Global visual localization in LiDAR-maps through shared 2D-3D embedding space

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Abstract—Global localization is an important and widely studied problem for many robotic applications. Place recognition approaches can be exploited to solve this task, e.g., in the autonomous driving field. While most vision-based approaches match an image w.r.t. an image database, global visual localization within LiDAR-maps remains fairly unexplored, even though the path toward high definition 3D maps, produced mainly from LiDARs, is clear. In this work we leverage DNN approaches to create a shared embedding space between images and LiDAR-maps, allowing for image to 3D-LiDAR place recognition. We trained a 2D and a 3D Deep Neural Networks (DNNs) that create embeddings, respectively from images and from point clouds, that are close to each other whether they refer to the same place. An extensive experimental activity is presented to assess the effectiveness of the approach w.r.t. different learning methods, network architectures, and loss functions. All the evaluations have been performed using the Oxford Robotcar Dataset, which encompasses a wide range of weather and light conditions.

I. INTRODUCTION

Estimating the pose of an observer robot w.r.t. a map, i.e., localization, is a fundamental part of any mobile robotic system. It has such relevance also for autonomous cars, which usually operate in very large and dynamic environments, where this task is particularly challenging.

A typical localization pipeline usually, albeit not always, involves two steps. First, a rough pose of the robot is estimated, thus performing a global localization of the observer. Secondly, the initial rough pose is refined, and an accurate pose is estimated, therefore performing a local localization. Usually, the first step can be accomplished with the aid of Global Navigation Satellite Systems (GNSSs), which provides a global position. However, the localization reliability of GNSS systems is inadequate, particularly in urban environments, where buildings might block or deflect the signals from the satellites, leading to non-line-of-sight (NLOS) and multi-path issues. Inertial Measurement Units (IMUs) and computer vision techniques can mitigate these limitations by exploiting other types of information, and might allow a more reliable computation of the vehicle’s pose, complementing the one possibly provided by GNSSs.

Many different methods to solve the localization problem have been proposed, including vision-based and Light Detection And Ranging (LiDAR)-based approaches. Although

LiDAR sensors are the de facto standard for commercial large 3D geometric reconstructions, their price, weight, and mechanically-based scanning systems, which are not rated viable for the requirements of the automotive sector, make them still not suitable for mass installation on cars, to use them for local localization.

The research in the field of LiDARs is very active, with many promising approaches to the development of light weight, low-cost, and with a non-mechanical scanning systems devices, but the state-of-the art, as for today, is still no-LiDARs on mass-produced vehicles. Car-makers have different positions w.r.t. LiDARs on their vehicles, ranging from questionable a priori refusal to investing in LiDAR-developing startups. Besides the automotive-grade issue, however, LiDARs, differently from cameras, do not provide dense visual information, which could help greatly, and are prone to many failures in adverse weather conditions. Indeed, some approaches in the literature [2]–[5] tackle the localization task by matching high level features extracted from images on-board camera(s), e.g., buildings, road intersections, and/or road markings, with data available from online mapping services, e.g., OpenStreetMap.

Recent Machine Learning (ML) approaches, mainly based on Convolutional Neural Networks (CNNs) or random forests, solve the localization problem in a single step by

Fig. 1. A short description of the related existing Place Recognition methods. Our proposal brings together the local-localization methods that work on large city-scale maps and global localization methods without maps, allowing for the first time a global image localization of images within a city-scale 3D-LiDAR map.
regressing the robot’s position using only a single RGB image [6]–[8]. However, they have important drawbacks. First, they require a huge amount of images of the environment to train the model, and this problem is particularly relevant in outdoor environments (e.g., wide urban areas). Moreover, these approaches are not suitable for scenes that are not represented in the training set, since the model learns to perform localization only w.r.t. the specific places used during the training phase. Therefore, for new locations, the acquisition of a new dataset, together with a re-training stage is required. This characteristic makes these methods not suitable for autonomous road driving.

Nowadays, map-making companies, e.g., HERE and TomTom, are investing large amounts of resources in developing so-called HD maps. These maps are designed specifically for the automotive domain, and provide accurately localized high-level features, such as traffic lights, and road signs. An evolution of these maps include also accurate 3D large geometric reconstructions, in the form of point clouds. Therefore, it is quite likely that, in the future, these 3D HD maps will be used by autonomous vehicles, for more effective and safer systems [9]. Usually, albeit non exclusively, such 3D HD maps derive from the processing of data from LiDARs, through a variety of Simultaneous Localization And Mapping (SLAM) techniques.

While approaches that exploit the same sensor for both localization and mapping usually achieve good performances, localizing a vehicle w.r.t. a LiDAR-map exploiting only visual information is a difficult task, due to the different nature of the sensors used for mapping and for localization. An example of the different nature of the sensors is the different distribution of the measurement error, normal for LiDARs, with intensity and skew depending on the position of the measured point for vision. The difficulty of this cross-media task is confirmed by the relative absence of specific literature.

The few approaches to tackle the visual localization task w.r.t. LiDAR-maps fall in one of two categories. On the one hand, the 3D geometry of the scene, as reconstructed from cameras, can be matched to the 3D map [10]. On the other hand, the match can be performed in the image space, by comparing camera images to the expected projection of the map onto a virtual image plane, by means of Normalized Mutual Information (NMI) [11] or CNN-based techniques [12]. All the latter approaches tackle the local localization task, i.e., they need a rough estimate of the pose.

How to perform global visual localization w.r.t. LiDAR-maps when GNSSs are not available is still an open question, see Figure 1. In this paper we propose a novel DNN-based approach to the global visual localization problem, i.e., to localize the observer of an RGB image in a previously built geometric 3D map of an urban area. Specifically, we propose to jointly train two DNNs, one for the images and the other for the point clouds, in order to generate a shared embedding space for the two types of data, see Figure 2. This embedding space allows us to perform place recognition with heterogeneous sensors: an image query w.r.t. a point cloud database is just one of the possibilities. Besides allowing localization on a geometric map using visual information, our proposal does not need to be trained for every new environment. Instead, the neural networks are trained with samples from many different areas. In this way, the networks learn to associate similar descriptors to images and point clouds representing the same place. Therefore, our approach can associate an image, i.e., the query, to the corresponding point cloud, among those that constitute the map of the area, i.e., the database.

The paper is organized as follows: Section II describes the existing approaches for place recognition. In Section III we present the details of our approach. In Section IV we present and discuss the obtained experimental results. Finally in Sections V we shortly draw some conclusions.

II. RELATED WORKS

Historically, visual place recognition represents a relevant problem for the computer vision community. The aim of this task is to decide whether and where a place, observed in an image, has already been observed within a set of georeferenced images. This is relevant in mobile robotics, as it may serve as a starting point for local localization systems, or to detect loop closures in SLAM systems [13], [14].

Traditional methods involve an offline pre-computation of image descriptors for the images of a database of images, which are then compared online against the descriptors of a query image, to retrieve the most similar place. Methods to perform place recognition were based on approaches such as bag of words, which exploit handcrafted-features (e.g., SIFT and SURF [15], [16]), visual vocabulary [17], and query expansion [18]. More recently, methods that exploit deep learning techniques have been proposed. As an example, Arandjelovic et al. [19] exploited a CNN-based feature extractor and proposed a specific pooling layer, named NetVlad, designed for place recognition, which was inspired by the Vector of Locally Aggregated Descriptors [20].

The definition of discriminative descriptors represents a fundamental step of the place recognition task. Within ML methodologies, the definition of descriptors task is named metric learning; the resulting feature space is called embedding space, and the descriptors take the name of Embedding Vectors (EVs). A possible ML method, named contrastive,
provides sample pairs to a model by considering two cases: either the two samples represent the same concept or distinct ones [21]. This training method tries to minimize the distance between EVs of the same class while enforcing the distances between negative samples to be higher than a value. Another similar technique consists in comparing triplets of samples, which are organized such that a given input is associated with a positive sample and a negative one. In particular, positive samples represent the same concept of the input, while the negative samples belong to a different one. Different approaches extended the triplet embedding method by considering multiple negative samples at once instead of a single one [22], [23].

Although place recognition is a task traditionally reserved to vision-based systems, recently Uy et al. [24] proposed a DNN-based approach that performs place recognition on LiDAR-maps. Their point was to exploit the strong independence of LiDAR data w.r.t. lightening conditions. This method, named PointNetVlad, matches an input point cloud, e.g., acquired from a vehicle, to another one among those contained in a database representing a large urban area. It can match (the point cloud of) a LiDAR scan to a location in a LiDAR-map of a large urban area. PointNetVlad uses PointNet [25] as feature extractor, and NetVlad [19] to compute the descriptors.

To the best of our knowledge, the only work in the literature that treats the problem of image and LiDAR-map descriptors matching, using a metric learning approach, has been proposed by Feng et al. [26]. In their work a neural network, named 2D3D-MatchNet, performs descriptors extraction from 2D image and 3D LiDAR patches. The objective is to perform the metric localization of a camera through 2D to 3D patch matching. Although a neural network is used to compute the descriptors, 2D key-points are detected from images using the detector in the SIFT software, while 3D key-points are extracted from the point clouds using Intrinsic Shape Signatures [27]. The key-points are then used to define the patches used for computing the descriptors, from images and LiDAR-maps. The localization is finally computed solving a Perspective-n-Points (PnP) problem. Their work is limited also in that they do not handle LiDAR-maps whose extension is larger than a few tens of meters, which is not global localization.

There are many other contributions in the literature, which match image descriptors to 3D maps, but they refer to maps produced by Structure from Motion (SfM) approaches, where an image descriptor is used for matching from image to image, i.e., tracking, and can then be attached, and updated with the different appearance induced by the motion of the observer, to the 3D-reconstructed point. On the other hand, we need to handle descriptor-less point clouds, as naturally coming from LiDAR sensors.

III. PROPOSED APPROACH

Differently from visual place recognition techniques, our approach matches a single RGB image to a database of known-pose point clouds, to retrieve the point cloud representing the same place of the query image. In order to compare images and point clouds, we propose to learn a shared embedding space where data representing the same place live close to each other even though they have to be computed from different types of data. In particular, we propose two DNNs, one for the images and another for the point clouds, jointly trained to produce similar EVs, when the image and the point cloud come from the same place.

Our work was inspired by those of Uy et al. [24] and Feng et al. [26]. Differently from [24], which requires a LiDAR on-board the vehicle, our approach only requires a camera on-board, which is very common in modern cars. Differently from [26] our approach is designed to work on city-scale maps.

More formally, given a query image $I$ and a LiDAR-map $M$, we can split the map into multiple overlapping sub-maps $m_i$. We formulate the global localization task as a metric learning problem: we want to find two mapping functions $f(\cdot)$ and $g(\cdot)$, implemented as two DNNs such that $d(f(I), g(m_i)) < d(f(I), g(m_j))$ when $m_i$ represent the same place where $I$ was taken, and $m_j$ does not. $d(\cdot)$ is a distance function, such as the euclidean distance. The domain of $f(\cdot)$ is the image space ($\mathbb{R}^{H\times W}$, Height x Width x 3 channels: R, G, and B), while the domain of $g(\cdot)$ is the point cloud space ($\mathbb{R}^{N\times 3}$, $N$ points x 3 coordinates: $X, Y, Z$). The output of both functions is an EV of fixed length $K$; therefore the co-domain is $\mathbb{R}^K$. Once we have found the mappings between the input spaces and the EV space, to compute a global localization, i.e., to determine the most similar place in terms of EVs, is to just compare the EV of the query image with the EVs of all the sub-maps $m_i \in M$.

A. 2D Network Architecture

The network that computes the EVs from images is composed of two parts. First, a CNN extracts local features from the input image; then those features are aggregated to provide a fixed length EV. Concerning the CNN, we considered some of the most relevant architectures for the image classification task. In particular, we tested the following networks: VGG-16 [28], ResNet-18 [29] and ResNet-50 [29]. Since we are not interested in the classification task, we removed the fully connected layers from the latter architectures, cropping them after the last convolutional layer. For the aggregation step we tested two different methods: the NetVlad layer [19], that was specifically designed for the place recognition task, and a simple MultiLayer Perceptron (MLP).

B. 3D Network Architecture

Similarly to the 2D CNN architecture, for the 3D network we adopted the same approach: a DNN-based features extractor followed by a features aggregation layer. The best data structures and models that allow the extraction of discriminative descriptors from 3D point clouds are not clear in the literature, therefore a comparison between different architectures was needed. The first 3D feature detector considered was PointNet [25], since it was the first 3D DNN...
approach to directly process point clouds as a list of points. We also considered one interesting extension of PointNet, named EdgeConv [30]. The latter DNNs require point clouds composed of a fixed number of points, thus a down-sampling step of the input is necessary. The last option we considered is the feature extraction layer of the architecture proposed by Yan et al. [31]. Since we are not interested in classification or segmentation tasks, we modified the latter networks as follows:

- PointNet: we cropped the network before the MaxPooling layer;
- EdgeConv: we cropped the segmentation network after the concatenation layer;
- SECOND: we replaced the RPN with an Atrous Spatial Pyramid Pooling (ASPP) layer [32]

Finally, for the aggregation step, we used again the NetVlad layer and a MLP.

These models accommodate different representations of the input data (e.g., unordered lists, graphs, voxel grids), thus we think that providing an evaluation of the existing approaches is an important step forward for this type of research.

We propose two different learning methods to create a shared embedding space between the 2D-3D EVs: teacher/student, and combined.

C. Teacher/Student Training

Given a 2D and a 3D neural network, the teacher/student method first trains one of the models (the teacher) to create an effective embedding space for a particular task. In a second step, this pre-trained network will be used to help the second one (the student) to also generate a similar embedding space, i.e., similar EVs for similar concepts. For instance, initially a CNN model learns to perform place recognition with images, then a 3D DNN tries to emulate the CNN descriptors. In this way the network creates the embedding space, where EVs are defined and the student tries to also generate that space from a different kind of data.

In this work, we first train the 2D network with a triplet loss function [33]: given a triplet \((I_i^p, I_i^n, p_i^n)\) composed of an anchor image \(I_i^p\), an image depicting the same place \(I_i^n\) (positive) and an image of a different place \(p_i^n\) (negative), the loss function is defined as:

\[
L_{trp}^{2D-2D} = \sum_i [d(f(I_i^p), f(I_i^n)) - d(f(I_i^p), f(p_i^n)) + m]^+ \tag{1}
\]

where \(d(\cdot)\) is a distance function, \(m\) is the value, also called margin, \(f(\cdot)\) is the 2D network we want to train, and \([\cdot]^+\) means \(\text{Max}(0, [\cdot])\).

Once the 2D network (teacher) has been trained, the 3D network (student) was trained to mimic the output of the teacher (to obtain a Joint Embedding). In this case, given a pair \((I_i, m_i)\) composed of an image \(I_i\) and a point cloud \(m_i\) captured at the same time, the loss function is:

\[
L^{JE} = \sum_i d(f(I_i), g(m_i)) \tag{2}
\]

Please note that, during this step, only the student network \(g(\cdot)\) is trained, while the teacher \(f(\cdot)\) is kept fixed.

D. Combined Training

Alternatively, we propose a combined approach that simultaneously trains both the 2D and the 3D neural networks, in order to produce the same embedding space. In this case, the loss function proposed to jointly train both networks is composed of different components.

Same-Modality metric learning. The first components of the proposed combined loss are aimed at producing effective EVs for place recognition within the same modality, i.e., the same type of sensor data (query image w.r.t. image database and query point cloud w.r.t. point cloud database). The same-modality loss is defined as follow:

\[
L_{trp}^{SM} = L_{trp}^{2D-2D} + L_{trp}^{3D-3D} \tag{3}
\]

Here, \(L_{trp}^{2D-2D}\) is the 2D-to-2D triplet loss defined in eq. (1), while the 3D-to-3D \(L_{trp}^{3D-3D}\) can be derived similarly.

Cross-Modality metric learning. In order to learn 2D and 3D EVs that live in the same embedding space, we extend the triplet loss to perform cross-modality metric learning:

\[
L_{trp}^{2D-3D} = \sum_i [d(f(I_i^p), g(m_i^n)) - d(f(I_i^p), g(m_i^p)) + m]^+ \tag{4}
\]

\[
L_{trp}^{3D-2D} = \sum_i [d(g(m_i^n), f(I_i^p)) - d(g(m_i^n), f(p_i^n)) + m]^+ \tag{5}
\]

\[
L_{trp}^{CM} = L_{trp}^{2D-3D} + L_{trp}^{3D-2D} \tag{6}
\]

Joint Embedding loss. The last component of the proposed loss tries to minimize the distance between 2D and 3D EVs recorded at the same time, i.e., we want the EV of a point cloud to be as close as possible to the EV of the corresponding image. To achieve this aim we used the joint embedding loss defined in eq. (2); however, in this case both networks \(f(\cdot)\) and \(g(\cdot)\) are trained.

Full combined loss. The final loss used to jointly train the 2D and 3D networks is a combination of the aforementioned components (\(\lambda_1 = 0.1, \lambda_2 = 1, \lambda_3 = 1\)):

\[
L_{total} = \lambda_1 L_{trp}^{SM} + \lambda_2 L_{trp}^{CM} + \lambda_3 L^{JE} \tag{7}
\]

An example of the loss computed on a triplet is depicted in Figure 3.

E. Training details

During the training phase, to mitigate over-fitting, we use the following data augmentation scheme: for the images, we first apply a random color jitter (changing the saturation, brightness, hue and contrast). Then, we randomly rotate the image within a range of \([-5\degree, +5\degree]\); finally, we apply a random translation on both axes, with a maximum value of 10% of the size of the image on that axis. Regarding the point clouds, we applied a random rigid body transformation, with a maximum translation of 1.5 meters on all the axes, and a maximum rotation of 10\degree around the vertical axis and
the same path multiple times over a year. It includes a data of urban areas. These data were obtained by traversing LiDAR scans, images, and Global Positioning System (GPS) RobotCar [35] dataset. RobotCar contains geo-referenced seasonal changes), we worked on the well known Oxford queries using the EVs from 3D sub-maps or LiDAR scans. To produce a dataset of 2D image EVs and to then perform environmental conditions (i.e., scene structure, lights and structural changes for the scene, which are reflected in corresponding changes in the LiDAR-maps, e.g., in the presence of roadworks. RobotCar has also been used for training and testing 2D3D-MatchNet [26] and PointNetVLad [24], which inspired our research.

B. Regions Subdivision and Sub-maps Creation

We considered a total of 43 runs, the same used in [24]. For each run, an image is stored every five meters and the corresponding LiDAR sub-map is cropped from the whole map. For each 3D sub-map we considered a range of 50 meters on each axis. The training and validation sets have been created by performing a subdivision of the global path in different non-overlapping regions. The goal here was to make it possible to evaluate the performance in regions never provided to the neural network during the training phase. In particular, we used the same four regions defined in [24].

C. Evaluation metrics

The evaluation of a place recognition approach is usually based on the recall measure. When the number of samples in the database increases, the difficulty of the operation increases as well. For this reason metrics such as recall@k are used, in order to provide a fair evaluation. The term k represents the number of places that our system determines to be the most similar w.r.t. the input query. If at least one of the retrieved k elements corresponds to the location of the input query, then the retrieval is considered correct. We fixed k to the 1% of the samples contained in the database in order to ensure the invariance of the measure with respect to the database size. In our experiments, we considered two poses to belong to the same place if they are spaced less than 20m, as in [24].

To test the performance of our approach we proceeded as follows. For every possible pair of distinct runs, again in [24], we used all samples of the first run as database, and only the samples within the validation area of the second run as query. In this way, we tested our method in places never seen during the training phase. Finally, we compute the mean of the recall@k metric over all pairs.

D. Results

We based on the networks proposed in [19] (VGG16+NetVLAD), and on a modified version of [31] (SECOND+ASPP+NetVLAD) in order to extract EVs from both 2D and 3D data. We applied the teacher/student learning method with the smooth-L1 distance function [36], fixing the 2D architecture as teacher, since it represents the state of the art in the place recognition task with images. In particular, we took a pre-trained version of the 2D backbone (SECOND+ASPP+NetVLAD) in order to extract EVs (VGG16+NetVLAD), and on a modified version of [31] [24].

The results of these experiments are provided in Table I, where we show the performance w.r.t. all the possible query-database combinations. Even though our work is mainly
focused on the 2D-to-3D modality, we also obtained comparable results in the 2D-to-2D place recognition modality, and even state-of-the-art performances for 3D-to-3D. Considering the novelty of the proposed approach, the obtained results are promising. An important aspect concerns the recall achieved when performing 3D queries on 3D database: we found that our approach, which exploits SECOND, outperforms Uy et al. [24] on the same task, as shown in Table II. To perform a fair comparison we followed an evaluation scheme similar to theirs, considering images and point clouds with an interval of 20 m (instead of 5 m), over the same 43 runs.

**Table II**

| Modality          | Recall@1% | Recall@1 | Recall@5 |
|-------------------|-----------|----------|----------|
| 2D-to-2D          | 96.63     | 70.44    | 98.48    |
| 3D-to-2D          | 77.28     | 29.51    | 93.99    |
| 2D-to-3D          | 41.92     | 39.65    | 63.33    |
| 3D-to-3D          | 95.76     | 39.65    | 97.45    |

Retrieval performances comparison between our approach and PointNetVLAD [24]. Both recall@1% and recall@1 are reported.

Finally, we performed an ablation study to investigate the effect of different components of the system. In particular, we tested the system without the data augmentation techniques (mirroring and point clouds transformation), and without the ASPP. In these tests, we only considered a subset of 10 runs, to have a quick insight on the effect of the components. The results, shown in Table III, show that both data augmentation, and the ASPP bring substantial improvements to the performance.

**Table III**

| Ablation Study       |              | 2D-to-2D | 3D-to-2D | 2D-to-3D | 3D-to-3D |
|----------------------|--------------|----------|----------|----------|----------|
| Base                 |              | 96.67    | 61.53    | 73.17    | 96.92    |
| 1                    | ✓            | 96.67    | 65.31    | 73.99    | 97.75    |
| 2                    | ✓            | ✓        | 96.67    | 66.30    | 76.76    | 97.66    |
| 3                    | ✓            | ✓        | ✓        | 96.67    | 71.10    | 79.10    | 98.44    |

Retrieval performances of our approach in terms of recall@1% by varying different components of the system.

Furthermore, once we found the combination which provides the best results, we challenged the robustness of our approach by considering different weather conditions between EVs database and the queries provided to the trained system. For instance, we generated a database from 3D samples gathered during summer and then we provide to the model images acquired during winter. This approach has also been exploited by considering different lighting conditions. In Figure 4 we show the recall@k of the four modalities with different values of k. In particular, a query run with snow conditions and one recorded in night is compared against a “overcast” database.

**E. Further Improvement Attempts**

Having reached satisfactory results, we tried to increase our model’s performance by varying different sub-components of the system. Starting from the architecture type, we tested different backbones such as Vgg-16 and ResNet18 for what concerns the 2D data, and PointNet, EdgeConv and SECOND for the 3D data. Furthermore, we investigated various learning methods together with new loss functions and distance measures. Despite our best efforts, the results in Table IV show that these variations did not improve the performance of the model, instead they reduced the recall capability of our system.

**Table IV**

| Backbone | Modality | 2D | 3D | Loss | Dist | 2D | 3D | Loss | Dist |
|----------|----------|----|----|------|------|----|----|------|------|
| Vgg16    | PointNet | (1) | MSE | 85.51 | 31.98 | 51.32 | 94.53 |
| Vgg16    | PointNet | (2) | MSE | 86.62 | 38.77 | 53.46 | 95.61 |
| Vgg16    | PointNet | (2) | Cosine | 88.03 | 36.85 | 52.16 | 96.31 |
| Vgg16    | PointNet | (3) | I2   | 83.38 | 36.48 | 47.18 | 94.64 |
| Vgg16    | EdgeConv | (3) | I2   | 96.64 | 31.33 | 28.69 | 92.00 |
| Vgg16    | SECOND  | (2) | MSE | 89.27 | 53.90 | 59.50 | 97.21 |
| Resnet18 | PointNet | (1) | MSE | 51.13 | 20.61 | 9.93  | 95.30 |

Loss function are defined as follows: (1) $L_{CE} + \alpha L_{CE}$, (2) $L_{CE} + \alpha L_{CE} + \beta L_{RI}$ and (3) is the teacher/student method.

**V. CONCLUSIONS**

In this paper, we described a novel DNN-based approach to perform global visual localization in LiDAR-maps. In particular, we proposed to jointly train a 2D CNN and a 3D DNN to produce a shared embedding space. We trained and validated our DNN on the challenging Oxford Robotcar dataset, including all weather conditions, and promising results show the effectiveness of our approach. We also obtained comparable performance on 2D-to-2D and 3D-to-3D modalities, although this was not the focus of our research. To our knowledge, an approach that performs a global visual localization using LiDAR-maps has never been presented before.
R. W. Wolcott and R. M. Eustice, “Visual localization within lidar

T. Caselitz, B. Steder, M. Ruhnke, and W. Burgard, “Monocular

an “overcast” database. We also provide the plot of the average recall using

weather and time conditions, simple good weather conditions,

Fig. 4. Recall measures considering up to K = 25 similar places. Here

simple good weather conditions, i.e., Summer, as well as challenging

weather and time conditions, i.e., Snow and Night, were compared against an

“overcast” database. Also, we provide the plot of the average recall using

all available dataset runs.

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