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Automatic visibility estimation of a LiDAR point cloud

P. Biasutti^{1,2,3}

J-F. Aujol²

M. Brédif³

A. Bugeau¹

¹ Université de Bordeaux, LaBRI, CNRS UMR 5800, France

² Université de Bordeaux, IMB, CNRS UMR 5251, France

³ Université Paris-Est, LASTIG MATIS, IGN, ENSG, France
pierre.biasutti@labri.fr

Abstract

This paper presents a novel methodology to estimate if a point of a LiDAR point cloud is visible from a given point of view corresponding to the optical center of a camera. Visibility estimation is essential in order to improve LiDAR and optical data fusion. The LiDAR point cloud is first projected on the image plane of the camera. Then, a criterion on the neighborhood of each point is used to automatically estimate which points are visible from the given point of view.

1 Introduction

The fusion of multimodal data (here, LiDAR and optical) is a major issue for various applications such as autonomous driving, 3D mapping, road inventory, computer vision and point cloud visualization [2] [1]. A sparse 2D image can be derived from the point cloud by projecting it in the image plane of an optical camera. This sparse representation can be used to enhance the optical data by using channels such as reflectance, depth, etc. Nevertheless, the difference of location between the LiDAR sensor and the optical camera as well as the acquisition nature can lead to visibility ambiguities within the projection (*e.g.* an area in the projection where the points of different objects can get confused). Those ambiguities can compromise the multimodal fusion. Thus, they should be corrected by removing points that do not lie on foreground objects.

1.1 Related works

Estimating the visibility of a point cloud from a given point a view has been already studied for point clouds of homogeneous densities. The methods described in [5] and [6] have proven their efficiency on such data. These methods compute the visibility of each point by considering which points lie on the convex hull of the spherical symmetry of the point cloud. However, the variations of the density of points within a LiDAR point cloud limit the performances of such methods. Another method [3] relies on point clouds with very high sampling rate to estimate this visibility by projecting the point cloud at different scales. Although this method is very effective, LiDAR point clouds acquired by Mobile Mapping Systems (MMS) are often of low density.

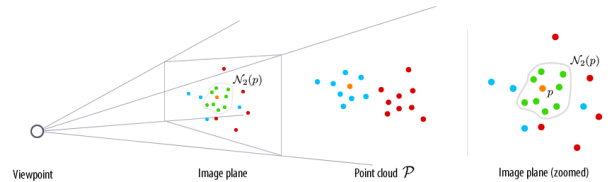


Figure 1: Illustration of 3D and 2D notations.

Therefore, these kind of method is not relevant in this context. In this paper, we propose a novel approach for estimating the visibility of points from point clouds with low and variable densities.

2 Methodology

Given a point cloud \mathcal{P} and an associated point of view ϕ , $\mathcal{P}_\phi \subset \mathcal{P}$ represents the set of points that project in the image spanned by ϕ . $\mathcal{N}_2(p)$ corresponds to the K -nearest neighbors of a point $p \in \mathcal{P}_\phi$ regarding its projection coordinates in the image domain of the point of view ϕ (Hereafter $K = 27$, $p \in \mathcal{N}_2(p)$). These notations are illustrated in Figure 1. The visibility of each point p is defined as follows:

$$\alpha_p = e^{-\frac{(d_p - d_p^{min})^2}{(d_p^{max} - d_p^{min})^2}} \quad (1)$$

having $d_p^{min} = \min_{q \in \mathcal{N}_2(p)} d_q$, $d_p^{max} = \max_{q \in \mathcal{N}_2(p)} d_q$. Values of α_p are defined from 0 (non-visible) to 1 (visible). The visibility of a point is a binary measure. Thus, we proposed the following criterion for the binarisation:

$$\hat{\alpha}_p = \begin{cases} 1 & \text{if } \alpha_p \geq \bar{\alpha} \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

with $\bar{\alpha} = \frac{1}{\text{Card}(\mathcal{P}_\phi)} \sum_{p \in \mathcal{P}_\phi} \alpha_p$ being the mean value of the estimated visibilities. Note that the median value as well as $\bar{\alpha} = 0.5$ were also tested to define the optimal threshold for the binarisation, with lowest results.

Table 1: Comparison of the scores of the different methods against our groundtruth

Threshold	HPR [5]	Proposed model $\bar{\alpha} = 0.5$	Proposed model α_p median	Proposed model α_p mean
POV #1 (337384 pts)	74.09%	90.15%	86.35%	90.96%
POV #2 (247682 pts)	69.09%	86.95%	86.78%	88.39%
POV #3 (463531 pts)	81.55%	82.21%	76.35%	83.75%
Total (1048597 pts)	74.91%	86.43%	83.16%	87.70%
Temps de calcul	7.82s	0.91s	1.03s	0.91s

3 Experiments and results

In order to validate our method, we propose a manually annotated dataset containing more than 1 million points as a groundtruth. This dataset consists in 3 point clouds acquired by the RobotCar system [4] at different locations. Two of these point clouds are acquired several meters from one other in order to test the stability of the results provided by our method. The third point cloud corresponds to another location and covers a much wider area to test the limit of the method in case of large distances ($> 100\text{m}$). Each point of the dataset comes with the label 1 or 0 depending if the point is visible or not. This dataset is publicly available online ¹. The archive contains 3 text files in the *.xyz* format where each line corresponds to $[x, y, z, u, v, label]$ where x, y, z are the 3D coordinates of the point, u, v being the 2D coordinates of the point when projected into ϕ and *label* being its label. Moreover, optical images corresponding to each of the 3D point clouds are given for understanding purposes.

3.1 Quantitative analysis

Table 1 presents the scores of the different methods for each of the 3D point clouds of our groundtruth dataset. The score corresponds to the percentage of points on which the visibility was correctly estimated. We can see that our method largely overcomes the HPR method [5] for every point cloud of the dataset. Moreover, using the mean of visibilities for $\bar{\alpha}$ provides the best results in every case. Finally, our method processes the full dataset (1048597 points) in less than a second, whereas the HPR method takes 7 seconds. Both algorithms were implemented in Matlab and used with the optimal parameters as defined by the authors.

3.2 Qualitative analysis

Figure 2 shows the result of the visibility estimation for each method. 2.b shows the annotation as provided by our dataset. Figures 2.c and 2.d present the visibility estimation result given by the HPR method and by our proposed method respectively. One can notice that the result provided by HPR over-estimates visible points, whereas our

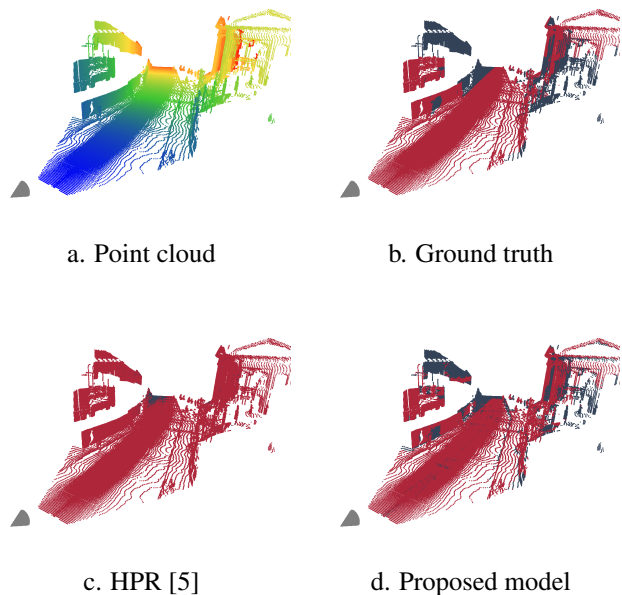


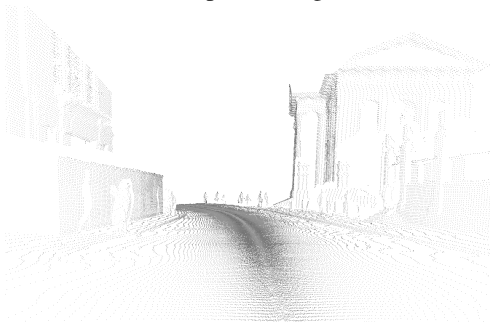
Figure 2: Example of the result of visibility estimation in the first point cloud of the dataset. (a) the point cloud where the heat of the color is proportional to the depth, (b) is the annotated point cloud (red: visible, grey: non-visible), (c) HPR result and (d) the proposed method result. The result brought by HPR estimates too many visible points, whereas our method provides a result that is very close to the groundtruth.

proposed model succeeds in correctly estimating the visibility of large areas with many occlusions. This analysis is confirmed in Figure 3 that shows the same scene observed from the corresponding ϕ point of view (*e.g.* the point of view from which the visibility is being estimated). Figure 3.a corresponds to the optical image associated with the point of view for understanding purposes. Figure 3.b shows the annotated groundtruth. Figures 3.c and 3.d display the results of HPR and our method. Misestimated points are denoted in red. Once again, one can see that our method better succeeds in discarding non-visible points from visible points.

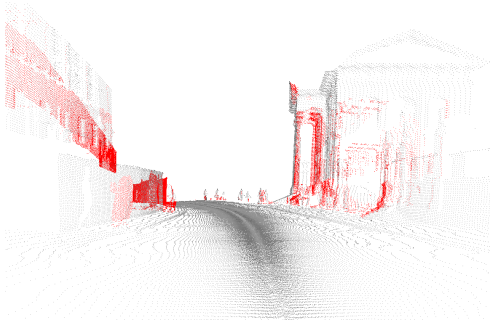
¹Point Cloud Visibility Dataset: <http://www.labri.fr/perso/pbiasutt/Visibility/>



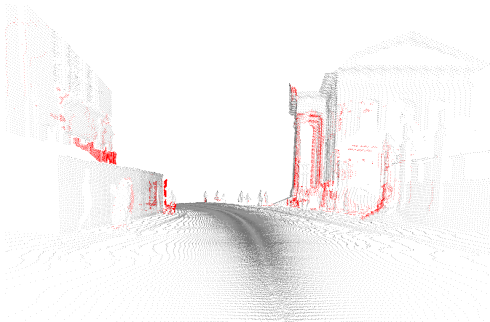
a. Optical image



b. Groundtruth



c. HPR [5]



d. Proposed model

Figure 3: Result of the visibility estimation once projected in the image domain. (a) the optical image associated with the point of view, (b) groundtruth, (c) HPR result and (d) our. Red points in (c) and (d) correspond to misestimated points.

4 Conclusions

In this paper, we proposed a novel, fully automatic, method for the estimation of the visibility of a low density point cloud given a point of view. Our method significantly improves the state-of-the-art results while keeping computational times near realtime. We prove its efficiency both quantitatively and qualitatively on a manually annotated dataset of over a million points, made publicly available.

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