097200 - Deep Learning Course Final Project: Adaptive Depth Sampling

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1 Introduction

In recent years, depth sensing has become essential for a variety of new significant applications. For example, depth sensors assist autonomous cars in navigation and in collision prevention [25]. The physical constraints on active depth sensing mobile devices, such as light detection and ranging (LiDAR), yield sparse depth measurements per scan. This results in a coarse point cloud and requires an additional estimation of missing data.

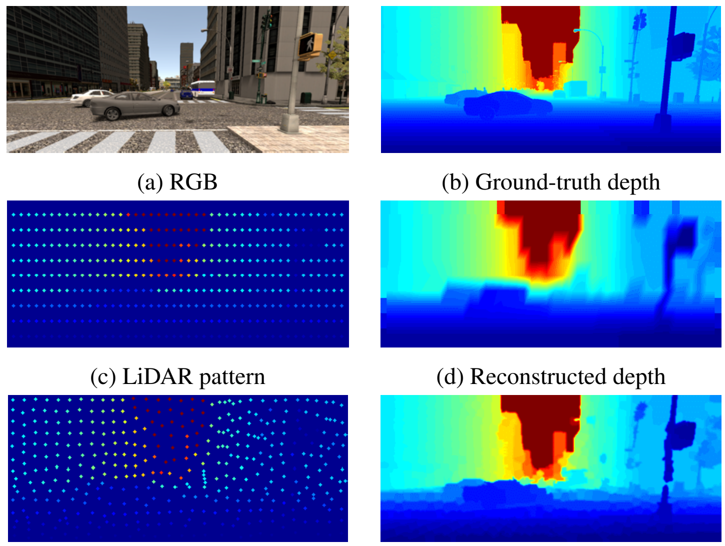
Traditional LiDARs have a restricted scanning mechanism. Those devices measure distance in specified angle intervals, using a fixed number of horizontal scan-lines (usually 16 to 64), depending on the number of transceivers. A new revolutionary technology is now emerging of solid-state depth sensors. They are based on optical phased-arrays with no mechanical parts, and can thus scan the scene fast in an adaptive manner (programmable scanning) [4, 21]. In addition, those innovative devices are much cheaper than those currently in use. This calls for the development of new, efficient, sampling strategies, which reduce the reconstruction error per sample. Since almost always autonomous platforms are equipped with RGB cameras, we investigate the possibility to improve the depth sampling process by taking the RGB information into account. Fig. 1 illustrates the task and clarifies our goal.

In this project, we address the topic of image-guided depth sampling. We use a deep neural network to find the optimal sampling locations for the task of depth reconstruction. Then, we demonstrate in experiments that our framework outperforms state-of-the-art depth completion methods for outdoor scenes.

2 Related Work

Depth completion: The task of depth reconstruction from scattered sparse samples is being increasingly investigated. The main methods can be divided to those which require only the sparse depth input (unguided) and to those assisted by additional information, e.g. color image (guided).

Among the unguided methods, some use classical approach [13, 17], while others rely on more advanced tools such as deep learning [6, 26].



(a) RGB (b) Ground-truth depth

(c) LiDAR pattern (d) Reconstructed depth

(e) Adaptive pattern (f) Reconstructed depth

Figure 1: An illustration of the adaptive depth sampling task. Using the information gained from a color image (a), the sampling pattern can be modified to the scene (e) and achieve more accurate depth reconstruction (f) than simple LiDAR pattern (c-d)

On the contrary, guided methods exploit the connection between depth maps and their corresponding color image. Earlier methods used traditional image processing tools [3, 8]. Recently, several deep learning-based methods [5, 9, 11, 12, 14, 15, 18, 19] achieved state-of-the-art results.

Guided depth sampling: Despite the intensive development in depth completion, the issue of adaptive sampling is yet little addressed. Only [10, 16] have offered a non-trivial (i.e uniformly random or grid) sampling pattern as a previous step to depth reconstruction. Both studies selected sampling at locations which are most probable to have strong depth gradient. Nonetheless, they failed dealing with very low sampling budget of less than 5% of ground-truth pixels. Lately, A. Wolff presented in his M.Sc thesis a fast and practical image-guided algorithm for depth sampling and reconstruction, based on super-pixels. However, he didn't involve any learning technique (and particularly not a deep-learning approach) in his framework.

Nonuniform sampling: Over the years, the field of nonuniform sampling has been well established [1, 2, 20, 27]. However, these studies focus on the reconstruction of the signal for a given nonuniform sampling pattern and not on how to design data-driven patterns, given side information.

3 Method

3.1 Challenges

As explained before, given an RGB image of the environment we intend to find N points that will allow a minimal depth reconstruction error. The coordinates of the points can be represented in two ways:

1. as a set of N (x, y) pairs which correspond to the RGB image pixels.
2. as a binary image corresponding to the RGB image containing 1's in the pixels that should be sampled and 0's elsewhere.

Outputting a set is a difficult task. The main reason for this difficulty is related to the fact that sets are permutation invariant. Thus, well known regression loss functions such as $L1$ or mean squared error (MSE) will not work correctly. For instance, consider the following set of 1D points: $s_1 : \{1, 2, 3\}, s_2 : \{3, 2, 1\}$. Those sets are the same, but $L1$ loss will output 4 because it is not permutation invariant.

Outputting a binary image can lead to issues as well when using regression or cross-entropy loss functions. For instance, consider a binary image x_1 of N sampling points and an identical image x_2 in which all samples are shifted 1 pixel to the left. Those image will probably allow very similar depth reconstruction but $L1(x_1, x_2) = 2N$.

3.2 Architecture

We use a convolutional neural network (CNN) model in order to choose the desired N sampling points. The input of the model is an RGB image and the output is another image in which the pixel intensity represents the probability of a point to be sampled.

The model is based on the u-net segmentation network [23] (see Fig. 2). Originally, the input of the image is a grayscale image and the output is 2 channeled segmentation map. We changed the input layer of the network to input RGB image and the last layer of the network to output one channeled image with the same height and width as the input image.

We trained the network using binary cross-entropy (BCE) loss function. The loss function was calculated between the network output, which is a probability distribution map, and the ground truth sampling map, which can also be interpreted as a hard probability distribution map. For experimentation, we also trained the same network using MSE loss function. For this purpose, we transformed the ground truth hard distribution map into soft distribution map using a gaussian filter. The loss function was then calculated between the network output and the ground truth soft distribution map.

3.3 Post-processing

In order to convert this map to a sampling map, a non-max-suppression algorithm should be used. To do so, we used GMM clustering [22] on the probabilities image. The center of each of the Gaussians was chosen to be the sampling point, because it corresponds to the mean of each cluster. Note that ideally, to get maximal similarity

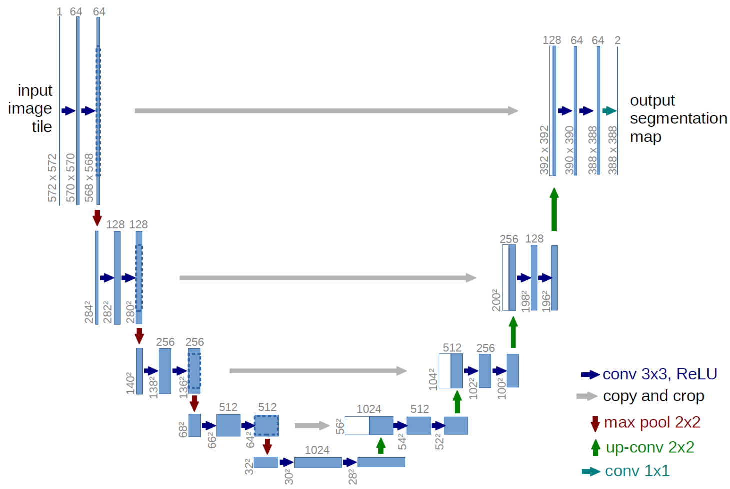


Figure 2: Original u-net architecture.

between the ground truth sampling map and the predicted sampling points, the loss should be computed after the fitting of the Gaussians. Unfortunately, this is not possible due to the fact that the above mentioned method is not differentiable - a property required for Gradient Descent optimization methods.

The predicted depth image is then reconstructed from the sparse depth image using interpolation. The interpolation can be performed with a linear or a higher order polynomial. A simpler reconstruction method is to assign for each pixel the depth value of the nearest neighbor from the sparse depth image. Note that the depth can be reconstructed more accurately using CNN [6] but this method is much more computationally expensive. A high-level block-diagram of our method is illustrated in Fig. 3.

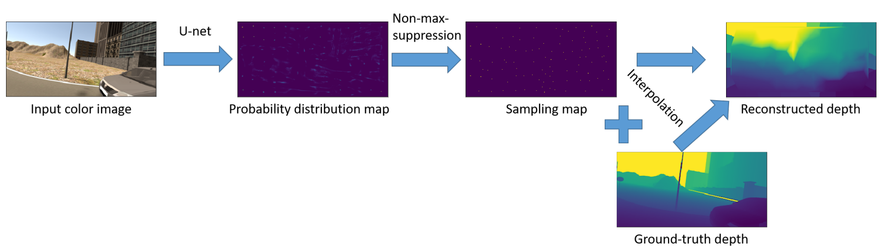


Figure 3: High-level block-diagram of our method.

4 Experiments

4.1 Dataset

The Synthia dataset [24] provides synthetic RGB, depth and semantic images for urban driving scenarios. We use synthetic data as for now there is no large non-synthetic dataset that provides a dense and accurate depth map. We need a dense depth map to be able to sample at any given point. Accuracy is required especially to show the increased resolution we obtain. Thus, two large real-life datasets do not apply: KITTI depth completion benchmark [26] has semi-dense depth, and Cityscapes [7] has low resolution depth, which is in some cases inaccurate. We randomly split the 6,296 images in summer sequence 5 to 6,000 for training and 296 for evaluation. All color and depth images are downsampled from originally 1280×640 pixels to 320×160 pixels.

Additionally, we implement the algorithm described in the M.Sc thesis of A. Wolff for 100 samples and use the received sparse sampling maps as ground-truth for training and testing.

4.2 Evaluation

To evaluate the benefit of our chosen sampling location, we apply a depth reconstruction over the resulting samples. Then, we measure the root mean squared error (RMSE) between the reconstructed and the ground-truth depth. We chose to make the reconstruction of the sparse depth samples by applying linear interpolation (with nearest-neighbor extrapolation) or nearest-neighbor (NN) interpolation, since other sophisticated methods are much more computationally expensive. We make the evaluation on 0-100m depth range, which is similar to the range of a typical vehicle-mounted LiDAR.

4.3 Results

The network was trained on a GPU machine until there was no further improvement in the validation set loss. The hyper are presented at Table 1. Note that the batch size was chosen according to the maximum memory capacitance of the GPU.

Hyper-Parameter	Value
Optimizer	Adam
Learning Rate	4e-3
No. of Epochs	250
Batch Size	10
Weight Decay	0

Table 1: Training hyper-parameters.

Quantitative results are presented in Table 2. Using our method, the resulting reconstructed depth is the second most accurate compared to other sampling methods, after Wolff's methods which we used as ground truth. Among our two proposed approaches, the one trained over BCE loss achieves better performance. Qualitative results, including sampling maps and NN and linear interpolated depth, are presented in Fig. 4.

Sampling	Interpolation	RMSE [m]
Grid	NN	56.09
Random	NN	65.37
Wolff (GT)	NN	**44.48**
Ours (BCE)	NN	47.24
Ours (MSE)	NN	50.70
Grid	Linear	45.25
Random	Linear	55.84
Wolff (GT)	Linear	**43.01**
Ours (BCE)	Linear	43.41
Ours (MSE)	Linear	43.52

Table 2: Quantitative comparison for different depth sampling and reconstruction methods. Our method achieves second best result after ground-truth method.

5 Conclusion

In this project, we introduced a novel approach for image-based sparse depth sampling. We presented state-of-the-art results compared to traditional and modern sampling methods. We believe that this new direction calls for additional extensive research, in order to develop advanced, cheap and accurate depth sensing systems. Future work could exploit temporal redundancy or use semantic information to further improve the performance and accuracy. In this work we used Wolff method to produce GT depth sampling maps - this method is by no means optimal. Future work could try to produce optimal GT maps offline by using more computationally expensive search and optimization methods such as genetic algorithms and train the network using them. This method can improve the performance of the network.

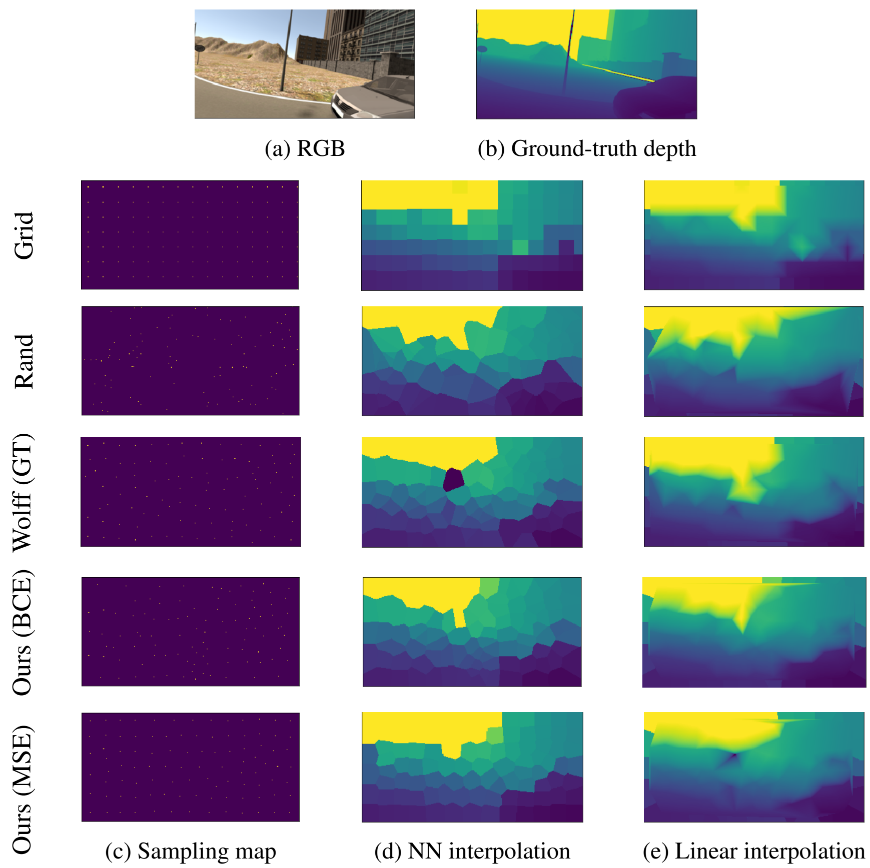


Figure 4: Qualitative results: an example of a RGB image (a) and its ground truth depth image (b), following sampling map (c) and interpolated depths using nearest interpolation (d) and linear interpolation (e) of different sampling methods.

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