Parkinson sEMG signal prediction and generation with Neural Networks

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Abstract. *Parkinson's Disease (PD) is a neurodegenerative disorder characterized by symptoms like resting and action tremors, which cause severe impairments to the patient's life. Recently, many assistance techniques have been proposed to minimize the disease's impact on patients' life. However, most of these methods depend on data from PD's surface electromyography (sEMG), which is scarce. In this work, we propose the first methods, based on Neural Networks, for predicting, generating, and transferring the style of patient-specific PD sEMG tremor signals. This dissertation contributes to the area by i) comparing different NN models for predicting PD sEMG signals to anticipate resting tremor patterns ii) proposing the first approach based on Deep Convolutional Generative Adversarial Networks (DCGANs) to generate PD's sEMG tremor signals; iii) applying Style Transfer (ST) for augmenting PD's sEMG signals with publicly available datasets of non-PD subjects; iv) proposing metrics for evaluating the PD's signal characterization in sEMG signals. These new data created by our methods could validate treatment approaches on different movement scenarios, contributing to the development of new techniques for tremor suppression in patients.*

1. Introduction

As one of the most common neurodegenerative diseases affecting approximately 10 million people around the world [Organization. 2006], Parkinson's Disease (PD) has been studied and investigated from different perspectives to minimize the disease's symptoms and impairments to patients, with many studies around rest and action tremors. Surface electromyography (sEMG) stands out as one of the most common ways to measure muscle response to voluntary or involuntary stimulation, being widely used as a primary input feedback signal for artificial stimulation devices [Philipson 2009, Bó 2010]. sEMG is widely used clinically for the diagnosis of neurological and muscular pathology [Ahad 2019] and has recently been used for several human-machine interface applications. Usually, these applications require datasets to train machine learning models.

However, acquiring such datasets from patients is a complicated and sometimes painful task, and a wide range of movements is usually not possible due to the patient's movement limitation and impairment. Therefore, collecting, processing, and using recorded sEMG signals for analysis is quite a challenging approach due to data scarcity and lack of dataset variation.

In this scenario, biological signal simulations could be employed. However, generating realistic models requires a profound understanding of the simulated signal patterns and morphology [Petersen and Rostalski 2019]. Also, since PD's tremor patterns differ in intensity and manner for each patient, it is quite challenging to create a generic mathematical model [Guerrero and Macías-Díaz 2019] that can effectively produce an artificial signal similar to real ones. Furthermore, such an approach cannot adapt to different movement protocols or adjust to an individual's specific sEMG tremor pattern, whose parameters are not known a priori, and present typical irregularities on frequencies and shape through time. Such adaptability is desired when augmenting a specific patient dataset instead of generating generic tremor patterns.

To overcome these restrictions, data augmentation is a promising alternative approach for extending existing datasets, allowing further research and analysis. In this work, we employ NN models to predict, generate, and transfer the style of patient-specific PD sEMG tremor signals. Our proposed approach aims at evaluating and comparing different neural network architectures to predict PD's sEMG signals. Our primary target is to successfully predict an entire window of the tremor pattern (approximately 0.2s). This method could enable real-time assisting devices, like Functional Electrical Stimulation (FES) devices, to operate with much more precise control over the stimulus and the patient's tremor.

Additionally, we propose two new approaches to generate surface EMG signals based on existing datasets. Neural Networks are trained to learn the specific sEMG signal tremor patterns in our first proposed method, hence reproducing such tremors for each patient. The resulting model can also be employed as a feature extractor model, allowing us to combine it with the second method's style transfer techniques. The resulting combination will enable us to generate a transformation model that simulates the tremor pattern not only on the original movement protocol but also on other movements based on healthy individuals' datasets. Such extension allows us to use healthy patients datasets to investigate how PD can affect patients' movements from a much broader perspective than those we can collect with real patients during measurement experiments.

2. Contributions

This dissertation proposes a **Neural Network-based approach for predicting PD's sEMG future tremor peaks**. To this end, we design and evaluate several architectures to predict both raw and envelope sEMG signals with different prediction windows. The resulting approach was published in the **IEEE International Conference on Systems, Man and Cybernetics 2018** [Zanini et al. 2019].

We also designed the **first method to generate sEMG PD signals**. By employing Deep Convolutional Generative Adversarial Networks (DCGANs) with domain-specific discriminator CNN pipelines, we successfully simulate sEMG tremor behavior, not only mimicking generic tremor patterns but patient and protocol-specific characteristics. With this approach, we could generate new sEMG signals that could tackle typical problems in generative approaches such as mode collapse. We also addressed how different input features such as FFT and Wavelet impact the generated signal quality.

Finally, we propose a **Style Transfer approach for augmenting Parkinson's sEMG signals by combining two distinct sEMG databases**. For this purpose, we use our trained discriminator as a feature extractor of the Parkinson's signal components. This discriminator is used in a Fast neural style transfer architecture to combine our learned

PD's signal components to data from the NinaPro (non-PD signals) dataset, creating a new dataset of PD's data. To assess the quality of the final generated signal, **we propose** using DTW distance, FFT MSE, and sEMG Envelope Cross-correlation as **metrics for sEMG signal generation**. The results from these methods were published in the **Sensors Journal** with the work "Parkinson's Disease EMG Data Augmentation and Simulation with DCGANs and Style Transfer" [Zanini and Colombini 2020].

3. sEMG Signal Prediction

Predicting Parkinson's Disease sEMG signals based on patient's readings as input is a typical time-series sequence prediction problem. Since PD's tremor typical frequency varies between 4-6 Hz, each tremor stimulus happens on a 0.2-second window. Considering a sampling rate of 2 kHz, we need to cover at least 400 points in the future to predict when the next tremor stimulus is happening.

To do that, we generate 400 points in the future based on the last 4,000 points, using two approaches: first, we used the **raw sEMG data** as input and evaluated different models based on MLP, LSTM, and Autoencoders as a prediction model, trying to predict the next 400 points. This approach can give us a good estimation of the shape and behavior of the sEMG signal but does not offer a good estimation of the complete amplitude of the tremor. To better predict tremor peaks and amplitudes, we employed a second approach, using a representation of **sEMG envelopes** as input. We have also evaluated MLP, LSTM, and Autoencoders prediction models to predict the shape and amplitude of the next tremor sEMG envelope. As a result, for the same sEMG signal, it is possible to predict its shape and specific sEMG raw signal frequencies and its envelope representation, giving us a complete prediction of PD's tremor signals (0.2s before they occur).

Results. Experimental results showed that MLP and LSTM-based networks could successfully predict sEMG tremor behavior, predicting sEMG envelopes and raw signals. By using the autoencoder approach, we successfully trained encoding models to compact sEMG information into a lower-dimensional space. We also compared different MLP and LSTM topologies, evaluating the hyperparameters' influence on the models and how the loss function affects the prediction quality, proposing a new loss metric to evaluate and train sEMG prediction models.

4. sEMG Signal Generation

This work proposed two methods for sEMG data augmentation. On the first one, based on DCGANs, we train a generator that is capable of simulating each patient's sEMG tremor pattern and its correlated discriminator. In the second, based on neural style transfer and the trained discriminator from the previous method, we apply the style from a PD patient on a set of healthy patient sEMG signals, simulating the expected tremor behavior on a different set of movements. We can also use the same inputs to train a Fast Neural Style Transfer transformer network to use it as a fast transformation method. Figure 1 presents a simplified diagram of the proposed methods.

4.1. sEMG Signal Generation with DCGANs

Despite their current success and results in image generation, DCGANs have been less explored on time series and biological applications. In this work, we shift their use to a

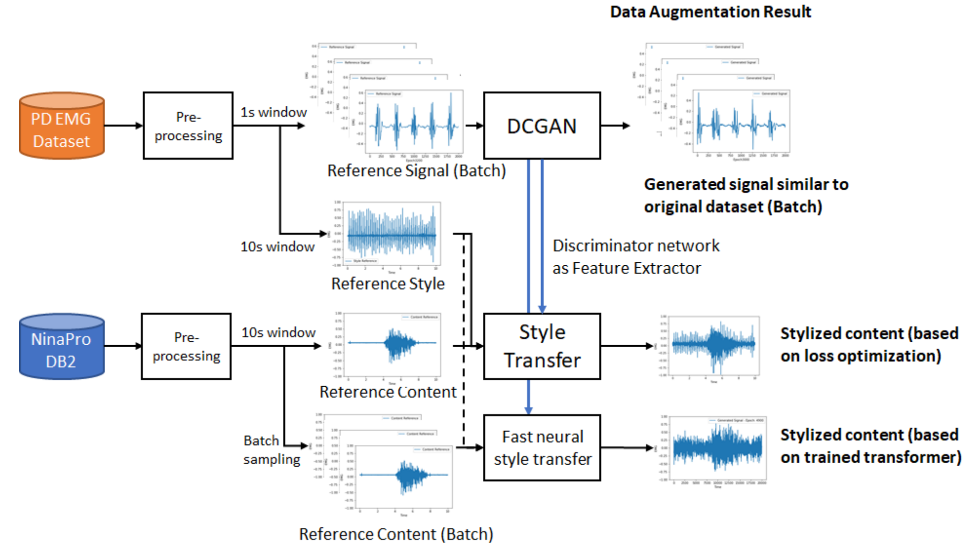

Figure 1. Proposed flow for the experimental setup for sEMG signal generation.

multi-variable 1D context with intricate patterns varying through time. Typically, while creating GANs, the generator is of primary interest—the discriminator is an adaptive loss function that gets discarded once the generator was trained. However, as we present in this work, the trained discriminator can also be used as a feature extractor that can be applied in combination with other techniques, such as style transfer.

Generator Model. Our best generator model consists of a deep convolution network – adapted for 1D convolutions – that takes 400 point samples (0.2 s) from the original sample and tries to generate a new dataset with 2,000 points (1 s). It includes a dense layer and moving average at the end of the generator pipeline to smooth the generated signal compared to the filtered sEMG input signal. We have evaluated several different parameters (such as the number of filters, layers, activation functions, and other settings), reaching a fine-tuned architecture.

Discriminator Model. Our best discriminator model consists of a deep convolution network that takes a batch of 100 randomly distributed samples with 2,000 sequential points and tries to distinguish if they come from the training dataset or the generator. We have combined parallel deep convolutional pipelines for such a task where each one generates extended features based on the input vectors. The pipeline combines four convolutional stacks with a final dense layer for classification between real and fake samples. They are i) Convolutional Filters on Raw Signal; ii) Convolutional Filters on FFT; iii) Convolutional Filters on an sEMG Envelope Signal, and iv) Convolutional Filters on Wavelet Expansion.

4.2. sEMG Generation with Style Transfer

Style Transfer (ST) was introduced in 2015 on the computer vision domain as a technique that allows us to recompose the content of an image in the style of another [Gatys et al. 2015]. In this work, we employ two style transfer approaches. In the first, we modify the algorithm introduced in [Gatys et al. 2015] to work for 1D time-series data, adjusting the proposed content loss and style loss functions to our domain. We also replace the original VGG16 used in [Gatys et al. 2015] with the trained discriminator network used for the DCGAN architecture. We took the four main discriminator convolutional stacks (raw signal, FFT, FFT over envelopes, and wavelet expansion) as the feature layers for the style loss, calculating the gram matrix for the convolutional filters for the style signal and the generated signal. For the second approach, we used the concept of fast neural style transfer [Johnson et al. 2016] to train a transformer network. This network receives an input sEMG signal from a healthy individual—performing some functional actions (like wrist flexion/extension, grasping, pointing index fingers, and others)—and applies a transformation based on a PD patient sEMG signal to simulate how the signal would look like if performed by a PD patient. The transformer network is trained based on a set of content examples (healthy individuals database coming from NinaPro) and the style (sEMG signals from our private PD patient dataset). For calculating the losses between content, style, and transformed signals, we use the pre-trained discriminator from the DCGAN architecture as a feature extractor—thus allowing the transformer network to learn the individual patterns of each patient, according to the trained discriminator and generator. We compare this approach with the ST-based model.

4.3. Proposed Metrics

We evaluate the quality of the signal generated by proposing three metrics to our domain: **Fast Fourier Transform (FFT) Mean Squared Error (MSE).** To measure the similarity between two-time series signals, one can use the mean square error (MSE) between signals FFT magnitudes. The FFT MSE was used to measure the similarity between generated data and real data and evaluate the similarity between the generated signal and the style and component signals on the style transfer step. **Dynamic Time Warping (DTW).** In time series analysis, DTW is one of the algorithms for measuring similarity between two temporal sequences by comparing both sequences' local cost functions. Delaney et al. (2019) [Delaney et al. 2019] showed that DTW could successfully evaluate the generated data quality since it is more robust against training instability and sensitivity to the relative amplitude between the real and synthetic data. **sEMG Envelope Cross-Correlation.** Cross-correlation is a measure of similarity of two series as a function of the displacement of one relative to the other. It has been commonly used for pattern recognition applications, mainly applied to neurophysiology. The cross-correlation function is similar to applying the convolution of two functions [Semmlow and Griffel 2014]. Since the shape and values of tremor peaks on sEMG might vary significantly from reference and generated signals, we have identified that the simple cross-correlation on raw signals would not capture the similarity between them. Therefore, we have calculated the normalized cross-correlation between the sEMG envelopes (with a 100-point moving average on absolute values) to check if generated signals correctly captured tremor peaks.

4.4. Results

We arrived at significant findings related to 1D complex bio-signals such as EMG tremor signals from the Signal Generation experiments. First, we emphasize that, although employing a DL-based approach, it is essential to add different convolutional pipelines that focus on specific features from the signal while replicating complex output shapes. In our case, adding both FFT analysis and wavelet decomposition to the discriminator model was essential for generating better results. Also, we found that 1D convolutions significantly outperformed 2D representations of the time-series signals. We identified that increasing the number of points and introducing the real signal sampling as input led to better results.

We also verified the importance of metrics that can effectively evaluate the generator's performance vs. the reference signals. FFT and DWT were the best evaluation metrics for our domain. It was also relevant to find that we could employ our discriminator as a meaningful feature extractor for the Style transfer technique. We also found that the loss-optimization approach from traditional style transfer led to more robust solutions. Finally, finding appropriate weights for the content and style signals is a challenging task. In our case, their impact might be further evaluated if real signals from PD patients performing the same types of movement from healthy individuals are available.

5. Main Advances in the State of the Art

In PD's sEMG signal prediction and generation, we have created the first methods for such tasks. We also employ the first Style Transfer-based approach for combining a signal style typical of a neurodegeneraitve disease to a healthy patient signal. It is important to remark that, although we validate our findings in the context of PD, the proposed models could be employed in other sEMG-based scenarios. We also hypothesize that EEG and ECG signals could be used instead of sEMG. The code is available in our public repository `www.github.com\larocs`

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