Evaluating Drift and Uncertainty in IMU-Based Bike and Rider Lean Angle Measurements During Downhill Mountain Biking

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***Abstract*— Accurate estimation of lean angles is crucial for analyzing athletes and their bikes in sports such as enduro and downhill mountain bike to assess performance and prevent falling. This study aimed to assess the drift of IMU-based lean angle estimations for both the rider and the bike and to assess the propagation of uncertainty from the IMU's gyroscope of bike lean angle measurements during real-world downhill and enduro mountain biking. Athletes were equipped with 2 IMUs, attached on the pelvis and sternum, to estimate the lean angle with OpenSim. The bike was equipped with an IMU on the frame to estimate the bike lean angle. Calibration movements were performed at the start and the end of the track to quantify drift by calculating the rms of the calculated angle around the two residual (non-leaning) axes during both calibration movements. Monte Carlo simulation was performed to assess the uncertainty. A difference in rms for the athlete lean angle between the two calibration movements was 4.2°, and values of the residual axes ranged from around -20° to 20°. For the bike, the difference in rms was found to be 3.0° and the values ranged from around -10° to 10° for the calibration movements at the end of the track. The Monte Carlo simulations showed the mean of the standard deviations to be 0.30°, which corresponds to an uncertainty of 0.60° when extended to 95%. Compared with an average difference between runs within athletes of 8.9° (±7.1°), this uncertainty is negligible. The results imply that angle estimation strategies in downhill and enduro mountain biking can be valuable and could be used in performance monitoring, and may also hold potential to be applicable in other fast-paced outdoor sports.**

Keywords—Kinematic analysis, Inertial Measurement Unit (IMU), Mountain bike, Uncertainty, Drift

I. Introduction

Mountain biking has grown significantly since the emergence during the 1970s in the United States (US), becoming one of the fastest-growing sports in both Europe and the US [1]. This growth is expected to continue, with a foreseen compound annual growth rate of 12% from 2024 to 2030 [2]. Among the various disciplines within mountain biking, one of the most popular ones are downhill and enduro mountain biking. Enduro mountain bike consists of timed downhill sections that contribute to overall race time, and non-competitive transition sections that must be completed within the provided time limit but does not contribute to overall race results [3]. While going downhill, riders must navigate high-speed, steep, technical descents on rugged trails [4]. Riders' top speed may reach up to 80 km/h, indicating that the biker must show commitment and a keen sense of piloting in order to overcome the obstacles encountered during the race [5].

Research in enduro/downhill mountain biking has overlooked biomechanical and kinematic factors, especially in on-field testing. This creates a gap in understanding how rider movement patterns and bike-rider interactions contribute to improved performance. Understanding how mountain bikers go downhill kinematically could provide valuable insights into performance optimization and/or injury and fall prevention. Downhill mountain bike presents a unique challenge due to its highly variable terrain, including high-speed sections, technical descents, jumps, and turns [6].

One of the key strategies to handle sharp turns and uneven surfaces is the use of leaning, where both the bike and rider tilt their bodies to counteract centrifugal forces and allow for controlled and stable turns [7]. However, unlike other sports such as road cycling or motocross, where lean angles have been studied more extensively [7], there is a lack of validation of measuring athletes in the field of downhill for quantifying these movements.

Inertial measurement units (IMUs) are an attractive way to measure the leaning behavior of athletes and their bikes in the field. IMUs offer high sampling rates, low cost, and the ability to track the orientation during downhill. However, IMU-based systems face their own challenges. When computing orientation and angular metrics such as lean angle, drift and sensor noise can significantly affect the accuracy of the resulting data, especially when measuring for longer periods of time. Factors such as sensor misalignment, noise, and drift could introduce cumulative errors, leading to unreliable measurements when not corrected [8]. This is particularly important in mountain biking, where accelerations and angular velocities could run high, and where constant changes in rider position and terrain make real-time validation difficult.

To ensure that IMU-derived lean angles are reliable and meaningful, it is necessary to quantify and validate the level of drift and uncertainty inherent in these measurements. Therefore, the aim of this study is to assess the drift of IMU-based lean angle estimations for both the rider and the bike and to assess the propagation of uncertainty from the IMU's gyroscope of bike lean angle measurements during real-world downhill and enduro mountain biking. The results could potentially help future research and trainers to reliably assess the lean angle of downhill and enduro mountain bikers to improve performance and prevent falling.

II. METHOD

A. Materials

Two Shimmer Inertial Measurement Units (IMUs) (Shimmer Research Ltd., Dublin, Ireland) were attached to the pelvis and the sternum of the athlete. The IMUs were strapped securely using Velcro straps to rule out oscillations between the athlete and the sensor due to poor attachment. One Shimmer IMU was attached to the frame of the bike using a Velcro strap. Shimmer IMUs were capable of measuring up to ±16g of accelerations, 2000°/s angular velocity and had built-in 9° of freedom quaternion calculation. The sampling frequency was set at 1024 Hz. In practice, the actual sampling rates were slightly lower, but all IMU signals were upsampled back to 1000 Hz.

B. Experimental setup and protocol

Athletes went down the 'Cagnolera' downhill trail in Brescia, Italy, located on Mount Maddalena. The athletes were allowed to use their own protection gear and bike. The track is approximately 1470 meter long, including an altitude drop of 235 meter. Before descending, near the start of the track, athlete and bike calibrations were performed to assess the drift. The calibration movements for the bike lean angle consisted of rocking the bike back and forth about its roll axis five times [9]. The calibration movements for the torso lean angle consisted of five times left-right bending of the torso on the frontal plane while keeping the lower body still. After the finish, post-trial calibrations were conducted, repeating the same calibration movements used before the descent. In total, 9 athletes participated in the study. Every athlete went down the track 3 times, which resulted in 27 total runs completed.

C. Methods

Torso lean angle was estimated through Inverse Kinematics (IK) using OpenSim's Rajagopal_2015 model [10][11] at a sampling rate of 60Hz. Quaternion data of the entire run from the pelvis and sternum IMUs were formatted to OpenSim, and used to calculate joint angles, particularly lumbar bending, extension and rotation.

To assess the drift in the calculated lean angle over time, we used a method based on the calibration movements. The person performed the same movements (left-right bending of the torso) at the start and at the end of the track. Ideally, this calibration movements should only include lateral bending motions of the torso. This means that if the movements are performed properly, the calculated values in the other two directions, lumbar extension (forward bending) or lumbar rotation (twisting) should stay close to zero. These two axes are named "residual axes" from now on. We used the rms value of the calculated angles to measure how much unwanted movements happened in those residual axes. We assess the drift in these residual axes since the drift that is found in these axes will come from the lean angle or will affect the leaning as well.

At the beginning, we checked how much the person was unintentionally moving in these residual axes during the calibration, and we did the same check for the calibration movements at the end of the track. With the assumption that the movements were performed the same way both times, increases in the rms for the residual axes from start to end would be caused by drift in the system, not by how the movement was performed. To do this, we extracted three cycles of the bending motion at the start and the end. We calculated the rms values in the residual directions for each, and then compared them. A higher rms at the end would suggest that drift affected the calculated angles over the course of the trial.

Bike lean angle (roll angle) was estimated by using calibration movements that were performed before and after the descent. These calibration movements at the start of the track were used to go from local IMU-fixed axes to relevant bike-fixed lean axis by calculating a covariance matrix and eigenvectors of the frame-mounted IMU during these calibration movements, following the procedure of [9][12]. With the eigenvectors, the lean rate could be calculated. Before the first calibration movements, the bike was put on a flat surface completely upright, which was seen as the point where all angles were zero. Integrating the lean rate from this zero-point gave the drift-polluted lean angle. To remove the drift, we high-pass filtered this signal with a 4th order Butterworth filter with a cut-off frequency of 0.02Hz [9], to obtain the lean angle.

To assess the drift in the two residual axes on the bike, the same method was used as the drift assessment in the torso lean angle. Three cycles of the bike calibration movements were cut out at the start and end of the track. For the runs during both the calibration movements, the rms of the two residual angles was calculated. The difference in rms of these runs at the start of the track and the end of the track was calculated. These rms values represent the deviation from the expected zero-mean angle during controlled motions and serve as a proxy for cumulative sensor drift.

A Monte Carlo simulation for the fastest recorded run was employed to assess the uncertainty associated with the bike's lean angle. The simulation was based on a single run of almost 14 minutes, containing both the calibration movements and the descent, for a total of approximately 820 000 samples. Random noise was used to perturbate the angular velocity signals on the x,y and z axes measured by the gyroscope of the IMU sensor mounted on the bike frame. The standard deviation of the random noise was computed taking into account that, according to [13], the Power Spectral Density for the gyroscope placed in the shimmer, the ICM-20948 resulted to be 20 mdps/√Hz. Therefore, the standard deviation of the noise perturbating the angular velocities for the Monte Carlo simulations was computed taking into account the sampling frequency of 1000 Hz and a *10 factor to consider the worst case scenario. Consequently, the standard deviation of the random noise introduced resulted in 6.3 °/s, as shown in (1)

$$20 * 10^{-3} * 10 * \sqrt{1000} = 6.3\,°/s \quad (1)$$

A Monte Carlo simulation consisting of a total of 30 000 runs was performed, computing the bike's lean angle over time for each realization. For each of the 820 000 samples, the standard deviation of the lean angle across the 30 000 simulations was calculated and used as an estimate of the propagation of uncertainty from the gyroscope's angular velocity measurements to the computed lean angle.

III. RESULTS

Of the total of 27 runs performed by the athletes, 24 runs for the torso and 23 runs for the bike were used for the analysis. Runs that were excluded had problems with the signal or with the calibration movements itself, or the athlete fell during the run which significantly changed the orientation of the IMUs.

Figure 1 shows the lean angle of the fastest athlete during his three runs at one part of the track, with the average difference between the three angles at every point in time. This figure shows how the same athlete can differ in movements between runs. In total, there were 7 athletes where in all three runs the bike lean angle was recorded properly. When looking at the three runs of these athletes, the average difference in lean angle between the three runs is 8.9° (±7.1°).

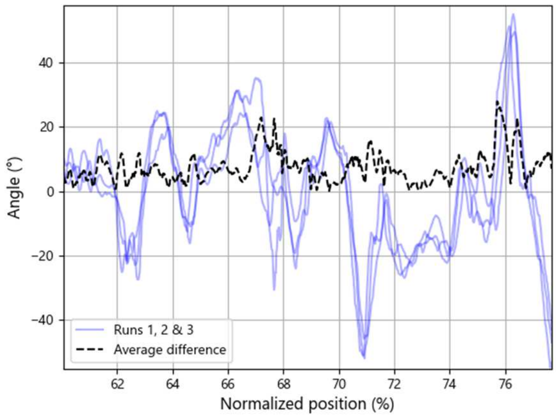

Figure 1 The bike angle during a part of the track during all three runs with the average difference of the angle between the three runs

For the athlete calibration, the rms for the two residual lumbar axes (extension and rotation) was 7.8° at the start and 12.0° at the end of the track, resulting in a difference of 4.2°. An example of the calibration signal of the lumbar movements is found in Figure 2. The values of the residual axes for the calibration movements at the start ranged from around -10° to 10°. For the calibration movements at the end of the track, these values ranged between -20° and 20°.

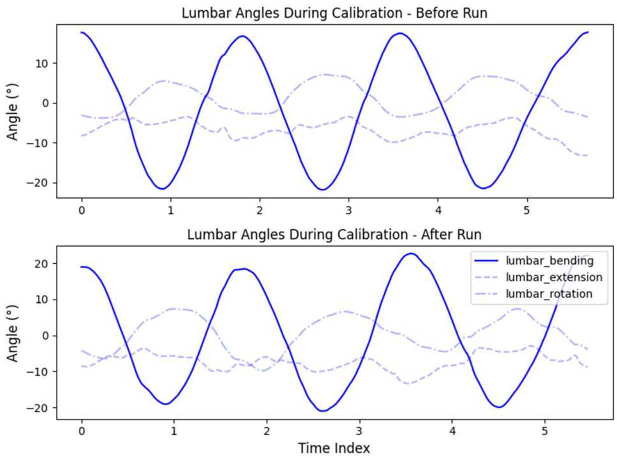

Figure 2 Example of the measured torso angles on all three axes during calibration movements at the start and end of the track.

An example of calculated bike angles during calibration movements is shown in Figure 3. For the bike, the rms of the residual axes during the calibration movements increased from 1.0° at the start of the track to 4.0° at the end, indicating a drift of 3.0°. The values of the residual axes ranged from about -10° to 10° for the calibration movements at the end. For the calibration movement at the start, the values of the residual axes ranged between -3° to 3°.

Monte Carlo simulation was executed on a 14 minutes recording, containing approximately 820 000 samples. For each of the 30 000 simulations, random noise with an amplitude of 6.3°/s was introduced to perturbate the xyz angular velocity signals recorded by the IMU placed on the 7

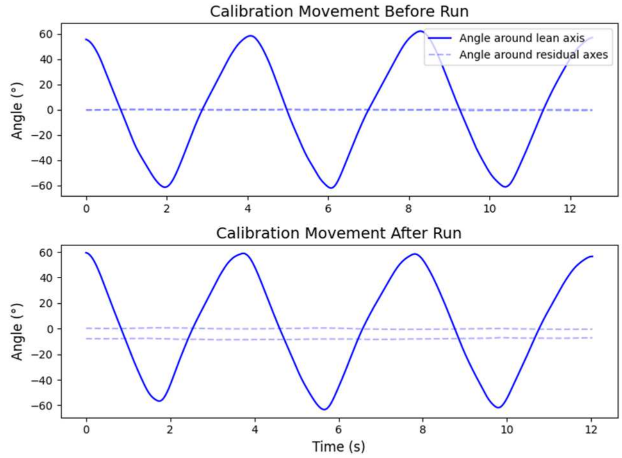

Figure 3 Example of bike calibration movements at the start and end of the track and the measured angles around the lean axis and the residual axes for both calibration movements.

bike frame that were used to compute the bike's lean angle. The standard deviations of the 30 000 samples for each time instant were computed to assess the propagation of uncertainty from the gyroscope's angular velocity measurements to the computed lean angle. The mean of the standard deviations resulted to be 0.30°, which corresponds to an uncertainty of 0.60° when extended to 95%. Figure 4 shows an example of the outcome of the Monte Carlo simulation, highlighting in red the original signal, in grey 10 of the 30 000 results of the bike's lean angle computations using perturbated signals and in purple the confidence interval extended to the 95%.

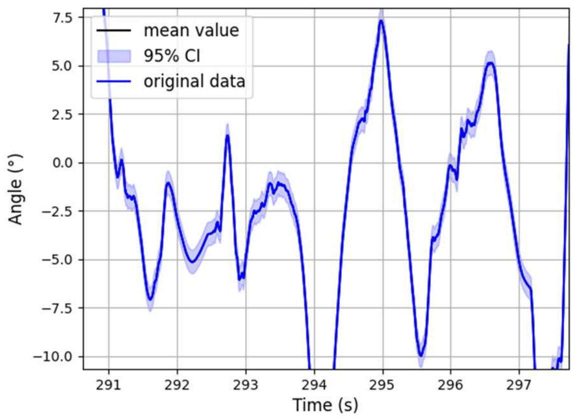

Figure 4: Details on the Monte Carlo simulation with the original signal in red, 10 of the 30000 bike's lean angle over time computed using perturbated signals, the confidence interval extended to 95% in purple.

IV. Discussion

This study aimed to assess the drift in lean angle estimation in both athlete and bike calculations. Besides, a Monte Carlo simulation was done to assess the propagation of uncertainty from the IMU's gyroscope to the bike lean angle measurements. This study is a first effort to quantify lean angle measurement in downhill and enduro mountain biking.

The rms drift observed in rider calibration movements (4.2°) appears to be moderate when compared with the initial rms of 7.8°. This suggests that drift could have an impact on the interpretation of the kinematic data, but does not alter overall findings. Considering the time in between the measurements was 11-17 minutes, these findings are not in line with [14], where the drift during normal walking was near-zero. However, aside from drift, one major contributing factor that could have influenced this result is likely human movement variability, particularly after physically intense descents, which was not the case in [14]. During the calibration movements at the end of the track, athletes could have been tired from the descent. When exhausted, people usually demonstrate a limited performance in smooth and controlled action [15] and can alter movements strategies during a task [16], which could have influenced the results at the end of the track.

Furthermore, mechanical and anatomical factors likely play a role. Sensor attachment may loosen due to sweat, impacts, or extended vibrations. Minor anatomical shifts or changes in muscle tone after descending can alter sensor orientation slightly. Soft Tissue Artefacts (STA) are known to influence IMU-based human motion analysis after workout [17], which could have a significant influence on results. Also, heavy breathing due to exhaustion influences the orientation of the sternum IMU. Taken together, these factors underscore the importance of both pre- and post run calibration movements for quantifying drift, and highlight the challenge of achieving consistent sensor values in high-intensity, real-world sport environment.

For the bike angles estimation, a difference in rms of 3.0° was observed at the end calibration compared to the start calibration. This difference might not only be influenced by sensor drift, but also environmental and procedural factors may have influenced the results. In particular, inconsistencies in ground level or slope at the start and finish zones may result in slightly altered calibration conditions, as the orientation of the bike during calibration directly influences the reference frame used for subsequent angle estimations. Although significant efforts were made to put the bike on a surface as much on level as possible during calibration movements, no perfect ground level surface was available at the start and end of the track, which meant that the bike orientation which was seen as 'zero' at the start of the track was not exactly the same as the bike orientation at the end of the track.

Interestingly, we did not observe any sinusoidal signal in the residual axes for the calibration movements at the start of the track, suggesting that all the leaning was indeed measured in only one axis. Moreover, aside from 1 of the runs, we did also not observe any sinusoidal signals for the calibration movement at the end of the track in the residual axes. So for both calibration movements, sinusoidal patterns were only consistently present in the roll axis. This implies that, despite the dynamic nature of the descent, high vibrations and quick movements, the alignment of the bike's IMU axes remained stable. Had the alignment shifted, we would expect some leakage to the residual axes from the roll axis, which would be seen as sinusoidal fluctuations around these axes at the calibration movement at the end. This supports the interpretation that the roll axis orientation in the IMU remained consistent throughout the run.

The results of the Monte Carlo simulation indicate that the methodology used to compute the bike's lean angle from the IMU-measured angular velocity signals is robust with respect to the propagation of sensor noise. Specifically, despite introducing a substantial noise perturbation of 6.3°/s, which also included a *10 factor to represent a worst-case scenario, the resulting uncertainty in the lean angle estimation remained low, with a mean expanded uncertainty of approximately 0.60° at the 95% confidence level. Comparing with an average difference between runs within athletes of 8.9° (±7.1°), this uncertainty is negligible. This low uncertainty demonstrates that the lean angle calculation algorithm effectively filters and integrates noisy angular velocity measurements, yielding reliable and precise estimates over the entire 14-minute measurement interval, encompassing both calibration and dynamic descent phases. The use of a high sampling frequency (1000 Hz) further contributed to the accuracy, as it allows the algorithm to capture rapid changes in angular velocity while maintaining noise robustness. Moreover, the quantified uncertainty of ±0.60° (95% confidence) is within acceptable limits for many applications involving bike dynamics monitoring, such as performance analysis, rider safety evaluation. This level of precision suggests that the IMU-based lean angle measurement system can provide meaningful data to support decision-making in cycling biomechanics and sports science.

V. Conclusions

The present work is a first effort in estimating the lean angle of both the rider and the bike in downhill and enduro mountain bike. The current study focused on assessing the drift in bike- and rider lean angle calculations, and assessing the propagation of uncertainty of the bike lean angle calculations. Results showed that IMU-based methods for estimating lean angles in enduro and downhill mountain biking are largely reliable but subject to minor drift. The alignment of the bike IMU's roll axis remained stable throughout the run, supporting the robustness of the initial calibration. The Monte Carlo simulations confirmed that the impact of sensor noise on lean angle estimation was minimal and within acceptable range. This suggests that these lean angle estimation strategies in downhill and enduro mountain biking can be valuable and could be used in performance monitoring, and may also hold potential to be applicable in other fast-paced outdoor sports.

The limitations of the present work consist in the fact that rider's lean angle estimation may have been influenced by factors such as posture variation, fatigue, or slight shifts in sensor placements. Additionally, due to the absence of a perfect level ground, variability in surface for bike lean angle calibration might have made the drift assessment not perfectly reliable. A strength of this study is that significant effort was required to overcome environmental challenges and ensure reliable data collection under dynamic outdoor conditions through extensive testing. First steps to measure athlete kinematics in these sports were done, which could open new avenues for exploring performance, safety, and riding techniques in enduro and downhill disciplines.

Future work could incorporate cross-validation of the lean angle calculation during the runs with the help of other measurement systems. Moreover, future studies could explore the impact of additional sources of uncertainty, such as temperature variations, which were not explicitly included in the current study, while IMU drift was already compensated. Incorporating these factors may further refine the overall uncertainty budget and provide an even more comprehensive assessment of the measurement system's reliability.

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