Enhanced Finger Movement Detection Using sEMG by Data Augmentation

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Abstract

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Surface Electromyography (sEMG) is a technique to capture electrical activity in muscles during contraction. Individual finger movement has not received much attention as a significant proportion of the current sEMG research targeting the hand has focused on gestures. Accurate classification of individual finger movements is essential for several applications including robotic prostheses and computer security applications. A problem we face in classifying individual finger movements is data sparsity resulting from device availability, acquisition time, and patient privacy laws. To alleviate the problem of limited training data, we propose to synthetically augment the training data. Although some sEMG data augmentation methods have been studied in the literature, their contribution in improving prediction performance is still limited. Pattern mixing has shown promising performance in general time series augmentation, but has not been studied for sEMG. However, one major limitation of pattern mixing is its expensive computational cost. Therefore, in this paper, we propose a random combination method which helps to diversify our training data, as well as to reduce the time required for building the synthetic data. Our empirical study on several subjects using sEMG demonstrates both the effectiveness and efficiency of our proposed method.

1 Introduction

Surface Electromyography (sEMG) is a non-invasive technique to acquire myoelectric signals [6]. These signals capture muscle contraction activities that may be utilized in an array of domains. For instance, sEMG signals may be used to control robotic prostheses or exploited to address the authentication problem in computer security [24,19]. An important step in facilitating these innovations is developing methods to identify and classify individual finger movements. However, to date, the majority of hand sEMG classification research has focused on hand gesture or multi-finger movement recognition [17,27]. Therefore, in this work, we focus on individual finger movement detection and classification.

It is well known that machine learning algorithms often require sufficient training data to give successful predictions. A realistic problem we face in developing classification models for the individual finger movement problem is limited training data. sEMG data is scarce for several reasons. First, the devices required to record said data are relatively expensive and specialized. Not a device a typical adult would purchase. Second, acquiring individual finger movements is both time-consuming and taxing. The acquisition process is taxing for the test subjects because Lactic Acid builds with each finger contraction, resulting in a burning sensation experienced during intense exercise. Lastly, patient privacy laws often prevent the release and distribution of data acquired by medical professionals.

Data augmentation is a technique that has yielded great performance gains in, most notably, computer vision [16]. Augmentation is the generation of new, synthetic samples using real samples. The goal is to produce synthetic samples which plausibly are contained by the target population. In our case, the target population is the set of all possible sEMG individual finger movement signals. Time series data augmentation has received significantly less attention with respect to computer vision. A number of time series data augmentation techniques exist and some of which have been applied to sEMG data [1,27,11,5,3]. Many of the augmentation techniques applied to sEMG data are random transformation methods. These techniques either yield relatively limited performance gains or, are mathematical models [5,11] requiring a solid understanding of the biological systems and processes involved. Pattern mixing augmentation techniques [18,15] have proven to be effective with considerable computation overhead. However, pattern mixing techniques have not yet been applied to sEMG data.

Considering that random transformation methods are efficient but less performant and pattern mixing methods are effective but less efficient, we, in this work, propose a random combination between these two methodologies. The first obvious benefit is that with less usage of the slow pattern mixing method, the computational time required to augment the same amount of data can be reduced. Moreover, different augmentation methods can capture unique regions of the problem population space, and thus the combination can effectively diversify our training data to provide better generalization performance. Our empirical study conducted on four different subjects using sEMG demonstrates both the effectiveness and efficiency of our proposed random combination method.

2 Related Work

This section briefly reviews data augmentation techniques previously applied either to sEMG data or general time-series data.

2.1 sEMG Data Augmentation

There exist copious sEMG simulation models which can be used to generate sEMG signals. Two primary purposes of these methods are to understand the influences of the electrical potential energy in muscles (i.e., the "forward problem") and how the extracellular electrical potential energy describes the underlying biological system (i.e., the "inverse problem") [21]. Furui et al. [11] introduced a mathematical model to generate sEMG signals and demonstrated its ability to produce samples to improve the classification accuracy of bicep contraction. Botelho et al. [5] introduced an sEMG model for index finger flexion and abduction. [12] proposes a free, open-source R software package for analyzing and generating sEMG signals. Problems with these models include the signals they generate depend upon many domain-specific variables, which requires a solid understanding of their meaning [1] and the validation of said models is challenging [20].

Additional augmentation techniques have been applied to sEMG data as well. Atzori et al. [3] applied Gaussian noise to double the data size yielding improved classification performance of hand movements using a simple convolution neural network (CNN). This study uses the Ninapro database [4]. Zanini et al. [1] applied a DCGAN with Style Transfer to augment a Parkinson's Disease dataset by transforming sEMG samples collected from healthy subjects into data closely resembling those of the Parkinson's data. The healthy subject samples were drawn from the Ninapro dataset [4], which contains hand kinematics acquired using a motion capture data glove and hand dynamics using a Finger-Force Linear Sensor (FFLS). Recently, Tsinganos et al. [27] evaluated several augmentation methods on the putEMG data [17] and Ninapro-DB1 data [4]. The evaluated methods include Gaussian noise, slicing, magnitude warping, wavelet decomposition, and two sEMG simulation models (including the one proposed in [11]). One of the sEMG simulation models applied was designed to generate Electromyographic signals for bicep muscle contraction [11]. The authors found improved classification performance from wavelet decomposition, Gaussian noise, and magnitude warping while noting a high degree of overfitting when applying the wavelet decomposition and Gaussian noise methods. However, their evaluation focused on multi-channel hand gesture sEMG signals, whereas we target individual finger movements captured by a single channel, which is more efficient for real-time applications such as the authentication problem in computer security and a robotic prosthesis.

2.2 General Time Series Augmentation

A recent survey [16] provides an in-depth analysis of data augmentation methods applied to general time series data for neural network classification. Existing techniques can be categorized into four groups: random transformations, pattern mixing, generative models, and decomposition methods.

Random Transformations Ordinary time series data augmentation involves randomly transforming the signals. These transformations include Gaussian noise injection, time warping, frequency warping, magnitude warping, scaling, permutation, cropping, and flipping or rotating signals. A few of these approaches were put into action in [28] where Um et al. leveraged these methods to improve the classification performance of wearable sensor data using a convolutional neural network (CNN). Later, Huang et al. [13] applied two types of rotation and Gaussian noise to radio modulation data to improve classification performance in a Long Short-Term Memory (LSTM) model. Synthetic Minority Oversampling Technique (SMOTE), proposed in [7], is a popular feature space augmentation method. This method, and its variants, select two samples of the same class and interpolate along each dimension to produce a new signal. This method can result in overfitting. Note that SMOTE is not limited to feature space. In [2], Arsian et al. applied SMOTE and Gaussian noise to a Long Short-Term Memory (LSTM) model to improve the predictive accuracy of air quality sensor data. Although a few of these techniques have been applied to sEMG data [27,3], no previous study has applied them to the single-channel sEMG data as in our work.

Pattern Mixing Recently, Iwana et al. [15] introduced Random Guided Warping (RGW) and Discriminative Guided Warping (DGW). Each of these methods uses pattern mixing to generate new samples. RGW randomly selects a reference sample of the same class. DGW, on the other hand, uses a discriminator to choose from a bootstrap of samples of the same class. Additionally, DGW uses shapeDTW, a variant of Dynamic Time Warping (DTW), to find the *warping path* between the two signals. SuboPtimAl Warped time-series geNEratoR (SPAWNER) introduced in [18] by Kamycki et al. is another pattern mixing technique. This method also leverages Dynamic Time Warping (DTW) to compute the *warping path* but forces a randomly selected point (cannot be an endpoint) from each of the signals to be aligned. The synthetic sample is the average of each of the aligned signals. Additionally, Gaussian noise is added to the synthetic sample because some artificial signals did not change much. To the best of our knowledge, pattern mixing techniques have not yet been applied to sEMG data, which will be explored in this work.

Generative Models WaveNet, proposed in [23], is an autoregressive generative model producing unique sequences from existing sequences. Each time step in the generated sequence is produced using conditional probability given a number of previous timesteps, which is accomplished using dilated causal convolutional layers. WaveNet was developed to generate audio signals, which is quite different from sEMG signals. Recently, GAN has become very popular in generating synthetic data for various applications, including time-series data. For example, Esteban et al. [9] introduced both Recurrent Generative Adversarial Networks (RGAN) and Recurrent Conditional Generative Adversarial Networks (RCGAN) to produce synthetic data for time-series data collected from an Intensive Care Unit (ICU). Each of these networks uses a Long Short-Term Memory network for the discriminator and generator models. The primary difference between these models is that the RCGAN is conditioned on some auxiliary inputs. However, GANs require a sufficient number of samples to produce viable synthetic data. Later, Fekri et al. [10] introduced a Recurrent Generative Adversarial Network to augment smart grid data with limited historical data. The authors apply Wasserstein GANs (W-GANs) and Metropolis-Hastings GANs (MH-GANs) techniques to encourage network convergence and yield higher quality synthetic data. A previous study [1] successfully applied a DCGAN to sEMG data. Considering limited data for training GAN in our work, we will study generative models in the future.

Decomposition A recent study applied Empirical Mode Decomposition (EMD) [14], a older decomposition method for analysing nonlinear and non-stationary signals, to augment an vehicle impact noise dataset in [22]. The authors applied their synthetic data to a CNN-LSTM and observed improved classification performance. A previous study [27] successfully applied Wavelet Decomposition to augment an sEMG hand gesture dataset. However, decomposition methods are often very time-consuming.

3 Methodology

In this section, we first describe the procedure of applying one of the state-of-art pattern mixing algorithms, i.e. SPAWNER [18], to sEMG data. Then, considering the expensive computational cost of pattern mixing, we propose our random combination algorithm to take the benefit of pattern mixing while alleviating the computational cost.

3.1 SPAWNER for sEMG

SPAWNER aligns two signals $X_0 = [x_0^1, x_0^2, \cdots, x_0^n], X_1 = [x_1^1, x_1^2, \cdots, x_1^m]$ via Dynamic Time Warping (DTW) [25]. DTW computes the minimal alignment path between X_0 and X_1 or the *warping path*. The *warping path* is found by computing the element-wise cost matrix C using some arbitrary distance metric (e.g., Euclidean Distance). We use L1 loss as

$$C[i,j] = |x_0^i - x_1^j| + min(C[i-1,j], C[i,j-1], C[i-1,j-1])$$

DTW assumes the first points and last points of both sequences are aligned and yields warping paths with monotonically increasing indices. To reduce computational overhead, a warping window ξ is used to limit the temporal advance and temporal delay of the alignment. We use 10 percent of the longest sequence (i.e., $\xi = \lceil max(n, m)/10 \rceil$). Note in our case all sequences have the same length by front padding zeros to samples where necessary. In addition to the assumptions made by DTW, SPAWNER assumes a randomly selected point (excluding end points) from X_0 and X_1 are aligned. More formally, SPAWNER forces the warping path to contain $C_p = (R_0, R_1)$ where $R_0 = \lceil rn \rceil$, $R_1 = \lceil rm \rceil$ and r is uniformly distributed random number between 0 and 1. This is accomplished by computing two alignments. First, $X_0^0 = [x_0^1, x_0^2, \cdots, x_0^{n-R_0}]$ is aligned with $X_1^0 = [x_1^1, x_1^2, \cdots, x_1^{m-R_1}]$. Then, $X_0^1 = [x_0^{n-R_0+1}, x_0^{n-R_0+2}, \cdots, x_0^n]$ is aligned with $X_1^1 = [x_1^{m-R_1+1}, x_1^{m-R_1+2}, \cdots, x_1^m]$. The alignments yielded by X_0^0 and X_0^1 are concatenated together yielding X_0^*. Similarly, X_1^0 and X_1^1 are concatenated together yielding X_1^*. X_0^* and X_1^* are then merged using their means. Finally, we inject Gaussian Noise on top of the aligned sample using a small σ: $\mathcal{N}(\mu = 0, \sigma = 1 \times 10^{-7})$.

3.2 Random Combination Algorithm

Due to the application of DTW in pattern mixing, the computational cost is very expensive. Inspired by the work of [27], we propose a random combination method to reduce the running time while still reaping the benefits of pattern mixing. Specifically, according to the desired ratio of augmentation γ, we aim to get a synthetic data set of size γN, where N is the total number of examples in the sEMG training data $\{X_i, y_i\}_{i=1}^N$. X_i is the i-th signal and y_i is the signal's finger class (e.g., 'pinky'). By distributing different augmentation numbers for each finger class, augmentation can also help solve the class-imbalance problem during the training. Motivated by this, we can calculate the total number of training examples after augmentation is $(\gamma + 1)N$. Then, with k finger classes, the number of augmented examples for the j-th class can be easily calculated as $(\gamma + 1)N/k - N_j$, where N_j is the number of original training examples of the j-th class. Note that γ should be large enough such that $(\gamma + 1)N/k - N_j$ does not yield a negative for each class j.

Next, we randomly select $(\gamma + 1)N/k - N_j$ samples from the corresponding class to perform data augmentation. Note when $N_j < (\gamma + 1/k)$, one or more samples will be used at least twice to achieve our target number of synthetic samples. Additionally, pattern mixing requires a reference sample for mixing as described in the above subsection (3.1). During the procedure, the reference sample is randomly obtained from the same finger class. However, we ensure that the reference sample is not the augmentation sample, and once X_i and X_j have been mixed once, they will not mix again. Most importantly, for each augmentation sample, we set a probability p to generate a synthetic sample using a random transformation method, otherwise the pattern mixing algorithm is applied. Alg. 1 summarizes the procedure.

With the above proposed random combination algorithm, we can tune the parameter of p to reduce/increase the chance of using the random transformation method for the augmentation. In this way, we reduce the computational overhead from only using a pattern mixing technique. Moreover, the combination of multiple augmentation methods can cover a greater portion of the problem

Algorithm 1: Random Combination

Input: sEMG Data set $\{X_i, y_i\}_{i=1}^{N}$, augmentation ratio γ, probability p to use random transformation
Output: Synthetic Data set $Syns$
Initialize $Syns \leftarrow \emptyset$
Initialize $sampsToAug \leftarrow \emptyset$
for each finger class $j = 1$ to k **do**
  $sampsToAug \leftarrow$ Randomly sample $(\gamma + 1)N/k - N_j$ from class j
end for
for each $X_i \in sampsToAug$ **do**
  $rand \leftarrow$ random value s.t. $0 \leq rand \leq 1$
  if $rand \leq p$ **then**
    $Syns \leftarrow$ RandomTransformation(X_i)
  else
    Sample X_r from the finger class of X_i
    $Syns \leftarrow$ PatternMixing(X_i, X_r)
  end if
end for
return $Syns$

population space than any individual augmentation method as shown in Fig. 1, which can diversify the training data to give better generalization performance.

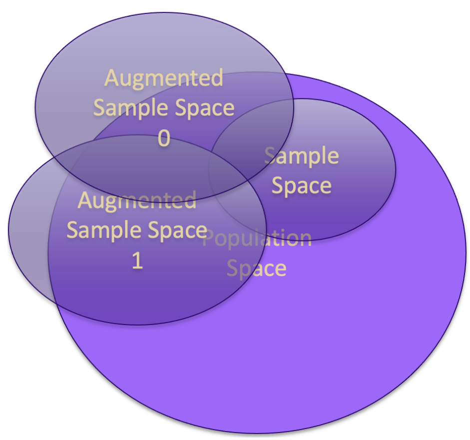


Fig. 1: Training data augmentation and diversifying through multiple augmentation methods.

4 Experiments

In this section, we will evaluate the proposed method to sEMG data collected from four different subjects.

4.1 Data Description

We have collected the individual finger movements of four subjects including male and female. It should be noted that three of the subjects used their left arm and the remaining one used their right arm. Data is collected by an epidermal electronic system (EES) proposed in [29]. The device records single-channel data at 250 Hz via an Android application over Bluetooth transmission. Data acquisition consisted of completing n individual finger flexions at regular time intervals, where n varied for each subject. We then apply three preprocessing steps to prepare the data for the supervised learning task ahead.

Data cleaning is applied by removing noise and null values. Noise in our case may be a considerable number of timesteps before the first finger flexion. Preceding noise accumulates when the test subject pauses after initiating acquisition before beginning the experimental procedure. An example of noise can be seen in Fig. 2. Then, we apply data filtering in three steps to prune unwanted noise and smooth the signal. Note that the noise we are filtering here differs from the noise removed in the data cleaning step. Here we are referring to both electrical noise and signal drift. Electrical noise is seemingly random and distorts signals of interest while drift can be seen in Fig. 2 as the signal value decreases approximately linearly with time. The first filtering step involves applying a first-order Butterworth Bandpass filter and extracting the high output as shown in Fig. 3. We then use a Hilbert transform to extract the upper envelope of the signal as illustrated in Fig. 4. Lastly, a second polynomial order Savitzky-Golay filter [26] is applied to smooth our data as described in Fig. 5.

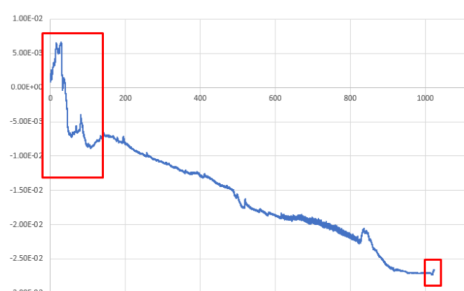


Fig. 2: A plot of raw acquisition data highlighting unwanted noise.

Finally, we need to split the individual finger movements, which is also a necessary step for real-time movement detection. To do this, we start by finding each of the positive peak values in our signal as shown in Fig. 6. Peaks are discovered via thresholding, where the threshold is the average value of our data (i.e., the output of the Savitzky-Golay filter). Next, we find the mid-point between each two peaks (Figure 7) to cut each movement out. An individual signal is depicted in Fig. 8. Fig. 9 summarizes the number of finger movements detected for each subject using the above strategy. It should be noted that

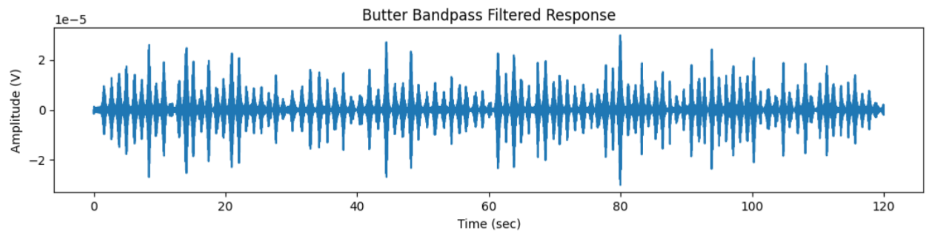


Fig. 3: The high output of a Butterworth Bandpass filter.

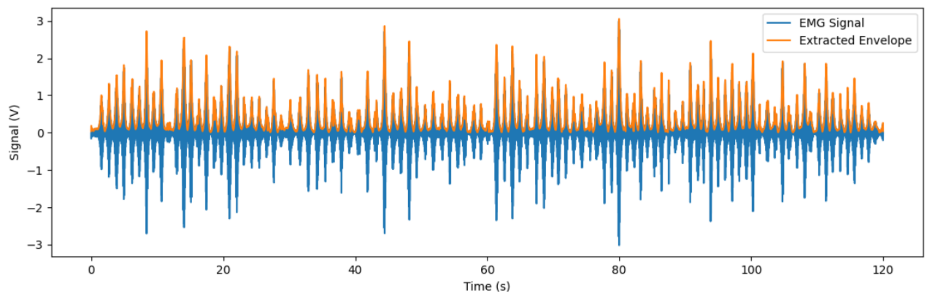


Fig. 4: Extracted upper envelope.

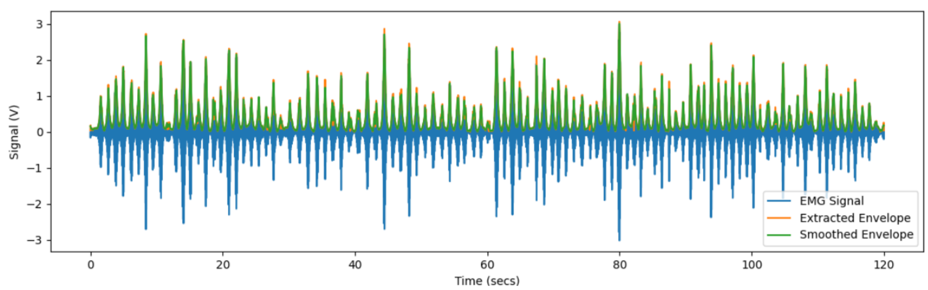


Fig. 5: Smoothed upper envelope.

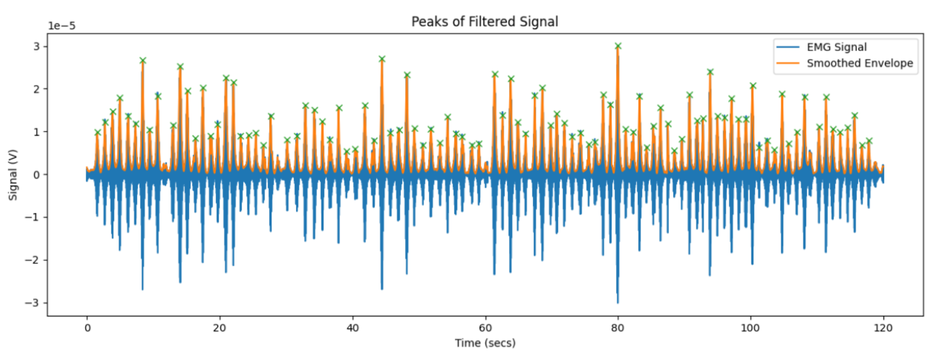


Fig. 6: A visual representation of the identified peaks.

each signal obtained from this procedure can be of different lengths. However,

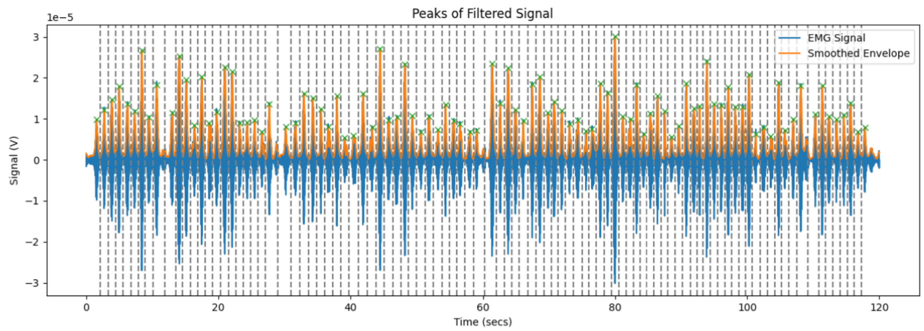


Fig. 7: A visualization of the midpoints between each peak.

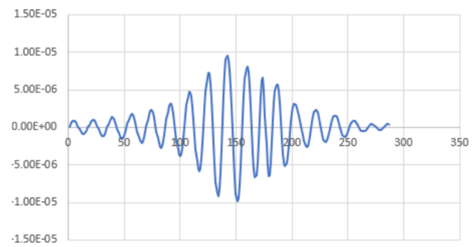
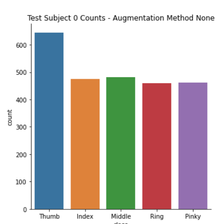
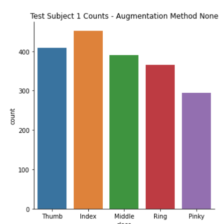


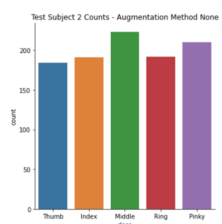
Fig. 8: An example of one of the extracted individual finger movements.



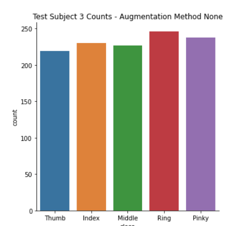
(a) Subject 0.



(b) Subject 1.



(c) Subject 2.



(d) Subject 3.

Fig. 9: Extracted finger movement counts of for each subject.

considering the signal strength, it is reasonable to pad zeros on either end of the samples to have the same length for all movements.

4.2 Experiment Setup

To evaluate the proposed methodology, we compare it with several state-of-the-art augmentation algorithms in Table 1. Each algorithm has one or more hyperparameters. For each, we use "Subject 0" with augmentation ratio of 1.8 by 10-fold cross validation using the random forest classifier to find the best parameters that are summarized in Table 1. It should be noted that augmentation ratio is another parameter we need to determine, which is the ratio of synthetic sample count to original sample count. We evaluated two random transformation methods on "Subject 0", where the augmentation ratio was varied from 0.05 to

Table 1: Baselines and their hyperparameter settings ("-" indicates not applicable).

	σ	Window	Batch Size
Gaussian Noise (GN) [27]	1×10^{-5}	-	-
Magnitude Warping (MW) [27]	0.2	-	-
SPAWNER (SPA) [18]	1×10^{-7}	0.1	-
Random Guided Warping (RGW) [15]	-	0.1	-
Discriminative Guided Warping (DGW) [15]	-	1/3	6

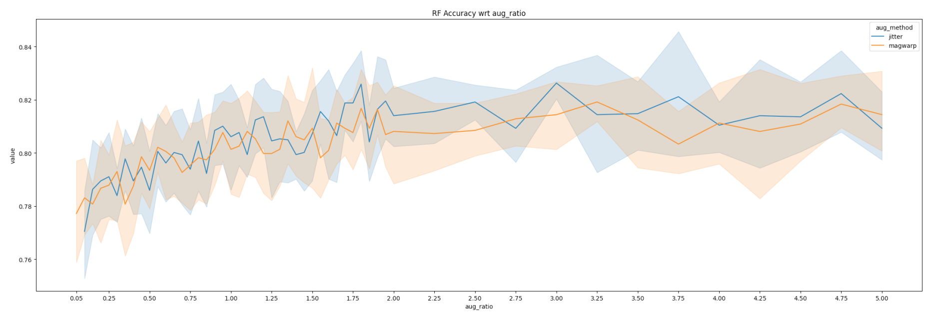


Fig. 10: Visualization of accuracy vs augmentation ratio for two random transformation methods.

5.0. Each augmentation ratio was repeated ten times. 2.0 turns out to be the optimal augmentation ratio as shown in Fig. 10, which is used in all experiments which follow unless stated otherwise explicitly.

4.3 Performance Comparison

To compare our proposal with the baselines, we consider a total of six random combinations: Gaussian Noise and Magnitude Warping, Gaussian Noise and Random Guided Warping, Gaussian Noise and Discriminative Guided Warping, Gaussian Noise and SPAWNER, and two variants of Gaussian Noise, Magnitude Warping and SPAWNER. Each augmentation method is evaluated ten (10) times with the average classification performance on 10-fold cross validation reported using a random forest classifier.Table 2 summarizes the performance in terms of both classification accuracy at augmentation ratio of 2.0 and augmentation running time at augmentation ratio of 1.0, on "Subject 0".

First, it can be observed that, with respect to the no augmentation results, all augmentation methods have a positive affect on classification accuracy, which demonstrates the effectiveness of data augmentation for sEMG data classification. Second, the two least performant methods are the two random transformation methods, i.e., Gaussian Noise and Magnitude Warping. Each of the pattern mixing techniques considerably outperformed the random transformation methods. DGW outperforms all the rest including our combinations, but it takes approximately 75 minutes to double the dataset. GN, on the other hand, takes only 0.579 seconds on average to double the dataset. This confirms that pattern

Table 2: Accuracy Comparison for augmentation ratio = 2.0 and running time comparison for augmentation ratio = 1.0. Note SPA is an abbreviation of SPAWNER. "-" means not applicable.

	Time (s)	Prob	Accuracy
No Aug	-	-	0.7693 ± 0.02236
GN	$\mathbf{0.5790 \pm 0.8709}$	-	0.8140 ± 0.01868
MW	1.9304 ± 0.34995	-	0.8081 ± 0.03047
RGW	113.0625 ± 1.79233	-	0.8607 ± 0.01394
DGW	4491.5675 ± 34.8091	-	$\mathbf{0.8841 \pm 0.02316}$
SPA	102.6032 ± 2.23313	-	0.8769 ± 0.02487
GN + MW	1.0412 ± 0.1270	$0.5, 0.5$	0.8215 ± 0.02197
GN + RGW	51.3093 ± 1.2451	$0.5, 0.5$	0.8524 ± 0.01785
GN + DGW	980.1049 ± 28.3504	$0.75, 0.25$	0.8575 ± 0.02867
GN + SPA	46.0989 ± 1.10578	$0.5, 0.5$	0.8619 ± 0.02368
GN + MW + SPA	31.3899 ± 1.04783	$0.33, 0.33, 0.34$	0.8437 ± 0.01978
GN + MW + SPA	45.2832 ± 0.99105	$0.25, 0.25, 0.5$	0.8485 ± 0.02594

mixing augmentations methods can be very effective in improving the classification performance but with high computational cost, which can be alleviated by our random combination methods as follows.

In terms of our random combination methods, we can first observe that with a certain probability setup for the chance to use each baseline, we can significantly reduce the running time by combining an efficient but less effective method and an effective but less efficient method. For example, when we combine GN and DGW with a probability of 0.75 and 0.25 respectively, we can decrease the running time from 75 minutes to 17 minutes, without too much detriment to the classification accuracy (i.e., from 88% to 85%). This demonstrates the efficiency of our proposed methodology. Second, based on the combination result of GN and MW, we can observe that combining baselines capturing different augmentation space can help improve the classification performance. In addition, it should be noted again that pattern mixing methods are considerably more effective than random transformation methods. Therefore, lower weights on the pattern mixing technique will result in reduced performance gains, which can be clearly observed from Table 2. Finally, by combining GN and SPA, we can reduce the running time to less than one minute with only 2% lower than the best performance we obtained from DGW. This further demonstrates the efficiency and effectiveness of our proposed method, where the performance can be further illustrated in Fig. 11.

Finally, we evaluate the most performant random combination method, GN + SPA, on each of our datasets with augmentation ratio fixed at 2.0 using the state-of-art classification algorithm, XGBoost [8]. The reported results are the means and standard deviations of ten (10) evaluations. We also report the results of GN and SPA individually along with the baseline for reference. The results are summarized in Table 3. The proposed method is the most performant for three of the four test subjects. SPA alone outperforms the proposed method on "Subject 3". However, SPA more than doubles the running time compared to our

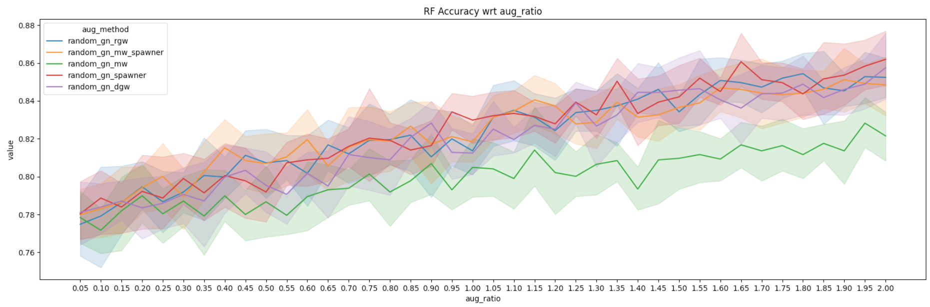


Fig. 11: Visualization of accuracy vs augmentation ratio for random combination augmentation methods.

combination. It should also be noted that the classification performance using XGBoost without augmentation is higher than random forest as expected. However, it is important to improve the performance as close to perfect as possible. We cannot imagine a user would ever find it acceptable for a robotic prothesis to malfunction or a password to erroneously grant an unauthorized user access.

Table 3: Final evaluation of the proposed random combination method on an XGB model for each of our test subjects. Note SPA is an abbreviation of SPAWNER.

	No Aug Acc	GN Acc	SPA Acc	GN + SPA Acc
Sub 0	0.9767 ± 0.0163	0.9846 ± 0.0058	0.9881 ± 0.0053	$\mathbf{0.9913 \pm 0.0056}$
Sub 1	0.9222 ± 0.0237	0.9493 ± 0.0188	0.9509 ± 0.0170	$\mathbf{0.9530 \pm 0.0066}$
Sub 2	0.9820 ± 0.140	0.9970 ± 0.0048	0.9950 ± 0.0053	$\mathbf{0.9980 \pm 0.0042}$
Sub 3	0.9914 ± 0.0115	0.9940 ± 0.0091	$\mathbf{0.9974 \pm 0.0042}$	0.9957 ± 0.0084

5 Conclusion

In this work, we considered the individual finger movement classification problem using sEMG data with the intentions of developing perfectly accurate models for the applications of robotic prostheses and computer security. Due to the limited availability of training data, we propose a data augmentation solution. Pattern mixing techniques yield fruitful synthetic samples in general time series augmentation but have not been applied to sEMG data. However, pattern mixing requires a considerable amount of compute time. Therefore, we propose a random combination algorithm yielding synthetic samples which covers more of population space than either of the individual, comprising methods. Additionally, our random combination technique leverages a random transformation method which greatly reduces the computational time to generate the same amount of synthetic data.

Random combinations, while useful, is limited by its comprising components. In future works, we intend on focusing our attention on generative models such as Generative Adversarial Networks (GAN), specifically for sEMG data. Another limitation of our study were the machine learning models applied; random forests and XGB. These methods, while effective, are limited by the fact they do not consider the temporal component of time series data. We believe capturing this component in sEMG is essential to improve classification accuracy for our robotic prostheses and computer security applications. In future works, we intend on evaluating our proposed technique on a recurrent neural network such as a Long Short-Term Memory (LSTM) model.

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