Using a Smartphone Accelerometer to Classify Longboarding Motion

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Abstract

The objective of this study is to explore the feasibility and effectiveness of using smartphone accelerometer data, combined with advanced machine learning techniques, to accurately classify three distinct motions–pushing, pumping, and coasting–that a longboarder might engage in over the course of a ride. The final goal is to integrate these concepts into a closed system of classification in the form of a mobile application. Utilizing a dataset collected from a smartphone carried by a longboarded, we apply a series of data processing techniques, including rotation matrices for orientation normalization, Verlet integration for handling unevenly-spaced time series data, and the discrete Fourier transform for feature extraction. We experiment with various machine learning algorithms, with a particular focus on the Random Forest classifier, which achieves an F1 Score of 96.8% in classifying the three primary longboarding actions. The F1 Score, a harmonic mean of precision and recall, serves as a critical metric in evaluating the model's accuracy, particularly in the context of imbalanced datasets. This study not only demonstrates a novel application of portable technology in sports analytics but also contributes to the broader field of machine learning by presenting an efficient approach to processing and classifying telemetric data from motion sensors. The implications of this research extend beyond longboarding, offering potential applications in enhancing athletic performance across a range of sports through accessible and real-time motion analysis.

Keywords: 3D analysis, Calculus, machine learning, time-series classification, Linear algebra.

1 Introduction

The intersection of wearable technology and sports science has opened new avenues for enhancing athletic performance and understanding physical activities through data analysis. Among the plethora of sports, longboarding—a variant of skateboarding known more for cruising long distances than for doing tricks in a skate park—presents unique challenges and opportunities for motion analysis. Traditional methods of motion capture and analysis often involve expensive and cumbersome equipment, limiting accessibility for amateur athletes and enthusiasts. In response to these challenges, this study proposes an innovative approach by leveraging widely available smartphone technology, specifically built-in accelerometer and gyro sensors, to collect and analyze motion data in the context of longboarding.

Perhaps the most recognizable longboarding motion, "Pushing" involves the rider placing one foot on the ground and pushing backward to produce forward acceleration. "Coasting" involves the rider using recurring inertia to move forward–velocity only increases if the rider is moving downhill. "Pumping" involves the rider oscillating in a left-and-right motion while moving forward. These side-to-side motions are extremely short so as to maintain forward motion in a single, primary direction. Each oscillation generates a small amount of forward acceleration. Under the right conditions (not too much incline or wind), this motion allows the rider to maintain speed and even accelerate without touching the ground. These three types of motion–illustrated in Figure 1–are the most common motions for a longboarder.

This paper presents a system that predicts longboard motion, either pushing, pumping, or coasting, based on accelerometer and gyroscope data collected from a smartphone app and the multi-step process within it. The process comprises the following steps: data collection, data normalization, data segmentation, feature extraction, training, and prediction. Along with the nuances, we detail the challenges inherent in motion data analysis, such as dealing with noise, varying sensor orientations, and the process of extracting features that accurately capture the essence of different longboarding techniques. By employing a suite of data processing techniques, including data segmentation, which demands experimentation with different window durations, rotation matrices for data normalization, Verlet integration for time series analysis, and the discrete Fourier transform for feature extraction, we lay the groundwork for applying machine learning algorithms. Our study evaluates several machine learning models, including logistic regression, support vector machines, neural networks, random

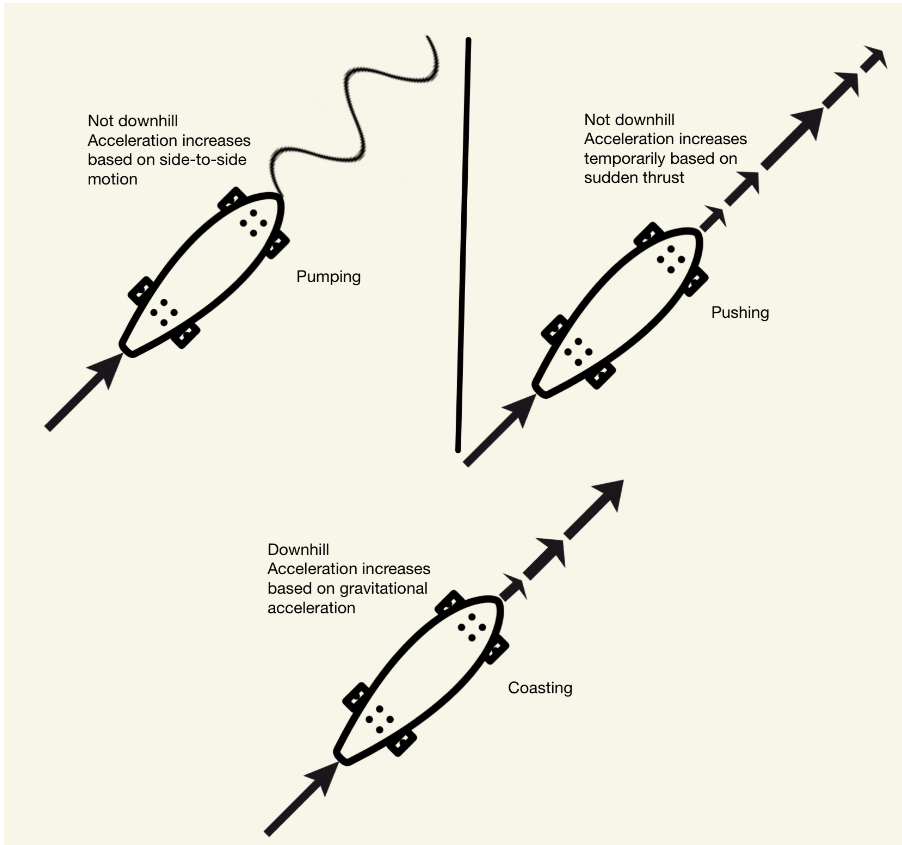

Figure 1: Illustration of the motion shape and acceleration trend of each of the longboard actions. From left to right, top to bottom: Pumping, Pushing, Coasting.

forest, and simple decision tree. In the end, the random forest model emerges as the most effective tool for this application, achieving a high F1 Score of 96.8% in classifying longboarding motions.

The proliferation of smartphones equipped with sophisticated sensors offers an opportunity to democratize sports analytics by enabling athletes to capture detailed motion data without specialized equipment. This research explores the potential of using such telemetric data, processed through advanced machine learning techniques, to classify distinct longboarding motions accurately. The core of this investigation lies in developing and validating a methodology that transforms raw accelerometer data into actionable insights, thereby contributing to both the fields of sports science and machine learning.

This research, aside from the obvious application area of longboard action classification, aims not only to create a wearable analyst for longboarders and advance the understanding of longboarding dynamics but also to illustrate the broader applicability of our approach to other sports and physical activities, and how these processes can be universal in all of them. By bridging the gap between sophisticated data analysis techniques and accessible, real-time sports performance feedback, this study contributes to the growing field of sports science, offering insights that could enhance training, performance, and injury prevention for athletes across disciplines.

2 Related Works

In the realm of time-series classification utilizing acceleration and gyroscope data, the prevailing body of research predominantly navigates the classification of human actions, such as walking, running, and climbing. Within this context, the pioneering work by Wu [10] and subsequent studies have laid the foundation by employing a spectrum of machine learning classifiers, spanning from decision trees and multilayer perceptrons to logistic regression and k-nearest neighbors (kNN)—to dissect the intricate patterns inherent in motion data. Of particular note is the collective endeavor to elucidate the underlying dynamics of human movement through sophisticated analytical lenses, such as probabilistic models and statistical modeling, which have been instrumental in inferring specific activities from extensive datasets [1, 9, 6, 2].

The strategic application of wearable sensors has further enriched the ability to capture high-fidelity motion data, underscoring the importance of methodical sensor placement in enhancing data accuracy and reliability. Mitchell's [5] innovative use of Discrete Wavelet Transform (DWT) for frequency extraction from wavelet data exemplifies the forward-thinking approaches being developed to refine the granularity of activity classification. Similarly, foundational contributions by Bao & Intille [1] and John C. Platt [8] have showcased the versatility of machine learning models, from decision tables and instance-based learning to support vector machines (SVMs), in parsing through acceleration data to discern distinct activities.

These endeavors, while varied in their methodological approaches, converge on the shared objective of distilling actionable insights from multidimensional acceleration data. Specifically, they illuminate the potential of data preprocessing operations—ranging from feature selection to extraction—in sculpting raw data into a form amenable to machine learning analysis. The sliding-window technique proposed by Nunavath [7], which segments data into discrete temporal windows, represents a significant advancement in structuring data to capture temporal dynamics effectively, facilitating a more nuanced understanding of motion patterns over time.

3 Data Preprocessing

The main data processing steps are illustrated in Figure 2. Each step is explained in detail in this section.

3.1 Data Collection

The data collection process was done by a single longboarder, with attempts to vary the configurations of the rides, e.g., phone in right pocket vs left pocket, riding in standard vs "goofy" stance, etc. For each longboard action, namely "coasting", "pumping", and "pushing", the longboarder completed a ride, with the device on board, repeatedly doing the action. Thus, we have three collections of files, each containing labeled data for the corresponding longboard action.

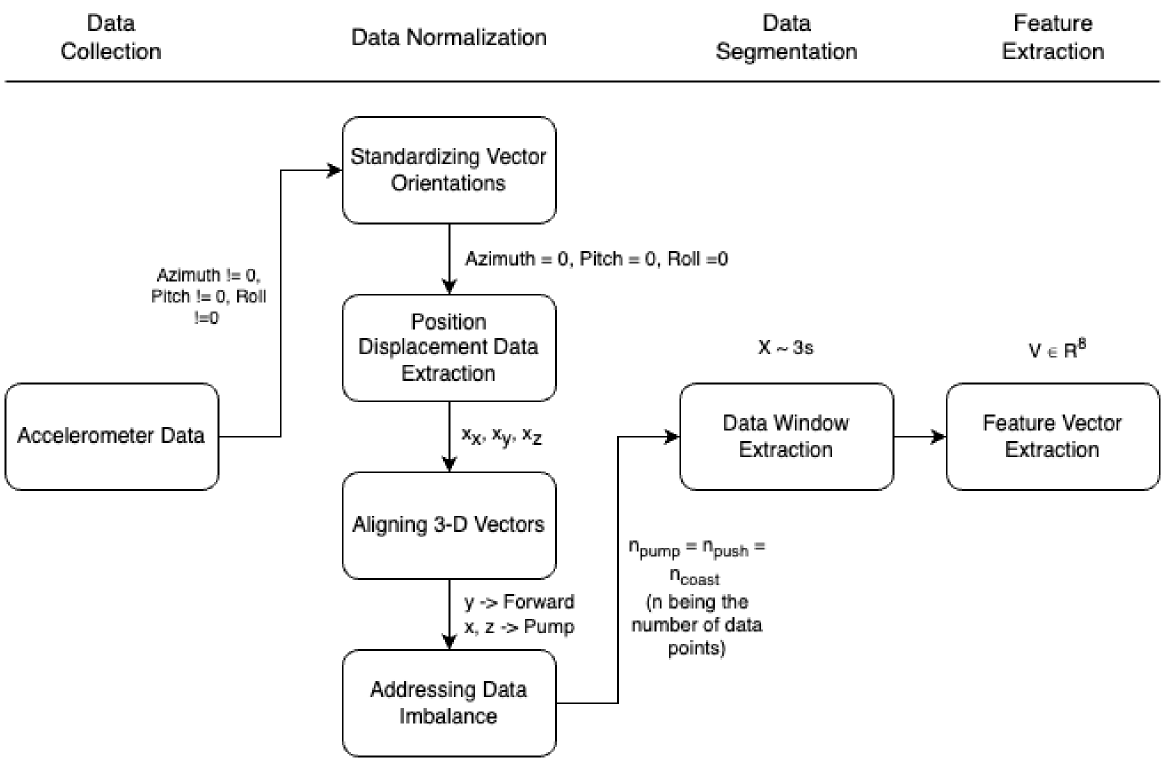

Figure 2: Data Preprocessing's workflow, i.e. all the steps occurring to the raw data since raw acceleration data to feature vectors used in classification.

Raw linear 3D acceleration (columns called a_x, a_y, a_z) and gyro-sensor (inclinometer) (columns called Azimuth, Pitch, Roll) data is collected using an Android mobile application called "Physics Toolbox Sensor Suite" which records data in irregular, random, time intervals, frequently 0.01s-0.03s. These data points are collected up until a window of collectively 3s (this interval length is explained further in the "Data Segmentation" section) is created, and then the data points in the windows are wrapped in an array, each being treated as a new data point. Thus, there is no overlapping of data points within this type of sliding window. Acceleration data is collected with respect to a straight line in three different dimensions. Linear acceleration changes whenever the mobile device speeds up, slows down, or changes direction. When the device is at rest with respect to the surface of the earth, it reads acceleration values of 0, 0, and 0, relative to x, y, and z. The device's gyroscope collects linear inclination data, which are numerical values indicating how much the device is rotated from a defined axis in angles, namely Azimuth, Pitch, and Roll, corresponding to the rotation of the device coordination in z, y, and x dimensions. This correspondence is illustrated in Figure 5. These values increase and decrease as the device rotates around the aforementioned axes. Thus, there exists an orientation of the device where these values are 0, 0, and 0.

3.2 Data Normalization

This section underlines in detail the data preprocessing methods and is ordered by the system's sequence of preprocessing events, which is:

1. Standardization of Vector Orientations
2. Extraction of Position Displacement Data
3. Alignment of 3D Vectors with Movement Direction
4. Data Imbalance Correction

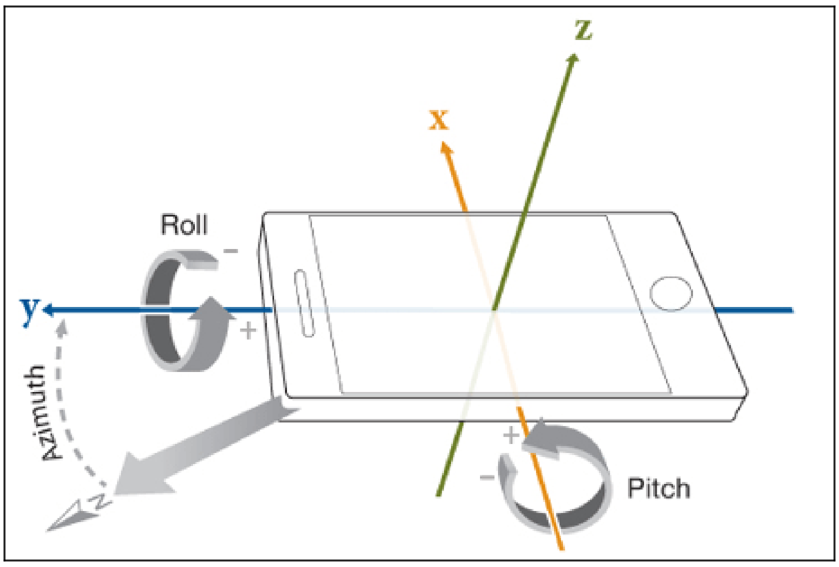

Figure 3: Coordinate system as illustrated with a longboard and the recording device aligning on the board.[4]

3.2.1 Standardizing Vector Orientations Using Three-Dimensional Rotation Matrices Based on Inclination Data

A significant challenge in this study is ensuring that the data from these sensors are dimensionally consistent, regardless of how the smartphone was oriented during the longboarding session. To address this, we applied a normalization technique using three-dimensional rotation matrices. These matrices—specifically designed for the x, y, and z axes—help us adjust the recorded acceleration vectors so they align with a common orientation.

Given a dataset, where each data point is segmented into vectors, we introduce a method involving three-dimensional rotation matrices. Let $\mathbf{R_x}$, $\mathbf{R_y}$, and $\mathbf{R_z}$ be the rotation matrices corresponding to rotations about the principal axes x, y, and z respectively. A vector $\mathbf{v}$ can be transformed into a normalized vector $\mathbf{v}'$ using these matrices:

$$\mathbf{v}' = \mathbf{R_z} \times \mathbf{R_y} \times \mathbf{R_x} \times \mathbf{v}$$

$$\mathrm{R}_x = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{pmatrix}$$

$$\mathrm{R}_y = \begin{pmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{pmatrix}$$

$$\mathrm{R}_z = \begin{pmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

With $\mathbf{v}$ being a given vector and α, β, and θ as the angles between $\mathbf{v}$ and its projections onto the z, y, and x axes, respectively. The inclination data corresponding to these angles are labeled as “Azimuth” (α), “Pitch” (β), and “Roll” (θ) within the data collection application. Formally, if v_z, v_y, and v_x are the magnitudes of the projections of $\mathbf{v}$ onto the z, y, and x axes, then:

$$\alpha = \cos^{-1}\left(\frac{v_z}{|\mathbf{v}|}\right),$$

$$\beta = \cos^{-1}\left(\frac{v_y}{|\mathbf{v}|}\right),$$

$$\theta = \cos^{-1}\left(\frac{v_x}{|\mathbf{v}|}\right).$$

The dominance of a particular component implies a more pronounced rotation about its corresponding axis. The sequence for the inverse rotation operation is determined as Azimuth → Pitch → Roll. By applying these inclination values inversely, we rotate acceleration data to a standardized coordinate system where $\alpha = \beta = \theta = 0$. Figure 4 provides a visualization of how the displacement data rotated based on the collected Azimuth, Pitch, and Roll during a specific interval. Ultimately, the trajectory vectors conform to a uniform coordinate system, effectively countering any variability introduced by device displacement.

3.2.2 Position Displacement Data Extraction Using Verlet Integration On Acceleration Data

For visualizing the position of the board in space, we apply Verlet integration. This application in our study addresses the inherent challenge of deducing precise movement trajectories from acceleration data collected

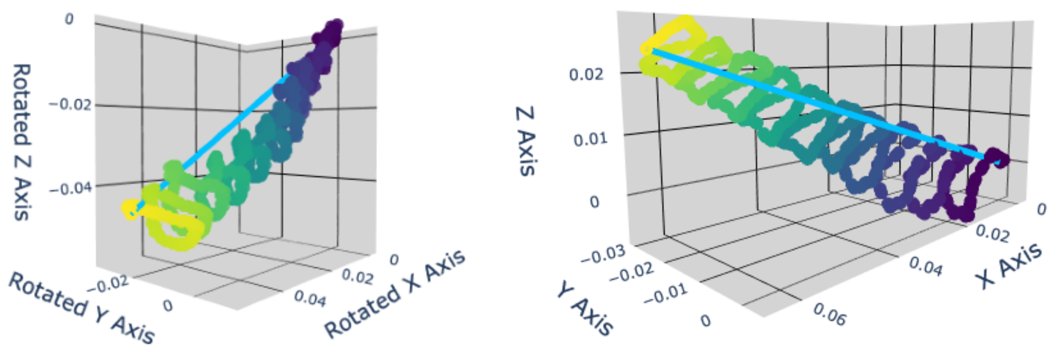

Figure 4: Rotation matrix applied on a small sample of the position displacement data. This specific sample is collected while pumping is done with the device facing backward from the moving direction. The figure above depicts the raw data, and the figure below depicts the rotated data.

via onboard sensors on a longboard. By iteratively applying this integration method over the acceleration data recorded during longboard sessions, we generate a continuous and accurate representation of the board's position displacement in 3D space. This detailed positional data is crucial for distinguishing the nuanced differences between the longboarding maneuvers of interest.

- **Coasting:** Characterized by minimal active propulsion, coasting primarily relies on momentum. Verlet integration allows us to capture the gradual deceleration and steady movements indicative of coasting, through subtle changes in position displacement.
- **Pumping:** Involves rhythmic, side-to-side weight shifts to generate forward motion. The oscillatory nature of pumping results in distinctive cyclic patterns in the displacement data, which Verlet integration helps to accentuate and quantify.
- **Pushing:** Manifested through periodic increases in acceleration as the rider pushes off the ground. The start-stop motion pattern, followed by a forward thrust, is effectively captured by analyzing the abrupt changes in position displacement derived from Verlet integration.

3.2.3 Aligning 3-D Vectors with Movement Direction Using Trigonometric Analysis

After collecting the position-displacement vectors, we would like to align these vectors with a fixed coordinate system, so that each longboard action is captured by a separate axis, namely, action dimensions. To achieve consistency and robustness in the action dimensions, we again rotate these vectors leveraging linear inclination data, specifically azimuth, pitch, and roll. We rotate these vectors such that the forward movement aligns consistently with a particular the y-axis, and the side-to-side movement aligns with a combination of the x and z axis. The final dimensions and their directions are illustrated in the diagram 5:

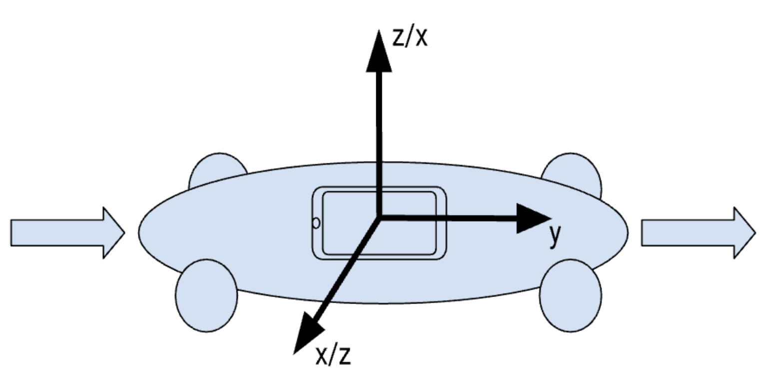

Figure 5: Coordinate system as illustrated with a longboard and the recording device aligning on the board

We present a trigonometric methodology to align position displacement vectors to a uniform orientation by calculating the angular displacement between planes and subsequently reorienting each vector by the inverse of this angle, ensuring the y-axis consistently represents the forward movement direction.

Given two 3-D vectors **a** and **b**, the sine of the angle ϕ between them can be determined using their cross product:

$$\sin(\phi) = \frac{||\mathbf{a} \times \mathbf{b}||}{||\mathbf{a}|| \times ||\mathbf{b}||}$$

Here, ϕ is the angle between the vectors **a** and **b**, and its sine provides information about the plane they form.

Let **c** be the reference vector aligned with the y-axis. To find the angular displacement θ between the plane formed by **a** and **b** and the reference plane of **c**, we can use:

$$\cos(\theta) = \frac{\mathbf{a} \times \mathbf{b} \cdot \mathbf{c}}{||\mathbf{a} \times \mathbf{b}|| \times ||\mathbf{c}||}$$

This provides the cosine of the angle between the normal to the plane formed by **a** and **b** and the reference vector **c**.

3.2.4 Addressing Data Imbalance using SMOTE and Ensuring Temporal Continuity in Synthetic Samples

Given that we have different numbers of instances, or data points, of each longboard action, the training and testing dataset has a great degree of imbalance. Such imbalance can lead to biased model predictions, particularly towards the majority classes. To address this imbalance, aside from using the F1 Score as the primary evaluation metric, we employ the Synthetic Minority Over-sampling Technique (SMOTE) [3]. Formally, for a given minority sample s_i (oftentimes, "coasting") and its nearest neighbor s_j in the feature space. Formally, SMOTE generates a synthetic sample s_{synth} by:

$$s_{\text{synth}}(t) = s_i(t) + \lambda \times (s_j(t) - s_i(t))$$

where λ is a random number between 0 and 1, and t represents the time index of the accelerometer data.

Considering $s(t)$ as a vector in a high-dimensional space, where each time point t corresponds to a dimension, SMOTE interpolates between these dimensions to generate s_{synth}. It is imperative to maintain the temporal continuity of s_{synth}, ensuring:

$$|s_{\text{synth}}(t+1) - s_{\text{synth}}(t)| \leq \delta$$

for some threshold δ, to prevent abrupt transitions in position displacement values.

This implementation allows us to have an equal number of instances of each class, which allows balanced learning across all labels.

3.3 Data Segmentation

To reduce the amount of data processed by the model and create vectors for normalization, data will be split into windows of similar time intervals, specifically 3-second windows.

The choice of a 3-second window was the result of a systematic exploration of various durations ranging from 1 to 10 seconds, the specific results are showcased in Figure 6. Each candidate duration was evaluated based on the model's performance in classifying the three primary longboarding actions: pushing, pumping, and coasting. Performance metrics, primarily the F1 Score, served as the benchmark for comparison.

As illustrated, the 3-second windows outperformed other durations, achieving the highest F1 Score of 0.968. This duration strikes a balance between providing sufficient data to capture the dynamics of longboarding maneuvers and maintaining a manageable dataset size for processing. It ensures that each window captures a full cycle of movements, especially the nuanced oscillations characteristic of pumping. Admittedly, a longboarder might change their motion–possibly more than once–during a given 3-second period, so this approach sacrifices some granularity in favor of extracting meaningful features. However, for a typical long-distance ride, a longboarder might switch motions about once every 30 seconds on average, so a shorter period of 3-second interval is a reasonable compromise to also capture more accidental shifts. Therefore, we determine a window duration of 3 seconds to yield the most accurate and consistent classification results and utilize it for the classification system.

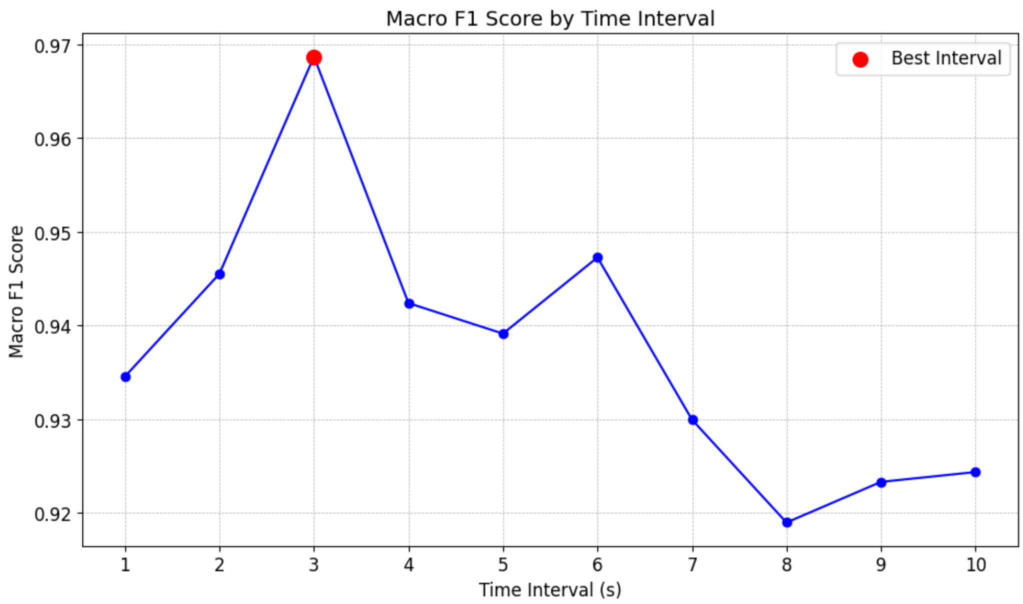

Figure 6: Macro F1 Score vs. Time Interval: The graph shows the macro F1 Scores for different time window durations. The peak at 3 seconds indicates the optimal performance of the model Random Forest.

3.4 Feature Extraction

Before feature extraction, we remark that all the acceleration and position displacement data are rotated into a fixed coordinate system that ensures that the forward direction aligns with the y dimension and the x, and z dimensions should align with the horizontal and vertical directions. However, the x and z dimensions are not fixed in place, so as the device rotates around the y-axis, the x and z coordinates cannot be determined in any fixed position or placement. Thus, we assume that, aside from the forward motion dimension, the side-to-side or turn dimension is a combination of x and z dimensions, which requires the needs for extracting features from both dimensions.

In the process of classifying longboarding motions using accelerometer data, we compute eight features from the normalized and aligned data. These features are instrumental in capturing the dynamics of longboarding maneuvers, enabling effective classification through machine learning techniques. Below, we outline each feature, its mathematical formulation, and its utility in motion analysis.

Each feature, delineated below, plays a pivotal role in the nuanced analysis and classification of longboarding motions, contributing to a comprehensive understanding of the dynamics involved in this sport.

From each of these time windows, 8 features are collected. For these features, we define a feature vector $\mathbf{v} \in \mathbb{R}^8$. These vectors are input into machine learning models as NumPy arrays to yield a labeled prediction. Specifically, we theorize the use of these features from the following insights:

Feature 1: $f_{\text{sum\_x}}$ - Sum of Frequencies in X Dimension (symbol in code: f_sum_x)

$f_{\text{sum\_x}}$ indicates dominant frequencies in the lateral (x) dimension:

$$f_{\text{sum\_z}} = \sum f_z \tag{1}$$

Given 3D accelerometer data $\mathbf{a}(t) = [a_x(t), a_y(t), a_z(t)]$ capturing longboard activities, we harness the capability of Fast Fourier Transform (FFT), given as

$$A(f) = \int \mathbf{a}(t)e^{-2\pi i f t}dt$$

transforming the DWT coefficients into the frequency domain. This spectral representation encapsulates dominant motion patterns, crucial for identifying specific longboard activities. FFT serves as a pivotal tool for efficiently extracting features and ensuring precise classification of longboard movements.

Through experiments, We ultimately decide to integrate FFT to extract maximum frequency during any window of time. One of the instances where we use this is illustrated in the following figure:

Analysis and motivation: $f_{\text{sum\_x}}$ reflect the aggregate lateral frequencies, essential for recognizing the rhythmic side-to-side motion characteristic of pumping. High $f_{\text{sum\_x}}$ values are indicative of active pumping, where the rider generates forward momentum through lateral oscillations, differentiating it from the more uniform motions of pushing or coasting.

Feature 2: $f_{\text{sum\_z}}$ - Sum of Frequencies in Z Dimension (symbol in code: f_sum_z)

Similarly, $f_{\text{sum\_z}}$ aggregates dominant frequencies in the vertical (z) dimension:

$$f_{\text{sum\_z}} = \sum f_z \tag{2}$$

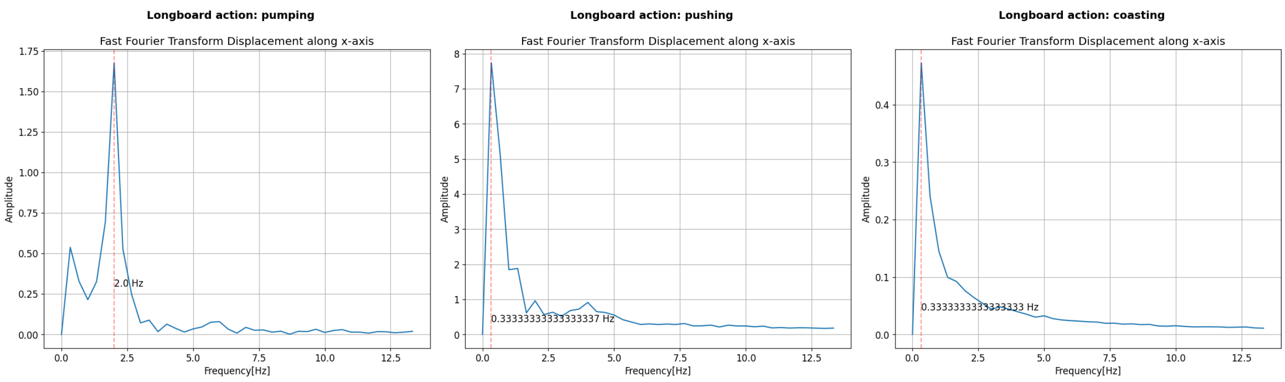

Figure 7: Frequency domain transformed from the position displacement data using Fast Fourier Transform. The corresponding position displacement values on the x-axis of the peaks are the frequency of each given 3-s windows of data of different longboard actions. From left to right: Pumping, Pushing, Coasting. In the pumping figure, we extract the peak in amplitude, which indicates the most prominent frequency, and then the corresponding frequency is 2.

Analysis and motivation: Vertical oscillation frequencies captured by $f_{\text{sum\_z}}$ can indicate the dynamic interaction with terrain during pushing, where the board may lift slightly off the ground. While less critical for coasting, variations in $f_{\text{sum\_z}}$ help distinguish between the consistent, ground-hugging motion of coasting and the more varied vertical dynamics of pushing.

Feature 3: $x_{\text{diff\_x}}$ - X-dimensional Displacement Range (symbol in code: x_diff_x)

This feature calculates the difference between maximum and minimum position displacements in the x dimension:

$$x_{\text{diff\_x}} = \max(x_x) - \min(x_x) \tag{3}$$

Analysis and motivation: $x_{\text{diff\_x}}$ quantifies lateral movement extent, with broader ranges suggesting vigorous pumping actions. Narrower $x_{\text{diff\_x}}$ ranges may correspond to the linear trajectory of pushing and coasting, making this feature pivotal for distinguishing pumping from other maneuvers.

Feature 4: $x_{\text{diff\_z}}$ - Z-dimensional Displacement Range (symbol in code: x_diff_z)

The range of position displacement in the z dimension is given by:

$$x_{\text{diff\_z}} = \max(x_z) - \min(x_z) \tag{4}$$

Analysis and motivation: The vertical displacement range, $x_{\text{diff\_z}}$, although generally minimal in longboarding, can offer subtle cues about the rider's engagement in pushing, where the foot contacts the ground. Minimal $x_{\text{diff\_z}}$ is expected in coasting, highlighting its utility in differentiating pushing efforts.

Feature 5: $a_{\text{diff\_y}}$ - Acceleration Range in Y Dimension (symbol in code: a_diff_y)

The difference in acceleration in the forward direction (y dimension) is quantified as:

$$a_{\text{diff\_y}} = \max(a_y) - \min(a_y) \tag{5}$$

Analysis and motivation: $a_{\text{diff\_y}}$ measures forward acceleration variance, directly relevant to the push phase's initiation and the sustained glide of coasting. Significant $a_{\text{diff\_y}}$ values may indicate pushing actions, whereas lower variability is characteristic of smooth coasting and efficient pumping.

Feature 6: $rms_{\text{pos\_x}}$ - RMS of Lateral Position Displacement (symbol in code: rms_pos_x)

The root mean square of lateral position displacement provides a measure of its variability:

$$rms_{\text{pos\_x}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{x,i}^2)} \tag{6}$$

Analysis and motivation: The RMS value for lateral position displacement, $rms_{\text{pos\_x}}$, is higher during active pumping due to continuous side-to-side motion. This contrasts with the relatively stable lateral position during pushing and coasting, underscoring the feature's importance in identifying pumping.

Feature 7: $rms_{\textbf{pos\_z}}$ **- RMS of Vertical Position Displacement (symbol in code: rms_pos_z)**

Similarly, the RMS value for vertical displacement:

$$rms_{\text{pos\_z}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{z,i}^2)} \tag{7}$$

Analysis and motivation: While $rms_{\text{pos\_z}}$ typically remains low across longboarding maneuvers, slight increases can reflect the vertical movements during aggressive pushing. Essentially stable in coasting, any variability in $rms_{\text{pos\_z}}$ can assist in recognizing the subtle dynamics of pushing.

Feature 8: $rms_{\textbf{acc\_y}}$ **- RMS of Acceleration in Y Dimension (symbol in code: rms_acc_y)**

The root mean square of acceleration in the y dimension assesses its consistency and intensity:

$$rms_{\text{pos\_z}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_{y,i}^2)} \tag{8}$$

Analysis and motivation: $rms_{\text{acc\_y}}$ highlights the consistency of forward motion, crucial for differentiating the continuous glide of coasting from the rhythmic acceleration patterns of pumping and the intermittent bursts of pushing. Stable $rms_{\text{acc\_y}}$ values are characteristic of coasting, with variability indicating active propulsion behaviors like pumping and pushing.

4 Model

To build a system that can classify these collected data, we utilize a spectrum of machine learning classifiers, each offering a unique algorithmic approach to the task. This diverse ensemble allows us to tap into the strengths of different computational models to recognize the intricate patterns in longboard movement data. These classifiers and the motivation around them are listed below.

- **Gradient Boosting Classifier** and **Random Forest** for their ensemble learning methods.
- **Logistic Regression** and **Linear SVM** for testing linear separability.
- **Nearest Neighbors** for similarity-based classification.
- **Decision Tree** for an interpretable model.
- **Neural Networks** for modeling complex, non-linear relationships.
- **AdaBoost** and **Gaussian Process** for advanced learning strategies.

With each classifier, we train it on the pre-processed training data, use it to make predictions on the testing data then compare them with the actual testing labels. For each classifier, we present two primary metrics, these metrics are essential to consider since the optimal model is integrated into an application:

- **Macro F1 Score:** A harmonic mean of precision and recall, considering both false positives and false negatives.
- **Training Time:** The time taken for the classifier to train on the provided dataset.

5 Experimental Results

With a total of 108,811 data points segmented into 381 instances, split into an 80:20 train-test ratio, we collected the following results:

Model	F1 Score	Training Time (s)
Gradient Boosting Classifier	0.953	0.599
Random Forest	**0.968**	**0.203**
Logistic Regression	0.905	0.011
Nearest Neighbors	0.939	0.003
Decision Tree	0.935	0.005
Linear SVM	0.934	0.005
Neural Net	0.931	0.248
AdaBoost	0.913	0.122
Gaussian Process	0.892	0.094

Table 1: F1 Score and training time of different classifiers on the test data.

We observe that the Random Forest classifier performs best in terms of F1 Score in a relatively short duration of time, which is suitable for a non-real-time system. These F1 Scores show that the predicted results from these trained models consistently match the given labels, indicating that these models have captured the quantitative patterns of the input data and can make accurate predictions from new, non-labeled data.

Additionally, we plot the Random Forest algorithm's feature importance:

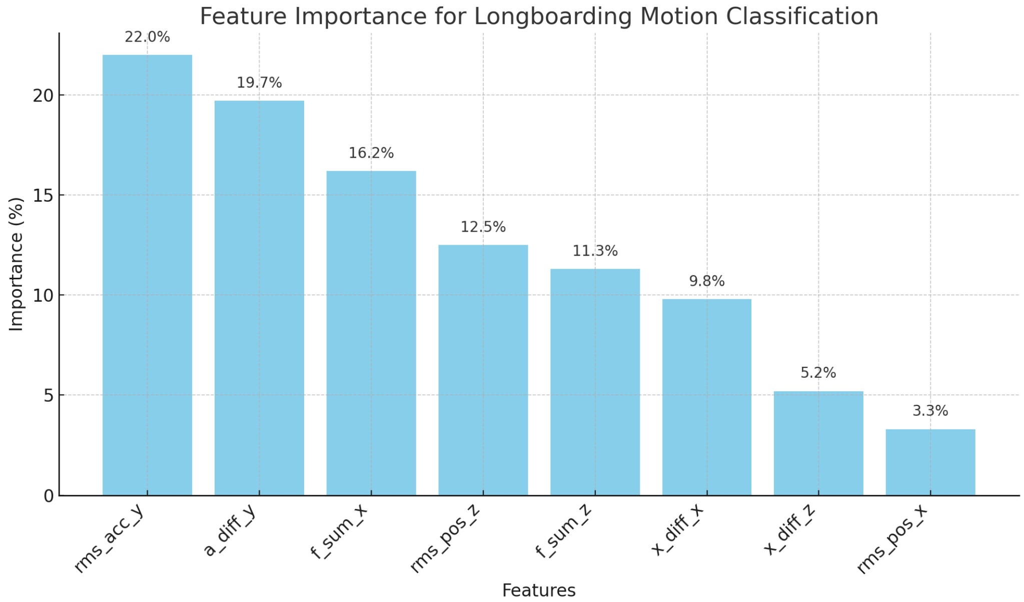

Figure 8: Feature importance when using Random Forest Classifier to classify Longboard Activity. From left to right: Root-Mean-Square of acceleration in y, Acceleration Difference in y, Sum of Displacement Frequency in x, Root-Mean-Square of position in z, Sum of Displacement Frequency in x, Position Range in x, Position Range in z, Root-Mean-Square of position in x.

We consistently find that differences in the maximum and minimum acceleration (19.7%), the root-mean-square of acceleration in the y dimension (22.0%), and frequency in the x dimension (16.2%) contribute most to the model's ability to distinguish between activities.

6 Conclusion and Future Steps

In this study, we delve into a comprehensive mathematical exploration centered around the classification of longboard activities using 3D accelerometer data. Beginning with the intricate preprocessing steps, we highlight the significance of data normalization and orientation correction. We emphasize the role of rotation matrices in aligning data with a fixed coordinate system to account for variability in the orientation of the recording device.

Through experimentations with machine learning classifiers, such as Random Forest, we demonstrate the potential of these mathematical tools in achieving precise classification of nuanced longboard movements. The results underscore the congruence between the model's predictions and the collected ground truth labels, attesting to the efficacy of our methodologies.

Building on the success of our mathematical model in classifying longboard activities, the next logical step is to operationalize these findings into tangible, real-world applications. In this vein, we aim to deploy the model into a mobile application for both Android and iOS platforms.

Mobile devices, with modern ones inherently equipped with 3D accelerometers, are ideal hosts for such applications. By employing a lightweight version of the model, we can ensure real-time processing and feedback to users without excessive computational overhead or battery drain. Frameworks such as TensorFlow Lite and Core ML have been explored to facilitate the seamless integration of our machine learning model into mobile environments.

The application is envisioned to serve both amateur and professional longboard riders. By providing instantaneous feedback on their maneuvers, riders can refine their techniques and optimize their performances. Furthermore, data collected from diverse global users can be harnessed (with due consideration to privacy norms) to iteratively refine the model, enhancing its accuracy and robustness.

Moreover, the app will be designed with a user-centric interface, ensuring ease of use and interpretation of results. Users will be able to initiate the accelerometer data collection, engage in their longboard activities, and subsequently receive a detailed breakdown of their performance based on the classifications determined by our model. Additional features, such as personalized tips, activity history, and performance metrics, are also under consideration to enrich the user experience.

In conclusion, the transition from a mathematical model to a mobile application embodies the convergence of theory and practice. Through this endeavor, we hope to democratize access to advanced analytical tools for longboard enthusiasts globally, fostering a community driven by data-informed insights. Personally, there emerge many ideas stemming from this discovery and application that we intend to try.

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