

LDSO: Direct Sparse Odometry with Loop Closure

Xiang Gao, Rui Wang, Nikolaus Demmel and Daniel Cremers

Abstract—In this paper we present an extension of Direct Sparse Odometry (DSO) [1] to a monocular visual SLAM system with loop closure detection and pose-graph optimization (LDSO). As a direct technique, DSO can utilize any image pixel with sufficient intensity gradient, which makes it robust even in featureless areas. LDSO retains this robustness, while at the same time ensuring repeatability of some of these points by favoring corner features in the tracking frontend. This repeatability allows to reliably detect loop closure candidates with a conventional feature-based bag-of-words (BoW) approach. Loop closure candidates are verified geometrically and Sim(3) relative pose constraints are estimated by jointly minimizing 2D and 3D geometric error terms. These constraints are fused with a co-visibility graph of relative poses extracted from DSO’s sliding window optimization. Our evaluation on publicly available datasets demonstrates that the modified point selection strategy retains the tracking accuracy and robustness, and the integrated pose-graph optimization significantly reduces the accumulated rotation-, translation- and scale-drift, resulting in an overall performance comparable to state-of-the-art feature-based systems, even without global bundle adjustment.

I. INTRODUCTION

Simultaneous Localization and Mapping (SLAM) has been an active research area in computer vision and robotics for several decades since the 1980s [2], [3]. It is a fundamental module of many applications that need real-time localization like mobile robotics, autonomous MAVs, autonomous driving, as well as virtual and augmented reality [4]. While other sensor modalities such as laser scanners, GPS, or inertial sensors are also commonly used, visual SLAM has been very popular, in part because cameras are readily available in consumer products and passively acquire rich information about the environment. In particular, in this work we focus on the monocular case of tracking a single gray-scale camera.

Typically, a visual SLAM system consists of a camera tracking frontend, and a backend that creates and maintains a map of keyframes, and reduces global drift by loop closure detection and map optimization. The frontend may localize the camera globally against the current map [4], [5], track the camera locally with visual (keyframe) odometry (VO) [6], [7], or use a combination of both [8], [9], [10].

There are several open challenges in adapting a direct, sliding-window, marginalizing odometry system like DSO to reuse existing information from a map. For example, in order

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This work was partially supported by the grant “For3D” by the Bavarian Research Foundation, the grant CR 250/9-2 “Mapping on Demand” by the German Research Foundation and the ERC Consolidator Grant 649 323 “3D Reloaded”.

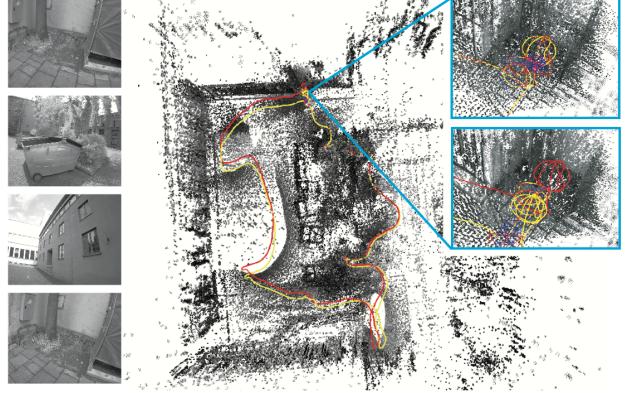


Fig. 1. Estimated trajectories with and without loop closing in the TUM-Mono dataset. The left part are sample images from sequence 31, whose end point should be at the same place as the start point. The right part shows the estimated trajectory by LDSO before (red) and after (yellow) loop closure. The zoom-in highlights how trajectories and point-clouds align much better after.

to evaluate the photometric error, images of past keyframes would have to be kept in memory, and when incorporating measurements from previous keyframes, it is challenging to ensure estimator consistency, since information from these keyframes that is already contained in the marginalization prior should not be reused. We therefore propose to adapt DSO as our SLAM frontend to estimate visual odometry with local consistency and correct its drift with loop closure detection and pose graph optimization in the backend. Note that DSO itself consists also of a camera-tracking frontend and a backend that optimizes keyframes and point depths. However, in this work we refer to the whole of DSO as our odometry frontend.

VO approaches can be divided into two categories: indirect (feature-based) methods that minimize the reprojection error with fixed, previously estimated correspondences between repeatable discrete feature points, and direct methods that jointly estimate motion and correspondences by minimizing the photometric error in direct image alignment. While feature-based methods have been the mainstream for a long time, recent advances in direct VO have shown better accuracy and robustness, especially when the images do not contain enough explicit corner features [1], [11]. The robustness in the direct approach comes from the joint estimation of motion and correspondences as well as the ability to also use non-corner pixels, corresponding to edges, or even smooth image regions (as long as there is sufficient image gradient). However, without loop closing, both indirect and direct VO suffers from the accumulated drift in the unobservable

degrees-of-freedom, which are global translation, rotation and scale in the monocular case. This makes the long-term camera trajectory and map inaccurate and thus limits the application to only short-term motion estimation.

In order to close loops, they need to be detected first. The state-of-the-art loop detection methods — sometimes referred to as appearance-only SLAM — are usually based on indexed image features (e.g. BoW [12], [13], [14], [15]) and thus can be directly applied in feature-based VO by reusing the features from the frontend. This, however, is not as straightforward in the direct case: If we detect and match features independently from the frontend, we might not have depth estimates for those points, which we need to efficiently estimate Sim(3) pose-constraints, and if instead we attempt to reuse the points from the frontend and compute descriptors for those, they likely do not correspond to repeatable features and lead to poor loop closure detection. The key insight here is that direct VO does not care about the *repeatability* of the selected (or tracked) pixels. Thus, direct VO systems have in the past been extended to SLAM either by using only keyframe proximity for loop closure detection [6] or by computing features for loop closure detection independently from frontend tracking and constraint computation [7]. Direct image alignment is then used to estimate relative pose constraints [6], [7], which requires images of keyframes to be kept available. We propose instead to gear point selection towards repeatable features and use geometric techniques to estimate constraints. In summary, our contributions are:

- We adapt DSO’s point selection strategy to favor repeatable corner features, while retaining its robustness against feature-poor environments. The selected corner features are then used for loop closure detection with conventional BoW.
- We utilize the depth estimates of matched feature points to compute Sim(3) pose constraints with a combination of pose-only bundle adjustment and point cloud alignment, and — in parallel to the odometry frontend — fuse them with a co-visibility graph of relative poses extracted from DSO’s sliding window optimization.
- We demonstrate on publicly available real-world datasets that the point selection retains the tracking frontend’s accuracy and robustness, and the pose graph optimization significantly reduces the odometry’s drift and results in overall performance comparable state-of-the-art feature-based methods, even without global bundle adjustment.
- We make our implementation publicly available¹.

Fig. 1 illustrates how LDSO corrects accumulated drift after closing a loop in the TUM-Mono dataset.

II. RELATED WORK

Many mature feature-based monocular SLAM systems have been presented in recent years, often inspired by the seminal PTAM [4], where splitting the system into a camera

tracking frontend and an optimization-based mapping backend was originally proposed, and later ScaViSLAM [16], which suggested to mix local bundle adjustment with Sim(3) pose-graph optimization. One of the more influential such systems has been ORB-SLAM [5]. It features multiple levels of map-optimization, starting from local bundle-adjustment after keyframe insertion, global pose-graph optimization after loop closures detected with BoW, and finally (expensive) global bundle adjustment. Since unlike LDSO it uses traditional feature matching to localize images against the current map, much emphasis is on map-maintenance by removing unneeded keyframes and unused features. Note that while loop-closure detection and pose graph optimization are similar in LDSO, we only need to compute feature descriptors for keyframes.

Visual odometry systems have been extended to SLAM systems in different ways. It is interesting to note that many systems propose to integrate inertial sensors [17], [9], [8], [10] and/or use a stereo setup [17], [10], [18], [19], since this can increase robustness in challenging environments and make additional degrees of freedom observable (global scale, roll and pitch). Lynen et al. [8] proposes to directly include 2D-3D matches from an existing map as Kalman Filter updates in a local MSCKF-style odometry estimator. Okvis [17] is a feature-based visual-inertial keyframe odometry that maintains a local map of feature points in a constant-size marginalization window (similar to DSO) that does not reuse points once it is out of the local window. Later, a similar visual-inertial weighted least-squares optimization strategy was adapted in maplab [10] for batch map optimization without marginalization, but as a camera tracking frontend, a Kalman Filter based estimator minimizing the photometric error between tracked image patches is used. Feature-based localization against an existing map is incorporated in the frontend as pose updates. VINS-Mono [9] in turn is a feature-based monocular visual-inertial SLAM system that employs a marginalizing odometry front-end very similar to okvis. It includes feature observations from an existing map in this sliding window optimization. Similar to ORB-SLAM and our work, loop closure and global map refinement are based on BoW and pose graph optimization, but with help of the inertial sensors, it suffices to use non-rotation-invariant BRIEF descriptors and do pose graph optimization in 4 degrees-of-freedom. While in ORB-SLAM the feature extraction step costs almost half of the running time, the frontend tracking in VINS-Mono is based on KLT features and thus is capable of running in real-time on low-cost embedded systems. This however means, that for loop closure detection additional feature points and descriptors have to be computed for keyframes.

As a direct monocular SLAM system and predecessor of DSO, LSD-SLAM [7] employs FAB-MAP [15] — an appearance-only loop detection algorithm — to propose candidates for large loop closures. However, FAB-MAP needs to extract its own features and cannot re-use any information from the VO frontend, and the constraint computation in turn does not re-use the feature matches, but relies on direct image

¹<https://vision.in.tum.de/research/vslam/ldso>

alignment using the semi-dense depth maps of candidate frames in both directions and a statistical test to verify the validity of the loop closure, which also means that images of all previous keyframes need to be kept available.

III. LOOP CLOSING IN DSO

A. Framework

Before delving into the details of how our loop closing thread works, we first briefly introduce the general framework and formulation of DSO. DSO is a keyframe-based sliding window approach, where 5-7 keyframes are maintained and their parameters are jointly optimized in the current window. Let $\mathcal{W} = \{\mathbf{T}_1, \dots, \mathbf{T}_m, \mathbf{p}_1, \dots, \mathbf{p}_n\}$ be the m SE(3) keyframe poses and n points (inverse depth parameterization) in the sliding window, the photometric error to be minimized is defined as [1]:

$$\min_{\mathbf{T}_i, \mathbf{T}_j, \mathbf{p}_k \in \mathcal{W}} \sum_{\mathbf{p} \in \mathcal{N}_{\mathbf{p}_k}} E_{i,j,k}, \quad \text{where}$$

$$E_{i,j,k} = \sum_{\mathbf{p} \in \mathcal{N}_{\mathbf{p}_k}} w_{\mathbf{p}} \left\| (I_j[\mathbf{p}'] - b_j) - \frac{t_j e^{a_j}}{t_i e^{a_i}} (I_i[\mathbf{p}] - b_i) \right\|_{\gamma}, \quad (1)$$

where $\mathcal{N}_{\mathbf{p}_k}$ is the neighborhood pattern of \mathbf{p}_k , a, b are the affine light transform parameters, t is the exposure time, I denotes an image and $w_{\mathbf{p}}$ is a heuristic weighting factor. \mathbf{p}' is the reprojected pixel of \mathbf{p} on I_j calculated by

$$\mathbf{p}' = \Pi(\mathbf{R}\Pi^{-1}(\mathbf{p}, d_{\mathbf{p}_k}) + \mathbf{t}), \quad (2)$$

with $\Pi : \mathbb{R}^3 \rightarrow \Omega$ the projection and $\Pi^{-1} : \Omega \times \mathbb{R} \rightarrow \mathbb{R}^3$ the back-projection function, \mathbf{R} and \mathbf{t} the relative rigid body motion between the two frames calculated from \mathbf{T}_i and \mathbf{T}_j , d the inverse depth of the point.

As a new frame arrives, DSO estimates its initial pose using direct image alignment by projecting all the active 3D points in the current window into this frame. If required, this frame thereafter will be added into the local windowed bundle adjustment. The sliding window naturally forms a co-visibility graph like in ORB-SLAM, but the co-visible information is never used outside the local window, as old or redundant keyframes and points are marginalized out. Although the windowed optimization becomes computationally light-weight and more accurate using the marginalization prior, the estimation will inevitably drift.

A global optimization pipeline is needed in order to close long-term loops for DSO. Ideally global bundle adjustment using photometric error should be used, which nicely would match the original formulation of DSO. However, in that case all the images would need to be saved, since the photometric error is computed on images. Moreover, nowadays it is still impractical to perform global photometric bundle adjustment for the amount of points selected by DSO. To avoid these problems we turn to the idea of using pose graph optimization, which leaves us several other challenges: (i) How to combine the result of global pose graph optimization with that of the windowed optimization? One step further, how to set up the pose graph constraints using the information in

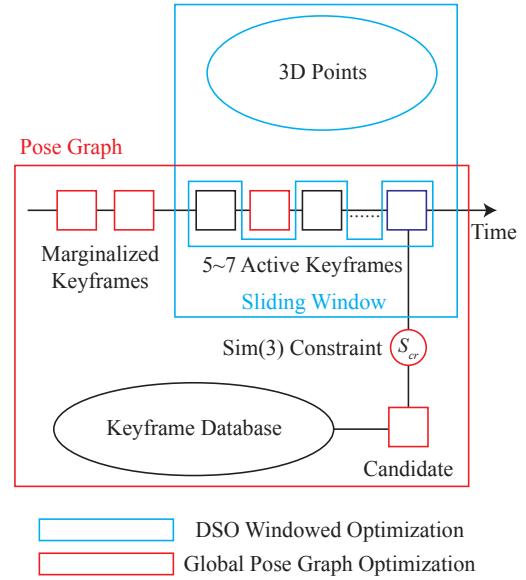


Fig. 2. Framework of the proposed system.

the sliding window, considering that pose graph optimization minimize Sim(3) geometry error between keyframes while in the sliding window we minimize the photometric error? (ii) How to propose loop candidates? While the mainstream of loop detection is based on image descriptors, shall we simply add another thread to perform those feature related computations? (iii) Once loop candidates are proposed we need to compute their relative Sim(3) transformation. In a direct image alignment approach, we need to set an initial guess on the relative pose to start the Gauss-Newton or the Levenberg-Marquardt iterations, which is challenging in this case as the relative motion may be far away from identity.

Taking these challenges into account, we design our loop closing module as depicted in Fig. 2. Alongside the DSO window, we add a global pose graph to maintain the connectivity between keyframes. DSO's sliding window naturally forms a co-visibility graph where we can take the relative 3D pose transformations between the keyframes as the pairwise pose measurements. For loop detection and validation, we rely on BoW and propose a novel way to combine ORB features with the original sampled points of DSO. In this way, if a loop candidate is proposed and validated, its Sim(3) constraint with respect to the current keyframe is calculated and added to the global pose graph, which is thereafter optimized to obtain a more accurate long-term camera pose estimation.

B. Point Selection with Repeatable Features

It is worth noting that even in direct methods like LSD-SLAM or DSO, point selection is still needed; One difference from indirect methods is that the repeatability of those points is not required by direct methods. DSO uses a dynamic grid search to pick enough pixels even in weakly textured environments. We modify this strategy to make it more sensitive to corners. More specifically, we still pick a given number of pixels (by default 2000 in DSO), in which part

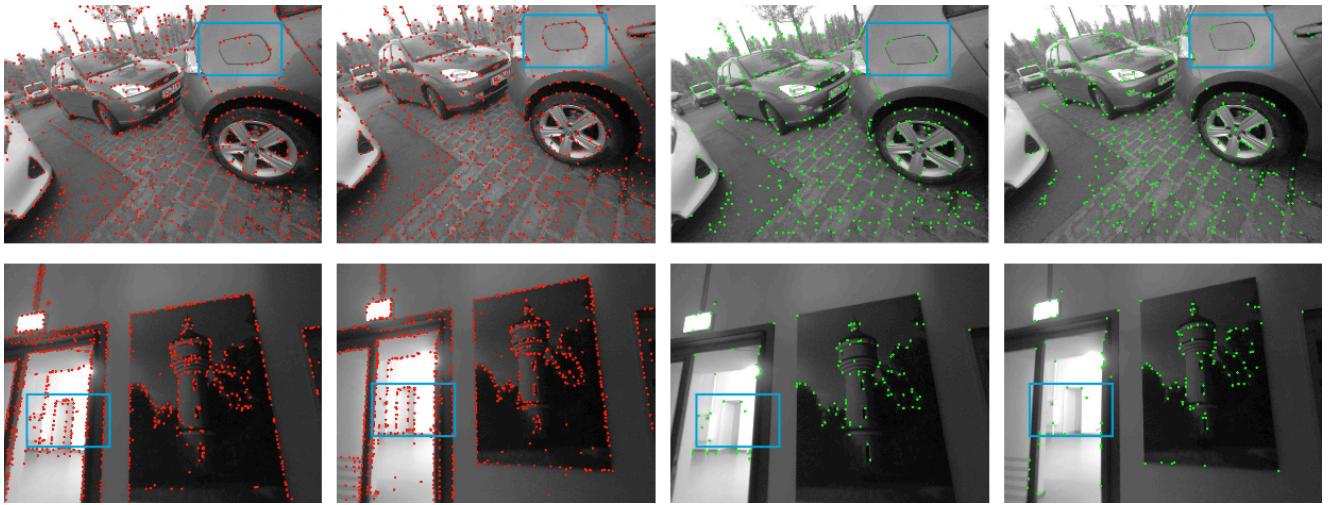


Fig. 3. Pixel selection in DSO and LDSO. The left part is pixels picked by DSO and the right part shows the corners of LDSO (we don't show the non-corners to make the image look clear). And the top part is a well textured environment and the bottom part is a weak textured one. Note that if the number of corners is less than the threshold, we will also pick extra pixels just like DSO to make the system robust against feature-less situations. The points in the blue box shows the difference of point repeatability.

of them are corners (detected by using the easy-to-compute Shi-Tomasi score [20]), while the others are still selected using the method proposed for DSO. Keeping the number of corners small, we compute their ORB descriptors [21] and pack them into BoW. The VO frontend uses both the corners and the non-corners for camera tracking, keeping therefore the extra overhead for feature extraction of the loop closing thread to a minimum.

Fig. 3 shows the pixel selection in the original DSO and the LDSO. It can be seen that the pixels picked by DSO have little repeatability and therefore it is hard to seek image matchings using those points for loop closure. In LDSO we use both corners and other pixels with high gradients, where the corners are used both for building BoW models and for tracking, while the non-corners are only used for tracking. In this way we can on one hand track the weak texture area, on the other hand also match features between keyframes if needed.

C. Loop Candidates Proposal and Checking

As we compute ORB descriptors for each keyframe, a BoW database is built using DBoW3 [14]. Loop candidates are proposed for the current keyframe by querying the database and we only pick those that are outside the current window (i.e., marginalized keyframes). For each candidate we try to match its ORB features to those of the current keyframe, and then perform RANSAC PnP to compute an initial guess of the SE(3) transformation. Afterwards we optimize a Sim(3) transformation using Gauss-Newton method by minimizing the 3D and 2D geometric constraints. Let $\mathcal{P} = \{\mathbf{p}_i\}$ be the reconstructed features in the loop candidate and $d_{\mathbf{p}_i}$ their inverse depth, $\mathcal{Q} = \{\mathbf{q}_i\}$ be the matched features in the current keyframe, \mathbf{D} be the sparse inverse depth map of the current keyframe which is computed by projecting the active map points in the current window into the current keyframe. For some features in \mathcal{Q} we can

find their depth in \mathbf{D} , for the others we only have their 2D pixel positions. Let $\mathcal{Q}_1 \subseteq \mathcal{Q}$ be those without depth and $\mathcal{Q}_2 = \mathcal{Q} \setminus \mathcal{Q}_1$ be those with depth, then the Sim(3) transformation from the loop candidate (reference) to the current keyframe \mathbf{S}_{cr} can be estimated by minimizing the following cost function:

$$\begin{aligned} \mathbf{E}_{loop} = & \sum_{\mathbf{q}_i \in \mathcal{Q}_1} w_1 \|\mathbf{S}_{cr} \Pi^{-1}(\mathbf{p}_i, d_{\mathbf{p}_i}) - \Pi^{-1}(\mathbf{q}_i, d_{\mathbf{q}_i})\|_2 + \\ & \sum_{\mathbf{q}_j \in \mathcal{Q}_2} w_2 \|\Pi(\mathbf{S}_{cr} \Pi^{-1}(\mathbf{p}_j, d_{\mathbf{p}_j})) - \mathbf{q}_j\|_2, \end{aligned} \quad (3)$$

where $\Pi(\cdot)$ and $\Pi^{-1}(\cdot)$ are the projection and back-projection functions as defined before, w_1 and w_2 are weights to balance the different measurement units. In practice the scale can only be estimated by the 3D part, but without the 2D reprojection error, the rotation and translation estimate will be inaccurate if the estimated depth values are noisy.

D. Sliding Window and Sim(3) Pose Graph

In this section we explain how to fuse the estimations of the sliding window and the global pose graph. Let $\mathbf{x} = [\mathbf{x}_p^\top, \mathbf{x}_d^\top]^\top$ with \mathbf{x}_p the poses of the keyframes in the current window parameterized using twist coordinates, \mathbf{x}_d the points parameterized by their inverse depth d , then the windowed optimization problem using Levenburg-Marquardt (L-M) iterations is:

$$\mathbf{H}\delta\mathbf{x} = -\mathbf{b}, \quad (4)$$

where \mathbf{H} is the Hessian matrix approximated as $\mathbf{J}^\top \mathbf{W} \mathbf{J} + \lambda \mathbf{I}$ in L-M iterations, $\delta\mathbf{x}$ is the optimal increment, \mathbf{W} is a weight matrix, $\mathbf{b} = \mathbf{J}^\top \mathbf{W} \mathbf{r}$ with Jacobian \mathbf{J} and residual \mathbf{r} . It can also be written in a block-matrix way

$$\begin{bmatrix} \mathbf{H}_{pp} & \mathbf{H}_{pd} \\ \mathbf{H}_{dp} & \mathbf{H}_{dd} \end{bmatrix} \begin{bmatrix} \delta\mathbf{x}_p \\ \delta\mathbf{x}_d \end{bmatrix} = - \begin{bmatrix} \mathbf{b}_p \\ \mathbf{b}_d \end{bmatrix}. \quad (5)$$

It is well known that \mathbf{H} has an arrow-like sparse pattern (in DSO's formulation \mathbf{H}_{dd} being a diagonal matrix) where we can exploit the sparsity in the bottom right part to perform sparse bundle adjustment [22], [23].

The marginalization strategy in DSO keeps the sparsity pattern in \mathbf{H}_{dd} and also keeps a motion prior expressed as a quadratic function on \mathbf{x} (for details please refer to Eq. (19) in [1]). This prior can be also regarded as a hyper edge in the pose graph which constraints all the keyframes inside. However, traditional pose graph optimization takes only pair-wise observations between two keyframes like \mathbf{T}_{ij} and compute the measurement error:

$$\mathbf{e}_{ij} = \mathbf{T}_{ij} \hat{\mathbf{T}}_j^{-1} \hat{\mathbf{T}}_i, \quad (6)$$

where $(\hat{\cdot})$ is the estimated value of a variable.

Since our loop closing approach computes relative pose constraints between the loop candidate and the current frame, we also approximate the constraints inside the marginalization window with pairwise relative pose observations. Specifically, we compute those observations from the frontend's current global pose estimates.

It is also important to note that, since we do not want to disturb the local windowed optimization (it contains absolute pose information), in pose graph optimization we will fix the current frame's pose estimation. Therefore, the pose graph optimization will tend to modify the global poses of the old part of the trajectory. Besides, the global poses of the keyframes in the current window are not updated after the pose graph optimization, to further make sure that the local windowed bundle adjustment is not influenced by the global optimization. Our implementation is based on g2o, a graph optimization library proposed in [25].

IV. EVALUATION

We evaluate our method on three popular public datasets: TUM-Mono [24], EuRoC MAV [26] and KITTI Odometry [27], all in a monocular setting.

A. The TUM-Mono Dataset

The TUM-Mono Dataset is a monocular dataset that consists of 50 indoor and outdoor sequences. It provides photometric camera calibration, but no full ground-truth camera trajectories. The camera always returns to the starting point in all sequences, making this dataset very suitable for evaluating accumulated drifts of VO systems. For this reason we disable the loop closure functionality of our method on this dataset, to first evaluate the VO accuracy of our method with the modified point selection strategy.

We evaluate three different point selection strategies: (1) random point selection; (2) the original method of DSO and (3) our method. For each strategy we run 10 times forward and 10 times backward on each sequence to account for the nondeterministic behavior. We compute the accumulated translational, rotational and scale drifts e_t , e_r , e_s in the keyframe trajectories using method described in [24].

Fig. 4 shows the color-coded alignment error in all the sequences. Fig.5 shows the cumulative error plot, which

depicts the number of runs whose errors are below the corresponding x-values (thus closer to left-top is better). In both figures we see that our integration of corner features into DSO does not reduce the VO accuracy of the original system. Another interesting point is, although random picking makes the tracking fail more frequently, it seems it does not increase the errors on those successfully tracked sequences like s01 to s10.

To show some qualitative results we also run LDSO with loop closing on TUM-Mono and get some $\text{Sim}(3)$ closed trajectories shown in Fig. 6. An example of the reconstructed map is shown in Fig. 7.

B. The EuRoC MAV Dataset

The EuRoC MAV Dataset provides 11 sequences with stereo images, synchronized IMU readings and ground-truth camera trajectories. We compare LDSO with DSO and ORB on this dataset by evaluating their root-mean-square error (RMSE) using their monocular settings. Same as before on each sequence we run 10 times forward and 10 times backward for each method and the results are shown in Fig. 8 and Fig. 9. Generally speaking, ORB-SLAM2 performs quite well on this dataset and it only fails consistently on sequence V2-03 when running forward. DSO and LDSO both fail on sequence V2-03, but on most of the others sequences LDSO significantly improves the camera tracking accuracy. The overall improvement after having loop closure can also be found in Fig. 9. From the plot we can see that ORB-SLAM2 is more accurate, whereas LDSO is more robust on this dataset.

C. The KITTI Odometry Dataset

On the KITTI Odometry Dataset, as shown previously in the thorough evaluation in [19], monocular VO systems like DSO and ORB-SLAM (the VO component only) suffer severe accumulated drift which makes them not usable for such large-scale scenarios. While the natural way to resolve this problem is to integrate other sensors like IMU or to use stereo cameras which has been proved quite successful [19], [18], here we want to see the potential of our monocular method after the integration of the loop closure functionality.

We compare LDSO with DSO and ORB-SLAM2 and show the Absolute Trajectory Errors (ATEs) on all the sequences of the training set in Table I. The ATEs are computed by performing $\text{Sim}(3)$ alignment to the ground-truth. Not surprisingly on sequences with loops (seq. 00, 05, 07), LDSO improves the performance of DSO a lot. Besides, our method achieves comparable accuracy to ORB-SLAM2, which has a global bundle adjustment in the loop closing thread and we only use pose graph optimization. Some qualitative results on the estimated camera trajectories can be found in Fig. 10.

D. Runtime Evaluation

Finally we present a short runtime analysis about the point selection step. Note that loop closure only occurs very occasionally and the pose graph is running in a single thread,

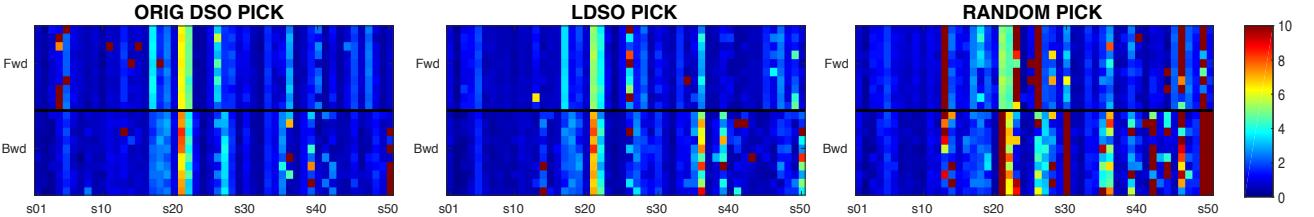


Fig. 4. The alignment errors e_{align} using different points picking strategies. Each small square block is the color-coded alignment error for one run as defined in [24] and each column corresponds to each sequence of the dataset. We run our method 10 times forward and 10 times backward on each sequence to account for the nondeterministic behavior.

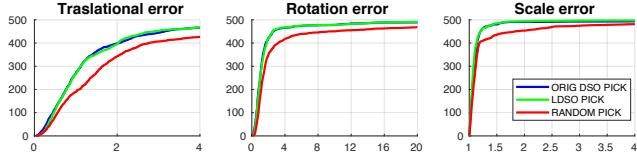


Fig. 5. Accumulated translational, rotational and scale drifts using different points picking strategies. X-axis is the error threshold, and Y-axis is the number of runs whose errors are below the threshold.

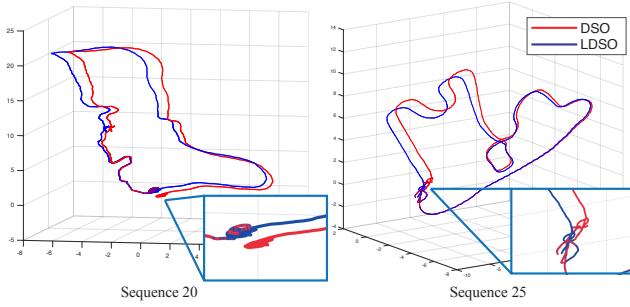


Fig. 6. Trajectories in TUM-Mono dataset. The red line is the estimated trajectory by original DSO where we can see obvious drift. The blue line is the loop-closed trajectory.

TABLE I

ATE ERROR (M) ON ALL KITTI TRAINING SEQUENCES.

Sequence	Mono DSO	LDSO	ORB-SLAM2
00	126.7	9.322	8.27
01	165.03	11.68	x
02	138.7	31.98	26.86
03	4.77	2.85	1.21
04	1.08	1.22	0.77
05	49.85	5.1	7.91
06	113.57	13.55	12.54
07	27.99	2.96	3.44
08	120.17	129.02	46.81
09	74.29	21.64	76.54
10	16.32	17.36	6.61

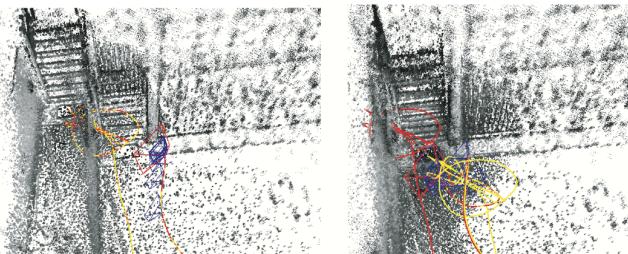


Fig. 7. Map before and after loop closure in LDSO (sequence 33).

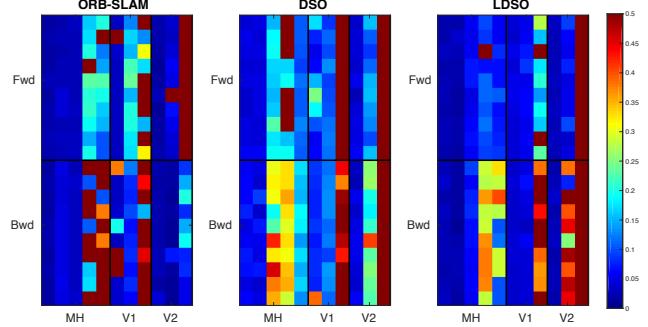


Fig. 8. Full trajectory RMSE of all sequences (Sim(3)) aligned to the ground truth. X-axis is the sequence name, which varies from MH_01 to MH_05 and then V1_01 to V2_03.

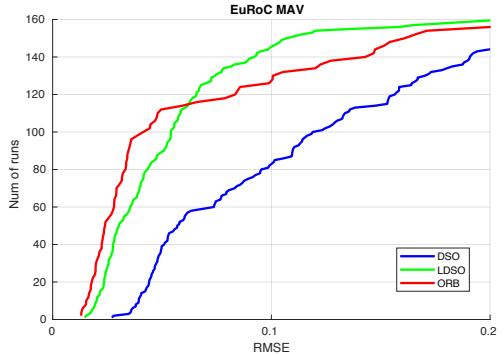


Fig. 9. RMSE on EuRoC MAV. The Y-axis shows the number of runs with errors below the corresponding values on the X-axis. All errors are calculated after Sim(3) alignment of the camera trajectories to the ground truth.

thus they do not affect much the computation time of the main thread. What we change in the main thread is adding an extra feature extraction and descriptor computation step. But unlike the feature-based approaches, they are not performed for every frame but only for keyframes. Table II shows the average computation time of the point selection step using different picking strategies. The point selection in LDSO takes slightly more time than that in DSO due to the feature and descriptor extraction. It is worth noting that the values are calculated over keyframes, thus the runtime impact will be further moderated when averaging over all frames. The program is tested on a laptop with Ubuntu 18.04 and Intel i7-4770HQ CPU and 16GB RAM.

V. CONCLUSION

In this paper we propose an approach to integrate loop closure and global map optimization into the fully direct

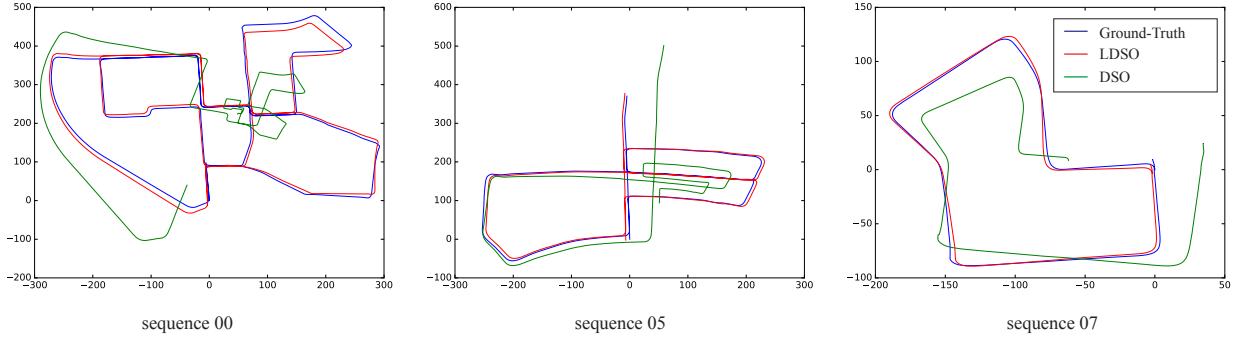


Fig. 10. Sim(3) aligned trajectories of Kitti sequence 00, 05 and 07, which contains closed loops.

TABLE II
RUNTIME OF DIFFERENT POINT SELECTION STRATEGIES

LDSO Pick	DSO Pick	Random Pick
0.0218s	0.0126s	0.0027s

VO system DSO. DSO's original point selection is adapted to include repeatable features. For those we compute ORB descriptors and build BoW models for loop closure detection. We demonstrate that the point selection retains the original robustness and accuracy of the odometry frontend, while enabling the backend to effectively reduce global drift in rotation, translation and scale. We believe the proposed approach can be extended to future improvements of VO or SLAM. For example, a photometric bundle adjustment layer might increase the global map accuracy. In order to ensure long-term operation, map maintenance strategies such as keyframe culling and removal of redundant 3D points may be employed. Combining the information from 3D points of neighboring keyframes after loop closure may help to further increase the accuracy of the reconstructed geometry.

REFERENCES

- [1] J. Engel, V. Koltun, and D. Cremers, “Direct Sparse Odometry,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 3, pp. 611–625, 2018.
- [2] C. Cadena, L. Carlone, H. Carrillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, and J. J. Leonard, “Past, Present, and Future of Simultaneous Localization and Mapping: Toward the Robust-Perception Age,” *IEEE Transactions on Robotics*, vol. 32, no. 6, pp. 1309–1332, 2016.
- [3] J. Fuentes-Pacheco, J. Ruiz-Ascencio, and J. M. Rendón-Mancha, “Visual Simultaneous Localization and Mapping: A Survey,” *Artificial Intelligence Review*, vol. 43, no. 1, pp. 55–81, 2015.
- [4] G. Klein and D. Murray, “Parallel Tracking and Mapping for Small AR Workspaces,” in *6th International Symposium on Mixed and Augmented Reality (ISMAR 2007)*, pp. 225–234, IEEE, 2007.
- [5] R. Mur-Artal, J. Montiel, and J. D. Tardós, “ORB-SLAM: a Versatile and Accurate Monocular SLAM System,” *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1147–1163, 2015.
- [6] C. Kerl, J. Sturm, and D. Cremers, “Dense Visual SLAM for RGB-D Cameras,” in *International Conference on Intelligent Robot Systems (IROS)*, 2013.
- [7] J. Engel, T. Schöps, and D. Cremers, “LSD-SLAM: Large-Scale Direct Monocular SLAM,” in *Computer Vision–ECCV 2014*, pp. 834–849, Springer, 2014.
- [8] S. Lynen, T. Sattler, M. Bosse, J. A. Hesch, M. Pollefeys, and R. Siegwart, “Get Out of My Lab: Large-scale, Real-Time Visual-Inertial Localization,” in *Robotics: Science and Systems*, 2015.
- [9] T. Qin, P. Li, and S. Shen, “VINS-Mono: A Robust and Versatile Monocular Visual-Inertial State Estimator,” *arXiv preprint arXiv:1708.03852*, 2017.
- [10] T. Schneider, M. T. Dymczyk, M. Fehr, K. Egger, S. Lynen, I. Gilitschenski, and R. Siegwart, “maplab: An Open Framework for Research in Visual-inertial Mapping and Localization,” *IEEE Robotics and Automation Letters*, 2018.
- [11] N. Yang, R. Wang, X. Gao, and D. Cremers, “Challenges in Monocular Visual Odometry: Photometric Calibration, Motion Bias and Rolling Shutter Effect,” in *arXiv:1705.04300*, May 2017.
- [12] T. Botterill, S. Mills, and R. Green, “Bag-of-Words-Driven, Single-Camera Simultaneous Localization and Mapping,” *Journal of Field Robotics*, vol. 28, no. 2, pp. 204–226, 2011.
- [13] D. Filliat, “A Visual Bag of Words Method for Interactive Qualitative Localization and Mapping,” in *2007 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3921–3926, IEEE, 2007.
- [14] D. Galvez-Lopez and J. D. Tardos, “Bags of Binary Words for Fast Place Recognition in Image Sequences,” *IEEE Transactions on Robotics*, vol. 28, no. 5, pp. 1188–1197, 2012.
- [15] M. Cummins and P. Newman, “FAB-MAP: Probabilistic Localization and Mapping in the Space of Appearance,” *The International Journal of Robotics Research*, vol. 27, no. 6, pp. 647–665, 2008.
- [16] H. Strasdat, A. J. Davison, J. M. Montiel, and K. Konolige, “Double Window Optimisation for Constant Time Visual SLAM,” in *IEEE International Conference on Computer Vision (ICCV)*, pp. 2352–2359, IEEE, 2011.
- [17] S. Leutenegger, S. Lynen, M. Bosse, R. Siegwart, and P. Furgale, “Keyframe-based Visual-Inertial Odometry using Nonlinear Optimization,” *International Journal of Robotics Research*, vol. 34, pp. 314–334, MAR 2015.
- [18] R. Mur-Artal and J. D. Tardós, “ORB-SLAM2: An Open-Source SLAM System for Monocular, Stereo, and RGB-D Cameras,” *IEEE Transactions on Robotics*, vol. 33, no. 5, pp. 1255–1262, 2017.
- [19] R. Wang, M. Schwörer, and D. Cremers, “Stereo DSO: Large-Scale Direct Sparse Visual Odometry with Stereo Cameras,” *International Conference on Computer Vision (ICCV)*, Venice, Italy, 2017.
- [20] J. Shi *et al.*, “Good Features to Track,” in *Computer Vision and Pattern Recognition, 1994. Proceedings CVPR’94., 1994 IEEE Computer Society Conference on*, pp. 593–600, IEEE, 1994.
- [21] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, “ORB: An Efficient Alternative to SIFT or SURF,” in *2011 IEEE International Conference on Computer Vision (ICCV)*, pp. 2564–2571, IEEE, 2011.
- [22] G. Sibley, L. Matthies, and G. Sukhatme, “A Sliding Window Filter for Incremental SLAM,” in *Unifying Perspectives in Computational and Robot Vision*, pp. 103–112, Springer, 2008.
- [23] B. Triggs, P. F. McLauchlan, R. I. Hartley, and A. W. Fitzgibbon, “Bundle Adjustment: A Modern Synthesis,” in *Vision Algorithms: Theory and Practice*, pp. 298–372, Springer, 2000.
- [24] J. Engel, V. Usenko, and D. Cremers, “A Photometrically Calibrated Benchmark For Monocular Visual Odometry,” in *arXiv:1607.02555*, July 2016.
- [25] R. Kummerle, G. Grisetti, H. Strasdat, K. Konolige, and W. Burgard, “G2O: A General Framework for Graph Optimization,” in *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3607–3613, IEEE, 2011.
- [26] M. Burri, J. Nikolic, P. Gohl, T. Schneider, J. Rehder, S. Omari, M. W. Achtelik, and R. Siegwart, “The EuRoC Micro Aerial Vehicle Datasets,” *The International Journal of Robotics Research*, 2016.
- [27] A. Geiger, P. Lenz, and R. Urtasun, “Are We Ready for Autonomous Driving? The KITTI Vision Benchmark Suite,” *2012 IEEE Conference On Computer Vision And Pattern Recognition (CVPR)*, pp. 3354–3361, 2012.