Project Notes:

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

Name: Bratane, Liam

Note Well: There are NO SHORT-cuts to reading journal articles and taking notes from them. Comprehension is paramount. You will most likely need to read it several times, so set aside enough time in your schedule.

Knowledge Gaps:

This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved
Types of sensors currently available to me.	Dr. C	In this box: Currently, I have access to an ultrasonic sensor. Other than this, I must research availability and costs of sensors such as lidar and radar.	10/10/25
How to wire, program, and collect data from sensors.	Sunfounder	In the sunfounder website, detailing various tutorials https://docs.sunfounder.com/projects/umsk/en/latest/05_raspberry_pi/pi_lesson21_vl53l0x.html This is specific to one lidar sensor, but the general knowledge about sensor use can be carried over to other models.	12/16/25
Types of sensors, and best sensor for this project.	Daniil Lisus	In the project notebook, within the notes taken by me during the meeting.	10/29/25

Literature Search Parameters:

These searches were performed between (Start Date of reading) and XX/XX/2019.
List of keywords and databases used during this project.

Database/search engine	Keywords	Summary of search
https://abstracts.societyforscience.org/	Ski, ENGINEERING: Electrical and Mechanical	No Data Available
https://abstracts.societyforscience.org/	LiDAR	Found many articles referencing the use of LiDAR in assisting navigation or collision avoidance.
https://abstracts.societyforscience.org/	Burns	Found varying results, including abstracts referring to sunscreen, burn treatment, and burn prevention.
https://wpi.primo.exlibrisgroup.com/discovery/search?query=any,contains,object%20detection,AND&query=any,contains,goggles,AND&tab=Everything&search_scope=MyInst_and_CI&sortby=rank&vid=01WPI_INST:Default&mode=advanced&offset=10	Object detection, goggles	Results varying from sensors to ensure people wear safety equipment to patents on glasses that can sense objects
https://wpi.primo.exlibrisgroup.com/discovery/search?query=any,contains,proximity%20sensors&tab=Everything&search_scope=MyInst_and_CI&sortby=rank%7D&vid=01WPI_INST:Default&mode=basic	Proximity Sensors	Mostly about small-scale infrared sensors: not useful.
https://patents.google.com/?q=(Proximity+Sensor)+AND+(goggles)+AND+(skiing)&oq=(Proximity+Sensor)+AND+(goggles)+AND+(skiing)	Patents, (Proximity Sensor) AND (goggles) AND (skiing)	Many different patents about eyewear that could track and display information about the user.

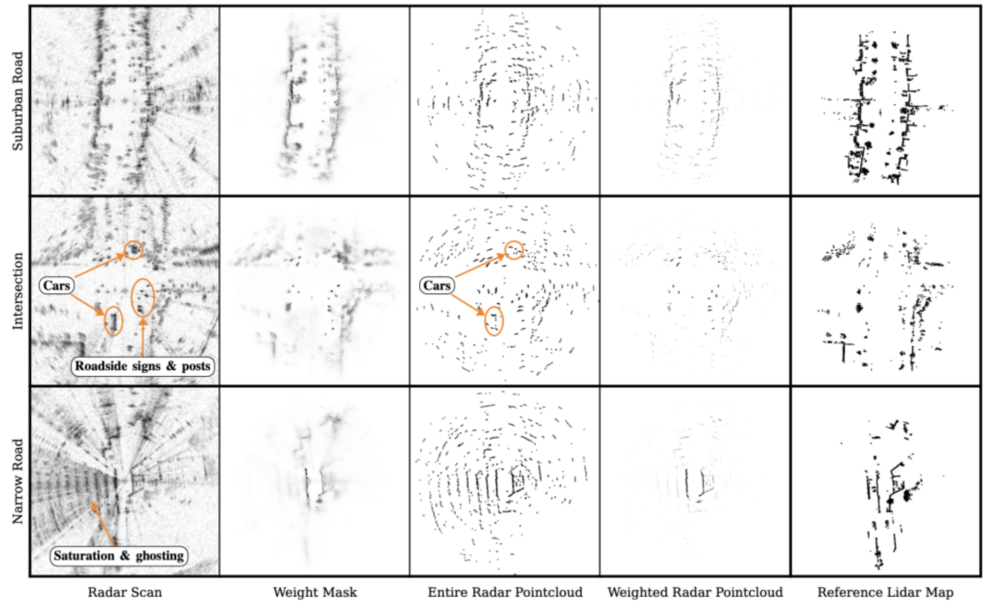
https://www.lens.org/lens/search/patent/list?q=Skiing%20AND%20Sensor%20AND%20Goggles%20AND%20Obstacle&p=0&n=10&s=date_published&d=%2B&f=false&e=false&l=en&authorField=author&dateFilterField=publishedDate&orderBy=%2Bdate_published&presentation=false&preview=true&stemmed=true&useAuthorId=false	Patents, Skiing AND (Sensor AND (Goggles AND Obstacle))	Many useful patents on object-detecting goggles, goggle displays, etc.
https://www.lens.org/lens/search/patent/list?%3Fp=0&n=10&s=_score&d=%2B&f=false&e=false&l=en&authorField=author&dateFilterField=publishedDate&orderBy=%2B_score&presentation=false&preview=true&stemmed=true&useAuthorId=false&q=Obstacle%20detection%20AND%20(Low%20visibility%20AND%20(Lidar%20OR%20Radar%20OR%20Sonar%20OR%20Camera))	Patents, Obstacle detection AND (Low visibility AND (Lidar OR Radar OR Sonar OR Camera))	Various patents of many different fields, all using some form of sensor to detect objects.
https://www.lens.org/lens/search/scholar/list?%3Fp=0&n=10&s=date_published&d=%2B&f=false&e=false&l=en&authorField=author&dateFilterField=publishedYear&orderBy=%2Bdate_published&presentation=false&preview=true&stemmed=true&useAuthorId=false&q=Obstacle%20detection%20AND%20(Low%20visibility%20AND%20(Lidar%20OR%20Radar%20OR%20Sonar%20OR%20Camera))	Scholar, Obstacle detection AND (Low visibility AND (Lidar OR Radar OR Sonar OR Camera))	Various articles about autonomous designs – not useful
https://www.lens.org/lens/search/scholar/list?%3F%3Fp=0&n=10&s=date_published&d=%2B&f=false&e=false&l=en&authorField=author&dateFilterField=publishedYear&orderBy=%2Bdate_published&presentation=false&preview=true&stemmed=true&u	Scholar, Comparison AND Sensors AND Camera AND Object AND Detection AND Optimal AND Environment AND (Lidar OR Radar OR Sonar OR Infrared) NOT Deep Learning NOT Neural Network	Various articles discussing differences between different strategies, solutions, or methods.

seAuthorId=false&q=Comparison%20AND%20Sensors%20AND%20Camera%20AND%20(Lidar%20OR%20Radar%20OR%20Sonar%20OR%20Infrared)		
https://www.proquest.com/science/results/911911430A334A31PQ/1?accountid=29120#mlditem1	Lidar and Radar and Ultrasonic	Articles describing various object detection methods Found articles #11, 12
https://www.proquest.com/science/results/170E61B50FC449B6PQ/1?accountid=29120	Skiing and object detection	Not incredibly useful – Mainly about just obstacle/wildlife detection or skiing, but not both together. Found article #13, 14
https://www.proquest.com/science/results/310D6ACEC29B4841PQ/1?accountid=29120	Skiing injury	Found articles about injury rates and types of injuries in skiing Found article #15
https://www.proquest.com/science/results/B30011C1408A48D3PQ/1?accountid=29120	All-Weather Sensors	

Article #1 Notes: Pointing the Way: Refining Radar-Lidar Localization Using Learned ICP Weights

Article notes should be on separate sheets

Source Title	Pointing the Way: Refining Radar-Lidar Localization Using Learned ICP Weights
Source citation (APA Format)	Lisus, D., Laconte, J., Burnett, K., Zhang, Z., & Barfoot, T. D. (2025). *Pointing the Way: Refining Radar-Lidar Localization Using Learned ICP Weights* (No. arXiv:2309.08731). arXiv. https://arxiv.org/pdf/2309.08731
Original URL	https://arxiv.org/pdf/2309.08731
Source type	Journal Article
Keywords	Robotics, Machine Learning, Autonomous-vehicle localization, radar perception, learned pointcloud filtering
Summary of key points + notes (include methodology)	This article attempts to combine lidar and radar sensing with centimeter-level accuracy, with the goal of using lidar's detail in sensing and radar's sensing through fog and other bad conditions to increase reliability in autonomous driving. The strategy they used was to train a program to weigh the data points and filter out the unnecessary noise given by radar, allowing them to beneficially merge the two sensors. They built on their own previous work with aligning radar and lidar points in a prior article, training and adding a learned weight mask in hopes of improving data quality.
Research Question/Problem/ Need	How can lidar and radar be combined to assist in autonomous driving?

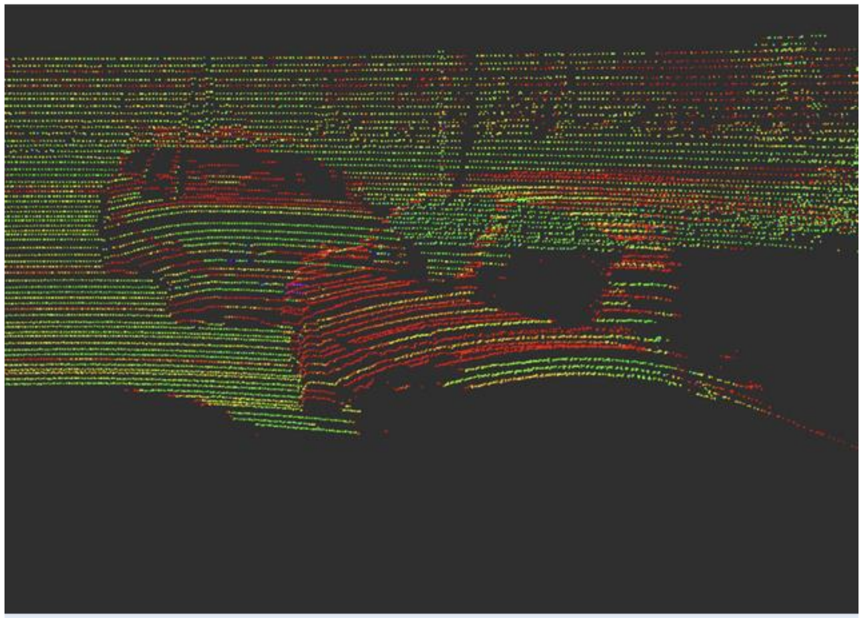
Important Figures	 Fig. 3. Three examples of the output from the pipeline in different scenarios. The mask highlights nearby structured areas when they exist (suburban road), focuses on reliable roadside signs and posts (intersection), all while ignoring cars (intersetion) and unique radar artefacts (narrow road). This figure visualizes the behavior of different sensor models and their components, displaying how different patterns can be derived from a certain dataset.
VOCAB: (w/definition)	- Radar: A system of sending pulses of electromagnetic waves, measuring the reflected waves to detect the presence of objects. - LiDAR: A system of object detection that works on the same principles as radar, but with the use of laser light. - ICP: Iterative closest point algorithm- An algorithm used on point clouds to minimize the difference between the clouds of points, typically used to construct surfaces from different scans and localize the positions of objects. - Localization: The process of finding and orienting a vehicle’s position within a preconstructed map. - Multi-modal: The attribute of having or using multiple methods to accomplish a task. - Differentiable: Able to be changed and developed. - Pointcloud: A collection of data points signifying a point on a surface, typically measured using LiDAR or other scanners. - CFAR: Constant False Alarm Rate- A form of algorithm used to distinguish likely points from likely noise or interference given input from a sensor such as LiDAR or radar. - BFAR: Bounded False Alarm Rate- A modified form of CFAR made to be more accurate in distinguishing points. - Kalman filter: An algorithm that takes a noisy input over time to predict the true state of the input. - Convergence: The act of moving towards a common point or value. - RMSE: Root mean squared error- A value used to determine the accuracy

	of a system, equal to the square root of the average of the squared difference between the prediction and the observed data.
Cited references to follow up on	Are We Ready for Radar to Replace Lidar in All-Weather Mapping and Localization? Safe Autonomous Driving in Adverse Weather: Sensor Evaluation and Performance Monitoring High Resolution Mapping of the Environment with a Ground-based Radar Imager
Follow up Questions	How does machine learning work in relation to interpreting sensing data? What hardware is needed for this technology? How can radar-lidar sensing fare in snowy weather?

Article #2 Notes: LiDAR Technology Could Improve Safety Features in Vehicles

Article notes should be on separate sheets

Source Title	LiDAR Technology Could Improve Safety Features in Vehicles
Source citation (APA Format)	University, U. S. (n.d.). *LiDAR Technology Could Improve Safety Features in Vehicles*. Retrieved September 2, 2025, from https://engineering.usu.edu/news/main-feed/2023/lidar-technology-could-improve-safety-features-in-vehicles
Original URL	https://engineering.usu.edu/news/main-feed/2023/lidar-technology-could-improve-safety-features-in-vehicles
Source type	News Article
Keywords	LiDAR, Autonomous Driving, Safety
Summary of key points + notes (include methodology)	This news article describes the potential benefits and problems of the use of LiDAR technology, or the use of light photons to scan distances and objects, in cars. Specifically, it outlines ideas from a research paper by Scott Budge and Chaz Cornwall, stating that LiDAR can allow cars to quickly tell different objects apart in varying environments. Additionally, it explains how Budge and Cornwall have attempted to fix problems of object distinction and noise, resulting in a scan able to successfully distinguish between objects.
Research Question/Problem/ Need	Can LiDAR be used to make autonomous driving safer?

Important Figures	 *LiDAR can recognize both stationary and moving objects by using billions of light photons, keeping drivers, occupants and other road users safe.* This figure provides a visual representation of the function of LiDAR, where the sensor sends points of light to record distances via the point's time of return.
VOCAB: (w/definition)	- LiDAR: A system of object detection that uses points of laser light to determine the distances to objects. - Noise: Interference in a signal, obscuring the actual data given by the signal. - LiDAR map: A representation of all data points collected by a LiDAR sensor, interpreted to get information about what objects are present. - Dynamic: Changing. In this article, they explain that LiDAR must be able to compensate for changing environments. - Object Movement Distinction: The ability for a sensor to distinguish between different types of moving objects.
Cited references to follow up on	https://www.spiedigitallibrary.org/journals/optical-engineering/volume-62/issue-3/031203/Obstacle-detection-using-range-difference-events/10.1117/1.OE.62.3.031203.short?SSO=1&tab=ArticleLink
Follow up Questions	How exactly did they modify the LiDAR maps to remove noise? Why use LiDAR, as opposed to other sensor types?

	What are the limits to the use of LiDAR?

Article #3 Notes: DeepFusion: Lidar-Camera Deep Fusion for Multi-Modal 3D Object Detection

Article notes should be on separate sheets

Source Title	DeepFusion: Lidar-Camera Deep Fusion for Multi-Modal 3D Object Detection
Source citation (APA Format)	Li, Y., Yu, A. W., Meng, T., Caine, B., Ngiam, J., Peng, D., Shen, J., Lu, Y., Zhou, D., Le, Q. V., Yuille, A., & Tan, M. (2022). DeepFusion: Lidar-Camera Deep Fusion for Multi-Modal 3D Object Detection. *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 17161–17170. https://doi.org/10.1109/CVPR52688.2022.01667
Original URL	https://openaccess.thecvf.com/content/CVPR2022/papers/Li_DeepFusion_Lidar-Camera_Deep_Fusion_for_Multi-Modal_3D_Object_Detection_CVPR_2022_paper.pdf
Source type	Conference Paper
Keywords	LiDAR, Camera, DeepFusion, Autonomous Driving
Summary of key points + notes (include methodology)	This article addresses how to improve object detection while using LiDAR. To do this, they suggest the fusion of camera sensing and LiDAR sensing. They explain that LiDAR can provide low-resolution input of distances, while cameras can provide high-resolution information on shape. However, fusing the two inputs can be difficult due to issues with alignment. This is explained to stem from transformations that must be performed on LiDAR images, as well as the low-resolution voxels created by LiDAR, making it difficult to accurately correspond camera objects to LiDAR objects. To fix this, they introduced InverseAug, a tool to reverse the augmentation process and correspond points, and LearnableAlign, a tool to analyze and fuse the high-resolution camera input to the low-resolution voxels created by LiDAR input. These new tools are applied to fuse the two inputs at the end stage of processing and fed into a preexisting 3D detection program. After explaining this method of fusion, the article compares its efficacy to that of other methods of fusion or with only LiDAR, showing that their methods result in better performance and object distinction than the others in the dataset.
Research Question/Problem/ Need	Can LiDAR and camera sensing be fused to improve object detection?

Important Figures

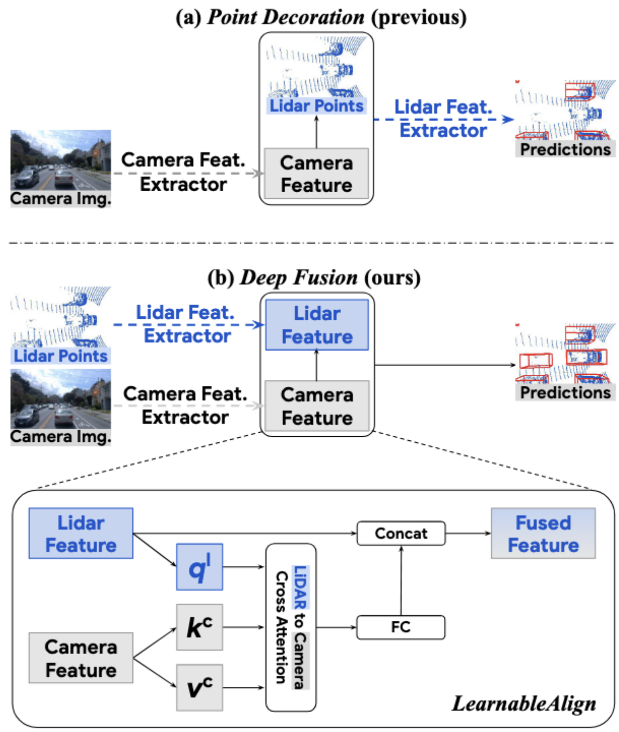


Figure 1. Our method fuses two modalities on **deep feature level**, while previous state-of-the-art methods (PointPainting [34] and PointAugmenting [36] as examples) decorate lidar points with camera features on **input level**. To address the modality alignment issue (see Section 1) for deep feature fusion, we propose two techniques **InverseAug** (see Figure 2 and 3) and **LearnableAlign**, a cross-attention-based feature-level alignment technique.

In this figure, the unique structure of this study's method of fusing lidar and camera data is explained. As opposed to the typical method of simply adding the two sets of points on top of one another, the Deep Fusion method is to use both the lidar and camera data to identify points of interest, then add this data of areas of interest on top of the lidar point set. This comparison is explained within the article, in which they use the new methods InverseAug and LearnableAlign.

VOCAB: (w/definition)

- Lidar: A system of object sensing that uses points of laser light to determine the distance to objects.
- InverseAug: A method of point cloud manipulation designed to reverse any rotation between two otherwise identical images. This is used in the article as one step in the process of comparing and combining lidar and camera input.
- LearnableAlign: A method of point cloud manipulation designed to find and match similarities between two different images. This is used in the article as another step in the process of comparing and combining lidar and camera input, helping to find areas of the input that are especially important.
- DeepFusion: A multi-modal 3D detection model made to be trained by

	data inputs and compatible with other pre-existing modules of 3D detection models. - Multi-modal: Having the ability to store and interpret multiple types of data.
Cited references to follow up on	Alex H Lang, Sourabh Vora, Holger Caesar, Lubing Zhou, Jiong Yang, and Oscar Beijbom. Pointpillars: Fast encoders for object detection from point clouds. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 12697–12705, 2019. Sourabh Vora, Alex H Lang, Bassam Helou, and Oscar Beijbom. Pointpainting: Sequential fusion for 3d object detection. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (CVPR), pages 46044612, 2020.
Follow up Questions	Can multi-modality be extended to accept three different data inputs, instead of just two? How well does the system function in varying environments, such as low visibility?

Article #4 Notes: Deep learning-based robust positioning for all-weather autonomous driving

Article notes should be on separate sheets

Source Title	Deep learning-based robust positioning for all-weather autonomous driving
Source citation (APA Format)	Almalioglu, Y., Turan, M., Trigoni, N., & Markham, A. (2022). Deep learning-based robust positioning for all-weather autonomous driving. *Nature Machine Intelligence*, *4*(9), 749–760. https://doi.org/10.1038/s42256-022-00520-5
Original URL	https://doi.org/10.1038/s42256-022-00520-5
Source type	Journal Article
Keywords	Autonomous driving, Lidar, Radar, Multi-modal, Deep learning, Odometry
Summary of key points + notes (include methodology)	This article focuses on solving the problem of self-location and object detection in autonomous vehicles. To approach this problem, they introduce and compare the uses of monocular cameras, stereo cameras, LiDAR sensing with cameras, and Radar sensing with cameras. They consider the ability of these options to distinguish objects and depth in varying conditions such as snow, rain, and fog. After testing, they conclude that the incorporation of other sensing options in addition to camera input is best in all conditions. Between the two other sensing options, they seem to conclude that radar is the best option for sensing in bad weather, due to its ability to be fully covered while sensing and ability to sense through most small obstructions such as rain or snow. These findings were used to claim that multimodal sensor systems are the most optimal for autonomous vehicles, as well as to introduce a deep learning program called GRAMME that used multiple sensors to estimate the vehicle's position and motion.
Research Question/Problem/ Need	What is the best use of sensors and algorithms for an autonomous car to accurately interpret its own position and movement?

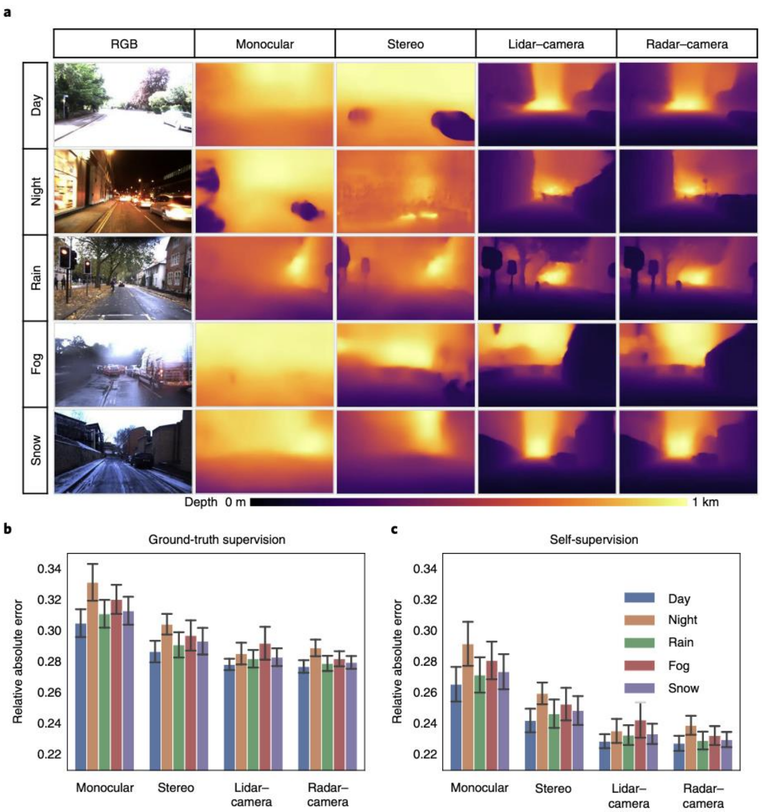
<table>
<tr>
<td>Important Figures</td>
<td>


Fig. 2 | Multimodal, modular, and generalizable depth prediction performance. a, Qualitative results and sample test frames[16] to visualize the generalization ability of GRAMME on depth prediction. We train each model using the day sequences in the training set and test them under diverse conditions to analyse the generalization performance. GRAMME successfully exploits the complementary aspects of the sensors. b, Comparatively weaker generalization performance of the supervised models. c, Quantitative results to compare the self-supervised generalization performance of GRAMME with respect to ground-truth supervision and intra-modality performance. The models trained only on camera are dramatically prone to failure in all of the challenging test conditions. Although lidar- and radar-based models provide qualitatively similar results and generally improve the overall performance, the model trained with radar provides greater immunity to precipitation. Error bars represent the depth prediction errors with respect to the ground truth. Camera fusion models employ the stereo setting.

This figure shows the performance of different sensor types in different environments. Through the results, it is shown that the incorporation of Lidar or Radar as a sensor improves the quality of the performance, as the visualizations are more detailed in range of depth. Additionally, the Lidar and Radar both have lower error values in regard to deviating from the true values as well as in generating a mask to ignore useless points.
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<tr>
<td>VOCAB: (w/definition)</td>
<td>

- Radar: A system of sending pulses of electromagnetic waves, measuring the reflected waves to detect the presence of objects.
- LiDAR: A system of object detection that works on the same principles as radar, but with the use of laser light.
- Multi-modal: Having the ability to store and interpret multiple types of data.
- Deep learning: Teaching a program to interpret data through the use of a calibrated neural network, where the program extrapolates and finds patterns within the given data.
- Odometry: The process of finding one’s own position and movement, crucial for navigation and autonomous driving.

</td>
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<tr>
<td>Cited references to follow</td>
<td>Cadena, C. et al. Past, present, and future of simultaneous localization and</td>
</tr>
</table>

up on	mapping: toward the robust-perception age. IEEE Trans. Robotics 32, 1309–1332 (2016). Fagnant, D. J. & Kockelman, K. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. 77, 167–181 (2015).
Follow up Questions	Can a multi-modal system be made with Lidar and Radar together, instead of always including cameras? Could this system be used for applications other than odometry, such as obstacle detection?

Article #5 Notes: Incidence of alpine skiing and snowboarding injuries

Article notes should be on separate sheets

<table>
<tr><td>Source Title</td><td>Incidence of alpine skiing and snowboarding injuries</td></tr>
<tr><td>Source citation (APA Format)</td><td>Wagner, M., Liebensteiner, M., Dammerer, D., Neugebauer, J., Nardelli, P., & Brunner, A. (2023). Incidence of alpine skiing and snowboarding injuries. Injury, 54(8), 110830. https://doi.org/10.1016/j.injury.2023.05.061</td></tr>
<tr><td>Original URL</td><td>https://doi.org/10.1016/j.injury.2023.05.061</td></tr>
<tr><td>Source type</td><td>Journal Article</td></tr>
<tr><td>Keywords</td><td>Injury, Ski, Rescue, Benchmark, COVID-19</td></tr>
<tr><td>Summary of key points + notes (include methodology)</td><td>Key points:
- There needs to be more standardization for the method of presenting snow sport injury statistics
    o Direct comparison between studies is currently impossible
- The rate of injury in snow sports has drastically decreased over time
    o Greater use of safety equipment
    o Higher levels of education about safety measures
    o More safety measures enacted by resorts
- Overall incidence of 0.44 injuries per 1000 skier days
    o Total of 43,283 patients over the study period of 5 years.
- Largest and most accurate study on alpine skiing and snowboarding injuries
- 9103 of cases had information about severity and location (21.03%)
    o Of this, most injuries (45.3%) were minor injuries
    o Few (2.7%) were major injuries
- Rate of injuries was slightly reduced during COVID-19
    o Reduction of tourism – fewer beginners
- Study limited by differences in previous studies and lack of differentiation in many aspects of data collection (gender, style of snow sport, outcome of injury).
Methods:
- Data collected over 5 winter seasons from the emergency dispatch center of Tyrol, Australia.
    o November 2017 to April 2022
    o All patients coming from ski slopes to any medical facility were included in data on rate of rescues
    o Data on injuries collected from emergency dispatch center
        ▪ Age
        ▪ Location
        ▪ Mechanism of injury</td></tr>
</table>

- Type of injury
- Location of injury
- Severity of injury

- Odds ratios calculated on the association between severity and mode of rescue
- Assessed with the number of skier days during the period
  - # of skier days collected from state ski resorts
  - Final data portrayed in the common method of # of incidents per 1000 skier days.
- One t-test to compare injury rates with other studies

Research Question/Problem/ Need

What is the data on injury rates while skiing, and how does this compare to previous studies?

Important Figures

Table 3
Number of injuries according to anatomic regions and age.

Age (y)	1–3	4–5	6–12	13–17	18–29	30–49	50–69	70–89	n/a	Total
Knee	2	11	216	319	598	1031	671	25	77	2950
Pelvis	0	1	6	25	39	53	78	12	6	220
Thoracic Spine	0	1	28	32	69	59	54	2	6	251
Thumb	0	0	1	0	7	6	1	0	2	17
Elbow	0	0	6	10	18	18	7	1	2	62
Heel	0	0	15	11	16	18	16	2	3	81
Foot	1	3	15	21	25	31	40	2	3	141
Hand	1	0	45	63	85	66	33	4	13	310
Head/Skull	1	6	76	93	163	246	268	50	25	928
Lumbar Spine	0	0	16	28	49	48	32	5	1	179
Upper Arm	0	0	9	25	32	47	54	8	6	181
Thigh	0	0	33	38	60	72	105	16	11	335
Rips	0	0	4	5	17	17	18	1	2	64
Shoulder	0	5	43	117	292	384	351	34	32	1258
Ankle Joint	0	0	15	19	24	29	28	2	2	119
Thorax	0	0	4	10	18	34	34	0	1	101
Forearm	0	1	31	57	52	77	42	3	11	274
Lower Leg	0	8	133	104	138	271	231	16	28	929
Collarbone	0	0	9	20	37	31	25	1	5	128
n/a	0	4	70	85	162	171	208	31	884	1249
Total	5	40	775	1082	1901	2709	2296	215	757	10,143

This figure gives data on ski hill injuries, showing ages and regions more commonly injured. The data given by this figure can be used to determine what any additional safety measure should target, such as ages of 30 to 49 and knee injuries.

VOCAB: (w/definition)

- Mio: An abbreviation for million, originating from German.
- Skier day: A day of skiing, estimated to equal around 20 ski-lift ascends.
- t-test: A statistical test to compare one population to a known value or to another population.
- Heterogeneity: Being diverse in content, in this case being a bad thing due to the difficulty in comparing studies with different methods of collecting and showing data.
- Mechanism of injury: How an injury occurred.

Cited references to follow up on

Niedermeier M, Gatterer H, Pococco E, Frühauf A, Faulhaber M, Menz V, et al. Mortality in different mountain sports activities primarily practiced in the winter season—A narrative review. Int J Environ Res Public Health 2020;17. https://doi.org/10.3390/ijerph17010259.

Burtscher M, Gatterer H, Flatz M, Sommersacher R, Woldrich T, Ruedl G, et al. Effects of modern ski equipment on the overall injury rate and the pattern of injury location in alpine skiing. Clin J Sport Med 2008;18. https://doi.org/10.1097/

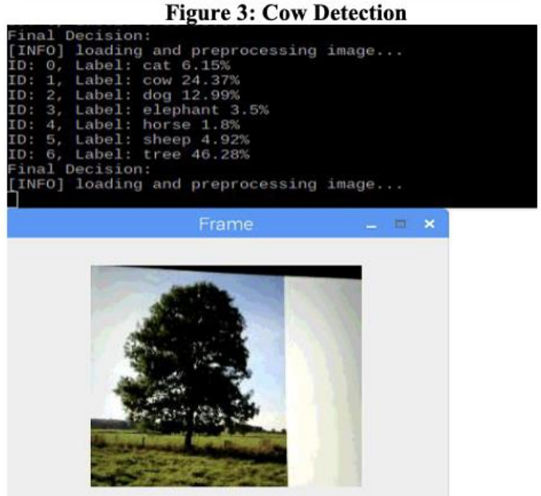
	MJT.0b013e31815fd0fe.
Follow up Questions	Is there evidence that more safety equipment will further decrease the rate of injury on ski hills? Are beginner skiers major contributors to the rate of injury on ski hills?

Article #6 Notes: AI Powered Glasses for Visually Impaired Person

Article notes should be on separate sheets

Source Title	AI Powered Glasses for Visually Impaired Person
Source citation (APA Format)	Satani, N., Patel, S., & Patel S. (2020). AI Powered Glasses for Visually Impaired Person. *International Journal of Recent Technology and Engineering (IJRTE)*, *9*(2), 316–321. https://doi.org/10.35940/ijrte.B3565.079220
Original URL	10.35940/ijrte.B3565.079220
Source type	Journal Article
Keywords	OCR, R-CNN, Transfer learning

Summary of key points + notes (include methodology)	Key points:
	- Current models of A.I. powered glasses are expensive
	- Proof of concept provided by article
	    ○ Function:
	        ▪ Provide voice identification of various objects when prompted
	        ▪ Detect and classify images
	        ▪ Recognize faces
	        ▪ Automatic alarm to incoming obstacles
	    ○ Drawbacks:
	        ▪ Comparatively slow at object detection
	        ▪ Limited ability to distinguish between objects due to limited processing power
	        ▪ Design still has relatively high cost
	Methodology:
	- Hardware:
	    ○ Raspberry PI
	        ▪ Good processing speed + wireless ability
	    ○ Raspberry PI camera module
	        ▪ Positioned on the top/side of the glasses
	    ○ Power bank
	    ○ Earphone
	- Software:
	    ○ Machine learning
	        ▪ Convolutional neural network
	            • Take inputs, run them through layers of interpretation, then provide a single output
	            • Take into account groups of pixels at a time

	to understand context of the image • Aim to find specific shapes or edges • Trained using a large quantity of manually collected data ▪ Trained a CNN model for image identification ▪ Tested model using various images, inspecting the probabilities given by the model ▪ Used Google's tesseract library to convert images to text, and allow for text to speech ▪ Used openCV's pre-trained model to train and detect faces
Research Question/Problem/ Need	Is it possible to make an affordable pair of A.I. powered glasses to assist visually impaired people?
Important Figures	 **Figure 3: Cow Detection**  **Figure 4: Tree Detection** These figures show the decision process of the A.I. glasses as different images are identified. This is important because it shows how the dataset can be expanded or diminished to include more possible identifications or increase the speed of identification.
VOCAB: (w/definition)	- CNN: A convolutional neural network, or a type of neural network that takes an input of a grid of values, comparing values and

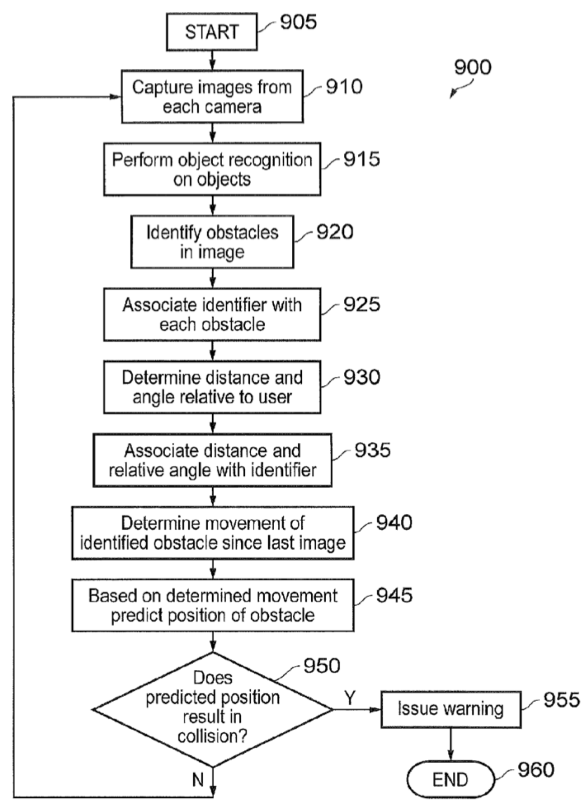
	identifying simple and complex patterns. This form of neural network is commonly used for the interpretation of images and videos. - RNN: A recurrent neural network, or a type of neural network that feeds the output of one step back into the input of another step, allowing the network to identify patterns in sequences while preserving order. - GAN: A generative adversarial network, or a method of training neural networks by having a competing neural network, where one neural network works to become better and fool the adversarial network. This provides a way to improve the training of neural networks. - GPU: A graphics processing unit is a part of a computer which processes data related to graphics and parallel processing. This is utilized in neural networks because of its ability to perform a large quantity of computations very quickly. - Kernel: A matrix used for the manipulation of graphics data.
Cited references to follow up on	Li, Xiang, et al. "Cross-Safe: A computer vision-based approach to make all intersection-related pedestrian signals accessible for the visually impaired." Science and Information Conference. Springer, Cham, 2019. Liu, Fayao, Chunhua Shen, and Guosheng Lin. "Deep convolutional neural fields for depth estimation from a single image." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
Follow up Questions	Can the object identification of this system be simplified to allow for faster computation times while preserving the ability for the goggles to warn of obstacles? What is the resulting cost of this prototype? What is a cost that would be affordable for the target customer?

Article #7 Notes: DISPLAY, METHOD AND COMPUTER PROGRAM

Article notes should be on separate sheets

Source Title	DISPLAY, METHOD AND COMPUTER PROGRAM
Source citation (APA Format)	Tobias, L. (2024). *System And Method For Uxo Detection* (Patent No. US 2025/0060504 A1). https://lens.org/033-294-580-855-80X
Original URL	https://link.lens.org/2lJr0miGvZi
Source type	Patent
Keywords	Snow-sports, augmented reality, obstacle detection

Summary of key points + notes (include methodology)	Key points:
	- Device to wear on head:
	  ○ Snow sports
	  ○ Augmented reality
	  ○ Detect obstacles
	    ▪ People
	    ▪ Ice patches
	    ▪ Drops
	    ▪ Fences
	    ▪ Trees
	    ▪ Rocks
	  ○ Calculate and display a safe path
	  ○ Sensors:
	    ▪ Gyroscopes
	    ▪ Accelerometers
	    ▪ GPS
	    ▪ Temperature sensors
	    ▪ Barometer
	    ▪ Cameras
	Methodology:
	- Skiers are detected by the presence of at least one ski
	  ○ Surrounding area is then scanned for a person
	  ○ Similar for snowboarders
	  ○ Streamlines process
	- Image recognition used for every frame to detect obstacles
	- Location and movement of objects calculated through analyzation of multiple frames

	○ Further predict the path of people by using data on how long each person has previously taken to change direction. ○ Method of prediction changes depending on the object type identified. - Path chosen by user-defined priorities ○ Slope of path ○ Range of options for a path - Warn if crash is imminent
Research Question/Problem/ Need	Create a head mounted device that can detect dangers during snow sports and display a safe path via augmented reality.
Important Figures	 FIG. 9 This figure shows the steps taken by the goggles in order to best provide assistance to the wearer.
VOCAB: (w/definition)	- Augmented reality: When real life experiences are paired with digital overlays, mixing real life and technology. - Accelerometer: A sensor that can detect changes in speed, or acceleration. - Barometer: A sensor that can detect atmospheric pressure, informing of what elevation the user is at. - Piste: A skiing term for path, where it is the main path of compacted

	snow. - Optical: Using visible light.
Cited references to follow up on	Embedding intelligent electronics within a motorcyle helmet https://link.lens.org/boh4mRC0YLk Computer-Aided System For 360° Heads Up Display Of Safety/mission Critical Data https://link.lens.org/qPX13L5tiCj
Follow up Questions	How does the simplification of skiers and snowboarders to skis and snowboards streamline the process of object detection if other objects and people have to be detected anyways? How fast can this system detect and react to obstacles?

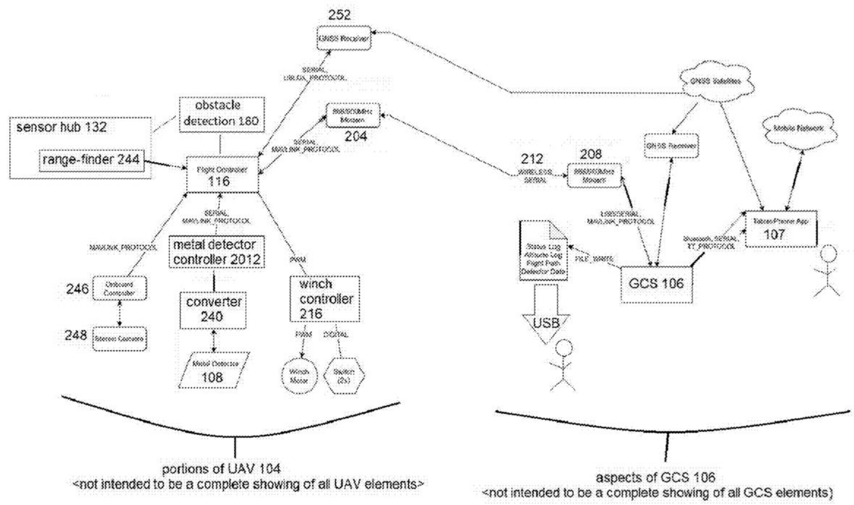
Article #8 Notes: System And Method For Uxo Detection

Article notes should be on separate sheets

Source Title	System And Method For Uxo Detection
Source citation (APA Format)	Tobias, L. (2024). *System And Method For Uxo Detection* (Patent No. US 2025/0060504 A1). https://lens.org/033-294-580-855-80X
Original URL	https://link.lens.org/DeF4WQfzacj
Source type	Patent
Keywords	Lidar, Sonar, Radar, UXO, Drone

Summary of key points + notes (include methodology)	Key points:
	- Drone
	    o Fly as low as 20cm above the ground
	- Detect UXO (unexploded ordinance)
	    o Lidar
	    o Radar
	    o Sonar
	    o Metal detection
	- Avoid obstacles
	- Mapping
	Methodology:
	- Drone
	    o Stays at low altitudes while flying back and forth between home and a set point
	    o Detects and records locations of explosives
	        ▪ Metal detection
	        ▪ Visual detection (shape)
	    o GCS controls the drone while also factoring in the results of sensor data.
	        ▪ Reduces necessary quantity of computation

Research Question/Problem/ Need	Can drones with sensor technology help detect hidden explosives?

Important Figures	 **FIG. 2** This figure exhibits the planned method of controlling the metal detector of the drone.
VOCAB: (w/definition)	- UAV: An unmanned aerial vehicle, or another term for drone. - UXO: An unexploded ordinance, or an unexploded bomb having been left behind in an area. - IED: A bomb made by unofficial sources, typically simple - EROW: Explosive remnants of war. - GCS: The ground communication system, or area from which a person controls the drone.
Cited references to follow up on	No cited references are provided
Follow up Questions	How do these sensors function in bad weather? Could a neural network be included to help the drone remember where it had already been, as well as learn about most likely areas for UXOs?

Article #9 Notes: Low Cost 3d Sonar, Lidar, All Weather Radar Imaging And 3d Association Method For Autonomous Vehicle Navigation

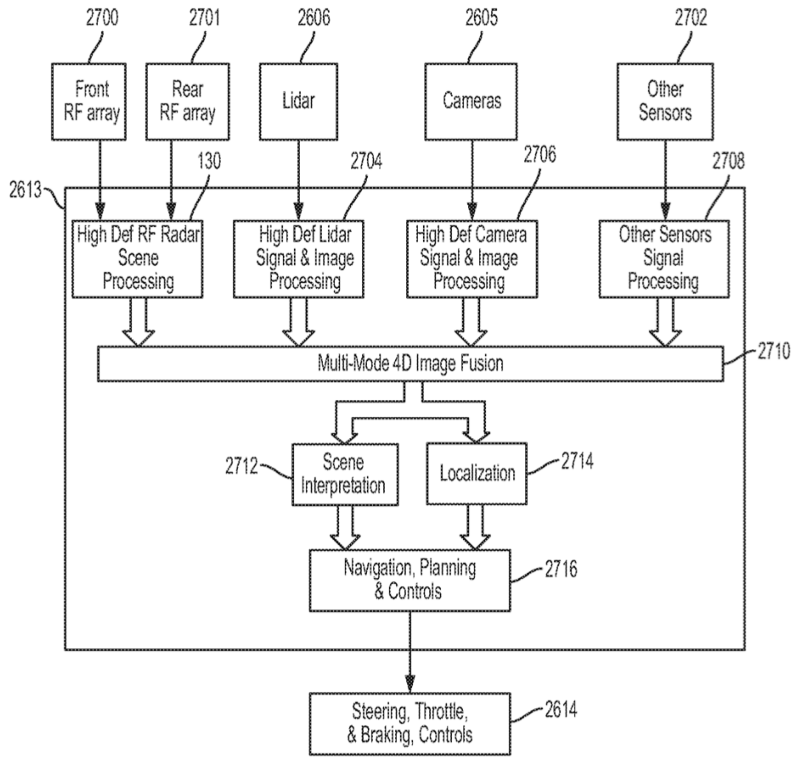
Article notes should be on separate sheets

Source Title	Low Cost 3d Sonar, Lidar, All Weather Radar Imaging And 3d Association Method For Autonomous Vehicle Navigation

Source citation (APA Format)	E, P. R., & M, W. J. (2017). *Low Cost 3d Sonar, Lidar, All Weather Radar Imaging And 3d Association Method For Autonomous Vehicle Navigation* (Patent No. WO 2017/165728 A1). https://lens.org/143-963-980-912-141
Original URL	https://link.lens.org/rjJAb33gOYg
Source type	Patent
Keywords	Cost, Radar, Lidar, Sonar, Autonomous driving

Summary of key points + notes (include methodology)	Key points:
	- Localization necessary for navigation
	- Provides a high definition radar sensor system.
	- Problems with typical sensing:
	    o Lidar and other sensors can be blocked by occlusions
	        ▪ Water droplets
	        ▪ Dust
	        ▪ Bad weather
	    o Visual cues can be obscured
	        ▪ Puddles
	        ▪ Accumulation of snow, dust, sand
	    o GPS sensors can be compromised
	Methods:
	- Starts with rough data from GPS systems
	    o Estimate general position
	    o Improve with various cues from optical sensors
	        ▪ Kalman tracking filter – detect road objects
	- Estimate position and velocity
	    o Use accelerometers and wheel encoders
	    o Integrate GPS info with visual cues to avoid outages of GPS.

Research Question/Problem/ Need	Create a cost-efficient design for a lidar, radar, and sonar sensor setup for autonomous vehicles.

Important Figures	 FIG. 24 This figure shows the method of combining sensors on a car, in which the process has been optimized for cost and efficiency.
VOCAB: (w/definition)	- Wheel encoder: A sensor that translates wheel position into data. - Ghost detection: A false detection of objects that are actually in a different position, a result of image artifacts. - Voxel: A value within a three dimensional grid. - Azimuth: A horizontal angle. - Convolution array: A method of manipulating data to get useful outputs.
Cited references to follow up on	Antenna Configuration For Parking Assist Radar https://link.lens.org/M0sBd1isCFi Radar for enabling accurate determination of false image of target https://link.lens.org/5WfssFDeBgi
Follow up Questions	How does the optimization of price affect the quality of the sensing?

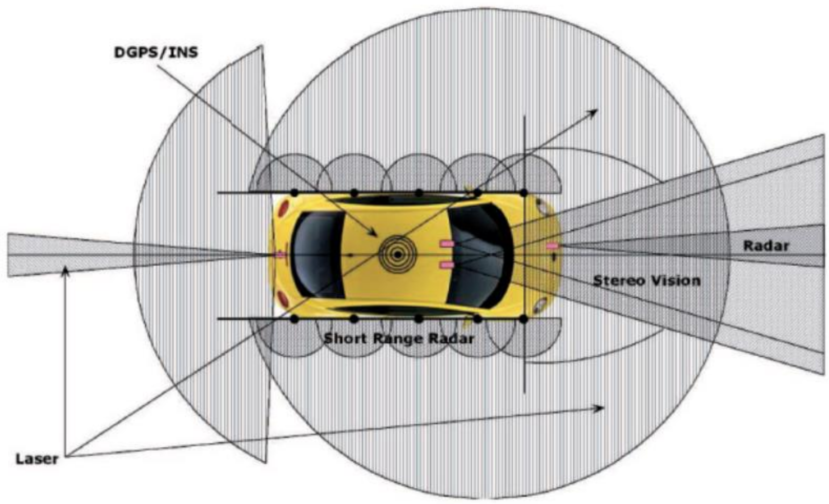
	Is there a more cost-friendly sensor than lidar, or is lidar the only option with its functionality?

Article #10 Notes: A Study on Recent Developments and Issues with Obstacle Detection Systems for Automated Vehicles

Article notes should be on separate sheets

Source Title	A Study on Recent Developments and Issues with Obstacle Detection Systems for Automated Vehicles
Source citation (APA Format)	Yu, X., & Marinov, M. (2020). A Study on Recent Developments and Issues with Obstacle Detection Systems for Automated Vehicles. *Sustainability*, *12*(8), 3281. https://doi.org/10.3390/su12083281
Original URL	**https://doi.org/10.3390/su12083281**
Source type	Journal Article
Keywords	Automated vehicles, review, obstacle detection, urban areas, technology, weather conditions

Summary of key points + notes (include methodology)	Focused on the section on sensors in weather
	Key points:
	- 50% of disengagement location breakdown occurs in urban areas
	    ○ Location of most variable and complex structures
	- Only 17% breakdowns due to weather
	- Laser sensors have poor performance in bad weather
	    ○ Small water droplets reflect light – false alarms
	- In fog, visibility inversely scales with temperature
	- Snowy weather greatly decreases quality of camera and lidar sensor data.
	- Snow can create “phantom obstacles”
	Methods:
	- Divide parameters into light levels and weather conditions
	- Use automatic rain removal technique
	    ○ Coefficient values less than 0.5 are replaced by 0
	        ▪ Gets rid of abrupt light spots created by rain
	- Use infrared sensor for foggy environments
	- Avoid phantom obstacles by using LGPR (localizing ground-penetrating radar)
	    ○ Involves additional equipment
	        ▪ Tubes + radar sensor on the bottom of the car

Research Question/Problem/ Need	How have obstacle detection systems changed in autonomous vehicles, and how have they been good or bad?
Important Figures	 **Figure 7.** The close-to-ideal layout of sensors [17]. This figure shows the optimal sensor positions and types for a car, demonstrating how different types of sensors have drastically different ranges and uses.
VOCAB: (w/definition)	- Radar: A medium to long range sensor that is relatively resistant to weather, but has a low resolution. - Lidar: A short to long range sensor that is affected by bad weather, but has high resolution depth sensing. - Ultrasound: A short range sensor with low cost and fast response times. - Camera: A sensor heavily affected by weather, but able to provide the full picture. - Infrared: A wavelength of light that, when incorporated into sensors, allows many sensors to function at night.
Cited references to follow up on	Wang, H.; Wang, B.; Liu, B.; Meng, X.; Yang, G. Pedestrian recognition and tracking using 3D LiDAR for autonomous. Robot. Auton. Syst. 2017, 88, 71–78. [CrossRef] https://doi.org/10.1016/j.robot.2016.11.014 Rasshofer, R.H.; Gresser, K. Automotive radar and lidar systems for next generation driver assistance functions. Adv. Radio Sci. 2005, 3, 205–209. [CrossRef] https://doi.org/10.5194/ars-3-205-2005
Follow up Questions	How dependent are these sensing methods to road specific cues? Can these cues be retrained for more abstract environments? Can the LGPR antenna be smaller, or utilized on a more erratic subject?

Article #11 Notes: Multiple target detection using photonic radar for autonomous vehicles under atmospheric rain conditions

Article notes should be on separate sheets

Source Title	Multiple target detection using photonic radar for autonomous vehicles under atmospheric rain conditions
Source citation (APA Format)	Chaudhary, S., Khichar, S., Meng, Y., & Sharma, A. (2025). Multiple target detection using photonic radar for autonomous vehicles under atmospheric rain conditions. *PLOS One*, *20*(5), e0322693. https://doi.org/10.1371/journal.pone.0322693
Original URL	https://doi.org/10.1371/journal.pone.0322693
Source type	Journal Article
Keywords	Radar, Rain, Turbulence, Signal Processing, Signal Bandwidth, Electromagnetic Interference, Light, Weather.

Summary of key points + notes (include methodology)	Key Points:
	- Photonic radar systems are promising, but heavily impacted by environment.
	    o Photonic uses modulated laser light instead of microwaves.
	- Rain a large influence – heavy rain decreasing received power of just 50 meters by 1 dBm.
	- Gamma-Gamma atmospheric turbulence introduces variability into the data.
	    o Gamma-Gamma being a form of turbulence modeling
	Methods:
	- Created a simulation model of a photonic radar system within empty and various environmental conditions
	    o “regular” environment modeled assuming no interference
	    o Random turbulence added through the addition of a Gamma-Gamma model
	    o Rain influence added through preset attenuation constants for various levels of rain.
	- Simulations modeled in python.

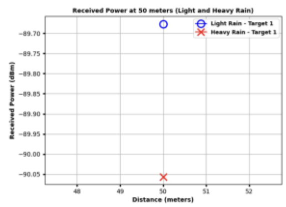
<table>
<tr><td>Research Question/Problem/ Need</td><td>How are photonic radar sensors affected by various environmental factors?</td></tr>
<tr><td>Important Figures</td><td>


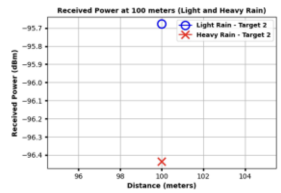
Fig 7. Received power at 50 meters for Target 1 under light rain and heavy rain conditions.


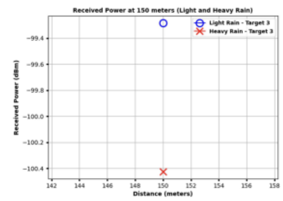
Fig 8. Received power at 100 meters for Target 2 under light rain and heavy rain conditions.


Fig 9. Received power at 150 meters for Target 3 under light rain and heavy rain conditions.
These figures show how different rain levels can affect object detection at different distances, with lower received powers indicating a greater degradation of signal.</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>
- Photonic radar: A type of radar sensor using optics, such as laser light, instead of the regular electronic signals.
- Gamma-Gamma atmospheric turbulence: A specific distribution widely used to model turbulence’s effects on optical intensity.
- Photons: Light.
- FMCW radar: A radar technique in which chirped signals are used for precise range and speed measurement.
- Bandwidth: The range of frequencies that can be detected by a sensor.</td></tr>
<tr><td>Cited references to follow up on</td><td>Yeong DJ, Velasco-Hernandez G, Barry J, Walsh J. Sensor and Sensor Fusion Technology in Autonomous Vehicles: A Review. Sensors (Basel). 2021;21(6):2140. https://doi.org/10.3390/s21062140 PMID: 33803889

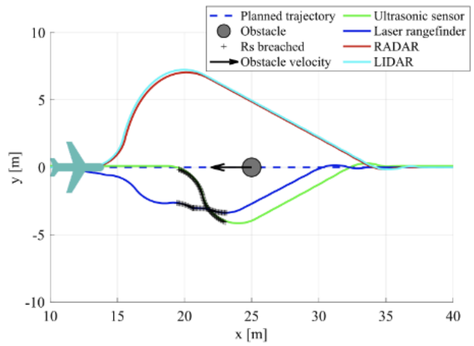
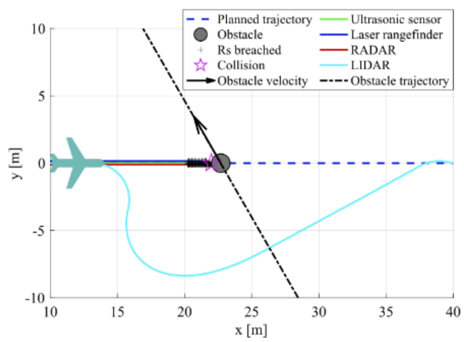
A. C. Sankaranarayanan, A. Veeraraghavan and R. Chellappa, "Object Detection, Tracking and Recognition for Multiple Smart Cameras," in Proceedings of the IEEE, vol. 96, no. 10, pp. 1606-1624, Oct. 2008, doi: 10.1109/JPROC.2008.928758.</td></tr>
<tr><td>Follow up Questions</td><td>Can computer modeling be extended to the prediction of other sensors’ performance?

How accurate are the predictions generated from this strategy?</td></tr>
</table>

Article #12 Notes: Optimal Multi-Sensor Obstacle Detection System for Small Fixed-Wing UAVs

Article notes should be on separate sheets

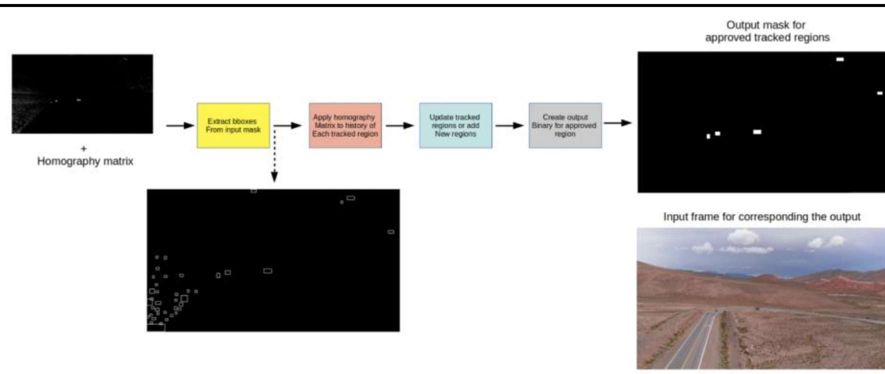
Source Title	Optimal Multi-Sensor Obstacle Detection System for Small Fixed-Wing UAVs
Source citation (APA Format)	Portugal, M., & Marta, A. C. (2024). Optimal Multi-Sensor Obstacle Detection System for Small Fixed-Wing UAVs. *Modelling*, *5*(1), 16-36. https://doi.org/10.3390/modelling5010002
Original URL	https://doi.org/10.3390/modelling5010002
Source type	Journal Article
Keywords	Sense and avoidance, collision avoidance, optimization, ultrasonic sensor, laser rangefinder, LIDAR, RADAR
Summary of key points + notes (include methodology)	Key Points: - LIDAR + two rangefinders or LIDAR + two RADARs is most optimal - Ultrasonic is least optimal - LIDAR and RADAR are good because of wide FOV Methods: - Simulation was developed to test different configurations - Ultrasonic, Rangefinder, LIDAR, RADAR - Genetic algorithm to optimize random configurations - Generated simulations in progressively more detailed approaches
Research Question/Problem/ Need	What are the best sensors and configurations for small flying autonomous vehicle object detection?

Important Figures	 (**a**) A head-on collision.  (**b**) A 60° angled collision. **Figure 9.** UAV collision avoidance response to obstacle detection when equipped with different sensors. This figure shows how different sensors react to the appearance of an obstacle. This is important as it visualizes how different the sensors are, and what drawbacks certain sensors contain.
VOCAB: (w/definition)	- UAV: Abbreviation for Unmanned Aircraft System - Laser Rangefinder: A similar sensor to a LIDAR sensor, except operating on a single point instead of a range of points. - LIDAR: A short to long range sensor that is affected by bad weather, but has high resolution depth sensing. - RADAR: A medium to long range sensor that is relatively resistant to weather, but has a low resolution. - Kalman Filter: An algorithm that takes a noisy input over time to predict the true state of the input.
Cited references to follow up on	Saunders, J.; Call, B.; Curtis, A.; Beard, R.; McLain, T. Static and dynamic obstacle avoidance in miniature air vehicles. In Proceedings of the Infotech@Aerospace, Arlington, VA, USA, 26–29 September 2005. [Google Scholar] [CrossRef] Skowron, M.; Chmielowiec, W.; Glowacka, K.; Krupa, M.; Srebro, A. Sense and avoid for small unmanned aircraft systems: Research on methods and best practices. *Proc. Inst. Mech. Eng. Part G J. Aerosp. Eng.* 2019, *233*, 6044–6062. [Google Scholar] [CrossRef]
Follow up Questions	How can this be applied to ground vehicles?

	How much are these systems affected by weather?

Article #13 Notes: Moving object detection method with motion regions tracking in background subtraction

Article notes should be on separate sheets

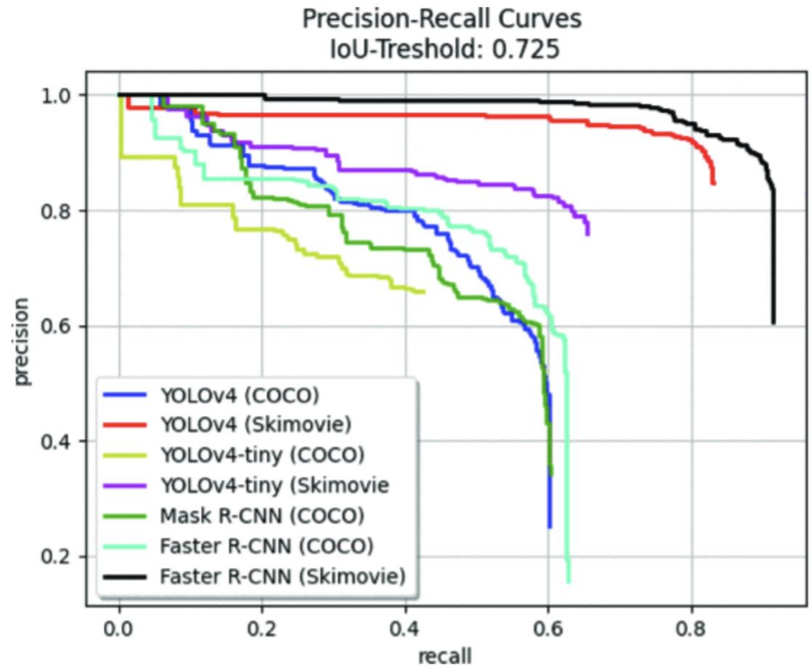
Source Title	Moving object detection method with motion regions tracking in background subtraction
Source citation (APA Format)	Delibaşoğlu, İ. Moving object detection method with motion regions tracking in background subtraction. *SIViP* 17, 2415–2423 (2023). https://doi-org.ezpv7-web-p-u01.wpi.edu/10.1007/s11760-022-02458-y
Original URL	https://doi.org/10.1007/s11760-022-02458-y
Source type	Journal Article
Keywords	Computer Vision, image processing, methedology of data collection and processing, motion detection, motion perception, object recognition
Summary of key points + notes (include methodology)	Notes: - This new strategy of object detection with a camera is better than average - Reliable across many different footage qualities - Small problem with false detections Methods: - Data from publicly available PESMOD dataset - Tested different values for accuracy - Higher accuracy means better movement detection
Research Question/Problem/ Need	Is moving object detection better with a different form of object isolation and background subtraction?
Important Figures	 Block diagram and sample output of motion region tracking This figure shows the layout of the object detection system, demonstrating how the program identifies important areas.

VOCAB: (w/definition)	- Homography: Am mathematical mapping of one plane to another. - MCD Method:A method of background subtraction aiming to prevent contamination of foreground pixels into background through Gaussian functions. - SCBU Method: A method of background subtraction using threshhold values. - BSDOF Method: A method of background modeling evaluated using a specific dataset. - Salient object detection: Detection of objects using analysis on batches of frames.
Cited references to follow up on	Moo Yi, K., Yun, K., Wan Kim, S., Jin Chang, H., Young Choi, J.: Detection of moving objects with non-stationary cameras in 5.8 ms: bringing motion detection to your mobile device. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 27–34 (2013) Heikkilä, M., Pietikäinen, M., Heikkilä, J.: A texture-based method for detecting moving objects. In: BMVC, vol. 401, pp. 1–10. Citeseer (2004)
Follow up Questions	Can other sensors be added to this to improve detection? How high quality do the sensors need to be for this to function?

Article #14 Notes: Evaluation of Object Detection Systems and Video Tracking in Skiing Videos

Article notes should be on separate sheets

Source Title	Evaluation of Object Detection Systems and Video Tracking in Skiing Videos
Source citation (APA Format)	P. Steinkellner and K. Schöffmann, "Evaluation of Object Detection Systems and Video Tracking in Skiing Videos," *2021 International Conference on Content-Based Multimedia Indexing (CBMI)*, Lille, France, 2021, pp. 1-6, doi: 10.1109/CBMI50038.2021.9461905.
Original URL	https://doi.org/10.1109/CBMI50038.2021.9461905
Source type	Conference Paper
Keywords	Convolutional neural network; Deep learning; Video tracking; Tracking; Object detection; Snowboarding
Summary of key points + notes (include methodology)	Notes: - Preexisting MS COCO models are already good - YOLOv4 is slightly worse but faster - Tracking algorithm works over long periods o Good at telling skiers apart Methods: - Evaluate and compare object detection models – 7 different models - Modify a tracking system to better evaluate skiing performance - Use Skimovie train dataset
Research Question/Problem/ Need	How can we improve or create a autonomous way of tracking performance?

Important Figures	 This figure shows the accuracy of the different detection strategies, informing the reader of the best identification strategies over long periods of tme.
VOCAB: (w/definition)	- Precision: Proportion of true predicted correct results. - Recall: Proportion of true correctly guessed results. - Convolutional layers: A layer applying filters to identify shapes. - Logistic regression: A statistical model. - Feature map: A plot of object or point values.
Cited references to follow up on	Matteo Dunnhofer, Luca Sordi, Niki Martinel, Christian Micheloni, "Tracking Skiers from the Top to the Bottom", *2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pp.8496-8506, 2024. Matteo Dunnhofer, Luca Sordi, Christian Micheloni, "Visualizing Skiers' Trajectories in Monocular Videos", *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp.5188-5198, 2023.
Follow up Questions	How do different types of sensor models affect this? Can this strategy be adapted to object detection?

Article #15 Notes: Incidence of skiing and snowboarding injuries over six winter seasons (2012 - 2018) in Japan

Article notes should be on separate sheets

Source Title	Incidence of skiing and snowboarding injuries over six winter seasons (2012 - 2018) in Japan
Source citation (APA Format)	Kuzuhara, K., Shibata, M., & Iguchi, J. (2021). Incidence of skiing and snowboarding injuries over six winter seasons (2012-2018) in Japan. *Journal of Physical Education and Sport, 21*(1), 73-80. https://doi.org/10.7752/jpes.2021.01010
Original URL	https://doi.org/10.7752/jpes.2021.01010
Source type	Journal Article
Keywords	Skiing; Snowboarding; Fracture; Injury; Bruise; Japan
Summary of key points + notes (include methodology)	Notes: - 1.59 ski injuries and 2.48 snowboard injuries every 1000 days. - Mostly knee injuries for skiing - Serious injuries can occur. Methods: - Survey skiing and snowboarding injuries at ski resorts in Japan - Standardize to # of injuries per 1000 days - Data published by Japan Association for Skiing Safety
Research Question/Problem/ Need	How dangerous is skiing and snowboarding, and in what ways are they dangerous.

Important Figures

Table 3. Skier-related factors for skiing and snowboarding injuries from 2012-2013 to 2017-2018 seasons

Factors	Skiing			Snowboarding			IRR (95%CI) (Snowboarding: Skiing)	P-Value
	N	%	IR (95%CI)	N	%	IR (95%CI)		
Age								
< 10	518	6.9	0.11 (0.10-0.12)	146	1.3	0.03 (0.03-0.04)	0.32 (0.27-0.39)	P<0.001
10-19	1558	20.7	0.32 (0.31-0.34)	1752	15.8	0.41 (0.39-0.43)	1.28 (1.19-1.37)	P<0.001
20-29	1284	17.0	0.26 (0.25-0.28)	6305	56.7	1.48 (1.44-1.51)	5.58 (5.26-5.93)	P<0.001
30-39	766	10.2	0.16 (0.15-0.17)	2023	18.2	0.47 (0.45-0.49)	3.00 (2.76-3.26)	P<0.001
40-49	1204	16.0	0.25 (0.23-0.26)	678	6.1	0.16 (0.15-0.17)	0.64 (0.58-0.70)	P<0.001
50-59	1007	13.4	0.21 (0.19-0.22)	167	1.5	0.04 (0.03-0.05)	0.19 (0.16-0.22)	P<0.001
≧60	1201	15.9	0.25 (0.23-0.26)	44	0.4	0.01 (0.01-0.01)	0.04 (0.03-0.06)	P<0.001
Sex								
Male	4312	52.9	0.89 (0.86-0.92)	6509	61.7	1.53 (1.49-1.56)	1.72 (1.65-1.78)	P<0.001
Female	3845	47.1	0.79 (0.77-0.82)	4045	38.3	0.95 (0.92-0.98)	1.20 (1.14-1.25)	P<0.001
Self-Reported Skill Level								
Novice	615	8.3	0.13 (0.12-0.14)	1090	10.1	0.26 (0.24-0.27)	2.02 (1.83-2.22)	P<0.001
Beginner	2394	32.3	0.49 (0.47-0.51)	4572	42.2	1.07 (1.04-1.10)	2.17 (2.07-2.28)	P<0.001
Intermediate	2818	38.0	0.58 (0.56-0.60)	4164	38.4	0.98 (0.95-1.01)	1.68 (1.60-1.76)	0.8338
Advanced	1550	20.9	0.32 (0.30-0.34)	975	9.0	0.23 (0.21-0.24)	0.72 (0.66-0.77)	P<0.001
Others	32	0.4	0.01 (0.00-0.01)	33	0.3	0.01 (0.01-0.01)	1.17 (0.72-1.91)	0.1568
Behavior before Injury Event								
Self sliding	5963	79.1	1.23 (1.20-1.26)	10727	97.0	2.51 (2.47-2.56)	2.05 (1.98-2.11)	P<0.001
School Events	796	10.6	0.16 (0.15-0.18)	112	1.0	0.03 (0.02-0.03)	0.16 (0.13-0.19)	P<0.001
Lessons	352	4.7	0.07 (0.06-0.08)	118	1.1	0.03 (0.02-0.03)	0.38 (0.31-0.47)	P<0.001
Athletic Events	333	4.4	0.07 (0.06-0.08)	32	0.3	0.01 (0.00-0.01)	0.11 (0.08-0.16)	P<0.001
Others	99	1.3	0.02 (0.02-0.02)	74	0.7	0.02 (0.01-0.02)	0.85 (0.63-1.15)	P<0.001
Helmet Use								
Use	2251	30.6	0.46 (0.44-0.48)	1337	12.3	0.31 (0.30-0.33)	0.68 (0.63-0.72)	P<0.001
No use	5112	69.4	1.05 (1.02-1.08)	9520	87.7	2.23 (2.19-2.26)	2.12 (2.05-2.19)	P<0.001

IR: injury rate, IRR: incidence rate ratio, CI: confidence

This figure shows data on injury rates, one important fact being how most injuries involve wearing no homework.

VOCAB: (w/definition)

- Skier Day: A full day of skiing for one skier.
- Groomed Slope: A slope, having been raked to make the surface uniform.
- Skiing: A winter sport involving quickly going down hills with two skis
- Snowboarding: A winter sport involving quickly going down hills with one board.
- Season: A year of skiing, starting when skiing conditions are suitable.

Cited references to follow up on

Ackery, A., Hagel, B. E., Provvidenza, C., & Tator, C. H. (2007). An international review of head and spinal cord injuries in alpine skiing and snowboarding. Injury Prevention, 13(6), 368-375. doi:10.1136/ip.2007.017285

Bianchi, G., Brugger, O., & Niemann, S. (2017). Skiing and snowboarding in Switzerland: Trends in injury and fatality rates over time. Snow Sports Trauma and Safety, 29-39.

Follow up Questions

How much of not wearing safety equipment adds to the injury rates?

Are injury rates influenced by visibility?

Article #16 Notes: Injuries among children and adults in alpine skiing and snowboarding

Article notes should be on separate sheets

<table>
<tr><td>Source Title</td><td>Injuries among children and adults in alpine skiing and snowboarding</td></tr>
<tr><td>Source citation (APA Format)</td><td>Ekeland, A., Rødven, A., & Heir, S. (2019). Injuries among children and adults in alpine skiing and snowboarding. Journal of Science and Medicine in Sport, 22, S3–S6. https://doi.org/10.1016/j.jsams.2018.07.011</td></tr>
<tr><td>Original URL</td><td>https://doi.org/10.1016/j.jsams.2018.07.011</td></tr>
<tr><td>Source type</td><td>Journal Article</td></tr>
<tr><td>Keywords</td><td>Age, Skiing, Skiing/Boarding Trauma, Snowboarding, Tibia Fracture</td></tr>
<tr><td>Summary of key points + notes (include methodology)</td><td>Notes:
- Shoulder injuries are 2x as common in adults than in children when skiing
- Wrist/leg fractures are common in children and can be reduced by skiing ability
- 7695 skiers + 8705 boarders recorded
Methods:
- Injuries in 14 major Norwegian ski resorts recorded by ski patroller
- Injury defined as an injury treated/consulted by ski patrol.
- Skill for skiers determined by test, self-estimated for boarders.</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>Are injury locations and frequencies different between children and adults in skiing and snowboarding?</td></tr>
<tr><td>Important Figures</td><td>Table 1
Ability for children and adult alpine skiers and snowboarders. n = number of injured skiers and boarders. Significant higher ability among adults than children both for alpine skiers and for snowboarders (p < 0.001).
<table>
<tr><th>Ability</th><th colspan="2">Alpine skiers</th><th colspan="2">Snowboarders</th></tr>
<tr><th></th><th>Children ≤12 years
n = 1178</th><th>Adults ≥20 years
n = 1989</th><th>Children ≤12 years
n = 243</th><th>Adults ≥20 years
n = 841</th></tr>
<tr><td>Beginner</td><td>31%</td><td>15%</td><td>29%</td><td>14%</td></tr>
<tr><td>Intermediate</td><td>34%</td><td>33%</td><td>36%</td><td>25%</td></tr>
<tr><td>Advanced</td><td>25%</td><td>33%</td><td>27%</td><td>38%</td></tr>
<tr><td>Expert</td><td>9%</td><td>18%</td><td>8%</td><td>23%</td></tr>
</table>
This figure shows the distribution of skill in injured patients, helping to get a better picture on how expertise affects chances of injury.</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>- Skier Day: A full day of skiing for one skier.
- Groomed Slope: A slope, having been raked to make the surface uniform.
- Skiing: A winter sport involving quickly going down hills with two skis
- Snowboarding: A winter sport involving quickly going down hills</td></tr>
</table>

	with one board. - Season: A year of skiing, starting when skiing conditions are suitable.
Cited references to follow up on	Kim S, Endres NK, Johnson RJ et al. Snowboarding injuries. Trends over time and comparisons with alpine skiing injuries. Am J Sports Med 2012; 40(4):770–776. Ekeland A, Rødven A. Injuries in alpine skiing, telemarking, snowboarding and skiboarding related to gender and ability, In: Johnson RJ, Shealy JE, Ahlbäumer MG, editors. Skiing Trauma and Safety, vol 15. West Conshohocken, ASTM STP 1464, 2005, p. 31–39.
Follow up Questions	How can the location of injury show the cause of the injury? How do these numbers compare to the general attending population?

Article #17 Notes: Incidence of Recreational Alpine Skiing and Snowboarding Injuries: Six Years Experience in the Largest Ski Resort in Finland

Article notes should be on separate sheets

Source Title

Incidence of Recreational Alpine Skiing and Snowboarding Injuries: Six Years Experience in the Largest Ski Resort in Finland

Source citation (APA Format)

Stenroos, A., Handolin, L. (2014). *Incidence of Recreational Alpine Skiing and Snowboarding Injuries: Six years experience in the largest ski resort in Finland*. (n.d.). https://doi.org/10.1177/1457496914532249

Original URL

https://doi.org/10.1177/1457496914532249

Source type

Journal Article

Keywords

Skiing, Snowboarding, Injury, Incidence

Summary of key points + notes (include methodology)

Notes:
- Sport provides high risk of injury
- Common injuries: knee, wrist
- 2911 injuries over the 6-year period.

Methods:
- 6 seasons
- Injury: any injury received while skiing or in lift
- Emergency responder team takes note of every event + related data

Research Question/Problem/ Need

How common are injuries while skiing, and what is most urgent to be solved?

Important Figures

TABLE 2

Injured body area and proportion of severe Grade 3 injuries regarding the mechanism of injury in skiers (clavicle bone injury was classified as upper extremity injury) and snowboarders.

Injured body area	Fall on the same level: Grade 3 (%)	Loss of control in jump: Grade 3 (%)	Collision with another person: Grade 3 (%)	Collision with immovable object: Grade 3 (%)
Skiers (total of 1911 injured persons)				
Lower extremity	14	26	14	35
Upper extremity	10	24	16	13
Spine	30	32	10	50
Head	6	21	5	5
Abdomen/thorax	5	17	–	13
Total	12	24	10	18
Snowboarders (total of 893 injured persons)				
Lower extremity	6	10	9	60
Upper extremity	7	26	17	11
Spine	20	41	33	25
Head	9	23	25	–
Abdomen/thorax	22	22	–	33
Total	616 (8)	216 (25)	24 (16)	26 (26)

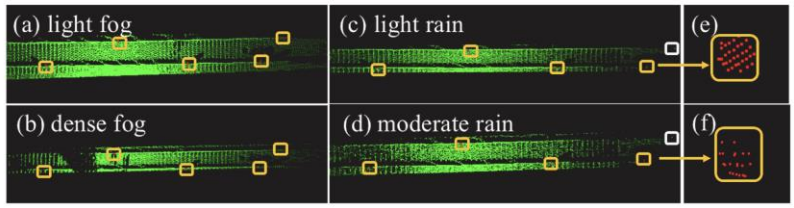
This figure shows the position and context of the injuries, helping to give a

	sense of how the injury occurred.
VOCAB: (w/definition)	- Skier Day: A full day of skiing for one skier. - Groomed Slope: A slope, having been raked to make the surface uniform. - Skiing: A winter sport involving quickly going down hills with two skis - Snowboarding: A winter sport involving quickly going down hills with one board. - Season: A year of skiing, starting when skiing conditions are suitable.
Cited references to follow up on	Johnson B, Ettlinger C, Shealy JE: Update on injury trends in alpine skiing. J ASTM Int 2009;17:11–22. Davidson TM, Laliotis A: Alpine skiing injuries—A nine year study. West J Med 1996;164(4):310–314.
Follow up Questions	What are the skill levels of the people getting injured? How do the different modes of injury effect later skiing?

Article #18 Notes: LiDAR-Camera Joint Obstacle Detection Algorithm for Railway Track Area

Article notes should be on separate sheets

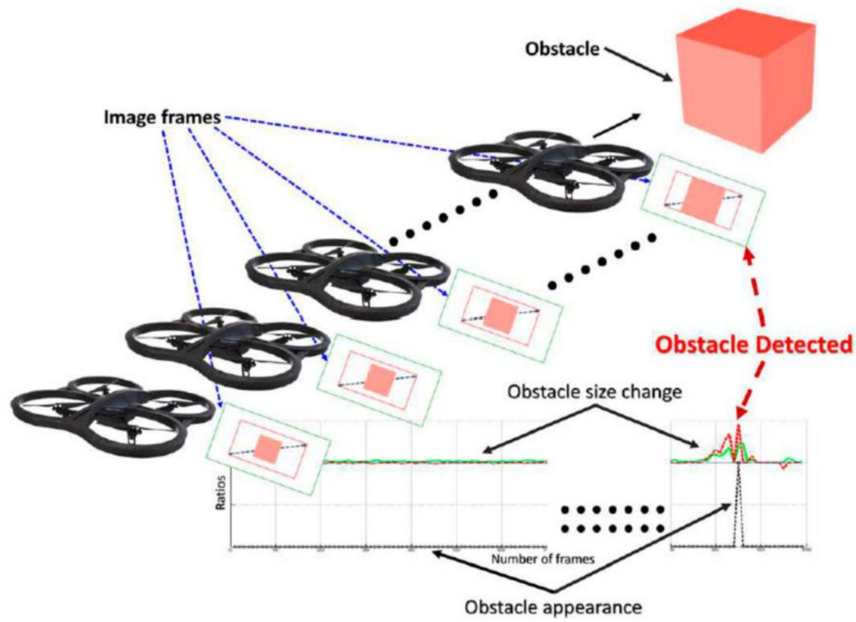
Source Title	LiDAR-Camera Joint Obstacle Detection Algorithm for Railway Track Area
Source citation (APA Format)	Nan, Z., Liu, W., Zhu, G., Zhao, H., Xia, W., Lin, X., & Yang, Y. (2025). LiDAR-Camera joint obstacle detection algorithm for railway track area. *Expert Systems with Applications*, *275*, 127089. https://doi.org/10.1016/j.eswa.2025.127089
Original URL	https://doi.org/10.1016/j.eswa.2025.127089
Source type	Journal Article
Keywords	LiDAR; Camera; ROI; Data fusion; MS-YOLO-DLKA
Summary of key points + notes (include methodology)	Notes: - Integrated system results in an 85% accuracy of object detection - Minimum size of 10 cm cubed - Consists of a camera and lidar scanner positioned close together - Camera detects the image of object, Lidar detects abnormal reflections. Methods: - Uses camera and lidar together for object detection - Multimodal – combines data - Various methods of filtering tested - Various conditions tested - Calibrated with a black and white grid
Research Question/Problem/ Need	Can cameras and LIDAR sensors be used to determine the danger of a obstacle obstructing a track?

Important Figures	 **Fig. 14.** The detection results of irregular stones under different weather conditions: As the weather conditions deteriorate, it will gradually affect the imaging features of the orbital area (Fig. 14 (b) and (d)), making the imaging points of the point cloud on obstacles become sparse (Fig. 14 (e) – (f)). This figure shows how the multimodal system deals with various conditions, showing how data becomes sparser with worse conditions.
VOCAB: (w/definition)	- Lidar: A short to long range sensor that is affected by bad weather, but has high resolution depth sensing. - Camera: A sensor heavily affected by weather, but able to provide the full picture. - OD: Obstacle Detection - Point Cloud: A representation of a 3d surface through a cloud of points at specific spots. - Cluster: A group of connected points
Cited references to follow up on	Abdelfattah, M., Yuan, K., Wang, Z. J., & Ward, R. (2023). Multi-Modal Streaming 3D Object Detection. IEEE Robotics and Automation Letters, 8(10), 6163–6170. https:// doi.org/10.1109/LRA.2023.3303696 Asvadi, A., Peixoto, P., Nunes, U., & Ieee. (2015). Detection and Tracking of Moving Objects Using 2.5D Motion Grids 2015 IEEE 18TH INTERNATIONAL CONFERENCE ON INTELLIGENT TRANSPORTATION SYSTEMS,.
Follow up Questions	Does this system have to be fixed at the tracks, or is it possible to make the system mobile? Can this system detect moving targets?

Article #19 Notes: **Image-Based Obstacle Detection Methods for the Safe Navigation of Unmanned Vehicles: A Review**

Article notes should be on separate sheets

Source Title	Image-Based Obstacle Detection Methods for the Safe Navigation of Unmanned Vehicles: A Review
Source citation (APA Format)	Badrloo, S., Varshosaz, M., Pirasteh, S., & Li, J. (2022). Image-Based Obstacle Detection Methods for the Safe Navigation of Unmanned Vehicles: A Review. *Remote Sensing*, *14*(15), 3824. https://doi.org/10.3390/rs14153824
Original URL	https://doi.org/10.3390/rs14153824
Source type	Journal Article
Keywords	obstacle detection; image-based; UAV; MAVs; deep learning methods
Summary of key points + notes (include methodology)	Points: - Most challenging issue is detecting small, fast, and moving obstacles - Deep learning is bad at new/complicated environments - Lidar is popular but inconvenient in size - Scale and variability of sensor values can be used to determine object proximity - Two types of detection: monocular, stereo o Monocular – generally limited to environments with clear distinction between object and background o Stereo – very complicated to compute, sensitive to illumination, difficult to calibrate. - Need to research high speed object detection Methods: No methods
Research Question/Problem/ Need	How can autonomous vehicles be made to detect obstacles by themselves?

Important Figures	 **Figure 4.** The change in obstacle size is demonstrated by approaching it [35]. This figure shows how a sensor can use ratios between values to determine true distance, as different types of variables change differently.
VOCAB: (w/definition)	- Monocular: the use of a single sensor to collect data - Stereo: the use of two sensors working together to gather data - Proximity: How close an object is - Neural network: An artificial system using programmed nodes. - Synchronized: working at the same time.
Cited references to follow up on	Barry, A.J.; Florence, P.R.; Tedrake, R. High-speed autonomous obstacle avoidance with pushbroom stereo. J. Field Robot. 2018, 35, 52–68. [CrossRef] Yılmaz, E.; Özyer, S.T. Remote and Autonomous Controlled Robotic Car based on Arduino with Real Time Obstacle Detection and Avoidance. Univers. J. Eng. Sci. 2019, 7, 1–7. [CrossRef]
Follow up Questions	Can stereo systems be expanded to recalibrate themselves? Can LIDAR be beneficial even as a simple single point sensor?

Article #20 Notes: Real Time Lidar and Radar High-Level Fusion for Obstacle Detection and Tracking with evaluation on a ground truth

Article notes should be on separate sheets

Source Title	Real Time Lidar and Radar High-Level Fusion for Obstacle Detection and Tracking with evaluation on a ground truth
Source citation (APA Format)	Hajri, H., & Rahal, M.-C. (2019). *Real Time Lidar and Radar High-Level Fusion for Obstacle Detection and Tracking with evaluation on a ground truth* (No. arXiv:1807.11264). arXiv. https://doi.org/10.48550/arXiv.1807.11264
Original URL	https://doi.org/10.48550/arXiv.1807.11264
Source type	Journal Article
Keywords	LIDAR, RADAR, Multimodal, Obstacle Detection
Summary of key points + notes (include methodology)	Points: - Algorithm was successful - Based on the GNN filter - Outputs relative position, velocity, and uncertainty - Fusion makes the sensor system robust against failure Methods: - Created an algorithm to merge and interpret the data - Kalman filter - Tested just lidar, just radar, and multimodal in all scenarios - Tracking a car in a straight line - Tracking a car through a bend - Plotted and compared values

<table>
<tr><td>Research Question/Problem/ Need</td><td>Can lidar and radar sensors be used together to improve object detection?</td></tr>
<tr><td>Important Figures</td><td>

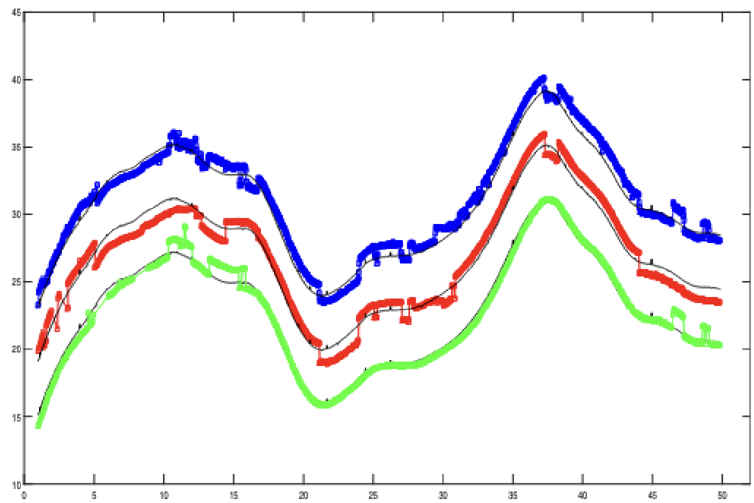


Fig. 4: variations of x (in m) with Radar (green)/Lidar (red)/Fusion (blue) in comparison with RTK (black) as a function of time (in s). Offset=4.

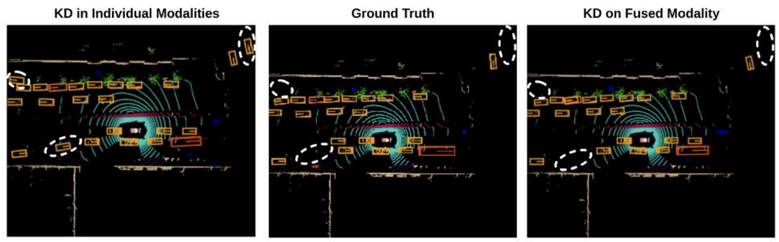
This figure shows the differences in measurements between radar, lidar, and multimodality. By doing this, it is easy to see how the values become different, affecting the final detection.
</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>

- GNN filter: the Global Nearest Neighbor standard filter
- Multimodal: Using multiple sensor inputs
- Kalman filter: An algorithm that takes a noisy input over time to predict the true state of the input.
- RTK sensors: Real Time Kinematic sensors
- Lidar: A short to long range sensor that is affected by bad weather, but has high resolution depth sensing.
- Radar: A system of sending pulses of electromagnetic waves, measuring the reflected waves to detect the presence of objects.
</td></tr>
<tr><td>Cited references to follow up on</td><td>D. L. Hall and S. A. H. McMullen, Mathematical Techniques in Multisensor Data Fusion. Artech House, 2004.
H. B. Mitchell, Multi-Sensor Data Fusion: An Introduction, 1st ed. Springer Publishing Company, Incorporated, 2007.</td></tr>
<tr><td>Follow up Questions</td><td>What are the computing limitations of the system?
How is the system affected by weather?</td></tr>
</table>

Article #21 Notes: IMKD: Intensity-Aware Multi-Level Knowledge Distillation for Camera-Radar Fusion

Article notes should be on separate sheets

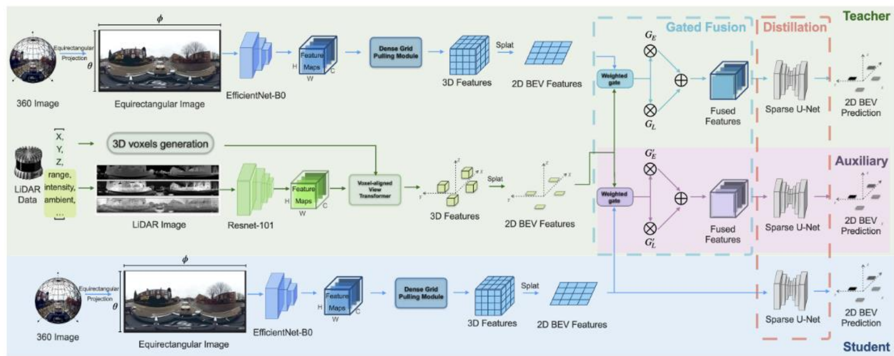
Source Title	IMKD: Intensity-Aware Multi-Level Knowledge Distillation for Camera-Radar Fusion
Source citation (APA Format)	Mishra, S., Patil, K., Stricker, D., & Rambach, J. (2025). *IMKD: Intensity-Aware Multi-Level Knowledge Distillation for Camera-Radar Fusion* (No. arXiv:2512.15581). arXiv. https://doi.org/10.48550/arXiv.2512.15581
Original URL	https://doi.org/10.48550/arXiv.2512.15581
Source type	Journal Article
Keywords	Camera, Radar, Multimodal, Knowledge Distillation
Summary of key points + notes (include methodology)	Notes: - IMKD is better than any baseline multimodal system - IMKD does not require any specific sensor pairs - IMKD is the first distillation based fusion framework Methods: - Extracts the various data types - Runs data through convolutional layers - Constructs a distilled spatially-weighted response - Experiments: o Implemented a Lidar "teacher" o Tested effectiveness - Analysis proves robustness
Research Question/Problem/ Need	How can sensor types be combined without sacrificing the benefit brought by one or the other?

Important Figures	 Figure 4. Comparison of distillation targets: individual modality KD yields extra false detections (white circles) and poor orientation, while merged feature KD aligns better with ground truth. This figure shows the slight differences that can come from slight differences in data management, where fusing modalities provide much better sensors.
VOCAB: (w/definition)	- Knowledge Distillation: To concentrate the important data - Radar: A system of sending pulses of electromagnetic waves, measuring the reflected waves to detect the presence of objects. - IMKD: Intensity-guided Multi-level Knowledge Distillation framework for radar-camera 3D object detection. - BEV: Bird's Eye View - Multimodal: Using multiple sensor inputs.
Cited references to follow up on	Holger Caesar, Varun Bankiti, Alex H Lang, Sourabh Vora, Venice Erin Liong, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, and Oscar Beijbom. nuscenes: A multimodal dataset for autonomous driving. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 11621–11631, 2020. 2, 6, 7, 8, 4, 5, 9, 10 Zehui Chen, Zhenyu Li, Shiquan Zhang, Liangji Fang, Qinhong Jiang, and Feng Zhao. Bevdistill: Cross-modal bev distillation for multi-view 3d object detection. arXiv preprint arXiv:2211.09386, 2022. 2, 6, 7
Follow up Questions	How does this system respond to bad weather? How many different sensor inputs can this system take at once?

Article #22 Notes: KD360-VoxelBEV: LiDAR and 360-degree Camera Cross Modality Knowledge Distillation for Bird's-Eye-View Segmentation

Article notes should be on separate sheets

Source Title	KD360-VoxelBEV: LiDAR and 360-degree Camera Cross Modality Knowledge Distillation for Bird's-Eye-View Segmentation
Source citation (APA Format)	E, W., Sun, Y., Liu, J., Shum, H. P. H., Atapour-Abarghouei, A., & Breckon, T. P. (2025). *KD360-VoxelBEV: LiDAR and 360-degree Camera Cross Modality Knowledge Distillation for Bird's-Eye-View Segmentation* (No. arXiv:2512.15311). arXiv. https://doi.org/10.48550/arXiv.2512.15311
Original URL	https://doi.org/10.48550/arXiv.2512.15311
Source type	Journal Article
Keywords	BEV, LIDAR, Camera, Multimodal, Knowledge Distillation
Summary of key points + notes (include methodology)	Notes: - Current BEVs either are very complicated due to multiple cameras or low quality because of a low pixel count from a 360° camera. - Lidar sensor added to provide needed detail - Creates a framework tailored to construct a BEV segmentation from a panoramic camera input - Outperforms existing camera-based designs - Runs in real time Methods: - Redistributes lidar data points into a shape suitable for combination with camera - Teacher: Lidar and 360° camera branches joined through a soft gated mechanism - Fuse at the BEV level

	- Student: only camera - Experiment: train and test against datasets ○ Ablation studies
Research Question/Problem/ Need	Can lidar be used with camera sensors to make an efficient bird's-eye-view display?
Important Figures	 Figure 4. **Overview of the proposed *KD360-VoxelBEV* architecture. Teacher network (green):** equipped with the **SGFM (blue dashed block**), which integrates LiDAR range, intensity, and ambient cues with 360-degree camera features to produce enriched BEV representations. **AM (pink):** fuses the Student and pre-trained LiDAR branch during training to reduce the feature gap between Teacher and Student, providing additional reliable guidance. **Student network (blue):** a camera-only BEV segmentation model that benefits from cross-modal distillation, achieving robust BEV predictions from a single 360-degree input image. **Distillation (red dashed block):** highlights the regions where multi-channel dense feature distillation is applied, specifically between Teacher–Student and Student–Auxiliary pairs. At inference, only the Student network is employed, ensuring lightweight and deployment-friendly BEV segmentation. This figure shows the order of steps and permutations needed to make the 360° sensors into a multimodal system, helping to visualize how complex the problem is while still being solvable.
VOCAB: (w/definition)	- Knowledge Distillation: To concentrate the important data - Lidar: A short to long range sensor that is affected by bad weather, but has high resolution depth sensing. - BEV: Bird's Eye View - Multimodal: Using multiple sensor inputs. - Segmentation: To split into parts
Cited references to follow up on	Zhiyu Chong, Xinzhu Ma, Hong Zhang, Yuxin Yue, Haojie Li, Zhihui Wang, and Wanli Ouyang. MonoDistill: Learning Spatial Features for Monocular 3D Object Detection. arXiv preprint arXiv:2201.10830, 2022. 8 Yihan Hu, Jiazhi Yang, Li Chen, Keyu Li, Chonghao Sima, Xizhou Zhu, Siqi Chai, Senyao Du, Tianwei Lin, Wenhai Wang, et al. Planning-Oriented Autonomous Driving. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 17853–17862, 2023. 1, 2
Follow up Questions	Can this system also detect and respond to obstacles? How is this system impacted by weather?