TABLE III
COMPARISON OF THE POTHOLE DETECTION ACCURACY AMONG DIFFERENT STATE-OF-THE-ART APPROACHES.

Dataset	Method	Correct Detection	Incorrect	Misdetection	Recall	Precision	Accuracy	F-score
1	1 [67]	11	11	0	0.520	0.543	0.989	0.531
	2 [68]	22	0	0	0.462	0.998	0.994	0.632
	3 [64]	22	0	0	0.499	0.987	0.994	0.663
	4 [63]	21	1	0	0.701	0.964	0.995	0.811
	our	22	0	0	0.853	0.993	0.991	0.918
2	1 [67]	42	10	0	0.975	0.971	0.999	0.973
	2 [68]	40	8	4	0.874	0.991	0.997	0.929
	3 [64]	51	1	0	0.980	0.980	0.999	0.980
	4 [63]	52	0	0	0.950	0.883	0.992	0.915
	our	40[2]	0	0	0.909	0.996	0.992	0.951
3	1 [67]	5	0	0	0.612	0.771	0.995	0.683
	2 [68]	5	0	0	0.534	0.992	0.996	0.694
	3 [64]	5	0	0	0.582	0.983	0.996	0.731
	4 [63]	5	0	0	0.702	0.996	0.996	0.823
	our	5	0	0	0.953	0.984	0.996	0.969
Total	1 [67]	58	21	0	0.800	0.822	0.994	0.800
	2 [68]	67	8	4	0.695	0.992	0.995	0.817
	3 [64]	78	1	0	0.771	0.982	0.996	0.864
	4 [63]	78	1	0	0.890	0.898	0.996	0.894
	our	67	0	0	0.899	0.994	0.992	0.945

[2] Only 40 of the refereed (52) models were founded online.

based on the analysis of point clouds which is challenged by the lack of benchmark datasets obtained from LiDAR devices. To overcome this problem, we created our own synthetic dataset and added it to the maps of the CARLA simulator, thereby creating realistic driving environments. The comparison of our method with other state-of-the-art approaches, regarding the accuracy of pothole detection in real datasets, has shown its effectiveness providing very promising outcomes.

Our future plans include the visualization of additional information that can facilitate the increase of driver's situational awareness (e.g., road boundaries), and the analysis of user preferences, e.g., via questionnaires, of the AR visualization system when driving (through a steering wheel chair) in the simulated environment of the CARLA simulator.

APPENDIX

A. Robust Principal Component Analysis (RPCA)

RPCA is a powerful mathematical tool that has been used in many scientific domains in order to decompose an observed measurement $\mathbf{E}$ into a low-rank matrix $\mathbf{L}$, representing the ideal data unaffected by any kind of noise, and a sparse matrix $\mathbf{S}$, representing the noisy data. Decomposition is performed by solving the following equation:

$$\arg\min_{\mathbf{L},\mathbf{S}} \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1, \quad \text{s.t. } \mathbf{L}+\mathbf{S}=\mathbf{E}, \tag{9}$$

where $\|\mathbf{L}\|_*$ is the nuclear norm of a matrix $\mathbf{L}$ (i.e, $\sum_i \sigma_i(\mathbf{L})$ is the sum of the singular values of $\mathbf{L}$).

A lot of works have been proposed all of these years, presenting excellent results. However, despite the effectiveness that some works [72], [73] have presented in the past, the execution times of the proposed algorithms need improvement. This convex problem can be solved using a very fast approach, as described in [74], according to:

$$\arg\min_{\mathbf{L},\mathbf{S}} \frac{1}{2}\|\mathbf{L}+\mathbf{S}-\mathbf{E}\|_F + \lambda\|\mathbf{S}\|_1 \quad \text{s.t. rank}(\mathbf{L}) = K \tag{10}$$

$$\mathbf{L}^{(t+1)} = \arg\min_{\mathbf{L}} \|\mathbf{L}+\mathbf{S}^{(t)}-\mathbf{E}\|_F \quad \text{s.t. rank}(\mathbf{L}) = K \tag{11}$$

$$\mathbf{S}^{(t+1)} = \arg\min_{\mathbf{S}} \|\mathbf{L}^{(t+1)}+\mathbf{S}-\mathbf{E}\|_F + \lambda\|\mathbf{S}\|_1 \tag{12}$$

In each (t) iteration, the Eq. (11) is updated with rank $= K$. If $\frac{u_K}{\sum_{i=1}^K u_i} > \epsilon$, where u denotes the singular values and ϵ is a small threshold, then the rank is increased by one (i.e., $K = K+1$) and the Eq. (12) is updated too. To update the Eq. (11), a partial SVD($\mathbf{E}-\mathbf{S}^{(t)}$) is estimated keeping K components. To update the Eq. (12), a shrinkage operator is used $\mathcal{D}(.)$, where:

$$\mathcal{D}(\mathbf{E}-\mathbf{L}^{(t+1)},\lambda) = \text{sign}(\mathbf{E}-\mathbf{L}^{(t+1)})\max\{0,|\mathbf{E}-\mathbf{L}^{(t+1)}|-\lambda\} \tag{13}$$

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