OverlapTransformer: An Efficient and Rotation-Invariant Transformer Network for LiDAR-Based Place Recognition

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Abstract—Place recognition is an important capability for autonomously navigating vehicles operating in complex environments and under changing conditions. It is a key component for tasks such as loop closing in SLAM or global localization. In this paper, we address the problem of place recognition based on 3D LiDAR scans recorded by an autonomous vehicle. We propose a novel lightweight neural network exploiting the range image representation of LiDAR sensors to achieve fast execution with less than 4 ms per frame. Based on that, we design a yaw-rotation-invariant architecture exploiting a transformer network, which boosts the place recognition performance of our method. We evaluate our approach on the KITTI and Ford Campus datasets. The experimental results show that our method can effectively detect loop closures compared to the state-of-the-art methods and generalizes well across different environments. To further evaluate long-term place recognition performance, we provide a novel challenging Haomo dataset, which contains LiDAR sequences recorded by a mobile robot in repetitive places across seasons. Both the implementation of our method and our new Haomo dataset are released here: https://github.com/haomo-ai/OverlapTransformer

I. INTRODUCTION

Place recognition plays an essential role for autonomously navigating systems. In contrast to camera-based place recognition [1], [12], [19], [27], [28], LiDAR-based place recognition [4], [15], [24], [31] is comparably robust to day-and-night light changes and different weather conditions. Therefore, LiDARs are an attractive sensing modality that can be used for autonomous driving in outdoor large-scale environments. LiDAR-based place recognition is the task to determine if the robot is currently in a place that has been visited before by comparing the current LiDAR observations with the map or a database of formerly taken observations. It supports tasks such as simultaneous localization and mapping (SLAM) to find loop closure candidates and global localization to obtain an initial guess of the robot’s position.

In this paper, we propose a novel place recognition method utilizing range images produced by 3D LiDARs installed on an autonomous vehicle. The range image is a natural representation of a single 3D scan from a rotating LiDAR sensor such as Velodyne or Ouster sensors. It is a compact representation and is especially suitable for online tasks such as online SLAM [2], [6], loop closing [3], [4], or localization [5], [7] due to its image-like structure. Instead of using handcrafted descriptors [13], [22], [23], we propose a new transformer neural network to extract yaw-rotation-invariant global descriptors from LiDAR scans. We apply a similar overlap concept as described in OverlapNet [3], [4] to supervise the network learning and to estimate the similarity between pairs of scans. Different to OverlapNet, which exploits multiple cues such as normal, intensity, and semantic information as the network input, in this work we only use the depth information of the range image to achieve faster online performance and make the approach easier to generalize. Due to the yaw-rotation-invariant design of the network, our approach can recognize places even when the vehicle driving in different directions, such as the reverse loop in our novel challenging Haomo dataset illustrated in Fig. 1.

The main contribution of this paper is a lightweight transformer neural network that exploits only depth information of range images to achieve place recognition. Our approach is very fast to execute and at the same time yields very good recognition results. Based on the attention mechanism of the Transformer [25] and the NetVLAD head [1], our proposed OverlapTransformer compresses LiDAR range images into a global descriptors. We build the architecture of our OverlapTransformer to ensure that each descriptor is yaw-rotation-invariant, which makes our method robust to viewpoint changes. We train the proposed OverlapTransformer only on a part of the KITTI dataset and evaluate it on both,
KITTI and Ford Campus datasets with the loop closure metric in line with OverlapNet [3]. Besides, we recorded and will release a new dataset, which contains three different challenges including place recognition for long time spans, reverses driving, and different appearances scenes to evaluate different methods.

In sum, we make the claims that our approach is able to (i) detect loop closure candidates for SLAM using only LiDAR data without any other information, and generalize well into the different environments without fine-tuning, (ii) achieve long-term place recognition on our Haomo dataset in outdoor large-scale environments with a different LiDAR sensor, (iii) recognize places with changing viewpoints exploiting the proposed rotation-invariant descriptors up to potentially rounding error, (iv) run faster than most state-of-the-art place recognition methods (<4 ms).

II. RELATED WORK

Place recognition is a common topic in computer vision and robotics with a large number of scientific work proposed using RGB images [1], [12], [27], [28]. We refer more image-based methods to survey by Lowry [19] and focus our discussion here more on 3D LiDAR-based approaches.

Due to the high accuracy of the range information and illumination invariance, LiDAR-based place recognition has attracted attention in the field of autonomous vehicles. For example, He et al. [13] propose M2DP, which projects point cloud maps into NDT cells and uses the attention mechanism to aggregate multi-level features and generate a fixed-length global descriptor for place recognition. Liu et al. [18] uses ten types of local features from raw point cloud clusters as input of a graph neural network to generate global descriptors. There are other learning-based approaches directly generating global descriptors on LiDAR scans for place recognition. For example, PointNetVLAD by Uy et al. [24] firstly uses PointNet [21] to map laser points into a higher dimension and then use the NetVLAD architecture [1] previously used for visual place recognition to generate global descriptor for LiDAR-based place recognition. SOE-Net by Xia et al. [33] combines the orientation-encoding module with PointNet to generate point-wise features and fed to a self-attention network to generate discriminative and compact global descriptors. Wiesmann et al. [32] propose a LiDAR-based place recognition that can be used with a compressed point cloud. Most recently, Zhou et al. [35] propose NDT-Transformer, which transforms raw point cloud into NDT cells and uses the attention mechanism of Transformer [25] to improve the representation ability. Our method also directly generates global descriptors on LiDAR scans. Different from methods that use local point cloud maps [18], [24], [33], [34], our method only uses range images generated from single 3D LiDAR scans. This yields fast computations suitable for online operation. Our method also uses the Transformer similar to the work by Zhou et al. [35] to boost place recognition performance, but our method operates on range images instead of NDT cells.

Most recently, there are also works exploiting semantic information for place recognition. For example, Chen et al. [4], [3] propose OverlapNet to exploit multiple cues generated from LiDAR scan, including depth, normal, intensity, and semantics for LiDAR-based loop closure detection and localization. SGPR by Kong et al. [16] exploits the semantics and topological information of the raw point cloud and extracts the semantic graph representation with graph neural networks to find loop closures. Li et al. [17] use semantics to enhance SC and proposed semantic scan context. Similarly, Cramariuc et al. [9] utilize semantic information to improve the performance of SegMatch. In contrast to these semantic-enhanced methods, our approach only uses depth information of the range images to achieve online performance and is easier to generalize to different environments and datasets collected by different LiDAR sensors.

III. OUR APPROACH

The overview of our OverlapTransformer is depicted in Fig. 2. The range image from raw point cloud is fed to an encoder, which is a modified OverlapNetLeg to extract features from range images (see Sec. III-A). Then, the encoded feature volume is fed to the transformer module, where we utilize a transformer to embed the relative location of features and the global information across the whole range image (see Sec. III-B). In the end, we use a VLAD.
module with multi-layer perceptrons (MLPs) to compress the features and generate a rotation-invariant 1-D global descriptor (see Sec. III-C). During training, we use the triplet loss with calculated overlap labels to better distinguish the positive and negative training examples (see Sec. III-D).

A. Range Image Encoder

We use range images from LiDAR scans as input data. The range image is an intermediate representation of LiDAR data obtained from a typical rotating LiDAR scanner. Given the LiDAR sensor parameters, there is a projection transformation between a point cloud and a range image. A point cloud $P$ can be projected to a range image $R \Pi : \mathbb{R}^3 \rightarrow \mathbb{R}^2$, where each pixel contains one 3D point. Each point $p_i = (x, y, z)$ is converted to image coordinates $(u, v)$ by

$$
\begin{pmatrix}
  u \\
  v
\end{pmatrix} = \begin{pmatrix}
  \frac{1}{2} [1 - \arctan(y, x)\pi^{-1}] w \\
  [1 - \arcsin(zr^{-1}) + f_{up}] f^{-1} h
\end{pmatrix},
$$

(1)

where $r = ||p||_2$ is the range, $f = f_{up} + f_{down}$ is the vertical field-of-view of the sensor, and $w, h$ are the width and height of the resulting range image $R$.

The yaw rotation $\theta$ of a point cloud is rotation-equivariant to the horizontal shift $s$ of the corresponding range image, and the following equations hold:

$$
\begin{pmatrix}
  u' \\
  v'
\end{pmatrix} = \begin{pmatrix}
  u + s \\
  v
\end{pmatrix}, \quad s = \frac{1}{2} [1 - \theta\pi^{-1}] w,
$$

(2)

$$
RCS = \Pi(R_\theta P).
$$

(3)

The term $C_s$ represents the column shift of the range image $R$ by matrix right multiplication, and $R_\theta$ represents the yaw rotation matrix of the point cloud $P$. Note that, there might be rounding errors in pixel coordinates when rendering the range images from point clouds.

The range image with size of $1 \times h \times w$ is fed to the modified OverlapNetLeg shown in Tab. I, where 1 refers to the one range channel, while $h, w$ are the height and width of the range image. Compared to OverlapNet [3], the convolution filters in our encoder only compress the range image in the vertical dimension but not the width dimension to avoid the rounding error to the rotation equivariance.

Besides, there is no padding and dropout in our proposed architecture to keep the rotation equivariance for every intermediate feature generated by each network layer. We denote the output feature volume of the range image encoder as $F = \text{Encoder}(R)$, with the size of $c \times 1 \times w$, and $FC_s = \text{Encoder}(\Pi(R_\theta P))$ holds. The variable $c$ refers to the channel number of the encoded feature.

B. Transformer Module

Inspired by NDT-transformer [35], we also exploit a transformer to extract more distinctive features for LiDAR place recognition. As shown in the middle of Fig. 2, our attentional feature transformer is composed of three modules, multi-head self-attention (MHSA), feed-forward network (FFN), and layer normalization (LN). Different from NDT-transformer, we use one transformer block in our transformer module, since more transformer blocks do not increase the performance but make our network harder to train based on the experiments.

The MHSA can learn the relationship between features captured by a self-attention mechanism. We denote the feature volume extracted by the MHSA as $A$, and the self-attention mechanism of the transformer can then be formulated as:

$$
A = \text{Attention}(\text{Conc}(Q, K, V)) = \text{softmax} \left( \frac{QK^T}{\sqrt{dk}} \right) V,
$$

(4)

where $F = \text{Conc}(Q, K, V)$, $\{Q, K, V\}$ are the query, key and value splits along the channels of the feature volumes.
generated by our range image encoder and \( d_k \) represents the dimension of splits.

\( A \) is then fed into the FFN and LN, where the self-attention mechanism is applied to build connections between different salient features at different locations of range images. We name the attentional feature volume as \( S \) and can be calculated as:

\[
S = \text{LN}(\text{FFN}(\text{LN}(\text{Conc}(F,A)))) + \text{LN}(\text{Conc}(F,A)),
\]

where \( \text{Conc}(\cdot) \) represents the concatenation operation across channels. In this way, a coarse feature \( F \) extracted by our range image encoder is upgraded to an attentional feature \( S \).

Here we further show that our transformer module is also rotation-equivariant. It is obvious that concatenation across channels, linear transformations, ReLU function, and LN are rotation-equivariant. Since the query, key, and value feature volumes in attention mechanism are split along the channel dimension, given a shifted feature generated by our range image encoder \( FC_s = \text{Conc}(QCs, KCs, VCs) \), we have:

\[
\text{Attention}(FC_s) = \text{Attention}(\text{Conc}(QCs, KCs, VCs))
\]

\[= \text{softmax}\left(\frac{QCs(KCs)^T}{\sqrt{d_k}}\right)VC_s \]

\[= \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)VC_s \]

\[= AC_s. \]

Since FFN is applied to each element in the feature volume separately and identically [25], it is therefore also rotation-equivariant towards features. Then, for the rest part of our attentional feature transformer, we also have:

\[
\text{LN}(\text{FFN}(\text{LN}(\text{Conc}(FC_s, AC_s)))) + \text{LN}(\text{Conc}(FC_s, AC_s))
\]

\[= \text{LN}(\text{FFN}(\text{LN}(\text{Conc}(F,A)))) + \text{LN}(\text{Conc}(F,A)))Cs
\]

\[= SC_s. \]  

The transformer module finds the inner connections between different parts of the input feature volume, which exploits the spatial relations of different features in the scene. Similar to humans using distinctive landmarks and their relationship to determine the places, our transformer module also focuses on spatial features and their relationship using the attention mechanism, which boosts the place recognition performance of our method.

### C. VLAD Module

NetVLAD was first proposed by Arandjelovic et al. [1] to tackle image-based place recognition in an end-to-end manner and outperform its non-learning-based counterparts. Uy et al. [24] transfer it for LiDAR-based place recognition and proof that NetVLAD is permutation invariant, thus suitable for unordered point clouds. The original NetVLAD, however, is hard to be directly used to generate rotation-invariant global descriptors for point cloud, because the yaw rotation of point cloud leads to a different input of point coordinates and features, which makes the PointNetVLAD less robust to the rotation or noise of the pose of autonomous vehicles.

In this work, we leverage the permutation invariance of NetVLAD together with our rotation-equivariant features to achieve a yaw-rotation invariance and generate rotation-invariant descriptors. We represent the input feature volume with size of \( c \times 1 \times w \) as a set of 1-D vectors over channel dimension \( S = \{z_1, z_2, \ldots, z_i, \ldots, z_w\} \), where \( z_i \) is the \( i \)-th vector with size of \( c \) channels. Given that NetVLAD is permutation invariant [24], we have:

\[
\text{VLAD}(ZCs) = \text{VLAD}(\{z_{w-s}, \ldots, z_w, z_1, \ldots, z_{w-s-1}\})
\]

\[= \text{VLAD}(\{z_1, z_2, \ldots, z_i, \ldots, z_w\}) \]

\[= \text{VLAD}(Z). \]

We denote the output descriptor of our VLAD module as \( \mathcal{V} \) and we have:

\[
\mathcal{V} = \text{VLAD}(S) = \text{VLAD}(SC_s),
\]

which means our VLAD module is rotation-invariant.

In Fig. 3, we depict a toy example to illustrate that our model can generate rotation-invariant descriptors with rotation-equivariant range image representations. We show at each row a different yaw rotation and the visualizations of the intermediate results of each module of our method. The yaw rotation of point clouds corresponds to the horizontal shift of range image pixels along the width dimension. Supposing the first row is the results of the raw LiDAR data, rotated 0 degree, the second and the third are rotated by 90 and 180 degrees along the yaw angle, which corresponds to the range images shifted by \( \frac{1}{3}w \) and \( \frac{1}{2}w \) respectively. As can be seen, the outputs of the rotation-equivariant OverlapNetLeg and transformer module are also shifted accordingly (shown by the second and the third column). Since the VLAD module is rotation-invariant, it thus generates the same global descriptor in all three cases as shown in the fourth column.

During online operation, we use the rotation-invariant global descriptors to represent LiDAR scans and use the Euclidean distance between pairs of descriptors to find the nearest reference places.

### D. Network Training

We follow OverlapNet [3] using overlap to define the places. For a query scan \( R_q \) and a reference scan \( R_r \), we use
TABLE II: Statistics of Haomo dataset

| Sequence | 1-1 | 1-2 | 1-3 | 2-1 | 2-2 |
|----------|-----|-----|-----|-----|-----|
| Date     | 2021.12.08 | 2021.12.08 | 2021.12.08 | 2021.12.28 | 2022.01.13 |
| N<sub>scans</sub> | 12500 | 22345 | 13500 | 100887 | 88154 |
| N<sub>pos.</sub> | 40000 | 40000 | - | 48000 | - |
| N<sub>neg.</sub> | 60000 | 60000 | - | 72000 | - |
| N<sub>queries</sub> | - | - | 1350 | - | 8815 |
| Length    | 2.3 km | 2.3 km | 2.3 km | 11.5 km | 11.1 km |
| Direction | Same | Reverse | - | Same | - |
| Role      | Database | Database | Query | Database | Query |

N<sub>scans</sub>, N<sub>pos.</sub>, N<sub>neg.</sub> and N<sub>queries</sub> are the numbers of scans, positive samples, negative samples and query scans respectively.

the ground truth poses to reproject $R_r$ into the coordinate frame of $R_q$ and get $R'_r$. The overlap between them is calculated as:

$$O_{R_q R_r} = \frac{\sum_{(u,v)} I\{(||R'_r(u,v) - R'_r(u,v)|| \leq \delta)\}}{\min(\text{valid}(R_q), \text{valid}(R'_r))},$$  

where $I(a) = 1$ if $a$ is true and $I(a) = 0$ otherwise, valid($R$) refers to the counts of valid pixels of range image $R$, and $\delta$ is the threshold to decide the overlapped pixel.

For each training tuple, we utilize one query descriptor $V_q$, $k_p$ positive descriptors $\{V_p\}$, and $k_n$ negative descriptors $\{V_n\}$ to compute lazy triplet loss:

$$L_T(V_q, \{V_p\}, \{V_n\}) = k_p(\alpha + \max_{V_p}(d(V_q, V_p))) - \sum_{k_n}(d(V_q, V_n)),$$

where $\alpha$ is the margin to avoid negative loss and $d(\cdot)$ is the squared Euclidean distance. We take a pair of scans whose overlap is larger than 0.3 as a positive sample, otherwise a negative sample. We use the triplet loss to minimize the distance between the query and the hardest positive global descriptors, and maximize the distance between the query and all sampled negative global descriptors.

IV. HAOOMO DATASET

There are several LiDAR-based datasets for autonomous driving [11], [20], [30], which can be used for evaluating loop closure detection methods. However, not many of the publicly available datasets show significant repetitive reverse routes for long-term large-scale place recognition of autonomous driving. In this work, we therefore provide such a new challenging dataset called Haomo dataset and will release it together with our code to support future research. As shown in Fig. 4, the dataset was collected by a mobile robot built by HAOMO.AI Technology company equipped with a HESAI PandarXT 32-beam LIDAR sensor, a SENSING-SG2 wide-angle camera, and an RTK GNSS in urban environments of Beijing. There are currently five sequences in Haomo dataset as listed in Tab. II. Sequences 1-1 and 1-2 are collected from the same route in 8th December 2021 with opposite driving direction. An additional sequence 1-3 from the same route is utilized as the online query with respect to both 1-1 and 1-2 respectively to evaluate place recognition performance of forward and reverse driving. Sequences 2-1 and 2-2 are collected along a much longer route from the same direction, but on different dates, 2-1 on 28th December 2021 and 2-2 on 13th January 2022, where the old one is used as a database while the newer one used as query. The two sequences are for evaluating the performance for large-scale long-term place recognition.

Our Haomo dataset will be made publicly available and will be frequently updated in the future to include highly dynamic and constantly updated traffic scenes. More sequences with different types of sensor data are also planned to be included.

V. EXPERIMENTAL EVALUATION

The experimental evaluation is designed to showcase the performance of our approach and evaluate the claims that our approach is able to: (i) detect loop closure candidates for SLAM using only LiDAR data without any other information, and generalize well into the different environments without fine-tuning, (ii) achieve long-term place recognition on our Haomo dataset in outdoor large-scale environments, (iii) recognize places with changing viewpoints exploiting the proposed rotation-invariant descriptors, (iv) run faster than most state-of-the-art place recognition methods.

A. Implementation and Experimental Setup

We use three different datasets to evaluate our method, including KITTI dataset [11] collected in Germany with a 64-beam LiDAR sensor, Ford Campus dataset [20] collected in U.S. with a 64-beam LiDAR sensor, and our Haomo dataset collected in China with a 32-beam LiDAR sensor. Following OverlapNet [3], we use range images of size 1 × 64 × 900 for 64-beam LiDAR data of KITTI and Ford Campus datasets, and range image with size of 1 × 32 × 900 for our Haomo dataset with 32-beam LiDAR data. For our transformer module, we set the embedding dimension $d_{\text{model}} = 256$, the number of heads $n_{\text{head}} = 4$, and the intermediate dimension of the feed-forward layer $d_{fhn} = 1024$. We do not utilize dropout to achieve rotation-equivariant. For NetVLAD, we set the intermediate feature dimension $d_{\text{inter}} = 1024$, the output feature dimension $d_{\text{output}} = 256$, and the number of clusters $d_{K} = 64$. The output of our VLAD module is
TABLE III: Comparison of loop closure detection performance

| Dataset       | Approach              | AUC  | F1max | Recall @1 | Recall @1% |
|---------------|-----------------------|------|-------|-----------|------------|
| **KITTI**     | Histogram [22]         | 0.826| 0.825 | 0.738     | 0.871      |
|               | Scan Context [15]      | 0.836| 0.835 | 0.820     | 0.869      |
|               | LiDAR Iris [31]        | 0.843| 0.848 | 0.835     | 0.877      |
|               | PointNetVLAD [24]      | 0.856| 0.846 | 0.776     | 0.845      |
|               | OverlapNet [3]         | 0.867| 0.865 | 0.816     | 0.908      |
|               | **Ours**               | **0.907**| **0.877**| **0.906**| **0.964**  |
| **Ford Campus**| Histogram [22]         | 0.841| 0.800 | 0.812     | 0.897      |
|               | Scan Context [15]      | 0.903| 0.842 | 0.878     | **0.958**  |
|               | LiDAR Iris [31]        | 0.907| 0.842 | 0.849     | 0.937      |
|               | PointNetVLAD [24]      | 0.872| 0.830 | 0.862     | 0.938      |
|               | OverlapNet [3]         | 0.854| 0.843 | 0.857     | 0.932      |
|               | **Ours**               | **0.923**| **0.856**| **0.914**| **0.954**  |

a vector of size 256. For calculating overlap ground truth by Eq. (14), we set \( \delta = 1 \) for KITTI odometry benchmark with provides 64-beam LiDAR scans, \( \delta = 1.2 \) for our Haomo dataset depending on the density of the points. We set \( k_p = 6 \), \( k_n = 6 \), and \( \alpha = 0.5 \) for the triplet loss.

### B. Evaluation for Loop Closure Detection

The first experiment supports our claim that our approach detects loop closure candidates for SLAM using only LiDAR data without any other information, and generalizes well into the different environments without fine-tuning. Following the experimental setup of OverlapNet [3], we train and evaluate our approach on the KITTI Odometry Benchmark [11]. We use sequences 03–10 for training, sequence 02 for validation, and sequences 00 for evaluation. To evaluate the generalization ability of our method, we also test it on sequence 00 of the Ford Campus dataset [20]. Note that we did not trained our approach on the Ford Campus dataset, which shows the generalization ability of our method.

Since the semantics are not always available for different environments, we compare our methods to existing methods which do not utilize semantic information, including Histogram [22], Scan Context [15] with augmentation, LiDAR Iris [31], PointNetVLAD [24], and OverlapNet (Delta-Geo-Only) [3]. Loop closure detection during SLAM takes previous scans as the database, excluding the nearby 100 scans to avoid detecting the most recent scans. We utilize AUC, F1 max scores, recall@1 and recall@1% for evaluation and the results are shown in Tab. III. As can be seen, our method outperforms all the baseline methods on the KITTI dataset. Using our network pre-trained on KITTI directly on an unseen environment, Ford Campus dataset, without any fine-tuning, our proposed method still outperforms other methods, and only for recall@1%, our method is on par with the state-of-the-art non-learning-based method Scan Context [15], which shows the good generalization ability of our method.

### C. Evaluation for Place Recognition

In the second experiment, we investigate the long-term place recognition of our method on our Haomo dataset in outdoor large-scale environments with a different type of LiDAR sensor. The difference between loop closure detection and place recognition is that for place recognition the database/map is usually given and we need to find the location of the vehicle within the database/map. For loop closing in contrast, the database grows during operation. We have three challenges in Haomo dataset. From easy to difficult, the first is a short-term same-direction challenge, sequence 1-1 as database and 1-3 for query. The second is the short-term inverse-direction challenge, sequence 1-2 as database and 1-3 for query. The last is a long-term large-scale challenge, sequence 2-1 as database and 2-2 for query. We use database sequences for training too. As shown in Tab. II, we firstly downsample the database and for each sampled laser scan, we calculate the overlaps between this scan and all other scans. For testing, we take one sample query scan from every ten scans in query sequences, and acquire its ground truth reference scans with overlap value larger than 0.3. Once one of the true references is found, we consider that query as a successful loop closure.

We utilize recall@N to evaluate the performance of algorithms on Haomo dataset as the most large-scale place recognition approaches do. The results of the first two challenges are shown in Fig. 5 and Fig. 6. As can be seen, our method outperforms other methods on these two challenges, especially for the reverse driving one due to the rotation-invariant architecture design of our method. Although Scan Context and Histogram are also robust to pure rotation, our method outperforms them, since in real application there is
not only pure yaw rotation but also changes in locations and environment appearance due to the dynamic objects. Our method is more robust to all challenging conditions compared to baseline methods. The evaluation on long-term large-scale sequences 2-2 and 2-1 are illustrated in Fig. 7, and our method keeps its superiority also on large-scale long-term datasets, which shows the ability of our method to be used for real autonomous driving applications.

D. Ablation Study on Rotation-Invariance

The third experiment investigates the rotation-invariance of our approach. The results support the claim that our method generates rotation-invariant descriptors and can recognize places with changing viewpoints. For that, we rotate each query scan of the KITTI dataset along the yaw-axis in steps of 30 degrees and search the places with respect to the same original database. In this experiment, we test all baselines and use Recall@1 as the evaluation metric. As illustrated in Fig. 8, our proposed OverlapTransformer is not influenced by pure rotation along the yaw-axis, and maintains the best performance compared to the baseline methods. On the contrary, PointNetVLAD, Scan Context, and OverlapNet are all affected by rotation. PointNetVLAD and OverlapNet lose efficacy quickly for increasing yaw angle discrepancies. Here, we only use OverlapNet with the head of the similarity estimation for a fair comparison. Scan Context loses efficacy to some extent but is better than PointNetVLAD since the ring key representing occupancy ratio is rotation-invariant. The LiDAR Iris and histogram-based method is also rotation-invariant as our method but has lower recall@1 than ours. LiDAR Iris achieves rotation-invariant by rotating its features multiple times and choosing the best scored one, which makes it very slow as shown in Sec. V-E. Our OverlapTransformer outperforms other baseline methods significantly due to our devised rotation-invariant model exploiting rotation-equivariant range images.

E. Runtime

The experiment evaluates the runtime requirements of our method. As we will see, it supports our last claim that our method runs faster than most of the state-of-the-art place recognition methods and that it can run at 250 Hz, i.e., much faster than the scanning rate. We compare the runtime of our OverlapTransformer with all baseline methods. We conduct all experiments on a system with an Intel i7-11700K CPU and an Nvidia RTX 3070 GPU. We run all the methods to find top-1 candidates for one query scan with respect to a database consisting of 2000 reference scans. We report the averaged results over ten experiments. As shown in Tab. IV, we count the runtime separately for descriptor generation and searching. For the time cost by generating the descriptor, we take also the LiDAR data preprocessing into consideration. As can be seen, for descriptor generation, our method is the fastest method among the state-of-the-art learning-based method with 3.28 ms for each scan, and slightly slower than the pure geometric histogram-based method [22]. PointNetVLAD needs an extra downsampling process for raw point cloud, which is accelerated by GPU. OverlapNet needs to estimate the normals. For the time cost by searching, our method outperforms all baselines including the non-learning-based methods. Since Histogram, PointNetVLAD and our method do not need an ad-hoc function to compute the similarity of descriptors, thus FAISS library [14] is used to accelerate the searching. For Scan Context using ring key for first-step retrieval is also be accelerated by FAISS library, but the final retrieval uses a special scoring function which cannot be accelerated by FAISS. LiDAR Iris needs an ad-hoc function to compare binary feature maps, which cannot be accelerated, and OverlapNet needs also a small network to estimate the overlaps, which cannot be accelerated by FAISS and leads to inefficient retrieval. Note that, PointNetVLAD generates descriptors with the same size ($1 \times 256$) as ours, but consumes more time. The reason could be that the descriptors generated by our method are more descriptive than those by PointNetVLAD, and thus need less time for searching.
VI. CONCLUSION

In this paper, we presented a novel approach for LiDAR-based place recognition that is fast to execute (~4 ms) and outperforms the state of the art in terms of place recognition performance. Our approach utilizes a lightweight network with a Transformer attention mechanism to generate rotation-invariant descriptors, which allows us to handle challenging place recognition effectively and efficiently. We trained our method on the KITTI dataset and evaluated it on both, the KITTI and the Ford Campus dataset for loop closure detection, which shows a solid generalization capability. For further evaluating the place recognition ability on long time spans, reverse driving, and large-scale scenes, we developed a new challenging Haomo dataset and conducted extensive evaluations with multiple baseline approaches on it. The experimental results suggest that our method outperforms the other state-of-the-art methods in different challenging environments in terms of recognition performance and speed.

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