BACHELOR THESIS

CHARACTERIZING A SPRING-BASED INDUCTANCE SENSOR AND INVESTIGATING EXTERNAL OBJECT INTERFERENCE

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Abstract

Accurately sensing the shape and position of flexible and continuum robots is a significant challenge that hinders their functionality and effectiveness in various applications. This study is focused on characterizing a spring-based inductance sensor and investigating the interference of external objects. Existing sensing solutions face limitations when dealing with high elongation rates that exceed their measurement range. To overcome this limitation, a simplified instrumentation method using a commercially available measurement board and springs was developed. A measuring setup was designed and prototyped, and experiments were conducted to establish a mathematical relation between measured inductance and elongation of the spring. Additionally, the impact of large external objects on the sensor's measurements was investigated. Results showed that metal objects had the largest and most unpredictable impact on the measured inductance, while the impact of plastic and human tissue was stable and can be filtered out with proper calibration. The study contributes to the understanding of accurate sensing in high elongation rate applications and provides insights for advancing sensing capabilities in the field of flexible and continuum robotics. Further research is recommended to explore the effect of movement near the sensor.

Contents

1 Introduction

Flexible and continuum robots have demonstrated significant potential in various fields, including medical, industrial, and space applications, owing to their ability to navigate confined spaces and perform complex tasks. However, accurate shape sensing and positioning of these robots remains a challenge, which limits their functionality and effectiveness [1].

Various sensing solutions, such as resistive, capacitive, and optical sensors, have been developed to address this challenge. Resistive sensors, including strain gauges and piezo-resistive sensors, measure changes in resistance due to deformation and find wide usage in industrial applications [2]. Capacitive sensors, on the other hand, detect deformations by measuring changes in capacitance and offer high accuracy, albeit being sensitive to environmental noise [3], [4], [5]. Optical sensors, such as fiber Bragg grating sensors, utilize light to detect deformations and provide high precision, but they often require complex instrumentation [6], [7], [8], [9].

Despite the benefits offered by these sensing solutions, they encounter difficulties in high elongation rate applications, where the deformation exceeds their measurement range [10], [11]. To overcome this limitation, researchers have explored alternative approaches, such as the utilization of commercial springs and the principle of inductance sensing [12]. Springs, characterized by their high elongation range and low stiffness, serve as deformable structures to measure elongation or bending in robots. Inductance sensing, based on the change in inductance due to deformation, provides high sensitivity and is effective across a wide range of elongation rates [12]. Previous studies have successfully employed custom-made inductive sensors to measure the elongation and bending of soft robots.

However, the practical application of inductance sensing is hindered by the complexity and cost associated with the required instrumentation. In this context, previous research proposed a solution that simplified the instrumentation for inductance sensing by using a peak-to-peak (P-P) voltage measurement, thus addressing the limitations posed by conventional inductance measurement techniques. By optimizing circuit parameters and establishing a single calibration curve for linear actuators and flexible manipulators, the method enhanced measurement performance. The performance of the sensor was investigated in terms of hysteresis, precision, and accuracy, and its effectiveness was demonstrated through two proof-of-concept prototypes [12].

Based on the outcomes of this prior research, this study aims to further evaluate the performance of the spring-based sensor for measuring elongation and investigate the impact of nearby objects, such as large metal, tissue, and plastic materials, on the sensing performance. Specifically, a commercially available measurement board and a set of springs are used to determine the potential effects of these materials, for example electromagnetic interference, on the sensor performance. The evaluation will encompass analyzing precision and accuracy of the setup, followed by an assessment of the influence of nearby objects on these sensing characteristics.

The main objective of this study is to provide insights into the performance of the spring-based sensor for measuring elongation and the influence of external objects on the sensing accuracy. By advancing understanding in these areas, the aim is to enhance the sensing capabilities of flexible and continuum robots, thus expanding their potential applications in real-world scenarios.

2 Methods

The inductance through the spring is measured using a commercially available circuit board (LDC1614EVM) and the accompanying software. In order to hold the spring in place and to be able to move it by an accurately known distance a plexiglass setup was used. The plexiglass parts can be seen figure 1.

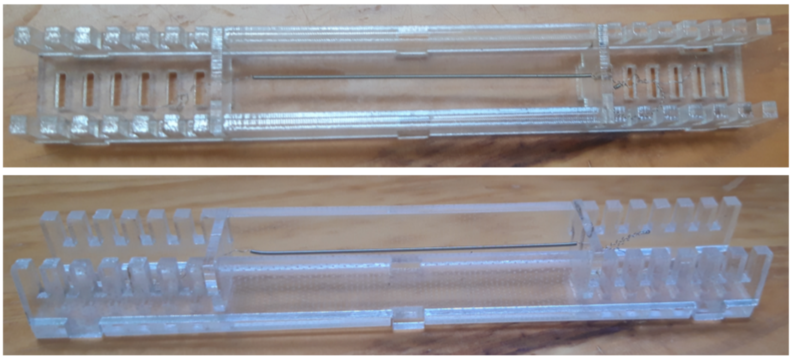

Figure 1: Picture of the holding chamber for a spring during induction measurement

The parts were laser cut and designed to fit with .01 mm precision, however the precision of the laser cutter is only .1 mm. Because of that some parts had more room to move around which lowered the overall precision. The chamber has 14 slots, 7 on both sides, where the spring holders can be placed. When every slot is used a total of 13 different elongations can be used. The spring holders themselves are 2 mm thick.

In order to maximize use of this setup the spring needs an l_0 that is equal to the distance between the inner slots, which is 74.25 mm. This way, when using the entire length of the setup the spring is elongated by about 100%. The distance between the slots is 3.4 mm, this distance was chosen to prevent the chamber from braking while still ensuring there is a high amount of known distances for the measurements. It should be noted that not every spring can be elongated by 100% because plastic deformation can occur before that. The advantages of this chamber are that it has low interference, is easy to use and easy to make, while still providing high precision. It also makes it easy to repeat a set of measurements. The main disadvantages of this setup are that the spring has to be elongated by hand and the spring is only held in place by friction, making it difficult to use at high elongation. The full induction measurement setup can be seen in figure 2. To minimize variability in the interference caused by the setup itself the same wooden table and laptop positioning was used during every measurement.

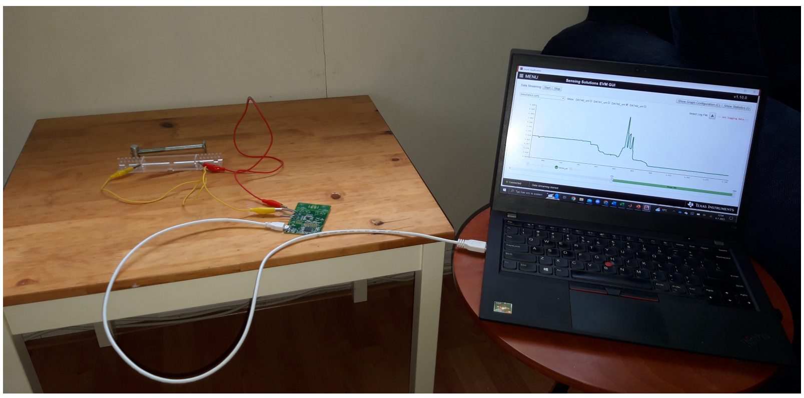

Figure 2: Picture of the full induction measurement setup

2.1 Calibration

The sensor is meant to measure elongation of the spring based on the change in induction through the spring, however in order to do this a relation between elongation and induction has to be determined. By using the experimental setup and having the accurate elongation of the spring, the corresponding induction is measured. This is done 5 times for each position. The average of those five positions is then used to determine a trend line that will be the relation between elongation and induction. In order to be able to compare data between different measurements the data has to be converted to percentages using the following equations:

$$\%dL = \frac{100 \cdot (L - L0)}{L0} \tag{1}$$

Where:
L = Induction in µH (micro Henry)
L0 = Induction at no elongation of the spring
%dL = Change of induction in % compared to induction measured at no elongation of the spring.

A similar equation is used for the elongation of the spring:

$$\%dl = \frac{100 \cdot (l - l0)}{l0} \tag{2}$$

Where:
l = Length of spring in mm (millimeter)
l0 = length at no elongation of the spring
%dl = Change of length in % compared to length measured at no elongation of the spring.

L0 is measured at the beginning of a measurement sequence before elongating the spring. The spring has to be under tension. In the measurement setup l is a set sequence of distances that are 5.4 mm apart starting from l0.

Using the measurement data a second order polynomial curve is fitted to relate the change in length to the change in induction.

2.2 Measuring Interference

In order to measure the effects of nearby objects an object is placed according to figure 3.

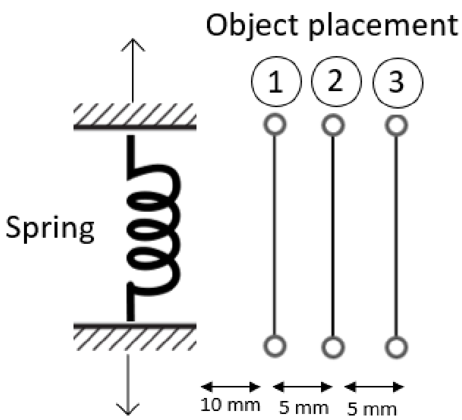

Figure 3: Sketch of the object placement during interference measurement

Where the induction is measured 5 times for a position and the moved to the next position, until all three positions have been measured. Then the spring is elongated by one slot in the chamber and the cycle is repeated. This is done for a metal object, a plastic object and a human hand. A trend line is then found for each of the in total 9 combinations of material and distance to the spring. These trend lines can then be compared to the trend line from the calibration which was done with minimal interference to find the error interference causes in the sensors elongation measurement.

3 Results

3.1 Establishing the relation between Induction and Elongation of a spring

In order to establish the relation between the measured inductance and the elongation of the spring a second order polynomial trend line is fitted through the measured data-points $R^2 = 0.986$, as can be seen in figure 4. The highest measured standard deviation was 0.002 µH (micro Henry). This is the standard deviation for the measured values which are the average of 5 sets of measurements.

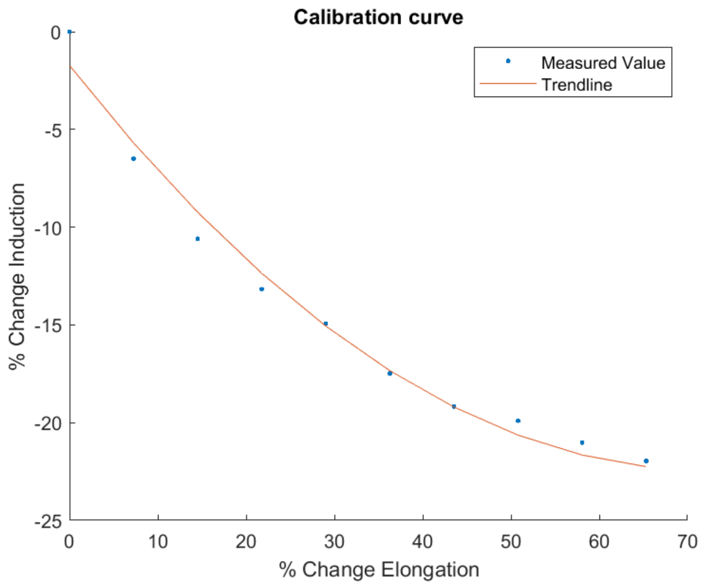

Figure 4: Calibration curve of a spring-based sensor

3.2 Resulting Interference

In figure 5 the established relation from figure 4 is plotted in blue, along with the results from the interference experiment, which were affected by the inference of different objects. Being a metal screw, a solid plastic figure and a human hand with the little finger closest to the spring.

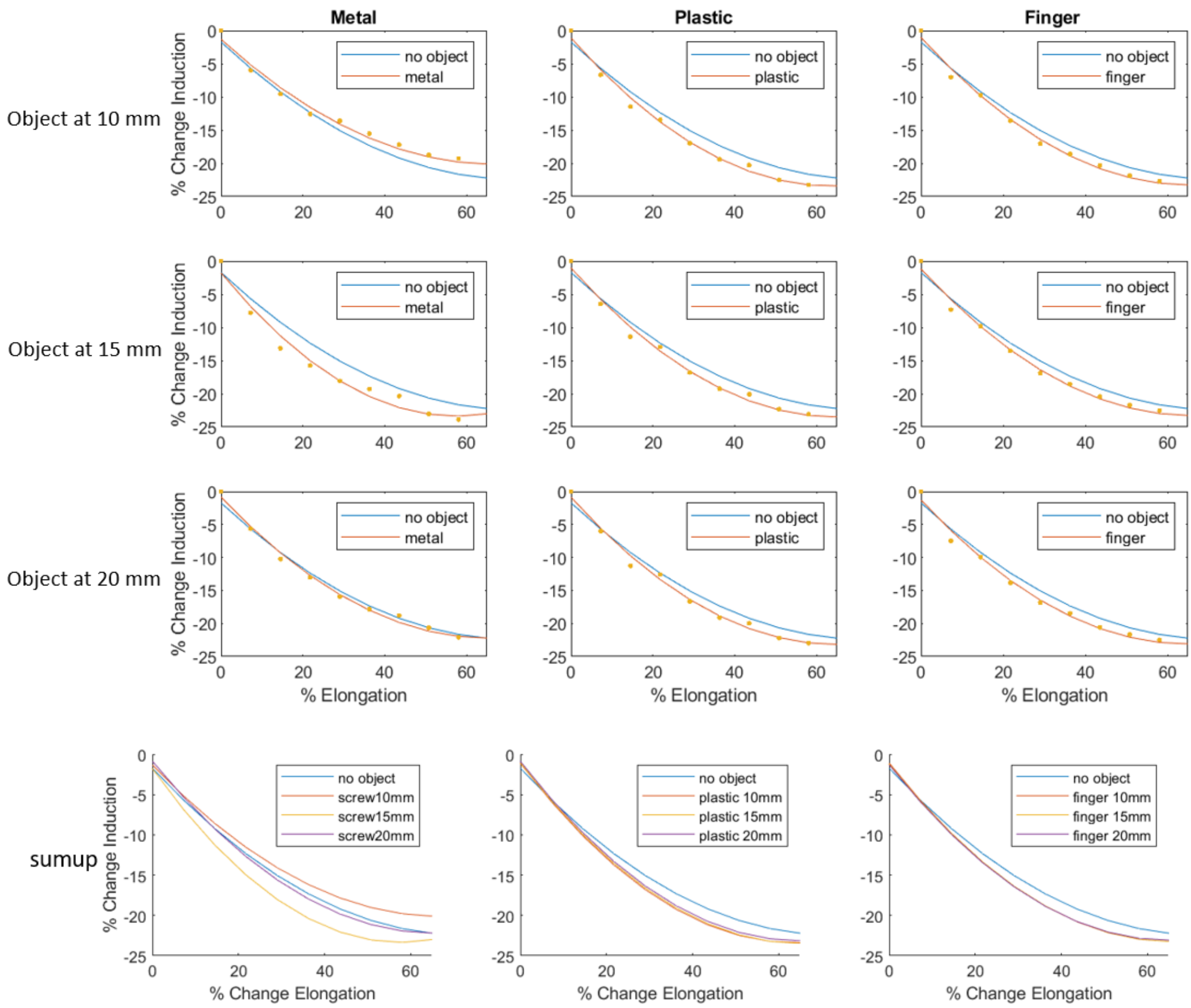

Figure 5: Comparison in measured inductance between metal, plastic and human tissue at 10, 15 and 20 mm from a spring based sensor

Table 1: Resulting average error of the external object impact on the measurement.

Error (% Elongation)	Metal	Plastic	Finger
At 10 mm	-1.410%	+1.845%	+1.393%
At 15 mm	+3.135%	+1.655%	+1.405%
At 20 mm	+0.372%	+1.301%	+1.457%

As can be seen in figure 5 and table 3, first of all the metal screw had the largest impact on the sensor readout with an average error of 3.1% at 15 mm from the spring. The plastic figure had a diminishing impact as it got further away from the sensor. As can be seen from table 1 the average error is decreasing from 1.8% to 1.3% and for the finger/ hand there is a constant effect on the sensor, however it does not decline significantly as the hand/ finger is moved further away from the sensor.

4 Discussion

From the calibration measurement in figure 4, a clear non-linear inverse relation between elongation and induction can be observed, as expected. Using this relation a position sensor can be built combining the measured induction values from multiple spring-based sensors to give a position and shape for a soft robot. This relation will be slightly different for every spring, so a proper calibration should be performed for different springs. Ideally that calibration would be a fully automated version of the current setup. During the calibration and in the real world interference will also affect the inductance.

4.1 Interference

When looking at different materials a clear difference in interference can be observed. The screw is the only object that increased the induction at close proximity, when getting further away it also decreased the most and at the furthest distance it had the most similar curve to no interference of all the objects tested. Based on these results, metal objects will have the largest and most unpredictable impact on the measured inductance and therefore should be avoided when using this spring-based sensor. The impact of human tissue is stable and by performing a proper calibration can be mostly filtered out. What is not shown in the results as it was not part of this research is the effect of movement near the sensor, which was the main reason for using a python script to find the steady moments in the data. From early tests it could be observed that moving a finger near the sensor would change the measured inductance differently from holding the finger in place. This could be the topic of future research. Apart from the interference caused by movement, or sudden introduction of an object, there were also sudden drops in signal while measuring at 0% to 20% elongation. These drops were filtered out by the script, which can be found in the appendix. In the script is a definition for a steady value and whenever a point does not meet that definition it is not used to calculate the average value of the steady value. That made it difficult to get a long streak of steady values, for most measurements a set of at least 50 consecutive steady values is used to calculate the average, however because of these drops in signal for some measurements only 30 consecutive steady points were in the measurement. The drops may have been caused by a loose connection in the setup, though after changing out all cables except for the spring the drops remained.

4.2 Measuring

If an improved version of the measurement setup is ever used for further research or calibration a few things should be noted. During the experimental phase the plexiglass chamber started to wear out as the number of experiments became higher. Because of that, measurements at high elongation rates become difficult because the spring slips out of the slit. That is the main reason for only elongating the spring by 65%. During initial measurements the spring could be elongated by 80%. However in order to compare data between measurements only the measured inductance up to 65% elongation was used to determine the trend line. There are ways in which this issue can be dealt with better, for example by replacing the slits after each set of measurements, as long as it is made out of the same material this should not cause a difference in interference. A redesign of the chamber with a better holding mechanism is also an option. Because of this issue the l_0 of the spring was decreased by three windings in length during the last measurements in order to better connect it to the crocodile clamps.

5 Conclusion

During this study a simplified instrumentation method was developed. Furthermore, through the experiments the effects of interference caused by objects made of various materials were quantified. Showing that metal objects have an unpredictable impact on the sensor and should be avoided, while plastic objects and human tissue both had predictable impacts. The outcomes of this research will provide valuable insights for the advancement of sensing capabilities in the field of flexible and continuum robotics.

6 Appendices

```python
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

# Load the data from the CSV file
df = pd.read_csv('...\data_interferencev2_meting_805.csv') # Specify the path and filename

# Extract the columns we want to plot
data0 = df['DATA0_uH']
data1 = df['DATA1_uH']
data2 = df['DATA2_uH']
data3 = df['DATA3_uH']
print(data2)

# Create a time array based on the index of the DataFrame
time = df.index.values

# Plot the data, the sensor is connected to channel 2
#plt.plot(time, data0, label='DATA0_uH')
#plt.plot(time, data1, label='DATA1_uH')
plt.plot(time, data2, label='DATA2_uH')
#plt.plot(time, data3, label='DATA3_uH')

# Set the plot title and labels
plt.title('Effect of moving finger near sensor')
plt.xlabel('Time (ms)')
plt.ylabel('Inductance (uH)')
plt.legend()
plt.show()

# Define parameters for finding a steady moment in the data
threshold = 0.0003  # Define the threshold for insignificant change
window_size = 20  # Number of consecutive points to consider
data=data2 # Again, the sensor is connected to channel 2

# Calculate the differences between consecutive data points
differences = [abs(data[i] - data[i-1]) for i in range(1, len(data))]

# Identify the moments where the change is below the threshold
stable_moments = []
for i, diff in enumerate(differences):
    if diff <= threshold and all(d <= threshold for d in differences[i+1:i+window_size+1]) and all(d <= threshold for d in differences[i-window_size:i]):
        stable_moments.append(i+1)

```

```python
# Group together consecutive stable points
stable_groups = []
group = [stable_moments[0]]
for i in range(1, len(stable_moments)):
    if stable_moments[i] == group[-1] + 1:
        group.append(stable_moments[i])
    else:
        stable_groups.append(group)
        group = [stable_moments[i]]
stable_groups.append(group)

# Calculate the average values of the stable groups
unfiltered_average_values = [sum(data[i] for i in group) / len(group) for group in stable_groups]

# Specify the indices of the average values to exclude
exclude_indices = [] # The program sometimes picks up points in the beginning of a measurement that should not be considered when calculating the average

# Exclude the specific average values from the set
average_values = [avg_value for i, avg_value in enumerate(unfiltered_average_values) if i not in exclude_indices]

#print("Moments of insignificant change:", stable_moments)
plt.plot(range(len(data)), data, label='All Data')
plt.scatter(stable_moments, [data[i] for i in stable_moments], color='red', label='Stable Moments')
plt.xlabel('Index')
plt.ylabel('Value')
plt.legend()
plt.show()

# Plot the average values
x = np.arange(len(average_values))
plt.scatter(x, average_values, color='blue', label='Average Values')
plt.xlabel('Group Index')
plt.ylabel('Value')
plt.title('Plotting of Average Values')
plt.legend()
plt.show()

print(average_values)
# Using all three plots the user of the script has to determine which one of the found average values actually represents a steady point in the measurement,
# usually all of the found average values are very close and the last value in the set of average values is used
```

References

[1] Katzschmann RK, Santina CD, Toshimitsu Y, Bicchi A, Rus D. Dynamic Motion Control of Multi-Segment Soft Robots Using Piecewise Constant Curvature Matched with an Augmented Rigid Body Model. 2019 2nd IEEE International Conference on Soft Robotics (RoboSoft). 2019 4:454-61.

[2] Tang X, Li K, Liu Y, Zhao J. Coiled Conductive Polymer Fiber Used in Soft Manipulator as Sensor. IEEE Sensors Journal. 2018 8;18:6123-9.

[3] Nakamoto H, Oida S, Ootaka H, Tada M, Hirata I, Kobayashi F, et al. Application of stretchable strain sensor for pneumatic artificial muscle. 2014 IEEE Symposium on Robotic Intelligence in Informationally Structured Space (RiiSS). 2014 12:1-5.

[4] Yuen MC, Tonoyan H, White EL, Telleria M, Kramer RK. Fabric sensory sleeves for soft robot state estimation. 2017 IEEE International Conference on Robotics and Automation (ICRA). 2017 5:5511-8.

[5] Yuen MC, Kramer-Bottiglio R, Paik J. Strain sensor-embedded soft pneumatic actuators for extension and bending feedback. 2018 IEEE International Conference on Soft Robotics (RoboSoft). 2018 4:202-7.

[6] Zhuang W, Sun G, Li H, Lou X, Dong M, Zhu L. FBG based shape sensing of a silicone octopus tentacle model for soft robotics. Optik. 2018 7;165:7-15.

[7] Wei J, Wang S, Li J, Zuo S. Novel Integrated Helical Design of Single Optic Fiber for Shape Sensing of Flexible Robot. IEEE Sensors Journal. 2017 10;17:6627-36.

[8] Sefati S, Hegeman R, Alambeigi F, Iordachita I, Armand M. FBG-Based Position Estimation of Highly Deformable Continuum Manipulators: Model-Dependent vs. Data-Driven Approaches. 2019 International Symposium on Medical Robotics (ISMR). 2019 4:1-6.

[9] He Y, Zhang X, Zhu L, Sun G, Lou X, Dong M. Optical Fiber Sensor Performance Evaluation in Soft Polyimide Film with Different Thickness Ratios. Sensors. 2019 2;19:790.

[10] Kim JM, Kim CM, Choi SY, Lee BY. Enhanced Strain Measurement Range of an FBG Sensor Embedded in Seven-Wire Steel Strands. Sensors. 2017 7;17:1654.

[11] Liu R, Wang S, Yang H, Shi C. Highly Stretchable Strain Sensor With Spiral Fiber for Curvature Sensing of a Soft Pneumatic Gripper. IEEE Sensors Journal. 2021 11;21:23880-8.

[12] Sahu SK, Tamadon I, Rosa B, Renaud P, Menciassi A. A Spring-Based Inductive Sensor for Soft and Flexible Robots. IEEE Sensors Journal. 2022;22(20):19931-40.