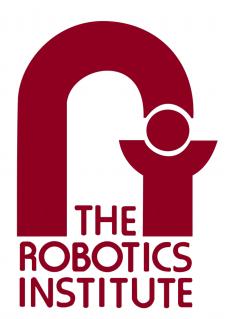
Detection of static pedestrians from vertically sparse 3D point clouds

Ivana Collado, ITESM Dr. Luis E. Navarro-Serment, CMU



Motivation

Precise pedestrian detection is an essential capability for autonomous mobile robots navigating in populated areas.

PROBLEM

Low resolution LiDARs are particularly attractive for use in small robots. However, they produce vertically sparse point clouds which are difficult to interpret.

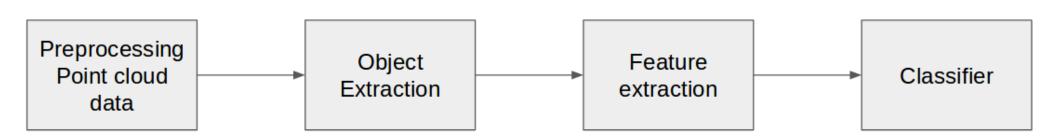
GOAL

Provide a human detection method that:

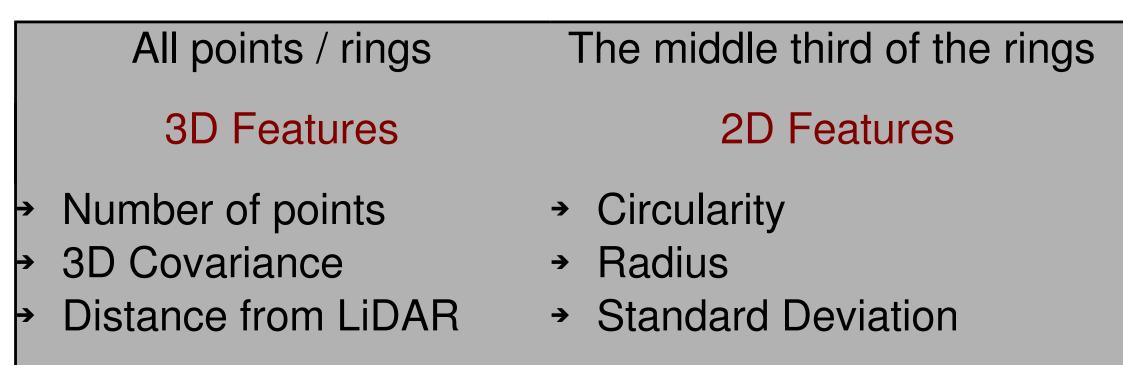
- Deals with increasing vertical sparsity for distant objects.
- Eliminates use of motion features, thus enabling the robust detection of **static pedestrians**.
- Successfully interprets **partially seen** pedestrians at close ranges from 0 3 meters.
- Is suitable for **low computing** and **power** budgets while running in **real-time**.

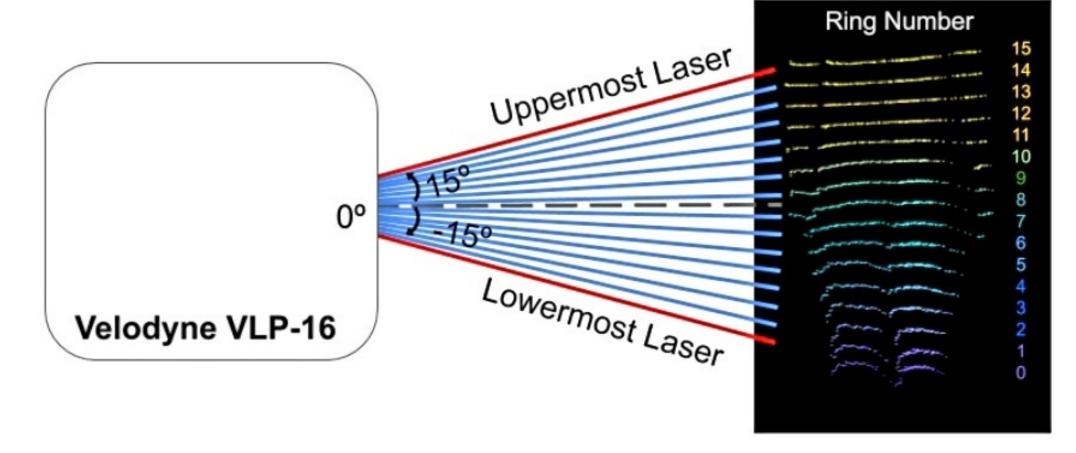
Methodology

General pipeline for pedestrian detection framework.



Simple feature set does not relay on motion. Instead, it focuses on horizontal characteristics for robustness against the increasing vertical sparsity of the point cloud, which degrades the human detection accuracy.



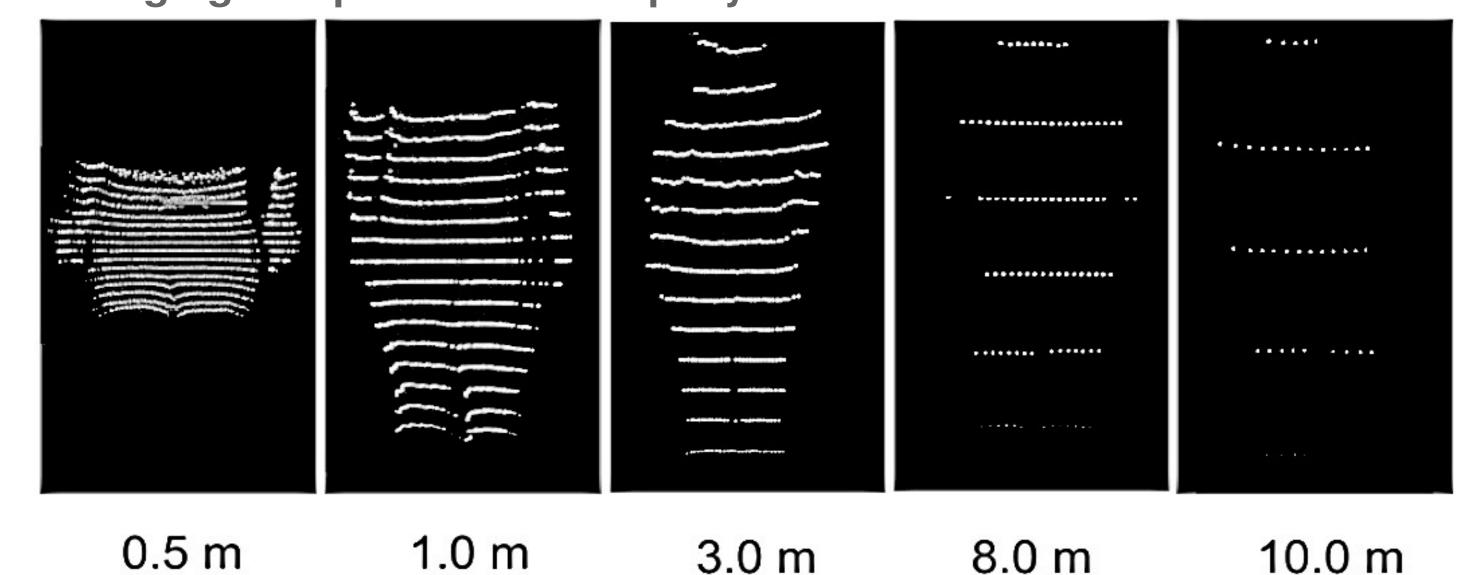


Vertical FOV of a sensor with low vertical density and rings produced by each scan line

Advantages of using Adaboost [2] to trained classifier:

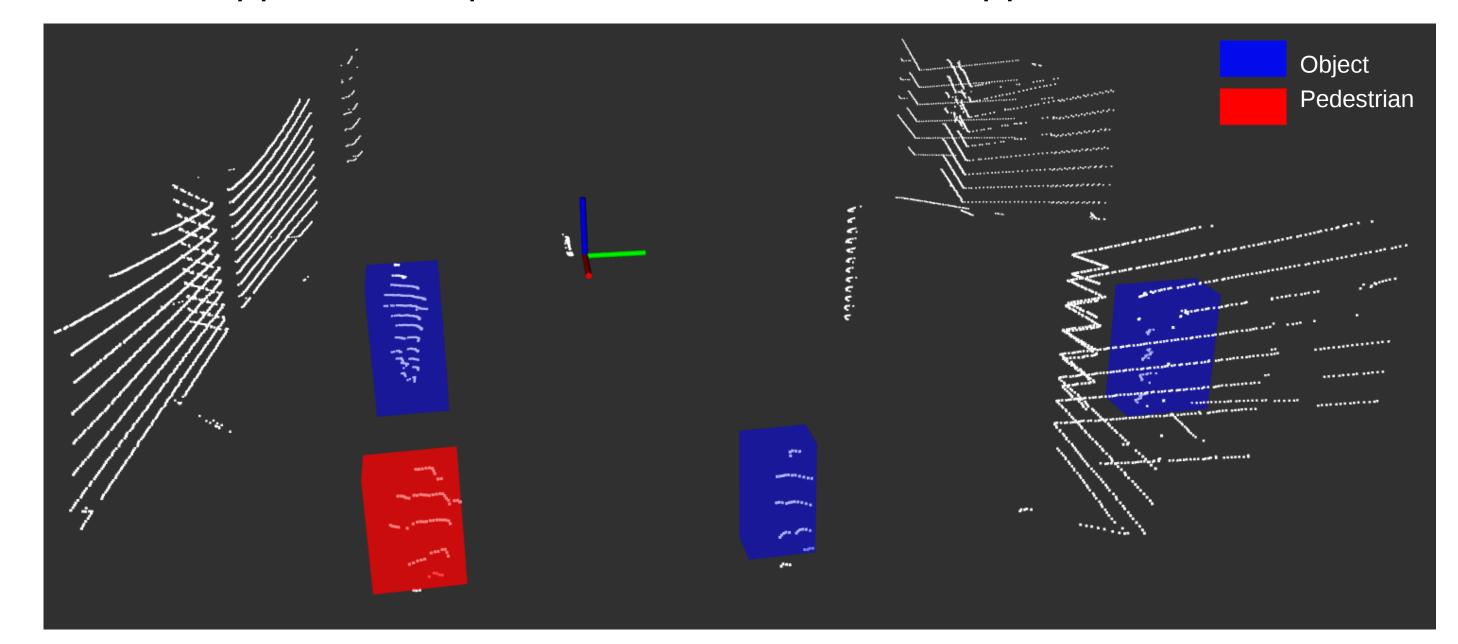
- Easy implementation
- → Low processing time
- High performance
- → Small data-set

Using a low resolution 3D LiDAR, the amount of point cloud data belonging to a pedestrian is rapidly reduced whilst distance increases.



Experiments

Our static approach vs. previous motion centered approach.



Detection using previous approach. Moving pedestrian in red is labeled correctly, while two other static pedestrians are incorrectly labeled as objects.

- Previous approach [1]: classification depends on object size and movement.
- Our approach: it extracts a geometric feature vector form each detected object and uses a binary classifier trained with Adaboost.

The approach was implemented on a low density 3D LiDAR Velodyne VLP-16 mounted on a mobile Husky Robot.



- Point cloud data was recorded and used to obtain point cloud samples.
- For each sample set, the corresponding feature vector was calculated and manually labeled as human or non-human.
- The data set created for training and testing had a total of 1,214 static samples, including 300 human examples.
- Training and results of the Adaboost classification model is done implementing a five fold cross-validation technique.

Results

Results using only static samples

Results	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	AUC (%)
Previous Approach	77.19	9.67	15.06	36.66	53.54
Proposed Approach	96.38	94.38	92.38	91.02	95.53

	Previous Approach		Proposed Approach		
	Detected Label		Detected Label		
True Label	Human	Non-Human	Human	Non-Human	
Human	29 (10.28%)	253 (89.71%)	265 (93.97%)	17 (6.03%)	
Non-human	26 (2.78%	906 (97.21%)	35 (3.75%)	897 (96.24%)	

Misclassification errors at various distances

Distance (m)	Total Samples	Misclassified Samples	Error Percentage (%)
0 - 1	10	0	0.00
1 - 2	58	2	3.44
2 - 3	86	6	6.97
3 - 4	81	8	9.87
4 - 5	44	0	0.00
5 - 6	60	0	0.00
6 - 7	41	5	12.19
7 - 8	307	2	0.65
8 - 9	161	2	1.24
9 - 10	186	4	2.15

Conclusion

The experimental results suggest that the proposed method is better at detecting static humans in vertically sparse point clouds than the previous motion-dependent approach.

- True positive detections have increased by more than 80%, while reducing the percentage of false negative detections.
- Results show acceptable performance at all distances in considered range from 0 10 meters.
- Potential improvements include:
- Selecting additional features to deal with common error cases.
- Integration with target platform.

References

[1] Navarro-Serment, L. E., Mertz, C., Hebert, M. (2010). Pedestrian detection and tracking using three-dimensional ladar data. The International Journal of Robotics Research. 2010.
[2] R. E. Schapire and Y. Singer, Improved boosting algorithms using confidence-rated predictions, Mach. Learn. 1999.

Acknowledgements

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