Force myography benchmark data for hand gesture recognition and transfer learning

Thomas Buhl Andersen, Rógvi Eliasen, Mikkel Jarlund, Bin Yang
Department of Computer Science, Aalborg University, Denmark
tbuhla@gmail.com rogvieliasen@gmail.com mikkel.jarlund@gmail.com byang@cs.aau.dk

ABSTRACT
Force myography has recently gained increasing attention for hand gesture recognition tasks. However, there is a lack of publicly available benchmark data, with most existing studies collecting their own data often with custom hardware and for varying sets of gestures. This limits the ability to compare various algorithms, as well as the possibility for research to be done without first needing to collect data oneself. We contribute to the advancement of this field by making accessible a benchmark dataset collected using a commercially available sensor setup from 20 persons covering 18 unique gestures, in the hope of allowing further comparison of results as well as easier entry into this field of research. We illustrate one use-case for such data, showing how we can improve gesture recognition accuracy by utilising transfer learning to incorporate data from multiple other persons. This also illustrates that the dataset can serve as a benchmark dataset to facilitate research on transfer learning algorithms.

CCS CONCEPTS
• Human-centered computing → Gestural input; • Computing methodologies → Neural networks; Transfer learning; • Computer systems organization → Sensors and actuators.

KEYWORDS
Datasets, neural networks, gesture detection, transfer learning, force myography

1 INTRODUCTION
Gesture recognition is increasingly becoming more popular, as it can be used in various fields, such as rehabilitation in healthcare, smart-homes where gestures can be used as commands, and prosthetic limbs [8, 16, 21]. Different technologies can be used for collecting gesture recognition data, most common among them is Surface Electromyography (sEMG) which measures the electrical signals when activating the muscles and Force Myography (FMG) which measures the mechanical activity of the muscles, i.e., how a muscle changes shape when it is used [22].

Recent studies using FMG often collect their own data, e.g., different sets of gestures, using their own custom hardware [2, 7, 11, 15]. This creates a reproducibility problem where the custom hardware settings cannot be exactly configured by other researchers and the results obtained on different setups cannot be effectively compared to each other.

We argue that using a commercially available product eases the hardware configuration issues and publishing a FMG benchmark dataset collected from the product makes the comparison of different results easier. In addition, having a publicly available dataset allows for easier entry into the field of hand gesture recognition using FMG as it will not require everyone entering the field to first collect their own data. As such we have used a commercially available product BIOX Armbands\(^1\) for collecting data from 20 persons, each person covering 18 unique gestures. The collected data is made publicly available [1] such that those entering the field of FMG based hand gesture recognition can use this data during their research, and also contribute to the dataset.

In addition, in this paper we show a use case of the dataset on hand gesture recognition using transfer learning [17] and multi-task learning [12]. Here, different persons are considered as different domains (or tasks) and we hope to use data from other persons, i.e., other domains (or tasks), to improve the accuracy of hand gesture recognition of a person. More specifically, we train a baseline Fully-Connected Neural Network (FCNN) only using the data from a specific person, and a Combined Progressive Neural Networks (CPNN) model also using data from different persons. We then evaluate the improvement of using transfer learning. The source code is also available in the same GitHub repository. By doing this, we hope to illustrate that the dataset not only contributes to hand gesture recognition, an increasingly important application area, but can also facilitate research on transfer learning, a significant research direction in machine learning.

2 RELATED WORK
We review four independent research papers that utilise FMG data to uncover their data collection process. Henceforth we will refer to the people that data has been collected for as subjects.

In the first paper we examined [2], data was collected using a custom armband with 8 sensors wrapped around the upper forearm. Data was collected for 10 subjects each performing 6 gestures with a sampling frequency of 10 Hz. In the second paper, data was collected using a custom wristband with 15 sensors wrapped around the wrist fraction of the arm. Data was collected for 10 subjects each performing 6 gestures 12 times with a sampling frequency of 30 Hz [7]. In the third paper, data was collected using a custom armband with 16 sensors wrapped around the forearm fraction of the arm. Data was collected for 12 subjects each performing 48 gestures 5 times with a sampling frequency of 10 Hz [11]. In the fourth paper, data was collected using a custom armband with 16 sensors on the dorsal side and 16 sensors on the volar side of the forearm. Data was collected for 6 subjects each performing 17 gestures 4 times with a sampling frequency of 100 Hz [15].

In summary of the related work, we observe that FMG data collection varies widely in method and execution, making it hard to perform any kind of meaningful method comparisons to assess

\(^1\)https://www.bioxgroup.dk/product/biox-armband/
the performances of different methods and to identify the state-of-the-art methods. Our data set includes sensors for both the wrist and forearm, specifically, 7 sensors for the wrist and 8 sensors for the forearm. The data set is collected at up to 1000 Hz from 20 subjects, covering 18 unique gestures. Thus, it is possible to sample our data set to derive subsets, e.g., which represent data sets that are collected with a lower frequency and data sets that are with less gestures and subjects.

3 DATA COLLECTION

We have collected data from a total of 20 subjects. We will here describe the collected data for each subject as well as the protocol we followed during our data collection process. For each subject we collected contextual information, fitted the sensors, performed calibration and collected sensor readings.

3.1 Equipment

For this study we have used a setup of 2 BIOX Armbands, one with 7 sensors for the wrist and a larger one with 8 sensors for the forearm. Both sensors were connected to our laptop, and during data collection we gathered sensor readings from both sensors with a frequency of 975 Hz-1000 Hz, limited by our laptops processing speed. We sampled at as high frequency as possible to avoid limiting the potential applications, as users can down sample to a lower frequency as appropriate for their application.

3.2 Consent

All data was gathered from volunteers. Before any data was collected, subjects were presented with a disclaimer informing them of what data we would collect and how we intended to use it, including informing them of our intent to make the data publicly available:

We are a research group at Aalborg University attempting to break new ground in the field of gesture recognition, and we need your data to do so. We will collect data such as your age, gender, fitness as well as record your arm / wrist while you do different gestures. That is to say, we will not collect any personally identifiable information (PII) such as your name, address etc. By participating in our data collection, you agree to have your data shared in a public dataset. We share the data such that our results may be reproduced and improved upon in the future.

3.3 Subject information

The subjects were presented with a form and asked to provide some contextual information that we expect to have some impact on the gesture identification process. As part of this, we measure the circumference of wrist and arm at the locations we will apply the sensor armbands. For the armband with 7 sensors, this is ~5 cm below the wrist, while for the 8 sensor armband it is below the elbow at the maximal bulge of the forearm. The contextual information is described below and the distribution of the data is noted in Table 1.

3.4 Sensor fitting

We then apply the BIOX armbands at the wrist and forearm. The armband is laid on a flat surface with the cables to the left and the subjects are asked to lay their right forearm on the middle of the armband with the wrist prone, such that the armband match the measured location. Once the subjects have positioned the arm correctly we close the armbands.

The subjects are then told to sit such that there is ~1 m free space in front of them and ~0.5 m to their sides and back. They are then asked to position their arm so the upper arm is parallel to the body, the elbow does not touch their side, and their forearm is perpendicular to the upper arm. They are asked to hold their elbow as still as possible and keep their forearm horizontal and straight in front of them.

When they are positioned correctly they are given a remote controller and instructed to follow the prompts on the screen and click the remote when they have assumed the shown gesture, and then hold the position shown until collection is done and a new

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Table 1: Subject distribution. For numeric properties, mean ± standard deviation (SD).  

| Category       | Number  |
|----------------|---------|
| Gender         | 17 Male, 3 Female |
| Age            | 23.85 ± 1.53 |
| Handedness     | 18 Right, 2 Left |
| Weekly Exercise| 2.35 ±1.79  |
| Injury         | 1 Yes, 19 No |
| Wrist circumference | 17.86 ±1.07 |
| Forearm circumference | 26.9 ±1.66 |

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https://www.bioxgroup.dk/product/biox-armband/
prompt is given. During the calibration and collection processes we will keep watch to ensure correct execution of the gestures. Should we see any errors we will intervene and ask them to redo the gesture and giving directions for correct execution.

3.5 Calibration

Calibration is performed because the sensors will likely only utilise part of the possible output range. We thus perform calibration in order to better utilise the full output range from the sensors. In order to capture the upper limit of the subjects muscle activation, the subjects were told that they should try to exert their muscles as much as possible when the sensors were being calibrated. A side-effect of calibration is that the resting value of the sensors is also increased, depending on the number of calibration steps (i.e., how much the sensitivity is increased).

Since the two sensor armbands are activated differently for each gesture, they are calibrated separately using the two gestures that we found to best activate the sensors of the respective armband. These gestures were Figure 1a and Figure 1r for the arm and wrist, respectively. Since the armbands are calibrated separately they will likely require a different number of calibration steps, leading to different resting values. For this reason we have for each subject recorded the number of calibration iterations for each armband as well as the final sensor values on calibration in the belief that this could be used to account for these factors.

3.6 Data collection

The subjects are instructed that they do not need to exert maximum force for the rest, and that they should proceed at their own pace, taking rests as necessary between gestures.

We collect data for a set of 6 hand gestures with 3 different wrist positions, for a total of 18 different combinations of hand and wrist positions which can be seen in figure 1. We collect data for each gesture 5 times, each time collecting 5 seconds of sensor readings at a frequency of 975 Hz-1000 Hz.

In addition to the value of each sensor we record a label signifying which gesture was performed, as well as which subject the reading is from. Each reading has a timestamp, though only the difference in time between sensor readings of the same subject is valid, not the time of day due to the implementation of the timer. As we collected data over several repetitions of the gestures we have also included a numeric indicator of which repetition the reading is from.
The collected data is of the following form:
\[
(arm\_sensors, wrist\_sensors, timestamp, repetition, subjectID, gestureID)
\]
where \(arm\_sensors\) is a 8 dimensional vector and \(wrist\_sensors\) is a 7 dimensional vector of sensor readings. When considering a sequence of such data along the time dimension, it gives multi-dimensional time series data \([9, 14]\).

### 3.7 Risks and Assumptions

There are a couple of areas of potential risk with our data collection protocol. Firstly, with respect to the contextual information, we relied on the subjects to provide the information which may have inaccuracies, especially on fields such as frequency of exercise where subjects may have embellished their details.

Further, there is some degree of inaccuracy in regards to the wrist and arm measurements. Though we tried to measure as consistently as possible, when dealing with something as inherently soft as an arm it is difficult to manually measure at exactly the same tightness each time.

The same applies to the fitting, which while we strived for consistency likely exhibits some degree of variance, which could lead to difference in the needed calibration and subsequent data collection. As described in subsection 3.5, we have included the calibration information in order to alleviate this issue.

In regards to the gesture data collection, we chose to let the subjects determine their own pace, signifying when they had assumed the next gesture. While we supervised the data collection, and asked the subjects to redo any gestures where we observed errors, it is possible that some subjects may have pushed the button a bit too early.

Additionally since we left it up to the subjects to decide when and how long they needed to rest between gestures there may be some variance in their fatigue levels throughout the data collection.

### 4 Example Use-Case

One use of FMG gesture recognition might be to control an exoskeleton, such as for assisting patients during rehabilitation. In such a case, it might be infeasible to collect large amounts of data from the patient. As such it would be helpful if we could use data gathered from other people to supplement the patients data through transfer learning.

Transfer learning uses domains \(D\) and tasks \(T\), where in \(D\) we have a source domain \(D_s\) and a target domain \(D_t\) for which we want to transfer knowledge to. A domain consists of a feature space \(X\) and a marginal probability distribution \(P(X)\), where \(X = \{x_1, \ldots, x_n\}\) and a task \(T = \{Y, f(\cdot)\}\) where \(f(\cdot)\) is a predictive function and \(Y\) the label space \([17]\).

There are various approaches to transfer learning depending on how knowledge can be transferred effectively from source domain to target domain \([17]\).

We utilise domain adaptive transfer learning, where we assume that \(D_s\) and \(D_t\) are different but \(T_s\) and \(T_t\) are the same \([17]\), which is appropriate for our problem, as we have different domains (i.e. different subjects) but the gesture recognition task for all domains is to recognise the gestures shown in Figure 1.

### 4.1 Feature Engineering

For this use-case example we scale the dataset to take into account how the calibration functions, so as to normalize the data while considering the resting values of the sensors.

Let \(D\) be the raw dataset collected for a given subject, consisting of 15 dimensional vectors containing a sensor reading from each of the sensors (7 wrist + 8 arm sensors). Let \(d^i\) be the set of data readings from sensor \(i\), and \(d^j\) be the \(j\)th sample of \(D\). The \(j\)th reading of sensor \(i\) is thus \(d^j_i\). For each \(d^j_i \in D\) we subtract the minimum reading for the corresponding sensor, \(\min(d^i)\), and divide by the overall maximum reading across every sensor \(\max(D) = \max(\{\max(d^i)|i \in \{1, \ldots, 15\}\})\) which is also adjusted by \(-\min(d^i)\).

\[
\text{Scale}(d^j_i) = \frac{d^j_i - \min(d^i)}{\max(D) - \min(d^i)} \quad (1)
\]

We consider the local minimum of each sensor, as the resting values may be different due to calibration (see section 3). We are also interested in preserving the relative values between the sensors, we therefore consider the global maximum of the sensors, as the amount of force exerted vary when performing different gestures.

### 4.2 Models

We experiment with different deep learning models and evaluate the potential of applying transfer learning to this task.

#### 4.2.1 Baseline

Our non-transfer learning baseline simply consists of a series of FCNN layers, using the Rectified Linear Unit (ReLU) activation function, followed with a Softmax layer. In order to avoid overfitting we apply dropout between each layer. This architecture also serves as the basis for the columns of our transfer learning approach. As we consider a non knowledge transfer setup, we train a baseline model for each subject.

#### 4.2.2 Transfer Learning

Progressive Neural Networks (PNN) were proposed by \([18]\) as a way of applying transfer learning to a sequence of tasks while avoiding catastrophic forgetting. It works by training on the source domains in sequence, and utilizing these through lateral connections to later models. However, as the PNN architecture exhibits quadratic growth in the number of parameters when increasing the number of source domains \([18]\), there is a limit to the number of source domains we can reasonably draw on.

Hence, if we want to be able to learn from a large set of source domains we need an alternative to having a column for each. One possible approach which was proposed by \([6]\) is to combine the source domain datasets and only train a single column on this combined source domain as seen in Figure 2a, which like with PNN is connected to the target column with lateral connections, as seen in Figure 2b. Combining the source domains is possible because, unlike what the original PNN was proposed for \([18]\), we do not have different tasks in addition to the different domains. We can thus combine the source domains and train a single column to learn the general features across the source domains which are helpful for our task. It is thus possible to draw on a large number of source domains without increasing the number of parameters of the model.
As mentioned in section 3, we have collected data for a series of repetitions, each repetition covering 5 seconds of data for every gesture. Of the 5 total repetitions we have collected for each subject we will use the last repetition for testing and the remaining repetitions for training. We believe this best fits a case where a person may equip the device and collect some initial data to train a model that should then perform predictions on subsequent data. For each of the models, we split the training data into a training and validation set 75/25% and utilise early stopping monitoring the validation loss delta with a patience of 5 and delta threshold of 0.001 to determine when to stop training.

4.3 Training and Evaluation

4.3.1 FCNN. For the baseline FCNN model, we train a model for each subject using the data collected for the last repetition as test data and the remainder as training data.

4.3.2 CPNN. During the training of CPNN we start by combining the data for all subjects except the one we want to train the current model for. This combined dataset includes all 5 repetitions for these subjects. With this combined dataset we pretrain a model as described in section 4.2. We then take the data for the target subject and separate the last repetition for testing as mentioned above, before training on the remaining repetitions.

4.4 Results

Based on three model configurations, we fit FCNN and CPNN models. Based on the best and worst subject models, derived from the models with the highest mean accuracy, we construct a confusion matrix such that we can observe the classifications differences.

Table 2: Evaluation Results. Mean accuracy $\mu$ and standard deviation $\sigma$. Optimal number of neurons per layer and dropout rate were identified by hyperparameter optimisation.

| # Dense 1 | Dense 2 | Dense 3 | Dropout | FCNN $\mu$ | FCNN $\sigma$ | CPNN $\mu$ | CPNN $\sigma$ |
|-----------|---------|---------|---------|------------|--------------|------------|--------------|
| 1 256     | -       | -       | 0.4     | 77.99%     | 13.20%       | 78.12%     | 12.83%       |
| 2 256     | 32      | -       | 0.1     | 77.81%     | 13.06%       | 78.28%     | 12.88%       |
| 3 256     | 64      | 32      | 0.3     | 78.14%     | 12.63%       | 77.11%     | 14.01%       |

4.4.1 FCNN. Looking at the test results in Table 2, we observe that deeper models outperform the shallower ones.

Looking at the confusion matrix for our best and worst performing FCNN subject models in Figure 3, we observe some interesting misclassifications. Looking at the confusion matrix for our worst performing FCNN model in Figure 3a, we observe that the gesture supine closed is predicted correctly, however the model cannot distinguish between supine closed and supine rest, both of which it classifies as supine closed. Likewise in the confusion matrix for our best performing FCNN model in Figure 3b, we observe that the model cannot distinguish between supine straight and supine wide as well as prone rest and prone wide.

4.4.2 CPNN. We base our CPNN models on the best performing baseline FCNN architectures, from our Hyperparameter Optimisation (HPO). CPNN accuracy for the first two model configurations, shows a higher mean accuracy than FCNN, however the mean accuracy for CPNN when using three layers is worse than that of FCNN.

Looking at the confusion matrix for our best and worst performing CPNN subject models in Figure 4 and compare with Figure 3, we observe some interesting differences. The worst performing subject model correctly classifies prone closed, but has a harder time
classifying gestures such as prone flexion and neutral rest. The best performing subject model has a hard time classifying neutral wide as it is often misclassified with neutral straight.

5 DISCUSSION
In this section, we will discuss our use of and the potential use of our benchmark dataset, as well as future plans for the dataset.

5.1 Transfer learning
Our transfer learning model, CPNN, performed slightly better than our baseline FCNN in two out of three cases. This suggests that there is potential for knowledge transfer but that one should be careful when applying transfer learning lest one end up with negative transfer. We thus hope that this dataset may also serve as a resource for further transfer learning and multi-task learning research on this domain.

5.2 Data collection
While we provide a dataset collected from 20 subjects including some contextual information, those 20 subjects were drawn from a relatively narrow demographic. We had hoped to collect data more extensively from other segments of the population to achieve a more diverse dataset, especially in regards to the subjects age and gender. However, due to the circumstances surrounding the Covid-19 pandemic and the resulting quarantine\(^4\), we had to halt our data collection. 20 subjects is still decent compared to the number of subjects for which data was collected in the related work, mentioned in section 2, and as such we feel it is still a valuable contribution.

\(^4\)https://politi.dk/en/coronavirus-in-denmark

In the future, we would like to extend the dataset to make it more diverse. Furthermore we would like to collect more long term data, such as collecting data from an impaired subject throughout their rehabilitation period.

6 CONCLUSION
We have collected a FMG benchmark dataset for hand gesture recognition using a commercially available sensor setup. We have collected benchmark data for 20 subjects, including contextual information about the subject, for a total of 18 unique gestures. The data is collected at a very high frequency up to 1000 Hz, which makes it possible for a wide variety of applications, as users can down sample to a lower frequency as appropriate for their applications. This also provides opportunities for time series analytics, such as prediction [5] and outlier detection [13].

We have used this dataset to show that transfer learning has the potential to increase recognition accuracy by incorporating knowledge learned from other subjects. However, negative transfer may happen. Both the dataset and the source code of the use-case have been made publicly available on GitHub [1]. We believe that this dataset will facilitate research both on FMG based hand gesture recognition and on transfer learning.

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Figure 4: Confusion matrix for best performing baseline CPNN based on our results in Table 2.