Performance Analysis and Robustification of Single-query 6-DoF Camera Pose Estimation

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ABSTRACT

We consider a single-query 6-DoF camera pose estimation with reference images and a point cloud, i.e. the problem of estimating the position and orientation of a camera by using reference images and a point cloud. In this work, we perform a systematic comparison of three state-of-the-art strategies for 6-DoF camera pose estimation, i.e. feature-based, photometric-based and mutual-information-based approaches. The performance of the studied methods is evaluated on two standard datasets in terms of success rate, translation error and max orientation error. Building on the results analysis, we propose a hybrid approach that combines feature-based and mutual-information-based pose estimation methods since it provides complementary properties for pose estimation. Experiments show that (1) in cases with large environmental variance, the hybrid approach outperforms feature-based and mutual-information-based approaches by an average of 25.1% and 5.8% in terms of success rate, respectively; (2) in cases where query and reference images are captured at similar imaging conditions, the hybrid approach performs similarly as the feature-based approach, but outperforms both photometric-based and mutual-information-based approaches with a clear margin; (3) the feature-based approach is consistently more accurate than mutual-information-based and photometric-based approaches when at least 4 consistent matching points are found between the query and reference images.

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1. Introduction

Camera pose estimation is a fundamental technology for various applications, such as augmented reality (Taylor 2016), virtual reality (Ohta and Tamura 2014), and robotic localization (Castellanos and Tardos 2012). The aim of 6 degrees of freedom (DoF) camera pose estimation is to find the 3-DoF location and 3-DoF orientation of the query image in a given reference coordinate system. In the literature, the classical approach for 6-DoF camera pose estimation is to register the 3-DoF location and 3-DoF orientation of the query image in a given reference coordinate system. In the literature, the classical approach for 6-DoF camera pose estimation is to register a 2D query image with previously acquired reference data, which often consist of a set of reference images and corresponding 3D point clouds. In practice, this is a fundamental yet challenging problem due to large displacements between the query and reference images, as well as image variations caused by changes in the appearance of the scenes, weather and lighting conditions (Maddern et al. 2017; Mishkin et al. 2015). Depending on the way to compute the 6-DoF camera pose for the query image, the state-of-the-art methods can be divided into 2 main categories: direct and indirect approaches. In our context, direct approach means the 6-DoF camera pose is directly optimized by a cost function at the space of 6D camera pose. For example, 6-DoF camera pose can be computed by directly minimizing a cost function which compares the query image with a rendered synthetic view from a 3D point cloud, and the rendered view can be determined by either gradient or grid search (Pascoe et al. 2017; Ikkala et al. 2013; Newcombe et al. 2011ab). In the indirect approach, the query image is registered to the 3D point cloud by matching against the reference images (Mishkin et al. 2015; Song et al. 2016; Irschara et al. 2009; Kim et al. 2014), and the reference images and the 3D point cloud are defined in the same world coordinate system. This indirect approach can be considered as a combinatorial optimization method, because we need to find the 2D-3D correspondences between the query image and the 3D point cloud for computing the 6-DoF camera pose. Both direct and indirect approaches have shown good performance in different litera-
tures and different datasets with different setting (Pascoe et al., 2017; Mishkin et al., 2015; Song et al., 2016), but the relative performance of the direct and indirect approaches have not been intensively analyzed in the same working conditions with large real-life dataset.

Even though both the indirect and direct approaches have been widely utilized for 6-DoF pose estimation, we have identified two important questions that warrant further research: first, there is still no consensus in the community about which strategies yield the best performance in real-life conditions where the appearance of the reference and query images change significantly according to different weather, lighting and season conditions. Second, in the literature, pose estimation strategies are often assessed as a part of full pipelines that involve additional pre- or post-processing steps, e.g., the incorporation of information from previous poses in sequential data or global optimization strategies in simultaneous localization and mapping approaches. As a result, the contribution of pose estimation methods on the overall performance of the system, as well as their response to different imaging factors, remains unclear. In order to tackle the aforementioned problems, we implemented and studied three start-of-the-art camera pose estimation approaches, to estimate 6-DoF camera pose of a single-query image using reference images and 3D point clouds. Specifically, these 3 approaches consist of 1 indirect approach: a feature-based approach (Kim et al., 2014), and 2 direct approaches: a photometric-based method (Tykkälä et al., 2013) and a mutual-information-based method (Pascoe et al., 2017). The motivation of studying the 3 chosen approaches is that they are state-of-the-art, have good speed performance and are convenient to be implemented (Pascoe et al., 2017; Tykkälä et al., 2013; Kim et al., 2014). We perform a systematic and extensive experimental comparison of the studied approaches and analyze their performances.

Based on the obtained results, we propose a hybrid approach, consisting of the fusion of the feature-based and mutual-information-based camera pose estimation methods, and present an architecture for computing the 6-DoF camera pose from rough 2-DoF spatial position estimates. Our main contributions can be summarized as follows:

- We perform an extensive comparison and analysis of three strategies for 6-DoF camera pose estimation: feature-based approach, photometric-based approach, and mutual-information-based approach. We find that the feature-based approach is more accurate than the photometric-based and mutual-information-based approach with as few as 4 consistent feature points between the query and reference images. However, we also found that the mutual-information-based approach is often more robust and can provide a pose estimate when the feature-based approach fails.

- We propose a hybrid approach that combines feature-based and mutual-information-based approaches based on the number of the feature matches between the query and reference images. We experimentally demonstrate that the hybrid approach outperforms both the feature-based only or the mutual-information-based only approaches.

- All code of the 3 implemented camera pose estimation methods and the performance evaluations will be made public.

We evaluate the performance of the hybrid approach by implementing an architecture that allows computing camera pose with multiple reference images and allows to naturally integrate and refine pose priors in large uncertainty cases. For the experiments, we use two publicly available datasets: the KITTI dataset (Geiger et al., 2012) and Oxford RobotCar Dataset (Maddern et al., 2017). The KITTI dataset provides 11 individual sequences with ground truth trajectories. The recently released Oxford RobotCar Dataset (Maddern et al., 2017), contains many repetitions of a consistent route and provides different combinations of weather, traffic and pedestrians, along with longer term changes such as construction and roadworks, which allows a more challenging evaluation in extreme changing conditions. Our comparison shows how the hybrid approach outperforms feature-based-only, photometric-based only or mutual-information-based-only approaches. Furthermore, the experiments show the using multiple reference images improves the robustness of all pose estimation pipelines.

1.1. Related work

Camera pose estimation using vision has received significant attention in recent decades. We are focused on the case of registering a single query image with one or several reference images and 3D point clouds. The approaches can be divided into 2 main categories: the indirect approach (Irshara et al., 2009; Kim et al., 2014) and the direct approach (Pascoe et al., 2017; Tykkälä et al., 2013; Newcombe et al., 2011a).

The indirect approaches establish 2D-3D correspondences between the query image and the 3D point cloud. The reference images and the 3D point cloud are pre-registered, so the 2D-3D correspondences are achieved by establishing 2D-2D correspondences between the query image and the reference images. Specifically, the query image is registered with the reference images by utilizing feature detectors for finding the useful image structures for localization, e.g., corners (Rosten and Drummond, 2006; Mikolajczyk and Schmid, 2004), blobs (Lowe, 1999; Bay et al., 2006; Kadir and Brady, 2001) or regions (Matas et al., 2004; Tuytelaars and Van Gool, 2000; 2004; Mori et al. 2004). Then feature descriptors (Calonder et al., 2010; Rublee et al., 2011; Leutenegger et al., 2011; Alahi et al., 2012; Lowe, 1999; Bay et al., 2006; Dalal and Triggs, 2005; Tola et al., 2010; Ambai and Yoshida, 2011) are used to provide robust representation regardless of appearance changes due to different viewpoints, weather, lighting, etc. Given the set of 2D-3D correspondences, a Perspective-n-Point solver (Torr and Zisserman, 2000) or RANSAC (Fischler and Bolles, 1981) are applied to compute the relative 6-DoF camera pose between the query image and the reference 3D point cloud. Because different combinations of 2D-3D correspondences lead to different camera pose estimations, the indirect approach can be considered as a combinatorial optimization method.

The direct approaches compute the 6-DoF camera pose by minimizing a cost function directly at the space of 6D cam-
era pose (Pascoe et al., 2017; Tykkälä et al., 2013; Newcombe et al., 2011a,b), and do not need to extract local features of images. One commonly used cost function is photometric error between the query image and the reference view, where the reference view can be generated from the reference 3D point cloud (Tykkälä et al., 2013; Newcombe et al., 2011a,b). The direct photometric-based methods are easy to implement and have good speed performance, however they are not robust to real-world global illumination changes (Newcombe et al., 2011a,b). A recent work (Pascoe et al., 2017) utilizes a mutual-information-based cost function for direct 6-DoF camera pose estimation outperforming both the feature-based and photometric-based approaches in two challenging datasets with large image variations. This mutual-information-based approach is targeting on the application of SLAM problem, and it relies on well-initialized reference image (Pascoe et al., 2017). However, it is still unclear what the performance of the mutual-information-based approach would be without accounting for the initialization problem, where a single query image is to be registered with no prior on the pose. To the best of our knowledge, there is lack of prior art comparing the standalone performance of direct and indirect camera pose estimation approaches in this scenario.

1.2. Overview

Based on our literature review, we selected and implemented three state-of-the-art 6-DoF pose estimation methods: (1) indirect feature-based method (Kim et al., 2014), (2) direct photometric-based method (Tykkälä et al., 2013) and (3) direct mutual-information-based method (Pascoe et al., 2017). We choose these 3 approaches because they have good performance and are convenient to be implemented. The details of these methods are presented in Section 2. In order to conduct a rigorous and systematic analysis of their practical performance, the studied methods were compared in three different scenarios: the single-reference case, the multi-reference case and the large uncertainty case. Each one of the experimental setups for these 3 cases is described in Section 3. For the large uncertainty case, we also present an architecture that allows the incorporation of external pose information, e.g. GPS data. Experimental results on real datasets are presented in Sections 4. Based on the experimental results, we propose to integrate both direct and indirect methods into a hybrid approach for an improved performance. The final discussion and the conclusion of this work are presented in Sections 5 and 6 respectively.

2. Evaluated pose estimation methods

The evaluated pose estimation methods in this work are: (1) indirect feature-based method (Kim et al., 2014), (2) direct photometric-based method (Tykkälä et al., 2013) and (3) direct mutual-information-based method (Pascoe et al., 2017). These three methods are good examples of direct and indirect approaches, presents have state-of-the-art performance and are convenient to be implemented. In this section, we describe each one of the methods in the simplest scenario, where the inputs of all these three methodologies are a query image $I_Q$ and a single reference tuple $(I_R, P_R)$ that is formed by a reference image $I_R$ and its registered 3D point cloud $P_R$, as illustrated in Fig. 1.

\[ I_Q \quad I_R \quad P_R \]

**Fig. 1.** Inputs for the pose estimation methods in the simplest scenario: a query image $I_Q$ and a reference tuple $(I_R, P_R)$, where $I_Q$ is a single reference image and $P_R$ is the registered 3D point cloud associated to $I_R$. Both the the point cloud $P_R$ and the camera pose of the reference image $I_R$ are defined in a common world coordinate system.

### 2.1. Indirect feature-based (FB) pose estimation

A standard feature-based pose estimation method can be divided into four main steps: (1) feature detection, (2) feature matching, (3) 2D-3D correspondences grouping, and (4) Perspective-n-Point pose estimation. The block diagram of this method is shown in Fig. 2. In the first step, a feature detector and a feature descriptor are applied to both query and reference images to find interest-points or regions and form their descriptors from pixels surrounding each detected region. Secondly, based on the descriptors of the feature points, 2D-2D correspondences are sought between query and reference images with a feature matcher. Thirdly, since the 3D point cloud is registered with the reference image, the 2D-3D correspondences between the query image and the 3D point cloud can be computed through the 2D-2D correspondences between the query and reference image. Finally, a Perspective-n-Point solver (Gao et al., 2003) and RANSAC (Fischler and Bolles, 1981; Torr and Zisserman, 2000) are applied for computing the 6-DoF camera pose of the query image. The algorithm and implementation details of each stage of the feature-based pose estimation can be found in Appendix A.

### 2.2. Direct photometric-based (PB) pose estimation

The direct photometric-based approach (Tykkälä et al., 2013) is defined as a direct minimization of the cost function at the space of 6D camera pose, and it does not need to extract local features. The pixel intensities of the query image and rendered synthetic view from the 3D point cloud are directly compared in the cost function (Tykkälä et al., 2013). The photometric-based approach can be divided into three main steps: (1) synthetic image generation, (2) photometric matching, and (3) coarse-to-fine search.

The block diagram of this method is shown in Fig. 3. In summary the algorithm works as follows: firstly, for rendering a colored 3D point cloud must be generated. This is generated by projecting each 3D point of the cloud $P_R$ to the reference
Fig. 2: Block diagram of feature-based camera pose estimation. \( I_Q \) is the query image. The reference image \( I_R \) and the 3D point cloud \( P_R \) are pre-registered and defined in the world coordinate system. \( M^* \) is the estimated transformation matrix. For the detailed descriptions of each step see Appendix A.

Fig. 3: Block diagram of direct photometric-based and mutual information based camera pose estimation. \( I_Q \) is the query image. The reference image \( I_R \) and the 3D point cloud \( P_R \) are pre-registered and defined in the world coordinate system. \( M^* \) is the estimated transformation matrix. For the detailed descriptions of each step see Appendix B.
image frame and then assigning colors from the points of the reference image at that location. Subsequently, we generate a synthetic image by projecting the colored 3D point cloud into an image plane, where the transformation matrix of the reference image is used as the initial matrix. Then, we optimize the transformation matrix $M$ by a grid search. In the end, the 6-DoF camera pose is obtained from the final transformation matrix $M^\star$. It should be noted that in common tracking applications where transformation baseline is small, fast optimization can be implemented by using Jacobian and gradient-based optimization ([Tykkälä et al., 2013]). However, in the case of big appearances changes between the query and references images, the gradient tends to go to local minimum, so we conduct a grid search in our experiment.

A more detailed description of the stages and implementation details of the photometric-based pose estimation method can be found in Appendix B.

2.3. Direct mutual-information-based (MI) pose estimation

The direct mutual-information-based approach ([Pascoe et al., 2017]) is a direct method similar as the photometric-based pose estimation, and it has more robust similarity measurements. Because the above described direct photometric-based pose approach is sensitive to photometric changes, e.g. due to illumination change. To compensate these effects, a more robust similarity measure – Mutual Information (MI) ([McDaid et al., 2011]) – that can be used to replace the direct pixel-based photometric error in the pose estimation cost function. The mutual information is the measure of the mutual dependence between two variables and can be used over different modalities, and mutual-information-based image registration approaches are widely used in medical image registration over different modalities ([Mani and rivazhagan, 2013]). In turn, the normalized mutual information has the advantage that its values are in the bounded range of $[0, 1]$ ([McDaid et al., 2011]).

The direct mutual-information-based approach is similar to the direct photometric-based pose approach in Section 2.2 with the main difference being that in the cost function the normalized mutual information (NMI) is used instead of the photometric error (see Fig. 3). Specifically, mutual information based pose estimation is formulated as a minimization problem as:

$$M^\star = \arg \min_M 1 - \text{NMI}(I_Q, I_S),$$  

(1)

where $M^\star$ is the estimated camera pose, $I_Q$ is the query image, $I_S$ is the synthetic image for which the generation process is described in Appendix B.1 and the Normalized Mutual Information (NMI) is computed as:

$$\text{NMI}(I_S, I_Q) = \frac{\text{MI}(I_S, I_Q)}{\max(H(I_S), H(I_Q))}$$  

(2)

with

$$\text{MI}(I_S, I_Q) = H(I_S) + H(I_Q) - H(I_S, I_Q),$$  

(3)

where $H(I_S, I_Q)$ is the joint entropy of $I_S$ and $I_Q$, $H(I_S)$ and $H(I_Q)$ are the marginal entropies of $I_S$ and $I_Q$, and $\text{MI}(I_S, I_Q)$ is the mutual information between $I_S$ and $I_Q$.

2.4. Hybrid (HY) pose estimation

The hybrid approach for camera pose estimation takes the advantages of both indirect feature-based pose estimation and direct mutual-information-based pose estimation. This method is inspired by the strong empirical evidence in our experiments that: (1) the feature-based method is superior in accuracy if a sufficient number of matches can be found (see detail at Section 4.3 and 4.5); (2) the feature-based approach can completely fail where mutual-information-based approach can still provide a moderate estimate. Therefore, our hybrid approach first executes the feature-based method and if that fails ($< 4$ consistent 2D-3D correspondences) ([Torr and Zisserman, 2000] [Gao et al., 2003]), then switches to the MI-based method.

Given one query image $I_Q$ and one reference tuple $(I_R, P_R)$ (see definition at Fig. 1 and Section 2), a feature detector is firstly applied to both the query image $I_Q$ and reference image $I_R$, and then we apply feature matching to get 2D-2D matched features. Since the point cloud $P_R$ is registered with the reference image $I_Q$, the 2D-3D correspondences can be found. Then a PnP solver ([Gao et al., 2003] and RANSAC ([Torr and Zisserman, 2000]) are applied to the 2D-3D correspondence.
3. Comparative methodology

In this work, we systematically compare camera pose estimation approaches in three stages: firstly, we compare the performance of different pose estimation methods for single query image in the simplest scenario by using one reference tuple, defined in Fig. 1 (methodology in Section 3.1 and experimental results in Section 4.3). Secondly, we increase the number of reference images and evaluate the improvement in accuracy for the studied approaches (methodology in Section 3.2 and experimental results in Section 4.4). Thirdly, we evaluate the different approaches with large uncertainties, where the reference images and their corresponding 3D point clouds can be far away from the query image (methodology in Section 3.3 and experimental results in Section 4.5).

3.1. Single-reference pose estimation

The aim of using a single reference image for different pose estimation methods is to compare their performance at the most basic level without pre- or post-processing steps. As illustrated in Fig. 5, the experiment starts by firstly defining a uncertainty range with a radius of $r$ around the ground truth location of the query image, and $r$ represents the initial uncertainty of the query image’s location. In this paper, initial uncertainty value $r$ is given by the author and it determines the region where the possible reference images can be chosen from. The reference image is randomly selected in the region within the circle, and the aim of introducing the random selection is to evaluate how the studied algorithms respond to different displacements between the query and reference images, because one concern about the performance of pose estimation methods is the need of a proper initialization (i.e., a good estimate of the current camera location). Therefore, After randomly selecting one reference image within the radius, the inputs of the single-reference case are the query image $I_Q$ and a reference tuple $(I_R, P_R)$, where where $I_R$ is a single reference image and $P_R$ is its corresponding 3D point cloud (an example of reference tuple is shown in Fig. 1). The quality of the estimated pose is then assessed in terms of the translation error and rotation error (see Section 4.2).

3.2. Multiple-reference pose estimation

In this section we explain the case of incorporating the information obtained from multiple reference images to estimate the camera pose of a single query image. Therefore, the inputs are one query image and multiple reference tuples which consist of $k$ pairs of reference images and their corresponding 3D point clouds, $[(I_{R1}, P_{R1}), \ldots, (I_{Rk}, P_{Rk})]$ as shown in Fig. 4. The quality of the estimated pose is then assessed in terms of the translation error and rotation error (see Section 4.2).

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The aim of using multiple reference images is to leverage the additional information of different reference images to improve accuracy of the camera pose estimation.

In the prior art, Song et al. [2016] fuse multiple candidate camera poses by: (1) averaging three rotation angles to compute the final rotation matrix; (2) minimizing a geometry error term to estimate the final translation. However, 3D point clouds are not utilized in their approach, so from each of their candidate camera pose only a line where the camera pose of the query image should lie on is obtained. In contrast, in our approach, each reference image together with the 3D point clouds are already sufficient to compute a unique 6-DoF camera pose for the query image. Therefore, we have considered 4 strategies, which can be easily adapted to different camera pose estimation methods.

1. Maximum number of matched features ($maxf$): we match the query image with all the available reference images, and select the reference image with the most matched features after the feature matching stage (Section A.2). Then, we compute the camera pose of the query image with only the reference tuple contains the selected reference image. The remaining processing steps are the

Fig. 6: Example of inputs for multi-references case: one query image $I_Q$ and multiple reference tuples $[(I_{R1}, P_{R1}), \ldots, (I_{Rk}, P_{Rk})]$ which consist of $k$ reference images and $k$ 3D point clouds.
3.3. Camera pose estimation with large uncertainties

In real-life applications, the query image may or may not have a GPS tag, and even with a GPS tag, the precision of the GPS can be poor \cite{Linegar2016, Miura2015}. Therefore, the initial uncertainty radius \( r \) of the query camera’s location can be as large as shown in Fig. 7. In the case of large uncertainty, choosing the reference image by random selection is not practical anymore, but the use of image retrieval methods is a widely accepted practice. Therefore, we compare the performances of the studied pose estimation methods with large uncertainty, and evaluate how image retrieval improves their performance.

Specifically, for the case of the query image with large initial uncertainty, image retrieval methods such as \cite{Song2016, Philbin2007, Radenovic2016, Iscen2017} are used to effectively identify a few good reference images from the reference database. To replicate this procedure we selected the method by \cite{Philbin2007}, which is easy to implement and performs the image retrieval task with large scale data by quantizing low-level image features based on randomized trees and using an efficient spatial verification stage to re-rank the results returned from our bag-of-words model. Furthermore, we apply all evaluated camera pose estimation methods with multiple reference images to compute the final 6-DoF camera pose.

4. Experiments and results

4.1. Datasets

In this work, experiments were conducted using two public datasets: the KITTI Visual Odometry dataset \cite{Geiger2012} and the Oxford RobotCar dataset \cite{Maddern2017}. The KITTI dataset was captured by driving around the mid-size city of Karlsruhe (Germany), in rural areas and on highways. The accurate ground truth is provided by a Velodyne laser scanner and a GPS localization system. There are 11 sequences in KITTI Visual Odometry dataset with provided ground-truth camera pose, and we use all of them in our experiments. All 11 sequences are summarized in Table 1. For
Table 1: Overview of the 11 sequences in the KITTI dataset (Geiger et al. 2012).

| id | # images | tag  | total length (km) | mean distance between consequent images (m) |
|----|----------|------|-------------------|-------------------------------------------|
| 00 | 4541     | urban| 3.7               | 0.8                                       |
| 01 | 1101     | highway| 2.5              | 2.2                                       |
| 02 | 4661     | urban | 5.1               | 1.1                                       |
| 03 | 801      | urban | 0.6               | 0.7                                       |
| 04 | 271      | urban | 0.4               | 1.5                                       |
| 05 | 2761     | urban | 2.2               | 0.8                                       |
| 06 | 1101     | urban | 1.2               | 1.1                                       |
| 07 | 1101     | urban | 0.7               | 0.6                                       |
| 08 | 4071     | urban | 3.2               | 0.8                                       |
| 09 | 1591     | urban | 1.7               | 1.1                                       |
| 10 | 1201     | urban | 0.9               | 0.8                                       |

The recently released Oxford RobotCar dataset (Maddern et al., 2017) provides multiple traversals of the same route and allows a more challenging evaluation in extreme changing conditions, e.g., different time of the day, lighting and weather condition. 5 sequences of the Oxford RobotCar dataset with completely different environment conditions were selected for our experiments. The sequence route is shown in Fig. 9 (Oxford RobotCar dataset).

Fig. 9: The route used for all 5 sequences in Table 2 (Oxford RobotCar dataset).

Table 2: Overview of 5 sequences with different environmental conditions in Oxford RobotCar dataset (Maddern et al., 2017).

| id | # images | tag  | total length (km) | mean distance between consequent images (m) |
|----|----------|------|-------------------|-------------------------------------------|
| 00 | 1916     | overcast | 6.3             | 3.3                                       |
| 01 | 2873     | sun    | 8.6               | 3.0                                       |
| 02 | 2931     | night  | 9.1               | 3.1                                       |
| 03 | 2614     | rain   | 8.8               | 3.4                                       |
| 04 | 3019     | snow   | 8.7               | 2.9                                       |

4.2. Performance measures

We use translation error, maximum orientation error and the success rate of each methods to compare the performance of the different approaches.

1. The translation error is the absolute translation between the ground-truth location and the estimated location of the query image.

2. Based on the rotation matrix between the ground-truth camera pose and the estimated camera pose of the query image, we convert the rotation matrix into 3 Euler angles. Then the maximum absolute Euler angle is used as the maximum orientation error.

3. Different camera pose estimation methods can fail to estimate a 6-DoF camera pose of the query image under some circumstances, e.g. no enough feature matches between the query and reference images in indirect feature-based approach, or searching cannot converge within given search ranges in direct photometric-based approach. We classify the pose estimation failure as either self-reported by each method or the translation errors are greater than a predefined threshold (see details in the each experiment). The success rate of each methods is the percentage of the successfully processed query images with an valid camera pose as the output.

4.3. Experiments with single reference image

We performed 12 experiments for KITTI dataset and 12 experiments for Oxford RobotCar dataset. The goal of these experiments was to compare the performance of different pose estimation methods under the single reference scenario. In Section 3.1 we discussed the camera pose estimation for one query image $I_Q$ with single reference tuple $(I_R, P_R)$ where $I_R$ is a single reference image and $P_R$ is its corresponding 3D point cloud. Similarly, we firstly gathered all reference images within the uncertainty radius $r$ around the given query image’s GPS location, and $r$ was varied between 10 to 25 meters, since most of the photos are taken in the streets of urban area, and these search ranges were used so that the reference image and query images would have some overlaps but without being too close to each other. Within the gathered reference images, we applied random selection to choose one reference image $I_R$ and its corresponding 3D point cloud $P_R$. The reasons for using random selection is to evaluate how the studied algorithms respond to different displacements between the query and reference images (i.e., different initializations).
The experiments with KITTI dataset tested the performance of different camera pose estimation methods under “ideal conditions”, i.e., same time of the day, lighting and weather conditions. For the KITTI dataset listed in Table 1, all 11 sequences have different routes, so each sequence was processed individually. In other words, the query image and the reference images come from the same drive. In order to separate the query and reference images, we randomly selected 10% of the images in one sequence as query images, and the rest images from the same sequence were used as reference images.

The experiments with Oxford RobotCar dataset tested the performance of camera pose estimation methods at challenging conditions since the query and reference data capture large variation in appearance and structure of a dynamic city environment over long periods of time. For the Oxford RobotCar dataset presented in Table 2, all 5 traversals with complete different environmental settings share the same route. The sequences were processed jointly in order to allow the query and reference images come from the different sequences. For example, when the summer sunny sequence (01 in Table 2) was used for the reference images, the winter snow sequence (04 in Table 2) was used for the queries.

Table 3 shows the translation errors and orientation errors of different pose estimation methods by using a single reference image. The results are reported in median values, and both the translation and orientation errors are calculated based on the estimates obtained by the studied methods and the ground-truth camera poses. The success rate of each pose estimation method with Oxford RobotCar and KITTI datasets are shown in Fig. 11.

The main findings of this experiment are that (1) the mutual-information-based method (MI) outperforms other fusion strategies (Table 4), and (2) feature-based approach is the most accurate in terms of both translation accuracy and orientation accuracy (Table 4). Again, the results are collectively summarized in the discussion section (Section 5).

4.5. Experiments at large uncertainty

Based on the strong empirical results in Section 4.3, we proposed a hybrid approach that takes the advantages of both the feature-based and the mutual-information-based approaches as described in Section 2.4. In this Section, we tested these 4 camera pose estimation methods (feature-based, photometric-based, mutual-information-based, and hybrid approaches) with maximum 5 reference images under large uncertainty condition.

In Section 3.3 we introduced a framework for camera pose estimation under large location uncertainty. In the extreme case this means that no prior location estimate is available, but the query image must be matched to the whole reference database, so an image retrieval method (Philbin et al. 2007) is applied to find the reference images. In our experiment we used 200 meters as the initial uncertainty radius for the KITTI and 50 meters for the Oxford dataset, adopted the multiple reference (up to 5 reference images) to improve robustness of all investigated methods. The KITTI dataset correspond to an “ideal case” where query images and references images are from the same environmental setting, while Oxford RobotCar dataset represents results for a more realistic case where the query and references images have completely different environmental setting.
Table 3: Translation error (in meters) and max orientation error (in degrees) comparison for three strategies using single reference image. For KITTI dataset, 454 images (random 10% of the whole sequence) in sequence 00 are used as queries, and the rest are used as the reference images. For Oxford RobotCar dataset, summer sequence (01) is used as references and 302 images (random 10% of the winter sequence) from winter sequence are used as query images. Second row shows the number of images which are successfully processed by all three pipelines. Third row shows the percentage of the successfully processed images among all the testing images.

|          | uncertainty radius (m) | #images | FB (Kim et al., 2014) | PM (Tykkälä et al., 2013) | MI (Pascoe et al., 2017) |
|----------|------------------------|---------|-----------------------|--------------------------|--------------------------|
|          |                       | 10      | 15                    | 20                       | 25                       |
|          |                        | (100%)  | (90%)                 | (75%)                    | (60%)                    |
| KITTI    |                        | 406     | 328                   | 282                      | 259                      |
|          |                        | (89%)   | (72%)                 | (62%)                    | (57%)                    |
|          | FB                     | 0.13    | 0.40                  | 0.48                     | 0.30                     |
|          | PM                     | 1.44    | 6.66                  | 7.77                     | 14.85                    |
|          | MI                     | 1.56    | 5.41                  | 6.15                     | 10.26                    |

|          | uncertainty radius (m) | #images | FB (Kim et al., 2014) | PM (Tykkälä et al., 2013) | MI (Pascoe et al., 2017) |
|----------|------------------------|---------|-----------------------|--------------------------|--------------------------|
|          |                       | 10      | 15                    | 20                       | 25                       |
|          |                        | (100%)  | (90%)                 | (75%)                    | (60%)                    |
| Oxford   |                        | 67      | 60                    | 53                       | 38                       |
|          |                        | (22%)   | (20%)                 | (18%)                    | (13%)                    |
|          | FB                     | 2.77    | 2.48                  | 2.40                     | 2.91                     |
|          | PM                     | 10.44   | 16.23                 | 20.09                    | 26.32                    |
|          | MI                     | 8.71    | 13.36                 | 16.27                    | 14.94                    |

Fig. 11: Success rate comparison for three strategies with single reference image at different uncertainty ranges in two public datasets. (a): in the experiments with KITTI sequence 00, random 10% images in sequence 00 are used as query image and the rest are used as references. (b): in the experiments with two sequences in Oxford RobotCar sequences, summer sequence (01) is used as references and snow sequence (04) is used as query images.

|          | uncertainty radius (m) | #images | FB (Kim et al., 2014) | PM (Tykkälä et al., 2013) | MI (Pascoe et al., 2017) |
|----------|------------------------|---------|-----------------------|--------------------------|--------------------------|
|          |                       | 10      | 15                    | 20                       | 25                       |
|          |                        | (100%)  | (90%)                 | (75%)                    | (60%)                    |
| KITTI    |                        | 406     | 328                   | 282                      | 259                      |
|          |                        | (89%)   | (72%)                 | (62%)                    | (57%)                    |
|          | FB                     | 1.76    | 3.83                  | 5.42                     | 3.33                     |
|          | PM                     | 1.07    | 2.40                  | 3.37                     | 3.12                     |
|          | MI                     | 1.07    | 2.30                  | 3.45                     | 2.70                     |

|          | uncertainty radius (m) | #images | FB (Kim et al., 2014) | PM (Tykkälä et al., 2013) | MI (Pascoe et al., 2017) |
|----------|------------------------|---------|-----------------------|--------------------------|--------------------------|
|          |                       | 10      | 15                    | 20                       | 25                       |
|          |                        | (100%)  | (90%)                 | (75%)                    | (60%)                    |
| Oxford   |                        | 67      | 60                    | 53                       | 38                       |
|          |                        | (22%)   | (20%)                 | (18%)                    | (13%)                    |
|          | FB                     | 3.44    | 3.79                  | 2.72                     | 3.25                     |
|          | PM                     | 3.48    | 5.82                  | 2.64                     | 1.88                     |
|          | MI                     | 6.16    | 4.00                  | 2.42                     | 1.93                     |

Fig. 12: Success rates comparison for three pipelines with multiple reference images and robust weighted average merge method in two datasets.
Table 4: Performance of 4 pose merge methods used by each camera pose estimation approach in KITTI dataset. 10% images from one sequence are used as query image and the rest are used as references, and uncertainty radius is 10 meters. The reported results are computed from all processed images by each camera pose estimation approach.

| #reference images | RMSE (m) | RMSE (deg) | RMSE (m) | RMSE (deg) | RMSE (m) | RMSE (deg) | RMSE (m) | RMSE (deg) | RMSE (m) | RMSE (deg) |
|-------------------|----------|------------|----------|------------|----------|------------|----------|------------|----------|------------|
| **Feature-based (FB)** |          |            |          |            |          |            |          |            |          |            |
| avg               | 0.125    | 1.76       | 0.216    | 2.07       | 0.248    | 2.20       | 0.212    | 1.80       | 0.195    | 1.61       |
| wavg              | 0.125    | 1.76       | 0.148    | 1.67       | 0.151    | 1.78       | 0.103    | 1.22       | 0.090    | 1.11       |
| maxf              | 0.125    | 1.76       | 0.106    | 1.82       | 0.093    | 1.79       | 0.060    | 1.21       | 0.049    | 1.03       |
| r-wavg            | 0.125    | 1.76       | 0.117    | 1.70       | 0.104    | 1.59       | 0.059    | 1.13       | 0.045    | 0.93       |
| **Photometric (PM)** |          |            |          |            |          |            |          |            |          |            |
| avg               | 1.67     | 1.22       | 2.39     | 1.36       | 2.20     | 1.42       | 2.09     | 1.23       | 1.90     | 1.05       |
| wavg              | 1.67     | 1.22       | 1.79     | 1.08       | 1.55     | 1.07       | 1.29     | 0.80       | 1.12     | 0.70       |
| maxf              | 1.67     | 1.22       | 1.37     | 1.07       | 1.22     | 1.02       | 1.20     | 0.73       | 1.07     | 0.67       |
| r-wavg            | 1.67     | 1.22       | 1.40     | 1.01       | 1.22     | 0.87       | 1.12     | 0.68       | 0.99     | 0.58       |
| **Mutual Information (MI)** |          |            |          |            |          |            |          |            |          |            |
| avg               | 1.75     | 1.35       | 1.71     | 1.28       | 1.84     | 1.46       | 1.69     | 1.25       | 1.61     | 1.13       |
| wavg              | 1.75     | 1.35       | 1.51     | 1.14       | 1.39     | 1.21       | 1.17     | 0.79       | 1.18     | 0.78       |
| maxf              | 1.75     | 1.35       | 1.43     | 1.10       | 1.29     | 1.06       | 1.17     | 0.80       | 1.13     | 0.68       |
| r-wavg            | 1.75     | 1.35       | 1.43     | 1.07       | 1.26     | 0.95       | 1.10     | 0.69       | 1.03     | 0.62       |

5. Discussion

5.1. Camera pose estimation with single reference image

Table 3 reports both translation errors and orientation errors comparisons for three strategies using a single reference tuple. In Table 3, the numbers of images in the second line of each sub-table are the number of images that all methods successfully processed and therefore the error numbers are comparable between the methods, and the percentages on the third line of each sub-table are the corresponding percentages of the successfully processed images among the total number of images.

From Table 3a and 3b, we have two findings:

1. By looking into each column, we find that as long as the feature-based approach is able to estimate the camera pose (minimum 4 consistent 2D-3D correspondences are required to compute the camera pose by the PnP method (Gao et al., 2003)), its estimated camera poses have smaller translation errors than the other two methods in both KITTI and Oxford RobotCar dataset. This result indicates that the feature-based approach is more accurate in pose estimation in both ideal environment conditions (KITTI dataset) and realistic environment conditions (Oxford RobotCar dataset).

2. By looking into each row, we find that the translation errors of both photometric-based and mutual-information-based approach increase with the increase of the uncertainty radius, but the translation errors of feature-based approach do not vary much. Since the closer reference images bring better initialization for both the photometric-based and mutual-information-based approach, the results indicate that both the photometric-based and mutual-information-based approach are sensitive to the initialization. However, the feature-based approach is much less sensitive to the location of the reference images.

1. We report results for all 11 KITTI sequences, and a 100-fold experimental results for the Oxford RobotCar dataset where one sequence used as the reference dataset and other sequences as the query dataset.

The results for the 11 KITTI sequences are shown in Table 5. This table consists of 44 experiments, each of the 11 sequence in KITTI dataset processed by the four camera pose estimation methods. The uncertainty radius was set to be 200 meters, the maximum number of reference images was set to 5, and we classify the localization failure as either system-reported or 20 meters absolute translation error. The results for the Oxford RobotCar dataset are shown in Table 6. The uncertainty radius was set to 50 meters, the maximum number of reference images was set to 5, and we classify the localization failure as either system-reported or 20 meters absolute translation error.

The most interesting finding of these experiments is that our hybrid method that combines the complementary properties of the feature-based and mutual information based approaches is the most effective and robust for all query-reference pairs with the difficult and realistic Oxford dataset. The detailed analysis is presented in the discussion Section 5.

Table 3c and 3d compare the orientation errors for the studied methods. Among these different camera pose estimation methods, the differences between their orientation errors are small. In other words, all these methods perform similarly in terms of orientation error for both KITTI and Oxford RobotCar datasets. The reason might be that all the images are taken by a camera mounted on a car driving along the street, so the query images and the reference images may share similar viewpoints.

Fig. 11 records the success rate (see definitions in Section 4.2) comparison for the three strategies with single reference tuple.
Table 5: Large uncertainty pose estimation results for 11 sequences in the KITTI dataset combining image retrieval and pose estimation. The uncertainty radius is 200 meters and the number of automatically retrieved reference images is 5. Note these two original papers (Tykkäliä et al., 2013; Pascoe et al., 2017) were designed for slam problem, but we modified the algorithms to adjust to our problem.

| #sequence ID | 00 | 01 | 02 | 03 |
|--------------|----|----|----|----|
| RMSE (m) | % | RMSE (m) | % | RMSE (m) | % | RMSE (m) | % |
| FB (Kim et al., 2014) | 99.8 | 0.031 | 0.676 | 89.1 | 0.505 | 0.562 | 99.8 | 0.025 | 0.415 |
| PM (Tykkäliä et al., 2013) | 98.2 | 0.603 | 0.423 | 97.8 | 0.633 | 0.415 | 99.8 | 0.025 | 0.415 |
| MI (Pascoe et al., 2017) | 98.2 | 0.603 | 0.423 | 97.8 | 0.633 | 0.415 | 99.8 | 0.025 | 0.415 |
| HY (proposed) | 99.8 | 0.031 | 0.676 | 89.1 | 0.505 | 0.562 | 99.8 | 0.025 | 0.415 |

Table 6: Large uncertainty pose estimation results for the 5 different sequences in Oxford dataset (5-fold experiment where each sequence was paired with each sequence to form query-reference pairs). The uncertainty radius was set to 20 meters. Note these two original papers (Tykkäliä et al., 2013; Pascoe et al., 2017) were designed for slam problem, but we modified the algorithms to adjust to our problem.

| #sequence ID | 00 | 01 | 02 | 03 |
|--------------|----|----|----|----|
| RMSE (m) | % | RMSE (m) | % | RMSE (m) | % | RMSE (m) | % |
| FB (Kim et al., 2014) | 99.8 | 0.031 | 0.676 | 89.1 | 0.505 | 0.562 | 99.8 | 0.025 | 0.415 |
| PM (Tykkäliä et al., 2013) | 98.2 | 0.603 | 0.423 | 97.8 | 0.633 | 0.415 | 99.8 | 0.025 | 0.415 |
| MI (Pascoe et al., 2017) | 98.2 | 0.603 | 0.423 | 97.8 | 0.633 | 0.415 | 99.8 | 0.025 | 0.415 |
| HY (proposed) | 99.8 | 0.031 | 0.676 | 89.1 | 0.505 | 0.562 | 99.8 | 0.025 | 0.415 |

Table 7: Large uncertainty pose estimation results for the 5 different sequences in Oxford dataset (5-fold experiment where each sequence was paired with each sequence to form query-reference pairs). The uncertainty radius was set to 20 meters. Note these two original papers (Tykkäliä et al., 2013; Pascoe et al., 2017) were designed for slam problem, but we modified the algorithms to adjust to our problem.

| #sequence ID | 00 | 01 | 02 | 03 |
|--------------|----|----|----|----|
| RMSE (m) | % | RMSE (m) | % | RMSE (m) | % | RMSE (m) | % |
| FB (Kim et al., 2014) | 99.8 | 0.031 | 0.676 | 89.1 | 0.505 | 0.562 | 99.8 | 0.025 | 0.415 |
| PM (Tykkäliä et al., 2013) | 98.2 | 0.603 | 0.423 | 97.8 | 0.633 | 0.415 | 99.8 | 0.025 | 0.415 |
| MI (Pascoe et al., 2017) | 98.2 | 0.603 | 0.423 | 97.8 | 0.633 | 0.415 | 99.8 | 0.025 | 0.415 |
| HY (proposed) | 99.8 | 0.031 | 0.676 | 89.1 | 0.505 | 0.562 | 99.8 | 0.025 | 0.415 |

Table 8: Large uncertainty pose estimation results for the 5 different sequences in Oxford dataset (5-fold experiment where each sequence was paired with each sequence to form query-reference pairs). The uncertainty radius was set to 20 meters. Note these two original papers (Tykkäliä et al., 2013; Pascoe et al., 2017) were designed for slam problem, but we modified the algorithms to adjust to our problem.
robust weighted average method is a light approach and can be easily adapted with any pose estimation method.

5.3. Camera pose estimation at large uncertainties

By looking at the columns of success rates in Table 5, we see that the hybrid and feature-based approaches outperform other methods in cases where the query and reference images have been captured at similar imaging conditions (KITTI dataset). The hybrid approach performs similarly as the feature-based approach which indicates that the proposed hybrid method can retain good properties of the feature-based method. For the sequence 01 hybrid is superior. This has the explanation that 01 is captured from highway (Table 1) where there are less reliable features to be found than in urban scenes. In urban scenes hybrid and feature-based methods provide practically the same accuracy.

Table 6 summarizes the results from 100 experiments where the four camera pose estimation methods were used in 25 query-reference combinations of the Oxford RobotCar dataset. In addition to a large displacement, query and reference images have been acquired at very different imaging conditions. Table 6 provides a confusion matrix for the experiment combining different imaging conditions. By looking into the columns of success rate in that table, our findings are as follows:

1. mutual-information-based approach is more robust than the feature-based or photometric-based approaches, which is consistent with the findings from both Fig. 11 and Fig. 12
2. The hybrid approach outperforms all other approaches in success rate when the query and reference images have very different imaging conditions. This confirms that the proposed hybrid method leverages complementary properties of the feature-based and mutual-information-based methods.

The results on the diagonal of Table 6 are consistent with previous experiments in the KITTI dataset in Table 5 i.e. in the ideal case when query and reference images come from the same sequence and imaging conditions. In this case, feature-based and our hybrid method outperform the other approaches. A remarkable result in Table 6 is that, even in the worst case scenario, the lowest success rate of the proposed hybrid method is 35.8%. Recent results in the same dataset in similar conditions have reported success rates as low as 0 % using SLAM (Pascoe et al., 2017). Notice that the experimental settings in that work (Pascoe et al., 2017) are different from ours, but this helps understanding the difficulty of the pose estimation problem under challenging environmental conditions.

6. Conclusion

We performed systematic and extensive comparisons of three different strategies in 6-DoF camera pose estimation using reference images and 3D point cloud: an indirect feature-based
approach, a direct photometric-based approach and a direct mutual-information-based approach. “Direct” in this context means the minimization of the cost function is done directly in the space of 6D camera pose. In our experiments, the feature-based approach is more accurate than both the photometric-based and mutual-information-based approaches when as few as 4 consistent feature points are found between a query and reference image. The mutual-information-based approach is the more robust than the feature-based and photometric-based approaches which means that it can provide a moderate estimate even in the cases when the feature-based method fails. Robustness and accuracy of all methods were improved with increased number of reference images, and robust weighted average method outperformed other fusing methods for multiple reference images. Based on the strong empirical results and inspired by the complementary properties of the feature-based and mutual-information-based approaches, we proposed a computationally cheap and easy-to-adapt hybrid approach that combines these two methods. In all experiments, the hybrid method is on pair or superior. This is particularly so in challenging scenarios such as the Oxford RobotCar dataset, where the hybrid approach outperforms feature-based and mutual-information-based approaches respectively by the average of 25.1% and 5.8% in terms of success rate.

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Zwicker, M., Pfister, H., van Baar, J., Gross, M., 2001. Surface splatting, in: ACM SIGGRAPH.
Appendix A. Indirect feature-based pose estimation

This appendix presents the detailed description of the four stages of the indirect feature-based pose estimation method presented in Section 2.3.1.

Appendix A.1. Feature detection and description

The first step of the system is to detect and extract features of salient locations in the query and reference images. Specifically, a feature detector is used for finding the salient points of an image, and a feature descriptor is used to describe the neighborhood surrounding that salient point.

Feature detectors can extract different types of image structures, e.g., corners (Rosten and Drummond 2006; Mikolajczyk and Schmid 2004), blobs (Lowe 1999; Bay et al. 2006; Kadir and Brady 2001) or regions (Matas et al. 2004; Tuytelaars and Van Gool 2000, 2004; Mori et al. 2004). In turn, feature detectors can be divided into following categories based on their approaches: local binary descriptors (Ojala et al. 2002; Guo et al. 2010; Zhao and Pietikainen 2007; Proba and Ernst 2004; Calonder et al. 2010; Rublee et al. 2011; Leutenegger et al. 2011; Alahi et al. 2012), spectral descriptors (Lowe 1999; Lienhart and Maydt 2002; Bay et al. 2006; Dalal and Triggs 2005; Tola et al. 2010; Ambati and Yoshida 2011), basis space descriptors (Zahn and Roskies 1972; Csurka et al. 2004), polygon shape descriptors (Matas et al. 2004; Belongie et al. 2001), 3D and volumetric descriptors (Klauser et al. 2008; Seovamner et al. 2007). In the literature, many feature detectors, such as SURF (Bay et al. 2006), BRISK (Leutenegger et al. 2011) and others, provide their own detector method along with the descriptor method. DoG (Lowe 1999) and SURF (Bay et al. 2006) detectors were designed for efficiency, and the other properties are slightly compromised. However, for most applications they are still more than sufficient (Tuytelaars et al. 2008).

In this work we have utilized SURF for both feature detection and description due to its speed, performance, and widespread use in multiple applications.

Appendix A.2. Feature matching

Based on the previously computed feature descriptors, the aim of feature matching is finding 2D-to-2D correspondences between feature points in the query and reference image.

The popular approaches for feature matching are exhaustive search, hashing (Strecha et al. 2012), and nearest neighbor techniques (Friedman et al. 1977; Lowe 2004; Muja and Lowe 2009). Exhaustive search is achieved by minimizing pairwise distance measures between the feature vectors of the reference and query image. The hashing approach reduces the size of the descriptors by finding a more compact representation, e.g., binary strings (Strecha et al. 2012). In nearest neighbor techniques, KD-trees (Friedman et al. 1977) and their variants (Lowe 2004; Muja and Lowe 2009) are commonly used to quickly find approximate nearest neighbors in a relatively low-dimensional real-valued space. The algorithm works by recursively partitioning the set of training instances based on a median value of a chosen attribute (Friedman et al. 1977).

Appendix A.3. 2D-3D correspondences

The 2D-3D correspondences between the query image and the 3D point cloud are established by using the set $c$ of 2D-2D matches and the pre-registered point cloud $P_R$. Since the point cloud $P_R$ and the reference image $I_R$ are pre-registered and defined in the same world coordinate system, with the 2D-2D matched features, we could indirectly link the 2D-3D correspondences as illustrated in Fig. A.13.

We use the exhaustive search approach and adopt a minimum Euclidean distance on the descriptor vector. For each feature point in one image, we find the nearest neighbor as its corresponding feature point in the other image. Besides, we reject some ambiguous matches by comparing the distance of the closest neighbor to that of the second-closest neighbor. In other words, correct matches need to have the closest neighbor significantly closer than the second closest match to achieve reliable matching (Lowe 2004). The output of the feature matching steps is a set $c$ of $n$ 2D-to-2D correspondences between the query image $I_Q$ and reference image $I_R$:

$$c = \{ (p_Q^{(1)}, p_R^{(1)}), (p_Q^{(2)}, p_R^{(2)}), \ldots, (p_Q^{(n)}, p_R^{(n)}) \}$$ (A.1)

where $p_Q^{(i)} = [u_Q^{(i)}, v_Q^{(i)}]^T$ and $p_R^{(i)} = [u_R^{(i)}, v_R^{(i)}]^T$ are the $i$th 2D feature locations on reference and query images.

![Fig. A.13: Build 2D-3D correspondences through the 2D-2D matched features and the pre-registered point cloud.](image-url)
where $\mathbf{M}$ is the world to camera transformation matrix and $\mathbf{K}$ is the intrinsic matrix of the reference image. $\mathbf{M}$ and $\mathbf{K}$ can be represented by (A.3) and (A.4):

$$
\mathbf{M} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix}
$$

where $\mathbf{R}$ is a $3 \times 3$ rotation matrix, and $\mathbf{t}$ is a $3 \times 1$ translation vector.

$$
\mathbf{K} = \begin{bmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix}
$$

where $f_x$ and $f_y$ are focal length in terms of pixels along $x$ and $y$ axis directions; $\gamma$ represents the skew coefficient between $x$ and $y$ axis and it is often 0; $u_0$ and $v_0$ represents the principle point which would ideally be in the center of the image. In the experiments of this paper, we assume the query image and the reference images share the camera intrinsic matrix, because the images from each dataset are captured with the same camera.

Secondly, we use nearest-neighbor search ([Friedman et al., 1977]) to find the closest point among 2D projections $p$ for each 2D feature point in $c$ at the reference image. In particular, the $j$-th feature point $\mathbf{p}_R^{(j)}$ in the reference image, is associated to the $k$-th point of the 2D projection set $p$ by:

$$
k = NN(\mathbf{p}_R^{(j)}, p), \quad k \in \{1, 2, \ldots, m\}
$$

Finally, we find the 3D coordinates for each 2D feature point. In particular, the $k$-th depth value corresponding to $\mathbf{p}_R^{(k)}$, namely $z^{(k)}$, is then used to find the 3D coordinates in the reference image frame corresponding to $\mathbf{p}_R^{(j)}$ as:

$$
\mathbf{p}_Q^{(j)} = \left[ \mathbf{K}^{-1} \mathbf{p}_R^{(j)} \right]_{z^{(k)}}
$$

As a result, the final 2D-to-3D correspondences can be expressed as:

$$
\hat{c} = \{(\mathbf{p}_Q^{(1)}, \mathbf{p}_R^{(1)}), (\mathbf{p}_Q^{(2)}, \mathbf{p}_R^{(2)}), \ldots, (\mathbf{p}_Q^{(m)}, \mathbf{p}_R^{(m)})\}
$$

where $\mathbf{p}_Q^{(j)}$ is the $i$-th 2D feature location in the query image, and $\mathbf{p}_R^{(j)}$ is the $i$-th corresponding 3D location in the reference image coordinate.

### Appendix A.4. Perspective-n-Point and RANSAC

The set of 2D-3D correspondences $\hat{c}$ establishes one-to-one correspondences between 2D points in query image frame $\mathbf{p}_Q^{(j)}$, and 3D points in the reference image frame $\mathbf{p}_R^{(j)}$, for $j = 1, 2, \ldots, m$. The last step is to apply Perspective-n-Point solver ([Gao et al., 2003]) to compute the relative 6-DoF camera pose $\mathbf{M}$ between the query image and the reference image. For this purpose, two approaches are combined to solve the problem: the algebraic approach and the geometric approach. In the algebraic approach, we use Wu’s zero decomposition method to find a complete triangular decomposition of a practical configuration for the P3P problem ([Gao et al., 2003]). We can obtain up to 4 solutions for the pose using 3 points, and in the geometric approach, we choose the solution that results in the smallest squared re-projection error for the 4th point ([Gao et al., 2003]).

$$
\mathbf{M}^* = \arg \min_{\mathbf{M}} \sum_{i} ||\mathbf{p}_Q^{(i)} - \mathbf{K}\mathbf{M}\mathbf{p}_R^{(i)}||, \quad i \in \{1, 2, \ldots, m\}
$$

where $\mathbf{M}$ is the sought word-to-camera transformation matrix, $\mathbf{M}^*$ is its best estimate, $\mathbf{K}$ is the intrinsic matrix, $\mathbf{p}_Q^{(i)}$ is the $i$-th feature point at the query image and $\mathbf{p}_R^{(i)}$ is its corresponding 3D coordinate.

In reality, the set of 2D-3D correspondences $\hat{c}$ can be corrupted by outliers, so it is common to use a robust estimator together with PnP solvers. RANSAC ([Fischler and Bolles, 1981]) estimator is a popular choice, and in our work we use a generalization of the RANSAC estimator, MLESAC ([Torr and Zisserman, 2000]). MLESAC adopts the same sampling strategy as RANSAC to generate putative solutions, but chooses the solutions by maximizing the likelihood rather than just the number of inliers.

Finally, the 6-DoF camera pose can be obtained by means of the decomposition of $\mathbf{M}^*$ via (A.3).

### Appendix B. Direct photometric-based camera pose estimation

This appendix explains the details of the three stages of the direct photometric-based camera pose estimation, namely, generation of synthetic views, direct photometric matching and coarse-to-fine search.

#### Appendix B.1. Generation of synthetic views

The reference 3D point cloud $\mathbf{P}_R$ does not have any color or intensity information, but this information can be retrieved from the reference image as follows. Firstly, we project 3D point clouds $\mathbf{P}_R = [\mathbf{p}_R^{(1)}, \mathbf{p}_R^{(2)}, \ldots, \mathbf{p}_R^{(m)}]$ onto the reference image plane using (A.2) and get a set of 2D projections, $p = [\mathbf{p}_Q^{(1)}, \mathbf{p}_Q^{(2)}, \ldots, \mathbf{p}_Q^{(m)}]$. This process is the same as Fig. A.14. Secondly, we use cubic interpolation to compute the intensity values for each 2D projection and assign the intensity values to the 3D point cloud as:

$$
I(\mathbf{p}_R^{(i)}) \leftarrow f(\mathbf{p}_Q^{(i)}, I_R), \quad I_R \in \mathbb{R}^2
$$

where $I_R$ is the reference image, $\mathbf{p}_Q^{(i)}$ is the $i$-th 2D projection, $I(\mathbf{p}_R^{(i)})$ is the intensity value of the 3D point $\mathbf{p}_R^{(i)}$, and $f$ is the cubic interpolation function. As a result, we assign intensity (or color) information to the 3D point cloud $\mathbf{P}_R$.

Synthetic views can now be rendered by projecting the colored 3D point cloud using a transformation matrix $\mathbf{M}$ using
and the intensities of the synthetic view \( I_S \) can be obtained as:
\[
I_S(\text{KMP}^{(i)}_R) \leftarrow I(P^{(i)}_R),
\]
where \( I(P^{(i)}_R) \) is the intensity value of the \( i \)-th 3D point \( P^{(i)}_R \). \( K \) is the intrinsic matrix, \( M \) is the world-to-synthetic-view transformation, and \( I_S(\text{KMP}^{(i)}_R) \) is the intensity value of the projection of the 3D point \( P^{(i)}_R \) at the synthetic frame. Synthetic views are quickly rendered by the standard computer graphics procedure of surface splatting (Zwicker et al., 2001).

**Appendix B.2. Direct photometric matching**

The direct photometric-based approach (Tykkälä et al., 2013) is defined as a direct minimization of the cost function at the space of 6D camera pose, and in the cost function it compares the pixel intensities of the query image \( I_Q \) and rendered synthetic view \( I_S \) from the colored 3D point cloud (Tykkälä et al., 2013). The task is to find the best relative camera transform \( M^* \) that minimizes the photometric-error between query image \( I_Q \) and synthetic image \( I_S \):
\[
M^* = \arg \min_M \text{RSE}(I_Q, I_S),
\]
where,
\[
\text{RSE}(I_Q, I_S) = \frac{1}{\mu} \sum_{(u,v) \in I_S} (I_Q(u,v) - I_S(u,v))^2
\]

In (B.4) the synthetic view \( I_S \) is generated by (B.2), and \( \mu \) is the number of pixels in \( I_Q \).

To improve the robustness of the matching process, we smooth the query image \( I_S \) by using a Gaussian filter and then we use the smoothed version of query image in the image matching process. Moreover, we use M-estimator to improve the matching process, since the M-estimator can be used for managing outliers when the residual vector is of sufficient length for statistical purpose (Huber, 2011). The main idea is to generate small weights for residual elements that are classified as outliers by analyzing the distribution of residual values. Inliers always have small residual values whereas outliers may have any error value. In our work, we use the median filter to find the median value among the residuals, \( \text{RSE}(I_Q, I_S) \), then give zero weights to all the residual values that are greater than the median value, and give normalized weights to the remaining residuals.

With the M-estimator, we can rewrite (B.4) as the average of the weighted sum-of-square difference:
\[
\text{RSE}(I_Q, I_S) = \frac{1}{\lambda} \sum_{(u,v) \in I_S} (E(u,v))^2 w(u,v)
\]
where \( \lambda \) is the number of nonzero weights, \( E(u,v) \) and \( w(u,v) \) are defined in (B.5) and (B.7) as follows:
\[
E(u,v) = (I_Q(u,v) - I_S(u,v))^2, (u,v) \in I_S
\]
where \( I_Q \) is the query image, \( I_S \) is the synthetic image, and \( E \) is the difference between the two images.

In the pixel intensities of the query image \( I \) space of 6D camera pose, and in the cost function it compares is defined as a direct minimization of the cost function at the surface splatting (Zwicker et al., 2001). Quickly rendered by the standard computer graphics procedure of the 3D point \( P \) that minimizes the photometric-error between query image \( I_Q \) and rendered synthetic view \( I_S \) as:
\[
\text{RSE}(I_Q, I_S) = \frac{1}{\mu} \sum_{(u,v) \in I_S} (I_Q(u,v) - I_S(u,v))^2
\]

In (B.4) the synthetic view \( I_S \) is generated by (B.2), and \( \mu \) is the number of pixels in \( I_Q \).

To improve the robustness of the matching process, we smooth the query image \( I_S \) by using a Gaussian filter and then we use the smoothed version of query image in the image matching process. Moreover, we use M-estimator to improve the matching process, since the M-estimator can be used for managing outliers when the residual vector is of sufficient length for statistical purpose (Huber, 2011). The main idea is to generate small weights for residual elements that are classified as outliers by analyzing the distribution of residual values. Inliers always have small residual values whereas outliers may have any error value. In our work, we use the median filter to find the median value among the residuals, \( \text{RSE}(I_Q, I_S) \), then give zero weights to all the residual values that are greater than the median value, and give normalized weights to the remaining residuals.

With the M-estimator, we can rewrite (B.4) as the average of the weighted sum-of-square difference:
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\]
where \( \lambda \) is the number of nonzero weights, \( E(u,v) \) and \( w(u,v) \) are defined in (B.5) and (B.7) as follows:
\[
E(u,v) = (I_Q(u,v) - I_S(u,v))^2, (u,v) \in I_S
\]
where \( I_Q \) is the query image, \( I_S \) is the synthetic image, and \( E \) is the difference between the two images.

Firstly, we defined a 2D search grid along x (towards the right of the camera) and z (towards the front of the camera) axis directions, and the origin is in the middle of the 2D search grid. We start to search the minimum with a big step (step 1) in a grid manner, then follow a smaller step (step 2) search in a grid manner again at the previous minimum location.

**Appendix B.3. Coarse-to-fine grid search**

we use a two-step coarse-to-fine grid search to solve for the matrix \( M^* \) in (B.3). The coarse-to-fine grid search concatenates search with a coarse step for the local minimum with a subsequent search with a finer step at the location of the previous minimum location. We apply the coarse-to-fine search firstly to the translation, and based on the previous minimum, we then apply it to the orientation. The process of the coarse-to-fine grid search is illustrated in Fig. B.15 and Fig. B.16.

Firstly, we defined a 2D search grid along x (towards the right of the camera) and z (towards the front of the camera) axis directions, and the origin is in the middle of the 2D search grid. We start to search the minimum with a big step (step 1) in a grid manner, then follow a smaller step (step 2) search in a grid manner again at the previous minimum location. Fig. B.15 illustrated the coarse-to-fine search for translation.
Secondly, based on the previous minimum location, we further apply the coarse-to-fine grid search for orientation. We could search the optimal orientations along one more multiple axis. For our experiments, we search the optimal orientations along the z axis (toward up direction of the car). As shown in Fig. B.16, we start to search the minimum with a big orientation search range $2 \times \alpha_1$ with $2 \times N - 1$ steps, then follow a smaller orientation search range $2 \times \alpha_2$ with $2 \times N - 1$ steps in a grid manner again at the previous minimum orientation.