CGS-Net: Aggregating Colour, Geometry and Semantic Features for Large-Scale Indoor Place Recognition

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Abstract—We describe an approach to large-scale indoor place recognition that aggregates low-level colour and geometric features with high-level semantic features. We use a deep learning network that takes in RGB point clouds and extracts local features with five 3-D kernel point convolutional (KPConv) layers. We specifically train the KPConv layers on the semantic segmentation task to ensure that the extracted local features are semantically meaningful. Then, feature maps from all the five KPConv layers are concatenated together and fed into the NetVLAD layer to generate the global descriptors. The approach is trained and evaluated using a large-scale indoor place recognition dataset derived from the ScanNet dataset, with a test set comprising 3,608 point clouds generated from 100 different rooms. Comparison with a traditional feature based method and three state-of-the-art deep learning methods demonstrate that the approach significantly outperforms all four methods, achieving, for example, a top-3 average recall rate of 75% compared with 41% for the closest rival method.

I. INTRODUCTION

Place recognition is a key capability to enable autonomous robots to operate in large-scale environments. It has been a popular research area in the past decades in both robotics and computer vision communities. Place recognition is frequently mentioned together with global localisation and relocalisation, serving as the first step to solve the latter tasks. To solve the place recognition problem, a two-step approach is usually adopted with the first step extracting the local features and the second one constructing global descriptors.

When using images as the input, the problem is also known as visual place recognition. Pre-deep-learning approaches tackle this problem with handcrafted local feature descriptors followed by global feature embedding such as a vector of locally aggregated descriptors (VLAD) [1] or bag of words (BoW) [2]. These approaches along with early attempts of using convolutional neural networks (CNN) as feature extractors are reviewed in [3]. More recently, NetVLAD [4] first proposed an end-to-end place recognition network by using a CNN for feature extraction and a differentiable NetVLAD layer for global aggregation. This inspired a series of end-to-end visual place recognition networks [5], [6], [7], [8], [9]. To utilise 3-D information, PointNetVLAD [10] and its successors [11], [12], [13], [14], [15] use point clouds as inputs and achieve very high average recall rates in outdoor environments with 3-D features aggregated with the NetVLAD layer. Together with these works, many large-scale outdoor datasets are published with focuses on appearance and view-point differences [16], [17], [18].

However, compared to outdoor place recognition, less attention has been paid to place recognition in indoor environments. We believe indoor place recognition is more challenging because, in addition to the outdoor challenges caused by view-point or illuminance changes, the structural complexity of indoor scenes is in general much higher than outdoor scenes. Besides, the appearance and structure similarities between different indoor scenes are also higher especially when the sensor only captures a small part of the indoor scene. Therefore, methods only using RGB images or 3-D point clouds often demonstrate poor performance for indoor place recognition even though they prevail in outdoor scenes. Nonetheless, the sufficient semantic entities in the indoor scenes are more distinguishable. For example, “table” and “counter” are structurally alike but semantically different. With the help of additional low-level features to describe the details of semantic entities, indoor place recognition performance can be significantly improved.
Thus, in this paper, we propose to solve the indoor place recognition utilising low-level colour and geometric features and high-level semantic features, as illustrated in Fig. 1. The proposed CGS-Net includes a semantic encoder, a semantic decoder and a feature embedding with inputs being coloured point clouds generated from RGB-D frames. To ensure the extracted local features are semantically meaningful, we first train the semantic encoder and semantic decoder on a semantic segmentation task. Then, the semantic features extracted from the last layer are concatenated with the low-level features from previous layers, forming the inputs of the feature embedding to get the global description vector.

Since there are few large-scale indoor place recognition datasets that support both images and point clouds, we introduce a new one created from the ScanNet dataset [19]. The new dataset consists of 35,102 training point clouds generated from 565 different rooms, 9,693 validation point clouds from 142 rooms and 3,608 test point clouds from 100 rooms. Among these test point clouds, 236 form the retrieval database, and the rest 3,372 make up the final test set.

The proposed network is compared with SIFT+BoW, NetVLAD [4], PointNetVLAD [10], and the state-of-the-art MinkLoc3D [15] on the new dataset and strikingly outperforms all 4 methods.

II. RELATED WORK
A. Indoor place recognition

Place recognition is commonly formulated as a retrieval problem and many works on indoor place recognition adopt the same formulation. [20] builds the hierarchical BoW using ORB features with BRIEF descriptor as colour features and intrinsic shape signatures (ISS) with fast point feature histogram (FPFH) as depth features. Using more structural features, [21] extracts planer surfaces and edges from the depth images and performs recognition by matching these extracted structural features. These pre-deep-learning methods achieve great performance in small datasets, but the performance considerably degrades as the scene grows larger. To make the global descriptor more general, deep neural networks are introduced to recent place recognition works. [22] replaces the handcraft features extraction with a Siamese network to simultaneously compute the features and descriptors from a pair of RGB-D frames. Using additional line features, LCD [23] inputs both RGB-D frames and line clusters into the recognition network. Thus, enforcing that the learned global descriptors maintain structural information. Also utilising structural features, SpoxelNet [24] extracts features at different levels and introduces a quad-view integrator on Laidar point clouds to handle the occlusion in the indoor environments. Our CGS-Net also uses features at different levels but we only use a single extraction network while [24] uses two separate feature extraction networks.

B. Semantic place recognition

Most semantic place recognition methods use explicitly represented semantic information. [25], [26], [27], [28] construct graphs of known objects to perform efficient place recognition. In a similar setup, [29], [30] also perform place recognition with graphs of more general semantic entities extracted by semantic segmentation networks. Rather than graphs, [31] creates a histogram of the pixel-wise semantic label predicted on the panoramic images and uses it as the global descriptor. [32] proposes to build local semantic tensors that explicitly describe the extracted semantic information of each input image. More recently, [33] proposes a vector semantic representation that further encodes the layout of the semantic entities in a given input image. On the other hand, semantic information can also be implicitly incorporated into the global descriptor. [34] constructs global descriptors using NetVLAD layers with local features being the semantic edges extracted from the input images. Furthermore, [35] trains an auto-encoder on a semantic scene completion task and then uses the latent code in-between the encoder and the decoder to create the semantic vocabulary for place recognition. The network architecture of CGS-Net proposed in this work is indeed inspired by these two works.

C. Indoor scene classification

Indoor scene classification is similar to indoor place recognition but the main difference between these two tasks lies in the output of the methods. For classification, the output is a label that represents the room type or ID of the input while for recognition, the method needs to output a specific part of a room that is the closest to the query input. Prior to deep learning, [36], [37], [38] use different handcraft features followed by SVM to perform classification. [39] proposes to use separate CNNs to extract colour and depth features, [40] further improves the classification performance by introducing a differentiable local feature selection module, achieving classification with single RGB-D frames. [41] proposes a network with one branch trained for the semantic segmentation task and the other branch for the classification task. In this way, the high-level semantic information is fully utilised in the classification task. Following this idea, [42] uses a 3-D CNN on the reconstruction of an entire room. This work is the closest one to our work but differs in the following aspects. First of all, [42] inputs an entire reconstruction of rooms built with a full sequence of RGB-D frames while our work only takes in a small point cloud generated from the views of single RGB-D frames. Secondly, given a query point cloud, we not only need to know which room the point cloud is captured but also which part of the room it is captured. Finally, in addition to the high-level semantic features, we also take advantage of the low-level colour and geometric features to boost the performance of indoor place recognition in large-scale environments.

III. METHODOLOGY

We follow the most popular place recognition formulation, casting the problem as a retrieval problem. Considering
that the indoor scenes are generally more complex than the outdoor scenes, we choose to use coloured point clouds as the inputs to the network to fully utilise both colour and 3-D geometry information. We also propose to use semantic features to achieve better indoor place recognition. Inspired by [35], instead of using explicitly segmented point clouds, we use the implicit semantic vectors generated by a semantic encoder.

A. Network Architecture

The architecture of the proposed CGS-Net is illustrated in Fig. 2 which is built on the state-of-the-art 3-D point cloud segmentation network, KP-FCNN [43] with deformed kernels. Specifically, the proposed network consists of three main components, in addition to the semantic encoder and semantic decoder from KP-FCNN, another feature embedding is introduced to learn global descriptors given RGB-D inputs. KP-FCNN has demonstrated its efficiency and robustness in handling input point clouds with various densities, thus providing more flexibility in the indoor place recognition task. As it is reported in their original paper [43], the lower KPConv layers in the semantic encoder tend to extract low-level geometric features such as points and lines, and the latter KPConv layers usually focus more on complex and semantically meaningful features. We propose to use features extracted from all the 5 KPConv layers in the semantic encoder to learn all the low-level and high-level features. Before concatenating these multi-level features into a single feature map, fully connected (FC) layers are applied to stretch them into the same length. Then, this concatenated feature map is fed into a NetVLAD layer [4] to generate the global description vector. To achieve more efficient retrieval operations, another FC layer is appended to the end of the NetVLAD layer for dimension reduction.

B. Multi-task learning

To ensure the features extracted by the encoder are semantically meaningful, we specifically train the encoder and decoder of the KP-FCNN on a pixel-wise semantic segmentation task in a standard supervised approach with the cross-entropy loss. Note that the SLAM segmentation setup from the KP-FCNN paper [43] is adopted here, i.e. the input coloured point clouds are in the local camera coordinate system rather than the global coordinate system as in point cloud segmentation setup.

The KP-FCNN sub-network is trained with stochastic gradient descent (SGD) optimiser for 500 epochs. The general initial learning rate is set to 0.01 and the learning rate for deformed kernels is set to 0.001, both with learning rate decay applied. Momentum is also included in training with the value set to 0.98.

After the encoder and decoder are fully trained, we refer to them as the semantic encoder and the semantic decoder. We fix the weights of the semantic encoder and start training the feature embedding. Similar to PointNetVLAD [10], metric learning with the lazy quadruplet loss is chosen to train the feature embedding. To construct a training tuple given an anchor point cloud \( P_{\text{anc}} \), \( m \) positive point clouds \( \{P_{\text{pos}}^0, ..., P_{\text{pos}}^{m-1}\} \), \( n \) negative point clouds \( \{P_{\text{neg}}^0, ..., P_{\text{neg}}^{n-1}\} \), and an additional point cloud which is negative to all the previous point clouds \( P_{\text{neg}}^* \) are selected from the entire dataset. In our implementation, we choose \( m = 2 \) and \( n = 6 \). When determining positive and negative point clouds, we, in addition to the distance threshold used in the PointNetVLAD, also use scene ID as the criterion. Specifically, given an anchor point cloud, a point cloud is considered as a positive match if both point clouds are from the same scene and the distance between the point cloud is less than 2 meters. If the two point clouds are from different scenes or the distance between them is larger than 4 meters, we say that the point cloud is a negative match to the anchor point cloud. Note that we use a smaller distance threshold for the positives and a larger one for the negatives to maximise the difference between a negative pair.

Once the training tuples are generated for all training point clouds, the feature embedding sub-network is trained with Adam optimiser for 60 epochs. The initial learning rate is set
to 0.0001 and learning rate decay is also applied. To prevent overfitting, weight decay is also applied with the value set to 0.001. The number of clusters in the NetVLAD layer is set to be $K = 64$ and the dimension of the final output vector is $d_{out} = 256$. Additionally, the margin parameters in the lazy quadruplet loss are chosen to be $\alpha = 0.5$ and $\beta = 0.2$.

IV. Experiments

A. Dataset

We create the indoor place recognition dataset from the annotated 3-D indoor reconstruction dataset, ScanNet [19]. The ScanNet dataset contains 1,613 RGB-D scans of 807 different indoor scenes. It also provides rich semantic annotations with 20 semantic labels, making it perfect to test the proposed large-scale indoor place recognition network. The whole dataset is divided into training, validation, and test with 565, 142, and 100 scenes and 1,201, 312, and 100 scans respectively. Because the provided RGB-D frames are generated at the frame rate of 30 frames per second, the data is in fact very redundant and, depending on the movement of the RGB-D camera, there are tens or even hundreds of frames capturing the same place. Therefore, to make the data spatially sparser, we select keyframes from these scans based on the movement of the camera, both translationally and rotationally, resulting in 35,102 training keyframes, 9,693 validation keyframes, and 3,608 test keyframes.

Then, the coloured point clouds are generated from these selected keyframes, forming the input of the proposed network. Rather than directly using the raw coloured point clouds back-projected from single RGB-D frames, we crop the coloured point clouds out of the complete reconstruction of the room using the viewing frustum of the given RGB-D frames. By doing so, we best alleviate the effect of the noisy depth measurements and the incomplete reconstruction of single views. We also store the RGB images and 3-D point clouds for each keyframe for comparison experiments.

B. Evaluation

From the previous sections, we know that there are 100 indoor scenes in the test dataset with one RGB-D scan per scene. We assume these 100 indoor scenes form a virtual large-scale indoor environment. Thus, to perform place recognition in this large-scale environment, we first generate a database for later retrieval. Based on the distance between the point clouds, we store a new database point cloud if the new point cloud is either from a new scene or is at least 3 meters apart away from the previously stored database point clouds. In this way, we end up with 236 database point clouds and the rest 3,372 point clouds from the test dataset will be used as query point clouds.

Once we have the database point clouds, we obtain the final retrieval database by passing the database point clouds through the CGS-Net and store the resulting global description vectors. Then given a query point cloud, it is also passed through the CGS-Net to compute the query vector. Following which nearest neighbour (NN) search is performed between the query vector and all database vectors to retrieve $K$ nearest database vectors in the feature space. K-d tree is used for efficiency purposes. We say the point cloud corresponding to the retrieved database vector is a correct match to the query point cloud if the two point clouds are from the same scene and the distance between them is less than 3 meters. Then the average recall rates of all query point clouds for Top-$K$ retrievals are computed and used as the main criterion to evaluate the place recognition performance.

C. Comparison

In comparison, we first set a baseline performance with a pre-deep-learning method. The input to the pre-deep-learning method is RGB images with local features extracted by SIFT and global descriptors generated by BoW. For deep-learning-based methods, we compare the proposed network to NetVLAD [4], which uses RGB images as network input, and PointNetVLAD [10], which inputs point clouds. A state-of-the-art place recognition network, MinkLoc3D [15], is also compared here.

These 3 comparison networks are re-trained on the indoor dataset with the same setup on the VLAD layers as our CGS-Net. Examples of query and retrieved ones are shown in Fig. 3 and quantitative evaluations are provided in Table I. The results exhibit that our CGS-Net outperforms the other 4 methods to a large extend, thus demonstrating the effectiveness of the proposed method in solving large scale indoor place recognition. Additionally, we notice that although PointNetVLAD and MinkLoc3D achieved very high average recall rates in the outdoor environments, their performance drops notably in the indoor scenes. One obvious reason causing this is that the indoor point clouds generated from RGB-D cameras are not as complete as the outdoor ones obtained with Lidar sensors. We also believe that colour information, geometric features, semantic cues, and the point cloud density play vital roles in indoor place recognition. We will discuss these influences in detail below.

V. Ablation Study

A. Colour features

Noticing that the state-of-the-art outdoor 3-D place recognition network performs so poor that even the pre-deep-learning method using RGB images as inputs has better...
Fig. 3. Example of Top-1 retrievals with the succeeded ones labelled with red checkmarks and the failed ones labelled with red crosses. The query entities are visualised in point clouds with and without colours and the retrieved database entities are visualised in the same form as the inputs to the methods, i.e. coloured point clouds for our method, images for SIFT+BoW and NetVLAD [4], and point clouds for PointNetVLAD [10] and MinkLoc3D [15].

performance, we argue that colour information is crucial for indoor place recognition. To prove this, we remove the colour information on the input point clouds and re-train the CGS-Net with only 3-D points. Note that under this setup, we have to re-train not only the feature embedding sub-network of the proposed network but also the semantic encoder and decoder of the KP-FCNN sub-network.

The performance is reported in the first row of Table II, demonstrating that the performance of the CGS-Net drops hugely without the additional colour information in the input point clouds. We argue that the reasons cause the degradation are two-fold. First of all, lack of colour jeopardises the performance of the semantic segmentation, leading to a more inconsistent segmentation result. Hence, the final place recognition performance is also jeopardised. Secondly, the variety of the structural complexity and the structural repetitiveness of indoor scenes are generally much higher compared to those of outdoor scenes, making it not distinguishable enough to only using 3-D points for indoor place recognition.

B. Geometric features

In the default setting, as we described in the methodology section, we concatenate features extracted from all the five KPConv layers of the semantic encoder. In this experiment, we focus on the features with semantic meanings and only concatenate the features from the last three KPConv layers.

Examples of the retrieved point clouds with the CGS-Net trained with 5-layer features and 3-layer features are shown in Fig. 4. We observe that the network trained with 3-layer features tends to find point clouds that contain the same semantic entities as the ones in the query, such as “bed”, “door”, and “bookshelf” from the first three examples. However, only focusing on the semantic entities is not enough as the same semantic entities exist in different rooms. Therefore, utilising the additional low-level features is necessary to achieve better performance. The quantitative results are provided in the second row of Table II, which demonstrate that using the geometric features extracted from the first two KPConv layers indeed boosts the recognition performance. However, we have to admit that the network using all 5-layer features sometimes gets lost in the tiny details in the scene while focusing on the semantics, like “sofa” in the last example, can retrieve the correct database point cloud.

C. Semantic features

To further investigate how much improvement in indoor place recognition performance is brought by the implicit semantic cues learned in the semantic segmentation task, we redesign the architecture of the proposed network architecture by removing the semantic decoder. Note that the architectures of the encoder and the feature embedding remain the same as the original CGS-Net. Under this setup, multi-task learning doesn’t fit anymore. Therefore, we re-train the new network without a specific semantic segmentation training process using the lazy quadruplet loss as the original network with Adam optimiser for 60 epochs.

The quantitative evaluation results are reported in the third row of Table II. When compared to the performance of
the network trained with the semantic segmentation training process, shown in the first row of Table I, we observe a roughly consistent 5% improvement in Top-1, Top-2 and Top-3 average recall rates, thus demonstrating the importance of semantic cues in indoor place recognition.

Additionally, we also provide examples of retrieved point clouds with the network trained with and without semantics, shown in Fig. 5. The first 3 rows in the figure show the cases when the network trained without semantics failed while the originally proposed network, i.e. trained with semantics, succeeded. We can observe that without forcing the network to learn semantic cues, the retrieved point clouds tend to be similar to the query point clouds in terms of colour and 3-D structure. However, as we already demonstrated in the previous sections, indoor scenes contain a lot of entities with similar colours or structures but completely different semantic meanings. Therefore, semantic cues are indispensable for robust indoor place recognition.

The last 2 rows in Fig. 5 are examples of failed retrievals. From these failed cases we can also observe that the network trained with semantic cues trying to find point clouds not only with similar colours and structures but also the same semantic object. Such as the “counter” in the first failed case and the “bed” in the second one.

D. Point cloud densities

KP-FCNN [43] is good at handling point cloud inputs of various densities. However, PointNet [44] used in PointNetVLAD [10] and MinkLoc3D [15] can only take in point clouds with a fixed number of 4096 points. To make it a fairer comparison and also to prove that denser points leads to better recognition performance, we re-train the proposed network with exactly the same input as the PointNetVLAD and the MinkLoc3D, i.e. point clouds with a fixed number of 4096 points and without colour information. In this setup, the KP-FCNN sub-network also needs to be re-trained to perform semantic segmentation without the RGB channels.

The results of this training setup are shown in the last row of Table I. Compared to the results from the network trained without colours, shown in the first row of Table I, the recognition performance suffers a considerable drop, especially for the Top-1 average recall rate. This result proves that a denser point cloud is preferred to better capture 3-D geometric features of indoor point clouds. On the other hand, although the performance is worse compared to the default training setup, it is still much better compared to the PointNetVLAD and MinkLoc3D. Hence, this result also proves the strength of the proposed approach.

VI. CONCLUSIONS

In this paper, we proposed the CGS-Net for large-scale indoor place recognition. The network employs colour, geometry and semantic features to construct the global descriptors. We evaluated the proposed network on an indoor place recognition dataset collected from the ScanNet dataset. The performance of the proposed CGS-Net remarkably exceeds a traditional feature-based method and three recently proposed place recognition networks.
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