Deep Learning in EMG-based Gesture Recognition

P. Tsinganos[1], B. Cornelis[2], J. Cornelis[2], B. Jansen[2], and A. Skodras[1]

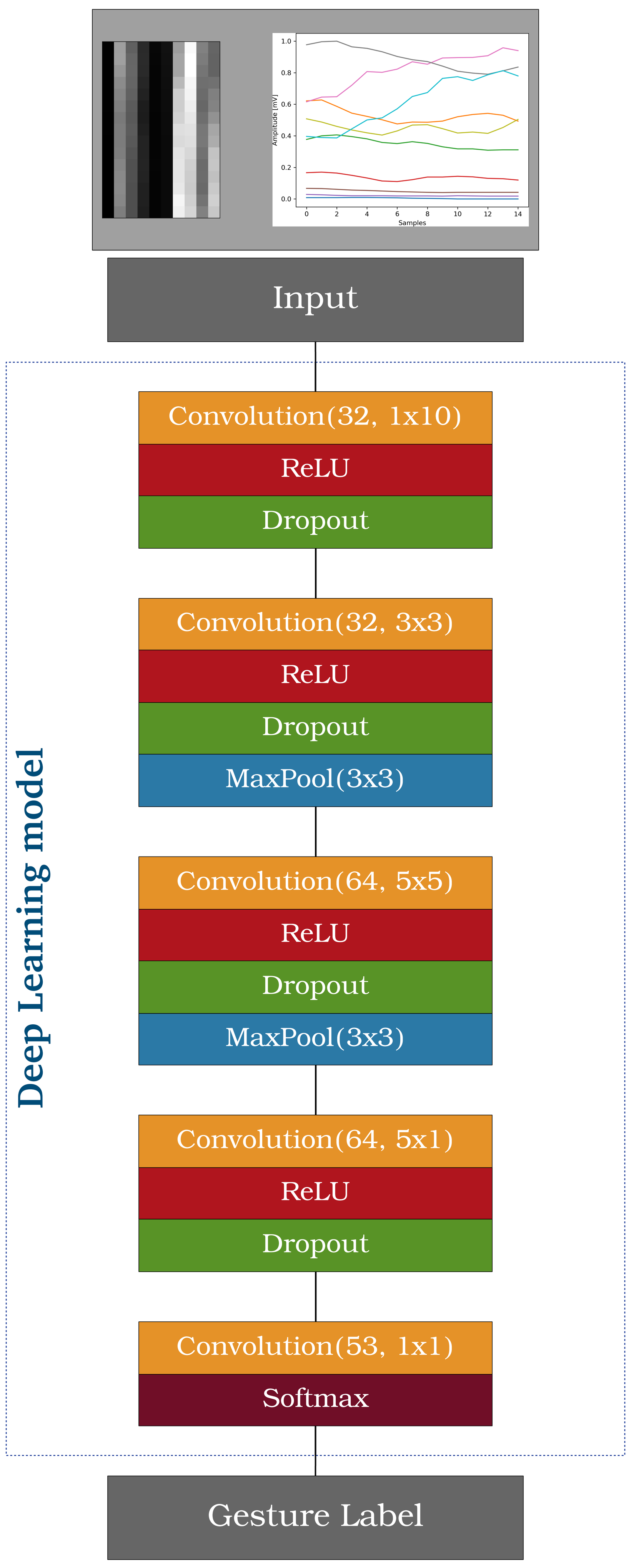
[1]University of Patras, Department of Electrical and Computer Engineering, Patras, Greece
{panagiotis.tsinganos, skodras}@ece.upatras.gr
[2]Vrije Universiteit Brussel, Department of Electronics and Informatics, Brussels, Belgium
{bcorneli, jpcornel, bjansen}@etrovub.be

Abstract

In recent years, Deep Learning methods have been successfully applied to a wide range of image and speech recognition problems highly impacting other research fields. As a result, new works in biomedical engineering are directed towards the application of these methods to electromyography-based gesture recognition. In this paper, we present a brief overview of Deep Learning methods for electromyography-based hand gesture recognition along with an analysis of a modified simple model based on Convolutional Neural Networks (CNNs). The proposed network yields a 3% improvement on the classification accuracy of the basic model, whereas the analysis helps in understanding the limitations of the model and exploring new ways to improve the performance.

Methods

The problem of sEMG-based gesture recognition is formulated as an image classification task using CNNs. The input sEMG images are generated with the sliding windows method, where the window length of 150ms and the 10 electrodes result in an image size of 15×10×1 (Height×Width×Depth). The CNN model is adjusted from the work of [1] through the introduction of dropout layers and the use of max pooling instead of average pooling.



Network and optimization parameters (regularization, dropout, optimizer, learning rate, epochs) were identified via cross-validated random search and manual hyper-parameter tuning. Finally, an l_2 regularization of 0.0002 and a dropout rate of 0.15 were applied while the CNN weights were trained using stochastic gradient descent (SGD) for 100 epochs with 0.05 initial learning rate. The learning rate was reduced every 15th epoch by a factor of 50%.

Results

The proposed CNN is evaluated on the Ninapro-DB1 database that includes EMG data related to 53 hand movements of 27 subjects. The results of the model evaluation along with a comparison to the state of the art is shown in the following tables. Two evaluation procedures were followed:

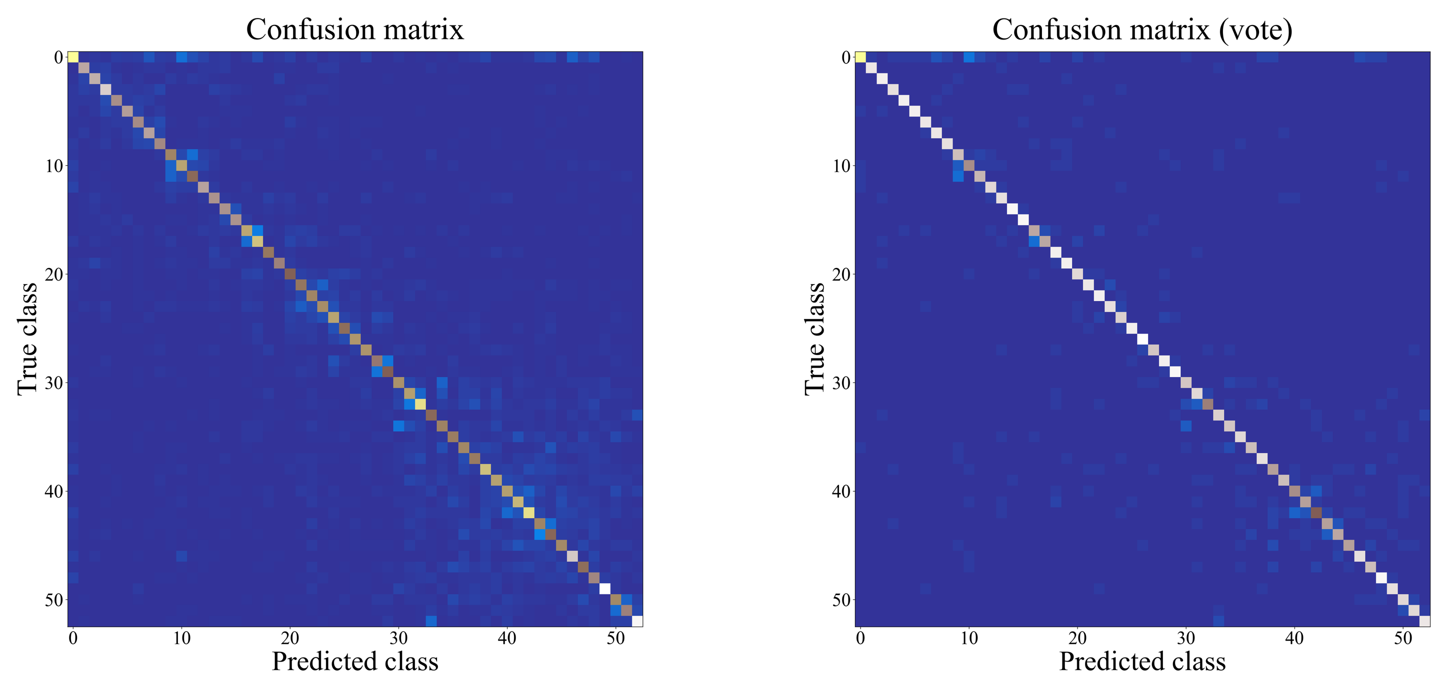
- intra-subject, where a different model is trained for each subject
- inter-subject with calibration, where a common model is calibrated for each subject

In the second case, the common model was initially trained with data from all available subjects.

Setting	Train accuracy	Test accuracy	Top-3 accuracy	Vote accuracy
Intra-subject	83.03%	70.48%	87.06%	92.31%
Inter-subject	81.21%	72.06%	88.06%	93.06%

Setting	This work	[1]	[2]	[3]
Intra-subject	70.48%	66.59%	-	-
Inter-subject	72.06%	-	76.10%	85%

One reason for the low accuracy is the fact that during the recording session there is a gradual transition between rest, gesture and rest, in contrast to the discrete changes of the gesture labels. Consequently, accuracy is lower during these transition periods where the change in movement is not yet clearly evident from the input EMG signal.



The average confusion matrix shows that most misclassifications occur around the main diagonal which means that similar movements are falsely recognized. Comparing the confusion matrices before and after the majority voting we see that most errors around the diagonal are reduced suggesting that many sEMG segments of these gestures generate similar features.

Conclusions

The proposed model follows the work of [1] and is compared to the state of the art. It improves on the basic model by 3%, yet the works of [2] and [3] outperform it under the same evaluation settings. As future work, we plan to investigate the utilization of time-frequency representations (e.g. Wavelet and Fourier transforms) as a preprocessing step, as well as more complex architectures based on recurrent networks to benefit from the temporal information in the data.

Acknowledgements

This work was supported by the VUB-UPatras International Joint Research Group (IJRG) on ICT.

References

[1] M. Atzori, M. Cognolato, and H. Müller, "Deep Learning with Convolutional Neural Networks applied to electromyography data: A resource for the classification of movements for prosthetic hands," *Frontiers in Neurorobotics*, vol. 10, Sep 2016.

[2] W. Geng, Y. Du, W. Jin, W. Wei, Y. Hu, and J. Li, "Gesture recognition by instantaneous surface EMG images," *Scientific Reports*, vol. 6, no. 36571, 2016.

[3] W. Wei, Y. Wong, Y. Du, Y. Hu, M. Kankanhalli, and W. Geng, "A multi-stream Convolutional Neural Network for sEMG-based gesture recognition in muscle-computer interface," *Pattern Recognition Letters*, Dec 2017.