

HAND GESTURE RECOGNITION USING TEMPORAL CONVOLUTIONS AND ATTENTION MECHANISM

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ABSTRACT

Advances in biosignal signal processing and machine learning, in particular Deep Neural Networks (DNNs), have paved the way for the development of innovative Human-Machine Interfaces for decoding the human intent and controlling artificial limbs. DNN models have shown promising results with respect to other algorithms for decoding muscle electrical activity, especially for recognition of hand gestures. Such data-driven models, however, have been challenged by their need for a large number of trainable parameters and their structural complexity. Here we propose the novel Temporal Convolutions-based Hand Gesture Recognition architecture (TC-HGR) to reduce this computational burden. With this approach, we classified 17 hand gestures via surface Electromyogram (sEMG) signals by the adoption of attention mechanisms and temporal convolutions. The proposed method led to 81.65% and 80.72% classification accuracy for window sizes of 300 ms and 200 ms, respectively. The number of parameters to train the proposed TC-HGR architecture is 11.9 times less than that of its state-of-the-art counterpart.

Index Terms— Attention Mechanism, Temporal Convolutions, surface Electromyogram, Hand Gesture Recognition.

1. INTRODUCTION

Hand gesture recognition via surface Electromyogram (sEMG) signals [1–5] has been investigated in the literature as the most promising approach for myoelectric control of prosthetic systems. In particular, Hand Gesture Recognition (HGR) has been the focus of different research works [6, 7], given its unique potentials to improve the quality of control and consequently to enhance the quality of life of amputees. Although academic researchers have used advanced Machine Learning (ML) and Deep Neural Network (DNN) models to achieve promising laboratory results in HGR, translating these new techniques into the daily lives of amputees has faced several critical challenges [8, 9]. One of the key challenges is the dependency of DNN models on a large number of trainable parameters, which leads to structural complexity and limits their applicability to clinical settings [10]. Therefore, there is an urgent and unmet quest to develop DNN-based learning frameworks that focus on reducing the number of parameters and maintaining high performance.

The performance of DNN models developed based on sparse multi-channel sEMG is still significantly lower than that of High-Density sEMG (HD-sEMG) systems which has a high number of densely located electrodes to significantly increase the information rate [11–13]. For instance, in Reference [12], the HGR accuracy of 99.7% is reported using HD-sEMG, which is reduced to 84.4% when sparse multi-channel sEMG signals are

used. In this context, we aim to design a novel DNN architecture using sparse multi-channel sEMG signals provided by the Ninapro [14, 15] database, which is one of the most widely accepted sparse multi-channel sEMG benchmark datasets. We designed the novel Temporal Convolutions-Hand Gesture Recognition architecture (TC-HGR) to reduce computational burden while maintaining high accuracy, which is of paramount importance to translate the classification results into smooth actions.

A common strategy for classifying hand movements with DNN-based algorithms is converting sEMG signals into images and then using Convolutional Neural Networks (CNNs) to detect hand movements [11, 12, 16, 17]. sEMG signals are, however, sequential in nature, and CNNs cannot extract temporal features. In this regard, recent literature [10, 13] used recurrent architectures such as Long Short Term Memory (LSTM) networks to consider the sequential nature of sEMG signals. In addition, LSTMs and CNNs can be combined as a hybrid architecture [6] to jointly extract the temporal and spatial properties of sEMG signals. Although sequence modeling with recurrent networks is a common approach, it can have disadvantages, such as lack of parallelism during training, exploding/vanishing gradient, and extensive memory/computation requirements [18]. Therefore, Reference [18] proposed Temporal Convolutions (TCs) for extracting temporal information in time series tasks while addressing the aforementioned challenges of the recurrent architectures. In addition Reference [10] proposed the concept of temporal dilation of LSTM to reduce the computational cost, memory, requirement, and model complexity. On the other hand, attention-based architectures such as Transformers [19, 20] show great potentials for widespread adoption in different Artificial Intelligence (AI) applications. In particular, the transformer-based architectures could improve the recognition accuracy compared to their state-of-the-art counterparts (where LSTM or hybrid LSTM-CNN are adopted). However, transformers are limited by the memory and computation requirements of the quadratic operation in attention for long sequences or images. Therefore, in [19], the authors proposed dividing the images into patches and then using the flattened patches as the input for the transformers. Inspired by the progress of attention mechanism and TCs, recent literature [1, 21, 22] proposed a Few-shot learning architecture, which is based on the combination of attention and temporal convolutions.

In this paper, to address the challenges with recurrent architectures and achieve high accuracy for sparse multichannel sEMG, we proposed the design of the TC-HGR, which is based on TCs and attention mechanism. More specifically, TCs use the dilated causal convolutions, which can increase the receptive field of the network and extract the temporal features of the sEMG signals. Moreover, by

inspiring from [19], we divided the sEMG signals into patches to reduce the computational cost. The contributions of the paper can be summarized as follows:

- The TC-HGR framework is proposed based on self-attention mechanism and temporal convolution to address the aforementioned challenges with the recurrent architectures.
- The TC-HGR reduces the number of parameters, which is a key step forward to embed the DNN models into prostheses controllers.
- The TC-HGR divides the sEMG signals into patches, which reduces the computational burden of the system.
- The TC-HGR can access a long history through temporal convolutions and also can pinpoint specific information in the sEMG signals through the attention mechanism.

2. THE PROPOSED TC-HGR ARCHITECTURE

Developing a DNN architecture with fewer parameters can tackle the challenge of structural complexity and reduce the gap between academic research and practical settings for myoelectric prosthesis control. In what follows, first, we present the pre-processing step of the proposed TC-HGR and then present its detailed architecture.

2.1. Preprocessing Step

For developing TC-HGR architecture, we used the raw time-domain sEMG signals. Following the recent literature [11, 15, 23, 24], the sEMG signals are pre-processed and smoothed using a 1st order 1 Hz low-pass Butterworth filter. Moreover, to amplify the magnitude of sensors with small values, we scaled the sEMG signals logarithmically [2]. This technique is known as μ -law transformation and is used for quantization in the speech domain. However, we use it for normalizing the sEMG signals, i.e.,

$$F(x_t) = \text{sign}(x_t) \frac{\ln(1 + \mu|x_t|)}{\ln(1 + \mu)}, \quad (1)$$

where t represents the time; x_t shows the sEMG signal, and μ is the parameter that indicates the new range. In Reference [2], the authors showed that scaling sEMG signals with μ -law technique results in better performance than normalizing with Minmax. This completes the steps performed to pre-process the sEMG signals and prepare the input to be provided to the TC-HGR architecture. Next, we present the detailed structure of the proposed architecture.

2.2. The TC-HGR Architecture

In this section, the proposed TC-HGR architecture is described in detail. After pre-processing, we segment the sEMG signals based on a window of size $W \in \{200 \text{ ms}, 300 \text{ ms}\}$, resulting in the dataset $\mathcal{D} = \{(\mathbf{X}_i, y_i)\}_{i=1}^M$. More specifically, $\mathbf{X}_i \in \mathbb{R}^{C \times L}$ is the i^{th} segment with label y_i , for $(1 \leq i \leq M)$. Here, C indicates the number of channels in the input segment, and L is the length of the segmented sequence, which represents the number of samples obtained at a frequency of 2 kHz for a window of size W . As illustrated in Fig. 1, the TC-HGR framework has been developed based on “Embedded Patches” and two modules, namely *Temporal Convolution Block* and *Self-Attention Module with Residual Connection*, which is described below:

(i) **Embedded Patches:** In a similar way to the Vision Transformer (ViT) architecture [19], the input segment \mathbf{X}_i is divided into N non-overlapping patches. Here, $N = L/P$, where P shows the size of each patch. This patching mechanism helps reduce memory and computation requirements. As shown in Fig. 1, the sequence of linear projections of these patches is fed as input to the TC-HGR architecture. More specifically, each patch is first flattened and then is

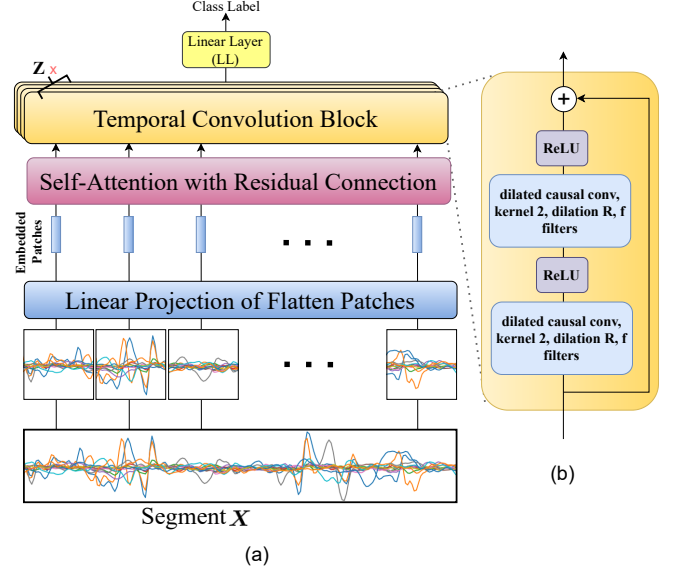


Fig. 1: The proposed TC-HGR architecture: (a) Each input segment \mathbf{X} (for simplicity, we dropped the index i) is divided into N non-overlapping patches. Then, each patch is flattened and mapped to model dimension D (blue block). We refer to the output of this process as Embedded Patches. The sequence of the Embedded Patches is passed into the Self-Attention module, which includes the residual connection (purple block). Afterward, we used Z number of Temporal Convolution Blocks to access a long history (orange block). (b) Each Temporal Convolution Block consists of two dilated causal convolutions, each followed by a ReLU activation function. Again, we used residual connections to concatenate the output and input. Finally, a Linear Layer (LL) is adopted to output the class label.

mapped into the model dimension D with a trainable linear projection. The output of this projection is called the “Embedded Patches”. (ii) **Temporal Convolution Block:** In recent literature (such as [18]), the authors represented TCs for the sequence modeling tasks and showed that temporal convolutions could outperform recurrent networks such as LSTMs in a wide range of datasets and time-series tasks. More specifically, TCs offer several advantages over recurrent networks such as processing the input sequence as a whole rather than sequential training, low memory requirements, stable gradient, and capturing the past information with flexible receptive field size. Inspired by the performance of TCs for the sequential data, we used “Temporal Convolution Block” (represented via an orange box in Fig. 1) instead of recurrent networks for the sEMG-based HGR. As shown in Fig. 1, each Temporal Convolution Block consists of dilated causal convolutions, where the dilation rate R increases exponentially, i.e., $(1, 2, 4, 8, \dots)$, to access a receptive field that exceeds the length of the input sequence. Moreover, each dilated causal convolution is followed by a ReLU activation function. The number of Temporal Convolution Blocks are based on the logarithmic scale with the number of patches N . More specifically, we used $Z = \lceil \log_2 N \rceil$ number of Temporal Convolution Block for an input segment \mathbf{X} with a sequence length of L .

(iii) **Self-Attention Module with Residual Connection:** In the proposed TC-HGR architecture, we used the “Temporal Convolution Block” along with the “Attention” mechanism. In [20], the authors showed that the attention mechanism allows a model to present important information in a given input sequence. Moreover, the attention mechanism has recently been used [1] in the context of sEMG-based hand gesture recognition, where experiments have demonstrated the ability of attention to identifying specific pieces of information in the sequential nature of the sEMG signals. On the other

Table 1: Descriptions of TC-HGR architecture variants.

Window size W	Model ID	Number of Patches N	Model dimension D	Params
200 ms	1	10	12	49,186
	2	10	16	68,445
	3	16	12	69,076
	4	16	16	94,965
300 ms	1	10	12	52,066
	2	10	16	72,285
	3	15	12	67,651
	4	15	16	92,945

hand, in References [21, 22], it was shown that temporal convolutions and attention are complementary mechanisms, i.e., the former captures a long history while the latter identifies a specific type of information. An attention block measures the pairwise similarity of each query and all keys to assign a weight to each value. Then, the output is computed, which is the weighted sum of the values [20]. The keys, values, and queries are packed together into matrices \mathbf{K} , \mathbf{V} , and \mathbf{Q} , respectively. The output matrix is then computed as

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}, \quad (2)$$

where d_k denotes the dimension of \mathbf{K} and \mathbf{Q} . In the TC-HGR architecture, we also used residual connections to concatenate the output and input. This completes the description of the proposed TC-HGR architecture, next, evaluation results are presented.

3. EXPERIMENTS AND RESULTS

In this section, first, the database used for evaluation is described followed by the presentation of different experiments and results.

3.1. Database

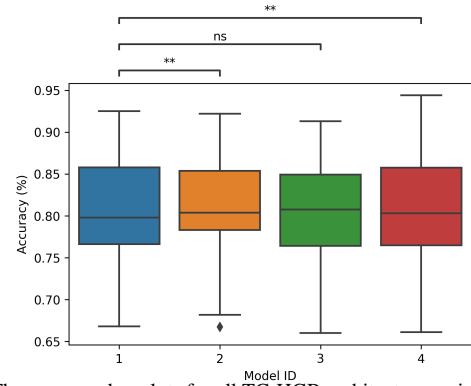
To train and evaluate the proposed TC-HGR architecture, we used the second Ninapro dataset [15] called DB2, which is a widely used public dataset. More specifically, DB2 is collected by the Delsys Trigno Wireless EMG system, which has 12 channels and records the electrical activities of muscles at 2 kHz. Moreover, the DB2 dataset consists of the sEMG signals from 40 healthy subjects (28 males and 12 females with age 29.9 ± 3.9 years among which 34 are right-handed and six are left-handed) performing 50 different hand gestures. Each gesture is repeated 6 times, each lasting for 5 seconds followed by 3 seconds of rest. The 50 different gestures in the DB2 dataset are presented in three sets of exercises (i.e., B, C, and D). In this paper, we focus on Exercise B, which consists of 17 different gestures. More specifically, Exercise B consists of 9 basic wrist movements with 8 isometric and isotonic hand movements. Following the recommendations provided by the Ninapro dataset, the training set consists of 2/3 of the repetitions of each gesture (i.e., 1, 3, 4, and 6), and the test set consists of the remaining repetitions.

3.2. Results and Discussions

In this section, the performance of the proposed TC-HGR architecture is evaluated through a comprehensive set of experiments. In Table 1, different variants of the TC-HGR architecture are presented based on a window size of $W \in \{200 \text{ ms}, 300 \text{ ms}\}$. For training, Adam optimizer was used across all the models with a learning rate of 0.0001. Furthermore, we used a mini-batch size of 32. The performance of each model is evaluated using Cross-entropy loss. In Table 2, the averaged recognition accuracy of the proposed TC-HGR architecture and its variants are reported over all subjects. In what follows, we focus on three different experiments:

Table 2: Classification accuracies for TC-HGR architectures variants for different Window Size (W).

	Model ID	1	2	3	4
$W = 150 \text{ ms}$	Accuracy (%)	79.78	80.22	80.00	80.72
	STD (%)	6.5	6.5	6.5	6.4
$W = 200 \text{ ms}$	Accuracy (%)	80.29	80.63	80.51	80.83
	STD (%)	6.7	6.8	6.7	6.6
$W = 250 \text{ ms}$	Accuracy (%)	80.34	80.99	80.73	81.35
	STD (%)	6.4	6.5	6.6	6.6
$W = 300 \text{ ms}$	Accuracy (%)	80.84	81.59	80.95	81.65
	STD (%)	6.4	6.5	6.5	6.7

**Fig. 2:** The accuracy boxplots for all TC-HGR architecture variants for window size 300 ms. Each boxplot is representing the Interquartile Range (IQR) of each model across 40 users. (ns: $0.05 < p\text{-value} \leq 1$, **: $0.001 < p\text{-value} \leq 0.01$).

Experiment 1 - Effect of the Model's Dimension D : In this experiment, the objective is to investigate the effect of D of the proposed TC-HGR architecture on the recognition accuracy. In this regard, Table 2 has shown the results for $D \in \{12, 16\}$ for both window sizes. From Table 1 and Table 2, it is observed that the accuracy of the model will improve when the D is increased from 12 to 16 for the same Number of Patches N . More specifically, “Model 2 versus Model 1” and “Model 4 versus Model 3” are more accurate in both the 200 ms and 300 ms window sizes. However, from Table 1, it can be observed that the number of trainable parameters has increased when D is increased from 12 to 16, which leads to more complexity. For instance, for $W = 200 \text{ ms}$ and $N = 10$, Model 2 has 68,445 parameters, while this number is 49,186 for Model 1 (Table 1). While increasing D can potentially improve performance, the implementation of prosthetic controllers is limited by its structural complexity.

Experiment 2 - Effect of the Number of Patches N : This experiment is included to evaluate the effect of increasing N on the performance of the proposed TC-HGR. From Tables 1 and 2, it is observed that for the same W and D , accuracy increases as the number of patches N increases from 10 to 16. More specifically, “Model 3 versus Model 1” and “Model 4 versus Model 2” classified the hand gestures with higher accuracies in both window sizes. This is because use of more patches results in a larger effective sequence length, which in turn improves the overall performance. Increasing the number of patches, however, makes the structure more complex. For instance, for $W = 300 \text{ ms}$ and $D = 12$, Model 3 has 67,651 parameters, while Model 1 has 52,066 parameters (Table 1).

Experiment 3 - Effect of Window size W : As shown in Table 2, increasing the window size leads to more accuracy. This is because

Table 3: Comparison between the proposed TC-HGR methodology and previous works [10], which used recurrent architectures (LSTM).

		200 ms		300 ms	
		Params	Accuracy (%)	Params	Accuracy (%)
Reference [10]	4-layer 3rd Order Dilation	1, 102, 801	79.0	1, 102, 801	82.4
	4-layer 3rd Order Dilation (pure LSTM)	-	-	466, 944	79.7
	SVM	-	26.9	-	30.7
Our Method	Model 1	49,186	80.29	52,066	80.84
	Model 4	94, 965	80.72	92, 945	81.65

Table 4: Gestures' classification results for Model 4. The description of the gestures are presented in the References [14, 15].

Gesture Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Accuracy (%)	89.39	84.63	84.20	82.51	74.80	84.39	82.32	77.72	83.19	77.16	72.25	76.55	84.25	83.56	87.76	77.08	86.22

Table 5: Adjusted Wilcoxon signed rank test p-values by Benjamini-Hochberg method for window size 300 ms.

	Model 1	Model 2	Model 3
Model 2	0.007		
Model 3	0.572	0.007	
Model 4	0.017	0.572	0.017

the larger the window size, the more information is provided for the proposed TC-HGR architecture. In other words, machine learning model would have higher exposure to the signals from the gesture. For instance, for both “Models 2 and 1”, the window size 300 ms leads to greater accuracy and complexity. However, both “Models 3 and 4” classified hand gestures more accurately while reducing the complexity because number of patches for $W = 300$ ms is less than $W = 200$ ms. We would like to point out the window length is required to be under 300 ms to satisfy the acceptable delay time [25]. With a larger window, the results would likely improve. However, the use of shorter windows (e.g., 200 ms) provides an extra time (100 ms) to perform the pre-processing and classification tasks, which allows staying within the target 300 ms. We have also trained/evaluated window sizes of 150 ms and 250 ms.

We have also obtained the average of classification results per each gesture for our proposed Model 4. As shown in Table 4, each gesture is presented with an index (e.g., 1-17) exactly matched with the Ninaprodataset. We followed References [14, 15] and presented each gesture with an index. The full description of these movements is given in References [14, 15]. As shown in Table 4, the accuracy of model degrades when the gestures are similar. For example, the model distinguish index 11 and 12 which corresponds to the wrist supination and pronation with a lower accuracy. This result is not far from expectation as the muscle groups which are predominantly used during these two gestures are exactly the same [27]. Finally, we evaluated effectiveness and robustness of the proposed method through Monte Carlo (MC) simulations [28]. For evaluating the convergence of proposed approach, in particular 100 MC runs are performed where at each run sensor measurements are contaminated by additive Gaussian noise based on a specific level of signal to noise ratio (SNR). MC simulation results (100 times and SNR = 25 dB) for the proposed Model 4 is $81.19\% \pm 6.6\%$, while without MC simulation (Table 2) the accuracy for the same model is $81.65\% \pm 6.7\%$.

Statistical Comparisons of the Different TC-HGR Variants for Window Size 300 ms: To examine the importance and significance of TC-HGR variants, we perform statistical tests for all models considering $W = 300$ ms. By following [22], the Wilcoxon signed-rank test [26] is used in which each user is considered as a separate dataset. As illustrated in Fig. 2, we conduct comparison between

the model with the least number of parameters (i.e., Model 1) and other models. (i.e., Model 2, 3, and 4). The performance distribution between 40 users for each model is illustrated in Fig. 2. We adjusted the resulted p-values using Benjamini-Hochberg false discovery rate. The results are given in Table 5 for window size 300 ms.

Comparison with the State-of-the-art Research [10]: We have also compared the results with a recent state-of-the-art model [10] in which the same dataset is used for performance evaluations. More specifically, Reference [10] proposed models based on recurrent architectures (i.e., LSTM) with dilation. As shown in Table 3, for window size of 200 ms, our methodology can outperform both recurrent networks and traditional ML approaches such as Support Vector Machine (SVM). For instance, it can be observed that the accuracy for our proposed Model 4 is 80.72% with only 94,965 number of parameters, while the best accuracy for the Reference [10] is 79% with 1, 102, 801 parameters. Moreover, as shown in Table 3, for window size of 300 ms, the accuracy of the proposed Model 4 is 81.65%, while for “pure LSTM with dilation” and SVM proposed in [10], the accuracy is 79.9% and 30.7%, respectively. Although in [10] the authors reached to 82.4% accuracy with “4-layer 3rd Order Dilation” which is a hybrid dilation-based LSTM, they used 1, 102, 801 number of parameters which is 11.9 times larger than the number of parameters used in our proposed Model 4. Therefore, we provided a compact DNN model with far fewer number of trainable parameters compared to previous works.

4. CONCLUSION

In this paper, we proposed a novel architecture referred to as the TC-HGR for Hand Gesture Recognition from sparse multichannel sEMG signals. The proposed model showed strong capability in addressing several existing challenges of gesture recognition based on the temporal convolutions and attention mechanism. We showed that by proper design of convolution-based architectures, we can extract temporal information of the sEMG signal and improve the performance. Moreover, the proposed architecture can reduce the required number of trainable parameters with respect to the state-of-the-art, which is a key enabling factor to reduce the complexity and embed DNN-based models into prostheses controllers. Extension of this work for classification of more varied gestures in the DB2 is a directions for future research. Moreover, misplacement or displacement of sensors is an open topic of research that has not been addressed in this paper. This can be considered as a limitation for the current study and a fruitful future direction of research, which is the focus of our ongoing research.

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