



LiCAR: Pseudo-RGB LiDAR Image for CAR Segmentation

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Abstract. With the advancement of computing resources, an increasing number of Neural Networks (NNs) are appearing for image detection and segmentation. However, these methods usually accept as input a RGB 2D image. On the other side, Light Detection And Ranging (LiDAR) sensors present a different number of horizontal layers, making those with a large number more expensive, but able to obtain data that is similar to that obtained by traditional low-resolution RGB cameras. With the purpose of whether or not is possible to perform object segmentation on pseudo-RGB images obtained from a large number of horizontal layer LiDAR sensor, a new dataset has been generated. This dataset combines the information given by the LiDAR sensor into a Spherical Range Image (SRI), concretely the reflectivity, near infrared and signal intensity 2D images. These images are then fed into instance segmentation NNs. These NNs segment the cars that appear in these images, having as a result Bounding Box (BB) and mask precision of 88% and 81.5% respectively with You Only Look Once (YOLO)-v8 large. By using this segmentation NN, some trackers have been applied so as to follow each car segmented instance along a video feed, having great performance in real world experiments. Results show that even with a small dataset, NNs are able to learn how to segment cars in pseudo-RGB images, leaving only the pending task of providing more samples so as to improve accuracy.

Keywords: Artificial intelligence · Mobile robots · Neural networks · Instance segmentation · LiDAR · YOLO

1 Introduction

The first Artificial Intelligence (AI) models date back to 1943 [9]. Initially, the goal was to simulate the function of a single neuron. Since then, several advances have led to the development of more complex structures, the most recent of which are data storage [6] and Graphics Processing Units(GPUs) [3], in 2006 and 2010 respectively.

Regarding object detection and segmentation methods, there are three different approaches; single, two and multi-stage methods [5]. Among them, the first one is the one that receives more attention, since they are usually faster [14], allowing to have inference times close to realtime. Some examples of these single-stage methods are You Only Look Once (YOLO) or Single Shot DetectorSSD [8].

Normally, these methods require a RGB image as input. However, variations have been introduced in recent years that allow the input of pseudo-RGB images generated from Light Detection And Ranging (LiDAR) sensors. For example, [4] uses a combination of RGB and LiDAR images to perform object detection by first identifying regions of interest in the LiDAR point cloud. Using these regions, a RGB image is extracted from the original RGB image and used as input to a YOLO Neural Network (NN), which finally detects the cars. Although this method gives good results, it requires the handling of LiDAR and RGB images and does not detect objects accurately. Other papers, such as [10], generate a pseudo-RGB image from a LiDAR sensor. This is used to detect and track pedestrians across the image. To do this, they slide the Bounding Box(BB) in 5 parts to build the descriptor. However, it only performs object detection, not segmentation, using an old YOLO distribution, since at the time of submission new YOLO distributions had appeared. Finally, [20] demonstrates the generation of a pseudo-RGB image from a LiDAR sensor in a process that is comparable to the aforementioned method. By using detection and segmentation methods, they are able to achieve good results in both indoor and outdoor environments. However, the preliminary processing of the image from 2048×128 to 1000×300 is necessary due to the limitations of the selected NN, which is not fully capable of handling high-distortion images. Therefore, a denoising and interpolation process is required to enhance the image quality. Furthermore, the limited number of images and instances in the dataset raises questions about the quality of the results. By contrast, generating pseudo-RGB images and using the latest State Of The Art (sota) detection and segmentation methods enable us to eliminate this pre-processing step.

In this work, we perform the segmentation of car instances on Spherical Range Images (SRIs), obtained by combining three different channels from a LiDAR sensor, with several single-stage methods from the YOLO family.

The main contributions of this work are:

- A new dataset for segmenting cars in pseudo-RGB 2D images has been generated. These images are SRIs obtained by combining several channels from a LiDAR sensor.
- The aforementioned dataset has been used to train several SOTA NNs for instance detection and segmentation. As a result, it has been validated that it is possible to successfully detect and segment objects in images generated from LiDAR sensors.
- Once the best instance segmentation method was obtained, a tracker was incorporated, achieving excellent results without affecting real-time inference.

This paper is organised as follows: Sect. 2 introduces both the image generation process and the segmentation NNs used, Sect. 3 shows the experimental setup of the system, Sect. 4 shows the results obtained on the test set and also on completely new real world scenarios and Sect. 5 summarises the results of the paper, as well as introduces the main lines of future works.

2 Methodology

In this Section, the process used to generate the SRIs and the segmentation NNs that were used in Sect. 3 are presented.

2.1 Image Generation

The generation of images from a LiDAR sensor is a two-step process. Initially, a point cloud is created, comprising the reflectance, intensity and illumination of each point derived from the data provided by the LiDAR. Subsequently, this point cloud is transformed into a SRI, which represents the XYZ point cloud in polar coordinates.

In the initial process, data is obtained from the LiDAR sensor. The used sensor provides 4 different 2D images:

- Range (Rg): depth is expressed in mm and discretised to the nearest 1 mm, with a maximum range of 524 m, in accordance with the specifications outlined in the sensor manual.
- Calibrated reflectivity (Rf): the measurements on the signal photons are scaled based on measured range and sensor sensitivity at that range, providing an indication of target reflectivity.
- Signal photons (It): intensity of the photons in the signal returned.
- Near infrared photons (If): Near InfraRed (NIR) photons associated with the natural environmental illumination.

A pseudo-RGB point cloud is generated, in which each point is characterised by a 3D position and a set of luminance factors. The former is obtained from Rg , whereas the latter is the consequence of a value combination, resulting in the formation of pseudo-RGB images in the format $[Rf, If, It]$.

The generated point cloud is then transformed into a SRI. This method was initially presented in [17] and subsequently elaborated by [18]. In general terms, each layer of the LiDAR is transformed into a row, with the horizontal viewing angle of the LiDAR becoming each column (in this case, 360°). An example of the process of combining the LiDAR channels to produce the final pseudo-RGB SRI is shown on Fig. 1. The images have been cropped in order to facilitate closer examination.

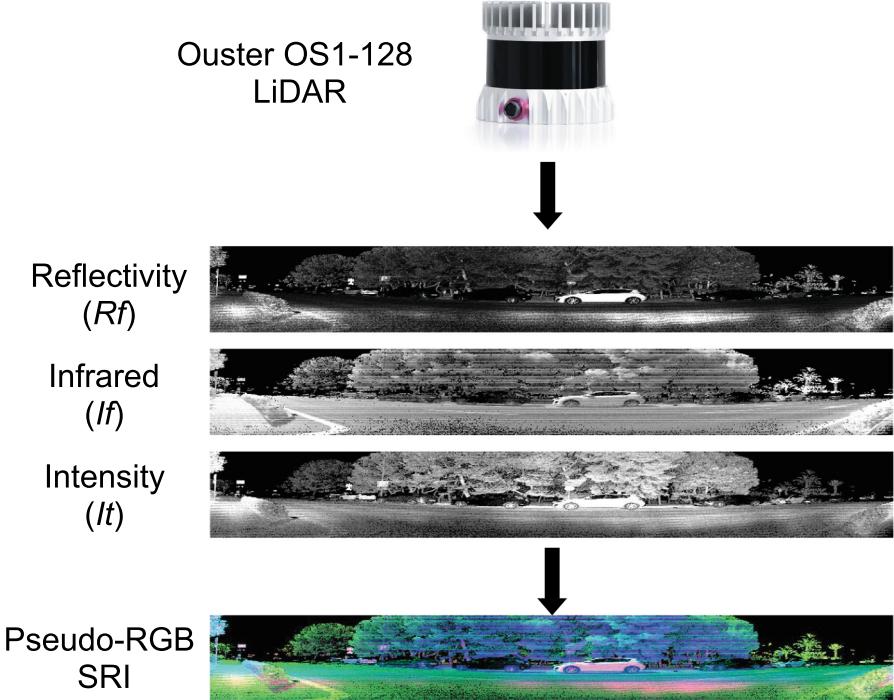


Fig. 1. Partial view of the combination of LiDAR channels for generating the pseudo-RGB SRI.

2.2 Segmentation NNs

A fast but accurate method is required to perform instance segmentation. For this purpose, single-stage SOTA methods such as YOLO-v5 [7], YOLO-v7 [19] and YOLO-v8 [16] were chosen.

YOLO-v5 appeared online on 2020. This model was the first in the YOLO NNs family to support instance segmentation, as well as being released by a private company. There is not much hindsight on this model, as no official paper was published. But it seems that the anchor box selection process was built into the model, allowing it to automatically learn the most appropriate size for each dataset [21].

YOLO-v7 appeared online on 2022, but the paper was published in 2023. They introduced a trainable bag-of-freebies, a new reparametrization module, and a composite scaling method. All these features were used to achieve an improvement in the loss function, label assignment, support for multiple architectures, or a good trade-off between network parameters, computation, inference speed, and accuracy.

YOLO-v8 also appeared online on 2022, but later than YOLO-v7, having its paper publication in 2024. To improve on previous versions, a new loss function

called focal loss, a new data enhancement method called mixup [22], and a new evaluation metric called Average Precision Across Scale (APAS) were introduced. These allow to focus on complex images instead of simple ones, to improve the generalisation and strength of the model by merging images and labels, and to ensure the accuracy of the model over different scales.

3 Experiments

In this Section, the elements used for the execution of the experiments are presented, as well as details from the generated dataset. The NNs training procedure and the results obtained are shown in Sect. 4.

3.1 Setup

The Ouster OS1-128 3D-LiDAR was used to obtain the dataset. This sensor is mounted on roBot for Localization in Unstructured Environments (BLUE), a mobile robotic platform [12, 13] which is still being updated today [2]. The NNs were trained on a computer with a NVIDIA DGX-A100 Tensor Core GPU with 40 GB of RAM. For data acquisition and inference, an on-board computer with an AMD Ryzen 7 5700G as Central Processing Unit (CPU), a NVIDIA RTX 3060 with 12 GB as GPU and 32 GB of Random-Access Memory(RAM) was used. The BLUE robot with the Ouster OS1-128 3D-LiDAR and the on-board computer is shown in Fig. 2.



Fig. 2. BLUE robot with both the Ouster OS1-128 3D-LiDAR and the on-board computer.

3.2 Dataset

After obtaining the data from the LiDAR sensor and converting it to SRIs, 400 images were obtained, each with approximately 14 car instances. These images contain different outdoor environments from the University of Alicante and have a resolution of 2048×128 pixels. The cars appearing in the images were labelled using the LabelMe [15] tool.

The generated dataset has been divided into training/validation/test sets according to the 85/10/5 ratio. A summary of the generated dataset can be found in Table 1. This dataset is available online at [LICAR dataset¹](https://www.iuui.ua.es/licar/index.html)

Table 1. Generated dataset specifications.

Set	Images	Instances
Train	340	4784
Validation	40	569
Test	20	299

3.3 NN Training

All trainings were performed using transfer learning from previously trained models provided by each NN model, as it has shown to improve model accuracy while training the models in [11].

YOLO-v5 was trained for 300 epochs with a batch size of 128 and 8 workers, using a single channel rectangular image with an image size of 2048 pixels as the longest side. YOLO-v7 was trained for 100 epochs with a batch size of 64 and only 1 worker, also using single channel rectangular images of 2048 pixels. YOLO-v8 was trained for 100 epochs with a batch size of 256, again using single channel rectangular 2048 pixel rectangular images.

The rest of the parameters used are the default ones, provided by each model as recommended for performing instance segmentation task.

4 Results

This section presents the results obtained after training the previously mentioned NNs with the generated dataset.

4.1 Test Set

After training the aforementioned models using the training and validation sets, the final results are obtained. The test set contained 20 images with 299 instances. However, in order to have a fair comparison, some parameters of the

¹ <https://www.iuui.ua.es/licar/index.html>

used NNs are given in Table 2, as well as the computation times per image (executed in the on-board BLUE computer with a NVIDIA RTX 3060 GPU). These computation times are expressed as the sum of three values, which consist of the time spent during preprocess, inference and postprocess steps. So, for example, YOLO-v7 has a similar number of layers to YOLO-v8 medium, but is between YOLO-v8 medium and YOLO-v8 large in terms of number of parameters. Another example is YOLO-v5, which has fewer layers than YOLO-v8 nano, but is between YOLO-v8 small and YOLO-v8 medium in terms of number of parameters.

Table 2. Some NN specifications.

NN	Speed (ms)	Number of layers	Number of parameters
YOLO-v8 nano	0.3+6.5+0.5	261	3263811
YOLO-v8 small	0.3+8.3+0.5	261	11790483
YOLO-v8 medium	0.3+18.2+0.6	331	27240227
YOLO-v8 large	0.3+28.7+0.5	401	45912659
YOLO-v7	0.9+23.7+0.7	325	37842476
YOLO-v5 medium	0.9+15.9+0.7	220	21652358

The results for BB detection and mask segmentation are shown in Tables 3 and 4, respectively. In terms of BB detection, YOLO-v8 medium and large have very close results, with the precision being higher for the YOLO-v8 large model. However, when moving to the mask segmentation task, YOLO-v8 is the model with the best results in 3 of the 4 metrics evaluated.

Also, all the trained models fall within the real-time specification, as their computation time should be between 33.3 and 66.6 ms for 30 and 15 Frames Per Second (FPS). So our final choice is YOLO-v8 large.

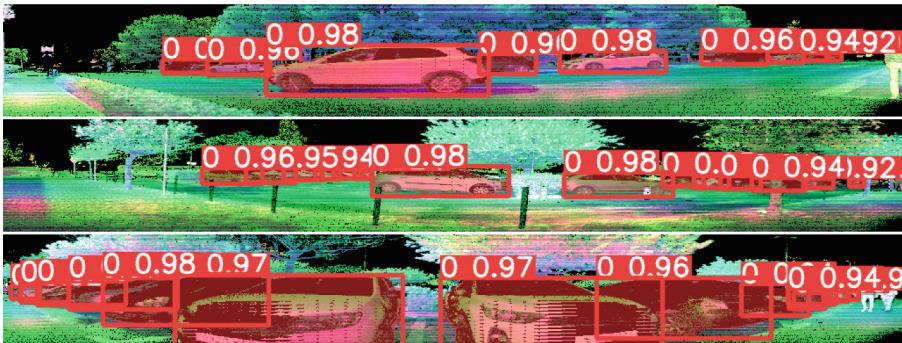
Table 3. Results in BB detection.

NN	Precision	Recall	mAP @0.5	mAP@0.5-0.95
YOLO-v8 nano	0.858	0.756	0.85	0.589
YOLO-v8 small	0.836	0.832	0.871	0.633
YOLO-v8 medium	0.824	0.832	0.888	0.654
YOLO-v8 large	0.88	0.811	0.881	0.649
YOLO-v7	0.81	0.823	0.87	0.62
YOLO-v5 medium	0.783	0.835	0.849	0.587

Table 4. Results in mask segmentation.

NN	Precision	Recall	mAP @0.5	mAP@0.5-0.95
YOLO-v8 nano	0.795	0.676	0.758	0.448
YOLO-v8 small	0.77	0.749	0.803	0.471
YOLO-v8 medium	0.782	0.732	0.807	0.477
YOLO-v8 large	0.815	0.751	0.826	0.509
YOLO-v7	0.803	0.679	0.769	0.474
YOLO-v5 medium	0.831	0.605	0.732	0.431

Some images of the test subset segmented by YOLO-v8 large can be seen in Fig. 3. As can be seen, cars are correctly segmented in both near and far distance in all images, representing the 360° of the LiDAR sensor Field Of View (FOV).

**Fig. 3.** Some partial view samples from test set segmented by YOLO-v8 large.

4.2 Real Experiments

Once the best segmentation method was found, it was tested in a completely new and unseen environment. Also some trackers like BoT-SORT [1] and ByteTrack [23] were added to keep the position of different segmented instances across a video. Figure 4 illustrates a subset of frames cropped for clarity from a sample video² using the BoT-SORT tracker.

This tracker was chosen over ByteTrack because it represents an evolution, including some improvements such as a camera compensation based feature tracker and a suitable Kalman filter. BoT-SORT was used with 0.7 as the threshold for first and second association, 0.75 as the threshold for initialising a new track if the detection does not match any previous track, 20 as the buffer size for removing tracks and 0.8 as the threshold for matching tracks.

² <https://youtu.be/FNemm0QZXo4>



Fig. 4. Several partial view frames running YOLO-v8 large using BoT-SORT as tracker.

As shown in Fig. 4, the detection and tracking of cars is generally successful across frames, with the tracker ID remaining consistent. It should be noted that some cars present problems, such as the black vehicle located in the central left portion of the image. Additionally, some segmentations are not entirely accurate, as evidenced by the white car that appears in the left portion of the final frame. Nevertheless, the issue could be addressed by labelling a greater number of samples across a wider range of images, thereby demonstrating that it is feasible to segment cars on a pseudo-RGB image obtained from a LiDAR sensor.

5 Conclusion

This paper presents the segmentation of instances in SRIs using several single-step methods such as YOLO-v5, YOLO-v6 and YOLO-v8. Specifically, the aim was to detect cars in pseudo-RGB images obtained from a LiDAR sensor by combining the different channels available. The results have shown that it is possible to perform instance segmentation in a LiDAR image using YOLO-v8 large, having a precision of 81.5%. This model provided the best accuracy in mask segmentation, allowing real-time inference on BLUE's on-board computer and the mobile robot to segment cars in outdoor environments. The augmentation of the dataset with a greater number of images and a more diverse range of scenarios will enhance the overall performance of this method, which has already proven to be effective and opens the way for the use of LiDAR object detection and segmentation.

Future work will consist of using the designed system to segment different types of objects, as well as designing a new method for calibrating LiDAR and the camera using the segmented masks obtained with this method.

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