Multi Modal Semantic Segmentation using Synthetic Data

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Abstract—Semantic understanding of scenes in three-dimensional space (3D) is a quintessential part of robotics oriented applications such as autonomous driving as it provides geometric cues such as size, orientation and true distance of separation to objects which are crucial for taking mission critical decisions. As a first step, in this work we investigate the possibility of semantically classifying different parts of a given scene in 3D by learning the underlying geometric context in addition to the texture cues BUT in the absence of labelled real-world datasets. To this end we generate a large number of synthetic scenes, their pixel-wise labels and corresponding 3D representations using CARLA software framework. We then build a deep neural network that learns underlying category specific 3D representation and texture cues from color information of the rendered synthetic scenes. Further on we apply the learned model on different real world datasets to evaluate its performance. Our preliminary investigation of results show that the neural network is able to learn the geometric context from synthetic scenes and effectively apply this knowledge to classify each point of a 3D representation of a scene in real-world.

I. INTRODUCTION

Semantic segmentation and understanding of a scene is one of the fundamental requirements for any robotics applications. The task of semantic segmentation involves classifying each element of a scene to a set of predefined categories/classes. For instance, in a point wise representation of a 3D world, the task involves classifying each point to a specific category. The role of semantic segmentation and challenges thereby is further emphasized in mission critical tasks such as self-driving technologies. For e.g. during path planning stage it is important to understand pose, size and distance to an object and make a decision whether to apply brakes or negotiate with the obstacle.

Research community has made tremendous progress in developing semantic segmentation methods in the two dimensional (2D) image space using Deep Neural Networks (DNN) [9]. However segmentation based on image information alone might not be sufficient for applications like self-driving since its difficult to obtain accurate 3D information such as pose, size, distance to an object to make critical decisions. In addition, color information could be misleading as shown in Fig. 1a which are synthetically generated overcast/rainy scene. We can observe both road (denoted by A) and wall (denoted by B) have similar color and might confuse the segmentation algorithm while assigning a class to a pixel.

To address the above shortcomings of image based scene segmentation, self-driving technologies from companies like Waymo [1], Lyft [2] use multiple perception modules such as Light Detection And Ranging (LiDAR) devices in addition to cameras. LiDARs work based on active illumination and represent a scene in discrete set of points in 3D, also known as a Point Clouds (PC). For instance, in Fig. 1b the LiDAR information is fused with color information which helps to distinguish horizontal road and vertical wall based on their distinct orientation in 3D, resulting in better segmenting as shown in Fig. 1d. The corresponding Ground Truth (GT) labels are shown in Fig. 1c where each class is represented by a distinct color (e.g. Road is represented by dark pink and Wall is represented by Gray). Based on the above factors it is
important to develop and extend existing techniques to handle
3D representation of a scene such as PC inputs in addition to
images. Currently there is far less work on how to adapt 2D
image based segmentation techniques to 3D point clouds. One
of the major bottlenecks being non-availability of labelled real
world PC datasets.

Considering the above mentioned factors, in this work
we investigate the usability of computer generated labelled
synthetic datasets for semantic segmentation of PC. Along this
direction our contributions include:

- Developing a run-time and memory efficient implemen-
tation of state of art PC segmentation algorithm —
  Pointnet++ [18] and is described in section III-D
- Validating the effectiveness of resulting segmentation
  algorithm to learn geometric cues from synthetic datasets
  and transferring the learnt knowledge to real world
data sets as presented in section IV

In this paper we first briefly review some of the publicly
available labelled 3D point cloud datasets and methods in
3D semantic segmentation in section II followed by problem
description and proposed solution and contributions in section
III We deliberate on experiments and results in section IV and
finally conclude in section V.

II. RELATED WORK

A. Datasets for 3D semantic segmentation

There are a few available labelled datasets [5] [3] [6], but they suffer from lack of sufficient representation of relevant
classes for self driving applications [3] [6] or consist of few labelled points [5]. The most recent Sem-kitti [11] and Synth-
city [7] datasets are promising but suffer from unavailability of
labelled data for rare events (e.g. collision between vehicles)
which are crucial to evaluate the practicality of developed
techniques in the context of self-driving.

To study the usability of synthetic data for semantic seg-
mentation of real world point clouds, in this work we test
our approaches predominantly on KITTI dataset [10] which is
closer to our use case and will be described in section IV.

B. Segmentation of Point clouds

Semantic segmentation of 3D point clouds has been one of
the most well researched problem. Related techniques
involve non-parametric approaches based on region growing
[13], segmenting based on graph partitioning [14] [16], robust
statistics to fit a pre-defined parametric model [12] [15]. Most
of these methods perform well on constrained data sets with
very limited variation in operating conditions. With the advent
of large scale image data sets with high variations and the
potential shown by DNN in semantically segmenting them [9],
it is natural that most of the recent point cloud segmentation
methods [17] [18] [19] are exploring similar ideas.

Most of these techniques initially transform a 3D PC to
a suitable representation like Voxel grid [17] or to images
using projection techniques [19] and then apply well studied
methods based on DNN for images. Since the processing is
performed on a derived representation of raw point clouds
which incurs loss of information, it might not be the most
effective way to understand the benefits of synthetic data.
For this reason we investigate Pointnet++ [18] which directly
process raw 3D point clouds and will be discussed in III.

III. PROBLEM STATEMENT AND SOLUTION

As discussed in section II-B it is well proven that fully
supervised techniques based on DNN are ideal for semantic
segmentation of images and some of the early work show
potential by extending these techniques to segment 3D point
clouds. However there are three major bottlenecks which
hinders the progress of research in the field of 3D PC
segmentation. 1) Sensor setup to acquire 3D PC that are
suitable for self-driving applications is extremely expensive.
2) Complexity and thereby huge costs involved in manual
labelling of PC and 3) which partly is a consequence of 1) and
2) is the scarcity of real-world labelled PC data in both
normal and rare events. In the following section we propose
our solution to address the listed problems.

To overcome the problem of scarcity of labelled data for
normal and rare events we propose to leverage synthetic
data. The synthetic data generator should represent a realistic
operating environment of self-driving vehicle and should be
able to provide labels for the underlying classes. It should
also provide a programming interface to enable generation
of rare events such as vehicle collisions. To fulfill the above
conditions we leverage the CARLA simulator [4]. The detailed
description of CARLA is provided in section III-A.

To reduce efforts in labelling of real-world 3D PC we pro-
pose a coarse to fine approach. The coarse labelling is provided
by initially learning 3D representations from synthetic data
using DNN that directly works on 3D points. The learnt model
is then applied on real-world 3D PC to obtain coarse labels.
The coarse labels could then be further refined or corrected
manually. This could potentially save huge amounts of manual
labor and consequently minimize cost of labelling. The details
of DNN employed in this work is provided in section III-C.

A. Synthetic data generation

1) Sensor suite : In this work we use CARLA [4], an open
source driving simulator for self-driving research to generate
synthetic data. CARLA simulates commonly used sensors in
autonomous driving such as cameras and LiDARs as shown in
Fig 2.

We fuse the point clouds with color information and seman-
tic labels to obtain labelled 3D PC. The details of generated
data set will be provided in section IV-A.

B. Scenario Generation using CARLA simulator

Rare scenarios such as accidents and near misses do not
appear in datasets in abundance in real world. To address
this gap we generate scenarios in CARLA using the provided
application programming interface and include them as part of
our training and validation set. An example scenario of two
cars crashing each other is shown in Fig. 3.
Fig. 2: A snapshot of sensors rendered in CARLA. The available sensor information are Color image, Semantic labels of 2D image, LiDAR and depth camera (from top-left in clockwise manner). Zoomed view of LiDAR is shown in the right image.

The simulator offers flexibility to configure different weather conditions, actor (e.g. pedestrians, vehicles) density and town layouts. We use these configuration parameters to create a diverse set of synthetic dataset. More specifically we performed the following procedure:

- Define the actors in the scenario, along with their desired behaviour (run in a straight line or autopilot motion) and location of spawning in the CARLA world.
- Define the ego-vehicle along with its initial spawning point and sensors for collecting data.
- Define the behaviour of the actors and when to trigger them with respect to the location of the ego-vehicle.
- Create the CARLA server and launch the actors and ego-vehicles in the simulation.
- Maneuver the ego-vehicle along the desired path and capture the scenario of how the actors respond to the ego-vehicle by dumping the data from the sensors.

Fig. 3: Generated scenario of two cars crashing into each other.

C. Deep Neural Network for point cloud segmentation

In this work we base our investigation on Open3D implementation of PointNet++ [20] which is one of the popular DNN architecture that takes point clouds as input and predicts class labels for each individual point.

A typical LiDAR point cloud consists of a few million 3D points. Considering the fact that these data points needs to be represented as data type double, the required memory footprint to load the whole data-set at once, for the purpose of training a DNN becomes impractical and sluggish assuming a standard desktop RAM of 8GB. Even in case of batch-wise loading from a secondary memory like hard drive the process of reading every batch sequentially while training is too time consuming. To address this gap in default implementation, we developed an efficient way to generate and load batches of data as described below.

D. Runtime and memory optimizations

The main idea is to store very limited data on RAM which are accessed from a parallel process at the time of training for generating and feeding continuous batches of data. The pseudo code of our method is shown in Algorithm 1 below.

Algorithm 1 Training Data Stacking Algorithm

Result: Queue : queue to store batches for training
1: Initialize:
2: Queue : queue to store batches for training
3: QueueLimit : limit on the size of the queue
4: Buffer : temp buffer before filling the queue
5: BufferLimit : limit on the size of buffer
6: Dataset : class designed to manage the dataset
7: FillQueue :
8: while True do
9: if len(Buffer) < BufferLimit then
10: Buffer. Append(GetBatch)
11: for P in Buffer do
12: if len(Queue) >= QueueLimit then
13: return
14: Queue. Put(P)
15: Buffer. Remove(P)
16: time.sleep(0.01)
17: GetBatch:
18: return Dataset. SampleBatch

The FillQueue method runs in parallel with the training script to continuously feed generated batches of data to the Queue which resides on RAM. We first initialize an array to contain batches of training data. This acts as a buffer for Queue. Next, the data is appended to Buffer. Subsequently the data in the Buffer is pushed to the Queue and corresponding elements are cleared from the Buffer. BufferLimit and queue limit are two parameters that limit the size of data stored on RAM so that memory footprint can be controlled. GetBatch is the method which generates batches of data from secondary memory using information on RAM such as filename, no. of points and location of data points which belongs to the Dataset class.

By limiting the amount of data residing on RAM and on-demand creation of batches of data in a parallel manner makes the training process run-time efficient.

IV. EXPERIMENTS AND RESULTS

A. Datasets

We have used three datasets for our experiments - Semantic 3D [3], KITTI [10] and in-house generated dataset using CARLA simulator. Each of these datasets are unique with respect to number of scenes captured, total number of 3D
points, number of classes and type of sensor used while data acquisition. The above aspects are summarized in Table I.

We used a standard split of 80%-20% for training and validating the Pointnet++ method on Semantic 3D and CARLA datasets. We used KITTI for testing the effectiveness of trained models using synthetic data generated by CARLA. We register the semantic GT with corresponding PC to form the labelled 3D representation prior to training and evaluation. An example of GT semantic labels are shown in Fig. 6b and corresponding 3D labelled PC is shown in Fig. 6c.

For diverse data acquisition in CARLA we spawned ego vehicle mounted with single camera and LiDAR from different locations and drove it on autopilot to cruise through the provided urban and semi-urban town environments. The traffic density was varied between 40 to 80 vehicles and number of pedestrians varied between 10 and 30. In addition, we cycled through 14 different weather conditions. In total we generated a set of 4000 scenes (having over 1.6 billion points). The dataset also consists of 3D PC corresponding to generated rare scenarios as shown in section III-B. Considering each time an ego vehicle is spawned at a different location, with varying vehicle and pedestrian density along with change in weather conditions and town settings we ensure that the generated dataset provides a diverse training and validation set.

Since each of the mentioned datasets have different number of semantic classes (Semantic 3D has 8 semantic classes, KITTI has 19 semantic classes and CARLA has 12 semantic classes) it is important to understand the classwise distribution to support quantitative evaluations. We show the classwise distribution of KITTI and CARLA in Fig. 4 as both of them represent similar operating environment. There are five dominant classes in the two datasets namely Building, Road, Sidewalk, Vegetation and Car. Since side-walk class is not present in Semantic-3D we restrict our evaluations to remaining 4 classes and mark the side-walk as unlabelled. The re-mapping of Semantic-3D and KITTI classes to CARLA is shown in Table II.

### TABLE II: Mapping of semantic classes of different datasets to common 4 classes

| Common 4  | Semantic-3D* | CARLA* | KITTI* |
|-----------|--------------|--------|--------|
| Building  | Building     | Building | Building |
| Road      | Road         | Road-line, Road | Road |
| Car       | Car          | Car     | Car, Motorcycle, Bus, Bicycle |
| Vegetation| High-vegetation, Low-vegetation | Vegetation | Vegetation |

*All remaining classes were mapped to unlabelled.

### B. Evaluation metrics and criteria

To assess labeling performance, we used the standard Jaccard Index, commonly known as the PASCAL VOC intersection-over-union metric (IoU) [8]. To evaluate overall performance of our model, we used the standard mean intersection-over-union metric (mIoU), which was calculated by taking the average of IoU values of individual classes.

\[
    IoU = \frac{TP}{TP + FP + FN} 
\]

\[
    mIoU = \frac{\sum_{i=1}^{n} IoU_i}{n} 
\]

where where \( TP \), \( FP \), and \( FN \) are the numbers of true positive, false positive, and false negative pixels, respectively and \( n \) is the number of semantic classes of the dataset.

### C. Training setup

As mentioned in section III we use our modified version of Pointnet++ for training and testing the effectiveness of synthetic data. We train the model on point clouds with and without color information denoted as RGB-D, and D respectively. Here * represents the type of training dataset, \( i \) represents the number of training classes (excluding unlabelled class), RGB stands for Red, Green, Blue channel of image and D stands for Depth information. We trained all models until saturation, and used Adam optimizer with learning rate of 0.001, momentum of 0.9 and learning rate decay of 0.7. All models are trained on a sample size of 8192 points per batch.

### D. Results

We trained and tested the Pointnet++ model on Semantic-3D dataset to establish a baseline on a real-world dataset. The results are captured in second row of Table III. We attribute the high performance of the model mainly due to large population of labelled points for the 4 classes and the quality of static LiDAR scans which is less noisy. Further on we trained the models using the CARLA dataset and tested on Semantic-3D and KITTI datasets. Our aim is to understand how close we
can match the baseline performance by training only on the synthetic dataset. The results are captured in rows three and four of Table III.

As expected the model performs well on Semantic-3D due to very high quality of TLS. Also the contribution from color information is minimal which is reflected in less difference in mIoU values of RGB-D and D-model. One of the possible reason could be that majority of the classes have well defined geometry that is quite distinctive. On the KITTI dataset the performance of model trained on CARLA is lower and can be attributed to the relatively lower quality of LiDAR scan and resulting artifacts due to motion of the ego-vehicle.

**TABLE III: Experimental comparison on 4 semantic classes**

| Training Set  | Validation Set | Test Set | mIoU* [epochs] | mIoU-D* [epochs] |
|---------------|----------------|----------|----------------|------------------|
| Semantic 3D   | Semantic 3D    | Semantic 3D | 0.92 [100]     | 0.82 [100]       |
| CARLA         | CARLA          | Semantic 3D | 0.836 [20]     | 0.809 [20]       |
| CARLA         | CARLA          | KITTI     | 0.7 [20]       | 0.56 [20]        |

*Values computed on Test-set

In Table III we see that the model trained using CARLA dataset comes close to the model trained on Semantic 3D dataset in only 20 epochs.

1) **Experiment A:** In this experiment we show the inference results of RGB-D\textsubscript{4-CARLA} and D\textsubscript{4-CARLA} on a scene from KITTI in Fig. 5. We train both RGB-D\textsubscript{4-CARLA} and D\textsubscript{4-CARLA} models after remapping 12 classes of CARLA to 4 common classes as mentioned in column 3 and column 1 of Table II respectively. While testing on KITTI we remap the 19 semantic classes in KITTI GT images to 4 common classes as mentioned in column 4 and column 1 of Table II respectively. The resulting GT labels are then reprojected to the corresponding PC and is shown in Fig. 5b. By visual inspection we can observe from Fig. 5c and Fig. 5d that RGB-D\textsubscript{4-CARLA} has lesser mis-classifications at shorter distances and relatively higher mis-classification at far-away distance as compared to D\textsubscript{4-CARLA}. For e.g. Vegetation (marked in green color) is labelled as Car (marked in blue). Since there are few points per object at far away distance, the contribution of mis-classification towards the mIoU is not significant. This is also reflected in fourth row of Table III with a higher mIoU score for RGB-D.

2) **Experiment B:** To understand the importance of geometric cues we compare our method which uses both geometric and color cues with a 2-D semantic segmentation network that uses only color information. For this purpose we chose pre-trained model of ERF-Net [21] and fine-tuned it using the GT semantic labelled images of KITTI after remapping the original 19 classes to 12 classes of CARLA, an example of such a remapping is shown in Fig. 5 which is GT semantic labels for scene in Fig. 6. We remapped Terrain, Sky, Rider, Truck, Bus, Motorcycle, Bicycle, and Train classes of KITTI to unlabelled and the remaining classes as listed in Fig. 4 were unaltered.

The GT for KITTI PC are obtained after re-projecting labels in Fig. 5b with corresponding PC and is shown in Fig. 6. The resulting GT PCs are used to evaluate the performance of our multimodal semantic segmentation models. To have a fair comparison we also trained our version of Pointnet++ on CARLA dataset with 12 classes and evaluated the performance on 12 class GT of KITTI PC after remapping. For this we predict all 12 classes using the models trained only on CARLA dataset whereas consider only the 5 major classes of KITTI namely Building, Road, Side-walk, Vegetation and Car for computing mIoU as the remaining classes are very less in population. The results are listed in Table IV.

**TABLE IV: Experimental comparison using All class model**

| Training Set | Validation Set | Test Set | mIoU* [epochs] | mIoU-D* [epochs] |
|--------------|----------------|----------|----------------|------------------|
| CARLA        | CARLA          | KITTI    | 0.6 [20]       | 0.54 [20]        |

*On Test set classes - Building, Vegetation, Road, Sidewalk, Cars

It can be seen form Fig. 6 and Fig. 7 that both RGB-D\textsubscript{12-CARLA} and D\textsubscript{12-CARLA} are able to segment the side-walk with reasonable accuracy, whereas the inference from ERF-Net (using only the color image in Fig. 6) as shown in Fig. 6c mis-classifies side-walk as Road. We speculate the presence of shadows and similar color of road surface and side walk as the main reason. Additionally when we induce a geometric cue from 3D PC, maybe the DNN is able to learn subtle characteristics such as relative difference in elevation (e.g.side-walk is above road), discontinuity in surface normal orientation at the border of two parallel planar surfaces (road and sidewalk) which leads to treat them as two different objects.
The fence on the extreme right is mis-classified as vegetation by all models as shown in Fig. 6, primarily due to very less representation in the training set. \(D_{12-CARLA}\) fails to identify the car at the far end at the middle of the street whereas the \(RGB-D_{12-CARLA}\) is able to better classify the far away car. This suggests both color and geometric information is necessary for better semantic segmentation of a 3D Point Cloud.

V. Conclusion and Future Work

In this work we have shown that it is possible to effectively make use of synthetic data to segment real world 3D Point clouds using multiple modalities namely images and point clouds. In this regard we generated synthetic dataset using CARLA and trained a DNN which is an in-house optimized version of Pointnet++. From our experiments we found that segmentation of static classes such as roads, side-walk, building and objects with rigid geometry such as Cars generalize well when tested on real-world datasets. We also showed that it is possible to obtain better results by training DNN using both color and 3D Point clouds as compared to using either one of them. The methods presented in this work emphasize the role of synthetic datasets especially in cases like segmentation of 3D PC where its difficult to find real-world labelled data and secondly involves huge costs for manual labelling. In such a case the DNN trained on synthetic data can be used to pre-label a large corpus of real-world dataset which potentially would lessen the labelling efforts and thereby significantly reduce labeling cost.

As part of future work we would like to extend and validate our proposed solution on a much larger corpus of synthetic and real-world datasets.

References

[1] https://waymo.com/open
[2] https://level5.lyft.com/dataset/
[3] http://www.semantic3d.net
[4] carla.org
[5] https://www.cs.cmu.edu/ vmr/datasets/
[6] Huang, X., et al. The apolloscape dataset for autonomous driving. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 954-960), 2018.
[7] Griffiths, D. and Boehm, J. 2019. SynthCity: A large scale synthetic point cloud. arXiv preprint arXiv:1907.04758.
[8] M. Everingham, et al. The PASCAL visual object classes challenge: A retrospective. IJCV, 111(1):98136, 2015.
[9] https://www.cityscapes-dataset.com/benchmarks/
[10] http://www.cvlibs.net/datasets/kitti/
[11] http://semantic-kitti.org/
[12] R. Unnikrishnan and M. Hebert, Robust extraction of multiple structures from non-uniformly sampled data, in Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems, 2003, pp. 1322-1329
[13] R. L. Hoffman and A. K. Jain, Segmentation and classification of range images, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 9, no. 5, pp. 608620, Sep. 1987
[14] Guruprasad M. Hegde, Cang Ye, ”A Recursive Planar Feature Extraction Method for 3D Range Data Segmentation,” IEEE International Conference on Systems, Man, and Cybernetics, 2011.
[15] V. Don and H. Maarten Uijt de, Near real-time extraction of planar features from 3d flash-ladar video frames, in Proc. SPIE, vol. 6977, pp. 69770N-69770N-12, 2008.
[16] W. Tao, H. Jin and Y. Zhang Color Image Segmentation Based on Mean Shift and Normalized Cuts, IEEE Transactions on Systems, Man, and Cybernetics, part B, vol. 37, no. 5, pp. 1382-1389, 2007.
[17] Jing Huang and Suya You. Point Cloud Labeling using 3D Convolutional Neural Network. In Proc. of the Intl. Conf. on Pattern Recognition, 2016
[18] Charles R. Qi et.al. PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space. In Proc. of Conf. on Neural Information Processing Systems, 2017
[19] Bicheng Wu et al. SqueezeSegV2: Improved Model Structure and Unsupervised Domain Adaptation for Road-Object Segmentation from a LiDAR Point Cloud. Proc. of the IEEE Intl. Conf. on Robotics & Automation, 2019
[20] https://github.com/intel-isl/Open3D-PointNet2-Semantic3D
[21] Romero, et al.: Efnet: Efcient residual factored convnet for real-time semantic segmentation. IEEE Trans. on Intelligent Transportation Systems, 2018