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Correcting Ski Resort Trajectories Extracted from Video

Buchuan Zhang * and Andreas Schadschneider *

Institute for Theoretical Physics, University of Cologne, 50937 Cologne, Germany
* Correspondence: bzhang@thp.uni-koeln.de (B.Z.); as@thp.uni-koeln.de (A.S.)

Abstract: Accidents at ski resorts present a significant safety concern, underscoring the urgency of addressing these issues. This study aims to enhance safety protocols by providing resort operators with more effective data analysis methodologies. We present and test methods for analyzing video footage from downhill ski areas where detailed information needed to correct errors, due to perspective, lens distortion, etc., is not available. This can be the case, e.g., for webcam footage and accidental videos (e.g., on YouTube). As much of this kind of video is available and could be used for statistical analysis, methods are needed that allow for at least for an approximate consideration of such aspects. Using video footage obtained from various ski resorts, we developed and tested several methods for analyzing and correcting the trajectories of skiers captured in the videos. Our analysis revealed that using five reference lines, along with the most appropriate x and y coordinate corrections, is an effective approach for achieving precise calibration of the video data. The corrected trajectory data, adjusted for perspective distortions and scaling inaccuracies, provide a detailed basis for analyzing skier behavior and identifying high-risk zones prone to collisions.

Keywords: ski resort safety; trajectory correction; video data analysis; accident prevention

1. Introduction

Accidents at ski resorts are a significant safety concern, particularly as skiing and snowboarding grow in popularity. Despite the implementation of safety regulations by organizations like the International Ski Federation, injuries remain a prevalent issue, highlighting the need for more effective safety measures [1]. The dynamics of these injuries are influenced by a range of factors, including skier behaviour, environmental conditions, and the effectiveness of safety equipment, making it critical to understand these elements in depth [2].

For example, the design and adjustment of ski boots play a crucial role in preventing lower extremity injuries. Research has shown that poorly fitted or adjusted ski boots can lead to severe fractures, underscoring the importance of proper equipment [3]. Additionally, demographic factors such as age and gender also influence injury patterns, with different groups showing varying susceptibility to certain types of injuries [4]. In particular, older adults and younger, less experienced skiers are at higher risk, which necessitates tailored safety strategies [5]. Studies have also highlighted that children and inexperienced skiers often display insufficient knowledge of safety rules, further increasing their risk [6]. Moreover, the risks associated with skiing can be exacerbated by improper training and the lack of physical preparation, leading to a higher incidence of injuries among certain populations [7].

To address these issues, this study develops advanced methodologies for analyzing and correcting the trajectories of skiers captured on video. Leveraging video footage

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from various ski resorts, we apply a combination of scaling factors, reference systems, and mathematical models to adjust the raw trajectory data [8]. Video analysis has become an indispensable tool in sports research, offering detailed insights into complex movements in dynamic environments like skiing [9]. This approach allows for precise calibration of skier trajectories, ensuring that the corrected data accurately reflects actual skier movements, which is essential for reliable safety assessments [10]. The use of such data-driven approaches is crucial, especially as more skiers and snowboarders hit the slopes, increasing the risk of accidents [11]. Here, we deal with a common situation were precise data that allow for a correction of perspective effects, lens distortion, change in landscape, etc., are not available. This can happen, e.g., when footage from webcams or private sources (YouTube, etc.) is used. Despite the limitations, such videos might provide valuable information and deserve to be considered in more detail. Here, we explore different approaches that allow at least for an approximate consideration of these aspects.

Moreover, refined data enable a deeper analysis of the conditions under which collisions and other accidents are most likely to occur. By adjusting scaling coefficients and exploring different correction models, this study aims to develop a flexible framework adaptable to various scenarios at ski resorts [12]. This framework not only enhances our understanding of collision risks, but also informs the development of strategies to mitigate these risks, ultimately contributing to improved skier safety [13]. The integration of predictive models and biomechanical analyses can further assist in tailoring preventive measures to the specific needs of different skier populations [11]. Video analysis aids experts in identifying skier injuries and analyzing their biomechanical characteristics during the racing process. This approach not only enhances skier safety, but also helps bridge the gap in understanding the mechanisms of ACL injuries in alpine skiing [14]. Additionally, understanding the specific environmental factors that influence skier behavior can also contribute to more effective risk management strategies [10].

Video analysis in sports, including skiing, has gained significant attention. Shih [9] provided an overview of content-aware video analysis techniques, essential for processing large volumes of sports footage. Wu et al. [15] extended this discussion by reviewing video action recognition in sports, highlighting the challenges and advancements in the field. Papic et al. [16] demonstrated the application of neural networks to enhance the accuracy and speed of data acquisition in sports, a technique highly relevant for analyzing skiing videos. In the context of trajectory analysis, Boltes and Seyfried [8] and Zhang et al. [10] used tools like PeTrack to extract and analyze skier trajectories, forming the basis for the trajectory correction methods employed in this study. Further advancements in video analysis tools, such as those discussed by Barris and Button [17], provide crucial improvements in tracking and analyzing skier movements in real-time.

The use of scaling factors and reference systems in trajectory analysis is well-supported by existing research. Zhong and Chang [18] developed algorithms for real-time event detection in sports video, and Xu et al. [19] proposed a framework for semantic annotation of sports video, which enhances the contextual analysis of skier trajectories. Roh et al. [20] explored gesture recognition in low-resolution sports video, providing methodologies that can be adapted for analyzing skier movements. These approaches offer a robust framework for understanding the dynamic movements of skiers and developing strategies to improve safety. Moreover, the integration of machine learning with traditional data analysis methods, as discussed by Duan et al. [21], provides a comprehensive approach to sports video analysis. This is further complemented by recent advancements in AI-assisted video tracking systems, which have shown potential for real-time application in dynamic sports environments such as skiing [22].

The visualization and interpretation of sports data have also been significant areas of research. Afzal et al. [23] surveyed visualization and visual analytics approaches for image and video datasets, emphasizing the importance of translating raw data into actionable insights. Huang and Deng [24] utilized data mining and image feature retrieval in tennis match analysis, offering techniques that could be applied to skiing. The effective visualization of sports data is critical for understanding complex movement patterns and communicating findings to practitioners in the field. Additionally, the importance of visual analytics in safety assessment is highlighted by studies such as Silva et al. [25], who applied video analysis to assess physical activity intensity in sports.

In the following, we first describe the problems faced dealing with video footage where relevant information on the perspective is missing or only approximately known. We then introduce a method for perspective correction, describe its principles, and explain how it is applied to correct the trajectory data. Finally, we discuss our findings and possible improvements.

2. Perspective Correction

To obtain more accurate insights into skiers' movements, our current focus is on processing and analyzing their trajectory data. Accurately capturing and interpreting this data is crucial for understanding the dynamics of skiing, such as speed, direction, and turning patterns. We use video footage provided by KFV (Kuratorium für Verkehrssicherheit, Board for Safety in Traffic), Vienna (Austria). The data were collected for different slopes in the downhill skiing resort Grosseck–Speiereck in Austria using a single camera with a fixed position. We identified all of the trajectories using the software PeTrack (Version 0.10.3) [8] in this study.

The following configurations and parameters were used (Table 1). While PeTrack performed reliably under most conditions, it exhibited certain limitations in handling motion blur during rapid skier movements and detecting objects in frames with low contrast due to varying lighting conditions. These challenges have been acknowledged and discussed in Section 3.

Table 1. Configuration and limitations of PeTrack software in skiing videos.

Parameter	Value/Observation
Resolution	1920 × 1080 pixels
Frame Rate	25 fps
Motion Blur	Minor inaccuracies in rapid skier movements
Low Contrast	Challenges in detecting skiers in poor lighting
Camera Perspective Variations	Reduced accuracy at field of view edges

2.1. Problems in Data Extraction

For the analysis of the collective motion of skiers, we are interested in the individual trajectories. These can be extracted from the videos similar to the techniques used, e.g., in pedestrian dynamics. However, whereas data in the latter case are usually obtained in laboratory conditions where all relevant parameters are known, here, we have to rely on observational data with several unknowns, e.g., the exact geometry, especially the slope of the area, and the distance of the camera to the objects. Furthermore, other corrections might be relevant, e.g., lens corrections. Therefore, we have to use approximations and estimates when correcting the extracted trajectories.

Figure 1 illustrates the geometry and coordinate systems, with the intention of providing a clearer understanding of the issues related to mapping the video trajectories onto the "real" trajectories. In the video, the coordinates are represented as (x', y'), given in pixels, while the corrected coordinates in the real-world plane are denoted as (x, y).

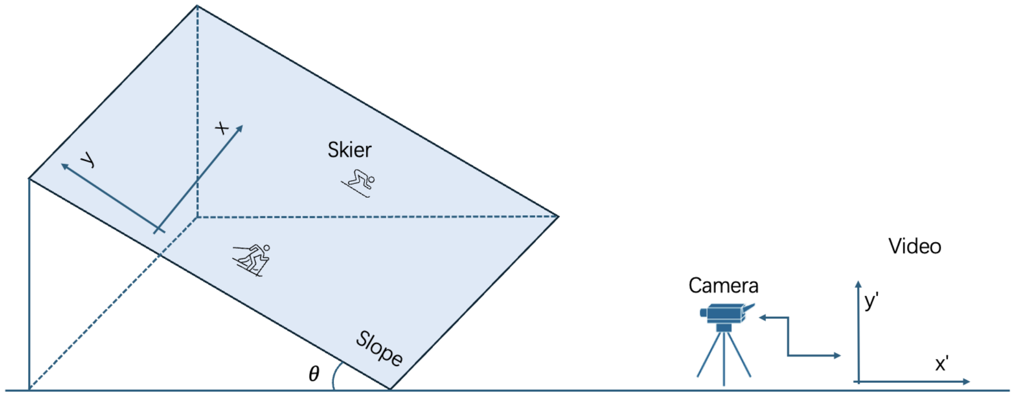


Figure 1. Geometry scheme: The camera is positioned at the front of the slope, allowing for comprehensive monitoring of all skiers on the slope.

2.2. Determination of Correction Coefficient

Figures 2 and 3 present screenshots that have been extracted from the video footage. We use these screenshots to determine approximate scaling factors for the x- and y-coordinates that account for perspective and distortion effects. Assuming that the width of the slope is almost constant, a scaling factor for the x-coordinate can be determined. Based on the apparent size of the same person at different positions on the slope, a correction factor for the y-coordinates is derived.

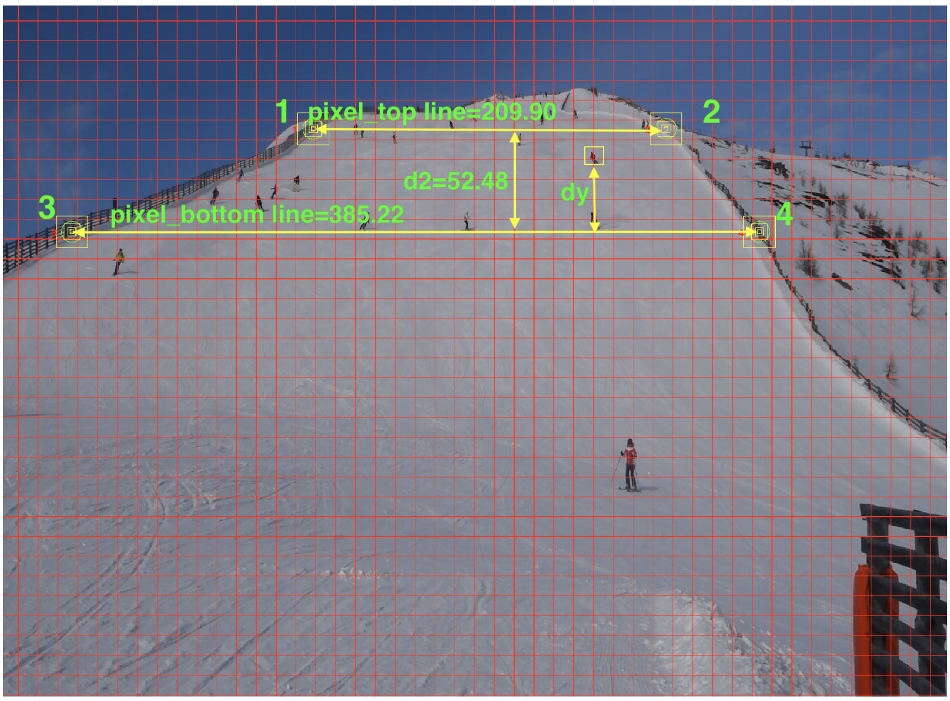
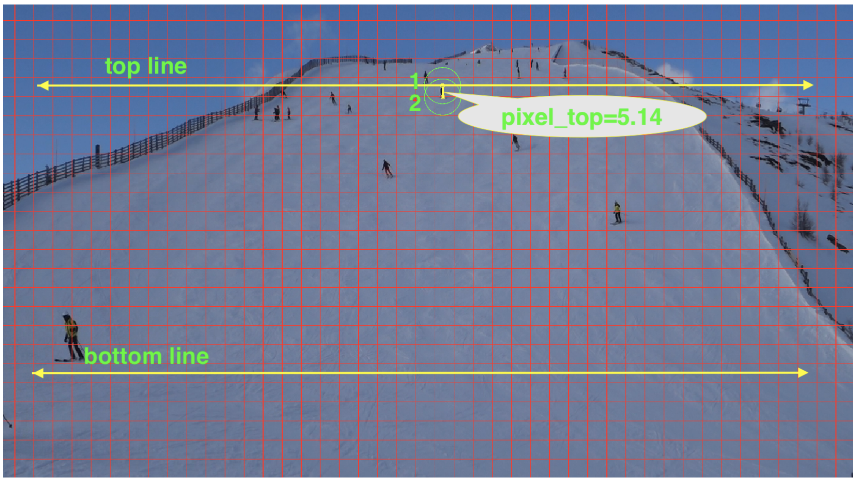
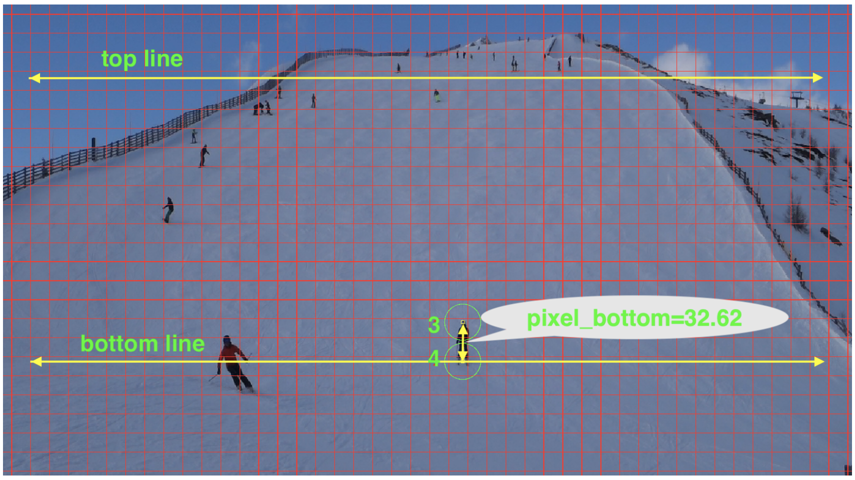


Figure 2. Screenshot of the PeTrack working platform. The red lines represent the grid system of the PeTrack platform, corresponding to the coordinates (x', y'). The yellow lines at the top and bottom indicate the width of the slope. The pixels of the top and bottom lines are noted, and d_2 and d_y represent the distance in pixels.



(**a**) Top of the slope



(**b**) Bottom of the slope

Figure 3. The pixel size of a person at the top and bottom of the slope is illustrated, with the two reference lines—the top line and the bottom line—also noted for comparison.

To determine the correction in x-direction we perform the following steps:

1. **Selection of reference lines**: Reference lines were selected based on two key criteria: (1) visual uniformity of the slope width in the video frames and (2) their position in areas where skier movement trajectories were well-defined and less affected by out-of-frame distortions. The lines were drawn at positions where the slope appeared to have minimal curvature and variability, ensuring reliable scaling. For example, in Figure 2, the top and bottom lines were chosen where the slope width appeared consistent and measurable.
2. **Scaling factor determination**: The scaling factor for the x-coordinate s_x was calculated as the ratio of the pixel widths between the top and bottom reference lines, minimizing perspective distortions. For the y-coordinate, the vertical scaling coefficient s_y was derived by comparing the pixel heights of the same skier at different vertical positions (Figure 3). These steps ensure the coefficients reflect both horizontal and vertical variations caused by perspective distortions.
3. **Deriving the correction factor**: Using this scaling factor, we derive the correction factor as $f_x(d_y) = \frac{s_x \cdot d_y}{d_2}$, where d_y is the distance between any point in the slope and the bottom line, whereas d_2 is the distance between the two reference lines (see Figure 2).

4. **Application to correction**: Finally, this correction factor is applied to the x-coordinates to correct for distortions from the perspective.

As shown by the relevant data in Figure 2, we can determine both the scaling factor and the correction factor in the x-direction,

$$s_x = d_{\text{bottom}}/d_{\text{top}} = 385.22/209.90 = 1.84 \tag{1}$$

$$f_x(d_y) = \frac{s_x \cdot d_y}{d_2} = \frac{1.84 \cdot d_y}{52.48} = 0.035 \cdot d_y \tag{2}$$

Note that we do not calibrate the positions. Instead, all coordinates, including the corrected ones, will be given in pixels. This is sufficient to obtain a qualitative understanding of the skiers' trajectories.

The correction in y-direction is determined by the following steps:

1. **Selection of reference points**: As shown in Figure 3, we selected a person at the top of the hill and the same person at the bottom of the hill, recording their height p_{bottom} and p_{top} (in pixels) at these two different locations.
2. **Scaling factor determination**: Next, we calculate the ratio of the two pixel values, which allows us to determine the scaling factor $s_y = \frac{p_{\text{bottom}}}{p_{\text{top}}}$.
3. **Deriving the correction factor**: The correction factor for an arbitrary point on the slope depends on its y-coordinate. Using the scaling factor, we derive a correction factor as $f_y(d_y) = \frac{s_y \cdot d_y}{d_2}$, where d_y is the distance between the location of the point and a reference line at the bottom, and d_2 the distance between the top and the bottom point.
4. **Application to correction**: Finally, this correction factor is applied to the y-coordinates to correct for distortions.

In Table 2, the end point coordinates (x', y') for a skier at the top and bottom of the slope are extracted from the video. The apparent size of this skier is 5.135 pixels at the top and 32.622 pixels at the lower position. This results in a scaling factor of 6.35, which leads to the correction factor

$$f_y(d_y) = \frac{6.35 \cdot d_y}{209.97} = 0.03 \cdot d_y \tag{3}$$

Table 2. Coordinates of the top and bottom points in Figure 3.

Points	Frame	x'	y'
1	213	−258.107	316.847
2	213	−258.107	311.712
3	925	−252.335	134.364
4	925	−252.227	101.742

With this, we have nearly completed the y-axis correction. Next, our focus will shift to correction. First, we need to select a baseline to transform the raw trajectory obtained from PeTrack. We have chosen the line connecting points 3 and 4 in Figure 2 as the baseline. To start, we will explore perspective correction using the trajectory shown in Figure 4.

We applied a processing step to the original coordinates obtained from the software as follows:

$$x_i = x'_i + \alpha_x \cdot d_y \tag{4}$$

$$y_i = y'_i + \alpha_y \cdot d_y \tag{5}$$

Here, we have introduced the abbreviations $\alpha_x = 0.035$ and $\alpha_y = 0.03$ for the correction coefficients in the x- and y-directions. d_y is the distance of the object to the reference line (see Figure 2), i.e.,

$$d_y = y_i' - y_{\text{base}} \tag{6}$$

where y_{base} is the y-coordinate of the baseline.

Figure 4. Original trajectory from video, the red line here shows one skier's movement path.

In addition, to further clarify the correction factors $f_x(d_y)$ and $f_y(d_y)$, the correction coefficients α_x and α_y, and the scaling factors s_x and s_y, we provide the following explanation:

$$s_x = \frac{d_{\text{bottom}}}{d_{\text{top}}}, \quad s_y = \frac{p_{\text{bottom}}}{p_{\text{top}}}$$

$$f_x(d_y) = \frac{s_x \cdot d_y}{d_2} = \alpha_x \cdot d_y, \quad f_y(d_y) = \frac{s_y \cdot d_y}{d_2} = \alpha_y \cdot d_y$$

Figure 5 provides a diagram illustrating how the model works.

The above two Formulas (4) and (5) were used for the correction of the (x', y')-coordinates extracted from the video to determine the real coordinates (x, y).

As we can see from Figure 6, the overall shapes of the two trajectories are basically the same, indicating that after the correction, the change in the trajectory did not lead to a strong deviations of the path. As expected, the correction is much larger for large y-values, but the overall shape of the trajectory is not significantly changed.

The derivation of the correction factors used so far was based on some assumptions. In the following, we will use improved correction methods to see whether this will have a stronger effect on the extracted trajectories.

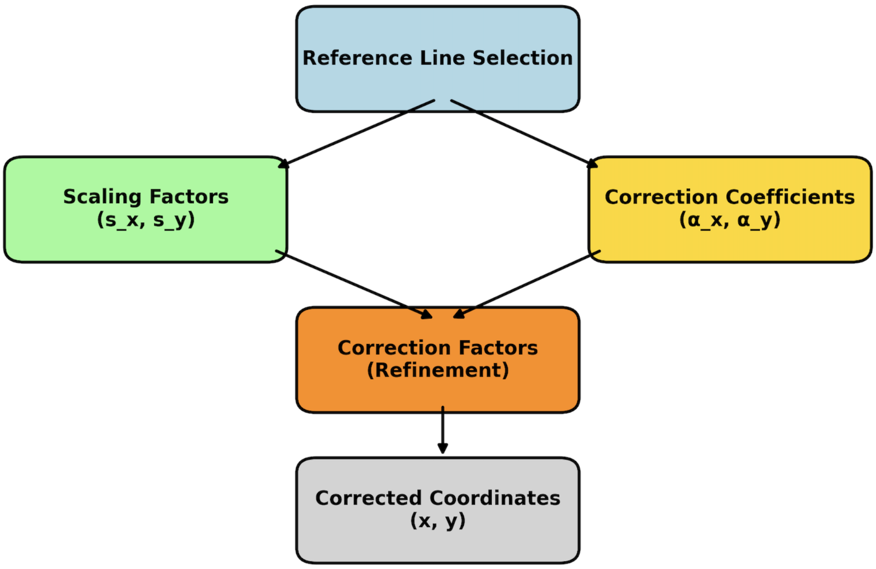


Figure 5. Flowchart of the model.

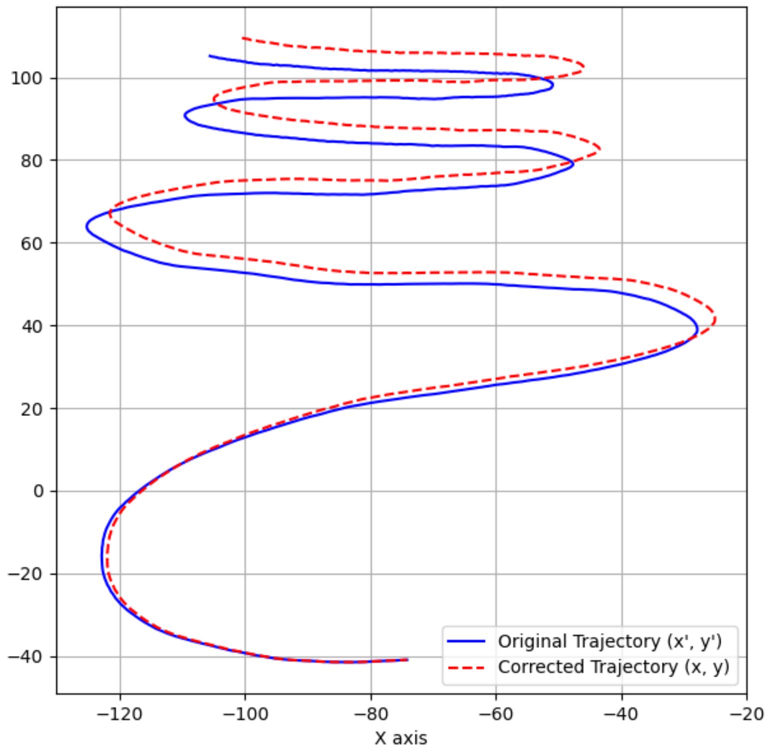


Figure 6. Original vs. corrected trajectory.

2.3. Refinement of the Correction Coefficient

In the previous section, we assumed that the correction coefficients were constant because we only chose two reference points for the correction. However, in reality, the width and slope of the hill are not uniform, necessitating additional reference points to account for these variations. To address this, we selected more reference lines to determine more accurate correction coefficients, making the correction more representative of real-world conditions. In this approach, the correction coefficient is no longer constant, but varies with position on the slope.

The reference system was expanded to include five lines to account for slope irregularities and variations in terrain. Five lines were chosen as a balance between computational efficiency and accuracy. By adding more reference lines, we were able to derive position-dependent correction coefficients that reflect finer variations in slope geometry.

To derive the equation for the dependence of α on the position on the slope, we need to collect more data points. After obtaining six additional points, we can perform a regression analysis. The results of this analysis can be seen in Table 3, which illustrates how the correction coefficient α varies with the variation in the y-coordinate.

Both linear and nonlinear regression analyses were applied to test their effectiveness in capturing the variations in correction coefficients. Linear regression provides a simpler model that approximates global trends, while nonlinear regression (e.g., polynomial regression) can capture finer variations at different vertical positions.

Table 3. Scaling factor α determined at different positions (see Figure 7).

Points	Width (in Pixel)	y-Coordinate	$alpha(y)$
1, 2	$p_{12} = 181.95482$	155.4505	0.0316
6, 7	$p_{67} = 261.4292$	130.05	0.0338
8, 9	$p_{89} = 316.269$	111.9395	0.0451
3, 5	$p_{35} = 392.048$	93.47985	0.0982
10, 11	$p_{1011} = 418.945$	82.603	0.109

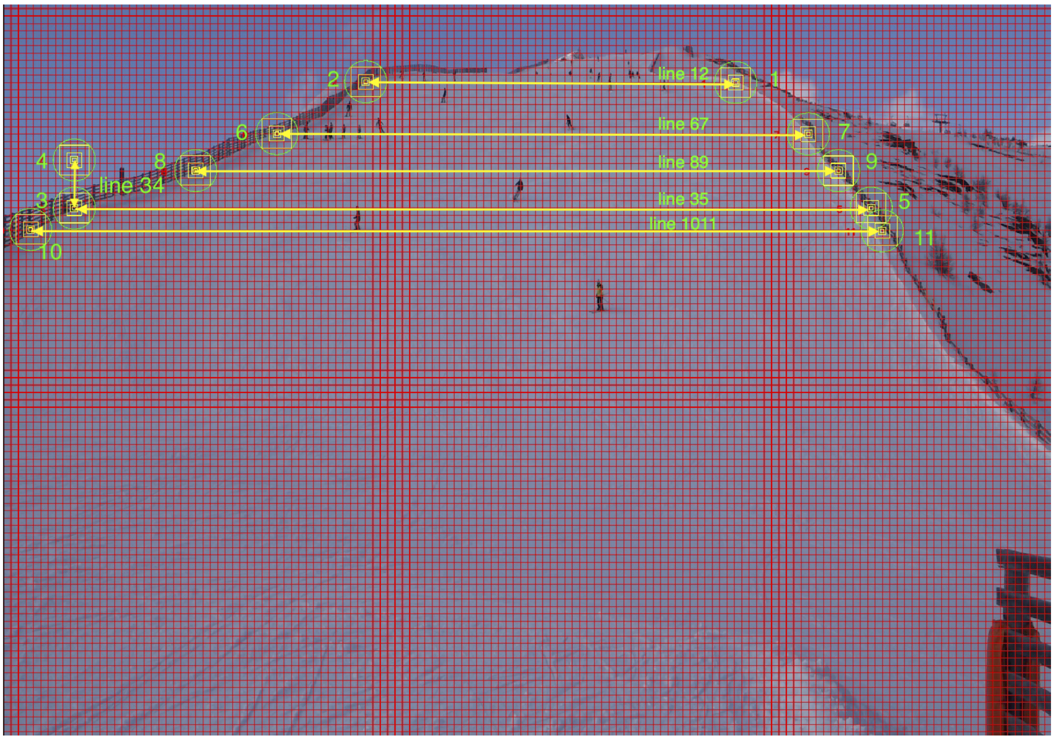


Figure 7. Screenshot with more points from PeTrack working platform.

The data from Table 3 are plotted in Figure 8. Performing a linear regression analysis we find

$$\alpha(y) = -0.0012 \cdot y + 0.1958 \tag{7}$$

for the dependence of the correction coefficient on the y-coordinate.

Considering Figure 9, a non-linear regression analysis seems to be more appropriate. We utilized a polynomial regression of the form

$$\alpha = \beta_0 + \beta_1 \cdot y + \beta_2 \cdot y^2 \tag{8}$$

and obtain

$$\alpha = 0.000023 \cdot y^2 - 0.006583 \cdot y + 0.502847\,. \tag{9}$$

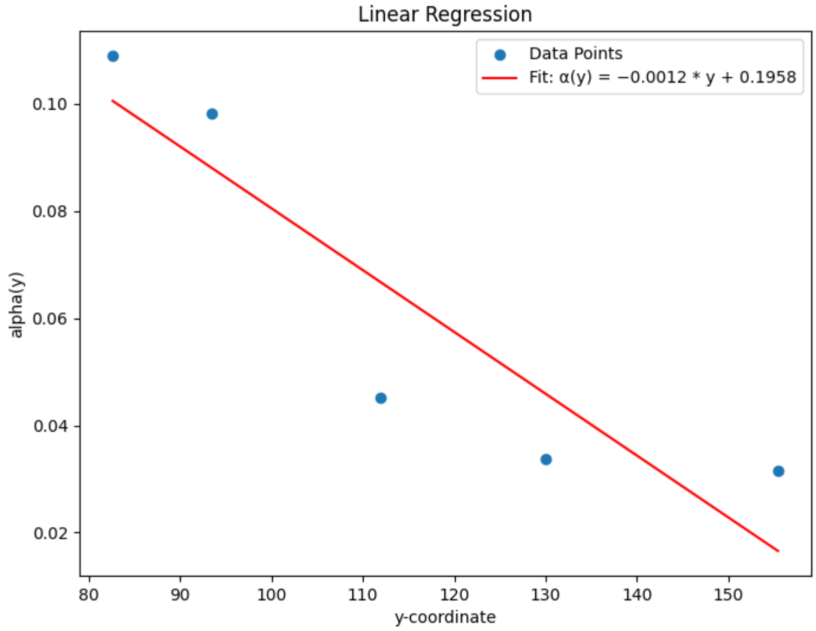


Figure 8. Linear regression analysis for the dependence of α on the position using the data from Table 3.

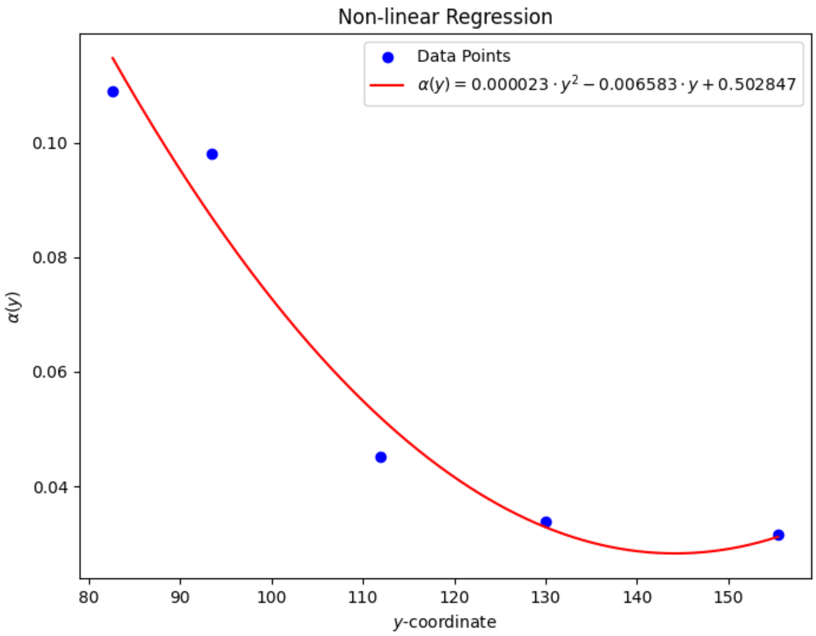


Figure 9. Nonlinear regression analysis using the same points as in Figure 8.

2.4. Corrected Trajectories for Improved Corrections

As we have determined the correction coefficient function, we can now apply the two regression models to our trajectory data, processing the raw data we obtained. This processed data allows us to visualize and analyze the adjusted trajectory effectively.

As shown in Figure 10, there is a clear difference between the two correction methods. The linear correction exhibits a smaller amplitude, noticeably expanding the movement range in the x direction. In the higher y region, the linear correction closely aligns with the original trajectory, whereas the nonlinear correction is shifted further to the left of the original trajectory. Additionally, in the lower y region, the nonlinear correction (green dotted line) consistently shows the corrected trajectory lower than the original one (blue solid line) in the y direction. Conversely, the linear corrected trajectory (red dotted line) starts lower than the original trajectory and then surpasses it as it progresses.

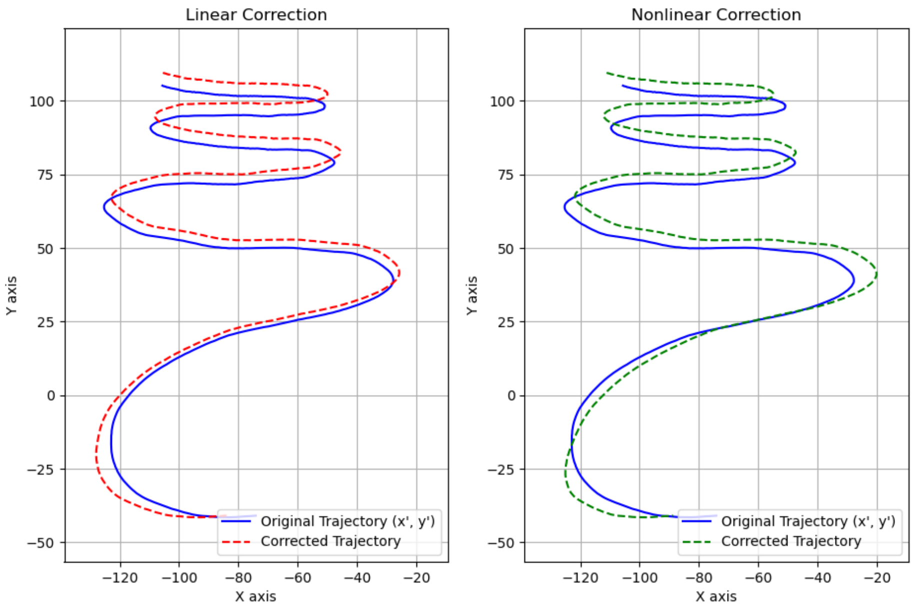


Figure 10. Comparison of original and corrected skier movement trajectories for the linear (**left**) and non-linear (**right**) correction.

Due to the lack of direct ground truth data, we adopted an internal consistency approach to evaluate our methods. The deviations were quantified using RMSE and MAE, with the five-reference-line nonlinear regression method serving as the refined reference standard. Table 4 summarizes these results, which highlight the superior performance of this approach.

Table 4. Performance comparison of alternative methods relative to the five-reference-line nonlinear regression (baseline).

Method	RMSE (Pixels)	MAE (Pixels)	Correlation Coefficient (R)
Two Reference Lines	2.84	1.67	0.91
Linear Regression (5 Lines)	2.12	1.12	0.94

In this section, we applied basic perspective correction to the original trajectory and then refined the correction coefficient. We implemented both linear and nonlinear corrections based on two regression formulas and compared their effects on the trajectory. The results suggest that further refinement of the correction methods is necessary to achieve a more accurate representation of the skier's movement. It may be essential to explore alternative models or incorporate additional factors into the correction process to better align the visualized trajectory with the actual dynamics of the skier. Some alternative correction schemes have been explored in [26].

3. Discussion

While PeTrack has proven effective for extracting skier trajectories, its performance is influenced by certain environmental and video-specific factors: 1. Motion blur: Rapid skier movements occasionally caused motion blur, leading to minor inaccuracies in trajectory tracking. 2. Low resolution or contrast: Frames with poor lighting or distant skiers posed challenges for consistent detection and tracking. 3. Camera perspective variations: Changes in camera perspective impacted the consistency of trajectory extraction, particularly at the edges of the field of view. These limitations may slightly impact the precision of the extracted trajectories but do not undermine the overall trends and conclusions drawn from the data. Although PeTrack was sufficient for the scope of this study, future work will involve a comparison with other state-of-the-art trajectory extraction tools, such as DeepLabCut or OpenPose, to assess their suitability for dynamic skiing environments.

Our study provides a novel methodology for correcting skier trajectories extracted from video data, offering a foundational tool for safety assessments in ski resorts. The methodology is specifically designed for cases where much information needed to properly correct the extracted data for effects like perspective and lens distortion is not available. This is often the case for webcame footage or private videos, which otherwise provide interesting insights into the dynamics of downhill skiing. The practical implications of this work are noteworthy. Corrected trajectory data allow ski resort operators to identify high-risk zones, optimize trail designs, and implement effective safety protocols. Furthermore, safety engineers can utilize the refined data to design better collision-prevention systems, such as predictive monitoring tools. Policymakers, on the other hand, can leverage these insights to establish evidence-based safety regulations, ensuring safer skiing environments for diverse populations.

Although this study focuses on video-based trajectory correction methods, we recognize the potential of integrating digital terrain models (DEM) or digital surface models (DSM) to improve ski slope modeling accuracy. DEM/DSM data can provide detailed information about slope gradients, surface irregularities, and terrain features, which are crucial for enhancing trajectory corrections. For instance, combining DEM/DSM data with video-derived trajectories could allow for a more realistic representation of skier movements, especially in areas with complex terrain. However, the integration of DEM/DSM data presents certain challenges. Co-registering trajectory data with terrain surfaces requires accurate alignment of video coordinates and DEM/DSM spatial data, which involves additional computational steps and precise calibration. Furthermore, obtaining high-resolution DEM/DSM data may be subject to limitations in data availability and cost. Despite these challenges, the potential benefits of such integration are substantial and warrant further exploration.

Real-world ski slopes often exhibit non-uniform geometries, including varying widths and gradients. These irregularities introduce challenges when applying manually selected reference lines for perspective correction. To overcome these limitations, automated approaches, such as homography transformations, can be employed. Homography transformations use multiple reference points to map distorted video planes to real-world planes, enabling dynamic correction of perspective effects. This technique has been widely used in computer vision and could be integrated into future versions of our methodology. Additionally, incorporating calibration markers or grids on the ski slope could provide a systematic means of defining reference points and improving the accuracy and consistency of the corrections. These grids, combined with homography transformations, would allow for automatic scaling and adjustment based on the slope's unique geometry.

4. Conclusions

In this study, we have explored various methodologies to correct the trajectories extracted from skiing videos, focusing on improving the accuracy of the data through different calibration techniques. Our goal was to identify the most effective method for trajectory correction by comparing the outcomes of these different approaches.

Initially, we used two reference lines as the baseline to calculate the scaling factor and correction coefficient. This approach is based on the assumption that the slope of the hill is constant. To incorporate the effect of changing slopes, we expanded the reference system to include five lines and conducted a regression analysis based on this new setup. During the regression process, both linear and nonlinear methods were employed, allowing for a comparison of their outcomes. Ultimately, we concluded that incorporating additional factors into the model could result in improved outcomes, offering potential for further refinement beyond the current results.

This study highlights the importance of using corrected trajectory data for accurate skier behavior analysis. By addressing perspective distortions and slope variations, our methods provide a reliable framework for identifying high-risk zones and supporting the design of safety measures. The results obtained from our comparisons provide valuable insights into the effectiveness of various approaches, which can be applied to future studies or practical implementations. Although we encountered challenges along the way, the final outcomes demonstrate that with the right methodology, accurate and reliable trajectory corrections can be achieved. We are optimistic that these findings can be further refined and utilized in real-world scenarios, contributing to the advancement of sports video analysis and data accuracy in motion tracking.

5. Future Work

In the future, we plan to integrate artificial intelligence (AI) into the trajectory correction process. Specifically, employing neural networks to analyze skier trajectories offers several advantages over traditional methods, including enhanced accuracy, adaptability to diverse environmental conditions, and the capability for real-time data processing.

Data Requirements and Preprocessing: The implementation of neural networks would require large-scale, high-quality datasets consisting of trajectory data, environmental parameters (e.g., slope gradients and snow conditions), and potential collision events. These data would need to be preprocessed to ensure consistency, such as normalizing input variables and addressing missing or noisy data.

Model Training and Validation: The neural network training process would involve defining appropriate architectures (e.g., convolutional neural networks for spatiotemporal data) and optimizing the hyperparameters using training datasets. Validation would be conducted with unseen test data to assess the model performance and generalizability.

Benefits of AI Integration: Compared with traditional methods, AI-powered systems can dynamically adapt to diverse terrains and skier behaviors, making them particularly valuable for real-time applications. Additionally, AI can identify complex patterns in large datasets, leading to more precise risk assessments and improved collision-prevention systems.

These advancements would enable the development of intelligent safety management systems at ski resorts, leveraging AI for dynamic risk monitoring and adaptive safety interventions.

By the way, we plan to collaborate with ski resort operators to obtain ground truth data using GPS-based systems or motion capture technologies. This will allow us to validate the corrected trajectories more rigorously and further enhance the robustness of the proposed methodology.

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Conflicts of Interest: The authors declare no conflicts of interest.

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