CNN-Driven Hand Prosthetic for Neurorehabilitation

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Objective

- Offline: Train Convolutional Neural Networks (CNN) model to classify recordings of high-density surface electromyography (HD-sEMG) feature maps for 8 hand gestures with at least 80% accuracy
- Online: Implement CNN model to operate robotic hand with live HD-sEMG data for 8 hand gesture with 70% accuracy

Background

- Due to interruption of blood supply in the brain,795,000 individuals suffer from strokes each year in the US, leading to long-term disability effect including lack of voluntary control of muscles.
- 9 stroke patients participated in a neural rehabilitation program; 78% were able to demonstrate gain in motor control when training with myoelectric prosthesis every week for 60 – 90 minutes per session.

Methods

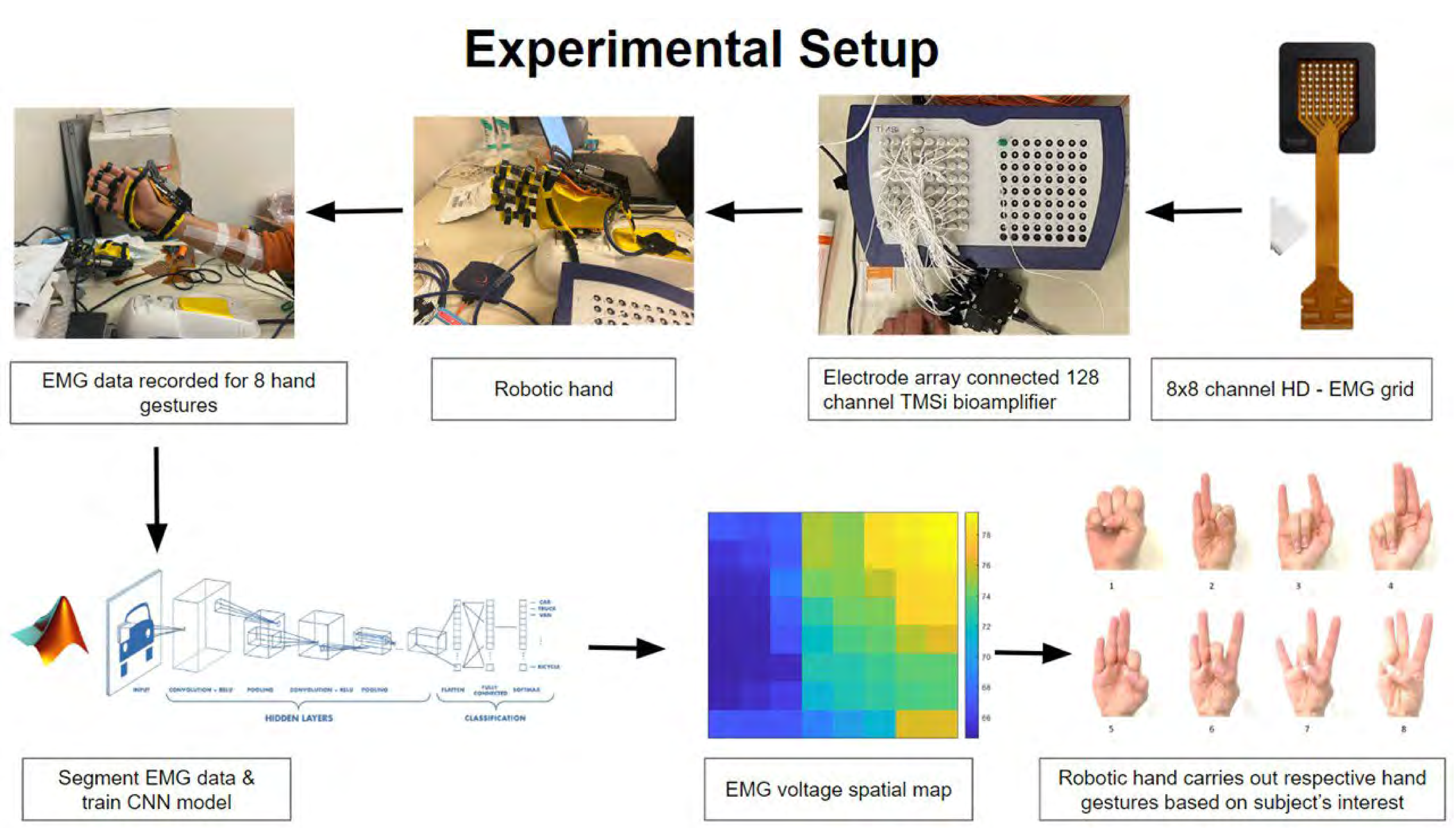

Figure 1. Experimental setup. An 8x8 HD-EMG grid was attached to the subject's right forearm and connected to a TMSi-REFA bioamplifier connected to a PC via USB. The subject performed 8 hand gestures, and the recorded data was stored in the PC and pre-processed in MATLAB.

Offline Stage

- The subject's hand was placed in the exoskeleton, as shown in figure 1. The subject was asked to perform 8 hand gestures 10 times each for 1 second, followed by a 3 second rest.
- Inner forearm muscle activity was collected using an 8x8 HD-sEMG grid and segmented to produce 8x8 voltage distribution maps, as shown in figure 2. Grayscale feature maps served as input to the CNN.

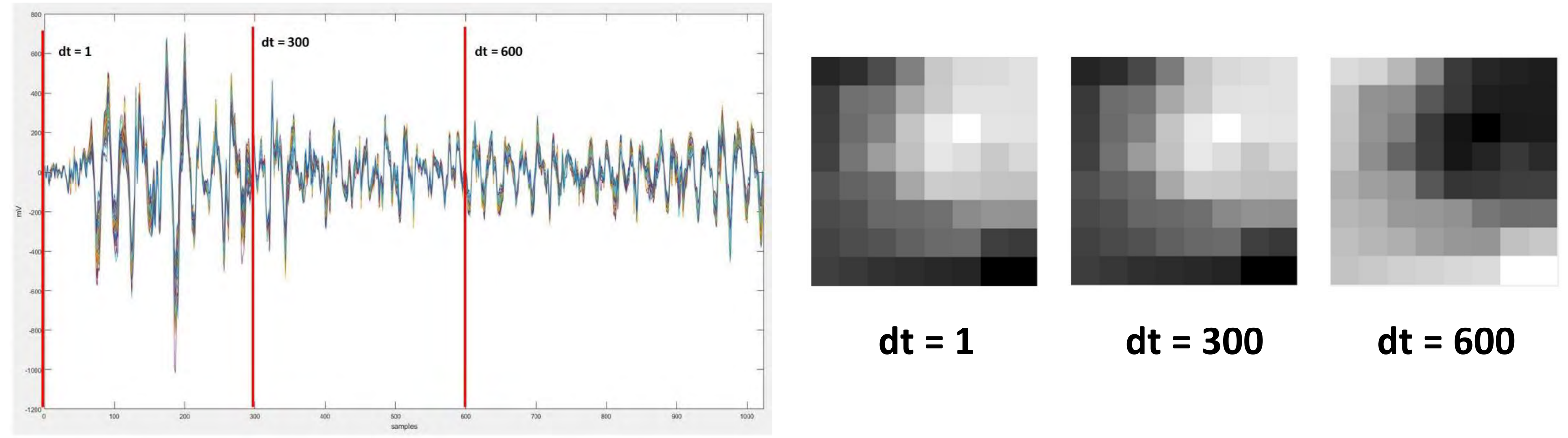

Figure 2. Instantaneous values of HD-sEMG signals arranged in 8x8 voltage distribution maps translated to color intensity with pixel values [0,1]

- Images produced from HD-sEMG data were used to train a CNN model. Half of all trials were used for training and the other half were used to test the model.

Online Stage

- Used MATLAB to connect to prosthetic hand and create computer-robotic hand interface. Load in CNN model to receive real time EMG data
- Filter and preprocess real time data to detect movement vs no movement based on amplitude root mean square (RMS)
- Feed real time EMG data into CNN model to classify hand gestures
- Use CNN predicted labels to give gesture specific commands to move prosthetic hand by sending 8 bytes of information to move motors for assisted hand movements
- Once prosthetic hand has completed gesture, commands were sent to return hand back to relaxed position

Results

Offline Stage

- Figure 3 displays the results for the trained CNN model. Row elements correspond to true labels for each gesture, while columns show the labels predicted by the CNN model. Correctly classified gesture are found along the diagonal.
- The validation accuracy for model was 98.3±0.02%, showing high accuracy distinction between gestures from HD-sEMG recording

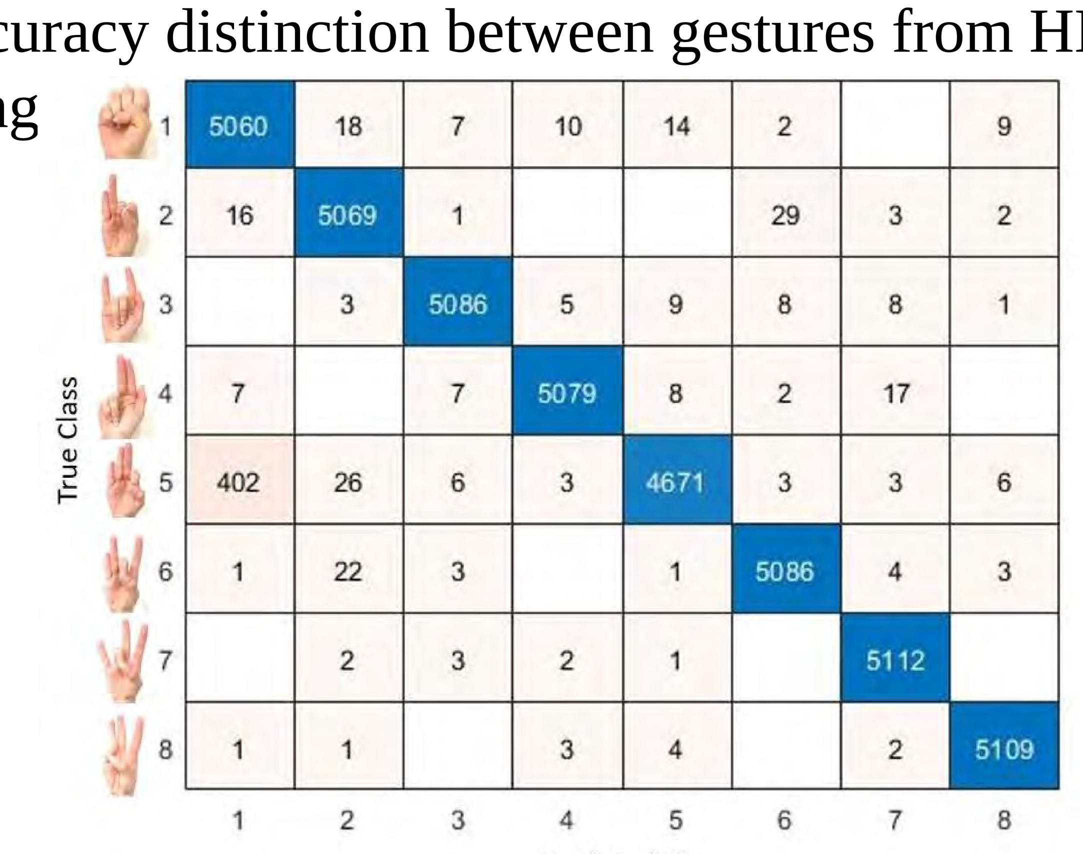

Figure 3. Confusion matrix showing the results for the trained CNN model with a 98.3 ± 0.02% validation accuracy.

Online Stage

- While recording real time EMG signals, subject was instructed to produce all 8 hand gestures 5 times. The hand gesture produced by the robotic hand was recorded to evaluate online performance. The validation accuracy based on these trials was found to be 87.5%.
- Table 1 shows the gesture produced by robotic hand for each trial as well as confidence level.
- Figure 5 shows correct classification and misclassification from the online results as confusion matrix

TRUE LABEL	GESTURE PRODUCED				
	Trial #1	Trial #2	Trial #3	Trial #4	Trial #5
1	**1**	**1**	**1**	**1**	**1**
	0.98	0.98	1.00	0.97	0.98
2	**2**	**2**	**2**	**2**	**2**
	0.98	0.96	0.95	0.99	0.94
3	**3**	**3**	**3**	**3**	**3**
	0.96	1.00	0.97	1.00	0.99
4	**7**	**7**	**4**	**7**	**7**
	1.00	0.54	0.51	0.96	0.49
5	**5**	**5**	**5**	**5**	**5**
	0.89	0.97	0.96	0.84	0.53
6	**6**	**2**	**6**	**6**	**6**
	0.96	0.94	0.54	0.51	1.00
7	**7**	**7**	**7**	**7**	**7**
	0.95	0.95	0.99	1.00	0.99
8	**8**	**8**	**8**	**8**	**8**
	0.99	0.98	0.99	0.99	0.99

Table 1. Online performance evaluation for each gesture done for 5 trials. Decimal values below gestures produce show the confidence value for CNN prediction

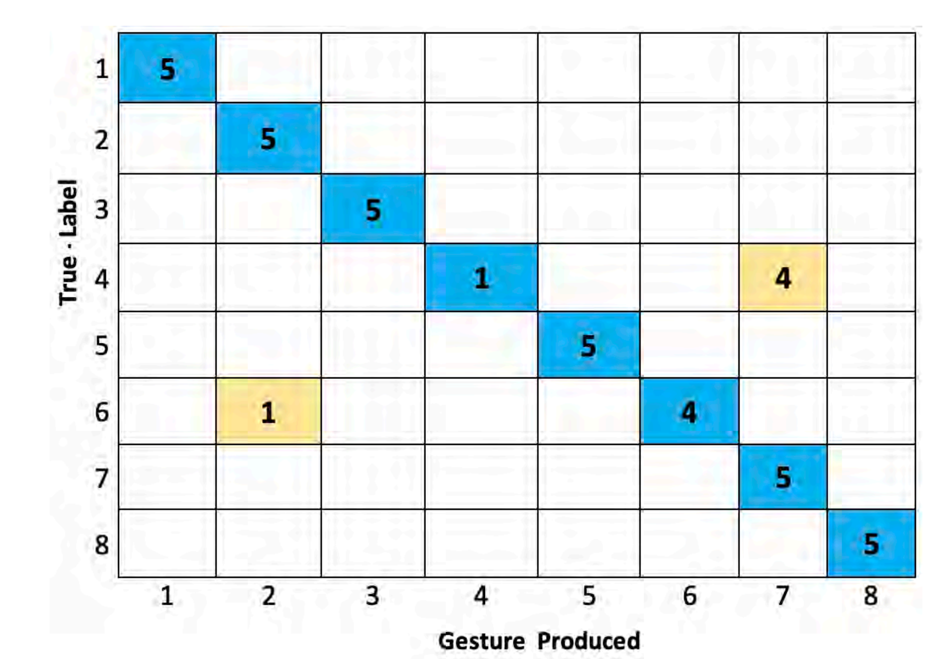

Figure 5. Online accurate classification vs misclassification recordings from trial data found in table 1.

QR Code. Online Results Video

Conclusion

- CNN model can decipher the recorded EMG datasets and classify movement intent during real time depicting the respective hand gestures modulated by the subject.
- Limitations: Electrode array must be specifically placed on the subject's forearm where EMG data to train the CNN model was recorded to return consistent results. The reliability of the presented results are based on a healthy subject.
- Future directions: Test it out on stroke survivors based on their specific myoelectrical activity and assess the effectivity of the therapeutic treatment contingent to stroke patients' ability to regain fine control movements.

References

1. "Stroke Facts." *Centers for Disease Control and Prevention*, Centers for Disease Control and Prevention, 14 Oct. 2022, https://www.cdc.gov/stroke/facts.htm.
2. McCabe, J. P., Henniger, D., Perkins, J., Skelly, M., Tatsuoka, C., & Pundik, S. (2019). Feasibility and clinical experience of implementing a myoelectric upper limb orthosis in the rehabilitation of chronic stroke patients: A clinical case series report. PloS one, 14(4), e0215311. https://doi.org/10.1371/journal.pone.0215311