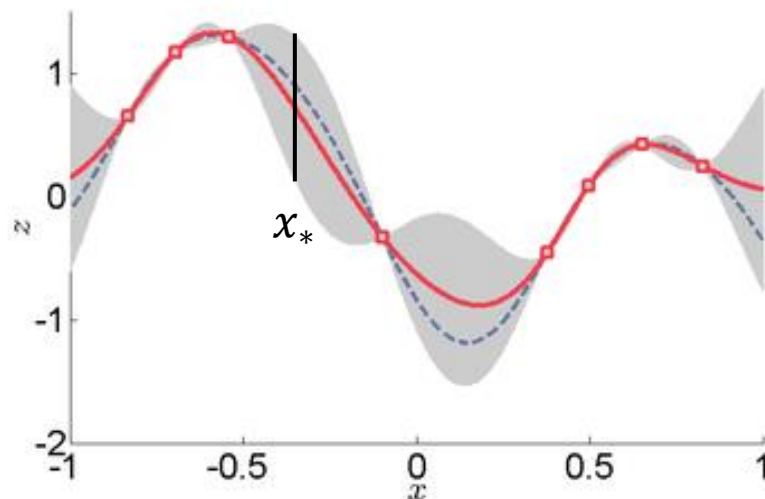
The prediction of sampling location  $x_*$  using GP regression:

$$p(f_* | X, f, X_*) \sim N(f_* | \mu(X_*), \sigma(X_*))$$

where

$$\mu(X_*) = K(X_*, X) [K(X, X) + \sigma_{noise}^2 I]^{-1} f$$

$$\sigma(X_*) = K(X_*, X_*) - K(X_*, X) [K(X, X) + \sigma_{noise}^2 I]^{-1} K(X, X_*)$$



Subsurface object  
existence likelihood:  
 $f(x,y)$



# Bayesian Optimization

Query the next point by an **acquisition function**: trade-off between exploitation  $\mu(x)$  and exploration  $\sigma(x)$ .

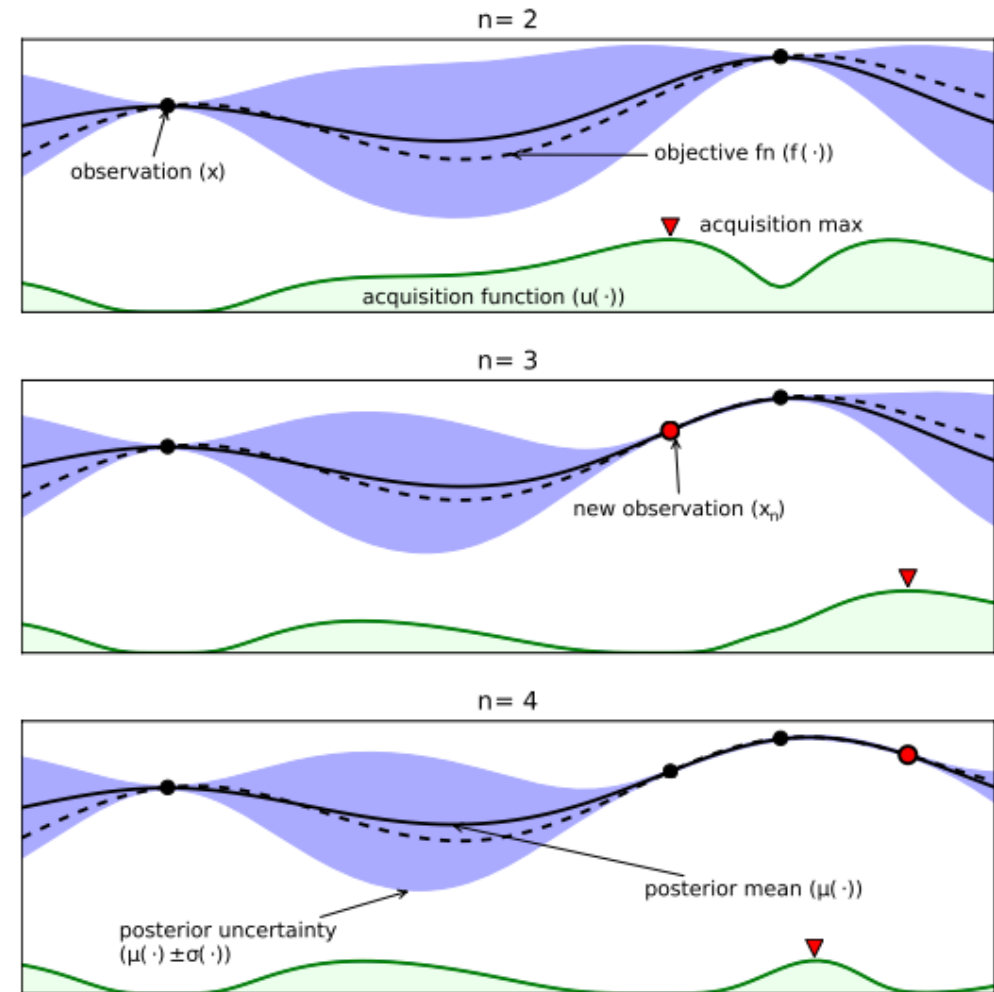
Acquisition function: **Expected Improvement**

$$EI(x) = \begin{cases} (\mu(x) - f(x^+) - \xi)\Phi(Z) + \sigma(x)\varphi(Z), & \text{if } \sigma(x) > 0 \\ 0, & \text{if } \sigma(x) = 0 \end{cases}$$

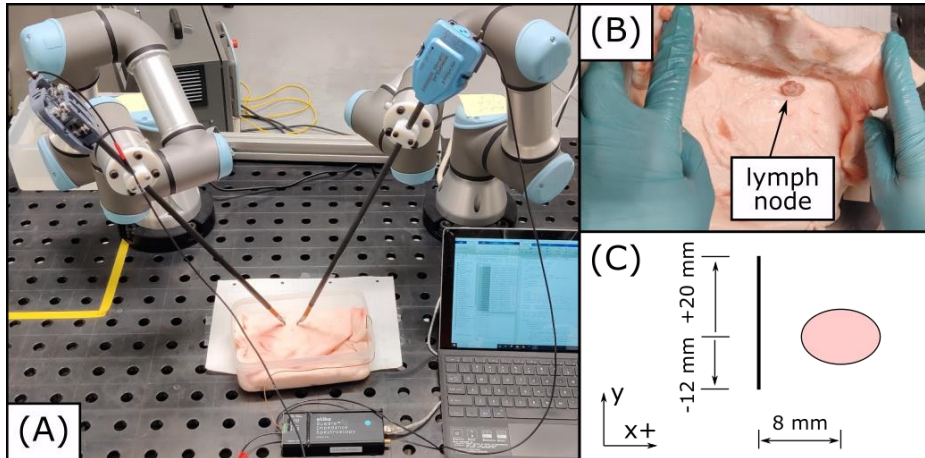
where

$$Z = \begin{cases} \frac{\mu(x) - f(x^+) - \xi}{\sigma(x)}, & \text{if } \sigma(x) > 0 \\ 0, & \text{if } \sigma(x) = 0 \end{cases}$$

- $\Phi(Z)$  and  $\varphi(Z)$  are the cumulative density function and the probability density function respectively.
- $\xi$  is a hyperparameter for tuning exploration and exploitation.



# Active Search in Subsurface lymph node detection



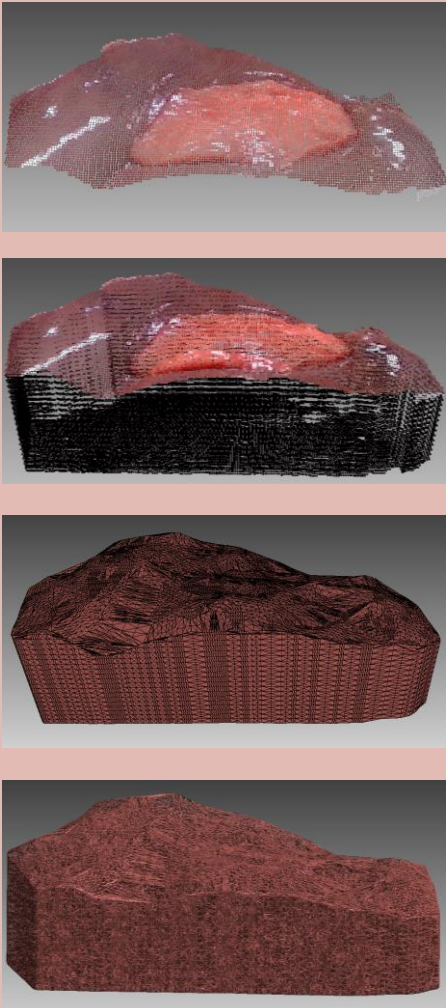
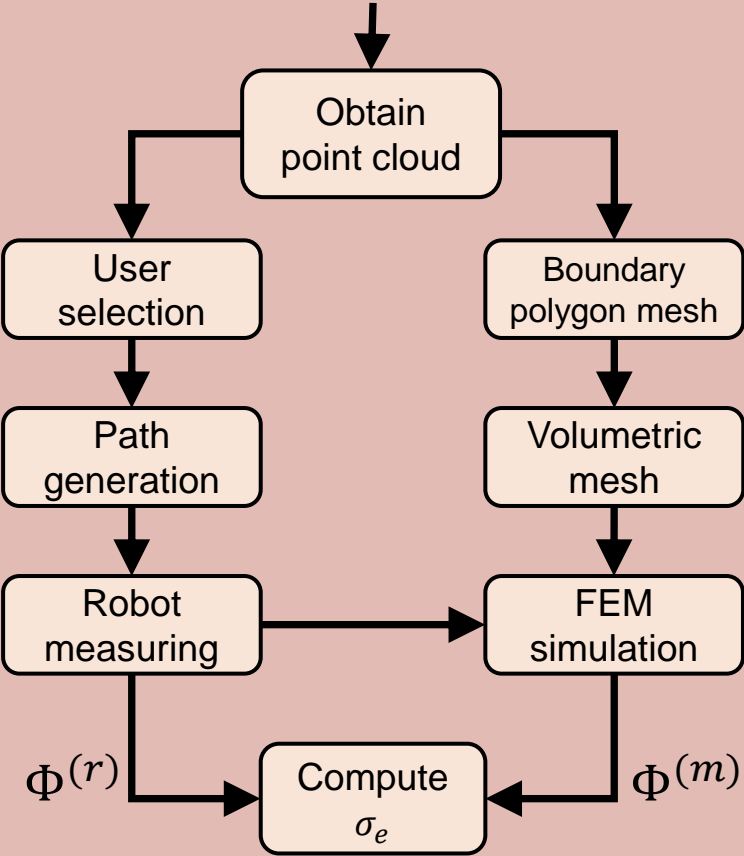
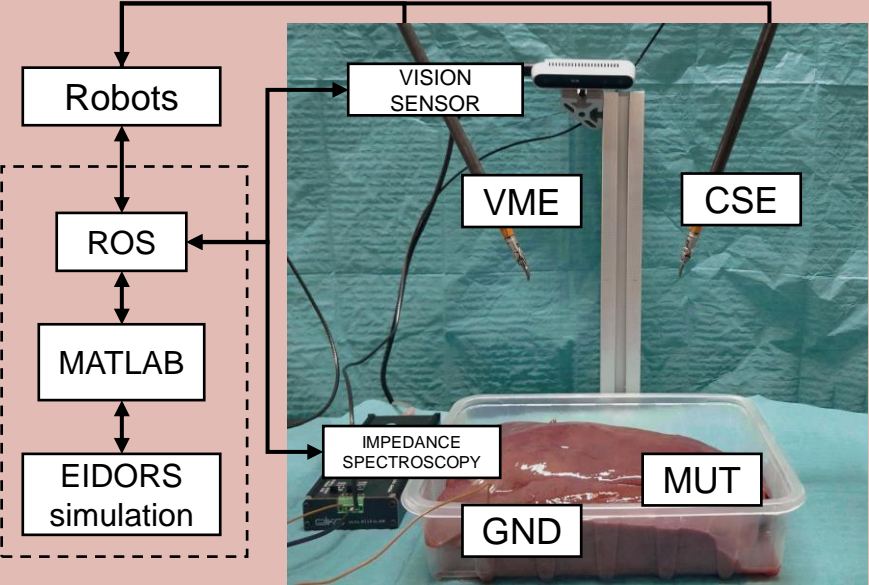
- Compared to the grid scanning, the Active Search method has higher precision, and recall;
- The AS method takes about **4min** to explore the area and localize the lymph node.





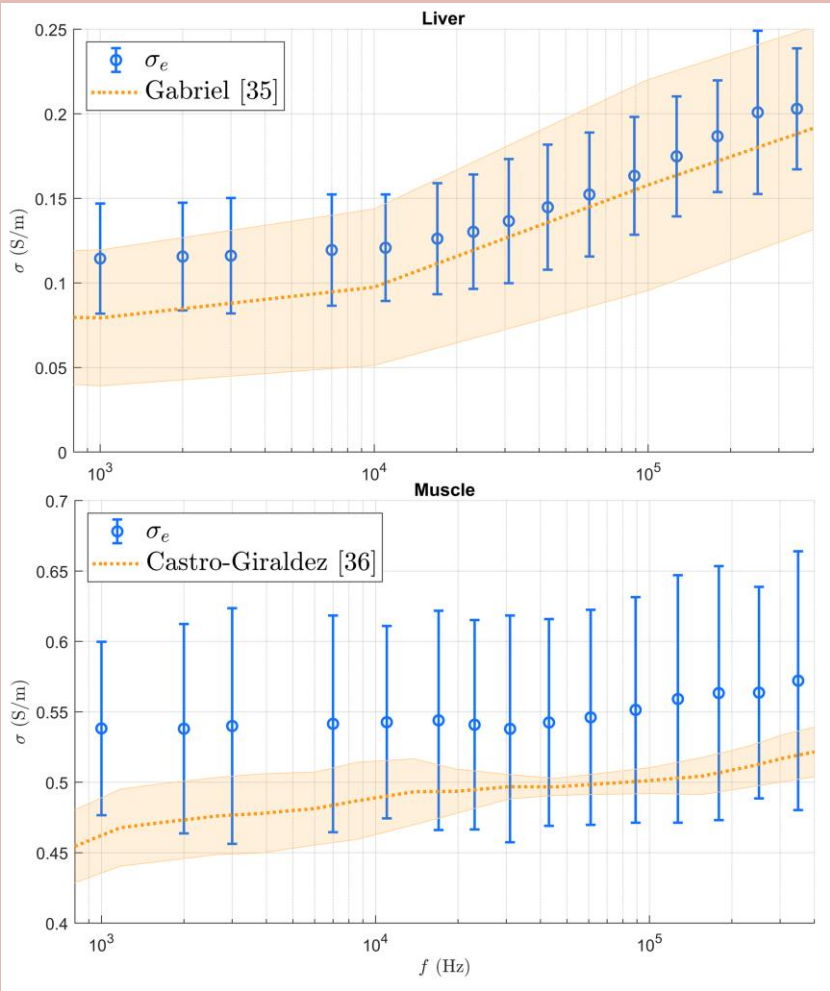
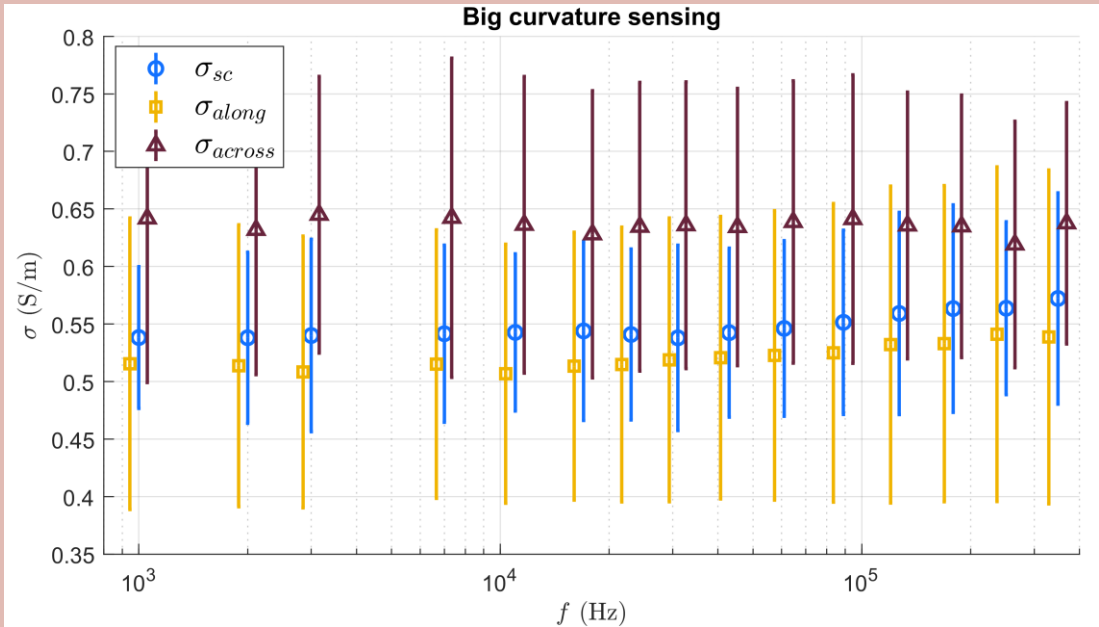
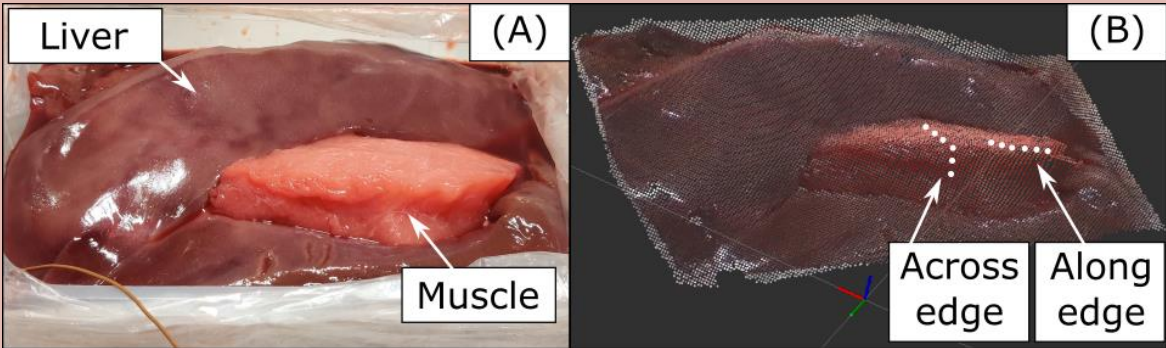
# Sensing on curved tissue surface

#sdudk



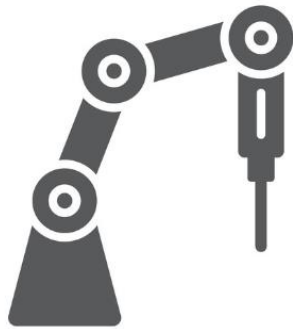
$$\frac{\sigma(r)}{\sigma(m)} = \frac{\Delta\Phi(r)}{\Delta\Phi(m)}$$

# RAEIS sensing on curved tissue surface

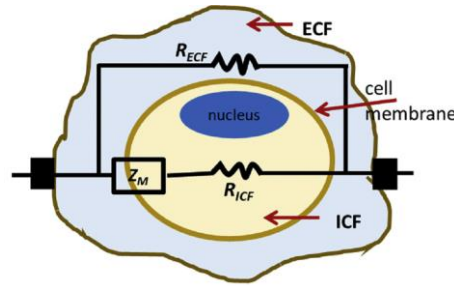
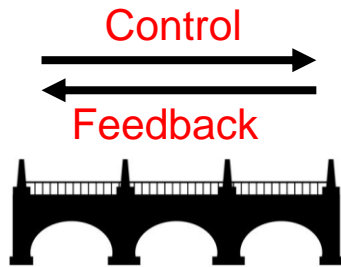


# Summary

## Robot Assisted Electrical Impedance



**Medical Robotics**



**Electrical Bioimpedance**

- Robot can improve the EBI sensing flexibility, efficiency and stability;
- EBI sensing can be an important sensing modality in robotic system for robotic surgery.

Crack detection/ material homogeneity



**Biomimetic robot**

