Machine Tyson: Classifying Boxing movements using Machine Learning and Signal Processing⋆

Tom de Haas[1][2782444], Mojgan Hosseini[2,3][2700520], and Yixing Wang[3][2696690]

Vrije Universiteit Amsterdam

Abstract. The abstract should briefly summarize the contents of the paper in 150–250 words.

Keywords: Machine Learning · Signal Processing · Movement Science.

1 Introduction

The quantified self method, prominent in today's data-driven and machine learning-focused world, enables everyone to monitor and evaluate their biological, physical, behavioral, or environmental information. This application of machine learning is more complex compared to typical machine learning tasks due to the inherent noise in the data. By utilizing the Phyphox app and its active sensors, this research aims to track these boxing movements to gather sufficient data, enabling an exploration and analysis of the patterns and characteristics of each action. It incorporates several active sensors, such as the accelerometer, linear acceleration sensor, position sensor and more[3].

This study focuses on boxing within the context of the quantified self, specifically predicting punch types such as straight (jab and cross), hook, uppercut, and block. These sensors are essential for capturing detailed motion data. Measurements will be taken by performing these punch movements in boxing exercises, at a sampling size of 50Hz to ensure the balance of data between computational cost for later preprocessing and training, and resolution. Each boxing move will be recorded individually to properly tag each data sample, facilitating the use of supervised machine learning techniques. In this study, we aim to examine the distinct patterns and traits of various boxing techniques in order to forecast them effectively.

Consequently, the primary research question we are addressing is: "What is the accuracy of the Machine Learning (ML) algorithm when predicting boxing movements with rotation and acceleration data?" The findings from this research have the potential to greatly influence the analysis of boxer performance and enhance training efficiency.

⋆ Supported by organization x.

2 Methods

Data Acquisition

To measure the boxing motions of participants (n = 3) a phone will be fixed on a participants arm to perform the different movements we intent to classify using our model. The phone will provide measurements of position in 3d-space (the rotation rate measured by the Gyroscope on phone), acceleration, and pressure. These motions will be collected using the Phyphox app: a free app that can administer data from many different measurements using the phone sensors, from the magnetic field to the sound of applause. The measurement data will be written to a .csv file for further processing.

Generating Training and Test Data, Feature selection and Labels

To generate test data. Participants will undergo sessions of the three different movements that we tend to classify. These are the basic boxing movements known by any beginner-, intermediate- and professional boxer; straight punch (jab and cross), hook, and uppercut. We expect these movements to be classifiable by just positional data alone. Participants will undergo sessions of each punching variant of several minutes to an hour. These sessions will be labelled with the respective punching variant. These sessions will be shuffled in the data. Afterwards, part of the data will be held separately accoring to a 40-60 test-train split. The model will be trained on the training data and final evaluation will be done on the test set.

Training the Model

To train the model. A k-nearest neighbor algorithm will be tried first. Because these tend to be computationally less intensive than other methods and could produce good results. Additionally, a random forest algorithm will be tried, as this ML technique tends to work well for classification.

3 Preliminary Data Analysis

This section will demonstrate a few results of the *Jab* dataset for demonstration purposes. The Collection and Feature Engineering approaches mentioned in the following sections were performed on all types of punch datasets. If was observed that the behavior of data of each punch type follows the same pattern.

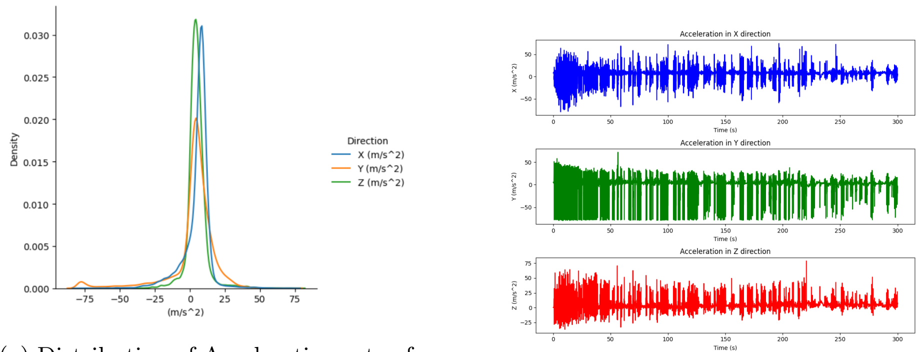
Data Collection

Example data were collected to preliminarily investigate its behavior and the expected methods to use for data preprocessing and transformation. Six continuous datasets were collected for different punches (jab, cross, lead hook, rear hook, lead uppercut, rear uppercut) by continuously performing each of these punch exercises in a duration of 300 seconds, in Orthodox stance; two continuous datasets were collected for the left and right arms when the subject remained standing and jogging around, but no punches were performed, to serve as a control dataset to compare with the behavior of punching data. Both datasets were collected with a duration of 120 seconds. Each dataset has 8 features, respectively: *Rotation on x-axis; Rotation on y-axis; Rotation on z-axis; Acceleration on x-axis; Acceleration on y-axis; Acceleration on z-axis; Barometer (pressure); Time.* All Rotation and Acceleration datasets were collected at a sampling rate of 50Hz, the reasons are as follows: firstly, professional boxers take 60-100 milliseconds (ms) to throw a jab, and 150-200 ms to throw other punches,considering the fact that participants are hobby-level boxers, a lower velocity of punches would be expected, hence we assume that a punch will be thrown in approximately 250ms; secondly, an ideal temporal resolution for a detail-orientated data collection would be sampling a datapoint per ms, meaning to sample at a rate of 250Hz; however, this will result in an extremely large and computationally expensive dataset, as an optimal trade-off, we took a datapoint at per 10ms instead to balance the computational cost and the quality of data, which means to record a punching behavior with a frequency width of 25Hz; lastly, according to Nyquist Shannon Sampling Theorem, the sampling rate must be twice the sampling range of the incoming signal to record a full-scale event including possible buffers (e.g.: time and movement to reposition the arm after throwing a punch) [2], we therefore duplicated the frequency width and determined to apply a sampling rate of 50Hz. The sampling rate of the Barometer was 1Hz by default due to the limitation of Phyphox that manually adjusting the sampling rate on this feature was impossible.

Table 1 shows the statistical data of *Jab*. Figure 1a demonstrates the distribution of Jab's acceleration and figure 1b shows the time series of Jab's acceleration.

Table 1: Statistics of *Jab*

	Time (s)	**Acc X**	**Acc Y**	**Acc Z**	**Rot X**	**Rot Y**	**Rot Z**	**Pressure**
count	15113	15113	15113	15113	15113	15113	15113	279
mean	149.987	5.132	2.282	4.807	-0.375	0.058	-0.157	1012.954
std	86.609	10.011	17.616	7.115	1.955	5.441	2.955	0.021
min	-0.002	-79.372	-79.789	-36.767	-15.981	-24.418	-19.893	1012.916
25%	74.989	3.317	1.295	1.758	-0.634	-1.818	-0.918	1012.935
50%	149.984	7.298	4.704	4.414	-0.063	-0.221	-0.210	1012.958
75%	224.987	9.696	9.842	7.349	0.411	0.958	0.340	1012.970
max	299.987	74.363	72.294	78.842	10.618	23.592	15.858	1012.996



(a) Distribution of Acceleration rate of *Jab*

(b) Time series of Acceleration of *Jab*

Fig. 1: Time Series Data of punch movement *Jab*

Feature Engineering

We transformed the datasets as follows: first, we aggregated each feature of dataset, except the time and the pressure, at a window of 50 datapoints by grouping the mean of absolute value, in other words, we calculated the mean of the absolute value of every 50 datapoints of each feature except the time and the pressure, and the remainder with less than 50 datapoints were discarded; second, for each punch type, we concatenated each of their (aggregated) features to generate a complete, transformed dataset of each punching behavior; third, we investigated the distribution, outliers, and missing values - a small number of missing values were discovered for barometers, caused by a slight misalignment during the measurement, hence these were filled in by the mean of the barometer; finally, we labeled the data by adding one extra column of its punch type. Table 2 shows the head of the transformed *Jab* data.

Table 2: Sample data of transformed dataset of *Jab*

Acc X	**Acc Y**	**Acc Z**	**Rad X**	**Rad Y**	**Rad Z**	**Pressure**	**Punch Type**
8.925	14.832	4.943	1.414	2.987	1.559	1012.981	jab
8.740	15.640	8.607	1.587	5.303	2.169	1012.969	jab
10.453	15.200	8.417	1.608	4.786	2.158	1012.956	jab
12.217	19.120	7.228	1.326	4.604	2.515	1012.956	jab
13.070	20.061	9.513	2.197	7.206	3.114	1012.965	jab

We chose to aggregate at a window of 50 datapoints by grouping the mean of absolut value because we considered this metric the most optimal. First, a window of 50 datapoints would allow us to label a punching behavior per second, by taking the buffer between each punch into account equally. Second, data we observed an approximately normal distribution of each feature of the raw data we collected, and acceleration and rotation range within a symmetrically positive and negative value, where the positive values indicate the measurement towards a given axis forward, and negative indicates backward. This might be problematic for other aggregation options such as mean, median, and sum - the presence of positive and negative values might offset each other if we took the mean or the sum of each feature, and the median often occurred around Zero, neither one of these aggregating options would preserve the informativeness of the data. The mean of absolute values would minimize the information loss as both forward and backward movements would be treated equally, which would ensure a complete measurement and statistical analysis of a full-range punch.

Next Action

Outlier and noise removeal: Outliers were spotted in each punch datasets which will be removed before training if necessary. The precious feature engineering method ensured that outliers and noise would be detected efficiently - we can detect if a datapoint is demonstrating a punch behavior insufficiently by taking its acceleration and the rotation data: if a subject did not punch, the acceleration and rotation point would lie out of the range of its distribution. figure 2 illustrates the boxplots of acceleration and rotation of *Jab*.

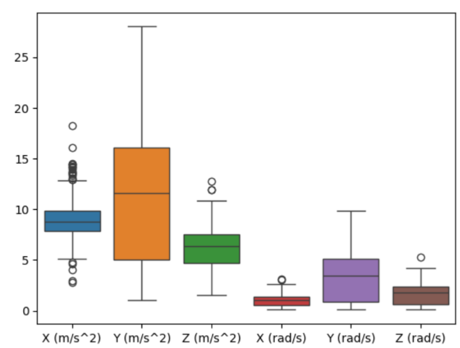


Fig. 2: Boxplots of acceleration and rotation of *Jab*

Alternative aggregation method: Previous study shown that a jab can be thrown with a higher velocity than the other punches [1]. Therefore, we would consider an alternative sampling window for *Jab* data to acquire a more accurate data collection.

References

1. Dennis Kim and David V. Thiel. Hand speed measurements in boxing. In *7th Asia-Pacific Congress on Sports Technology, APCST 2015*, pages 123–128, St Augustin,

Germany, 2015. University of Applied Sciences Bonn-Rhine-Sieg, Griffith School of Engineering University, Elsevier. Conference held in Nathan, Qld, Australia.
2. Danny C. Price. 4 - real-time stream processing in radio astronomy. In Linghe Kong, Tian Huang, Yongxin Zhu, and Shenghua Yu, editors, *Big Data in Astronomy*, pages 83–112. Elsevier, 2020.
3. S Staacks, S Hutz, H Heinke, and C Stampfer. Advanced tools for smartphone-based experiments: phyphox. *arXiv preprint arXiv:1804.06239*, 2018. Institute of Physics I and II, RWTH Aachen University, 52062 Aachen, Germany.