Stress-Testing LiDAR Registration

Amnon Drory  Shai Avidan  Raja Giryes
Tel-Aviv University, Israel

Abstract

Point cloud registration (PCR) is an important task in many fields including autonomous driving with LiDAR sensors. PCR algorithms have improved significantly in recent years, by combining deep-learned features with robust estimation methods. These algorithms succeed in scenarios such as indoor scenes and object models registration. However, testing in the automotive LiDAR setting, which presents its own challenges, has been limited. The standard benchmark for this setting, KITTI-10m, has essentially been saturated by recent algorithms: many of them achieve near-perfect recall.

In this work, we stress-test recent PCR techniques with LiDAR data. We propose a method for selecting balanced registration sets, which are challenging sets of frame-pairs from LiDAR datasets. They contain a balanced representation of the different relative motions that appear in a dataset, i.e. small and large rotations, small and large offsets in space and time, and various combinations of these. We perform a thorough comparison of accuracy and runtime on these benchmarks. Perhaps unexpectedly, we find that the fastest and simultaneously most accurate approach is a version of advanced RANSAC. We further improve results with a novel pre-filtering method.

Full code is available¹.

1. Introduction

In many fields such as autonomous driving, one may be interested in calculating the relative transformation between two scans of a scene that are taken from different locations and directions. This process is known as rigid registration, and in recent years, point-cloud registration (PCR) methods have seen a significant increase in their abilities, thanks to deep learning. This has been demonstrated in various settings, such as indoor scenes and object registration. In the automotive LiDAR setting, however, testing has been limited. The standard benchmark in recent years, KITTI-10m, is saturated, i.e., various algorithms have achieved essentially perfect recall (see Fig. 3). Our aim is to test PCR algorithms in a challenging automotive LiDAR setting.

So what makes KITTI-10m easy? Figure 1 gives a graphic illustration. In KITTI-10m, pairs of LiDAR scans for registration are selected using a simple heuristic: pairs with an offset of 10 meters between scanner positions (pairs connected by pink lines). Our selection algorithm returns a challenging set of frame-pairs (connected by double yellow line) that is a balanced sampling of all relative motions in the sequence, including short and long offsets in time and space, various rotation angles, etc.

Figure 1. Challenging and balanced frame-pair sets. Automotive LiDAR datasets contain sequences of point-clouds scanned throughout a driving session. The vehicles in this diagram mark the position of the scanner in each frame. To test registration algorithms, one must select a set of frame-pairs. The standard KITTI-10m set uses a simple heuristic rule: take pairs with an offset of 10 meters between scanner positions (pairs connected by pink lines). Our selection algorithm returns a challenging set of frame-pairs (connected by double yellow line) that is a balanced sampling of all relative motions in the sequence, including short and long offsets in time and space, various rotation angles, etc.

¹https://github.com/AmnonDrory/LidarRegistration
Figure 2. Comparison of registration set statistics. Comparison of marginal statistics between one of our proposed balanced registration sets, Apollo-Southbay-Balanced (top row), and the popular KITTI-10m set (bottom row). We show the distribution of samples by (from left to right): distance between the pair of point clouds, time offset, overlap between scans, and rotation in three separate axes. Apollo-Southbay-Balanced includes a balanced representation of all the relative motions that are encountered in a real driving scenario. It is also much more challenging, as the overlap between point-clouds is as low as 0.2.

showing that the registration algorithms are not truly challenged.

Our first contribution is an algorithm for selecting a set of frame pairs that more faithfully represent all the different situations that a registration algorithm could face in an automotive LiDAR setting. Our algorithm, described in Sec. 3, returns a balanced sampling of the different relative motions that appear in a dataset, i.e. small and large rotations, small and large offsets in space and time, and various combinations of these. The frame pairs selected by our method are illustrated by yellow lines in Fig. 1.

At the heart of many of the recently successful registration algorithms lie deep-learning based local descriptors. These descriptors represent the local neighborhood of a point, making it possible to reliably recognize a semantically matching point in another point cloud. Given a set of putative matches, one can estimate the rigid motion between the two point clouds. However, special attention needs to be given to the presence of outliers: point-matches whose relative motion does not agree with the overall rigid transformation. In the LiDAR setting these are created by independently moving objects in the scene, in addition to other causes such as partial overlap between the point clouds.

To handle outliers, one must use robust estimation algorithms. As an alternative to the classic RANSAC approach, which was claimed to be slow, new algorithmic based solutions such as TEASER++ [31], and deep learning based methods including DGR [8] and PointDSC [2] were proposed. Our second contribution is a thorough comparison of these algorithms in a challenging LiDAR setting.

We use high-quality deep-learned features for the point-matching step. A variety of such features were presented recently, e.g., in the D3Feat [3] and PREDATOR [18] works. We opted to use the FCGF [10] features that have recently demonstrated state-of-the-art results (in some settings) when used with PointDSC.

Our third contribution is a study of the limitations of deep-learned features (using FCGF as a representative). Specifically, we test what happens when they are trained on data of one type, e.g. LiDAR scans in the San Francisco Bay Area, and tested on data of a different type, e.g. scans collected by a different team in Singapore. We refer to this as cross-domain testing, and compare the performance of registration algorithms between the same-domain and cross-domain settings. We find that deep features suffer some degradation in accuracy. This implies that some of the learning is over-fitting to the specifics of the train set.

In our experiments, we find, perhaps surprisingly, that the fastest and simultaneously most accurate registration algorithm is an advanced version of RANSAC. The basic RANSAC algorithm, proposed over 40 years ago, has been shown in some recent works [2, 8, 31] to be accurate but slow. However, various improvements to it, such as PROSAC [11], LO-RANSAC [12] and others improve its speed considerably, as well as its accuracy.

One element that affects the performance of RANSAC, as well as that of TEASER++, is pre-filtering the putative-match set. Our fourth contribution is proposing a novel method called Grid-Prioritized Filtering (GPF), described in Sec. 4, and showing that it allows RANSAC to achieve...
even higher accuracy when replacing the commonly used mutual-nearest neighbors filtering.

2. Related Work

Algorithms for rigid registration can roughly be divided into local and global ones. Local registration algorithms are based on the assumption that the motion is small. Global registration algorithms aim to handle any relative motion, but might be less accurate. Often their results are refined by running a local registration algorithm.

Local Registration: Iterative Closest Points (ICP) [5] is one of the earliest successful approaches to local point cloud registration, and it remains popular to this day. The ICP algorithm has been developed in various different directions [24]. Chen and Medioni [7] replaced the point-to-point loss function of ICP with a point-to-plane one, by using local normals. Segal et al. [28] presented the popular Generalized-ICP (G-ICP) [28] approach, which reformulated point-to-plane ICP in probabilistic terms and achieved improved accuracy. Rusinkiewicz recently suggested symmetric-ICP [25], which uses a surface-to-surface distance function that treats both point clouds symmetrically. It has been demonstrated to be superior to G-ICP in accuracy, and to have larger convergence basins. Drory et al. [13] presented Best-Buddies Registration, specifically BBR-F, which uses a set of mutual-nearest-neighbors in the registration to improve accuracy.

Global Registration: A successful strategy for global registration is to generate a set of point-matches based on local descriptors, and estimate a motion from these matches. A popular classical descriptor is FPFH [26] which uses histograms of gradients of neighboring points.

As in other fields, learned features have been shown to be superior to hand-crafted ones [1,17,21,27,29,30,33,34]. Various such descriptor have been suggested, e.g. [10, 18, 20]. Fully Convolutional Geometric Features (FCGF) [10] are based on sparse convolutions over a voxelized representation of the point cloud. The FCGF network is very fast, and produces dense features.

Robust optimization: The set of descriptor matches typically includes a significant fraction of outliers, which must be taken into consideration when estimating the relative motion. This can be done for example by using robust loss functions and algorithms, or by filtering the set of matches to remove outliers [32]. RANSAC [14] is a popular method, which works by repeatedly sampling a minimal set of point-matches, estimating a motion from the sample, and calculating its score by the fraction of matches that agree with this motion. This is repeated until a preset number of iterations is performed, or until early stopping occurs when the best-so-far motion has a fraction of inliers that is sufficient (relative to a confidence value supplied by the user [4]). This simple framework has been greatly enhanced over the years, improving RANSAC in both speed and accuracy.

PROSAC [11] performs a prioritized selection of candidate sets. It accepts the putative pairs sorted according to a quality measure, and orders the selection of sets so that sets with higher quality pairs are examined earlier. This simultaneously makes RANSAC faster and more accurate, by making it more likely that a good model is found early.

LO-RANSAC [12] adds a local-optimization step: when a best-so-far model is found, its inliers are used to find a better model, for example by performing RANSAC only on the inliers. Local optimization can be repeated several times, as long as the best-so-far model keeps improving significantly. Though the local-optimization step is expensive, it is only performed a few times over the run time of the RANSAC algorithm, and so its amortized time is small. The recently proposed GC-RANSAC [4] uses a Markov-Random Field formulation and solves it with Graph-Cuts to divide pairs into inliers and outliers.

Another important addition to RANSAC are early rejection methods, that can be applied quickly to reject a minimal set without going through the full scoring stage. In this work we consider two such methods: Sequential Probability Ratio Test (SPRT) [23], a general domain method, and Edge-Length Consistency (ELC) [2], which is specific to point cloud registration.

In addition to producing local descriptors, deep-learning has also been used for robust estimation. Deep Global Registration (DGR) [5] is based on training a second FCGF-like deep network for the task of recognizing outliers. PointDSC [2] too is based on a second network, but not to simply recognize outliers. Instead, it learns an embedding space where one can locate groups of mutually-consistent pairs, that can be used to generate candidate motions. PointDSC integrated ELC into the neural network, to encourage spatial consistency.

A novel approach that is not based on deep learning is TEASER, which is based on truncated least squares esti-
Figure 4. Selection of Balanced Registration Set. Toy example of our selection method, using a 2DOF motion model (instead of 6DOF). Each black point represents the relative motion between a frame-pair. The space of all motions is normalized into the unit square. Iteratively, we randomly sample a location (green asterisk), and select one of the frame-pairs that is close enough to this location (within green circle).

Dataset Generation. Fontana et al. [15] present a collection of datasets to be used as a benchmark for registration algorithms, and specify the method for the creation of these datasets. Unlike them, we focus specifically on LiDAR point cloud datasets, and registration sets that are challenging for global registration. We adopt their idea of achieving a balanced set of relative motions by random sampling. However, in their method a random motion is applied to an existing point cloud, thus creating a synthetic sample. Instead, we produce natural samples by selecting a pair of point clouds from a recorded sequence, so that their relative motion is as close as possible to the randomly selected one.

Huang et al. [18] present the 3DLoMatch set, that contains pairs of low-overlap scans from the 3DMatch [35] dataset. They define an overlap of between 10% and 30% as low. We set the minimum-overlap of our registration sets to 20%, which is in the same range. In line with their findings, our experiments show that low-overlap is a strong indicator for registration failure.

3. Balanced LiDAR Registration Sets

Popular registration benchmarks for the automotive LiDAR setting have become too easy for the newest registration algorithms (see Fig. 3). We believe the main cause for that are the simple heuristics used for selecting frame-pairs for registration: a constant offset in space or time, which is typically not very large (e.g. 10 meters, or 1 second).

How could we instead select a more interesting set of frame-pairs? A naive approach would be to enumerate all possible frame-pairs in each driving-sequence, and then select randomly from them. This approach has two problems: first, many frame-pairs have no overlap, making registration impossible. Second, and more importantly, for a large majority of frame-pairs, the relative motion between them is simple, e.g. "small offset, no rotation".

We suggest a different approach: sample uniformly from the space of motions. We think of the space of all relative motions as a 6-dimensional hyper-cube, whose axes are x-offset, y-offset, z-offset, roll, pitch and yaw. Different areas in this cube represent different types of motions: small-offset with large yaw, large-offset with small yaw but large pitch, etc. By sampling uniformly at random from this hyper-cube, we end up with a set of frame-pairs that is challenging and contains representatives of all the types of motion that appear in the LiDAR dataset.

Generating a pool of candidates. In theory, every pair of point-clouds from the dataset could be considered as a candidate for the registration set. Yet, the total number of pairs is quadratic in the size of the dataset making this impractical. To generate a reasonably sized candidate pool, we take each kth frame in a sequence to be a source frame. For each source frame we find the set of frames whose overlap with it is above min_overlap, and randomly choose the target frame from this set.

Random selection of samples. We wish to select uniformly at random from the space of all relative motions that appear in the candidate pool. We iteratively repeat the following procedure (demonstrated in Fig. 4): First, we normalize each axis of the 6D hyper-cube separately to the range [0,1], to overcome different ranges for different axes (x-offset, yaw, etc.). Then, we randomly generate a location in the unit hyper-cube. If our location is farther than a radius r from any candidate, we discard it and generate another. Otherwise, we consider the set of candidates within a radius r. They represent essentially the same type of motion, and we choose between them according to a second criterion: which driving sequence they come from. This allows us to encourage a fair representation for each driving sequence in the dataset, which is important since different
sequences often include different challenges: highways vs. residential areas, daytime vs. nighttime etc.

We find it important to discard random locations that are farther than \( r \) from any candidate. Allowing such locations to select the candidate nearest to them would have distorted the distribution of samples that we select. For instance, candidates that lie next to a large empty region of the hyper-cube would have a much higher probability of being selected.

**Balanced registration sets.** Various Automatic LiDAR datasets are available, including KITTI-Odometry [16], NuScenes [6], Apollo-Southbay [22] and others. We use our algorithm to create three registration sets, that we use in our experiments. The sets are built over the Apollo-Southbay and NuScenes datasets. We divide NuScenes into two parts: Boston and Singapore. We name our registration sets Apollo-Southbay-Balanced, NuScenes-Boston-Balanced and NuScenes-Singapore-Balanced. We set \( \text{min\_overlap} = 0.2 \) and \( r = 0.1 \). The number of samples in each set is shown in Table 1. Notice that our sets are considerably larger than KITTI-10m. We believe this is beneficial in training, and also allows finer-grain comparison between algorithms in testing.

In Fig. 2 we compare the distribution of samples in Apollo-Southbay-Balanced to that in KITTI-10m. We show marginal distributions according to different parameters: time-offset, distance, overlap, roll, yaw and pitch. In all parameters, our set includes a wider range of values than KITTI-10m. This is especially evident for distance, which for KITTI-10m is by definition always approximately 10 meters, and in our set is a wide range, up to 50 meters. KITTI-10m includes only high-overlap pairs, while our dataset contains a range, actually focusing on the harder, low-overlap cases. Regarding yaw, KITTI-10m includes only small rotations, while our dataset includes a wide range, up to 90 degree turns and even some complete U-turns. Our dataset also contains more samples with significant roll and pitch than KITTI-10m does.

4. Grid-Prioritized Filtering (GPF)

Pre-filtering the set of putative pair-matches, to reduce the fraction of outliers in it, is important for methods such as RANSAC and TEASER++. Popular methods include mutual-nearest neighbors (MNN, a.k.a reciprocity check), and ratio test [19]. Both methods work on each point-pair separately, and therefore do not take into consideration the spatial spread of the pairs that remain after filtering. This can be an issue when the overlap between the two point-clouds is limited.

We propose the Grid-Prioritized Filtering (GPF) method to explicitly ensure spatial spread in the selected pairs. As illustrated in Fig. 5, GPF works by dividing the source point cloud into an \( M \times M \) grid in the x-y plane. Then, \( \ell \) matches are selected from each grid cell (or all matches if there are fewer than \( \ell \) in the cell). The priority of pairs to select follows two criteria: First, matches that are MNNs are preferred. The secondary ordering criterion is the ratio \( S \):

\[
S(p) = \frac{d(p, q_2)}{d(p, q_1)},
\]

where \( p \in P, q_1, q_2 \in Q \), \( q_1 \) is the nearest neighbor to \( p \) in \( Q \), \( q_2 \) is the second-nearest, and \( d() \) is the \( L_2 \) distance.

The number of pairs per cell, \( \ell \) is determined by the total requested number, \( R \). The simple calculation \( \ell = R/M^2 \) is only valid when all cells contain at-least \( \ell \) pairs. Instead, we perform a quick binary search to find the value of \( \ell \) that brings the overall selected number closest to \( R \). \( R \) can be
specified explicitly, but we believe that matching it to the properties of each point-cloud is preferable. To do so, we define it by:

$$ R = \phi \cdot |N|, $$

where $N$ is the set of mutual nearest neighbors for each cloud, and $\phi$ is the user supplied $GPF$ factor. We use notation like $GPF(2.0)$ to refer to running $GPF$ with $\phi = 2.0$.

5. Experiments

In this section we present several experiments, comparing different registration algorithms on the proposed LiDAR registration sets. All methods use FCGF local-descriptors that were trained on this dataset. We show wall-time and recall, with and without ICP refinement. Advanced RANSAC is simultaneously faster and more accurate than all other algorithms. Its two versions differ in the pre-filtering method used; The faster one (mutual) uses mutual-nearest neighbors, and the more accurate one (GPF) uses our proposed Grid-Prioritized Filtering.

Figure 6. Comparison of registration algorithms on a balanced LiDAR dataset. We use NuScenes-Boston-Balanced to compare recent point-cloud registration algorithms. All algorithms use FCGF local-descriptors that were trained on this dataset. We show wall-time and recall, with and without ICP refinement. Advanced RANSAC is simultaneously faster and more accurate than all other algorithms. Its two versions differ in the pre-filtering method used; The faster one (mutual) uses mutual-nearest neighbors, and the more accurate one (GPF) uses our proposed Grid-Prioritized Filtering.

We start all registration algorithms by producing a set of putative matches as follows: down-sampling with an 0.3 meter voxel-grid filter, calculating FCGF features and finding nearest-neighbors in the feature space. When reporting running time we omit the time taken by this pre-processing. We use ICP for refinement of the registration results, and usually report results with and without it.

Code: for RANSAC we use the GC-RANSAC [4] code base, which is efficiently implemented and offers multiple options (PROSAC, local-optimization, etc.). We added an ELC implementation based on the one in open3d (version 0.13) [36]. The open3d implementation of RANSAC offers fewer options, and is somewhat slower, though still quite fast (see appendix). We run the GC-RANSAC code with $distance\_ratio=0.6$ and $spatial\_coherence\_weight=0$, which effectively makes it LO-RANSAC and not GC-RANSAC. We also enable PROSAC and ELC. For ICP we use open3D, with $threshold=0.6$.

For DGR, PointDSC and TEASER++ we use the official implementations, with slight modifications. We use our own implementation for training FCGF features.

We train the FCGF network for 400 epochs, the PointDSC network for 50 epochs and the DGR network for 40 epochs. In training the FCGF network, instead of augmenting with general rotations, we augment with nearly-planar rotations, where yaw is in the range $\pm 180$ degrees, but pitch and roll are only up to $\pm 5$ degrees. That represents the rotations expected between pairs of LiDAR frames.

We use two machines for our experiments:

A GPU: 4x Titan X, CPU: 20-core 2.20GHz Xeon E5-2630

B GPU: GTX 980 Ti, CPU: 8-core 4.00GHz i7-6700K

Most of our tests are performed on machine A, using a single GPU. TEASER++ code is run on machine B, due to its code failing to work on machine A. To compare running time, we extrapolate TEASER++’s presumptive running time on machine A. To do so, we calculate a normalizing ratio by running RANSAC on both machines. In the experiments, and add a second filtering with GPF when testing on Apollo-Southbay-Balanced (see ahead).

For each registration task we measure the rotation error (RE) and translation error (TE), defined as

$$ RE(\hat{R}) = \arccos \frac{\text{Tr}(\hat{R}^T R^*) - 1}{2}, \quad TE(\hat{t}) = ||\hat{t} - t^*||_2, $$

where $R, t$ is the ground-truth motion. We follow [2] in defining a successful registration as one with RE<5 degrees and TE<0.6 meters. Recall is the percentage of test samples for which registration succeeded, and we also refer to it as accuracy.

5.1. Implementation Details

We analyze the effect of cross-domain testing on deep feature accuracy. We compare the following algorithms:

**Learned:**

- DGR [8], PointDSC [2], algorithmic: TEASER++ [31] and RANSAC. We tried various flavors of RANSAC (see appendix), and the best combination found includes:

  1. Prioritized selection of candidates (PROSAC), using the same priority order used in GPF
  2. Fast-rejection by edge-length consistency (ELC)
  3. Local-optimization step (LO-RANSAC), without graph-cuts

We compare two kinds of pre-filtering for RANSAC: mutual-nearest neighbors (MNN), and the novel GPF, with a $10 \times 10$ grid. TEASER++ also requires filtering, as it tends to get stuck indefinitely when receiving too many putative pair-matches as input. We use MNN for TEASER++ in all
apple to analyze the differences in CPU and GPU running times across machines.

5.2. Stress-Testing LiDAR registration

In Tab. 2 and Fig. 6 we present the results of using the NuScenes-Boston-Balanced dataset to compare between DGR, PointDSC, TEASER++, and RANSAC with two pre-filtering algorithms: MNN (with max-iterations=1M, confidence=0.9995), and GPF(3.0) (with max-iterations=1M, and confidence=0.999). The fastest results are achieved by RANSAC with mutual-nearest neighbors filtering. The highest accuracy is achieved by RANSAC with Grid-Prioritized Filtering (GPF).

We analyze the failures of RANSAC in this experiment in Figure 7. We show the distribution of successful registrations and failed ones, according to several measures: distance between the point clouds, overlap, time offset, and three axes of rotation. Large distance and small overlap emerge as the most influential parameters for failure. Other parameters seem to have little influence, except in the most extreme cases.

In Tab. 3 we look at the setting of cross-domain testing. Here, all networks (FCGF, DGR and PointDSC) are trained on the Apollo-Southbay-Balanced dataset, but the testing is on NuScenes-Boston-Balanced. The ordering between algorithms remains the same as in the previous experiment, except here TEASER++ is faster than PointDSC. However, all recall values suffer a significant drop in the cross-domain case. Figure 8 visualizes this drop in accuracy for the case with ICP, showing a mean drop in recall of 16 percentage points. Cross-domain accuracies are significantly lower than the same-domain accuracies that we have seen in Tab. 2. We believe this shows that though FCGF features are quite transferable, some of their learning is location specific. In this experiment, we use GPF(2.0) with max-iterations=50K, and confidence=0.999. To allow clearer comparison, we use the same parameters also for the same-domain experiment in Fig. 8.

Table 4 presents a thorough test of our new datasets Apollo-Southbay-Balanced, NuScenes-Boston-Balanced and NuScenes-Singapore-Balanced. In each of the 9 experiments, one dataset is used for training, and another for testing. We test four algorithms: PointDSC, TEASER++, RANSAC with MNN filtering, and RANSAC with GPF. ICP is used for refinement in all cases. Point clouds from the Apollo-Southbay dataset are \sim 2x larger than those from NuScenes, and this ratio is maintained even after mutual-nearest neighbor filtering. As a result, TEASER++
We show the distribution of failed samples when running RANSAC (GPF) on the NuScenes-Boston-Balanced dataset, with ICP refinement (see Tab. 2). On the top row we show the distribution of successful registrations (blue) and failed ones (red), according to several parameters. On the bottom row, we show the ratio of failures for each bin in the corresponding top row histogram. Large distance and small overlap emerge as the most influential parameters for failure. Other parameters seem to have little influence, except in the most extreme cases.

Figure 7. Analysis of Failures. We show the distribution of failed samples when running RANSAC (GPF) on the NuScenes-Boston-Balanced dataset, with ICP refinement (see Tab. 2). On the top row we show the distribution of successful registrations (blue) and failed ones (red), according to several parameters. On the bottom row, we show the ratio of failures for each bin in the corresponding top row histogram. Large distance and small overlap emerge as the most influential parameters for failure. Other parameters seem to have little influence, except in the most extreme cases.

Figure 8. The effects of cross-domain testing. When FCGF features are trained using a training set which is substantially different from the test set, we see a drop in accuracy. Here, the test set is from NuScenes-Boston-Balanced, and the training set is either from NuScenes-Boston-Balanced (same-domain, blue), or instead from Apollo-Southbay-Balanced (cross-domain, orange). We see a drop in accuracy across all algorithms, of approximately 16 percentage points on average.

tends to get stuck often (~15% of cases) when working on Apollo-Southbay point clouds. To overcome this, we use two mechanisms. First, a stricter filtering than usual for TEASER++: we first filter with MNN, and then filter with GPF, keeping a maximum of 2000 pairs. Second, we use a time-out of 10 seconds, after which registration is marked as failed. This happens very rarely (less than 0.1% of cases). The larger point-clouds in Apollo-Southbay also affect our settings for RANSAC+GPF. We use GPF(1.0) when testing on Apollo-Southbay, and GPF(2.0) when testing on NuScenes. All other settings for RANSAC are as in the previous experiment.

We can see that Apollo-Southbay-Balanced is in a sense the simplest: it achieves the highest same-domain and cross-domain test results, but when networks are trained on it, they achieve the lowest cross-domain accuracy. Training on the NuScenes-Singapore-Balanced dataset, on the other hand, leads to the highest cross domain accuracies. As far as algorithm comparison, RANSAC (GPF) is the most accurate, and RANSAC (mutual) the second except in one setting where TEASER++ is the second. Both RANSAC variants are also faster than the other algorithms in all cases (see appendix for running times).

Balanced datasets can also be used to compare local registration algorithms, such as ICP. Such algorithms take an initial coarse motion estimation, and refine it to achieve a high accuracy alignment. To use them with our balanced registration sets, we supply a standard set of initial motions, produced by performing RANSAC registration with FCGF features. These initial motions are generally close enough to the ground truth motion to allow local registration algorithms to succeed. In Tab. 5 we show the results of using the Apollo-Southbay-Balanced dataset, and comparing three local registration algorithms: ICP [5], symmetric-ICP [25], and BBR-F [13]. We use the official implementations of symmetric-ICP and BBR-F, and the open3d implementation of ICP. The point clouds are downsampled with a voxel-grid filter with a voxel size of 0.3 meters, and we set ICP’s threshold to 0.6 meters (as we do in all experiments, following [8]). We report Recall, as well as translation error (TE) and rotation error (RE). We report mean, median and 95th percentile of TE and RE, and these statistics are taken over all test samples. The results show that ICP is more accurate than BBR-F, and both are considerably more accurate than symmetric-ICP. This differs from previous experiments in [13] that used a subset of KITTI. We believe the central factor is overlap between point-clouds: small overlap is common in our sets but not in KITTI. ICP explicitly filters point pairs whose distance is above a threshold, and BBR-F uses spatial mutual-nearest neighbors. These elements apparently gives them an edge over Symmteric-ICP in this setting.
|       | Recall | TE (cm) | RE (deg) |
|-------|--------|---------|----------|
|       |        | mean    | 50%      | 95%      |
| ICP   | 98.99% | 80.65   | 11.76    | 30.29    |
|       |        | 0.37    | 0.13     | 0.33     |
| BBR-F | 96.33% | 86.98   | 15.10    | 52.84    |
|       |        | 0.47    | 0.19     | 0.66     |
| sym-ICP | 67.74% | 548.85  | 17.68    | 3544.49  |
|       |        | 2.31    | 0.22     | 10.66    |

Table 5. Refinement Experiment: We compare refinement algorithms using Apollo-southbay-Balanced and a set of initial (coarse) motions generated by RANSAC registration. We report mean, median and 95th percentile taken over all test samples. ICP does better than its competitors.

6. Conclusion

We propose an algorithm for producing balanced and challenging registration set for the automotive LiDAR setting, and use these sets to stress-test several point-cloud registration algorithms. In our experiments, the most accurate results are achieved by using deep-learned features (specifically FCGF) that were trained and tested on the same domain, combined with advanced RANSAC with Grid-Prioritized Filtering (GPF). We believe that our provided set of tools will help in advancing the field. Clearly, while we demonstrated our approach on one set of learned features (FCGF), all our analysis can be used and is also applicable to other types of learned features [3, 18].

References

[1] Yasuhiro Aoki, Hunter Goforth, Rangaprasad Arun Sivrat-san, and Simon Lucey. Pointnetlk: Robust & efficient point cloud registration using pointnet. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019. 3

[2] Xuyang Bai, Zixin Luo, Lei Zhou, Hongkai Chen, Lei Li, Zeyu Hu, Hongbo Fu, and Chiew-Lan Tai. Pointdsc: Robust point cloud registration using deep spatial consistency. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 15859–15869, June 2021. 2, 3, 6, 13

[3] Xuyang Bai, Zixin Luo, Lei Zhou, Hongbo Fu, Long Quan, and Chiew-Lan Tai. D3feat: Joint learning of dense detection and description of 3d local features. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020. 2, 3, 9

[4] Daniel Barath and Jiri Matas. Graph-cut ransac. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2018. 3, 6, 13

[5] Paul J. Besl and Neil D. McKay. A method for registration of 3-d shapes. IEEE Trans. Pattern Anal. Mach. Intell., 14(2):239–256, Feb. 1992. 3, 8

[6] Holger Caesar, Varun Bankiti, Alex H. Lang, Sourabh Vora, Venice Erin Liang, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, and Oscar Beijbom. nuscenes: A mul-timodal dataset for autonomous driving. arXiv preprint arXiv:1903.11027, 2019. 1, 5

[7] Yang Chen and Gérard Medioni. Object modelling by registration of multiple range images. Image Vision Comput., 10(3):145–155, Apr. 1992. 3

[8] Christopher Choy, Wei Dong, and Vladlen Koltun. Deep global registration. In CVPR, 2020. 2, 3, 6, 8, 13

[9] Christopher Choy, JunYoung Gwak, and Silvio Savarese. 4d spatio-temporal convnets: Minkowski convolutional neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3075–3084, 2019. 13

[10] Christopher Choy, Jaesik Park, and Vladlen Koltun. Fully convolutional geometric features. In ICCV, 2019. 2, 3, 6, 13

[11] O. Chum and J. Matas. Matching with prosac - progressive sample consensus. In 2013 IEEE Conference on Computer Vision and Pattern Recognition, volume 2, pages 220–226, jun 2005. 2, 3

[12] Ondrej Chum, Jiri Matas, and Josef Kittler. Locally optimized ransac. In DAGM-Symposium, volume 2781 of Lecture Notes in Computer Science, pages 236–243. Springer, 2003. 2, 3

[13] Amonn Drory, Tal Shomer, Shai Avidan, and Raja Giryes. Best buddies registration for point clouds. In Proceedings of the Asian Conference on Computer Vision (ACCV), November 2020. 3, 8, 13

[14] Martin A. Fischler and Robert C. Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of The ACM, 1981. 3

[15] Simone Fontana, Daniele Cattaneo, Augusto L. Ballardini, Matteo Vaghi, and Domenico G. Sorrenti. A benchmark for point clouds registration algorithms. Robotics and Autonomous Systems, 140:103734, 2021. 4

[16] Andreas Geiger, Philip Lenz, and Raquel Urtasun. Are we ready for autonomous driving? the kitti vision benchmark suite. In Conference on Computer Vision and Pattern Recognition (CVPR), 2012. 5

[17] A. Hertz, R. Hanocka, R. Giryes, and D. Cohen-Or. Pointgmm: A neural gmm network for point clouds. In IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 12051–12060, 2020. 3

[18] Shengyu Huang, Zan Gojcic, Mikhail Usvyatsov, Andreas Wieser, and Konrad Schindler. Predator: Registration of 3d point clouds with low overlap. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 4267–4276, June 2021. 2, 3, 4, 9

[19] David G. Lowe. Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vision, 60(2):91–110, Nov. 2004. 5

[20] Fan Lu, Guang Chen, Yinlong Liu, Lijun Zhang, Sanqing Qu, Shu Liu, and Rongqi Gu. Hregnet: A hierarchical network for large-scale outdoor lidar point cloud registration. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pages 16014–16023, October 2021. 1, 3
[21] Weixin Lu, Guowei Wan, Yao Zhou, Xiangyu Fu, Pengfei Yuan, and Shiyu Song. Deepvcp: An end-to-end deep neural network for point cloud registration. 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Oct 2019.

[22] Weixin Lu, Yao Zhou, Guowei Wan, Shenhua Hou, and Shiyu Song. L3-net: Towards learning based lidar localization for autonomous driving. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6389–6398, 2019.

[23] Jiri Matas and Ondrej Chum. Randomized RANSAC with sequential probability ratio test. In 10th IEEE International Conference on Computer Vision (ICCV 2005), 17-20 October 2005, Beijing, China, pages 1727–1732. IEEE Computer Society, 2005.

[24] François Pomerleau, Francis Colas, and Roland Siegwart. A review of point cloud registration algorithms for mobile robotics. now, 2015.

[25] Szymon Rusinkiewicz. A symmetric objective function for ICP. ACM Transactions on Graphics (Proc. SIGGRAPH), 38(4), July 2019.

[26] Radu Bogdan Rusu, Nico Blodow, and Michael Beetz. Fast point feature histograms (fpfh) for 3d registration. In ICRA, 2009.

[27] Vinit Sarode, Xueqian Li, Hunter Goforth, Yasuhiro Aoki, Rangaprasad Arun Srivatsa, Simon Lucey, and Howie Choset. Pcrnet: Point cloud registration network using pointnet encoding. ArXiv, abs/1908.07906, 2019.

[28] Aleksandr Segal, Dirk Hähnel, and Sebastian Thrun. Generalized-icp. In Jeff Trinkle, Yoky Matsuoka, and José A. Castellanos, editors, Robotics: Science and Systems. The MIT Press, 2009.

[29] Yue Wang and Justin M. Solomon. Deep closest point: Learning representations for point cloud registration. In The IEEE International Conference on Computer Vision (ICCV), October 2019.

[30] Yue Wang and Justin M. Solomon. Pcrnet: Self-supervised learning for partial-to-partial registration. In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d’Alché-Buc, Emily B. Fox, and Roman Garnett, editors, Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, 8-14 December 2019, Vancouver, BC, Canada, pages 8812–8824, 2019.

[31] Heng Yang, Jingnan Shi, and Luca Carlone. Teaser: Fast and certifiable point cloud registration. IEEE Transactions on Robotics, 37(2):314–333, 2021.

[32] Jiaqi Yang, Ke Xian, Yang Xiao, and Zhiguo Cao. Performance evaluation of 3d correspondence grouping algorithms. In 2017 International Conference on 3D Vision (3DV), pages 467–476, 2017.

[33] Zi Jian Yew and Gim Hee Lee. Rpm-net: Robust point matching using learned features. In Conference on Computer Vision and Pattern Recognition (CVPR), 2020.

[34] Wentao Yuan, Benjamin Eckart, Kihwan Kim, Varun Jampani, Dieter Fox, and Jan Kautz. Deepgmr: Learning latent gaussian mixture models for registration. In ECCV, 2020.

Figure 9. **RANSAC Ablation:** PROSAC and ELC/SPRT. We show the accuracy and running time of different variants of RANSAC, with ICP (right) and without (left). For each setting, we repeat the run 4 times and show the spread of results by a polygon (the convex hull). We also show their mean. The best results are when we use both PROSAC and ELC.

[35] Andy Zeng, Shuran Song, Matthias Nießner, Matthew Fisher, Jianxiong Xiao, and Thomas Funkhouser. 3dmatch: Learning local geometric descriptors from rgb-d reconstructions. In CVPR, 2017.

[36] Qian-Yi Zhou, Jaesik Park, and Vladlen Koltun. Open3D: A modern library for 3D data processing. arXiv:1801.09847, 2018.

**Appendix A. Ablation Studies**

**A.1. RANSAC**

The version of RANSAC that we use in our experiments includes several improvements over classical RANSAC:

1. Prioritized selection of candidate sets (PROSAC).
2. Quick rejection of candidate sets (with ELC).
3. Local-Optimization step (LO-RANSAC).

We perform ablation studies to show the importance of each element. We both train and test on NuScenes-Boston-Balanced, and use the same settings as in the experiment shown in Tab. 2 of the main paper, for the nearest-neighbor filtering case. All variants of RANSAC tested in this section are both faster and more accurate than the other algorithms we consider in our paper: TEASER++, PointDSC and DGR. The results of our first experiment are shown in Fig. 9. We compare PROSAC to random selection of candidate sets, and in the quick rejection step, we compare ELC to SPRT. To show variance, we repeat each experiment 4 times, and plot both the mean and the convex hull of the 4 results. The results demonstrate that adding PROSAC improve accuracy but also adds to running time, and that...
LO-RANSAC achieves higher recall than GC-RANSAC in our setting. We also tested other values of the parameter (not shown), and the best accuracy was achieved with 0 (i.e. LO-RANSAC).

In Fig. 11 we compare the open3d implementation of RANSAC to the GC-RANSAC implementation which we use for most experiments (we refer to it as GC-code). The open3d implementation includes ELC, but does not include local-optimization and PROSAC. For the fairest comparison, we run the GC-code in a "compatible" setting, also using ELC but no local-optimization and no PROSAC. For reference, we also run the GC-code with our default setting (ELC, PROSAC and LO-RANSAC). Open3D is considerably slower than either GC-code setting. It is less accurate than our default setting of GC-code, but interestingly more accurate than the "compatible" setting. Possibly, this is due to differences in the implementation of early stopping. Open3d RANSAC is both faster and more accurate than all other algorithms we tested, (compare Fig. 11 here to Fig. 6 in main paper).

A.2. GPF

In Fig. 12 we demonstrate the effect of the number of iterations and of the GPF parameter when running RANSAC+GPF. We can see that when adding iterations, running time always increases, but accuracy reaches saturation and plateaus at some point. Increasing the GPF parameter $\phi$, which corresponds to keeping a larger set of point-pairs, leads to an increase in both running time and in accuracy. However, the increase in accuracy does become considerably slower as we advance the parameter above 3.0. In our main experiments we used the parameter values of 1.0, 2.0 and 3.0.

Appendix B. GPU and CPU Running Time on Different Machines.

Some of the registration algorithms that we compare rely mostly on GPU for processing (PointDSC, DGR), while others mostly use the CPU (TEASER++, RANSAC). Therefore, a comparison of running times between these algorithms depends on the specific machine being used. We demonstrate this in Tab. 6, by running the same experiment on two machines. The machines that we use are:

A GPU: 4x Titan X, CPU: 20-core 2.20GHz Xeon E5-2630
B GPU: GTX 980 Ti, CPU: 8-core 4.00GHz i7-6700K

On either machine, we use only one GPU for testing. The experiment consists of testing PointDSC and RANSAC on the NuScenes-Boston-Balanced dataset (training was also performed on the same dataset). We report the running times on both machines. The ratio between the running times of PointDSC and RANSAC is different between the
Figure 12. GPF Ablation. We show the effects of different values of max-iteration (top) and of $\phi$ (bottom). Increasing max-iterations improves accuracy only up to a point, after which accuracy plateaus while running time increases. Increasing $\phi$ improves accuracy and increases running time, and the plateau phenomenon is much less pronounced.

Appendix C. Additional Data for All-Set Cross-Domain Experiment

In Tab. 7 we show the running times for the All-Set Cross Domain experiment (Tab. 4 in main paper). RANSAC with MNN is the fastest, and RANSAC+GPF the second fastest in every experiment.

We mention in the paper that Apollo-Southbay-Balanced has larger point clouds than the other datasets we use, and that this is also true after mutual-nearest neighbor filtering.

Table 6. Running Times on Two Machines: Comparison of times between CPU bound algorithms (such as RANSAC) and GPU bound ones (such as PointDSC) depends on the specific machine. We demonstrate this by running the same experiments on two machines. The ratio of running times between PointDSC and RANSAC is different on each machine, reflecting each machine’s mix of CPU and GPU capabilities.

Table 7. Running Times for All Registration Sets Cross-Domain Experiment: Running times in seconds for the experiments in Tab. 4 in the main paper. Fastest in each row (always RANSAC mutual) is in bold, second fastest (always RANSAC+GPF) is underlined.

Table 8. Pair-Match Set Sizes: The number of putative pair-matches for different experiments, before and after mutual-nearest neighbor (MNN) filtering. The datasets are Apollo-Southbay-Balanced (A), NuScenes-Boston-Balanced (B) and NuScenes-Singapore-Balanced (S). The values shown are averaged over all samples in each dataset.

In Tab. 8 we show these sizes for all our experiments.
Appendix D. Code Bases

In our work we make use the following code bases:

**FCGF** [10]: [https://github.com/chrischoy/FCGF](https://github.com/chrischoy/FCGF) (MIT License)

**DGR** [8]: [https://github.com/chrischoy/DeepGlobalRegistration](https://github.com/chrischoy/DeepGlobalRegistration) (MIT License)

**Minkowski Engine** [9]: [https://github.com/NVIDIA/MinkowskiEngine](https://github.com/NVIDIA/MinkowskiEngine) (MIT License)

**PointDSC** [2]: [https://github.com/XuyangBai/PointDSC](https://github.com/XuyangBai/PointDSC)

**TEASER++** [31]: [https://github.com/MIT-SPARK/TEASER-plusplus](https://github.com/MIT-SPARK/TEASER-plusplus) (MIT License)

**Open3d** [36]: [https://github.com/isl-org/Open3D](https://github.com/isl-org/Open3D) (MIT License)

**GC-RANSAC** [4]: [https://github.com/danini/graph-cut-ransac](https://github.com/danini/graph-cut-ransac) (new BSD License)

**Symmetric-ICP** [25]: [https://gfx.cs.princeton.edu/proj/trimesh2/](https://gfx.cs.princeton.edu/proj/trimesh2/) (GPL Version 2 License)

**Best-Buddies Registration** [13]: [https://github.com/AmnonDrory/BestBuddiesRegistration](https://github.com/AmnonDrory/BestBuddiesRegistration)