Domain and Modality Gaps for LiDAR-based Person Detection on Mobile Robots

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Abstract

Person detection is a crucial task for mobile robots navigating in human-populated environments and LiDAR sensors are promising for this task, given their accurate depth measurements and large field of view. This paper studies existing LiDAR-based person detectors with a particular focus on mobile robot scenarios (e.g. service robot or social robot), where persons are observed more frequently and in much closer ranges, compared to the driving scenarios. We conduct a series of experiments, using the recently released JackRabbot dataset and the state-of-the-art detectors based on 3D or 2D LiDAR sensors (CenterPoint and DR-SPAAM respectively). These experiments revolve around the domain gap between driving and mobile robot scenarios, as well as the modality gap between 3D and 2D LiDAR sensors. For the domain gap, we aim to understand if detectors pretrained on driving datasets can achieve good performance on the mobile robot scenarios, for which there are currently no trained models readily available. For the modality gap, we compare detectors that use 3D or 2D LiDAR, from various aspects, including performance, runtime, localization accuracy, robustness to range and crowdedness. The results from our experiments provide practical insights into LiDAR-based person detection and facilitate informed decisions for relevant mobile robot designs and applications.

1. Introduction

Person detection is an important task in many robotic applications, including safe autonomous navigation in human-populated environments or during human-robot interactions. LiDAR sensors are well-suited for person detection, thanks to their accurate depth measurements, long sensing range, and large field of view. There are many successful object detection methods using 3D LiDAR sensors in driving scenarios [63, 54, 56, 24, 47, 45, 55, 58], where pedestrian is typically one of the classes to be detected. Meanwhile, in mobile robot scenarios persons have successfully been detected using range scans from 2D LiDAR sensors [3, 33, 26, 6, 21, 22].

In this work, we study the existing LiDAR-based person detection methods for mobile robots. Our studies revolve around the domain gap between driving scenarios (left) and scenarios encountered by mobile robots navigating around humans (right), as well as the modality gap between person detectors using 3D LiDAR (top-right) and 2D LiDAR data (bottom-right).

Figure 1: In this work we study LiDAR-based person detection methods for mobile robots. Our studies revolve around the domain gap between driving scenarios (left) and scenarios encountered by mobile robots navigating around humans (right), as well as the modality gap between person detectors using 3D LiDAR (top-right) and 2D LiDAR data (bottom-right).
however, it is not clear if these pre-trained detectors can perform well when naively deployed on mobile robots due to the large domain gap. Alternatively, since mobile robots are often equipped with safety-certified 2D LiDAR sensors for navigation and collision avoidance, one could rely on 2D-LiDAR-based person detectors. However, the performance difference, i.e. the modality gap, between 2D and 3D LiDAR sensors for this task has not been properly studied. Understanding these differences in various aspects (e.g. detection accuracy, runtime, cost, etc.) is crucial towards well-informed decisions for designing and deploying mobile robots with person detection capabilities.

Enabled by the recently released JackRabbot dataset [32], this work presents a study on the aforementioned domain gap and modality gap (see Fig. 1). We use the state-of-the-art CenterPoint [58] and DR-SPAAM [21] as representatives for methods based on 3D and 2D LiDAR sensors, and analyse their performances through a series of experiments. We find that naively deploying a detector pre-trained on driving datasets does not result in meaningful detections in mobile robot scenarios, but pre-training can be beneficial when fine-tuning on the target domain with proper detector parameters. Furthermore, somewhat surprisingly, we find that, when only visible persons are considered, the 2D-LiDAR-based DR-SPAAM performs on par with the 3D-LiDAR-based CenterPoint. However, due to 2D LiDAR sensors being constrained to a single planar scan, it is easier for persons to be invisible to the sensor and detecting such persons is impossible (e.g. they may be occluded by objects or other persons, or they could be standing on structures above the scan plane). We additionally conduct numerous experiments comparing these two detectors in their localization accuracy, robustness with respect to range or crowdedness, as well as their runtime and memory consumption. We believe these findings provide valuable insights on person detection using LiDAR sensors for mobile robots, and will facilitate relevant robotic applications.

2. Related Work

Person detectors based on 3D LiDAR data estimate 3D bounding boxes of persons in a scene. Most such detectors have been designed for multi-class detection relying on autonomous driving datasets [18, 8, 50, 23], in which the pedestrian class is one of the classes to be detected. Existing deep-learning-based methods can largely be grouped into two categories. Single-stage detectors [16, 63, 54, 24, 62, 30, 52, 11, 55, 60, 58, 61] use backbone networks, either based on points [36, 51] or voxels [63, 24, 19, 13] to process the scene and generate bounding boxes directly from the extracted features. Two-stage detectors [46, 35, 56, 47, 12, 45] additionally introduce a bounding box refinement stage, which pools features within the box proposals and generates refined predictions.

The KITTI dataset [18] is a forerunner in providing a standardized benchmark for testing LiDAR-based 3D object detectors, but it is now succeeded by newer and larger datasets, including the nuScenes dataset [8] and the Waymo Open Dataset [50]. However, these driving datasets differ from the mobile robot scenarios, where the robot moves in close proximity to humans (e.g. the JackRabbot dataset [32]). It is not clear if a person detector, developed and tested using driving datasets, can perform well in mobile robot scenarios, for which there is currently no pre-trained model readily available. In this paper, we study the domain gap between these two scenarios using the state-of-the-art CenterPoint [58] detector.

There are, in addition, 3D methods developed primarily on datasets collected by scanning static indoor scenes with RGB-D cameras [48, 10, 14, 2]. While in theory some of these approaches could be adapted for detecting persons in LiDAR data, we do not experiment with them in this work.

Domain adaptation seeks to directly bridge the gap between the source and target distribution, generalizing trained models to unseen scenarios, and has found successful applications in image tasks [7, 42, 34, 40]. For point cloud, several approaches deal exclusively with driving scenarios [39, 57, 25, 53, 59, 41], focusing either on adapting different LiDAR models [39, 57, 25], or on synthetic-to-real transfer [53, 59, 49]. There are also domain adaptation approaches that focus on generic 3D point clouds, not necessarily obtained by LiDAR sensors [37, 1].

We aim to investigate the domain gap between driving and mobile robot scenarios, which differ not only on the specific LiDAR models, but also the environments and the distance at which persons are perceived. We focus on the impact of the domain gap for pretrained person detectors, rather than attempting to bridge the domain gaps between various datasets, and rely solely on supervised transfer learning.

Person detectors based on 2D LiDAR data focus on estimating centroids of person in the scene, parametrized as $x, y$ coordinates on the LiDAR scan plane. It has long been a relevant task in the robotics community, given it is crucial in order for a mobile agent to autonomously navigate in human-populated environments. Early approaches [17, 43, 44] detect blobs with manually engineered heuristics, and track these blobs in sequential scans, leveraging motion as a clue for detection. Later works [3, 33, 26] improved the detection stage, replacing the heuristics with learned classifiers (e.g. AdaBoost) on hand-crafted features, and still rely on motion-based filtering to obtain high quality detections [26, 33].

Most recent developments [5, 6, 21, 22] resorted to deep-learning techniques by applying 1D CNNs to range data, and no longer require motion-based filtering. The first of
these approaches is the DROW detector [5]. It was originally designed to detect walking aids, and was later extended to also detect persons [6]. The current state-of-the-art method is the DR-SPAAM detector [21, 22], which augments the DROW detector with a temporal aggregation paradigm, incorporating information over sequential LiDAR scans in order to improve the detection performance.

Although these approaches have been evaluated for their respective tasks and datasets, our work presents the first cross modality comparison where a 2D-LiDAR-based detector is compared to a 3D-LiDAR-based counterpart. Furthermore, we study the modality gap in multiple aspects, including localization accuracy, robustness, and runtime, beyond mere detector performance.

3. Person Detectors

The experiments in this paper are conducted with CenterPoint [58] and DR-SPAAM [21], state-of-the-art detectors based on 3D and 2D LiDAR sensors respectively. While we here very briefly recap the main ideas of the two detectors, we refer the interested reader to the main publications for a detailed overview.

CenterPoint [58] takes a voxelized 3D point cloud as input and uses either a VoxelNet [63] or PointPillars [24] to extract a 2D feature map on the bird’s-eye-view (BEV) plane. From the extracted features, a center head is used to produce heatmaps, corresponding to $x, y$ locations of bounding box centers on the BEV plane. This center head is supervised with 2D Gaussians produced by projecting bounding box centers onto the BEV plane, together with the focal loss [28]. In addition, regression heads are used to obtain $x, y$ center refinement, center elevation, box dimensions, and orientation (encoded with sine and cosine values). These regression heads are supervised at the ground truth centers with an $L_1$ loss. In this work, we use the CenterPoint with a VoxelNet backbone for our experiments.

DR-SPAAM [21] takes as input the range component of a 2D LiDAR scan encoded using polar coordinates. A preprocessing step is used to extract points within small angular windows (called cutouts), and each window is normalized and passed into a 1D CNN. The network has two branches: a classification branch, which classifies if the window center is in the proximity of a person, and a regression branch, which regresses an offset from the window center to the $x, y$ center location of the person. The classification branch is supervised with a binary cross-entropy loss, whereas the regression branch is supervised only for positive windows, using an $L_2$ loss. Finally, the predictions from all windows are postprocessed with a distance-based non-maximum-suppression to obtain the final detections.

4. Experimental Setup

4.1. Datasets

Experiments in our work are conducted with the nuScenes dataset [8] and the JackRabbot Dataset and Benchmark (JRDB) [32].

The nuScenes dataset [8] contains 1,000 short sequences (approximately 20 seconds each) collected from driving vehicles. These sequences are split into a train, validation, and test set, having 700, 150, 150 sequences respectively. The dataset is captured using a 32 beam LiDAR, producing scans with approximately 30,000 points at 20 Hz. Every tenth frame (0.5 seconds apart) is annotated with 3D bounding boxes, with a total of 10 classes, one of which being pedestrian. For the task of detection, a common practice is to combine the unlabeled scans to obtain a denser point cloud [8, 64, 55, 58].

JRDB [32] contains 54 sequences collected with a mobile robot (the JackRabbot) moving in both indoor and outdoor environments on university campuses. These sequences are split into 27 sequences for training and validation, and 27 for testing. The robot is equipped with two 3D LiDAR sensors (Velodyne 16 Puck LITE), on the upper and lower part of the robot respectively, each producing scans with approximately 18,000 points. Persons in the environment are annotated with 3D bounding boxes, with a total of roughly 1.8M annotations across the dataset. At the moment of writing, JRDB is the only large-scale dataset that focuses on mobile robot scenarios, while also featuring LiDAR point cloud with 3D person annotations.

In addition, the JackRabbot is equipped with two 2D LiDAR sensors (SICK LMS500-20000), front and rear facing respectively. They are mounted at the height of the lower legs, and their scans are merged to a single 360° scan, having 1091 points. Jia et al. [22] used these scans to evaluate 2D-LiDAR-based person detectors, by synchronizing and adjusting the 3D annotations. In this work, we use 2D LiDAR scans from JRDB, following the same data preparation procedure. All our reported numbers are based on the JRDB validation set obtained from the standard train-validation split.

4.2. Training Setup

For CenterPoint trained on nuScenes, we use the same hyperparameters from [58]. Namely, we voxelize the input point cloud with $(0.1m, 0.1m, 0.2m)$ grids, and limit the detection range to $[-51.2m, 51.2m]$ for the $x$ and $y$ axes, and $[-5m, 3m]$ for the $z$ axis. We follow the same training procedures and data augmentation scheme, training the network for 20 epochs with the AdamW optimizer [31] with batch size 16, max learning rate $1e-3$, weight decay 0.01, and momentum 0.85 to 0.95. For more training related details, we refer the reader to [58]. Following previous
works [8, 64, 55, 58], we use frames accumulated from 10 sweeps for a denser point cloud. However, in order to transfer the trained model to JRDB, we use only the \( x, y, z \) coordinate of the points as input feature, discarding the measured reflectance and time increment, as these features are not available in JRDB.

For CenterPoint trained on JRDB, we experiment with two groups of parameters: one uses the same parameters as for nuScenes, and the other reduces the voxel sizes to (0.05m, 0.05m, 0.2m) and limits the detection range to [-25.6m, 25.6m] for the \( x \) and \( y \) axes, and [-2m, 8m] for the \( z \) axis. This reduction in voxel size and detection range is motivated by the fact that scenes in JRDB are typically of a smaller scale compared to those in nuScenes. In the case of training from scratch, we train the network for 40 epochs with a batch size of 32, using the same optimization setup as during training on nuScenes. In the case of fine-tuning a pretrained network, we reduce the training duration to 10 epochs.\(^2\)

To train DR-SPAAM on JRDB, we follow the procedures from [22], and train the network for 20 epochs with a batch size of 6, using the same pre and postprocessing hyperparameters. The original DR-SPAAM only predicts \( x, y \) locations of the person, providing no information related to bounding boxes. In order to compare with 3D-LiDAR-based methods, we experiment with modifying the regression branch, additionally predicting the bounding box width, length, and orientation. The width and length are parameterized as \( \log(w / \bar{w}) \) and \( \log(l / \bar{l}) \), where \( \bar{w} = 0.5 \) and \( \bar{l} = 0.9 \), which represent the average box width and length in the JRDB training set. The orientation is parameterized by its sine and cosine as in [58]. Both the size and orientation regression are supervised with an \( L_2 \) loss, with a weighting factor of 0.2 for the orientation. In addition, assuming persons do not vary significantly in height, we experiment with generating 3D bounding boxes, using the predicted BEV boxes and the average height from the training set. We did not experiment with regressing box height from the LiDAR data.

4.3. Metrics

Following the standard for object detection, we use the Average Precision (AP) as the main evaluation metric. We use three variants, \( \text{AP}_{\text{box}}, \text{AP}_{\text{BEV}}, \) and \( \text{AP}_{\text{centroid}} \), each having different criteria for assigning detections to ground truth boxes. For \( \text{AP}_{\text{box}} \), a detection can be assigned to a ground truth, if their 3D IoU is above 0.3 (following the JRDB convention [32]). \( \text{AP}_{\text{BEV}} \) relaxes the requirement to a 2D IoU criterion on the bird’s-eye-view boxes, discarding the requirement related to box height and elevation. \( \text{AP}_{\text{centroid}} \) focuses on the center localization only, assigning a detection to a ground truth if their \( x, y \) location difference is smaller than 0.5m [26, 6, 21], dropping the requirements on box size and orientation. In all these three variants, a ground truth can only be matched with one detection.

Since ground truth boxes have different visibility to 3D and 2D LiDAR sensors, we compute all three APs under two settings. In the first setting, we evaluate detections against ground truth boxes that contain at least 10 points from the 3D LiDAR. This corresponds to the default evaluation procedure of JRDB and we thus refer to it as the default evaluation. In the second setting, which we term 2D-visible, we evaluate detections against ground truth boxes which have at least 5 points from 2D LiDAR within a 0.5m radius from the box \( x, y \) centroid. These two evaluation settings enable us to examine the detector performance from each modality, independent of factors that cause persons to be completely invisible to the sensor (thus being impossible to detect).

5. Results

In this section we first discuss our main results (see Table 1) with respect to the domain gap, and proceed with detailed comparisons of detectors using different modality.

5.1. Domain Gap

Looking at the performance of CenterPoint trained only on nuScenes, it directly becomes clear that a quite big domain gap exists between nuScenes and JRDB. The pretrained model from [58] only has a 9.9% \( \text{AP}_{\text{box}} \), due to the missing reflectance features and time increments (they are padded with 0, see Sec. 4.2). Our pretrained network, relying only on \( x, y, z \) point coordinates, has an improved performance, but still trails significantly behind the model trained directly on JRDB by a margin of 33.7% \( \text{AP}_{\text{box}} \). By fine-tuning the nuScenes pretrained CenterPoint version though, this domain gap can largely be bridged, leaving only a small 1.8% \( \text{AP}_{\text{box}} \) performance difference.

Given the different properties of the nuScenes and JRDB point clouds, another big performance boost can be obtained by using the more fine-grained voxelization which is better suited to the JRDB data. Compared to training with the nuScenes specific voxelization, this improves results by 6% \( \text{AP}_{\text{box}} \). Combining this variant with additional pre-training on nuScenes yields the best CenterPoint performance, even though the pre-training is done under a different (coarser) voxel resolution. This shows that, despite the domain gap between nuScenes and JRDB, there remains meaningful knowledge that can be transferred across datasets, and fine-tuning with proper parameters for the target domain is an effective way to bridge the gap.

\(^2\)Longer fine-tuning, using the full training schedule of 40 epochs, did not further improve performance.
Table 1: Performance of different CenterPoint and DR-SPAAM variants on the JRDB validation set. ∗:3D Bounding boxes are obtained using predicted BEV boxes and the average box height from the training set.

|                     | AP_{box} | AP_{BEV} | AP_{centroid} |
|---------------------|----------|----------|---------------|
|                     | Default  | 2D-visible | Default  | 2D-visible | Default  | 2D-visible |
| nuScenes training (from [58]) | 9.9      | 8.5      | 15.0   | 12.7     | 17.0    | 14.4      |
| nuScenes training (retrained) | 26.3     | 26.0     | 30.9   | 28.5     | 35.3    | 32.1      |
| + JRDB fine-tuning | 58.2     | 64.2     | 61.2   | 67.1     | 69.5    | 75.0      |
| JRDB training      | 60.0     | 68.2     | 62.6   | 69.9     | 67.9    | 75.1      |
| + fine-grained voxelization | 66.0     | 75.0     | 67.1   | 76.5     | 70.1    | 78.1      |
| + nuScenes pretraining | 70.0     | 78.6     | 71.4   | 80.7     | 74.9    | 82.7      |
| DR-SPAAM BEV      | 34.1∗    | 58.2∗    | 40.8   | 67.3     | 46.6    | 74.8      |
| Centroid only     | –        | –        | –      | –        | 47.6    | 77.2      |

5.2. Modality Gap

Turning to the modality gap, we compare the 3D-LiDAR-based CenterPoint and 2D-LiDAR-based DR-SPAAM. Being state-of-the-art detectors [58, 21], they are selected to represent the expected detection performance of the two sensor types. Under the default evaluation setting, DR-SPAAM trails CenterPoint trained on JRDB (with fine-grained voxelization) by a significant 26.3% AP\textsubscript{BEV}. However, when evaluated against ground truth that is visible to 2D LiDAR sensors, this gap shrinks to only 9.2% AP\textsubscript{box}. In many applications, the bounding box dimensions are only of secondary importance, compared to the person’s location. To this end, we also evaluate with AP\textsubscript{centroid} and found that DR-SPAAM and CenterPoint differ only by 3.3%. A DR-SPAAM that regresses centroid only (as it originally is in [21]) has a further improved performance, leaving only a small performance gap of 0.9% AP\textsubscript{centroid} to CenterPoint trained only with JRDB. These numbers show that, somewhat surprisingly, detectors using 2D or 3D LiDAR sensors have a similar performance. For the task of person detection, when a person is visible, a simple planar scan of the legs can thus be as effective as a full-body surface scan. However, it is important to be aware of the fact that, since the scans from 2D LiDAR sensors are restricted to a single plane, it is easy for a person to be fully occluded and detecting such persons becomes impossible. Depending on the application and other constraints such as runtime, both types of LiDAR sensors can be a good choice.

5.3. Detailed Detector Comparisons

The remainder of this section focuses on comparison of CenterPoint and DR-SPAAM in specific aspects. The best variants of each detector (CenterPoint pretrained on nuScenes, fine-tuned on JRDB with fine-grained voxelization, and centroid-only DR-SPAAM) are used for these comparisons with AP\textsubscript{centroid} as the evaluation metric.

Figure 2: AP\textsubscript{centroid} evaluated at different ground truth association radii. The CenterPoint curves are slightly steeper at the start, suggesting a better localization of the detections.

5.3.1 Localization Accuracy

Using only the default ground truth association radius of 0.5m does not capture how well localized the different detections are. To further evaluate the localization accuracy, we run the evaluation with a varying association radius and plot the development of the performance in Fig. 2. Note that for this evaluation the gradient of a curve is interesting and not so much the absolute performance.

After a quick increase, the performances slowly saturate, suggesting that most detections are made with a reasonable accuracy. The main difference between CenterPoint and DR-SPAAM is the slope of the curves for small association radii. Here the performance for CenterPoint increases faster, suggesting a slightly better localization of its detections. Furthermore, the CenterPoint curves are almost saturated after an association radius of ∼0.3m, indicating an upper bound for its localization inaccuracy. Here the DR-SPAAM curves are still slightly increasing, meaning that some of the detections are less well localized. Note that
small inaccuracies exist in the annotations. Thus, detection scores obtained with an overly small association radius (e.g. lower than 0.1m) do not provide meaningful information.

5.3.2 Distance-based Evaluation

The density of LiDAR data varies significantly with the distance to the sensor, which can affect the performance of detectors. Because of that we run an additional sliding-window evaluation, where we only consider ground truth annotations within a 2m window at varying distances from the sensor. For a meaningful evaluation we also constrain the detections to be in or near the evaluation window, as to not report unnecessary false positives. We do this by extending the window by 0.5m (the association radius) to the front and back and only consider detections within this larger window. This will still introduce additional false positives but also increase the true positive count, effectively being a trade-off between precision and recall. For this reason the overall performance is lower than reported in Table 1, but here the relative performance between the two detectors is the interesting part.

The top and middle plots in Fig. 3 shows how the detector performances behave for this experiment. In all evaluations the performance is best within the first few meters and drops at higher distances. For the default evaluation, CenterPoint performs significantly more stable across the whole range, whereas the DR-SPAAM performance decreases more at higher ranges. This means that CenterPoint is better equipped to deal with the large variation of point densities, potentially due to the fact that objects are still visible to multiple LiDAR beams, whereas the 2D LiDAR only uses a single beam. For the 2D-visible evaluation, the performance of both detectors is surprisingly similar across the whole range, suggesting that for visible persons, both detectors have similar range-robustness.

The bottom plot in Fig. 3 shows how many ground truth annotations are present within the windows for both types of evaluations. Here it becomes apparent that, from 2m and onward, a significant number of the persons are invisible to 2D LiDAR scans, and thus impossible to be detected. The largest chunk of annotations is found within the first 12m. After that only few annotations remain, for both the default and 2D-visible evaluation, and the evaluation becomes less meaningful. This highlights another difference between JRDB and autonomous driving datasets, where persons are regularly perceived at much higher distances.

5.3.3 The Influence of Crowds

People are often perceived while interacting amongst each other, typically resulting in them being quite close together. This results in many occlusions and could potentially lead to a more difficult task of detecting the separate persons properly. To investigate how the detection performance changes with the object density of a scene, we look at a radius of 1.5m around every ground truth annotation and count how many other annotations can be found. We categorize all annotations by this “group size” and perform a separate evaluation for all the different sizes. Fig. 4 shows the result of this experiment. Even though the overall detection performance seems to be reducing with larger group sizes, the detectors do not completely fail for larger group sizes and the effect seems to be very similar for both detectors. What Fig. 4 also shows, is that a significant amount of people in the JRDB dataset are observed in the vicinity of at least one other person making it significantly more realistic than some older datasets where one would often only observe a single person in an empty scene.
Figure 4: Evaluation split up by how crowded it is around annotations. While the performance for larger group sizes decreases a little, the effect is less pronounced than might be expected. We additionally plot how many groups of a specific size are present in the data, showing that JRDB is indeed fairly crowded.

5.3.4 Runtime

The runtime is a typical practical constraint when deploying detectors. Especially in robotic applications, computational resources are often limited and we cannot rely on powerful desktop GPUs. Table 2 shows the runtime of the evaluated detectors on three different platforms: a powerful desktop machine, a laptop equipped with a decent GPU, and the lower-powered Jetson AGX Xavier. Preprocessing (e.g., computing cutouts, or voxelization) and postprocessing (e.g., non-maximum-suppression) steps are included in the measurement, and no batching is used for inference. In other words, these numbers reflect the end-to-end runtime when the detector is deployed. Both DR-SPAAM and CenterPoint achieve real-time performance on strong desktop or laptop GPUs, but not on embedded GPUs. In general, DR-SPAAM is roughly twice as fast as CenterPoint, with the margin being smaller on the Jetson AGX.3

DR-SPAAM can, thanks to its cutout-based design, obtain higher runtime by subsampling the scan, without significantly lowering the detection performance [21]. Table 3 shows the performance and runtime of DR-SPAAM with different subsampling factors on the Jetson AGX. With times subsampling, DR-SPAAM can run at 26.6 FPS, while losing only 1.4% AP. In applications where the onboard computation is limited, DR-SPAAM presents a more favorable trade-off between performance and runtime, compared to the more accurate, yet slower CenterPoint.

5.4. Qualitative Results

Fig. 5 shows several qualitative results of both detectors. These results are obtained by using a detection threshold resulting in an equal error rate (EER), meaning the precision is equal to the recall for that threshold. We show cases where both detectors, one of the two, or neither detected a person. We specifically focus on the true positives and false negatives as these cases should contain a person. The predicted centroids, either coming from CenterPoint or DR-SPAAM, are well-localized to the actual person. The error in orientation estimation sometimes leads to misaligned boxes for CenterPoint, but the overlap with ground truth boxes is often sufficiently high.

Even though the numbers so far suggested that CenterPoint typically outperforms DR-SPAAM, we can here see that there are also cases where only one of the two detectors is able to detect a person. While Fig. 5 shows some cases where it clearly makes sense that a detector fails, e.g., due to missing points or partial occlusions. Most of the cases where only one of the detectors fails clearly show a person though and it is unclear why it was not detected. Interestingly, many ground truth bounding boxes missed by both detectors indeed do not look like they contain a person, potentially suggesting annotation errors.

Table 2: Detector inference speed (frames per second) on three different platforms.

| Platform        | Desktop (TITAN RTX) | Laptop (RTX 2080) | Jetson AGX Xavier |
|-----------------|---------------------|-------------------|------------------|
| CenterPoint     | 32.4                | 19.8              | 6.0              |
| DR-SPAAM        | 59.1                | 37.1              | 8.9              |

Table 3: DR-SPAAM performance and inference speed (frames per second) on Jetson AGX Xavier with different spatial subsampling.

| Subsampling factor | AP_{centroid} (Default) | AP_{centroid} (2D-visible) | FPS  |
|--------------------|--------------------------|---------------------------|------|
| 1                  | 47.6                     | 77.3                      | 8.9  |
| 2                  | 46.5                     | 76.5                      | 18.2 (×2.0) |
| 3                  | 45.2                     | 75.9                      | 26.6 (×3.0) |
| 4                  | 43.7                     | 74.9                      | 32.5 (×3.7) |
| 5                  | 42.0                     | 73.3                      | 36.4 (×4.1) |

3We additionally measured the memory usage on the Jetson AGX, 5311MB for DR-SPAAM, 6318MB for CenterPoint. These numbers are likely to vary depending on specific system setups (we used L4T 32.4.4 and PyTorch 1.6).
Figure 5: Qualitative results from both detectors evaluated at equal error rates. Green boxes represent the ground truth, yellow boxes/spheres are detections by CenterPoint and DR-SPAAM respectively. The blue and red spheres are the 3D and 2D LiDAR points. These examples are picked from the less crowded areas to avoid visual clutter. Note that in many cases where one of the detectors fails, the data seems to be sufficient for a detection to be possible.

| Detector       | Total GT | Both | CenterPoint | DR-SPAAM | None     |
|----------------|----------|------|-------------|-----------|----------|
| Default        | 189 579  | 95 711 (50.5%) | 53 136 (28.0%) | 7 212 (3.8%) | 33 520 (17.7%) |
| 2D-visible     | 96 039   | 71 619 (74.6%) | 12 432 (12.9%) | 5 263 (5.5%)  | 6 725 (7.0%)   |

Table 4: Detection statistics obtained using an equal error rate threshold for both CenterPoint and DR-SPAAM. The majority of persons is detected by both detectors, whereas a significant amount is only detected by one of the two.

detector to detect a person, there is a small but significant number of people only detected by DR-SPAAM, too. This suggests that an ensemble of both methods could be an interesting approach when both sensors are available.

6. Discussion

We investigate the modality gap using two state-of-the-art LiDAR-based detectors. We could have tried to adapt CenterPoint to run on 2D LiDAR data, allowing for an even more direct comparison. However, this would require a significant amount of tuning to make sure CenterPoint yields a representative performance on 2D LiDAR and our goal is not to develop a new 2D-LiDAR-based detector. Instead, we here rely on an existing and well-tuned state-of-the-art method. In both the 2D and 3D case, future developments might change the modality gap, however, with our detector evaluations we have at least set a lower-bound for the person detection performance on JRDB.

Apart from LiDAR-based person detection, one could consider other sensor modalities. In particular, image-based person detectors have a long history. While the person class is now typically seen as one of many classes by most deep-learning-based detectors [38, 9], a whole range of person-specific detectors existed before [15, 4]. Furthermore, RGB-D based person detectors are frequently used in robotics, which have the additional advantage that a person’s position can be estimated [20, 27, 29]. Both types of image-based detectors have the drawback though, that the field-of-view of most cameras is fairly limited. While image-based detectors will likely remain a viable source for person detections, a single LiDAR sensor can be sufficient to cover the complete surrounding.

7. Conclusion

In this paper we investigated LiDAR-based person detection for mobile robots. Using the state-of-the-art CenterPoint [58] and DR-SPAAM [21] detectors in combination with the JackRabbit dataset [32], we studied the domain
gap between driving and mobile robot scenarios, as well as the modality gap between 2D and 3D LiDAR sensors for the detection task. We found that, detectors pre-trained using driving datasets, when naively deployed, give subpar detection performance on mobile robot scenarios, and fine-tuning with proper detector parameters provide an efficient remedy. In addition, we found that, when only visible persons are considered, detectors from both 2D and 3D LiDAR sensors perform on a similar level, but 2D LiDAR sensors are more prone to persons being invisible to the sensor (and thus impossible to be detected). While 3D LiDAR sensors overall provide a more robust solution to person detection, 2D LiDAR sensors provide a more favorable trade-off between performance and runtime, an important trait for mobile robots with limited onboard computations.

Further analysis of the detectors showed that overall their detections are well-localized and they are not significantly affected by crowds. However, a significant number of people are only detected by one of the two detectors, suggesting that if computational resources allow it, an ensemble of the detectors will likely be able to improve upon the separate detector performances. We believe the findings in this paper provide valuable insights for sensors and detector selection in mobile robotic applications.

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