The STDyn-SLAM: A stereo vision and semantic segmentation approach for SLAM in dynamic outdoor environments

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Abstract—Commonly, SLAM algorithms are focused on a static environment, however, there are several scenes where dynamic objects are present. This work presents the STDyn-SLAM an image feature-based SLAM system working on dynamic environments using a series of sub-systems, like optic flow, orb features extraction, visual odometry, and convolutional neural networks to discern moving objects in the scene. The neural network is used to support object detection and segmentation to avoid erroneous maps and wrong system localization. The STDyn-SLAM employs a stereo pair and is developed for outdoor environments. Moreover, the processing time of the proposed system is fast enough to run in real-time as it was demonstrated through the experiments given in real dynamic outdoor environments. Further, we compare our SLAM with state-of-the-art methods achieving promising results.

Supplementary material

The implementation of our system is released on GitHub and is available under the following link: https://github.com/DanielaEsparza/STDyn-SLAM

In addition, this letter has a supplementary video material available at https://youtu.be/JafLh1NVLYk provided by the authors.

I. INTRODUCTION

Simultaneous Localization and Mapping (SLAM) systems are strategic for the development of the next navigation techniques. This is mainly due to its fundamental utility in solving the problem of autonomous exploration tasks in unknown environments such as mines, highways, farmlands, underwater/aerial environments, and in broad terms, indoor and outdoor scenes. The problem of SLAM for indoor environments has been investigated for years, where usually RGB-D cameras or Lidars are the main sensors to capture scenes [1], [2], [3]. In indoors, dynamic objects are usually more controllable unlike outdoors, where dynamic objects are inherent to the scene.

On the other hand, the vast majority of SLAM systems are focused on the static environment assumption, such as HECTOR-SLAM [4], Kintinuous [5], MonoSLAM [6], PTAM [7], SVO [8], LSD-SLAM [9] among others. Such an assumption is strong since it restricts the SLAM system to work only in static environments. However, in dynamic environments, the moving objects can generate an erroneous map and wrong poses; it is because dynamic features cause a bad pose estimation and erroneous data. For this reason, new approaches have arisen for solving the dynamic environment problem. There are few systems in the last two years focused on SLAM for outdoor environments, such as NeuroSLAM [10], hierarchical Outdoor SLAM [11], and Large-Scale Outdoor SLAM [12].

In this work, we propose a method called STDyn-SLAM for solving the problem of SLAM in dynamic outdoor environments using stereo vision [18]. Fig. 1 shows a sketch of our proposal in real experiments. The first raw shows the input images, where a potentially dynamic object is present on the scene and is detected by a semantic segmentation neural network. Fig. 1d depicts the 3D reconstruction excluding dynamic objects. To evaluate our system, we carried out experiments in different outdoor scenes, and we qualitatively compare the 3D reconstructions taking into account the excluding of dynamic objects. We conducted experiments using sequences from KITTI Dataset, and they are compared with state-of-the-art systems. Furthermore, our approach is implemented in ROS, which facilitates implementations in various applications. Also, the STDyn-SLAM approximately works to 10 frames per second using ROS.
TABLE I: The state of the art of the SLAM problem considering dynamic environments.

| System          | Sensor      | Environment | Dynamic Objects          | Real Time | Method                                                                 |
|-----------------|-------------|-------------|--------------------------|-----------|-------------------------------------------------------------------------|
| [13]            | RGB-D       | Indoor      | PASCAL VOC               | –         | Semantic segmentation, and optical flow                                 |
| [14]            | Mono        | Indoor/Outdoor | COCO                 | –         | Semantic segmentation network, depth prediction network and geometry properties |
| [15]            | Mono        | Indoor      | YOLO and MS-CNN         | GPU       | 3-D Box Proposal Generation, standard 3-D map point reprojection error, constant motion model with uniform velocity |
| [16]            | RGB-D       | Indoor      | COCO                    | –         | Mask R-CNN, edge refinement, and optical flow                           |
| [17]            | RGB-D/Stero and proprioceptive | Indoor/Outdoor | COCO                | –         | Factor graph and instance-level object segmentation algorithm          |
| Ours            | RGB-D/Stero | Indoor/Outdoor | PASCAL VOC         | GPU       | Semantic segmentation, optical flow and epipolar geometry              |

or offline from stored images. Further, we liberate the code, which is available in GitHub.

The rest of the paper is structured as follows. Section II presents the related work of SLAM in dynamic environments. In Section III, we present the main results and the algorithm STDyn-SLAM algorithm. Section IV presents the real-time experiments of STDyn-SLAM in outdoor environments with moving objects; we compare our approach with state-of-art methods using the KITTI dataset. Finally, the conclusions and the future work are given in Section V.

II. RELATED WORK

A. Classic Approaches

The classical methods do not consider artificial intelligence. Some of these approaches are based on optical-flow, epipolar geometry or a combination of the two. In [19], Yang et al. propose a SLAM system using an RGB-D camera and two encoders for estimating the pose and building an OctoMap. The dynamic pixels are removed using an object detector and a K-means to segment the point cloud. On the other hand, in [20], Gimenez et al. present a CP-SLAM based on continuous probabilistic mapping and a Markov random field; they use the iterated conditional modes. Wang et al. [21] propose a SLAM system for indoor environments based on an RGB-D camera. They use the number of features on the static scene and assume that the parallax between consecutive images is a constraint of movement. In [22], Cheng, Sun, and Meng implement an optical-flow and the five-point algorithm approach to obtain dynamic features. In [23], Ma and Jia proposed a visual SLAM for dynamic environments detecting the dynamic objects in the scene using optical flow. Furthermore, they use the RANSAC algorithm to improve the computation of the homography matrix.

B. Artificial-intelligence-based approaches

Thanks to the growing use of deep learning, in the last three years some SLAM systems use artificial-intelligence-based approaches. Table I resumes the state-of-art in this regard. Some of the works such as Dosovitskiy et al. [24], Ilg et al. [25] and Mayer et al. [26] use optical flow together with supervised learning for detecting and segmenting the moving objects.

In [27], Xu et al. proposed an instance segmentation of the objects in the scene based on the COCO dataset. The geometric and motion properties are detected and used to improve the mask boundaries, also they tracked the visible objects and moving objects and estimate the system’s pose. Several works are based on RGB-D cameras such as [13], [16], and [17]. Linyan Cui and Chaowei Ma [13] proposed the SOF-SLAM, an RGB-D system based on ORB-SLAM2, which combines a neural network for semantic segmentation, and optical flow for removing dynamic features. Lili Zhao et al. [16] proposed an RGB-D framework to dynamic scenes, where they combined the Mask R-CNN, edge refinement, and optical flow to detect the probably dynamic objects. Mina Henein et al. [17] proposed a system based on an RGBD camera and proprioceptive sensors, where they tackled the SLAM problem with a model of factor graph and an instance-level object segmentation algorithm to the classification of objects and the tracking of features. The

1 https://github.com/DanielaEsparza/STDyn-SLAM
Fig. 2: A block diagram showing the algorithm steps of the STDyn-SLAM.

proprioceptive sensors are used to estimate the camera pose. Also, there are works using a monocular camera, for instance the DSOD-SLAM presented in [14]. In that work Ping Ma et al. employs a semantic segmentation network, a depth prediction network, and geometry properties to improve the results in dynamic environments. Our work is built on the well-known ORB-SLAM2 [29] taking some ideas from DS-SLAM system [30]. In the DS-SLAM, the authors used stored images from an RGB-D camera for solving the SLAM problem in indoor dynamic environments. Nevertheless, the depth map typically obtained from an RGB-D camera is hard to get for external environments.

III. METHODS

In this section, we present and describe the framework of the STDyn-SLAM with all the parts that compose it. A block diagram describing the framework’s pipeline is depicted in Fig. 2 where the inputs at the instant time $t$ are the stereo pair, depth image, and the left image captured at $t-1$ (aka previous left image). The process starts with the extraction of ORB features in the stereo pair and the past left image. As a feature detector, we use the Oriented fast and Rotated Brief (ORB) feature detector, which throws the well-known ORB features [31]. Once the ORB features are found, optical flow and a process using epipolar geometry is conducted.

To avoid dynamic objects not classified by the neural network (explained in the following subsection), the STDyn-SLAM computes optical flow using the previous and current left frames. This step employs a Harris detector to compute the optical flow with its own features different to the ORB ones. The Harris points pair is discarded if at least one of the points is on the edge corner or close to it.

From the fundamental matrix, ORB features, and optical flow, we compute the epipolar lines. Thus, we can map the matched features from the current left frame into the previous left frame. The distance from the corresponding epipolar line to the mapped feature into the past left image determines an inlier or outlier.

A. Stereo Process

Motivated by the vast applications of robotics in outdoors, where dynamic objects are presented, we proposed that our STDyn-SLAM system be focused on stereo vision. A considerable advantage of this is that the depth estimation from a stereo camera is directly given as a measure of distance. The process described in this part is depicted in Fig. 2 where three main tasks are developed: feature extraction, optical flow, and epipolar geometry. Let begin with the former.

The first step of the stereo process is the acquisition of the left, right, and depth frames from a stereo camera. Then, a local feature detector is applied in the stereo pair and in the previous left image. As a feature detector, we use the Oriented fast and Rotated Brief (ORB) feature detector, which throws the well-known ORB features [31]. Once the ORB features are found, optical flow and a process using epipolar geometry is conducted.

For removing outliers (features inside dynamic objects) and estimate the visual odometry, it is necessary the computation of the semantic information and the movement checking process. Finally, the 3D reconstruction is computed from the segmented image, visual odometry, the current left frame, and depth image. These processes are explained in detail in the following subsections.
B. Artificial neural network's architecture

The approach we use is that of eliminating the ORB features on dynamic objects. For that, we need to discern the real dynamic objects among all the objects in the scene. It is here where the NN depicted in Fig. 2 is introduced. In the NN block of that figure, a semantic segmentation neural network is shown, with the left image as input and a segmented image with the object of interest as output. This NN is basically a pixel-wise classification and segmentation framework. The STDyn-SLAM implements a particular NN of this kind called SegNet [32], which is an encoder-decoder network based on the VGG-16 network [33]. The encoder of this NN architecture counts with thirteen convolutional layers with batch normalization, a ReLU non-linearity divided into five encoders, and also of five non-overlapping max-pooling and sub-sampling layers located at the end of each encoder. Due to each encoder is connected to a corresponding decoder, the decoder architecture has the same number of layers as encoder architecture, and every decoder has an upsampling layer at first. The last layer is a softmax classifier. SegNet classifies the pixel-wise using a model based on the PASCAL VOC dataset [34], which consists of twenty classes. The pixel-wise can be classified into one of the next classes: airplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, dining table, dog, horse, motorbike, person, potted plant, sheep, sofa, train and TV/monitor.

Notwithstanding the aforementioned, not all feature points in the left frame are matched in the right frame. For that reason and for saving computing resources, the SegNet classifies the objects of interest only on the left input image.

1) Outliers removal: Once the all the previous steps have accomplished, a threshold is selected to determine the features as inlier or outlier. Fig. 3 depicts the three cases of a mapped feature. Let \( x_1, x_2, \) and \( x_3 \) denote the ORB features from the previous left image; \( x'_1, x'_2, \) and \( x'_3 \) denote the corresponding features from the current left image; and \( l'_1, l'_2, \) and \( l'_3 \) are the epipolar lines. The first and second cases correspond to inliers, \( x'_1 \) is over \( l'_1 \), and the distance from \( x'_2 \) to \( l'_2 \) is less than the threshold. The third case is an outlier because the distance from \( x'_3 \) to \( l'_3 \) is greater than the threshold.

Remember that the SegNet, described before, semantically segments the left image in object classes. The semantic segmentation enhances the rejection of ORB features on the possible dynamic objects. The ORB features inside segmented objects, and thus possible moving objects, are rejected. The remained points are matched with the ORB features from the right image.

C. Visual odometry

Because the system is based on ORB-SLAM2, the SLAM visually computes the odometry. Therefore, the next step needs the ORB features for the estimation of the depth for each feature pair. The features are classified in mono and stereo and will be necessary to track the pose of the camera. This step is merely a process from ORB-SLAM2.

D. 3D reconstruction

Finally, using the visual odometry the STDyn-SLAM builds a 3D reconstruction from left, segmented, and depth images. First, the 3D reconstruction process checks each pixel of the segmented image to reject the point corresponding to the classes of the objects selected as dynamic in section II-B. Then, if the pixel is not considered as a dynamic object, the equivalent pixel from the depth image is added to the point cloud, and the assigned color of the point is obtained from the left frame. This section builds a local point-cloud only in the current pose of the system, and then the octomap [35] joins and updates the local point clouds in a full point cloud.

Remark 1: It is important to mention that we merely applied the semantic segmentation, optical flow, and geometry constraints to the left image for avoiding increasing the time executing. Moreover, the segmentation of the right frame is unnecessary because the step of features selection rejects the ORB features inside dynamic objects from the left image, so the corresponding points from the right frame will not be matched.
IV. Experiments

In this section, we test our algorithm STDyn-SLAM in real-time scenes under the KITTI datasets. The experiments of our system were compared to other state-of-art systems to evaluate the 3D reconstruction and the odometry. The results of the 3D map were qualitatively measured because of the nature of the experiment. We employ the Absolute Pose Error (APE) metric for the odometry.

A. Hardware and software setup

We tested our system on an Intel Core i7-7820HK laptop computer with 32 Gb RAM and a GPU GeForce GTX 1070. Moreover, we used as input a ZED camera, which is a stereo camera developed by Sterolabs. We selected an HD720 resolution. The ZED camera resolutions are WVGA (672 × 376), HD720 (1280 × 720), HD1080 (1920 × 1080) and 2.2K (2208 × 1242).

STDyn-SLAM is developed naturally on ROS. The main inputs for our system are the left and right images, but the depth map is necessary to build the point cloud. However, if this is no available, it is possible executing the STDyn-SLAM only with the stereo images and then to obtain merely the trajectory. On the other hand, the STDyn node in ROS generates two main topics; the Odom and the ORB_SLAM2/PointMap_R/Point_Clouds topics. The point cloud topic is the input of the octomap_server node; this node publishes the joint point cloud of the scene.

Fig. 4 depicts the required ROS nodes by the STDyn-SLAM to generate the trajectory and the 3D reconstruction. The camera node publishes the stereo images and computes the depth map from them. Then, the STDyn-SLAM calculates the odometry and the local point cloud. To visualize the global point cloud, the OctoMap combines and updates the current local point cloud with the previous global map. It is worth mentioning that the maximum depth of the local point cloud can be chosen by the user. All the ROS topics can be shown through the viewer.

B. Real-time experiments

We present real-time experiments under three different scenarios explained next.

First, we test the STDyn-SLAM in an outdoor environment where a car is parked, and then, it move forward. In this case, a static object (a car) becomes dynamic, see Fig. 5 This figure shows the 3D reconstruction, where the car appears static in the first images from the sequence, Fig. 5(a). Then, the car became a dynamic object when it moves forward (Fig. 5(b)), so the STDyn-SLAM is capable of filling the empty zone if the scene is covered again, as it is the case in Fig. 5(c).

The second experiment consists of a scene with two parked cars, a walking person, and a dog. Even though the vehicles are static, the rest of the objects are moving. Fig. 6a shows the scene taking into account the potentially dynamic entities. However, a car can change its position at any time; the STDyn-SLAM excludes the probable moving bodies (parked cars) to avoid the multiple plotting throughout the reconstruction. This is depicted in Fig. 6b.

As a third experiment, we compared the point clouds from the RTABMAP and the STDyn-SLAM systems. The sequence was carried out outdoors with a walking person and two dogs. Since RTABMAP generates a point cloud of the scene, we decided to compare it with our system. To build the 3D reconstructions from RTABMAP, we provided left and depth images, camera info, and odometry as inputs for the RTABMAP. While for our system, we used stereo and depth images; the intrinsic parameters are saved in a text file in the ORB-SLAM2 package. Fig 7 shows the 3D reconstructions. In Fig 7a our system excludes the dynamic objects. On the other hand, Fig 7b RTABMAP plotted the dynamic objects on different sides of the scene resulting in an incorrect map of the environment.

C. Comparison of state-of-art and our SLAM using KITTI datasets

We compare our SLAM with CubeSLAM and ORB-SLAM2 approaches. To evaluate the SLAM systems, we selected sequences with dynamic objects and no-loop closure. Therefore, we chose the 01, 03, 08, and 10 sequences from the odometry KITTI datasets [37]. Furthermore, we employed EVO [38] tools to evaluate the Absolute Pose Error, which computes the RMSE (m), mean, max, and min values.

Because of CubeSLAM is a monocular system, we only took the left images from each sequence to test it. Moreover, we manually completed the trajectory from CubeSLAM since it was not able to detect all the positions. Also, we adjusted the path scale of the SLAM systems to coincide with
Fig. 6: 3D reconstruction with the presence of static (two parked cars) and dynamic objects (a person and two dogs). Notice that the person and the two dogs are not seeing in the scene for the effect of the STDyn-SLAM. Fig. a) depicts the static objects. Nevertheless, the vehicles are potentially dynamic objects, thus in Fig. b), the STDyn-SLAM excludes the bodies considering its possible movement.

Fig. 7: Experiment comparison between the STDyn-SLAM and the RTABMAP [36]. Image a) shows the 3D reconstruction given by STDyn-SLAM; it eliminates the effect of dynamic objects on the mapping. Image b) shows the point cloud created by RTABMAP; notice how dynamic objects are mapped along the trajectory. This is undesirable behavior.

V. CONCLUSION

This work presents the STDyn-SLAM system for outdoor and even indoor environments where dynamic objects are present. The STDyn-SLAM is based on images captured by a stereo pair for 3D reconstruction of scenes, where the possible dynamic objects are discarded from the map; this allows a trustworthy point cloud.

A disadvantage of the point cloud is the range of reconstruction because the range of mapping is less to 100 meters; this is due to the cameras’ limitations. On the other hand, the system capability for computing a reconstruction and localization in real-time depends on the processing power of the computer since a GPU is necessary to support the processing. However, with a medium-range computer, the algorithms work correctly.

In the future, we plan to implement an optical flow approach based on the last generation of neural networks to improve the detection of dynamic objects. The implementation of neural networks allows replacing classic methods such as geometric constraints. Furthermore, we plan to increase the size of the 3D map to reconstruct larger areas and obtained longer reconstructions of the scenes. In addition, the next step is the implementation of the algorithm in an aerial manipulator constructed in the lab.

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| Sequence | rmse | mean | max | min |
|----------|------|------|-----|-----|
| 01       | 3.810| 2.168| 3.469| 2.040|
| 03       | 0.499| 0.256| 0.468| 0.237|
| 08       | 4.751| 3.318| 4.018| 2.796|
| 10       | 1.856| 1.020| 1.600| 0.901|

**TABLE II:** Comparison of Absolute Pose Error (APE) on KITTI Dataset.

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Fig. 8: Comparison experiments. These figures show the trajectories generated using the KITTI’s odometry dataset [37]. The dashed line corresponds to the ground truth, the red line is the ORB-SLAM2 output, the blue line corresponds to the Cube-SLAM, and the green line is the STDyn-SLAM.