Towards a Smart Luge that Measures Steering Input of the Rider

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Abstract: Luge is a high-speed Olympic Winter sliding sport that is timed in milliseconds. The athlete's steering performance is a crucial factor for success, but there are currently no objective methods to evaluate steering technique and timing. As a work in progress, we present a lab prototype of the 'smart luge', a sled retrofitted with six unobtrusive commodity force sensors. The results of a laboratory test with five simulated runs show that the current setup is capable of measuring the athlete's activity during steering. This work aims to advance data-supported training in the luge sport by enabling the in situ measurement of luge athletes' activity.

1 INTRODUCTION

Luge is an Olympic Winter sliding sport in which a single or a pair of athletes ('lugers') compete for the shortest time riding a sled down an icy track. Luge is also the name of the sled that is used.

While descending the track, the luger's main influence on their runtime is their steering performance. The ideal strategy is to stay on the shortest path downward with minimal steering in terms of frequency and magnitude (Gong et al., 2016). Lugers experience speeds over 150km/h (Schleinitz et al., 2022) so the window for optimal steering action is extremely small. Even minor mistakes can cost a race considering that run times are measured in milliseconds (Platzer et al., 2009).

Trainers currently assess their athlete's on-track performance using video analysis (e.g. Fedotova & Pilipivs, 2010). Given the high speeds and subtle movements involved in luge steering, this form of subjective feedback is inherently limited.

In some sports, trainers have already started to complement their observations with objective data from sensors that are either worn by the athletes or are integrated into the sports equipment (Rajšp & Fister, 2020). However, such sensors have not yet been integrated into luge training, and the scientific literature on this topic is sparse.

To advance data-driven luge training we started the development of a 'smart luge'. The goal is to build a sensor-equipped luge that can accurately and reliably measure steering input. The resulting data can be analyzed and visualized to give trainers detailed and objective information on how to improve their trainee's steering. This paper presents the first milestone of the ongoing project, a lab demonstrator of the 'smart luge'.

1.1 The Art of Luge Steering

The basic design of a luge consists of a fiberglass 'pod' in which the luger lies in a supine position during the race. The pod is tightly coupled to the left and right 'runners' at the bottom via a steel frame called the 'bridge'. The runners are made out of wood or fiberglass, and they end in upwards 'bows' near the luger's calves. At the bottom of the runners are the 'blades' made from steel that glide on the ice.

In their neutral position, the runners are slightly bent towards each other. Lugers steer by twisting them, which causes the blades to cut a leading grove that gets followed by the luge. The twisting of the runners can be achieved by a combination of (a) applying pressure to a bow using the calf, (b) lifting the bridge using handles that connect the pod and bridge, and (c) pressing down with one shoulder (Pareek et al., 2021). Depending on the desired direction change, these forces are applied differently between the left-hand and right-hand sides (Figure 1).

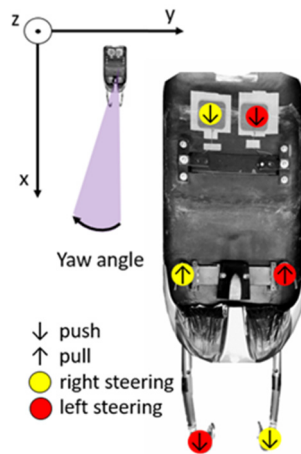* *Corresponding Author: wolfgang.kremser@salzburgresearch.at*

Figure 1: Our luge steering model with the anticipated pressure points drawn in.

1.2 Aim and Research Questions

The 'smart luge' aims to unobtrusively measure these theoretically derived steering movements using inexpensive commodity sensors in a laboratory environment. The objectives are (a) to develop a sensor-based luge prototype, (b) to calibrate the sensors, and (c) to capture and analyze basic left-right steering characteristics in a laboratory setting.

2 METHODS

2.1 Instrumentation

According to our theory of luge steering, we should be able to detect steering maneuvers by measuring the pressure that (a) the calves apply to the bows, (b) the hands apply to the handles, and (c) the shoulders apply to the pod.

We placed a FlexiForce™ sensor (Tekscan Inc., USA) at the anticipated steering points shown in Figure 1. These sensors are 0.2 mm thin force sensing resistors (FSR) that increase their electrical conductance in proportion to the force that is acting on them. We used the largest FSR model (A502) for the shoulders, the mid-size model (A401) for the bows, and the smallest model (A301) for the handles. We used thin double-sided adhesive tape to attach the sensors to the bows and the pod. The sensors for the handles were placed at the interface between the handles and the bridge.

For data acquisition, we used the KRYPTON® CPU with two strain gauge modules and the DewesoftX software (Dewesoft, Slovenia). This setup recorded the FSR sensors' voltage outputs at 20kHz. The changes in electrical resistance induced by the FSR sensors were converted into a reciprocal proportional output voltage (u_a). Calibration of the u_a was achieved through a 2-point calibration method using standardized weights, ensuring precise force measurements.

2.2 Study Design

The first author of the present paper who had participated in an Olympic luge competition was the test luger for this pilot study (sex: male, weight: 85 kg, height: 188 cm). The instrumented luge was placed on top of a table such that the luger faced the wall. We projected a pre-recorded point-of-view video of a luge run onto that wall. The track in the video was familiar to the test luger who was asked to steer as he would if he had been in the video. The same run was repeated five times. A webcam that was synchronized with the sensor hardware recorded the entire study setup.

We noted the frames in which the luger in the video entered and exited a curve, as well as the curve's direction (left, right), and noted them in an Excel sheet. We excluded the first curve because it follows the startup phase where the luger is trying to gain momentum with their hands in a sitting position. Thus, we did not consider it a regular curve. Furthermore, we excluded curve 11 (the 'Kreisel') which requires more complex steering motions and thus would not be comparable to the other curves of the track.

2.3 Data Analysis

The resulting data was analyzed with MATLAB (The MathWorks, Inc., USA). For each run, using the synchronized webcam footage, we discarded all data that was recorded before the pre-recorded video started and after it ended. Then we used the curve start and end points to segment the remaining data. We normalized the data for each curve to 1000 samples. Furthermore, each curve was split into three phases: 'entry' (0% - 25% of samples), 'core' (25%-75%), and 'exit' (75% - 100%). We plotted the average signal of each of the six FSR sensors, along with the standard error, across all five runs.

To quantify the (dis)similarity of the sensor signals we calculated Pearson's correlation coefficient (r) for each pair of sensors and each curve phase's mean. Coefficients higher than 0.1, 0.3, 0.5, and 0.7 represent small, moderate, large, and very large correlations, respectively (Hopkins et al., 2009).

3 RESULTS

Figure 2 shows the average signal (+/- standard error) for each sensor with the individual curves colored in. The maximum values for the bows (left: 12N ± 1, right: 17N ± 1) and the shoulders (left: 23N ± 3, right: 18N ± 2) differ considerably from the maximum values of the handles (left: 631N ± 81, right: 404 ±

72).

Figure 3 shows the three correlation matrices, one for each curve phase. In all three phases, the handles have a very large correlation (r between 0.85 and 0.87). The left and right shoulders have a consistently negative correlation (r at entry: -0.27, core: -0.88, exit: -0.42). The left and right bows show a moderate positive correlation at curve entry (r=0.37) which
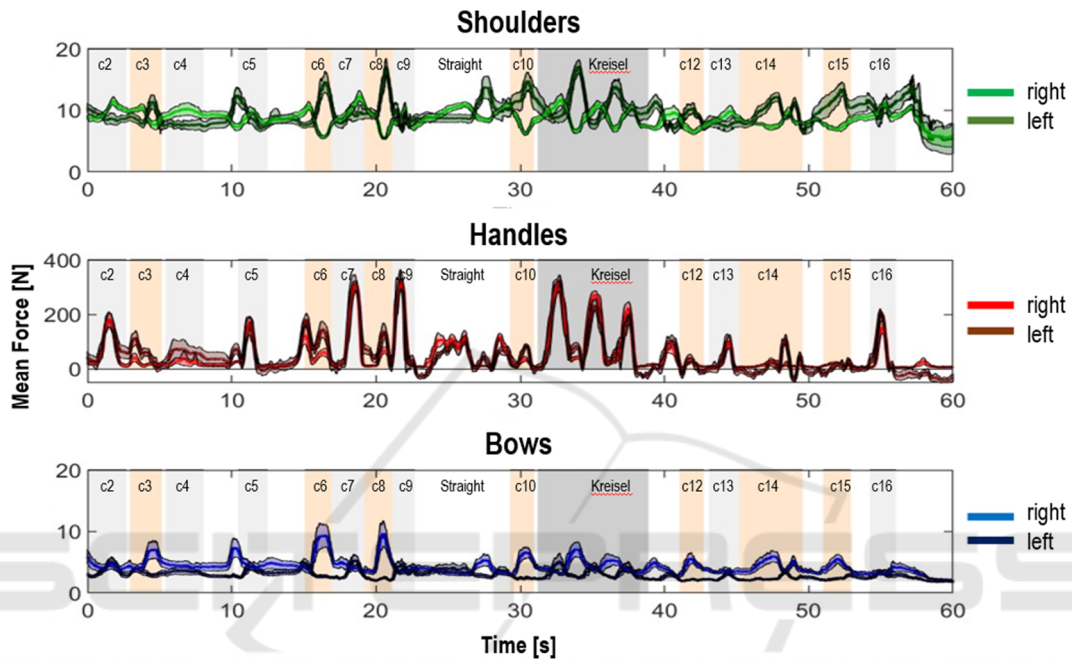

Figure 2: Plots of the calibrated force signal [N] with the standard error of all six FSR sensors averaged over all five runs. Grey sections mark right curves, orange sections mark left curves. The first curve and the dark gray "Kreisel" section were excluded from the analysis.
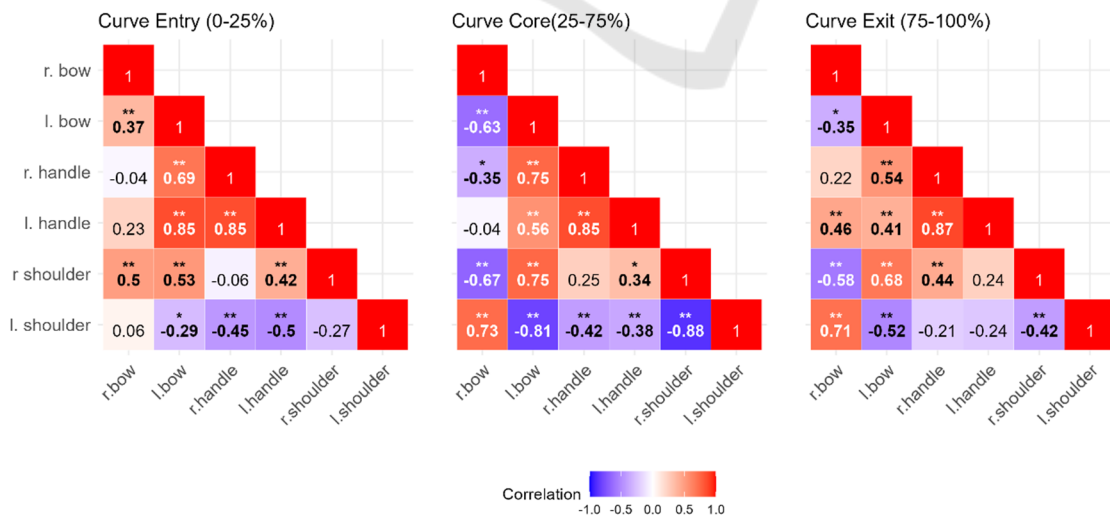

Figure 3: Correlation matrices of the average force signals from the six FSR sensors, grouped by curve phases. Significant correlations are printed in bold (significance levels *: $p < 0.05$, **: $p < 0.01$).

changes to a negative correlation in the core phase (r=-0.63) and at the exit (r=-0.35). Furthermore, we observed that in the core and exit phases, the shoulder and bow on opposite sides correlate strongly (r between 0.68 and 0.75) while the shoulder and bow on the same side have a large negative correlation (r between -0.81 and -0.52). In general, the mean absolute r value was highest in the core phase (0.56), followed by the exit (0.47) and entry (0.41) phases.

4 DISCUSSION

We demonstrated a lab prototype of the 'smart luge', a luge sled that was retrofitted with six FSR sensors to measure the force that is applied by the luger to induce steering.

Figure 4 compares the results with our expectations based on our luge steering model (Figure 1). We found that sensors that we expected to correlate positively had a very large positive correlation, and the sensors that we expected to negatively correlate had a large negative correlation. What was unexpected were the high peak force values of the left and right handles) and their continuously high correlation between the left-hand and right-hand side.
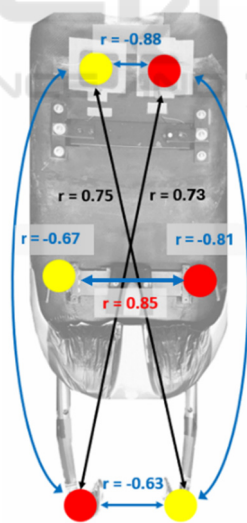

Figure 4: Correlations between the FSR sensor values in the core phase. Blue arrows indicate an expected negative correlation, and black arrows indicate an expected positive correlation.

One explanation might be the FSR sensor placement under the screwed-down handles. Since both handles are tightly coupled with the bridge, when one handle is pulled, the handle on the opposite side moves up as well and squeezes the sensor rather than twisting away as we had expected. Further attention is necessary to understand the deformations of the bridge and how they connect to the athlete's steering input.

5 CONCLUSION

In light of this pilot study's results, we consider the presented 'smart luge' demonstrator as capable of measuring a luger's steering maneuvers in a laboratory environment.

The next step would be to test the system on a real ice track. However, in its current state, the data acquisition hardware is too bulky to be safely transported on the luge. Furthermore, because we expect a considerable amount of vibration on the ice, a more sophisticated post-processing/filtering of the FSR sensor signals is likely necessary to detect the luger's steering input. Furthermore, we will optimize the sensors' surface sizes and geometries to better detect the applied forces.

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