Turn Detection in Alpine Skiing Using Smartphone Sensors

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Abstract. Alpine skiing is a complex sport where technique is the key. The ability to detect turns, along with their intricate patterns, can provide valuable insights into performance analysis and injury prevention for skiers. Modern turn detection systems are often costly or cumbersome to use, limiting accessibility for recreational skiers, professionals, and coaches alike. In this paper, we present our AI-based solution focused on IMU sensors embedded in smartphones, which are widely available to the general public. Our approach addresses the challenges posed by noisy IMU data from mobile devices, varying skiing techniques, and diverse environmental conditions. We collected skiing data from 11 skiers of varying skill levels, who skied freely (without designated tracks) across three different ski resorts. The dataset consists of measurements captured by smartphones, including IMU signals from accelerometers, gyroscopes, and orientation sensors. To process the data and extract individual turns, we developed a gradient-based algorithm paired with optimization techniques specifically tailored to the constraints of smartphone sensors. Our proposed algorithm achieves robust turn detection while maintaining computational efficiency, enabling analysis on mobile devices. Experiments demonstrate that the model achieves an F1 score of 0.943 on test data. This highlights the potential of using smartphone-embedded sensors for sports analytics, making advanced motion detection more accessible to a broader audience. Our findings open pathways for personalized feedback systems and scalable solutions in ski analytics.

Keywords: Skiing · AI coach · Sensors

1 Introduction

Skiing is a sport where technique plays a crucial role. Improving skills and technical proficiency directly contributes to the safety of the skier and others around him [5]. We aim to analyze skiing technique to prevent dangerous behaviors and improve overall safety at ski resorts.

In recent years, significant advances have been made in motion analysis across various sports. In skiing, most publicly available research focuses on video cameras, GPS sensors, or IMU sensors to monitor skier behavior. Commercial solutions have also emerged, such as Carv [1], which uses IMU sensors attached to ski boots and insoles under the skier's feet. The data is analyzed in real-time

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and provides a performance score. Nevertheless, these systems face accessibility issues, requiring users to buy hardware and maintain paid app subscriptions. Other solutions include applications like [12], which analyze ski routes and provide metrics such as speed, slope inclination, distance, and tracking. However, they lack style analysis, error detection, and turn detection, leaving skiers without feedback to improve technique.

An alternative approach to skier support is analysis based on video cameras [4], involving professional skiers navigating slalom courses. These studies demonstrate the feasibility of tracking skier movements and visualizing trajectories. Motion analysis has also been conducted under controlled conditions using ski simulators with IMUs attached to ski boots [8]. That study used a single experienced skier performing six runs, collecting accelerometer and gyroscope data. IMUs have also been used for turn detection in real slope conditions [6], where 50 turns were analyzed. A turn was considered correct if the model identified the direction (right or left) between start and end points. While all turns were correctly classified, two false positives occurred. It was found that placing sensors on the leg yields cleaner data than boot-mounted configurations. In another study [7], sensors were placed in ski boots, and a model was developed to detect turns by identifying their start and end. Data from 11 experienced skiers on a prepared giant slalom track produced 610 labeled turns. The method achieved 0.980 precision and 0.867 recall. While these solutions may be effective, they all share a key limitation: they require additional hardware such as sensors, simulators, or camera setups, making them impractical for general use. Moreover, most studies are limited to professional athletes on prepared slalom tracks, leaving uncertainty about their performance with recreational skiers in uncontrolled environments.

The motivation behind this article is to work toward developing a system that helps skiers improve safety, and receive feedback to enhance their skills, acting as a virtual AI coach. The development of smartphones (equipped with built-in accelerometers and gyroscopes) has opened new possibilities for motion monitoring [2]. This makes them a cost-effective and widely available solution for skier support, as they are already carried by the vast majority. To achieve this, data acquisition was carried out in various ski resorts, participants, and days during 2023/2024. Data was collected by attaching smartphones to skiers' bodies to record their movements in real time. Skiers were also filmed from behind to enable turn labeling and segmentation. A gradient-descent-based algorithm with filtering techniques was developed to detect turns. To ensure the best possible performance, hyperparameter optimization was performed, and metrics were created to evaluate each implementation of the algorithm.

2 Data Acquisition

2.1 Data Collection

To analyze skiing technique, we collected data using smartphones attached to skiers' calves, arms, and pockets. Ten devices recorded IMU and GPS signals at

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0.1s intervals. Eleven skiers participated, from beginners to instructors, skiing freely and performing styles such as snowplough, parallel, and carving.

Calf placement yielded the best signal quality. Data from hands and jacket pockets were chaotic; pants pockets were more stable but lacked strong signal changes during short turns. Our system focuses on phones attached to the left or right leg, offering a simple, widely accessible setup without specialized hardware.

2.2 Labeling

Ski turns consist of Initiation, Turning, Completion, and Transition phases [11]. We focus on Transition, marking it using four points: Right Start/Stop, Left Start/Stop, 0.1s apart. These points were annotated by a ski instructor based on video footage[1].

Ambiguous cases, such as continuing a turn after briefly skiing straight, were labeled a single turn if all phases were not completed. Data streams were synchronized via server-based time correction. The final dataset contains 105 runs with 1,781 labeled turns from a single phone on the skier's leg. A visualization with 3D models and graphs illustrates the labeling[2]. The dataset is publicly available[3].

3 Algorithm

Our method for detecting ski turns consists of four main stages: (1) data preparation, (2) prediction of turn transition points, (3) outlier removal, and (4) definition of final results. The procedure operates primarily on the yaw component of orientation data (converted from quaternions), as it provides the clearest representation of skier movement. The key goal is to detect transition points, i.e., the moments when a turn in one direction ends and the next begins. These points are then used to evaluate algorithm performance in turn detection, apex estimation, and coverage analysis. To illustrate the process, we selected a sample run from the dataset (`huawei_mate/2024-02-25/1.csv`) using arbitrary parameters. The phone (Huawei Mate) was mounted on the left leg of an intermediate level skier.

3.1 Data Preparation

The data is initially provided as quaternions, which are converted to Euler angles in the ZYX axis order (yaw, pitch, roll) [3]. As shown in Figure 1, the signal may contain discontinuities near the limits ($\pm\pi$). To address this, we apply phase unwrapping with cumulative shift (C_S), which detects jumps greater than $\pm\pi$ between consecutive values, that is, $\Delta\theta(t) = \theta(t) - \theta(t-1)$. When such a jump is detected, a correction of $\pm 2\pi$ is applied and the cumulative shift is updated to track full rotations, as shown in Equation 1. To further reduce noise, we used a centered moving average with a window size of 10.

[1] `https://www.youtube.com/playlist?list=PLJiiH3fKO3ecNMK3skFHv8iiq9qj735hP`
[2] `https://github.com/SkiUserAnonymous/SkiTurnDetection/tree/main/data`
[3] `https://www.youtube.com/playlist?list=PLJiiH3fKO3edsK61OmA1-5mfXZGPcQNKg`

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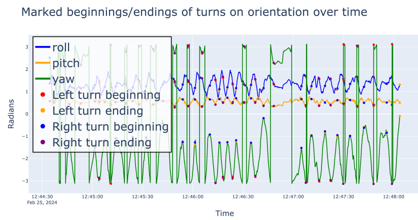

Fig. 1. Raw orientation data.

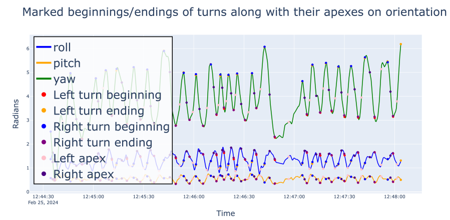

Fig. 2. Processed orientation data.

$$\mathrm{C\_S}(t) = \begin{cases} \mathrm{C\_S}(t-1) - 2\pi & \text{if } \Delta\theta(t) > \pi \\ \mathrm{C\_S}(t-1) + 2\pi & \text{if } \Delta\theta(t) < -\pi \\ \mathrm{C\_S}(t-1) & \text{otherwise} \end{cases} \tag{1}$$
$$\theta_{\text{unwrapped}}(t) = \theta(t) + \mathrm{C\_S}(t)$$

Lastly, we identify turn apexes based on previously labeled start and stop points. The apex index x is computed as the midpoint between valid Start/Stop pairs of the same turn type, as shown in Equation 2.

$$\begin{aligned} &0 \leq i < j \leq m, \quad m \text{ is the last index in the set,} \\ &x = \frac{i+j}{2}, \quad \text{for such } i, j \text{ that:} \\ &\quad \mathrm{State}(i) = \mathrm{Start}, \quad \mathrm{State}(j) = \mathrm{Stop}, \\ &\quad \mathrm{Type}(i) = \mathrm{Type}(j) \in \{\mathrm{Left}, \mathrm{Right}\}, \\ &\quad \forall k \in \{i+1, \ldots, j-1\}, \quad \mathrm{State}(k) = \mathrm{None}. \end{aligned} \tag{2}$$

At index 'x', a new feature, Apex, is assigned, such that $\mathrm{Apex}(x) = \mathrm{Type}(i) = \mathrm{Type}(j) \in \{\mathrm{Left}, \mathrm{Right}\}$, as can be seen in Figure 2.

3.2 Predict Turn Transition Points

After preprocessing, we identify turn transition points — the moments when a skier changes direction, labeled as Right/Left Start/Stop. These points typically correspond to local extrema in the yaw signal, as seen in Figure 1 and Figure 2. To detect them, we apply gradient descent with momentum twice: once to find maxima and once for minima. This method adapts dynamically to the signal, unlike fixed-threshold techniques, and is therefore more robust to variations across runs. The process is controlled by four parameters: learning rate, number of steps, momentum, and randomly chosen starting points.

Each local extremum (LE) found using this method is assigned a weight (W), based on the number of gradient start points that converged on it during the final iteration. Since local extrema often lie close to each other, we merge those within the fixed distance Merge Threshold and sum their weights, as shown in

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Equation 3. This reduces the total number of extrema and helps eliminate false positives, as illustrated in Figure 3.

$$\begin{aligned}
&\text{Merge all } LE_j \text{ within} \\
&\mathrm{dist}(LE_j, LE_k) \leq \text{merge threshold for } j \leq k \leq m \text{ into:} \\
&LE_{\text{merged}} = LE_k \quad \text{where } W_k = \max(W_j, \ldots, W_m), \\
&W_{\text{merged}} = \sum_{j=k}^{m} W_j .
\end{aligned} \tag{3}$$

3.3 Outlier Removal

As seen in Figure 3, some of the detected points are false positives (FP). To filter them out, we apply two steps. First, we use IQR-based outlier removal, with bounds defined by the IQR_Multiplier parameter, as shown in Equation 4.

$$\begin{aligned}
&\text{Lower bound} = Q_1 - IQR_Multiplier \cdot \text{IQR}, \\
&\text{Upper bound} = Q_3 + IQR_Multiplier \cdot \text{IQR}, \\
&\text{where IQR is the Interquartile Range}
\end{aligned} \tag{4}$$

Second, we remove a portion of extrema with the lowest weights, using a threshold value (Threshold), as defined in Equation 5.

$$\text{LE} = \{LE_j \mid W_j \geq \text{percentile}(\text{W}, \text{Threshold})\} \tag{5}$$

3.4 Obtain Final Results

This step includes two variants, depending on whether the algorithm is used to detect apexes of the turns or to define the full intervals of turns. In the first case, local minima (LMIN) and maxima (LMAX) are aligned so that their lengths differ by at most one. If the difference is greater, the longer list is trimmed, as shown in Equation 6.

$$\begin{aligned}
&\text{If } |\mathrm{len}(L_{\text{min}}) - \mathrm{len}(L_{\text{max}})| > 1, \\
&L_{\text{large}}^{\text{trimmed}} = \mathrm{Trim}\left(L_{\text{large}}, \min\left(\mathrm{len}(L_{\text{min}}), \mathrm{len}(L_{\text{max}})\right) + 1\right), \\
&\text{where} \quad \mathrm{Trim}(L, n) = \mathrm{Sort}(L, W)[1:n].
\end{aligned} \tag{6}$$

This ensures that LMIN and LMAX remain roughly balanced, although not necessarily alternating. Since our focus is on recall, we accept some redundancy—multiple extrema may refer to the same turn—if it helps avoid missing true transitions. Based on this alignment, apex points are computed using each extremum and its neighbors.

In the second variant, the goal is to identify full turn coverage. Here, extrema from LMIN and LMAX are selected in alternating order and the weights (WMIN/WMAX) are used to choose the best candidates. Some turns may be missed, but the algorithm avoids detecting multiple transition points within a

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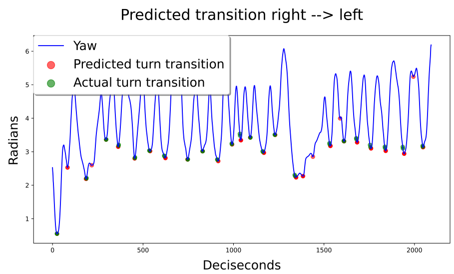

Fig. 3. Predicted transition points.

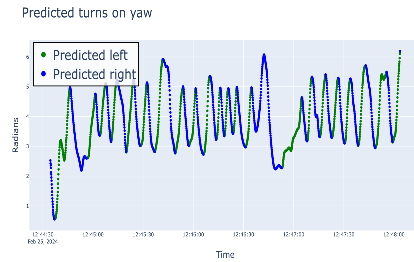

Fig. 4. Predicted turn coverage.

single turn in the same direction. Final right/left turn intervals are then constructed, as visualized in Figure 4.

4 Hyperparameter optimization

We optimized hyperparameters separately for each variant of the turn detection algorithm. The process involved preparing a parameter search space, splitting the dataset into training (80%) and test (20%) sets, applying five-fold cross-validation, and selecting the best configuration using the Ray Tune library with HyperOptSearch.

The model relies on Gradient Descent, so the main parameters included GD Learning Rate, GD Steps, GD Momentum, and the number of GD Start Points. Additional parameters such as Merge Threshold, IQR Multiplier, and a weight-based filtering threshold were also optimized. Parameter ranges included both continuous and discrete values.

The dataset was split randomly using a fixed seed (42) to ensure reproducibility. A random split was chosen due to the variability in external conditions (weather, slope, skier skill), which made skier-based or time-based splits unreliable. Cross-validation was performed using the KFold method from scikit-learn [10], returning an F1 score as the optimization metric.

We explored a search space of 10,000 hyperparameter combinations for each application variant. HyperOpt was selected due to its efficiency in handling sparse, irregular spaces with mixed parameter types [9].

5 Results

5.1 Metrics

The proposed algorithm was evaluated in three application scenarios: turn detection, apex estimation, and turn coverage. Each case was optimized independently and assessed using a dedicated metric.

The first metric evaluates whether the predicted turn occurred at the correct time and in the correct direction. A prediction is considered a true positive

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(TP) if it matches an actual turn, including its direction. False positives (FP) include incorrect direction, nonexistent turns, or duplicate predictions. False negatives (FN) refer to missed turns. True negatives (TN) represent non-turn segments that were correctly ignored. This metric is summarized using standard classification metrics such as Precision, Recall, F1, and Accuracy.

The second metric focuses on how accurately the algorithm detects the center of each turn. For every actual turn, the algorithm selects the best predicted apex (i.e., the one with the highest weight) and calculates its distance to the true center. This value is normalized by half the duration of the turn, yielding a score from 0 to 1. Missed turns or unmatched predictions receive a score of 0. The final result is the average across all turns.

The third metric assesses how much of the skier's path was correctly classified in terms of turn direction. The algorithm outputs the predicted direction at each point, which is compared to the actual direction. The final score is calculated as the percentage of points where the predicted direction matches the ground truth.

5.2 Results

The final results were obtained by optimizing the algorithm separately for each application, using a search space of 10,000 hyperparameter combinations. The best parameter values for each case are shown in Table 1.

For the first metric, the algorithm achieved an F1 score of 0.955 (train) and 0.943 (test), with precision, recall, and accuracy reaching 0.925/0.909, 0.987/0.979, and 0.996/0.995 respectively. Accuracy remains high due to the large number of non-turn points, but F1, precision, and recall better reflect the model's performance.

For the second metric, the average normalized distance to the true apex was 0.747 on the training set and 0.766 on the test set. For the third metric, which measures directional coverage across the full trajectory, the algorithm achieved 90.4% (train) and 89.7% (test).

A direct comparison is challenging due to the lack of open-source methods tackling this task in a comparable way.

Table 1. The best set of hyperparameters rounded to three decimal places for each metric.

Parameter	**Metric 1**	**Metric 2**	**Metric 3**
GD Learning Rate	0.0317	0.0112	0.054
GD Momentum	0.978	0.971	0.950
GD Steps	130	160	300
GD Start Points	500	100	200
Merge Threshold	12	16	13
IQR Multiplier	2.641	2.601	3.393
Threshold	0	0	0

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6 Conclusion and Further Work

The proposed algorithm effectively identifies turns in alpine skiing with a high F1 score of 0.943. Metric 2 demonstrates that the algorithm accurately detects turn apexes with minimal error, while Metric 3 shows that, on average, 89.7% of the ski runs were correctly mapped. It has been proven that smartphone IMUs can be effective for such tasks and could, in the future, provide a solution to the high entry barrier faced by skiers who want to analyze their performance. To ensure the reproducibility and transparency of our research, we have made the implementation of our algorithm[4], the dataset, and videos from skiers publicly available, as discussed in the Data Acquisition section. This enables others to validate our solutions or extend them in related areas of study. As part of future work, we aim to evaluate skiers' skills, classify their skiing style on specific sections, and provide feedback on mistakes and missteps during their runs. This will enhance safety on ski slopes and support skiers in improving their skills without the need for complex, expensive, and difficult to use equipment.

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