DiSCO: Differentiable Scan Context with Orientation

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Abstract—Global localization is essential for robot navigation, of which the first step is to retrieve a query from the map database. This problem is called place recognition. In recent years, LiDAR scan based place recognition has drawn attention as it is robust against the environmental change. In this paper, we propose a LiDAR-based place recognition method, named Differentiable Scan Context with Orientation (DiSCO), which simultaneously finds the scan at a similar place and estimates their relative orientation. The orientation can further be used as the initial value for the down-stream local optimal metric pose estimation, improving the pose estimation especially when a large orientation between the current scan and retrieved scan exists. Our key idea is to transform the feature learning into the frequency domain. We utilize the magnitude of the spectrum as the place signature, which is theoretically rotation-invariant. In addition, based on the differentiable phase correlation, we can efficiently estimate the global optimal relative orientation using the spectrum. With such structural constraints, the network can be learned in an end-to-end manner, and the backbone is fully shared by the two tasks, achieving interpretability and light weight. Finally, DiSCO is validated on the NCLT and Oxford datasets with long-term outdoor conditions, showing better performance than the compared methods.

I. INTRODUCTION

Large-scale place recognition is an essential component of global localization in outdoor autonomous mobile robotics applications. It provides candidate places for loop-closure which further corrects the drift during the long-term running and builds drift-free globally consistent maps. Thanks to the rich information in vision sensors, lots of successful visual place recognition methods were presented [1], [2], [3]. However, visual place recognition algorithms suffer from strong appearance and viewpoint changes, thus can not be robustly utilized in long-term outdoor scenarios. In contrast, 3D LiDAR captures more stable structural information and becomes a competitive sensor option for place recognition. In addition, based on the 360-degree view of the LiDAR sensor, LiDAR-based place recognition has a chance to recognize a scan captured at a similar place in the database that has a large orientation difference from the query scans. This is useful in practice, e.g., the database is built when running in one direction of a highway while the query scan is captured from the opposite direction.

However, many works on LiDAR-based place recognition directly imitate the visual place recognition pipeline ignoring the characteristics of LiDAR data. First, unlike vision, LiDAR data is represented as 3D point clouds. Hence network design useful for vision may be ineffective for LiDAR data. For instance, rotation within the image-plane is common in popular bird’s-eye view (BEV) representation of LiDAR scan but rarely exists in an image of a front-facing camera, which makes difference for convolution operation because convolution is only equivariant for image-plane translation. Another challenge is that existing point cloud registration techniques, e.g., ICP, are very sensitive to the initialization. They usually fail when the initial rotation has a 180-degree flip even if the initial position is perfect, essentially leading to the failure of the loop closure. Thus, for successful loop closure, we have to unreasonably discard these recognized places with correct position but large orientation difference, or use an exhaustive search for the correct relative orientation.

In this paper, we set to address the above issues by presenting a novel LiDAR-based place recognition method, called Differentiable Scan Context with Orientation (DiSCO) as shown in Fig. 1. Specifically, following the polar transformed bird’s-eye view representation utilized in the Scan Context [5], our end-to-end learnable DiSCO has a highly
explainable architecture to enforce the network to learn a rotation-invariant place signature. As rotation-invariance is converted into translation-invariance in the polar domain, we have a frequency spectrum based similarity evaluation metric that can be efficiently evaluated via Euclidean distance. In addition, for successful loop closure, we propose a differentiable phase correlation, which can reuse the frequency spectrum to generate a reliable relative orientation between the query and database scans. With this relative orientation as the initial value for scan registration, a precise relative pose can be expected. As the parameters are fully shared for both place retrieval and relative orientation estimation, our network architecture is lightweight. To summarize, the contribution of the paper includes

- A highly interpretable network architecture is proposed for extracting rotation-invariant place signature in the frequency domain, achieving efficient similarity evaluation.
- A differentiable phase correlation estimator is proposed for global optimal relative orientation estimation. This branch shares the network parameter with the signature extraction branch, further improving the efficiency.
- Evaluations on two large scale datasets with multiple sessions and seasonal environmental changes demonstrates the effectiveness of DiSCO.

II. RELATED WORK

A considerable amount of literature has been published on the place recognition task. These studies proposed different descriptors used to discriminatively represent places. Recent evidence suggests that pose can be estimated together with place candidates.

A. Handcraft Descriptors

Many works have been conducted for place recognition with 3D point clouds. Most of the previous works designed handcraft descriptors that describe either local or global features of a point cloud to discriminate places. Early approaches of 3D analysis using handcraft descriptors mainly adopt statistics ideas of histograms or signatures [6]. Signature-based methods [7], [8] voxelize a point cloud into different regions and calculate interest values of the regions, and aggregate information from all regions. Histogram-based approaches [9], [10], [11] count the trait values of each point and generate the descriptor. These handcraft methods focused on acquiring local features and manually aggregate them as global descriptors which are not efficient for complex scenes. Other works followed the visual place recognition idea that extracting keypoints on point clouds by projecting the point cloud to a range image. Steder et al. [12] presented a pipeline that uses NARF keypoint extracted on range images and generated global descriptors using bag-of-words. Following this projecting trend, He et al. [13] proposed M2DP which projects point cloud to multiple planes as a global descriptor.

B. Deep Learning Descriptors

With the big progress made by deep learning in computer vision, learning-based approaches have been proposed recently. A common idea is to learn the embedding of places and matching between them. Barsan et al. [14] presented a method that embeds point cloud with intensity information and achieved place retrieval by matching embeddings. Dube and Cramariuc [15], [16] preferred learning embeddings for segments. Similar to the handcraft descriptors, Yin et al. [17], [18] proposed a semi-handcrafted feature learning framework using the siamese network. Kim et al. [19] also developed a semi-handcraft descriptor called Scan Context which transforms point clouds to polar images and uses simple CNN for long-term place classification. Other methods tried to learning descriptors directly from 3D points. PointNetVLAD [20] is consist of point feature network PointNet [21] and the visual place recognition method NetVLAD [2] and generates global descriptor for 3D point clouds. However, these methods just consider the place retrieval part of global localization. PointNetVLAD discards the pose information at the very first steps. Scan Context also eliminated the rotation factor by augmenting the input. Eventually, many researchers realized this issue and some methods appear to solve the place recognition with yaw estimation. Schaupp et al. [22] proposed OREOS that not only estimate place candidates but also estimated the yaw discrepancy between scans. OverlapNet [23] estimated yaw with range images exploiting multiple types of information extracted from 3D LiDAR scans.

C. Pose Estimation

For pose estimation on the point cloud, traditional approaches followed the idea of ICP and suffer from the quality of the initial pose. Some learning-based methods’ solution is to directly regress the pose but lacks interpretability. In our case, we mainly estimate the relative orientation between two BEVs. OREOS [22] borrowed the idea of regressing the pose and achieved good performance. Barnes et al [24] deployed a correlation-based matching method to estimate translation but exhaustively search for the orientation. DPCN [25] modified the traditional correlation-based image registration pipeline to a differentiable manner and achieved 3-DoF pose estimation on heterogeneous sensor measurements. Our yaw estimation module is also based on correlation which provides interpretability as well as precision.

III. METHODOLOGY

In this section, two main modules of our method are introduced in detail. The feature extraction module transforms point clouds into the frequency spectrum to generate place signature. The differentiable phase correlation module estimates the relative orientation between two scans using the correlation that also derived from the frequency spectrum. An overview of our system can be seen Fig. 2.
A. Problem Statement

As the robot moves on the local planar ground surface, we consider the 3-DoF relative pose \((x, y, \theta)\) between a 3D LiDAR query scan \(P_q\) and a map scan \(P_s\) taken at a similar place. We define a similar place as the relative pose with slight translation \((x, y)\), but arbitrary \(\theta\). For global localization, we have to deal with two problems. First, given \(P_q\), recognize the \(P_s \in M\) without any prior knowledge, where \(M\) is the map database. Second, given \(P_q\) and \(P_s\), estimate the relative orientation \(\theta\) without referring to any initial value. Generally, a scan registration is followed to achieve precise relative pose \((x, y, \theta)\). However, as the precise pose estimation is mature, we mainly focus on place recognition and orientation estimation.

Rotation invariant signature learning: The BEV representation is an efficient way to down-sample a large amount of point data in a scan and it has also been widely studied in the community, demonstrating superiority for downstream tasks [26]. For place recognition, the BEV representation is robust for slight translation but is variant for large rotation caused by orientation. Regarding the BEV representation as a function \(B\), we have \(B(P, \theta)\). When we change \(\theta\), \(B\) changes accordingly, thus cannot achieve rotation invariance. Therefore, the core challenge of the first problem is to find a feature extractor \(F\), leading to

\[
F(B(P, 0)) = F(B(P, \theta)) \quad (1)
\]

Then we have

\[
F(B(P_q, 0)) = F(B(P_s, 0)) \quad (2)
\]

which means the signatures of query scan \(P_q\) and map scan \(P_s\) becomes the same no matter how large relative orientation \(\theta\) is, thus achieving rotation invariance.

Relative orientation estimation: On the contrary, when \(P_s\) is recognized, we seek for rotation variance that can be utilized to estimate the orientation globally. Regarding this, we have to find another representation \(\mathcal{H}\), and an estimator \(\phi\) that

\[
\theta = \phi(\mathcal{H}(B(P, 0)), \mathcal{H}(B(P, \theta))) \quad (3)
\]

An intuitive solution for this problem is that \(\mathcal{H}\) is an identity mapping, and \(\phi\) is an exhaustive solver. So the global optimal \(\theta\) can be found by enumerating all possible rotations, then picking the one yielding the best match between one scan and the other transformed scan. However, the main challenge for this second problem is that an efficient global solver \(\phi\) is expected, and the solver should be differentiable that can back-propagate the gradient.

B. Differentiable Signature in Frequency Domain

We first propose several options for \(B\) as shown in Fig. 3:

- **Multi-layer Occupied BEV** models occupied information. Voxelization is used to assign the original point cloud to grids. An empty grid is regarded as unoccupied, otherwise, a grid is occupied. The occupied information is commonly used in 3D shape representation validating its effectiveness.

- **Multi-layer Density BEV** models density feature. We still map the point cloud into voxel representation and then count points in every voxel. Moreover, we reorganize the voxel representation into multi-channel BEV images as our inputs. By using this method, we model the multi-layer density as well as the occupied information into our representation.

- **Single-layer Height BEV (Scan Context)** models max-height feature. For each pillar in the voxel volume, we pick the height of the top point as the feature of this pilar, resulting in a 1-channel BEV image. This representation is introduced in [5], which is a special form of the BEV representations. We also evaluate this data representation in experiments.

In addition to these representations, any other BEV representation is qualified for our pipeline.
Network architecture: To eliminate the effects of the rotation factor, we first convert the rotation factor into the translation factor by using the polar transform \( T \), then followed by a convolutional neural network (CNN), \( \mathcal{N} \), to learn the features in the polar domain. Finally, we apply Fourier Transformation \( \Omega \) to convert the polar BEV image representation from its original domain to a representation in the frequency domain. Note that after operator \( T \), the rotation of the scan is transformed into translation in the polar domain, as shown in Fig. 3. Then in the frequency domain, as the magnitude component of the frequency spectrum is translation-invariant, the signature actually becomes rotation invariant. Based on this character, we propose an operation for building signature \( D \) as the output of \( \mathcal{F} \) in Eq. (2) as

\[
D. = \mathcal{F}(\cdot) = |\Omega \circ \mathcal{N} \circ T(\cdot)|
\]

Note that in this pipeline, all operators are differentiable, and \( \mathcal{N} \) has parameters that can be learned.

C. Metric Learning

Theoretically, Eq. (4) is rotation-invariant. However, as the translation cannot exactly equal to 0, and the environmental structure may change slightly, exact rotation-invariance Eq. (2) is impossible. We instead set to build a weaker version

\[
D.P_s = \arg \min_{P_t \in M} d(D_P, D_{P_t})
\]

which means among all scans in the map database, the query scan \( P_q \) and the scan at a similar place, \( P_r \), have the minimal distance in the metric of \( d \). As \( D \) is rotation-invariant, we simply use Euclidean distance as the metric \( d \), which can be implemented efficiently with KD-tree. In contrast, Scan Context uses N-way augmentation [19] to alleviate translation-variant caused by the rotation variance after the polar transform, thus the metric for evaluating the distance between scan contexts calls for an expensive operation.

Quadruplet training: Inspired by Eq. (5), we follow quadruplet loss \( L_{quad} \) in PointNetVLAD [20] to train the parameters of \( \mathcal{N} \). In this paper, we use an encoder-decoder network architecture, U-Net, as \( \mathcal{N} \) to generate representation having the same resolution as the input. The loss is designed to force the network to learn a close distance between signatures taken at similar places and far apart distance between different ones. To fit in the metric learning pipeline, we flatten the signature \( D \). To eliminate the disturbance from high-frequency noise, we evaluate the distance only for the center part of \( D \), which is the low-frequency area, indicating the general structure of the surrounding environment. The loss term is given as

\[
L_{quad} = \sum_{q,i} \left[ ||D_{P_q} - D_{P_i}||^2 - ||D_{P_q} - D_{P_{n_1}}||^2 + \alpha_1 \right] + \\
+ \sum_{q,i,j} \left[ ||D_{P_q} - D_{P_i}||^2 - ||D_{P_{n_1}} - D_{P_{n_2}}||^2 + \alpha_2 \right]
\]

where \( D_{P_{n_1}} \) and \( D_{P_{n_2}} \) are the signatures of two negative samples i.e. scans taken at different places to that of query scan. \([ \cdot ]_+ \) is the hinge loss of \( \cdot \), \( \alpha_1 \) and \( \alpha_2 \) are the margins.

D. Differentiable Relative Angle Estimation

To estimate the relative orientation at the same time, we re-use part of \( \mathcal{F} \). Note that scans after applying \( \mathcal{N} \circ T \), denoted as \( G \), are represented in the polar domain, thus the rotation is parameterized by translation.

\[
G_s(\theta) = \mathcal{N} \circ T(B(P_s, \theta))
\]

Thus estimating the relative orientation \( \theta \) is equivalent to estimating relative translation between the two scans in the polar domain. As mentioned before, a global optimal solver for estimating the relative translation of two images is achieved by an exhaustive searcher.

\[
\theta = \arg \min_\delta ||G_q - G_s(\delta)||
\]

(8)

Note that the sweeping variable is the translation, this exhaustive search is equivalent to cross-correlation when the metric in Eq. (8) is replaced with an inner product as

\[
\theta = \arg \max_\delta G_q \ast G_s(\delta)
\]

(9)

where \( \ast \) is the convolution operator. As we know, the convolution of two images is equivalent to the point-wise multiplication of two frequency spectrums. Therefore, we can further share \( \Omega \) with the signature mapping operation \( \mathcal{F} \) as

\[
\theta = \arg \max_\delta \Omega^{-1}(\Omega(G_q) \otimes \Omega(G_s(\delta)))
\]

(10)
where $\odot$ is the point-wise multiplication. With GPU based FFT, this operation can be very efficient without losing global optimality. Thus $\mathcal{H}(\cdot)$ in Eq. (3) is specified as

$$\mathcal{H}(\cdot) = \Omega \odot \mathcal{N} \odot \mathcal{T}(\cdot)$$  \hspace{1cm} (11)

The whole pipeline is called phase correlation and it is used for estimating the relative pose of images. This solver is efficient and global optimal but not differentiable due to $\text{arg} \max$, which cannot be a valid form for $\phi$ in Eq. (3).

**Differentiable phase correlation:** To make the solver Eq. (10) differentiable, we replace the maximization based solver with an expectation based solver. Specifically, we regard the cross-correlation as a probability distribution $p(\delta)$ by applying a softmax block to keep every entry positive, and all entries summing up to 1. After that, the estimation of $\theta$ is assigned with the expectation of $p(\delta)$.

$$p(\delta) = \text{softmax}(W\Omega^{-1}(\Omega(G_q) \odot \Omega(G_s(\delta))) + b)$$  \hspace{1cm} (12)

$$\theta = \sum_{\delta} \delta p(\delta)$$  \hspace{1cm} (13)

where $W$ and $b$ are parameters of softmax. A cascaded connection of softmax and expectation is also called soft $\text{arg} \max$ sometimes. Finally, we propose the form of $\phi$ as

$$\phi(\cdot, \cdot) = \sum_{\delta} \delta \cdot \text{softmax}(W\Omega^{-1}(\cdot \odot \cdot) + b)$$  \hspace{1cm} (14)

For this task, we design the loss term as KL divergence between the probability distribution $p(\delta)$, with the supervision of a one-hot distribution $1(\delta - \theta^*)$ peaking at the ground truth angle $\theta^*$

$$\mathcal{L}_{\text{rot}} = KLD(p(\delta), 1(\delta - \theta^*))$$  \hspace{1cm} (15)

| APPROACH | PLACE RETRIEVAL | ORIENTATION |
|----------|----------------|-------------|
| PointNetVLAD [20] | ✓ | × |
| ScanContext [19] | ✓ | × |
| OREOS [22] | ✓ | ✓ |
| DiSCO (our) | ✓ | ✓ |

**E. Implementation and Training**

Based on the operators Eq. (4), (11) and (14), we have a fully sharable network backbone without any extra parameters to satisfy the both tasks, which is the benefit of the strong interpretable structure. In this pipeline, the convolutional network is enforced to learn features from the polar domain. Note that instead of adding CNN $\mathcal{N}$ before the polar transform, we add $\mathcal{N}$ after polar transform. We consider that it is more effective since rotation within the image-plane, which is very common in scan data, is transformed to translation, while the convolution operation is equivariant in translation. In vision data, as the rotation within the image plane is rarer than in laser data, the polar domain is less effective.

We train the network in a joint learning manner. To achieve this, two losses Eq. (6) and (15) are combined into a joined loss $\mathcal{L}$:

$$\mathcal{L} = \mathcal{L}_{\text{quad}} + \lambda \mathcal{L}_{\text{rot}}$$  \hspace{1cm} (16)

where $\lambda$ is a hyper-parameter to balance the two terms.

We use ADAM [27] as our optimizer and set the learning rate to 0.00001. The margins for quadruplet loss are $\alpha_1 = 0.5$, $\alpha_2 = 0.2$. We randomly rotate the input LiDAR scans as in [22]. All modules of DiSCO are trained together with these settings.

**IV. EXPERIMENTS**

The experiments we conduct is designed to support our claims about DiSCO: (i) It can simultaneously predict place candidates and orientation. (ii) It is efficient and lightweight. Furthermore, we separately analyze the place recognition and orientation estimation module and provide a detailed ablation study on dimensionality and resolution.

**A. Dataset and Experimental Settings**

**Oxford Dataset:** We use the benchmark dataset proposed by PointNetVLAD. The original point cloud data is from open-source Oxford RobotCar [28]. The benchmark contains LiDAR sensor data collected at different times of a 10km region. In [20], points in ground planes are removed and each submap is at fixed regular intervals of 20m for testing and 10m for training. All submaps are downsampled to a fixed 4096 points. The ground truth with the UTM coordinate is provided. The LiDAR sensor is at fixed regular intervals of 20m for testing and 10m for training. All submaps are downsampled to a fixed 4096 points. The ground truth with the UTM coordinate is also attached to each submap. To get the correct annotation of data, point clouds are split into positives and negatives pairs. Those point clouds that are at most 10m apart is defined as positive pairs while negative pairs are at least 50m apart. For evaluation, the query submap is successfully localized if the retrieved point cloud is in 25m. Same as the experimental settings in [20], we use 44 sets of full and partial runs to...
train our network. There are 21711 submaps for training and 3030 for testing.

**NCLT Dataset**: NCLT is the abbreviation of The University of Michigan North Campus Long-Term Vision and LIDAR Dataset [4] which consists of 27 sets of driving data on the University campus over 14 months. A Velodyne HDL-32 sensor is mounted on the driving platform to provide point clouds at 10 Hz.

Our process steps for metric learning follow the settings in [22] which requires sampling of positive pairs and negative pairs. In the NCLT dataset, point clouds are defined as positive pairs if they are at most 1.5m apart and negative pairs if they are to be at least 2m apart. After 5 epoch of training, we adopt a hard-negative mining strategy to boost the performance of the network. The input of our network is the original point cloud with the ground plane removed. We use 1 run (2012-02-04) to train our model and 6 runs (2012-03-17, 2012-05-26, 2012-06-15, 2012-08-20, 2012-09-28, 2012-10-28) to evaluate. The training part and evaluation part of the dataset is detached as shown in Fig. 4.

The query places in evaluation runs are from the yellow area and the rest of the dataset places are for training in only 1 run. For evaluation, the query scan is successfully localized if the retrieved point cloud is in 3m.

### B. Comparison Methods

We compare our metric learning algorithm with three competitive methods in recent years: PointNetVLAD [20], Scan Context [19], and OREOS [22]. General characters of these approaches are summarized in Tab. II.

- **PointNetVLAD** is a combination of PointNet and NetVLAD, so it can directly learn from point coordinates. We follow the original paper to setup our evaluation experiments and use the open-source code in PyTorch version to get 1024-dimensional descriptors.

- **Scan Context** is a handcrafted descriptor extracted from input point clouds. The original Scan Context regards the place recognition task as a combination of a place classification and a new place detection problem so that they use a classification network to predict a place index in the database. A new place detector that uses the entropy of the output vectors is then developed to decide whether the current place is in the database. To fit into our metric learning structure and evaluate performance, we reimplement the Scan Context as one kind of data representation of our system. We evaluate the original Scan Context and also use the Scan Context representation in our network named DiSCO-SC.

- **OREOS** is implemented by us following the paper’s elaboration. Unlike the original method that adopts ICP as post process, we only evaluate orientation estimation.

### TABLE II: Detailed experiment results.

| Dataset | Approach            | Recall@1 | Recall@1% | AUC  |
|---------|---------------------|----------|-----------|------|
| NCLT    | DiSCO-occupied(our) | 89.08    | 99.14     | 92.91|
|         | DiSCO-density(our)  | 86.71    | 97.87     | 90.76|
|         | DiSCO-range(our)    | 65.93    | 90.38     | 72.82|
|         | DiSCO-SC(our)       | 88.28    | 99.02     | 91.02|
|         | OREOS [22]          | 58.02    | 91.44     | 66.00|
|         | Scan Context [19]   | 63.58    | 92.35     | 71.39|
|         | PointNetVLAD [20]   | 44.1     | 76.27     | 51.62|
| Oxford  | DiSCO-occupied(our) | 75.01    | 88.44     | 78.81|
|         | OREOS [22]          | 46.46    | 68.47     | 52.10|
|         | Scan Context [19]   | 64.59    | 81.88     | 69.30|
|         | PointNetVLAD [20]   | 70.57    | 85.42     | 74.61|

Fig. 5: Place recognition performance on NCLT (top) and Oxford (bottom) datasets using different variants of DiSCO and comparison methods.

Fig. 6: Demonstration of the harmful pitch influence on range image. Three range images in the left column are at the same location. The corresponding BEV images shown in the right column are not badly affected. For Visualization, we use the same size for both kinds of representation.
C. Place Recognition Analysis

In a practical place retrieval scenario, we often test more than one place candidate to ensure the robustness. To this end, we evaluate the performance of the place recognition module with top $k$ candidates tested. Corresponding to the previous comparison methods, the $k$ in the Oxford dataset is 25, and 10 in the NCLT dataset [20], [22].

We evaluate the place recognition performance of baseline methods and our DiSCO variants using the precision-recall curve for the NCLT and Oxford datasets which both contain long-term conditions. The experimental results are shown in Fig. 5 and Tab. III DiSCO variants using BEV representation outperform methods using range images like OREOS and range image variant of DiSCO. In the Oxford dataset, due to the large sampling interval between two places, our polar BEV representation suffers from deformation and can not achieve its best ability. The deformation is mainly caused by the relatively small overlap area between some scans.

The results on NCLT dataset are shown in Fig. 5 and Tab. III we notice that the robot car suffers from large pitch disturbance which is harmful to the range image, the demonstration of the effect is shown in Fig. 6. This effect is not significant in the BEV images which shows the robustness of the BEV representations. The contrast between the original Scan Context and Scan Context with Fourier transform (DiSCO-SC) indicates the efficiency and effectiveness of our place recognition module. The drastic reduction of PointNetVLAD [20] on NCLT mainly results from different types of LiDAR. Unlike the submaps built by a 2D LiDAR sensor like SICK, point clouds collected by a 3D LiDAR sensor used in the NCLT Dataset is much sparser. Even so, our DiSCO shows its ability on dealing with different modalities.

D. Orientation Estimation Analysis

To evaluate the accuracy of the orientation estimation module, we use the NCLT dataset with ground-truth orientations attached. By using the ground-truth orientations of point clouds, we can calculate orientation estimation errors. Similar to the evaluation indicator in OREOS [22], we also assess the mean and standard deviations of the estimation errors, and results are listed in Tab. III. Note that the results of orientation estimation are those produced by the author of OREOS.

Our correlation-based orientation estimator not only provides interpretability but also improves the orientation estimation performance. The superior performance supports the idea that our differentiable geometric solver is more appropriate than the network-based regression solver.

In addition, the orientation estimation accuracy is sensitive to the resolution of the input. The polar transform discretizes the rotation space into a fixed-size so that the signature has its theoretical maximal precision. As in our orientation estimation, the input size along the orientation axis is 120 pixels, so the theoretical maximal precision is $360^\circ/120\text{pix} = 3^\circ/\text{pix}$. In the ablation section, we further discuss the influence of the resolution.

E. Ablation Study

Voxel resolution analysis: Our input data representation is based on voxelization. The resolution of voxelization is intuitively an essential factor of the final prediction. We test several resolutions in rotation to show the impact. The experiment results are shown in Tab. IV. The dense voxelization in rotation can bring higher precision in orientation estimation, but the large input dimension consumes more time.

Cutoff frequency analysis: We visualize the signatures of point clouds as shown in Fig. 7 and find that almost all information is gathered around the center of the frequency domain. The actual size of this signature is the same as the input size ($40 \times 120$), but the informative area is relatively small. So we implement some low-pass and high-pass filters with different cutoff frequencies for our network and study the discriminative ability of our method and the results are shown in Tab. V. Note that the dimension of the signature can make a great impact on runtime performance.

The middle part of the signature is the low-frequency component of the original representation indicating the general


TABLE VI: Average computational execution times of our DiSCO in the different dataset in [ms].

| Dataset | Preprocess | Generate signature | Estimate orientation | Total |
|---------|------------|--------------------|----------------------|-------|
| NCLT    | 0.80       | 6.20               | 2.50                 | 9.50  |
| Oxford  | 0.40       |                    |                      |       |

structure of the environment while the rest is often high-frequency details or noise. As shown in experiments, our network mainly learns to recognize the general structure of the environment.

F. Runtime evaluation

We test our method on a system equipped with an AMD Ryzen 7 3700X CPU with 3.6GHz and an Nvidia GeForce RTX 2060 Super with 8GB memory. The runtime of every component of our method is shown in Tab. VI. For the Oxford Dataset, the point clouds in the benchmark dataset have already been processed, so the preprocessing step is fast. As for the NCLT dataset, the input is the original point cloud contains almost 30k points. Implemented in parallel, we achieve almost the same process time as in the Oxford dataset. By using the KD-tree structure, retrieval through a submap database takes logarithm time complexity. Therefore, our system can realize online place recognition and orientation estimation in long-term tasks.

V. CONCLUSION

In this paper, we propose a novel framework for simultaneously estimating the relative orientation and place candidates in challenging long-term conditions. The main idea of the framework is to convert the rotation-invariant frequency spectrum. Based on such structure design as constraints, the two tasks can share the whole network without additional parameters, achieving effective and real-time performance.

In the future, we plan to combine the metric pose estimation into our method to achieve a long-term SLAM system.

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