MASKEDFUSION: RECONSTRUCT LIDAR DATA BY QUERYING CAMERA FEATURES

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Paper under double-blind review

ABSTRACT

In self-driving applications, LiDAR data provides accurate information about distances in 3D, but lacks the semantic richness of camera data. Therefore, state-of-the-art methods for perception in urban scenes fuse data from both sensor types. In this work, we introduce a novel self-supervised method to fuse LiDAR and camera data for self-driving applications. We build up-on masked autoencoders (MAEs) and train deep learning models to reconstruct masked LiDAR data from fused LiDAR and camera features. In contrast to related methods that use birds-eye-view representations, we fuse features from dense spherical LiDAR projections and features from fish-eye camera crops with a similar field of view. Therefore, we reduce the learned transformations to moderate perspective transformation and do not require additional modules to generate dense LiDAR representations.

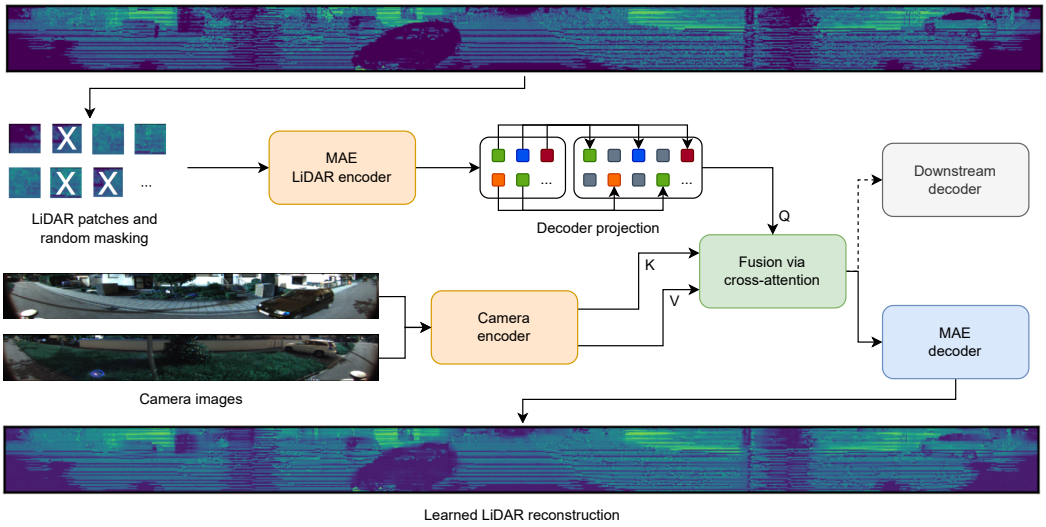

Figure 1: **Reconstruct LiDAR data by querying camera features.** Spherical projections of LiDAR data are transformed into patches, afterwards, randomly selected patches are removed and a MAE encoder is applied to the unmasked patches. The encoder output tokens are fused with camera features via cross-attention. Finally, a MAE decoder reconstructs the spherical LiDAR projections.

1 INTRODUCTION

Simple algorithms that scale well (He et al., 2016; Vaswani et al., 2017; Brown et al., 2020) drive deep learning research forward. A recent addition to this trend are self-supervised pre-training methods that leverage un-labeled data to improve downstream tasks in computer vision (He et al., 2020; Chen et al., 2020; Caron et al., 2021). For self-driving applications, self-supervised pre-training of perception models (Ma et al., 2019) or algorithms for domain adaptation (Wang et al., 2020) are examples. LiDAR data provides accurate information about distances in 3D, but lacks the semantic

richness of camera data. Therefore, state-of-the-art methods for perception in urban scenes (Li et al., 2022; Piergiovanni et al., 2021) fuse data from both sensor types. In this work, we introduce a novel self-supervised method to fuse LiDAR and camera features for self-driving applications. We build up-on masked autoencoders (MAEs) (He et al., 2022) and train vision transformers (ViTs) (Dosovitskiy et al., 2020) to reconstruct masked LiDAR data from fused LiDAR and camera features. Recent related methods (Li et al., 2022; Bai et al., 2022; Ku et al., 2018) fuse LiDAR and camera data in birds-eye-view (BEV) representations, which involves learning complex transformations from camera coordinates to birds-eye-view coordinates. Hess et al. (2023) and Min et al. (2022) apply masked autoencoding to voxel representations of LiDAR data, which requires additional modules for learning dense voxel embeddings from sparse LiDAR voxels. In contrast, we fuse features from dense spherical LiDAR projections with features from fish-eye camera crops with a similar field of view. Therefore, we reduce the learned spatial transformations to moderate perspective transformations. Moreover, our method does not require additional modules to generate dense LiDAR representations. Overall, our contributions are twofold, we introduce a novel self-supervised training regime to fuse LiDAR and camera data and perform initial evaluation on a self-driving dataset.

2 METHOD

Our proposed fusion method builds up-on masked autoencoding (He et al., 2022), which is a recent form of denoising autoencoding. Masked autoencoders (MAEs) consist of a ViT-based encoder and a ViT-based decoder. Accordingly, input images are divided into 16x16 pixel patches and processed as a sequence of tokens. During training, a large number of these patches (50 - 75%) are randomly masked and the training target is the reconstruction of the masked patches. We use a MAE encoder as LiDAR encoder (see Figure 1). After transforming the LiDAR data into patches, randomly selected patches are removed and the MAE encoder is only applied to the unmasked patches. Therefore, our LiDAR encoder achieves the same computational efficiency as a vanilla MAE encoder. The encoder output tokens are projected to the decoder tokens by re-introducing tokens for masked patches. The decoder tokens are fused with camera features via cross-attention. For this attention mechanism, the LiDAR tokens serve as querys Q and the camera tokens as keys K and values V. Accordingly, our model learns to reconstruct LiDAR data by querying camera features. Finally, a MAE decoder reconstructs the spherical LiDAR projections from the fused tokens.

Experiment. We perform an initial evaluation of our method with the KITTI-360 dataset (Liao et al., 2022) (Appendix A). Figure 2 shows crops of a masked LiDAR intensity channel and the corresponding reconstruction and target. The importance of camera features is demonstrated by the superior reconstruction quality (higher MSSIM scores (Wang et al., 2003)) when LiDAR and camera features are used. We simulate missing camera features by using zero matrices as camera input.

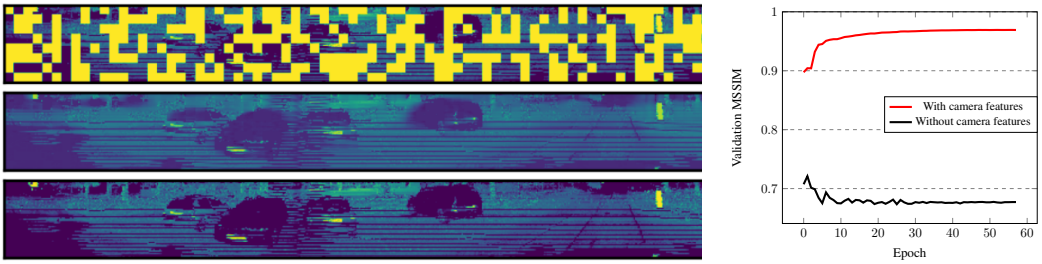

Figure 2: **Left:** Masked spherical LiDAR projection and corresponding reconstruction and target. **Right:** Comparison of reconstruction quality with camera features vs. without camera features.

3 CONCLUSION

In contrast to related methods that use birds-eye-view representations, we fuse features from dense spherical LiDAR projections and features from fish-eye camera crops. Therefore, we reduce the learned spatial transformations to moderate perspective transformation and do not require additional modules to generate dense LiDAR representations. Future steps include evaluating the performance of our fusion method as pre-training for semantic scene understanding in urban scenarios.

URM STATEMENT

The authors acknowledge that at least one key author of this work meets the URM criteria of ICLR 2023 Tiny Papers Track.

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A Appendix

Dataset. KITTI-360 contains recordings from driving in urban and sub-urban areas in Germany. The dataset contains 76k sets of fish-eye camera images and LiDAR scans. We use randomly selected 70k samples as training split and 6k samples as validation split. We transform all LiDAR scans into spherical projections and store range, height and intensity data as 3 channels.

Model and training. We use a patch size of 8x8 pixels for our model. The smaller patch size than in a vanilla ViT is chosen to better handle fine granular semantic correlations (Xie et al., 2021). Both our ViT-based encoders have an embedding dimension of 2048 and a depth of 8. The cross-attention block (Chen et al., 2021) for fusion has an embedding dimensions of 1024 and a depth of 2. The reconstruction decoder has an embedding dimensions of 1024 and a depth of 8. As loss, we compute the mean squared error between the target and the reconstructed patches. We choose AdamW (Loshchilov & Hutter, 2019) as optimizer with an initial learning rate of 10^{-4} and use cosine annealing to reduce the learning rate while training for 57 epochs. During training, we track the multiscale structural similarity index measure (MSSIM) between the learned reconstruction and the training target to asses the reconstruction quality.

Further results. Figure 3 shows additional qualitative results of our method. Overall, after training, our model is able to reconstruct the spherical LiDAR projections using our fusion algorithm.

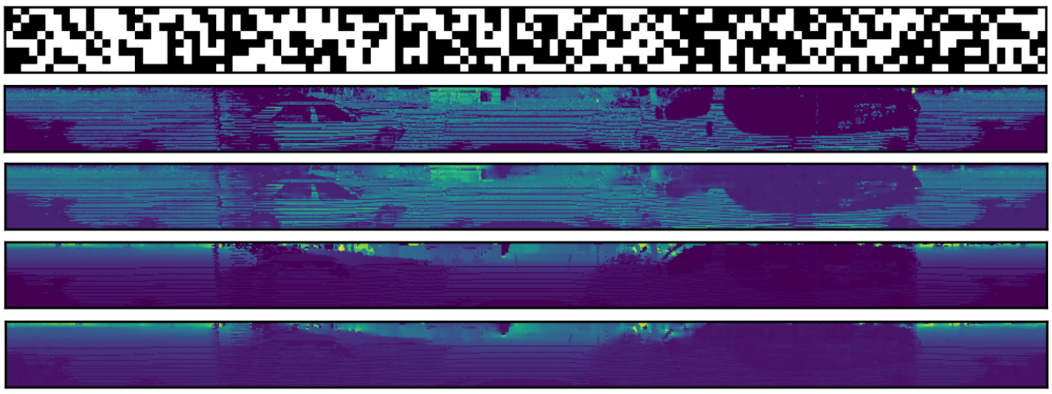

Figure 3: **Validation samples and corresponding LiDAR reconstructions.** First row: Masking scheme. Second row: Target intensity channel. Third row: Reconstructed intensity channel. Fourth row: Target range channel. Fifth row: Reconstructed range channel. To improve the visibility, all channels are pseudo-colorized using the viridis colormap.