Hazard Detection System for Skiers: A Modified Ski Design Utilizing Optimal Sensor Models

Grant Proposal

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Author Note

I would like to thank my parents for providing me with the materials needed for this project. I would also like to give thanks to my grandparents for connecting me with an expert in the field of sensor research. I could not have done this project without their support and discussion, so they have my utmost gratitude for their presence.

Executive Summary

While skiing, reckless skiers and low visibility can result in collisions and injury. All skiers experience difficulties because of this, but beginner skiers are most influenced due to their reduced ability to focus both on skiing and avoiding incoming obstacles. This issue cannot be well addressed by most current safety measures, as reckless skiers and bad conditions are unpredictable. The goal of this project is to engineer a new or modified design of ski goggles, utilizing sensors to detect and warn the skier of any possible obstacles. This design must function in varying weather conditions and must not significantly obscure the user's field of view or otherwise pose a detriment to the quality of skiing.

Keywords: skiing, object detection, lidar, radar, camera, safety, assistive technology.

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Although skiing is an enjoyable pastime for all ages, the risks associated with it can deter people from learning to ski. Even the smallest mistake or misfortune may lead to grave injury, so it is imperative to develop more ways to prevent any accident from occurring.

Injury Rates

To better understand the risks that any potential solution would mitigate, it is important to examine the injury rates of different ski hills. Most recently, a study in Austria reported a total of 10,143 injuries from 2016 to 2022, or a rate of 0.44 injuries per 1000 skier days (Wagner et al., 2023). This can be compared to earlier studies, such as a 2012-2018 study in Japan reporting an average 2.05 injuries per 1000 skier days, a 2010-2012 study in Norway reporting 1.27 injuries per 1000 skier days, and a 2006-2012 study in Finland reporting 0.98 injuries per 10000 lift runs (Kuzuhara et al., 2021; Ekeland et al., 2019; Stenroos & Handolin, 2014). As can be observed by these studies, a lack of standardization in the data reported makes it very difficult to compare between studies. It is still, however, possible and beneficial to compare different studies, as this comparison can show how injury rates have changed over time. Looking back at the data from the Finland study, this final report of data is 1.96 injuries per 1000 skier days, showing that the most recent rate of injury is significantly lower than earlier rates and indicating a decline in injury risk while skiing or snowboarding (Wagner et al., 2023). Table 1 supports this, showing how more injuries are more generally associated with earlier time periods. The cause of this decline is likely due to the more common use of safety measures, such as the normalization of helmet use.

Details of published studies assessing winter sport injuries.

Authors	Time period	Country	Source of data	Number of injuries	Injuries per 1000 Skier Days
Wagner et al. (this study)	2016–2022	Austria	State-wide emergency service dispatch center	43,283	0.44
Coury et al. [4]	1995–2000 and 2009–2010	USA	Questionnaire	1196	n/a
Kim et al. [2]	1988–2006	USA	Single hospital	9465	n/a
Stenroos and Handolin [1]	2006–2012	Finland	Regional emergency dispatch center	2911	1.96
Davidson and Laiotis [26]	1983–1992	USA	Ski patrol first-aid room documentation	24,340	2.6
Sulheim et al. [30]	2002	Norway	Questionnaire	3277	n/a
Ruedl et al. [31]	2010–2011	Austria	Federal Ministry of the Interior	2326	0.00079 (only fatalities)
Burtscher et al. [16]	1997–1998	Austria	n/a	17,914	1.43
Burtscher et al. [32]	2002–2003	Austria	Questionnaire	2433	n/a
Johnson et al. [33]	1991	USA	Single hospital	5701	3.37
Johnson et al. [34]	1972–1978	USA	Survey	1711	4.19

Table 1: A compiled and converted dataset of the injuries per 100 days of various studies, recording the authors, period, country, data source, number of injuries, and injuries per 1000 days (Wagner et al., 2023). Together, this data exemplifies the extreme diversity of tests for ski injury, and shows general trends that are otherwise inaccessible without very large-scale testing.

However, the risk of injury can still be lessened, potentially by examining and finding ways to mitigate possible factors influencing the risk of injury.

Role of Safety Equipment

Out of the various factors of risk mitigation, the lowered injury rates on ski hills are likely due to greater use and knowledge of safety equipment. For instance, 87.7% of snowboarding injuries and 69.4% of skiing injuries in a Japan study involved people without helmets (Kuzuhara et al., 2021). While this may be due to the protective nature of helmets, this data also demonstrates that individuals who do not regard their safety enough to wear helmets are more likely to be involved in an accident. To solve this issue, it may be beneficial to create an additional tool to help avoid injury, providing more of an incentive for people to care about safety. When considering potential aspects that could be augmented, the vision of the skier is a candidate, as simple ski goggles do not assist with actively revealing threats. This form of augmented safety device would help to incentivize safety because it would provide a new way to prevent collisions, not only improving the protection of helmets but also taking advantage of the novelty felt by potential users. In addition to this, it was also found that 20.1% of skier injuries and 15.7% of snowboarder injuries were due to collisions (Kuzuhara et al., 2021). If the solution can prevent most of these injuries by alerting the user of obstacles, then a significant number of injuries would be prevented.

Sensors

In detecting obstacles on an unpredictable ski hill, the utilization of sensors is crucial. However, there are multiple different types of sensors that must be evaluated. One candidate is a camera sensor, already used in the function of preexisting object detection glasses (Satani et al., 2020). A camera sensor records data from incoming light, giving a detailed and complicated view of the environment with the drawback of being limited by visibility and darkness (Yu & Marinov, 2020). In a preexisting model of glasses, the device uses machine learning to interpret the camera data, allowing for the identification of a diverse range of different objects such as different animals, faces, and immediate dangers (Satani et al., 2020). This specific model is not entirely suitable for skiing, however, as the complicated process of interpreting camera input created delays between object detection and response that would hinder object detection in ski goggles. The nature of the camera's drawbacks also makes this design unsuitable, as the glasses were not designed to combat low visibility environments. Other candidates can be observed through the technology used in autonomous driving. These systems must be able to detect and react to obstacles in varying conditions, posing a requirement that is very similar to the requirement set by this project, so the optimal sensor may be reflected in a beneficial sensor for autonomous driving. In one study on autonomous driving, lidar and radar sensors are evaluated as two similar sensors that can detect distances (Almalioglu et al., 2022). When paired with cameras and interpreted using machine learning models, as shown in Figure 1, the study finds that both lidar and radar sensors are much better at detecting obstacles than regular cameras (Almalioglu et al., 2022). Figure 1 makes this clear through the perceivable increase in distinction between light and dark zones when using lidar or radar, as opposed to the blurred distance measurements detected with camera sensors. Although lidar and radar seem to be similar in practice, there are tradeoffs when choosing between the two. Lidar utilizes pulses of light to determine depth through the time for light to return, providing high-resolution point maps of the surrounding environment with the drawback of a susceptibility to bad visibility (Yu & Marinov, 2020). An increased susceptibility to weather is due to the light sent by the lidar being easily scattered by obstructions such as snow, hindering the accuracy of the data. Inversely, radar sends

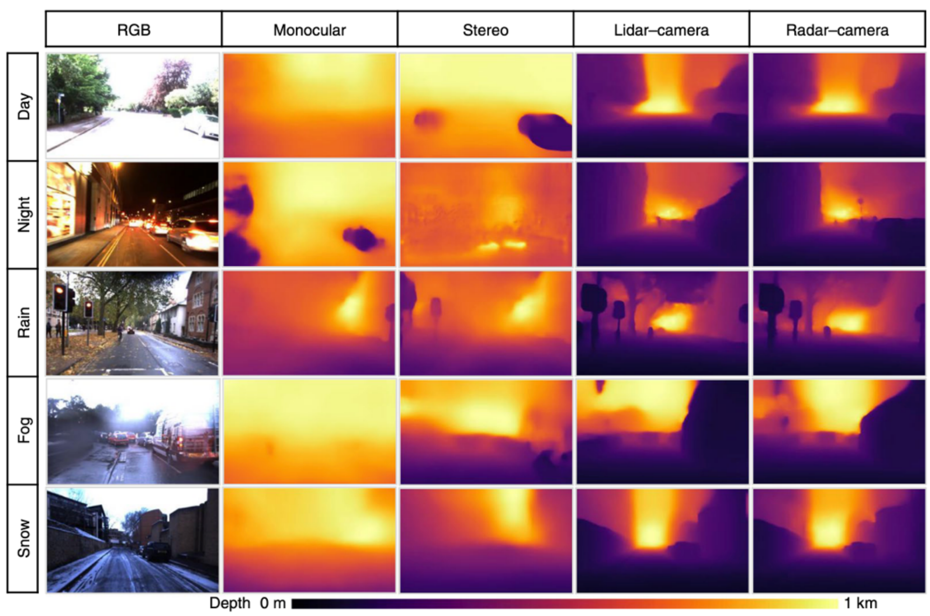

Figure 1: A visualization of depth values given by each sensor type in varying conditions (Almalioglu et al., 2022). This figure demonstrates the different types of sensors used, with camera sensors less able to accurately determine distance than the active lidar or radar sensors, sending points to directly determine distance

millimeter-length radio waves rather than light, providing more unreliable data that is less affected by weather (Yu & Marinov, 2020). This consistency is due to the longer wavelength of radar, able to sense past the small obstructions caused by varying conditions while also introducing more noise and reducing resolution (Yu & Marinov, 2020; Almalioglu et al., 2022). While each technology has drawbacks, an optimal configuration for the purposes of an enhanced pair of ski goggles is likely to be a combination of camera and distance sensors. This is due to the great number of resources present for camera sensors, balancing the more easily interpretable data collected by distance sensors. Although it is significantly more difficult to make a program that detects obstacles from camera input, there are already libraries of methods provided for the use of cameras, while the use of distance sensors is less common at the low-cost scale that this project operates in (D. Lisus, personal communication, October 29th, 2025). Therefore, it may be best to utilize the visual richness of camera sensors for the general aspects of object detection, incorporating a few of either lidar or radar sensors to maintain an object detection capacity within rough conditions.

Multimodal Detection

When using more than one sensor at once, a system is classified as multimodal (Almalioglu et al., 2022). Multimodality can be useful because it allows a system to make use of the benefits of multiple different sensors, instead of working around the deficiencies of a specific sensor type. However, multimodal systems are much more complicated than a system with only one sensor, as they must be able to correctly interpret multiple different potentially flawed datasets. Inevitably, datasets will become flawed to some extent because of interference or bad weather, so all multimodal systems need to have a system to handle it. For instance, multimodal systems must correctly manipulate data to allow the two different sets of data to align, accounting for any motion between the sensors (Almalioglu et al., 2022). In the previous study on autonomous driving, a multimodal system was used to incorporate both a camera sensor and a lidar or radar sensor, allowing the system to make better depth predictions by constructing data filters to eliminate noise and unwanted data (Almalioglu et al., 2022). In skiing, the use of a multimodal system is greatly beneficial, as it would allow for the inclusion of both cameras and lidar or radar, making a more reliable object detection system that can better adapt to changes in weather. An issue with this potential use is the drastic increase in size of the model, which will be most effectively tested and mitigated once the model has been built.

Specific Aims

Otherwise enthusiastic skiers can often be repelled from skiing by the presence of low visibility or reckless skiers, creating unseen obstacles. This project aims to design and construct a pair of ski goggles, utilizing sensors to detect and warn the skier of these potential obstacles. To accomplish this, multiple different sensors must be evaluated to determine the most optimal and viable method of sensing obstacles. Additionally, other potential modifications to the current model of ski goggles will be considered to create an improved model.

Sensor Data Interpretation: The primary aim of this project is to formulate a method of using low-cost sensors to receive high-quality results.

Low-Visibility Object Detection: The secondary aim of this project is to utilize strategies developed through the primary aim to accurately detect obstacles in limited-visibility environments.

Efficient User Interface: The tertiary aim of this project is to explore methods of efficiently transmitting warning signals to the user.

The expected outcome of this work is a functional pair of goggles, with equipment that can be housed on the user. Additionally, all components of this device must not be too expensive, as it must be possible for the final product to be accessible to a wide audience.

Project Goals and Methodology

Significance

The creation of an affordable method of collision prevention would allow for greater accessibility of skiing to the public. Not only this, this design, if successful, provides proof of concept to allow the expansion of this technology into other similar fields. For instance, biking is similar to skiing in the necessity to detect and track obstacles, as well as the current impracticality of using sensors to accomplish this endeavor.

Innovation

As stated previously, recent attempts to create cost-effective object detection systems for individual use have not been successful enough to be applicable, with problems with processing speeds and material costs (Satani et al., 2020).

Methodology

Sensor Data Interpretation:

The objective of this is to, through the analysis of a large set of recorded data points, determine the patterns in the inaccuracies of each sensor. From these patterns, it may be possible to determine a method to interpret inaccurate data points, improving the accuracy of the sensor while in use. To perform preliminary testing, three different types of distance sensors were purchased, being a low quality lidar sensor, a middle quality lidar sensor, and a middle quality radar sensor. For each of these sensors, a separate test is performed to determine the sensor's accuracy over different distances and light levels. In addition to this, a camera sensor was purchased, although testing for the camera needs to be different due to the different function of the sensor.

Low Quality Lidar Setup. To begin testing with these sensors, it was necessary to hook the sensor up to a raspberry pi 4B. Each of the four pins of the sensor was connected to the correct area on the raspberry pi, using instructions and diagrams from 38-3D, a site selling the same sensor, and Raspberry Pi Pinout, a site informing about the raspberry pi connections. After the hardware setup, software to initialize and display sensor data was implemented. This software was mainly sourced from Sunfounder tutorials, a publicly available resource for sensor setup and troubleshooting (Sunfounder, 2025). Once data could be collected from this sensor, 40 trials were conducted, in which the obstacle was placed at 50-

millimeter increments within a range of 50 to 1000 millimeters, switching between bright and dark lighting. In each trial, the sensor captured five datapoints within the span of a second, allowing for analysis to be conducted on not only accuracy but also variability within a short time span.

Medium Quality Lidar Setup. This testing will likely be similar to testing with low quality lidar sensors, using research to wire and program the sensor to execute the tests.

Medium Quality Radar Setup. This testing will likely be similar to testing with low quality lidar sensors. However, differences in the function of radar sensors may require differences in the interpretation of data or experimentation strategy, as the doppler function of the radar sensor model may only allow it to detect motion instead of distance.

Camera Setup. This setup will likely be much different from the other sensors, as the camera sensor is entirely different, requiring more complex code and not being able to directly record distances.

Justification and Feasibility. The analyzation of sensor accuracy should help to create more accurate methods of interpreting data, as recognizing patterns in how the sensors interpret inputs can lead to a greater understanding of even flawed data. This is most extremely displayed in the use of deep-learning-based pattern recognition, where machine learning is trained to combine and interpret sensor data to eliminate errors based on environment or sensor flaws. For instance, table 2 shows the data collected on the error of position measurements when applying and not applying a machine-generated mask (Lisus et al., 2025). Having learned from patterns in the previous datasets, the weight mask provides a perfect example of the most advanced application of pattern recognition in sensor testing. When looking at the

Noise Scale		Unweighted RMSE					Weighted RMSE (ours)				
[m]	[°]	Long. [m]	Lat. [m]	Head. [°]	Conv. [%]	Acc. [%]	Long. [m]	Lat. [m]	Head. [°]	Conv. [%]	Acc. [%]
0.0	0.0	0.135	0.095	0.252	99.79	13.27	**0.079**	**0.062**	**0.147**	**99.99**	**37.89**
0.5	2.5	0.140	0.097	0.285	99.63	11.51	**0.087**	**0.065**	**0.179**	**99.96**	**32.74**
1.0	5.0	0.142	0.097	0.294	98.13	11.56	**0.088**	**0.065**	**0.182**	**99.57**	**32.47**
1.5	7.5	0.145	0.098	0.319	89.95	11.58	**0.093**	**0.071**	**0.210**	**97.15**	**32.57**
2.0	10.0	0.176	0.124	0.634	73.52	11.63	**0.113**	**0.096**	**0.343**	**88.63**	**32.86**

Table 2: Root Mean Squared Error (RMSE) results for translation and heading in latitudinal and longitudinal directions. The standard deviations used in initial transformation sampling is shown under Noise Scale. Results are calculated with converged samples, with the percentage of samples shown in the Percent Converged (Conv.) column. The Percent Accurate (acc.) column shows the percentage of results that are within 0.05 m translation and 1° rotation of the ground truth (Lisus et al., 2025).

difference of accuracy between the data with and without the mask, it is shown to make a great difference, improving the accuracy from approximately 12% to approximately 35% (Lisus et al., 2025). Such a great increase in accuracy proves that analyzing patterns in sensor detection does lead to greater accuracy in measurements, indicating that the more primitive mode of sensor analysis conducted in this project will be beneficial.

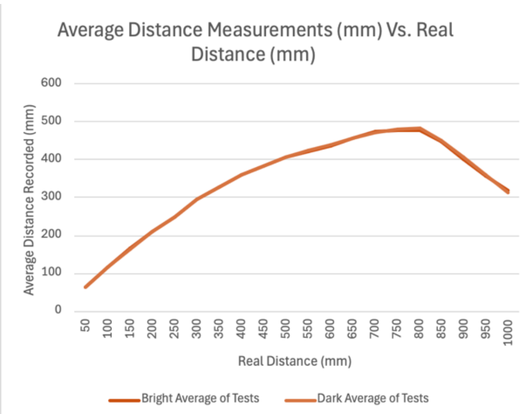

Figure 2a: Graph of the average distance measured in millimeters by the low quality lidar sensor, depending on the true distance of the obstacle.

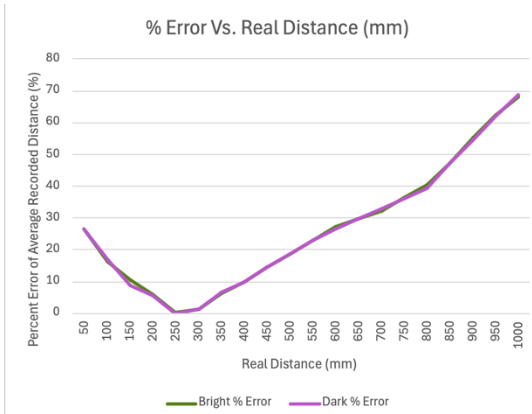

Figure 2b: Graph of the % error of the low quality lidar measurements, depending on the true distance to the obstacle.

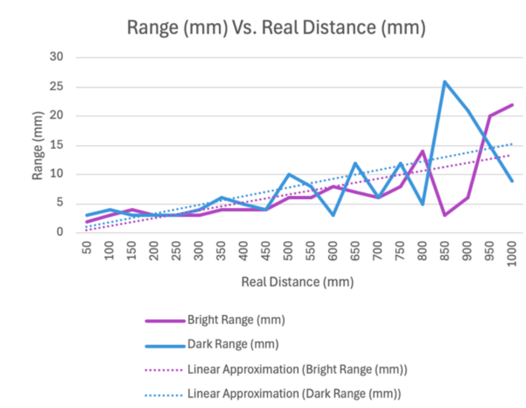

Figure 2c: Graph of the difference between the smallest value and largest value captured for each trial, with each trial corresponding to a test at a certain true distance.

Preliminary Data Summary. This data shows that the lidar distance detection becomes significantly worse as true distance increases, as seen in figures 2a and 2b. While light and dark detection do not change much, the variance increases as distance increases brings an interesting strategy to improve sensor detection. By correlating the higher variance to higher distances and increasing the number of distance measurements, it may be possible to eliminate false positives and be able to distinguish small distances from far distances.

Expected Outcomes. The expected outcome of this aim is the creation of a system or program that can accurately interpret potentially faulty data points, increasing the reliability of any system using the sensors.

Potential Pitfalls and Alternative Strategies. Difficulties are expected in observing accurate patterns and handling different types of sensors. This is due to the large quantity of variations in how sensors are labeled, need to be programmed, and provide data. To avoid this issue, it may be beneficial to focus efforts of pattern detection and data collection to a single type of sensor. With the current lineup of sensors, the most logical choice would be the lidar sensor, as two different qualities can be tested.

Resources/Equipment

This project will use store-bought sensors, electrical equipment, and other supplies. The main source of these materials will be Amazon, although other physical hardware stores such as Best Buy have been used for simple materials. The most important of the materials used are a raspberry pi 4B, VL53L0X lidar sensors, a TOFSense-F2 mini lidar sensor, RCWL-0516 radar motion sensors, a 1080P HD 0V5647 camera module V1, and various wires and connectors to connect the raspberry pi to a monitor and keyboard.

Ethical Considerations

Ethical considerations for this project are necessary if the results are successful enough to warrant production and distribution of the product. In this case, the potential user may be at risk of injury due to malfunctions within the device due to various circumstances, such as wear on the device or untested conditions. This possibility makes it important to run the device through rigorous testing and additional development given positive results, shifting focus from sensor optimization to product robustness.

Timeline

Bratane STEM Project Gantt Chart V1.xlsx

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