Dynamic Dense RGB-D SLAM using Learning-based Visual Odometry

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Abstract—We propose a dense dynamic RGB-D SLAM pipeline based on a learning-based visual odometry, TartanVO. TartanVO, like other direct methods rather than feature-based, estimates camera pose through dense optical flow, which only applies to static scenes and disregards dynamic objects. Due to the color constancy assumption, optical flow is not able to differentiate between dynamic and static pixels. Therefore, to reconstruct a static map through such direct methods, our pipeline resolves dynamic/static segmentation by leveraging the optical flow output, and only fuse static points into the map. Moreover, we rerender the input frames such that the dynamic pixels are removed and iteratively pass them back into the visual odometry to refine the pose estimate. Our code is available at https://github.com/Geniussh/Dynamic-Dense-RGBD-SLAM-with-TartanVO.

Index Terms—SLAM, Dynamic, Visual Odometry, Optical Flow, Segmentation

I. INTRODUCTION

VISUAL Simultaneous Localization and Mapping (SLAM) has the goal of estimating the current location and pose while reconstructing the environment. It is one of the most fundamental frameworks because of its ubiquitous availability and informational richness. Compared with sparse feature-based models in both reconstruction and tracking, a dense SLAM model has the advantages of getting more complete, accurate and robust results.

Instead of extracting feature points from images and tracking those sparse feature points in 3D space, a dense model uses all the pixels from camera frame to camera frame. Based on this, feature-based Visual Odometry (VO) cannot be applied to dense visual SLAM.

In this project, we build a dynamic dense RGB-D SLAM based on TartanVO [1], which is a generalized learning-based VO. This VO estimates optical flow from two consecutive RGB frames in its matching network. Since the optical flow is equivalent to the photometric error in tracking of direct SLAM, TartanVO is an eligible VO for dense visual SLAM. However, there are two key assumptions for optical flow that will fail when there are dynamic objects in the scene, brightness constancy assumption and small motion assumption, which assumes that the brightness of the same pixel looks the same in consecutive frames and pixels only move locally in a small scale. To reduce the negative impact caused by dynamic objects, we propose two methods to classify dynamic and static points by making use of the optical flow. Only the static points are fused during reconstruction. We also propose to rerender the images after removing dynamic pixels and to iteratively pass them back to TartanVO to refine optical flow estimation. Eventually the refined image pair and its corresponding depth pair are passed into the fusion part.

II. RELATED WORK

The emergence of commodity 3D cameras such as the Microsoft Kinect or the Asus Xtion has enabled great progress in dense visual SLAM in indoor environments. A seminal work in this field is KinectFusion [2], which incrementally tracks the camera motion and maps the environment densely in volumetric signed distance function (SDF) grids. Several other RGB-D SLAM approaches have been proposed that differ in tracking methods such as ICP [3], direct image alignment [4] or SDF alignment [5], and map representations such as surfel-based ElasticFusion [6]. Following and ongoing research on scalable extensions [7], loop closure capabilities [8], runtime limitation [4], [9] have achieved impressive performance in robust 3D scanning and mapping of indoor scenes.

However, the current mainstream SLAM algorithm uses static feature point for pose estimation and map reconstruction and they tend to ignore the dynamic object which provides dynamic visual feature points. Therefore, dynamic targets need to be removed to reduce its impact on SLAM algorithm. In addition, feature-based SLAM is not able to build dense maps with the sparse representation of the scene. To achieve dense
visual SLAM, we need to adopt direct methods that keep full images without abstracting them to feature observations.

Many researchers try to handle the dynamic environments using semantic labeling or object detection pre-processing to remove the dynamic objects. Co-Fusion (CF) proposed by Rünz et al. [10] used a real-time object segmentation and tracking method which combined the hierarchical deep learning based segmentation method and the static dense reconstruction framework of ElasticFusion. Xu et al. proposed Mid-Fusion [11] and used a Mask R-CNN to perform instance segmentation, followed by geometric edge segmentation and motion residuals from tracking to refine mask boundaries.

Other researches find out the dynamic objects by treating their point clouds as outliers from the dense RGB-D fusion scheme. Keller et al. [3] used points with no close model correspondence as input to seed a region-growing procedure to segment the current image into static and dynamic parts. Subsequently, model points which are matched with dynamic input points are removed from the reconstruction. Newcombe et al. developed DTAM [12], a monocular dense mapping system, where a specific threshold are set to discard the pixels with a higher photometric error. StaticFusion [13] proposed by Scona et al. performs segmentation by coupling camera motion residuals, depth inconsistency and a regularisation term. Distinguishing static and dynamic parts of the environment is achieved by jointly estimating the camera pose and whether clusters are static or dynamic.

Other direct SLAM methods are, in general, more sensitive to dynamic objects in the scene. Alcantarilla et al. [14] detected moving objects by means of a scene flow representation with stereo cameras. Wang and Huang [15] segmented the dynamic objects in the scene using RGB optical flow. Both feature-based and direct SLAM that map the static scene parts only from the information contained in the sequence fail to estimate lifelong models when an a priori dynamic object remains static, e.g., parked cars or people sitting. On the other hand, DynaSLAM [16] combines multi-view geometry and deep learning in order to address both moving and movable objects.

III. METHODOLOGY

In this section, we provide an overview of our pipeline as well as the design of each module.

A. TartanVO

A simplified view of TartanVO is embedded in our pipeline as shown in Fig. 2. It’s a two-stage network architecture, comprised of a matching network followed by a pose network. In particular, it takes two consecutive RGB-D frames as inputs, estimates the optical flow as an intermediate output through the matching network, and predicts camera motion from the optical flow through the pose network. TartanVO generalizes well over different datasets with various camera intrinsics due to its usage of an intrinsics layer as the input to the pose network. However, it fails to track the camera under dynamic scenes, especially indoor environments with dynamic objects taking up large portions in the field of view. The reason is that one cannot differentiate dynamic objects from the background by only looking at the optical flow output, which is subject to brightness constancy assumption. That is, under the motion \( \mathbf{u} \), the image brightness values of the first frame at time \( t \) and the second frame at time \( t + k \) remain constant in every pixel:

\[
f (x + \mathbf{u}(x), t + k) = f (x, t) \quad \forall x
\]

Therefore, whenever there’s motion other than the camera ego motion involved between frames, the brightness constancy assumption fails and the optical flow output becomes prone to mixed motions, which will only bring errors to the pose network. To resolve such an issue, we propose to remove the dynamic pixels through segmentation, and to re-render the image pair so it can be iteratively input back into TartanVO to refine the optical flow as well as the pose estimation.

B. Segmentation

To classify dynamic/static pixels by leveraging the optical flow output from TartanVO, we propose two methods for segmentation. One is based on the 2D scene flow as the difference between the optical flow and camera ego motion. The other is based on the geometric distance from pixels in one frame to their matched epipolar lines.

1) Approach 1: To deal with the dynamic objects, we define the optical flow residuals which directly indicate the non-rigid environment motions. The architecture of our dense RGB-D SLAM pipeline using 2D scene flow based segmentation is shown in Fig. 2. The optical flow is estimated from two consecutive RGB images using the matching network from TartanVO, followed by a pose network to predict the camera motion. Then the 2D scene flow is obtained by subtracting camera ego motion from the optical flow. Dynamic segmentation is performed by thresholding the cluster of 2D scene flow. The static background is feed forward to the networks iteratively update the ego motion of the camera. After several iterations, dynamic pixels are removed and RGB-D images with static pixels only are passed into point-based fusion for reconstruction.

Optical flows which can be easily obtained from image pairs are often applied to describe the moving objects captured by static cameras. The optical flows are defined as the pixel motions on the image coordinates, in which, the colors indicate flow direction and the intensity indicate the pixel displacement. Specifically, to estimate the optical flow \( \delta x_{i \rightarrow t}^{of} \) between time \( t \) and \( t + 1 \) is:

\[
\delta x_{i \rightarrow t+1}^{of} = \pi(T_{i+1}(x_{i} + \delta x_{i \rightarrow t+1}, D(x_{i} + \delta x_{i \rightarrow t+1}))
\]

where \( x_{i} \) is the pixel coordinate and \( D(x_{i}) \) is the depth value of this pixel at time stamp \( i \). Here we are also taking use of the depth information in for map construction. \( T_{i} \) in \( SE(3) \) denotes the camera extrinsic in the world frame, composed by the camera rotation and translation between the A and B frames. \( \pi \) is the projection of a point from a world coordinate to camera plane: \( \pi: \mathbb{R}^3 \rightarrow \mathbb{R}^2 \).

In the real scene (as Fig. 7 shows), the human was moving rightwards and the camera was moving rightwards. Thus the
Fig. 2: The architecture of our Dense RGB-D SLAM pipeline using 2D scene flow based segmentation. The optical flow is estimated from two consecutive RGB images using the matching network, followed by a pose network to predict the camera motion. Then the 2D scene flow is obtained by subtracting camera ego motion from the optical flow. Dynamic segmentation is performed by thresholding the 2D scene flow. After several iterations, dynamic pixels are removed and RGB-D images with static pixels only are passed into point-based fusion for reconstruction.

The red flows in the background were resulted from camera ego-motion. We define such kind of flow as the camera ego flow \( \delta x_e \), which means the observed optical flow was purely resulted from camera motion (without moving objects). For a 2D pixel \( x_i \) in frame A, given camera motion \( x \in se(3) \), the camera ego-motion flow can be computed as:

\[
\delta x_{A \rightarrow B}^e = W(x, \xi) - x \tag{2}
\]

\[
W(x, \xi) = \pi (T(\xi)\pi^{-1}(x, D_A(x))) \tag{3}
\]

where \( W \) stands for an image warping operation and \( \xi \in se(3) \) as the initial rigid motion guess of that frame.

Therefore, to get rid of the camera ego-motions, the optical flow residual is introduced [17], which is defined as projected 2D scene flow, to highlight the pixel’s dynamic property. If we subtract the ego flows from the optical flows, the projected scene flow components on the image plane can be obtained as:

\[
\delta x_{sf}^{A \rightarrow B} = \delta x_{of}^{A \rightarrow B} - \delta x_{A \rightarrow B}^e \tag{4}
\]

For the static pixels, Eqn. 4 is close to zero, since its optical flow comes from the camera motions. For the dynamic pixels, the 2D scene flows are non-zero, and their absolute values grow along with the moving speed. An illustration of using 2D scene flow to segment dynamic pixels is shown in Fig. 3.

Therefore, we define the flow residual \( r_F(x^p) \) as its corresponding \( \delta x_{sf}^{A \rightarrow B} \). Another residual is defined as geometric residual which is obtained from the depth measurement.

\[
r_D^p(\xi) = D_B \left( W(x^P, \xi) \right) = \left| T(\xi)\pi^{-1}(x^P, D_A(x^P)) \right| \tag{5}
\]

We distinguish whether a cluster is static or not according to its average residuals. This will be done in two procedures. Firstly, we compute a metric to combine these residuals, including flow residual \( r_F(x^p) \) and geometric residual \( r_D^p(\xi) \). Secondly, we compose a minimizing function to qualify the dynamic level of clusters.

2) Approach 2: Besides using 2D scene flow to segment the dynamic points, there is another way to leverage the optical flow output from TartanVO. The reasoning behind this approach is that ideally, if there’s no dynamic object in the scene, each pixel in the second image should lie on the epipolar line corresponding to its matched pixel in the first image. Therefore, using this approach, we have modified our architecture from 2 to 4, in which the only change is that we carry out segmentation given the camera pose estimation, the optical flow, and the intrinsics, rather than warping the
Fig. 4: The architecture of our Dense RGB-D SLAM pipeline based on Motion Consistency Detection. The optical flow is estimated from two consecutive RGB images using the matching network, followed by a pose network to predict the camera motion. Then calculate the distance from pixels in the second frame to their corresponding epipolar lines derived from matching pixels using optical flow. Dynamic segmentation is performed by distance thresholding. After several iterations, dynamic pixels are removed and RGB-D images with static pixels only are passed into point-based fusion for reconstruction.

first frame onto the second to get ego motion. We call this approach Motion Consistency Detection.

Fig. 5 expands the details of the Motion Consistency Detection module. The algorithm first obtains the matching pixel pairs by using the optical flow output, i.e. each pair of pixels in two frames are matched by directly imposing the optical flow vectors onto the first frame, and calculates the fundamental matrix with the matching pixel pairs. Then, the corresponding epipolar line of each pixel is calculated using the fundamental matrix and the position of the pixel. When the distance between the matched pixel in the second frame and its epipolar line is greater than a certain value, it is classified as a dynamic pixel. Supposing \( p_1 \) and \( p_2 \) is a pair of matching pixels, their homogeneous coordinates are shown as follows:

\[
\begin{align*}
    p_1 &= [u_1, v_1, 1] \\
    p_2 &= [u_2, v_2, 1]
\end{align*}
\]

where \( u \) and \( v \) are the corresponding horizontal and vertical coordinates of pixels. Then the epipolar line \( l_1 \) corresponding to \( p_1 \) is:

\[
l_1 = \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} = F p_1
\]

where \( F \) represents the corresponding fundamental matrix, so the geometric distance \( d \) from point \( p_2 \) to the epipolar line \( l_1 \) is:

\[
d = \frac{|p_2^T F p_1|}{\sqrt{\|x_1\|^2 + \|y_1\|^2}}
\]

If the distance \( d \) is greater than a certain threshold, \( p_2 \) is classified to be a dynamic pixel and will be removed from the image when input image is rerendered back to TartanVO. We visualize the dynamic/static pixels after thresholding with a heatmap shown in Fig. 4. The results of reconstruction using Motion Consistency Detection are shown in Section IV.

C. Iteration and Fusion

After masking the image pair so that only static pixels are left, we iteratively pass it back to TartanVO to refine the optical flow estimation and hence to get more accurate camera pose. Ideally, with enough iterations, the segmentation mask will remove all of the pixels associated with a dynamic object and leave only static backgrounds in the image. In practice, we find out that even with a coarse mask, we can still improve the ATE of TartanVO. Plus, in case the coarse mask allows some dynamic pixels to be passed into the final reconstruction, they will soon be considered idle by the fusion module and
will be removed from the map. Finally, in terms of rerendering the masked images, we find out that passing the raw masked images into the matching network works better than passing the inpainted images, which will be explained in detail in Section V-C.

After a fixed number of iterations, we pass the refined image pair in which most dynamic pixels are removed, along with its corresponding depth pair, into fusion. We implement the fusion part based on the Point-Based Fusion [3]. Given the camera pose, only static points in the input RGB-D pair are fused into the global map. The global map is simply a list of 3D points with associated weights and attributes. Points evolve from unstable to stable status based on the confidence they gathered (essentially a function of how often they are observed by both the sensor and the segmentation result). Data fusion first projectively associates each point in the input depth map with the set of points in the global map, by rendering the map as an index map. If corresponding points are found, the most reliable point is merged with the new point estimate using a weighted average. If no reliable corresponding points are found, the new point estimated is added to the global map as an unstable point. The global map is cleaned up over time to remove outliers due to visibility and temporal constraints, which also ensures that points that are false positives from the segmentation will be discarded over time as long as they are not consistently considered static across multiple frames. Because we leverage the dense optical flow and segments images on each pixel without downsampling, we reconstruct a dense RGB-D global map.

IV. EXPERIMENTAL RESULTS

A. Implementation

Same as TartanVO, we utilize the pretrained PWC-Net [18] as our matching network, and a modified ResNet50 [19] as the pose network, which is also pretrained using weights provided by TartanVO. The PWC-Net outputs optical flow is size of \(H/4 \times W/4\) and it’s scaled back to \(H \times W\) during segmentation. The overall inference time, including both the frontend and segmentation (but without iteration and fusion), reaches 5 FPS on a NVIDIA GeForce GTX 1080 Ti GPU.

Since TartanVO focuses on the monocular VO problem, it can only recover an up-to-scale camera translation given a pair of RGB frames, while we aim at recovering the full-scale dense RGB-D map. Therefore, we modified TartanVO so that during its inference, we pass in not only the RGB image pair, but also the depth image, and we are able to recover the scale of the translation.

Regarding hyperparameters, in the first approach, the threshold we have tuned to segment the 2D scene flow magnitude is
\[
\frac{1.3}{N} \sum_{N} \|\mathbf{u}\|
\]
where \(N\) is the number of pixels and \(\mathbf{u}\) is each 2D scene flow vector. In the second approach, we find \(2.5 \times 10^{-3}\) as a good threshold of the normalized geometric distances between matched pixels to epipolar lines, which gives reasonable segmentation as in the heatmap shown in Fig. 4. We also find a fixed number of 10 iterations is enough to refine the visual odometry and output a good dynamic/static mask.

B. Datasets

We have used the freiburg3_walking_xyz sequence from the TUM dataset [20] to examine the robustness of our Dynamic Dense RGB-D SLAM. Unlike the sequences from KITTI and EuRoC that are originally chosen to evaluate TartanVO, this dataset contains two people walking in an office and intends to evaluate the robustness of visual SLAM and odometry algorithms to quickly moving dynamic objects in large parts of the visible scene, which is suitable for our Dynamic Dense RGB-D SLAM.

C. Dynamic Segmentation

One of the main check points lies in the visualization of optical flow, projected scene flow, and dynamic segmentation of walking person. Fig. 6 and Fig. 7 show the result of segmentation using the first approach, i.e., segmenting pixels based on 2D scene flow. The second row shows masked images by removing all dynamic pixels that are classified as dynamic after a fixed number of closed-loop iterations.

D. Refined Visual Odometry through Iterations

As proposed in Section III-C, we assume that iteratively passing the rerendered image pair back to TartanVO will refine the optical flow estimation and hence will get more accurate camera pose, which is verified here in Fig. 8. The graph on the
left shows an control group ATE of 0.3127 using the original TartanVO without any refinement, while the second graph on the right shows a 0.2432 ATE. This direct comparison proves that with enough iterations, the segmentation step will remove most pixels associated with a dynamic object and leave only static backgrounds in the image, which facilitates the PWC-Net to output less "disturbed" and more accurate optical flow.

![Graphs showing trajectory estimation](image)

Fig. 8: Trajectory comparison between the original TartanVO and our closed-loop variant over the first 500 frames in *freiburg3_walking_xyz*. The ATE was improved by 22.2%.

**E. Map Reconstruction**

Fig. 9 shows our reconstruction result over the entire *freiburg3_walking_xyz* sequence. Dynamic objects (two moving persons) are removed from the scene and only the static background is stored in the global map.

![Map reconstruction](image)

Fig. 9: Map reconstruction via point-based fusion.

**V. CHALLENGES**

Throughout the whole project, we have encountered many challenges from theoretical verification to implementations. The major roadblocks for this project are primarily three-fold: invalid depth pixels, segmentation consistency, and input refinement to the visual odometry.

**A. Invalid Depth Pixels**

To effectively reconstruct the entire 3D scene, we used point-based fusion method [3] that aligns and merges projective point neighbor pairs across a maintained map and a target new frame upon each iteration. The merging technique uses euclidean distance and angular threshold to ensure only valid points are used. However, the *freiburg3_walking_xyz* from TUM [20] contains numerous pixels that have zero depths, which have to be filtered out to prevent computational waste on invalid normals. Otherwise, the normal estimation step from Open3D will be stuck finding nearest neighbors in regions with zero depth. This problem was solved by an extra filer that masks any point with such invalid depth information before passing the RGB-D pair into point-based fusion.

![Input types](image)

Fig. 10: Three attempted input types to TartanVO. Over the first 100 frames, the raw masked approach has lower ATE and the inpaint approach has higher ATE than the original TartanVO (baseline).

**B. Segmentation Consistency**

One of the key difficulties is to segment out dynamic objects (i.e., persons in our case), we need to select appropriate threshold values for both magnitudes of 2D scene flow and geometric distances to epipolar lines that can be consistently applied to all frames in a sequence. While tuning these thresholds, we could barely consolidate on a set of fixed values to maintain a consistent segmentation performance. This roadblock makes an context-aware adaptive thresholding mechanism necessary for next-level improvements.

**C. TartanVO Input Refinement**

Another big challenge for us is to retain the original performance of TartanVO and utilize its low-drift *sim2real* performance in our dynamic scenes. Since TartanVO framework is trained using static scenes and the PWC-Net estimates optical flow which is fundamentally subject to brightness constancy and small motion assumptions, we have to iteratively refine our image inputs and remove as much dynamic pixels as possible in order to have better inference from TartanVO.

To properly rerender input images, in Fig. 10, we first attempted masking raw images to filter out pixels corresponding to dynamic points in 3D, which results in an absolute trajectory error (ATE) of 0.0886 over the first 100 frames as an experiment. Then, on top of this mask, we attempted inpainting the masked holes with matching static pixels found in previous images, which results in an ATE of 0.1589 over the same 100 frames. Compared to the TartanVO baseline producing an ATE of 0.1248, the raw masked approach seems to produce more ideal optical flow while the inpainting approach might produce too much artifact hindering the computation of optical flow. Although not optimal, the raw masked input was found to be the most suitable out of the three approaches we attempted including the baseline.
VI. CONCLUSION AND FUTURE WORK

We propose a brand new Dynamic Dense RGB-D SLAM pipeline, a method based on a learning-based visual odometry, to reconstruct a static map with interference of dynamically moving objects. We conduct experiments on two input refinement approaches, on top of the baseline without any refinement, to dynamically segment out moving objects across frames (i.e., persons in freiburg3_walking_xyz dataset) and only use valid static points for map reconstruction. We fuse static frames into a dense global map which does not contain dynamic objects as expected for a dynamic SLAM algorithm. We show that the learning-based visual odometry performs better on refined input than raw input with moving objects.

To further exploit the potential of our work, there are a few aspects to improve upon. First, adaptive thresholding mechanism is needed to come up with a more consistent threshold for segmentation by leveraging flow, pose, and map, etc. Secondly, bundle adjustment on camera poses and optical flow may be used after warping to compensate the lack of large-scale motion awareness in the pretrained learning-based visual odometry. Third, we may replace the pose network in TartanVO by a dynamic-aware Iterative Closest Point (ICP) algorithm. And last but not the least, the framework may be tested and iterated on more diverse datasets to provide better robustness guarantees.

ACKNOWLEDGMENT

This work was carried out as the final project for 16-833 Robot Localization and Mapping (Spring 2022) at Carnegie Mellon University. Special thanks Prof. Michael Kaess and his PhD student, Wei Dong, from Carnegie Mellon University for their advise.

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