XceptionTime: A NOVEL DEEP ARCHITECTURE BASED ON DEPTHWISE SEPARABLE
CONVOLUTIONS FOR HAND GESTURE CLASSIFICATION

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ABSTRACT

Capitalizing on the need for addressing the existing challenges associated with gesture recognition via sparse multichannel surface Electromyography (sEMG) signals, the paper proposes a novel deep learning model, referred to as the XceptionTime architecture. The proposed innovative XceptionTime is designed by integration of depthwise separable convolutions, adaptive average pooling, and a novel non-linear normalization technique. At the heart of the proposed architecture is several XceptionTime modules concatenated in series fashion designed to capture both temporal and spatial information-bearing contents of the sparse multichannel sEMG signals without the need for data augmentation and/or manual design of feature extraction. In addition, through integration of adaptive average pooling, Conv1D, and the non-linear normalization approach, XceptionTime is less prone to overfitting, more robust to temporal translation of the input, and more importantly is independent from the input window size. Finally, by utilizing the depthwise separable convolutions, the XceptionTime network has far fewer parameters resulting in a less complex network. The performance of XceptionTime is tested on a sub Ninapro dataset, DB1, and the results showed a superior performance in comparison to any existing counterparts. In this regard, 5.71% accuracy improvement, on a window size 200ms, is reported in this paper, for the first time.

Index Terms— Surface Electromyography (sEMG), Depthwise Separable Convolution, Adaptive Average Pooling

1. INTRODUCTION

Recent evolution in deep learning architectures coupled with advancements in rehabilitation technologies has resulted in a promising future to develop intuitive myoelectric prostheses. The surface Electromyography (sEMG) signals [1, 3] derived from the muscle fibers’ action potentials, have been used in the literature for hand motion recognition in advanced myoelectric prostheses. In this regard, gesture recognition and classification has attracted a great deal of interest of many researchers due to the high potential for improving the quality of control over the actions of prostheses, which can significantly enhance the quality of lives of hand amputated individuals.

The sEMG signals can be collected based on sparse multichannel sEMG or in more advanced cases using high-density sEMG (HD-sEMG) devices [4, 6]. Multichannel system records electrical activity of muscles through a spatially distributed electrodes over stump muscles to extract temporal information regarding muscle activity. Multi-channel recording secures several advantages including the ability to obtain large amounts of data from different locations on the muscles which enhances the sparsity of the information space regarding the activities of distributed motor units in the muscles, which potentially allowing for enhancing the quality of classification. Despite the unique advantages of multichannel recording (such as high density systems), the multiplied size of the recorded information space with a high sampling frequency (which can be as high as 3KHz and is needed for enhancing the fine control) make the processing computationally demanding, which in turn can add latency to the processing pipeline challenging the real-time implementation (which is imperative for the control of prosthetic systems).

It should be also noted that although the performance of deep learning algorithms can motivate the use for multichannel electrode space, applying/training deep models based on signals obtained from sparse multichannel sEMG devices is very challenging as such datasets are typically shallow. The paper aims at addressing this gap by designing a novel deep architecture with reduced computational burden to achieve high accuracy using sparse multichannel sEMG signals. NinaPro [7, 8] database, which is the most widely accepted benchmark for sparse multichannel sEMG signal processing, is utilized to design the proposed novel deep architecture.

Prior Research: A common strategy used for hand gesture recognition is to convert the multichannel sEMG recording over fix time windows into images and then use Convolutional Neural Networks (CNN)-based image classification models [4, 5, 9, 10] to perform the recognition task. The problem with such an approach is that only the spatial information of sEMG signals are captured without considering the sequential nature of the sEMG signals. Motivated by this fact, Reference [3] proposed a hybrid CNN and Recurrent Neural Network (RNN) architecture where both spatial and temporal features of the sEMG signals are captured. However, in [6], raw signals are first converted to images (via six sEMG image representation approaches) and then fed to the hybrid CNN-RNN architecture. The results obtained in [6] show that accuracy in classification depends critically on the characteristic of the constructed images, revealing that there is still a major question what is the optimal approach for converting sEMG signals into images and if this is subject dependent [11]. Moreover, in this work, the algorithm proposed in Reference [12] is utilized, which fuses various signal sequences as an activity image used for training purposes. Although utilization of the aforementioned algorithm allows each sEMG sequence to be adjacent to all other sequences, this requires readjustment of the input signals adding to the complexity of the model. To overcome these problems, we have recently [14] developed a new composite architecture to eliminate the need for converting the raw sEMG signals into images. Instead, these new approaches directly fed the sEMG signals into their proposed temporal-convolutional network architectures capitalizing on the time-series nature of the underlying signals. Although the approach have advantages, i.e., there is no need for readjustment, and the number of parameters is much less than...
their counterparts using RNN modules, high accuracy can only be achieved by using the complete sEMG sequence (a large window of sEMG sequence). On the other hand, the model in [13] is trained separately for each subject limiting its generalization capabilities to use as a subject-independent model. Finally, in [15], the authors extracted 11 classical sEMG feature sets and then combined these features with a CNN framework. Although this can help with the computational expense of the technique, extraction of optimal engineered features and construction of optimal classifier are particularly challenging and can saturate the achievable accuracy in many cases.

**Contributions:** The paper aims to address the above-mentioned drawbacks of existing solutions capitalizing on the fact that the problem of recognizing a large set of hand gestures is still far from being solved using sparse multichannel sEMG signals, both in terms of the recognition accuracy and the complexity of the system. In this regard, we aim to design a novel deep-learning model to classify 52 hand movements from raw sparse multichannel sEMG signals, without any additional information (such as in [9]), data augmentation (such as in [13]) or manual design of feature extraction (such as in [15]). The paper proposes a novel CNN architecture, which is constructed based on an innovative module, referred to as The XceptionTime. The algorithm is designed using the concept of the Inception Networks [16,17]. In the proposed architecture, several XceptionTime modules are deployed to classify the hand gesture recognition where both temporal and spatial information-bearing contents of the sparse multichannel sEMG signals are captured. The proposed novel architecture is independent of the window size. This means that by changing the size of the input sequence there is no need to change/configure the architecture itself (in existing deepnet solutions, this is required due to incorporation of fully connected layers within the architecture). To achieve this goal, in the proposed architecture we employed Adaptive Average Pooling in the classification layer, which is less prone to over-fitting than traditionally-used fully connected layers [18]. Moreover, a novel method for normalization of the input inspired from [19] is proposed resulting in better performance both in terms of accuracy and the training speed. Finally, by utilizing the Depthwise Separable Convolutions, our network has far fewer parameters compared to situation when we use Conv1D convolutions [14], resulting in less complex network. The proposed algorithm is tested on DB1 sub-database from Ninapro and an accuracy of 93.91% is achieved which is significantly superior to its counterparts in the literature on the same dataset.

2. MATERIAL AND METHODS

In this section, first, the database on which the proposed model is evaluated is described. Then, the pre-processing approach for preparing the data set will be explained.

### 2.1 Database

As stated previously in Section[1], performance of deep learning techniques using sparse multichannel sEMG is yet far being optimal in terms of (i) Recognition accuracy, (ii) Complexity of the system, and (iii) Sufficiency of number of subjects and movements. Therefore, the proposed architecture will be evaluated on a public identified scientific benchmark database, Ninapro [7,8], which is the most widely accepted benchmark for evaluation of different models developed based on sparse multichannel sEMG signals. The first Ninapro database [7,8], referred to as the DB1, is used in this work, where the sEMG signals are acquired using Otto Bock MyoBock 13E200 with 10 wireless electrodes (channels) at a sampling rate of 100Hz. The DB1 consists of 27 intact (healthy) subjects, where each subject has to repeat 52 gestures including finger, hand, and wrist movements.

The subjects repeated each gestures 10 times, each time lasted for 5 seconds followed by 3 seconds of rest. For the sake of comparison and following the recommendations provided by the database and also previous studies [4,5,8,10], the testing set consists of repetitions 2, 5, and 7, where the remaining repetitions are considered as the training set. Evaluating the proposed model based on the sufficient number of subjects and hand gestures, shows its capability to generalize the results for practical use in daily life.

### 2.2 Preprocessing Step

Following the proposed preprocessing procedure in the previous studies [4,5,8,10], we adopted a 1st order 1Hz low-pass Butterworth filter to preprocess the electrical activities of muscles. However, we develop and propose a new approach for the normalization, referred to as the $\mu$-law normalization, of sEMG signals in a nonlinear fashion based on $\mu$-law transformation [20]. This normalization approach has been used traditionally in speech and communication domains for quantization purposes. We propose for the first time to use it for normalization in the context of sEMG processing. The $\mu$-law normalization is performed based on the following formulation:

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

where $x_i$ denotes the input scaler to be normalized, and $\mu = 256$ is utilized. The nonlinear normalization preprocesses the sEMG signals significantly better than linear normalization such as Minmax normalization, which is commonly used. In contrary to commonly used Minmax normalization, which linearly distributed signal values between the pre-defined range, the proposed $\mu$-law normalization magnifies the outputs of sensors with small magnitude (in a logarithmic fashion), while keeping the scale with those sensors having larger values over time. As an illustrative example, Fig. 2 shows the 1Hz low-pass filtered sEMG signals obtained from 10 sensors corresponding to the first repetition from Subject 1 performing the second gesture. As can be observed in Fig. 2(a), except from sensors 1, 8, and 9, the values of the remaining sensors are close to zero. However, by using the proposed $\mu$-law normalization (as shown in Fig. 2(b)), the outputs of the sensors will be amplified more nonlinearly.

### 3. THE PROPOSED XceptionTime ARCHITECTURE

In [16], inspired by the Inception V4 architecture, a new deepnet model has been recently proposed and named as “InceptionTime” for time series classification. In [16], it is shown that Inception-Time, which is an equivalent of AlexNet for time series data, is more accurate and faster than its existing counterparts in time series classification. On the other hand, in [17], by replacing the Inception modules with depthwise separable convolution, a new architecture is designed and named as Xception, which has better performance than Inception V3 on a large image classification.
Fig. 2: (a) XceptionTime Module, which consists of two parallel paths, the first path includes three Depthwise Separable Convolutions, while the second path includes a MaxPooling followed by a Conv 1 × 1. (b) XceptionTime Architecture, which includes series of XceptionTime modules with residual connections followed by Adaptive Average Pooling layers and Conv 1 × 1 layers.

In the following sub-sections, first, the proposed XceptionTime module is introduced followed by a description of the XceptionTime architecture consisting of stacked XceptionTime modules and adaptive average pooling layers.

### 3.1. XceptionTime Module

One of the challenging tasks in designing CNNs, is selecting the right kernel size, which has an important role in extracting global or local information. However, inspired by Inception [21], as shown in Fig. 2(a), instead of committing ourselves to pick a filter with a specific size, we adopt multiple one-dimensional filters with different kernel sizes to extract short and long time series’ features simultaneously with the resulted feature maps being concatenated to construct the output features. Moreover, for mitigating the computational cost problems, as well as lessening the overfitting problems, the bottleneck layer is used as the first component within the proposed XceptionTime Module. In the bottleneck layer, ƒ number of one-dimensional filters with kernel size one is utilized to transform the input with C_{in} channels into another time series with ƒ channels.

One key difference between the proposed XceptionTime module and Inception module previously proposed in [16], is deploying depthwise separable convolutions, which significantly mitigates the required number of parameters in the network. In Depthwise Separable Convolution [22, 23], two convolutions are deployed, i.e., the Depthwise Convolution, and the Pointwise Convolution. In Depthwise Convolution, each channel of the input is convolved separately and then stacked together; therefore, the temporal convolution is done without changing the depth. The consequent output from the Depthwise convolution is fed to the Pointwise convolution, where 1 × 1 convolutions are utilized to transform the number input channels from the Depthwise convolution into a new channel depth. Later in Section 4, it will be shown that by using the depthwise separable convolutions, not only the recognition accuracy will be increased, but also the number of parameters will be reduced significantly.

To summarize, as shown in Fig. 2(a), the time series input with C_{in} number of channels is first fed to two parallel paths. The first path consists of a bottleneck, reducing the dimensionality of the input, followed by three sets of depthwise separable convolutions each with ƒ number of filters with kernel size l, where l is set to 11, 21, or 41. In the second path, the input is fed to a MaxPooling layer followed by a Conv 1 × 1 component, which produces an output with ƒ channels. Finally, the resulted feature maps of Depthwise Separable Convolutions and skip connections are concatenated in a channel-wise fashion. As shown in Fig. 2(a), the time series input with C_{in} channels are transformed to output with C_{out} number of channels, where C_{out} is four times that of the number of filters (ƒ) used in the bottleneck as well as in the depthwise separable convolutions.

### 3.2. XceptionTime Architecture

The XceptionTime architecture is constructed based on the proposed XceptionTime modules described in Sub-section 3.1. More specifically, after preprocessing, sEMG signals acquired from 10 sensors are segmented by a window with a length of W ∈ {50ms, 100ms, 150ms, 200ms} (it is worth mentioning that W should be under 300ms to satisfy the acceptable delay time [24]). The sliding window with steps of 10ms is considered for segmentation of the sEMG signals. The proposed XceptionTime architecture (Fig. 2(b)), includes 4 XceptionTime modules where the number of filters (ƒ) are set to 16, 32, 64, and 128, respectively. Moreover, two residual connections [25] are deployed in the XceptionTime architecture to address the degradation problem. Each residual con-
Table 1: (First Exp.): Comparison between the proposed XceptionTime model and XceptionTime-V2 model. (Second Exp.): Result of the proposed model and XceptionTime-V2 when the input is normalized by Minmax.

| Exp. | Normalization | Model                  | Accuracy (%) | Model Parameters |
|------|---------------|------------------------|--------------|-----------------|
| First| μ-law         | XceptionTime           | 81.71        | 413,516         |
|      |               | XceptionTime-V2        | 81.24        | 1,918,476       |
| Second| Minmax       | First μ-law            | 81.71        | 413,516         |
|       |               | XceptionTime           | 77.87        | 87.64           |
|       |               | XceptionTime-V2        | 71.49        | 82.63           |
|       |               |                        | 68.95        | 86.17           |

Table 2: Accuracy when the proposed XceptionTime Model is trained on a combination of different window lengths (i.e., 50, 100, 150, 200) and then tested on different windows.

| Exp. | Model | Accuracy (%) | Model Parameters |
|------|-------|--------------|-----------------|
| Third| XceptionTime | 77.87        | 87.64           |
|      |        | 91.81        | 93.91           |
|      |        | 93.91        | 95.44           |

Table 3: Comparison of the proposed XceptionTime with the state-of-the-art literature (number of parameters for [4][5][10] are reported from [13]).

| Model                  | Accuracy (%) | Model Parameters |
|------------------------|--------------|-----------------|
| XceptionTime           | 81.71        | 77.87 87.64     |
| XceptionTime-V2        | 77.87        | 91.81 93.91     |
| GongNet [4]            | 77.87        | 84.44 85.1      |
| WeiNet [5]             | 85.8         | 87.4 88.2       |
| HuNet [6]              | 86.8         | 87.4 88.2       |
| AtzoriNet [10]         | 86.8         | 87.4 88.2       |
| TsinganosNet [13]      | 85.8         | 86.8 87.4       |

4. EXPERIMENTS AND RESULTS

In this section, the performance of the proposed architecture is evaluated through a comprehensive set of different experiments and provide comparisons with 6 state-of-the-art models [4][5][10][13].

**Experiment 1:** In this experiment, referred to as “First Exp.” in the results, the objective is to validate our claim that by incorporation of Depthwise Separable Convolutions within the proposed XceptionTime architecture, a much smaller model size with significantly reduced complexity will be achieved. For this purpose, we implemented a variant of the proposed architecture, where referred to as XceptionTime-V2, where standard convolutions are deployed within the XceptionTime Module instead of Depthwise Separable Convolutions. Table 1 shows the results, where it can be observed that while the accuracy associated with the XceptionTime is slightly better than XceptionTime-V2, the number of parameters is significantly reduced. For example, the accuracy for the proposed XceptionTime model for window length 200ms is 95.43% using 413,516 number of parameters, while XceptionTime-V2 achieves accuracy of 94.59% but using extensively higher 1,918,476 of parameters.

**Experiment 2:** In this experiment, referred to as “Second Exp.” in the results, the objective is to validate the effectiveness of using the proposed non-linear μ-normalization within the proposed XceptionTime architecture. In this regard, in Table 2, results trained by using Minmax normalization is shown for both variants of the proposed framework. From Table 2, it is observed that the accuracy of the model will decrease when Minmax normalization is applied to the input. For instance, accuracy of the proposed XceptionTime framework with μ-law normalization in window length of 50ms is 81.71%, whereas using Minmax normalization within the proposed XceptionTime framework reduces the accuracy to 71.49%. Another observation is that the degradation effect of discarding the proposed nonlinear normalization approach on XceptionTime-V2 is higher.

**Experiment 3:** The third experiment is performed to validate our claim that the proposed XceptionTime is applicable to different window sizes without the need for reconfiguration. We evaluate the performance when the proposed architecture is trained based on a combination of different window sizes. In other words, instead of training the XceptionTime model just with a specific time window (as is done for reporting the results in Table 1), inputs with different window sizes are fed into network to increase the robustness of the network during training. However, for the effectiveness of the training process, only windows with the length of 50, 100, 150, and 200 are used as input. Table 2 illustrates the results obtained from XceptionTime trained with a combination of different window lengths and then tested separately on each window size. As can be seen, the performance of the model, except for time window 50, is improved in comparison to the case where the model was just trained with a specific window length (Table 1, First Exp.). In other words, not only the proposed model can handle different window sizes simultaneously, by utilizing this property the performance can be boosted. Finally, Table 3 shows performance of the proposed model in comparison to the state-of-the-art results obtained over the same DB1 dataset of 52 hand gestures. As shown in Table 3, our architecture outperforms existing solutions while maintaining a reduced number of parameters.

5. CONCLUSION

With the goal of addressing identified shortcomings of existing models for recognition tasks via sparse multichannel surface Electromyography (sEMG) signals, the paper proposed the novel XceptionTime architecture. The proposed innovative XceptionTime is designed by integration of depthwise separable convolutions, adaptive average pooling, and a novel non-linear normalization technique. To the best of our knowledge, it is the first time that the proposed innovative XceptionTime architecture is introduced and has not been designed/utilized previously in any application. Its performance is evaluated via the benchmark sparse sEMG dataset outperforming any existing counterparts. As an attempt to achieve reproducibility, the code will be released on GitHub.
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