

Machine Learning Methods for Resolving Limb Position Effect

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Aim:

Mitigate the effect of limb position effect (**LPE**) by using unimodel (only EMG) data, thereby eliminate the need of using additional sensors such as accelerometers.

Background:

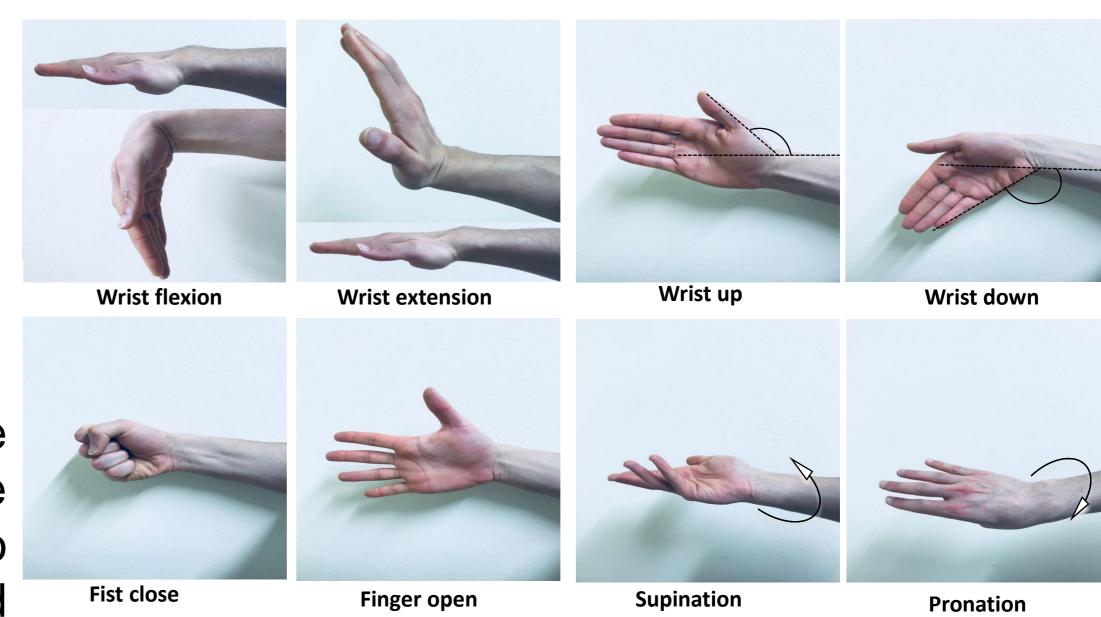
The limb position effect (LPE) is known for the affect it has on the performance of a machine learning (ML) based myoelectric control. To mitigate the LPE, researchers have used accelerometer (ACC) data together with EMG for ML based control. Additionally, ACC sensors will also be used during data collection, this will be done in-order to compare our purely machine learning based approach (using only EMG) with the previously proposed methods using data fusion (using EMG + ACC) multimodal. In this work, we show a different approach towards mitigating LPE. We hypothesize that the LPE introduces non-linearities in EMG and therefore, non-linear ML methods should be used to model EMG affected by LPE.

Materials & Methods:

EMG and ACC data was collected participants while performing 4 repetitions (REPs) of 8 hand gestures and in 4 different arm positions (APs). The collected data was used to train linear and nonlinear ML methods with unimodel and multimodal inputs. Thereafter, two different test scenarios were used to analyze the offline data as follows: (A) Training and Testing in all APs: here, the first 2 datasets collected from the first 2 REPs were used to train ML and the last 2 datasets from the last 2 REPs were used for testing. (B) Training and Testing in different APs: here, the first 2 datasets from the first 2 REPs in any three APs were used to train ML and the last 2 datasets from the last 2 REPs in the remaining AP were used for testing.

Results:

Nonlinear methods with only unimodel decreases the average of classification errors Fig.3. Accelerometer data show a very sensitive behavior according to the APs.



P1 P2 P3 P4

Training and Testing in all APs LDA:Unimodal ■ Linear: Multimodal NonLinear: Unimodal 19.0 16.0 13.0 10.0 7.0 4.0 1.0 **LDA Fougner** Geng **SVM** KNN **Classification Methods**

Fig. 3. Comparison of classifier traind in all Arm Positions (APs) based on Unimodal with Multimodal (Linear and Nonlinear Method).

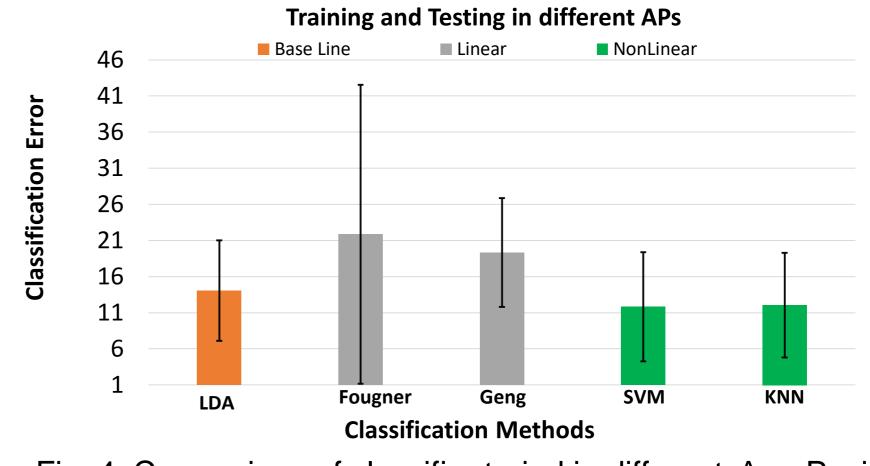


Fig. 4. Comparison of classifier traind in different Arm Positions (Aps).

Conclusion:

Fig. 2. Arm Positions

The influence of LPE can be minimized by using nonlinear methods to model EMG data. Moreover, using Multimodal data to resolve LPE may not be optimal for APs where ACC data is not available.

References:

[1] Y. Geng, O. W. Samuel, Y. Wei, and G. Li, "Improving the Robustness of Real-Time Myoelectric Pattern Recognition against Arm Position Changes in Transradial Amputees," Biomed Res. Int., vol. 2017, 2017.

[2] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the limb positioneffect in myoelectric pattern recognition," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 19, no. 6, pp.644–651, 2011.