Toward Robust High-Density EMG Pattern Recognition using Generative Adversarial Network and Convolutional Neural Network

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***Abstract*—High-density electromyography (HD EMG)-based Pattern Recognition (PR) has attracted increasing interest in real-time Neural-Machine Interface (NMI) applications because HD EMG can capture neuromuscular information from one temporal and two spatial dimensions, and it does not require anatomically targeted electrode placements. In recent years, deep learning methods such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid CNN-RNN methods have shown great potential in HD EMG PR. Due to the high-density and multi-channel characteristics of HD EMG, the use of HD EMG-based NMIs in practice may be challenged by the unreliability of HD EMG recordings over time. So far, few studies have investigated the robustness of deep learning methods on HD EMG PR when noises and disturbances such as motion artifacts and bad contacts are present in the HD EMG signals. In this paper, we have developed *RoHDE* – a Robust deep learning-based HD EMG PR framework by introducing a Generative Adversarial Network (GAN) that can generate synthetic HD EMG signals to simulate recording conditions affected by disturbances. The generated synthetic HD EMG signals can be utilized to train robust deep learning models against real HD EMG signal disturbances. Experimental results have shown that our proposed *RoHDE* framework can improve the classification accuracy against disturbances such as contact artifacts and loose contacts from 64% to 99%. To the best of our knowledge, this work is the first to address the intrinsic robustness issue of deep learning-based HD EMG PR.**

I. Introduction

Surface electromyography (EMG) is a non-invasive technique for assessing the muscle-amplified myoelectric output of motor units. Surface EMG-based Pattern Recognition (PR) has been widely used in Neural-Machine Interface (NMI) designs for identifying human movement intentions to control applications such as bionic prostheses, assistive devices, and augmented reality/virtual reality systems [1]–[4]

High density (HD) EMG signals recorded with 2-dimensional (2D) arrays of closely spaced electrodes over a muscle area can capture neuromuscular information from one temporal and two spatial dimensions. HD EMG-based PR has attracted increasing interest in real-time NMI applications because, compared to traditional single channel-based targeted muscle sensing method, HD EMG can capture richer neuromuscular information and does not require anatomically targeted electrode placement in practical use [5]–[8].

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Deep learning methods have been successful in tackling 2D data-based tasks such as image classification. An HD EMG electrode pad also generates a 2D data frame at each sampling time point. In recent years, deep learning methods such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid CNN-RNN methods have shown great potential in HD EMG PR [9]–[11]. Compared to traditional machine learning methods commonly used in EMG PR such as linear discriminant analysis and support vector machine, deep learning algorithms also have the advantage of automatically extracting HD EMG features without the cumbersome manual feature engineering step.

Due to the high-density and multi-channel characteristics of HD EMG, the use of HD EMG-based NMIs in practice may be challenged by the unreliability of signal recordings over time. Conditions such as movement artifacts, environmental noises, and loose electrode-skin contacts may cause variances in the HD EMG characteristics and potential threaten the reliability of EMG PR performance [12]. Our previous work has developed a Sensor Faculty-Tolerant Module (SFTM), which includes multiple sensor fault detectors that monitor the time-domain features of each EMG signal to detect abnormal sensor behaviors, and an LDA-based self-recovery algorithm to quickly retrain the classifier without the faulty sensors' data to recover the EMG PR performance in real time [13]. The SFTM model requires retraining when sensor faults are detected which makes it difficult to expand to other more complex machine learning methods.

Despite the promising results shown on normal HD EMG data, few studies have investigated the robustness of deep learning methods on HD EMG PR when noises and disturbances are present in the HD EMG signals. While, this issue could be relieved by methodically collecting augmented training datasets with disturbances and fine-tuning the CNN models, it is time-consuming and unrealistic to cover all aspects of unreliable recording conditions.

In this paper, we have made the first attempt to develop a Robust deep learning-based HD EMG PR (*RoHDE*) framework by introducing a Generative Adversarial Network (GAN) which generates synthetic HD EMG signals from a small sample of disturbance data to simulate unreliable recording conditions. The generated synthetic HD EMG signals can augment the normal HD EMG dataset to train robust deep learning models against real HD EMG signal disturbances. Experimental results have shown that our robust HD EMG PR

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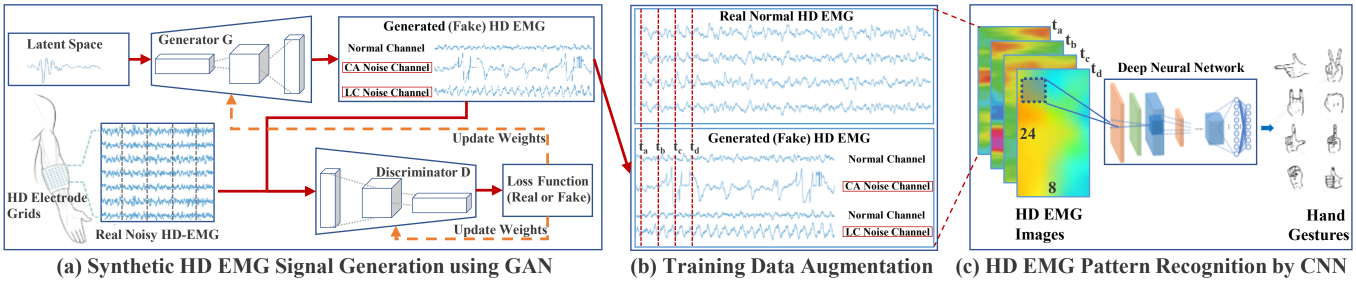


Fig. 1. Overall system architecture of *RoHDE* framework. **(a)** Synthetic HD EMG Signal Generation using GAN. **(b)** Normal and Generated Noisy HD EMG Training Data. **(c)** HD EMG Pattern Recognition by CNN.

framework can improve the classification accuracy of a CNN-based model affected by contact artifact and loose contact disturbances by up to 35%. To the best of our knowledge, this work is the first to address the robustness issue of deep learning-based HD EMG PR and can be applied to any deep learning models.

II. Method

A. Framework Overview

Fig. 1 shows the overall architecture of the *RoHDE* framework and consists of three major parts: (a) synthesizing noisy HD EMG data with the GAN, (b) augmenting normal HD EMG data with generated noisy HD EMG data, and (c) training a PR neural network with augmented HD EMG data. The primary goal of the GAN is to create realistic "fake" noisy HD EMG data to cover all aspects of unreliable recording conditions, including but not limited to such as Contact Artifacts (CA) and Loose Contacts (LC). By sampling only a small amount of real noisy HD EMG data, the artificially created noisy HD EMG data is fed into our Pattern Recognition (PR) CNN along with the normal HD EMG data. Trained with this augmented HD EMG dataset, the PR CNN can significantly improve its robustness.

B. HD EMG Pattern Recognition by CNN

In this paper, we leverage the one of the state-of-the-art CNN models, MobileNetV2 [14], for the HD EMG pattern recognition, which utilizes both depth-wise and point-wise convolution operations to reduce computational load for embedded devices.

As shown in the Fig. 1 (a), 2D-arrays arrangements of HD EMG electrodes grids are placed over a muscle area, which enables tracking of both temporal and spatial changes in the electrical potential. From Fig. 1 (c), the 2D HD EMG data frame at each sampling time point allows us to analyze HD EMG information in the spatial domain, which makes it possible to analyze EMG signals using image processing techniques. The number of pixels in an EMG images is defined by the matrix of electrodes (e.g., an electrode grid with 8 columns and 24 rows forms an EMG image with 8×24 pixels). An HD EMG image is defined as a single sample of a motor unit action potential distribution under an electrode grid at each sampling time (*e.g.*, t_a,t_b,t_c,t_d).

C. Synthetic HD EMG Signal Generation using GAN

As mentioned above, one of the main problems with training robust CNN models is the unreliability of HD EMG recordings. This issue could be relieved by collecting large noisy training datasets and fine-tuning the CNN models. However, building such a large database of noise EMG recordings to cover all types of possible disturbances is extremely time-consuming and often impractical.

To address this issue, we utilize a Generative Adversarial Network (GAN) to artificially generate the necessary data. GAN was first proposed by Goodfellow [15] in 2017 where he combined two Neural Networks, a Generator and a Discriminator, in a feedback loop to continuously improve the performance of each other. As shown in Fig. 1 (a), the primary goal of the Generator is to synthesize realistic "fake" noisy HD EMG data. This generated "fake" noisy data is fed into the Discriminator where it is compared with real noisy HD EMG data and outputs a loss function that indicates the differences between the real data and the fake data. The loss function and the updated weights are inputted back into the Generator in a feedback loop to allow it to synthesize more realistic data. This cycle is repeated until the Discriminator is no longer able to distinguish between real and fake noisy data. When the Generator and Discriminator reach this equilibrium point, the Generator can be utilized individually to generate an unlimited amount of "fake" noisy data for training our CNN model.

In order to preserve useful information in the generated HD EMG data, the generated HD EMG image needs to mimic both the spatial and temporal feature distributions of the real noisy HD EMG image. However, the 2D HD EMG image only contains spatial domain features because each image only contains HD EMG signal in a single time frame. To preserve both spatial and temporal in the generated "fake" noisy data, one solutions is to feed multiple time frames into the generator of the GAN, but the resulting training process can be extremely time-consuming. In this paper, we generate each noisy HD EMG channel (1D-vector) sequentially by aligning their gesture labels and reconstructing the HD EMG image (2D-matrix). Specifically, multiple GAN models for each channel will be trained by referencing the noisy channel, and each model will generate a single channel of the EMG data. After the GAN model is well trained, we reconstruct the generated EMG data of each channel into a 2-dimensional matrix in which each row represents a different channel and each column represents a different time frame. Thus, both spatial and temporal features can be captured and artificially reproduced.

Regarding the GAN model, we proposed a hybrid GAN based on the Wasserstein GAN [16] and DCGAN [17] which utilizes the Lipschitz constraint, Wasserstein gradient penalty and convolutional layers. First, the Lipschitz constraint is used to avoid mode collapse (the generator can only produce a single type of output or a small set of outputs), and the Wasserstein Gradient Penalty loss function makes GAN training more stable easier to train. Second, the convolutional layers from DCGAN are used to extract the temporal features. Finally, the HD EMG data with temporal features is reformed into a 2-dimensional matrix to restore the spatial feature.

D. Robust CNN Training by using Synthetic HD EMG Data

As shown in the Fig. 1 (b), after the GAN model reaches equilibrium, we can feed the synthesized noisy HD EMG data and the normal HD EMG data into our CNN model for training. The ratio of noisy to normal data is set as a hyper-parameter while training our model to optimize the training time and resulting recognition accuracy. The details and results of fine-tuning this hyper-parameter is explained and recorded in the following experiment section.

III. Experiments and Results

A. Experiment Setup

This study was conducted with the Institutional Review Board's (IRB) approval at San Francisco State University and the informed consent of the test subject. Data acquisition was conducted on a male able-bodied subject's dominant forearm with the OT Bioelettronica's Quattrocento amplifier at 2560 samples per second with three HD EMG electrode grids with 10mm spacing between electrodes in an 8 by 8 arrangement, resulting in 192 channels.

HD EMG Dataset: The HD EMG data set consists of the following seven hand and wrist gestures: no movement, wrist supination, wrist pronation, hand close, hand open, wrist flexion, and wrist extension. To evaluate its performance, we experimented with two common disturbances of EMG recordings in this study: Contact Artifacts (CA) and Loose Contacts (LC) [18], [19]. Fig. 2 shows two representative trials of HD EMG signals contaminated by LC (Left) and CA (Right), respectively. The LC disturbances were simulated by purposely peeling back the last two rows of an 8×8 HD EMG electrode grid (e.g., channels 8, 16, 24, etc), and placing a towel between those electrodes and the skin. In the CA trials, noise was introduced by tapping a pen on approximately the last 3 dozen electrodes (156-192) at a rate of 4-5 Hz. The exact electrodes affected vary from strike to strike.

Deep Learning Model: We utilized the MobileNetV2 for our PR CNN model, which was trained for 10 epochs with a batch size of 1000 and a learning rate of 3e-4. In addition, we applied the AdamW optimizer with a weight decay of 5e-4. We used simple majority voting to evaluate the overall gesture

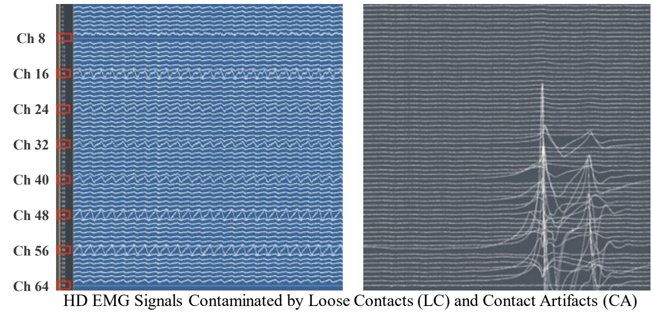


Fig. 2. Representative trial showing HD EMG signal contaminated by Loose Contacts (Left) and Contact Artifacts (Right)

recognition testing accuracy. For our hybrid GAN, we trained it for 3 epochs with a batch size of 1000 and a learning rate of 1e-4. To update the weights for comparisons between real and fake HD EMG images for the Generator, we utilized the Wasserstein Gradient Penalty Loss function.

Framework Implementation: *RoHDE* framework is based on the Pytorch platform [20] due to its low developmental complexity, and high performance. Key libraries including scikit-learn were used in our implementation. The code and pre-trained robust deep learning models can be found at: https://github.com/MIC-Laboratory/RoHDE.

B. Experiment Results

1) Overall Performance: We first tested real noisy EMG data on both our Robust PR CNN model and the regular PR CNN model to complete their performances. The robust PR CNN model was pretrained on synthetic noisy HD EMG data while the regular PR CNN model was only pretrained on clean HD EMG data. Fig. 3 (a) shows the testing accuracy results of our CNN models for varying majority voting frames where the x-axis represents the number of voting frames and the y-axis represents the recognition accuracy. The red (Robust CA) and orange (Robust LC) lines demonstrate the testing accuracy of our Robust PR CNN on HD EMG data contaminated with real CA and LC noise, respectively. The light blue (Regular CA) and dark blue (Regular LC) dot lines are the regular PR CNN models testing accuracies without robust training. The experiment shows that the Robust PR CNN model achieves up to 99.25% of accuracy. In comparison, the regular PR CNN model only achieves 63.97% and 72.79%accuracies on the CA/LC contaminated HD EMG data. From this simple comparison, the robust PR CNN model has over 35% improvement over the regular PR CNN model on testing accuracy.

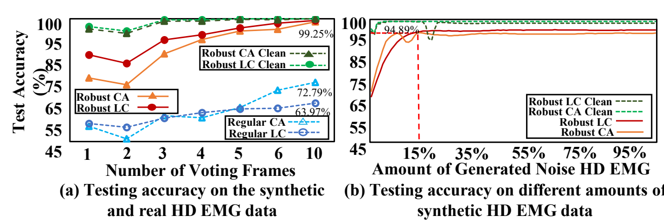
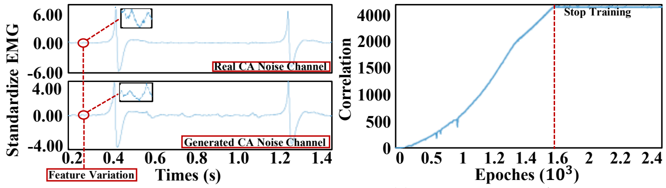
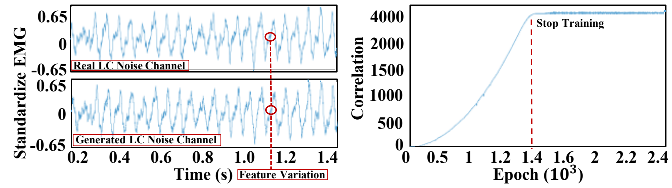


Fig. 3. **(a)** Testing accuracy of CNN that trained on the clean EMG data and tested on the noisy EMG data. **(b)** Testing accuracy of CNN trained with different amounts of synthetic HD EMG data



(a) Real and Synthetic CA noise HD EMG signal (b) The cross-correlation between the real and synthetic HD EMG signals

Fig. 4. **(a)** Real CA noise HD EMG signal ad Synthetic CA noise signal generated by GAN. **(b)** The cross-correlation between the real HD EMG signals and the synthetic HD EMG signals during GAN training.



(a) Real and Synthetic LC noise HD EMG signal (b) The cross-correlation between the real and synthetic HD EMG

Fig. 5. **(a)** Real LC noise HD EMG signal and Synthetic LC noise signal by GAN. **(b)** The cross-correlation between the real HD EMG signals and the synthetic HD EMG signals during GAN training.

In addition, we also evaluated our robust model on clean EMG data. The dark green (Robust CA Clean) and light green (Robust LC Clean) dotted lines represent the testing accuracies of our Robust PR CNN on real clean HD EMG data. From Fig. 3 (b), we can see that the Robust PR CNN model retains 99% testing accuracy on real clean HD EMG data.

In conclusion, our *RoHDE* framework can significantly improve the robustness of the PR CNN model on noisy data.

2) The Effect of Synthetic HD EMG Data Amount: The improved robustness of the PR CNN model comes from training on the generated noisy HD EMG data, which requires additional computational resources to train the GAN model. In this section, we quantitatively evaluate the effect of the amount of synthetic HD EMG data on model performance.

As shown on the Fig. 3 (b), we tested the Robust PR CNN model with different amounts of synthetic noisy HD EMG data. The red and orange solid lines represent the testing accuracies of the robust PR CNN model on real contaminated LC and CA HD EMG data, respectively. The dark green (Robust CA Clean) and light green (Robust LC Clean) dotted lines represent the testing accuracies of the robust PR CNN model on real normal data, respectively.

From our experimental results, we can see that only 15% of synthetic noisy HD EMG data in the dataset is needed for training a Robust PR CNN model that can achieve 94.49% testing accuracy. Compared to the existing open-source HD EMG datasets with more than 100k of training data, our framework enhances the robustness of the PR CNN model and while using a small amount of synthetic data. In conclusion, the benefit of our framework is that exponentially increased robustness far exceeds the drawbacks of the slight increase in computational resources.

3) Synthetic HD EMG Data Quality: In this section, we evaluate the quality of the synthetic noisy HD EMG. The cross-correlation was adopted to quantitatively measure the similarity between the synthetic noisy HD EMG data and real noisy HD EMG data [21]. Larger cross-correlation value indicates higher similarity between the generated and real data. In addition, we plot the generated noise EMG data to qualitatively measure the similarity with the real noisy data.

Fig. 4 (a) shows the visualization of the real and synthetic CA-contaminated data where the x-axis represents the time in seconds and the y-axis represents the standardized EMG value. We observed that real CA-contaminated data and synthetic CA-contaminated data are highly similar with little feature variations. It shows that the generated CA noise data contains the real CA features.

Fig. 4 (b) shows the quantitative measurement between the synthetic noisy HD EMG data and real noisy HD EMG data where the x-axis represents the training epochs and the y-axis represents the correlation value. We observe that over multiple training epochs, the cross-correlation value becomes larger and larger, indicating that the similarity between the synthetic and real noisy data is increasing as the training continues.

Fig. 5 (a) and Fig. 5 (b) show the visualization and correlation of the real and generated LC data. We observed similar trends in Fig. 4 (a) in which the synthetic LC-contaminated data contains real LC features with small variations. In conclusion, the experiment shows that our hybrid GAN can effectively mimic the original noisy HD EMG data's features for training a deep learning model.

IV. Conclusion

In this paper, we proposed *RoHDE*, a Robust HD EMG PR framework to improve the robustness of deep learning-based HD PR against EMG signal noises and disturbances. We identified that the unreliability of HD EMG recordings can significantly impact the overall gesture recognition accuracy of a deep learning model. A hybrid GAN model was proposed to generate realistic synthetic noisy data for training a deep learning model. To verify the quality of our synthetic data, we performed extensive experiments on the cross-correlation between the synthetic noisy data and real noisy data. Our Experimental results show that we were able to achieve up to 95% gesture recognition accuracy for HD EMG data contaminated with real LC and CA noise. In our future work, we will continue to investigate the robustness issue of deep learning-based gesture recognition by experimenting with other types of common external disturbances to further verify our robust framework. In addition, we plan to integrate our framework with RNN-based HD EMG PR to investigate its effectiveness on alternate deep learning models.

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