Functionalizing Soft Sensors for Collection of Biometric Data in Motor Neurone Disease

INSIGNEO
Institute for *in silico* Medicine

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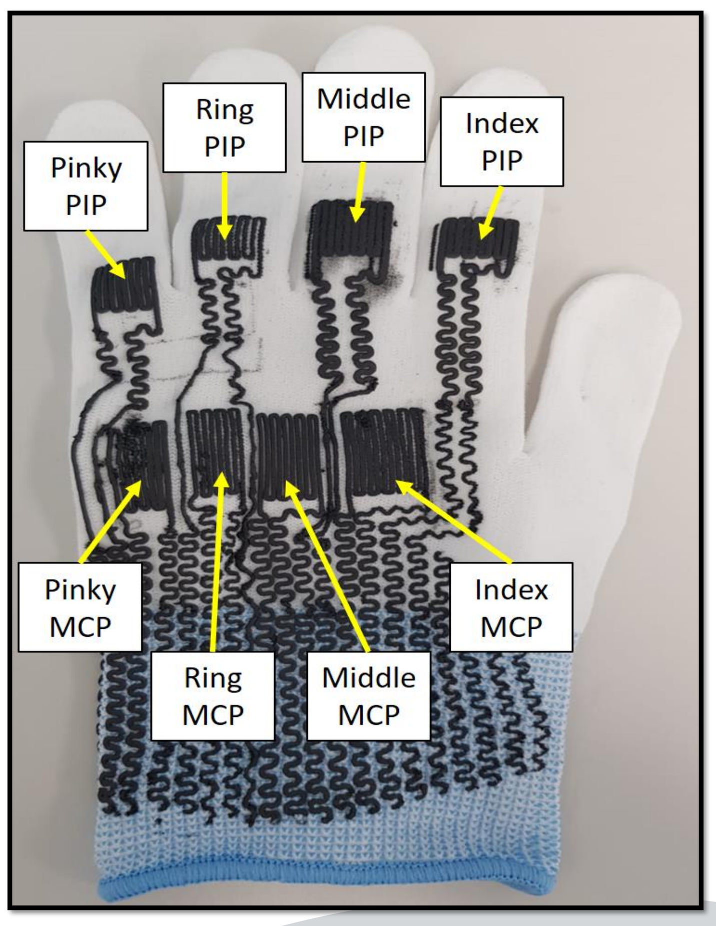
Project took place at Kroto building (Minev lab).



Background

Motor neuron disease or MND is a progressive neurodegenerative disease that destroy motor neurons causing weakness and limiting movement. Some of the first noticeable symptoms are in the hands [1]. Currently, there are no diagnostic test for MND, mainly due to the lack of biomarkers [2].

However, measuring factors such as muscle strength and quality, range of movement and volume of atrophied muscle in the hand can bring out biomarkers for MND diagnosis and monitoring.

The aim of this project was to develop a glove fitted with 3D printed bioelectronic sensors for measuring these simultaneously. Data from the glove and simultaneous readings from motion capture were used to build a model. This model was then used to develop a machine learning algorithm to estimate the geometry and motion of the hand using only the sensors on the glove.

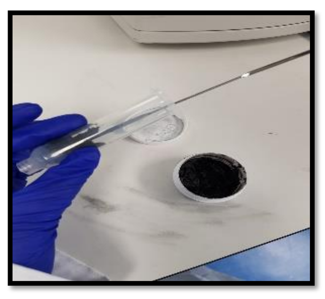
3D printed stretchable electronics do not limit hand movement or suffer from high mechanical stimuli unlike rigid electronics. The stretchable textile (cotton) gloves used also provide the added benefit of flexibility and comfort. For this project I have used my left hand.

Methods

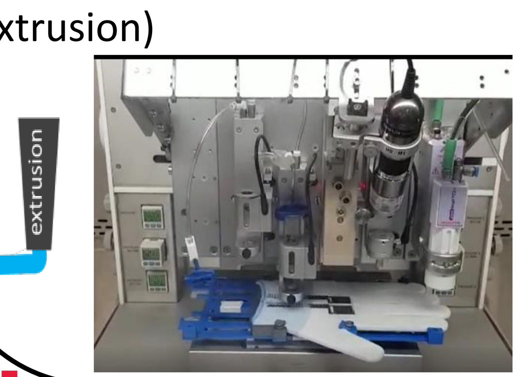
1. The sensor glove was first developed

a. *Material preparation*

- 45% graphite + 55% PDMS (total weight 5g)
- 10 minutes in centrifuge at 2000 rpm then mixed by hand before putting it back to centrifuge for another 10 minutes
- Material filled in a cartilage for 3D printing



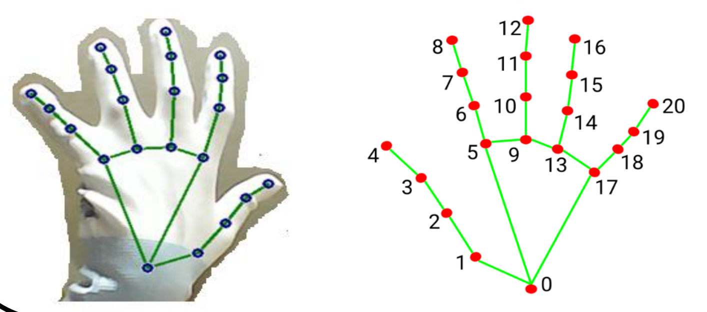
b. *3D printing strain sensors on the glove* (Method used: extrusion)



c. The glove was then placed in an *oven for curing at 60 degrees for 5 hrs*

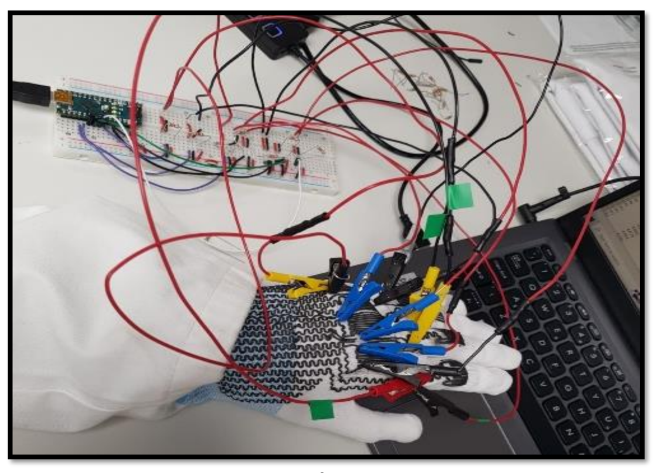
2. Video recordings were processed to obtain hand geometry data

Python's MediaPipe Hands [3] was used to capture hand coordinates using a webcam

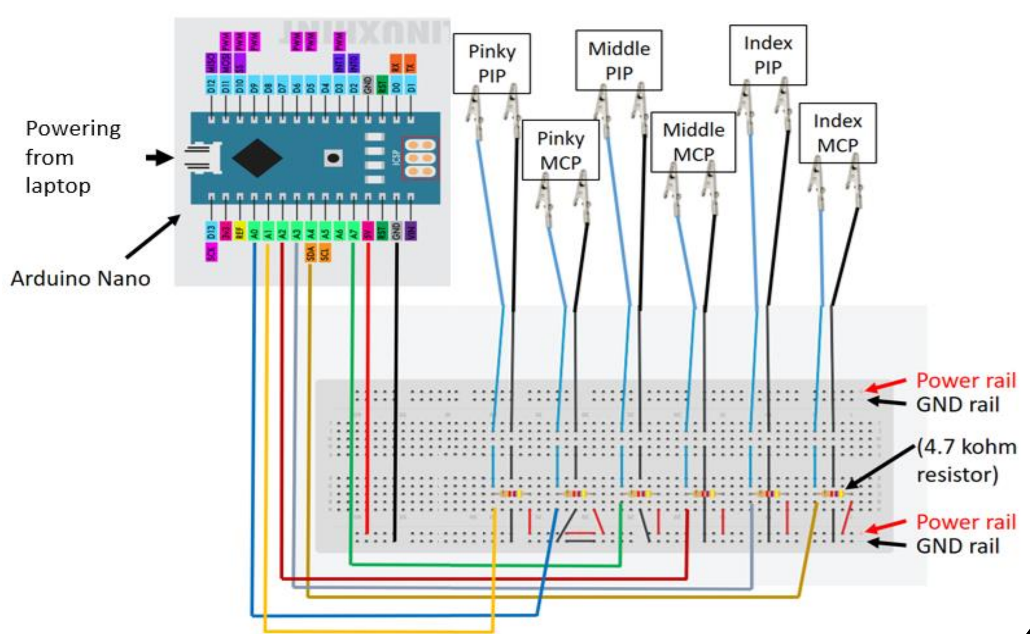


3. Simultaneous readings from strain sensors using Arduino Nano and motion capture of hand coordinates using Python were recorded

A total of 5 gesture types were recorded: (1) fist, (2) half fist, (3) one, (4) two and (5) palm. For each gesture type, 5 repeats were taken



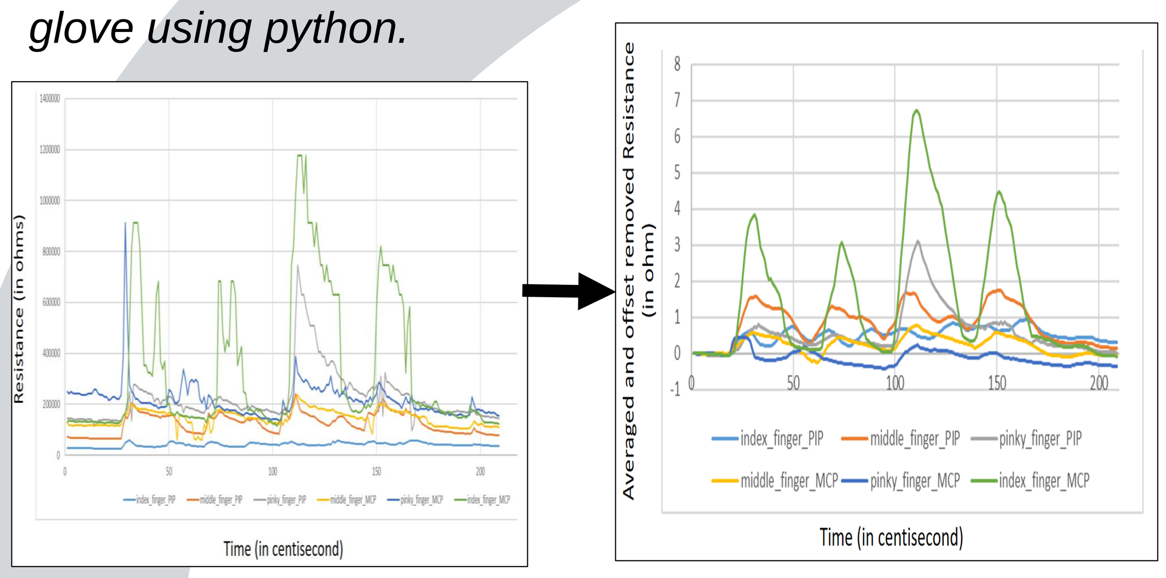
Sensor glove setup



Circuit Diagram of sensor glove

4. Pre-processing data

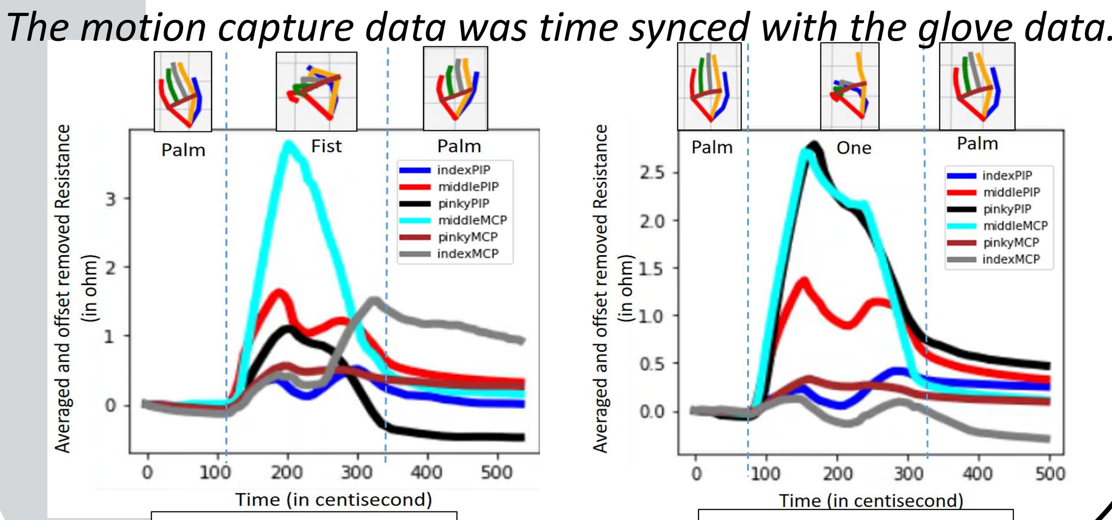
a. *The wrist coordinates of the hand were fixed to the origin and signal processing techniques (moving average of 10 samples and offset removal) were used to pre-process the resistance readings from the sensor glove using python.*



Glove sensor readings before pre-processing

Glove sensor readings after pre-processing

b. *The motion capture data was time synced with the glove data.*



'Fist' gesture once

'One' gesture once

5. Regression and Classification using Machine Learning

a. The motion capture and sensor glove data after pre-processing were then used to train and test a linear regression model using python. This model was then used to take glove readings as input and estimate the hand geometry as output.

b. Also, logistic regression was used for classification to predict the gesture types.

c. The code had the option of adding gesture labels (G) or no gesture labels (NG) to the data and the dataset was shuffled. Then 70% of the dataset was used for training and 30% for testing.

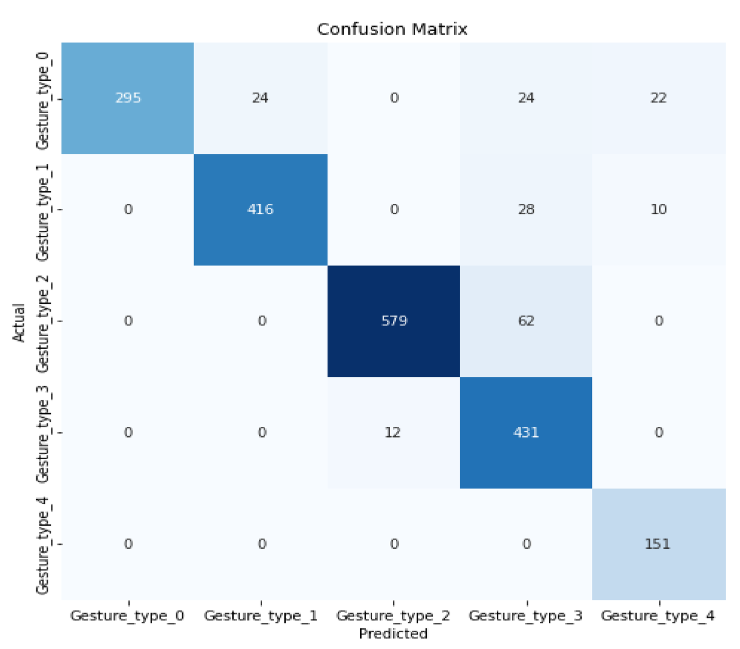
6. Statistical Analysis

Finally a statistical test was carried out to test the accuracy of these models. The results have been outlined in the 'Results' section.

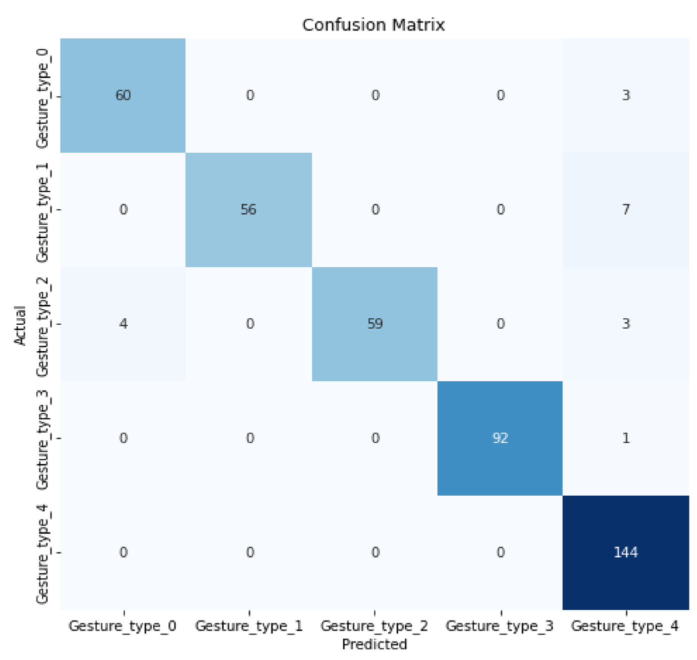
Results

Test 1 and Test 2 are two different sets of data that were used to build four models (two for classification and two for linear regression). Test 1 contains the data for the gestures being carried out but with some delay before actually making those gestures. Test 2 contains data without any of this delay. R squared test was used to measure the accuracy of model to 3 decimal places.

Test number	With Gesture Labels: G, Without Gesture Labels: NG	R squared test for Classification model	R squared test for Linear Regression model
Test 1	NG	91.139%	24.198%
	G	NA	54.067%
Test 2	NG	95.804%	55.749%
	G	NA	79.068%

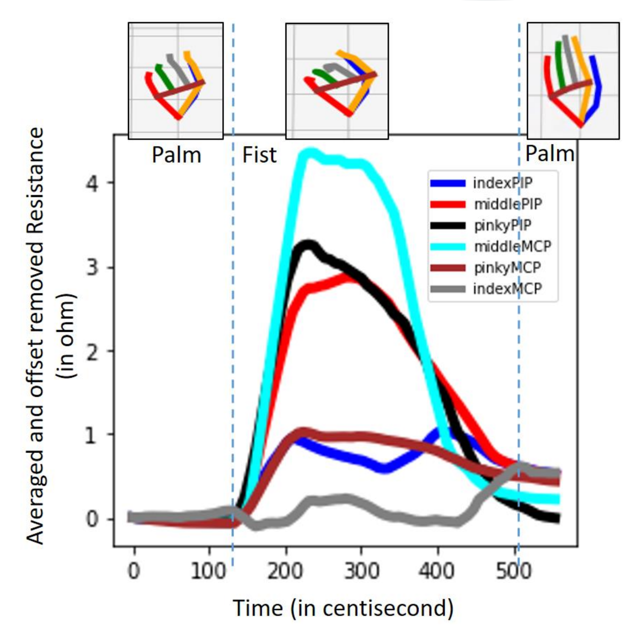


Test 1



Test 2

Confusion matric from classification model where the y-axis shows the actual gesture types and x-axis shows the predicted gesture types. The classification models are good because our predicted and actual gesture types match in most cases (the diagonal).



Hand coordinates prediction using Test 2 (with Gesture labels) Linear regression model. The input here was a fist gesture carried out once and the model was able to predict a fist most of the time.

Conclusions

Thus, our models predicted the hand coordinates and gesture types correctly most of the time for test 2 than test 1. This was because in test 1 all the delays contained palm gesture for few seconds before making eg. a fist that might have confused the model. In test 2 there was no delay, meaning for eg. for fist gesture the hand went quickly from palm to fist and back to palm. However, it was not able to detect precise changes in hand movement. Model accuracy and precise hand coordinate predictions can be achieved by taking more repeats of gestures and from multiple users. Also, improvements in sensor material and type can lead to better results in terms of prediction. Incorporating pressure sensors and electrodes can further assist in precise predictions.

References

[1] Healthtalk, "Motor Neurone Disease (MND)." healthtalk. https://healthtalk.org/motor-neurone-disease-mnd/first-symptoms-of-mnd#:~:text=Symptoms%20in%20arms%20and%20hands,can%20be%20uncomfortable%20at%20times) (Accessed: Sept. 21, 2022).
[2] M. R. Turner, et al., "Mechanisms, models and biomarkers in amyotrophic lateral sclerosis," *ALS and Frontotemporal Degeneration*, vol. 14, no. suppl 1, pp. 19-32, May. 2013. [Online]. Available: https://doi.org/10.3109/21678421.2013.778554
[3] GOOGLE LLC, "MediaPipe Hands." mediapipe. https://google.github.io/mediapipe/solutions/hands.html (Accessed: Sept. 25, 2022).

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