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All-ConvNet: A Lightweight All CNN for Neuromuscular Activity Recognition Using Instantaneous High-Density Surface EMG Images

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Abstract – Neuromuscular activity recognition using low-resolution instantaneous high-density surface electromyography (HD-sEMG) images present a great challenge. The recent result shows the high potentiality and hence opens up new avenues for the development of more fluid and natural muscle-computer interfaces. However, the existing approaches employed a very large deep ConvNet, which requires learning >5.63 million training parameters only during *fine-tuning* and *pre-trained* on a very large-scale labeled HD-sEMG training datasets, as a result, it makes high-end resource bounded and computationally expensive. To overcome this problem, we propose a lightweight All-ConvNet model that consists solely of convolutional layers, a simple yet efficient framework for learning instantaneous HD-sEMG images from scratch through *random initialization*. Without using any pre-trained models, our proposed lightweight All-ConvNet demonstrate very competitive or even state of the art performance on a current benchmarks HD-sEMG dataset, while requires learning only ≈460k training parameters and using ≈12×smaller dataset. The experimental results proved that the proposed lightweight All-ConvNet is highly effective for learning discriminative features for low-resolution instantaneous HD-sEMG image recognition and low-latency processing especially in the data and high-end resource constrained scenarios.

Keywords: Neuromuscular activity recognition, All convolutional neural networks, Feature learning, HD-sEMG, Gesture recognition, Muscle-computer interface, Deep neural networks.

I. Introduction

Neuromuscular activity recognition has been a driving motivation for some emerging biomedical applications such as non-invasive and intuitive control of active prosthesis, wheelchairs, exoskeletons or providing interaction methods for video games and neuromuscular diagnosis [1-4]. The sparse-channel surface electromyography (sEMG) and windowed descriptive and discriminative sEMG features are used by the conventional approaches [5-9], [28]. However, these methods are not practical for high sensitivity to electrode shift and positioning [10-11]. To overcome this problem, the high- density sEMG (HD-sEMG) based methods have been proposed in recent years [10-14], [26-27]. The HD-sEMG records myoelectric signals using two-dimensional (2D) electrode arrays that characterize the spatial distribution of myoelectric activity over the muscles that reside within the electrode pick-up area [12]. The collected HD-sEMG data are spatially correlated which enabled both temporal and spatial changes and robust against malfunction of the channels with respect to the previous counterparts [11]. However, the existing HD-sEMG based neuromuscular activity recognition methods [26-27], [28] are still depending on the windowed sEMG (e.g., 260 ms) which demands to find an optimal window length otherwise influence in the classification accuracy and controller delay especially in the application of assistive technology, physical rehabilitation and human computer interfaces [12].

To overcome this problem and develop a more fluid and natural muscle-computer interfaces (MCI's), more recently, W. Geng *et al.*, [12] and M. R. Islam *et al.*, [13] explored the patterns inside the instantaneous sEMG images spatially composed from HD-sEMG enables neuromuscular based gesture recognition solely with the sEMG signals recorded at a specific instant. Hence, the observational latency was reduced to 1 ms which would reduce controller delay significantly to the above-mentioned applications.

However, the current state-of-the-art methods [12], [14] employed a DeepFace [15] like very large deep convolutional neural network (CNN or ConvNet) architecture for sEMG image classification, which requires learning >5.63 million (M) training parameters only during *fine-tuning* and *pre-trained* on a very large-scale labeled HD-sEMG training datasets, as a result it makes high-end resource bounded and computationally expensive to be practical for real-world MCIs applications. The major limitations of using pre-trained networks are usually very deep, contains a massive number of parameters and trained on a large-scale training dataset. Therefore, it is totally not possible to any degree of mutation of the pre-trained networks during fine-tuning. If any mutation or employing a new architecture is necessary then the whole pre-training should be re-conducted on the large-scale training dataset, requiring a high computational cost. Fortunately training from scratch can cope with these problems [29].

Moreover, in their pre-trained ConvNet includes two locally connected (LCN) and three fully connected layers among the other convolutions and a *G*-way fully connected layer. The LCN layers assign an independent filter weight, θ_p to each of the local receptive field of a feature map i.e. $f_p = I_p^T\theta_p$,[1] while convolution (or CNN) layers adopt a filter weight sharing

[1] Given an input sEMG image *I*, LCN requires each filter is conducted on a patch vector I_p, where p stands for position of the patch in the input image.

strategy i.e. $f_p = I_p^T\theta$ [16]. Due to this unshared weight strategies of LCN, the number of learning parameters increases considerably from m to $m \times k$, where $m \gg k$, where m is the number of patches and k is the number of kernels. As a result, a very large-scale labeled training dataset is required to train the LCN [15]. However, the LCN may be useful in an application where the precise location of the feature is dependent of the class labels.

Considering the above-mentioned fact, we must investigate - *(i) Do we expect the devised networks model to produce a location/translation invariant feature representation?* or, *(ii) do we need a location dependent feature representation?* Following this finding and building on other recent works for finding a simple network architecture, we propose a lightweight All-ConvNet, a new architecture that consists solely of convolutional layers, a simple yet effective framework, which could learn neuromuscular activity from scratch and yields competitive or even state of the art performance using ≈12×smaller dataset while reducing learning parameters from ≈5.63M to only ≈460k than its pre-trained counterparts for instantaneous HD-sEMG image recognition.

For instantaneous sEMG image based neuromuscular activity recognition, the challenge remains open because very limited research has been done on it. We propose a lightweight All-ConvNet, to the best of our knowledge, this is the first All-ConvNet framework to date for instantaneous HD-sEMG recognition.

II. THE PROPOSED FRAMEWORK

The proposed framework for neuromuscular activity recognition using instantaneous HD-sEMG images includes the following three major computational components: (i) pre-processing and sEMG image generation (ii) architectural design of the All-ConvNet model and (iii) classification. A schematic diagram of the proposed framework of muscular activity recognition by instantaneous sEMG images is shown in Fig. 1. First, the power-line interferences were removed from the acquired HD-sEMG signals with a band-stop filtered between 45 and 55 Hz using a 2nd order Butterworth filter. Then, the HD-sEMG signals at each sampling instant were arranged in a 2-D grid according to their electrode positioning. This grid was further transformed into an instantaneous sEMG image by linearly transforming the values of sEMG signals from mV to color intensity as [-2.5mV, 2.5mV] to [0 255]. Thus, an instantaneous grayscale sEMG image was formed with a size of 16×8. Secondly, we devised a lightweight All-ConvNet model which describes in Section III. Finally, providing instantaneous HD-sEMG images and their corresponding labels, our devised All-ConvNet model is trained offline to predict to which muscular activity an instantaneous HD-sEMG image belongs. Then, this trained All-ConvNet model is used to recognize different neuromuscular activities at test time from the unseen instantaneous HD-sEMG images.

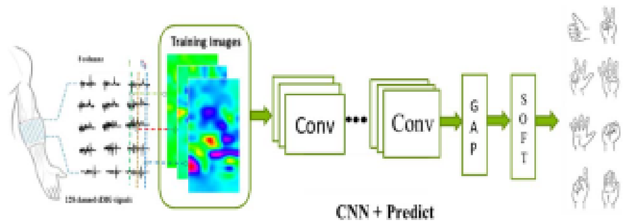

Fig. 1. Schematic diagram of the proposed framework of muscular activity recognition by instantaneous sEMG images.

III. MODEL DESCRIPTION- THE ALL CONVOLUTIONAL NEURAL NETWORK (ALL-CONVNET)

The All-ConvNet architectural design is adopted based on the following principle and observation:

(i) It was hypothesized that the different muscular activities produce different spatial intensity distributions, which is reproducible across the trials of the same muscular activities and discriminative among different activities. However, we observed that the spatial intensity distributions within the same muscular activities are not locally invariant and the precise location of the features is also independent to the class labels. Fig. 2 demonstrate a sequence of HD-sEMG images derived from the same class. CNN alone has the great ability to exploit locally translational invariance features by adopting local connectivity and weight sharing strategies [16]. Hence, the LCN's are ablated in designing our All-ConvNet models as the location of the features is not dependent to the class labels. Why the ablation of LCN's are so significant? Because it is not only increased the number of training parameters but also make the network totally unscalable. For example, only the two LCN in [12] requires learning of >2.13M parameters and the total learning parameters of [12] increased from ≈5.63M to ≈ 11M with just a little enhancement of input HD-sEMG image size from 16×8 to 16×16.

(ii) Inspired by [17], we make use of the fact that if the part of the instantaneous HD-sEMG image is covered by the units in the topmost convolution layers could be large enough to recognize its content (i.e., muscular activity class we want to recognize). Then, the fully connected layers can also be replaced by simple 1-by-1 convolutions. This leads to predictions of HD-sEMG image classes at different positions which can then simply be averaged over the whole image. This scheme was first described by Lin *et. al.,* [21], which further regularizes the network as the 1-by-1 convolution has much less parameters than a fully connected and LCN layer. Overall

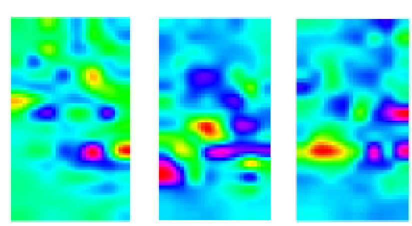

Fig. 2. HD-sEMGs derived from the same muscular activity class which demonstrates that the distributions are independent to the class labels.

TABLE I THE ALL-CONVNET NETWORK MODEL FOR NEUROMUSCULAR ACTIVITY RECOGNITION.

All-ConvNet
Input 16×16 Gray-level Image
3 × 3 Conv.64 ELU
3 × 3 Conv.64 ELU
3 × 3 Conv. 64 ELU with stride $r = 2$
3× 3 Conv. 128 ELU
3× 3 Conv. 128 ELU
3× 3 Conv. 128 ELU with stride $r = 2$
1×1 Conv. 128 ELU
1×1 Conv. 8 ELU
global averaging over 4×4 spatial dimensions
G-way SoftMax

our architecture is thus reduced to consist only of convolutional layers with ELU non-linearities [25] and a global average pooling (GAP) + SoftMax layer to produce predictions over the whole instantaneous HD-sEMG image. Table I describes our proposed All-ConvNet architecture. We did experiments with the variant of All-ConvNet as in [17], however, the All-ConvNet presented in Table I performs favorably.

We train our All-ConvNet on a multi-class neuromuscular activity recognition task, namely, to recognize an activity class through an instantaneous HD-sEMG image. As described in the Table I, in the proposed All-ConvNet network we consider use 1-by-1 convolution at the top to produce 8 outputs of which we then compute an average over all positions and fed to a G-way SoftMax layer (where G is the number of neuromuscular activity classes) which produces a distribution over the class labels. If we denote $\hat{y}^{(J)}$ as the jth element of the G dimensional output vector of the layer preceding the SoftMax layer, the class probabilities are estimated using the SoftMax function $\sigma(.)$ defined as below:

$$\sigma(\hat{y}^{(J)}) = \frac{\exp(\hat{y}^{(J)})}{\sum_G \exp(\hat{y}^{(G)})} \quad (1)$$

The goal of this training is to maximize the probability of the correct neuromuscular activity class. We achieve this by minimizing the cross-entropy loss [22] for each training sample. If y is the true label for a given input, the loss is

$$L = -\sum_j y^{(J)} \ln(\sigma(\hat{y}^{(J)})) \quad (2)$$

The loss is minimized over the parameters by computing the gradient of L with respect to the parameters and by updating the parameters using the state-of-the-art Adam (adaptive moment estimation) gradient descent-based optimization algorithm [23], which provides fast and reliable learning convergence than the stochastic gradient descent (SGD) optimization algorithm used in the fine-tuned pre-trained networks for instantaneous HD-sEMG image recognition.

Having trained the network, an instantaneous HD-sEMG image is recognized as in the neuromuscular activity class C by simply propagating the input image forward and computing:

$$C = argmax_j(\hat{y}^{(J)}) \quad (3)$$

IV. THE PERFORMANCE EVALUATION OF THE PROPOSED ALL-CONVNET MODEL

In order to quantify the effect of simplifying the proposed All-ConvNet network we perform experiments on CapgMyo data sets [14] (These data sets are made publicly available from the following website: http://zju-capg.org/myo/data/index.html). This dataset was developed for providing a standard benchmark database (DB) to explore new possibilities for studying next-generation muscle-computer interfaces (MCIs). The CapgMyo database comprises 3 sub-databases (referred to DB-a, DB-b and DB-c). However, DB-a has been used in our experiments to evaluate the performance of the proposed lightweight All-ConvNet for intra-session neuromuscular activity recognition because the maximum number of subjects (18) have participated in DB-a. In DB-a, 8 different isotonic and isometric hand gestures are performed by every subject and each hand gestures are recorded 10 times with a 1000 Hz sampling rate, which in total generates (8×10×1 000) = 80 000 or 80k instantaneous sEMG images individually. Then, our All-ConvNet network is trained from scratch through *random initialization*. We performed training, validation and testing using only 80 000 images produced by 18 subjects individually through a leave one trial out cross-validation. We kept one trial out from each of the 8 different hand gestures i.e. 8 000 images for validation and testing. The remaining 9 trials for 8 different hand gestures i.e. 72k images are used for training. The cross-validation accuracy A is computed for each class i, as the number of totals correctly recognized hand gestures, divided by the total number of tests sEMG images

$$\text{Accuracy, A} = \frac{\text{C}}{\text{N}} = \frac{\sum \text{C}_i}{\text{N}} \quad (4)$$

where $\text{i} = \{1, 2, \ldots, \text{G}\}$ and G is the number of gesture classes.

In contrast, existing approaches (e.g. [12] and [14]) for instantaneous HD-sEMG image recognition used a total of (18×40 000) = 720 000 or 720k training images for pre-training, while 40 000 images from each of the subject are used separately for *fine-tuning*. Therefore, the existing approaches involve a total of (720 000+40 000) = 760 000 or 760k images only in the training process. Fig. 3 shows the total number of images are used during training for *pre-training + fine-tuning vs random initialization.*

Fig. 3. Total number HD-sEMG images seen during training, for pre-training + fine-tuning vs. random-initialization.

In our experiments, the proposed All-ConvNet described in Section III were trained on the CapgMyo DB-a datasets without any *pre*-training or data augmentations. In order to facilitate in GAP, we only enhance the input HD-sEMG image size from 16×8 to 16×16 by horizontal mirroring. Unlike [12], this enhancement does not increase the learning parameters in the proposed All-ConvNet. The connection weights for All-ConvNet networks were *randomly initialized* using Xavier initialization scheme [18], [24] and were trained using Adam optimization algorithms [23] with a momentum decay and scaling decay are initialized to 0.9 and 0.999 respectively. In contrast to SGD, Adam is an adaptive learning rate algorithm; therefore, it requires less tuning of the learning rate hyperparameter. The learning rate of 0.001 is initialized to all our experiments. The smaller batches of 256 randomly chosen samples from the training dataset are fed to the network during consecutive learning iterations for all our experiments. We set a maximum of 100 epochs for training our All-ConvNet model. However, to avoid overfitting we have also applied early stopping in which the training process is interrupted if no improvements in validation loss are noticed for 5 consecutive epochs. The Batch normalization [19] is applied after the input and before each non-linearity. Dropout [20] was applied on all layers with probabilities 25%. The All-ConvNet model was trained on a workstation with an Intel Core, 3.60 (i7-4790) processor, 16GB RAM and an NVIDIA RTX 2080 Ti GPU. Each epoch was completed in approximately 5s. The test results for the All-ConvNet model are presented in Table II and compared with state-of-the-art methods. It is noteworthy that, the results in Table II are only compared with [12] because the same complex *fine-tuned and pre-trained* networks were subsequently employed in [14] and [30], though in [30] sparse channel sEMG were used.

As can be seen in Table II, the proposed All-ConvNet networks (on the order of only 460k learning parameters) consists of a stack of 3×3 convolutional layers with occasional subsampling by stride of 2 and trained from *random initialization* performs comparably on CapgMyo DB-a dataset to the S-ConvNet [29] and fine-tuned pre-trained networks [12] even though the [12] use more complicated network architectures and training schemes which requires to learn over 5.63 millions parameters during fine-tuning only and also pre-trained with over 720k instantaneous HD-sEMG images. The average recognition accuracy of 8 hand gestures for 18 different subjects 85.81% obtained with the proposed All-ConvNet. The high average recognition accuracies 93.10%, 95.57% and 97.64% are achieved by a simple majority voting

TABLE II THE AVERAGE RECOGNITION ACCURACY (%) OF 8 HAND GESTURES WITH INSTANTANEOUS HD-SEMG IMAGES FOR 18 DIFFERENT SUBJECTS AND RECOGNITION APPROACHES. MAJORITY VOTING (ON 40 SEMG IMAGE) RESULTS ARE SHOWN IN PARENTHESES

Model	Average Recognition Accuracy (%)	# Learning Parameters	Avg-run time (Sec.)
S-ConvNet [29]	87.95 (98.87)	≈ 2 090k	372.14
All-ConvNet (proposed)	**85.81 (97.64)**	**≈ 460k**	**348.54**
W.Geng *et.al.*, [12]	89.3 (99.00)	≈ 5 632k + *Pre-training*	2091.39 (*with no pre-training*)

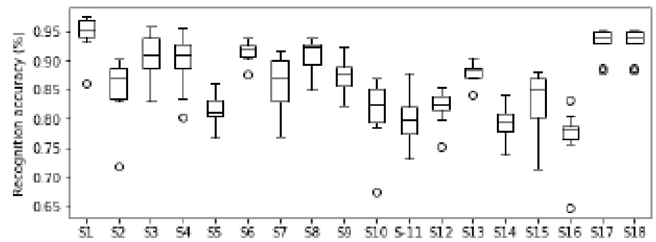

Fig. 4. The recognition accuracy of 8 hand gestures for 18 different subjects with our proposed All-ConvNet.

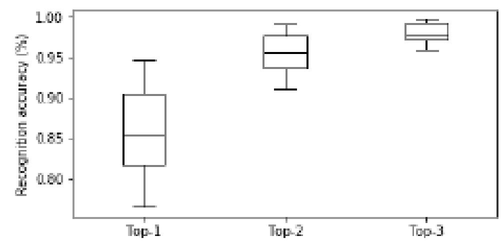

Fig.5 The proposed All-ConvNet - Top-K recognition accuracy (K = 1, 2, 3)

with 3, 20 and 40 instantaneous images respectively. The average run time of training, validation and predictions for an intra-subject test is also included in Table II. The proposed All-ConvNet outperformed the existing methods.

The recognition accuracy of 8 hand gestures of all 18 subjects in CapgMyo DB-a which obtained through leave one trial out cross validation for 10 different trials using All-ConvNet and their statistical significance are presented in Fig. 4. It is observed that the average recognition accuracy >92.21% and >87.36% have been achieved at least for 6 and 5 different subjects respectively.

Perhaps even more interesting, the proposed All-ConvNet achieved the state of the art recognition accuracy when the instantaneous HD-sEMG images are recognized by Top-2 or Top-3 performance metrics i.e. when the target gestures (neuromuscular activities) are matched to any of the 2 or 3 highest probabilities provided by the SoftMax layer of the All-ConvNet. Fig. 5 presents the Top-1, Top-2 and Top-3 accuracies respectively. The obtained average Top-2 and Top-3 recognition accuracies are 95.60% and 98.07% respectively. These outstanding results confirm that the proposed lightweight All-ConvNet trained from *random initialization* is highly effective for learning all the invariances for low-resolution instantaneous HD-sEMG image recognition and hence seem to be enough to address the aforementioned problem of employing high-end resource bounded fine-tuned pre-trained networks for low-resolution instantaneous HD-sEMG image recognition.

The existing neuromuscular activity recognition methods [12], [14] require a huge memory space to store the massive parameters. Therefore, the models are usually unsuitable for low-end hand-held devices and embedded electronics. Thanks to the proposed parameter-efficient All-ConvNet, our model is much smaller than the most competitive methods for instantaneous HD-sEMG image recognition.

V. Conclusion

We present a lightweight All-ConvNet network, a simple yet efficient framework for learning instantaneous HD-sEMG images from scratch for neuromuscular activity recognition. Without using any pre-trained models, our proposed All-ConvNet demonstrates very competitive or state of the art performance, while using $\approx 12\times$ smaller dataset and reducing learning parameters from $\approx 5.63\ M$ to only $\approx 460\ k$ than its fine-tuned pre-trained counterparts for neuromuscular activity recognition based on instantaneous HD-sEMG images. The proposed All-ConvNet has great potential for learning and recognizing neuromuscular activities on resource-bounded devices. Our future work will consider improving inter-session neuromuscular activity recognition performances, as well as learning All-ConvNet models to support resource-bounded devices.

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