DynPL-SVO: A New Method Using Point and Line Features for Stereo Visual Odometry in Dynamic Scenes

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Abstract—Stereo visual odometry is widely used in which a robot tracks its position and orientation using stereo cameras. Most of the approaches recovered mobile robotics motion based on the matching and tracking of point features along a sequence of stereo images. But in low-textured and dynamic scenes, there are no sufficient robust point features for motion estimation, causing lots of previous work failed to reconstruct robotic motion. While line features can be detected in low-textured and dynamic scenes.

In this paper, we mainly proposed a new cost function and dynamics grids containing both vertical and horizontal information of features, which can be used in frameworks like stvo_pl. The method can work robustly in a wide variety of low-textured and dynamic scenes. Stereo camera motion was obtained through Levenberg-Marquard minimization of re-projection error of point and line features. The experimental results on the KITTI and EuRoC MAV datasets showed that the proposed method has a competitive performance when compared with other state-of-the-art systems by producing more robust and accurate motion estimation in dynamic scenes.

Index Terms—Dynamic scenes, motion estimation, line feature, visual odometry (VO).

I. INTRODUCTION

VISUAL odometry is an emerging and hot research topic in the fields of robotics, autonomous driving and augmented reality. It usually uses a variety of cameras for mobile robotic motion estimation and some works [1] [2] [3] [4] [5] also combined with other kinds of sensors, such as IMU, wheel odometry, and so on. Most systems [6] [7] used points as the only visual feature to get motion estimation since points are easy to detect, track, and convenient to handle. The popular point feature detectors include oriented FAST and rotated BRIEF(ORB) [8], Scale Invariant Feature Transform(SIFT) [9], and Speeded Up Robust Feature(SURF), etc. Most methods used ORB as a point feature, because of the tradeoff between accuracy and speed. But in low-texture scenes, the systems with only point features can worsen the performance, since it is difficult to find enough reliable point features in an image. In contrast, line segments are usually abundant in any human-made environment, even in low-texture scenes. In addition, the line segment can provide more structural information for motion estimation.

The process of detecting and describing line segments can be handled by Line Segment Detector(LSD) [10] and Line Band Descriptor(LBD) [11], respectively. Line segments with rich structural information can improve the accuracy and robustness of motion estimation. The Plücker coordinates of the line had been proposed by Sola [12] to transform and project efficiently, however, over-parameterization of the spatial line will induce gauge freedom and internal consistency constraints [13]. To apply unconstrained optimization, Bartoli [14] proposed the orthonormal representation of lines with a minimum of four parameters, while still having a good performance.

The Jacobian plays an important role in estimating the mobile robotics motion through least-square minimization of the re-projection error between projected and detected features. The Jacobian of the proposed system includes three cost functions, i.e. 1) the distance from projected point features from the previous frame to matched point features in the current frame; 2) the distance between the endpoints of the matched line in the current frame and the projected infinite line from the previous frame; 3) the distance from the midpoints of matched lines to the midpoints of the projected lines. The Jacobians with the above-mentioned cost functions can make the best use of structural information from both point and line features.

A large number of start-of-the-art visual odometry methods are used in real-time and show promising results with high accuracy. However, all these methods [2] [15] [16] can only work well in static scenes. The real-world environment has not only numerous low-texture scenes but also contains a huge number of highly dynamic scenes. Features attached to dynamic objects could reduce the robustness and accuracy of the system. When dealing with dynamic and complex scenes, the traditional method cannot get correct inter-frame matching.
resulting in greatly reduced motion estimation accuracy. The idea to solve the above problem is to accurately remove the outliers in images before pose optimization, i.e., the system must remove the features introduced by the dynamic objects and only rely on trusted static features for motion estimation. Therefore, how to accurately extract moving objects and remove the dynamic features is critical to limit the performance of visual odometry (VO) systems.

In this paper, we propose a robust visual odometry system using both point and line features with a novel cost function. Our proposed method mainly solves two issues in the VO/visual simultaneous localization and mapping (vSLAM) systems. On one hand is that in low-texture scenes, traditional point-only VO systems can not detect a large set of point features for motion estimation, so more structural information of point and line features is needed to improve its performance in low-texture scenes. In the pose optimization, the spatial line was parametrized by the orthonormal representation. Based on this minimal parametrization, we further derived the analytical Jacobian of the line re-projection error. On the other hand is to solve the issue that dynamic scenes reduce the accuracy of VO using the motion model combines with the dynamic grids to mark dynamic regions and remove dynamic features inside the marked regions before pose optimization.

There are mainly four contributions for the paper.

- We proposed a complete stereo visual odometry system using both point and line features, which can cope with dynamic scenes using only stereo RGB images.
- In pose optimization, we used more structural information of line features. The vertical and horizontal re-projection error of line features and the re-projection error of point features were used to construct a unified cost function, and we further derived the analytical Jacobians of the line re-projection error.
- An effective and fast algorithm was used to remove the outliers using motion model and dynamic grids for visual odometry to solve the problem where dynamic scenes greatly reduced estimation accuracy.
- We conducted extensive comparative experiments on the KITTI dataset for ground vehicles and the EuRoC MAV dataset for aerial vehicles.

II. RELATED WORK

There are many research fields about visual odometry due to its wide scope of applications, and the visual sensors used mainly include monocular cameras, stereo cameras and RGB-D sensors. Monocular cameras are not as good as stereo systems in initialization and estimation accuracy [1] [17]. The RGB-D camera system can directly obtain the depth information of pixels. However, its application range is limited for outdoor scenes [18] [19]. In the past decades, a lot of researchers [6] [7] paid more attention to stereo visual odometry because of its low cost, robustness and wide range of applications for both indoor and outdoor scenes.

Visual odometry methods can be divided into direct-based [20] [21] and indirect-based (feature-based) [8] according to visual measurement processing. There are many feature-based work, which usually detected a large set of features in images, such as ORB points. Compared to the feature-based methods, the direct-based method directly uses intensity for each pixel to compute the camera motion by minimizing photometric errors, instead of detecting and matching features. However, most of the researchers used feature-based ones instead due to its robustness and accuracy of estimation.

Most feature-based methods detected and tracked point features using a feature descriptor. Then they estimated the motion by minimizing the re-projection errors between the corresponding detected and those projected point features from different frames. To ensure the real-time and reliability of the system, many point feature-based researches used the ORB method. These VO systems with only point features can obtain robust and accurate motion estimation in rich-texture scenes. But when facing scenes with poor information or harsh weather, such as a foggy environment, the motion estimation accuracy could degrade significantly. To achieve more robust and better accuracy performance, many researchers introduced line features to improve feature detection capability in the low-texture environment [16] [22] [23].

In order to introduce line features into VO/vSLAM, the first thing we need to do is to detect and match line features in the images. Many researchers achieved good results in line features extraction, such as FLD [24], EDLine [25] and Line Segment Detector(LSD) [10]. Among the above-mentioned methods, LSD is significantly better than other straight-line features detection methods in shortening straight lines and in blurred images. Therefore, we used LSD as a line segment detector from stereo images and Line Band Descriptor(LBD) [11] for line description.

How to represent a line segment in the system has always been a key issue in feature extraction, and the most intuitive and concise way is to use two endpoints to model a 3D line as in [26]. Besides, line features can be represented as infinite lines as in [27], utilizing Plücker coordinates to represent the infinite line in VO/vSLAM for more convenient projection and transformation of line features. If the position of the spatial lines is used as the key to the change of the re-projection error, all of the above methods have over-parameterized problems. In order to avoid optimization constraints due to the over-parameterized representation of line features in the optimization process, a lot of work [3] [16] cited the Plücker coordinate representation and the orthogonal representation [14] to realize the transformation and optimization, respectively, of the line features. However, we solved the issue by using the Jacobian relationship between the endpoints and the vertical re-projection errors of the line features.

The representation of the line features is different, and the corresponding cost function for optimization is also different. Koletschka [26] took the euclidean distance sum between equally spaced sampling points on the line segment as the cost function of the line features. Since the endpoints of the line detected by LSD are not stable, the line re-projection error was defined as a vector formed by the euclidean distance from the endpoints of the detected line segment in the current frame and the line projected in the previous frame in most methods [3] [16] [23] [27]. All the above cost functions can be easily formed by using the Plücker coordinate and the
Estimating motion in dynamic scenes is also one of the open challenges in visual odometry. To deal with this problem, many methods had been proposed. Some work [1] [2] [28] used vision information to fuse other sensors (such as IMU, wheel odometry, and so on) to reduce the impact of dynamic scenes in motion estimation. In addition, there are a large number of methods [29] [30] using RGB-D information to identify dynamic region. The unstable point features in the dynamic region were eliminated to ensure that only stable static point features were retained in the optimization part. Recently, learning-based computer visual methods are emerging, and there are also many feasible solutions [31] [32] to handle the impact of dynamic scenes on visual odometry by combining learning methods. However, the above-mentioned solutions all have strict requirements on scenario conditions and computer resources.

In this paper, we propose a stereo visual odometry method that can achieve high accuracy motion estimation without directly using image depth information and other sensor assistance in dynamic scenes.

III. DETECTION AND PRE-PROCESSING

In this section, we mainly introduce the front end of the proposed visual odometer system, including the detection and matching in each stereo image of visual features (point and line segment), the definition of dynamic grid and the parameterization of line segments.

A. Feature detection and matching

1) Point features: The performance of features detection work will directly affect the running time and motion estimation accuracy. The focus of point features detection is to ensure the real-time performance of the system, meanwhile detecting as many stable point features as possible. There are large amounts of point features that can be used, like ORB, which is not only fast to compute but also has been verified to be sufficient to meet the need of the system [6]. Therefore, the ORB method was utilized to detect stable point features in the stereo images and describe each detected point feature.

After detecting the point features in left \( p_{l}(u_{l}, v_{l}) \) and right \( p_{r}(u_{r}, v_{r}) \) images of a stereo frame (see Figure 1), it is required to match point features between the left and right images, we meshed all point features of stereo images, i.e. divided the image evenly into 64×48 grids and stored all point features according to their grid positions in the image. After that, we used the ORB point feature \( p_{l} \) in the grid \((a_{p}, b_{p})\) in the left image to match the point feature \( p_{r} \) to be matched in the right image. The feature matching in the stereo camera must follow the epipolar constraint, i.e. \( v_{l} = v_{r} \), and consider the imaging principle of the stereo camera, i.e. \( u_{l} > u_{r} \). The point features to be matched on the right image only include the point features in the horizontal \( c \) grids, ranging from \( grid(a_{p} - c, b_{p}) \) to \( grid(a_{p}, b_{p}) \) in the right image. This not only greatly improved feature matching efficiency, but also largely avoided the existence of error matching. A mutual consistency check was performed, i.e. the best-left match must correspond to the best-right match, and only these matches were considered valid and used for triangulation.

Figure 2 showed the features tracking process between adjacent frames. In order to avoid the influence of a large number of features attached to dynamic objects on the estimation...
results, we used the motion model, i.e., the pose transformation matrix $T_{2p}$ between the previous frame $prev_f$ and the $pprev_f$, which denotes the previous frame of the $prev_f$, to estimate the location of the matched point features of $p_c$ in the current frame. Since individual dynamic objects have more abnormal motion relative to the entire stationary scene, i.e. the dynamic spatial point $P$ moved to $P'$ during sampling time. The most intuitive response is that the dynamic features $p'_d$ have a larger re-projection error relative to the features $p_c$ estimated by the model motion. We calculated and averaged the sum of squared re-projection errors between the matched point features and the estimated point features of the detected point features in all the above grids. Once the value exceeds the threshold, the grid and its surrounding 8 grids in green are determined as dynamic grid, and the features in the dynamic grid are dynamic features.

Algorithm 1 shows the detail process of our proposed dynamic region marking based on the determined dynamic grid algorithm.

**Algorithm 1**: Dynamic region marking using dynamic grid

**Input**: Motion model $T_{2p}$ of the previous frame $prev_f$, the matched point feature set between the current frame $curr_f$ and $prev_f$.

**Output**: The location of the dynamic grid.

1: Divide $curr_f$ evenly into $64 \times 48$ grids and only keep $n(n <= 8)$ point features $p_j$ in each grid $g_i$;
2: for each $g_i \in curr_f$ do
3: for each $p_j \in g_i$ do
4: $e_{g_i} \leftarrow \text{PointErr}(p_j, T_{2p})$
5: end for
6: if $e_{g_i} > \rho$ then
7: $GRIDS\_LOCATION \leftarrow \{(x_{g_i} - 1, y_{g_i} - 1), (x_{g_i} + 1, y_{g_i} + 1)\}$
8: end if
9: end for
10: return $GRIDS\_LOCATION$

2) Line features: The detection of line features faces more challenges. In real-world scenes, some factors, such as changes of lighting, different point of views, and occlusions make it hard for all detected line features to be stable. The focus of line feature detection is to reduce running time and to improve robustness to light. LSD is a popular line segment detector, widely used in computer vision. It is designed to work on noisy images in various scenes without parameter tuning, and the detected line meets the system requirements in terms of accuracy.

Since the endpoints of the line detected by LSD are not stable, the line cannot be perfectly matched only using its endpoints. Similar to point features matching between the left and right images, we meshed the line features in the right image, i.e. all line features passing through the same grid in the image on the right were managed uniformly. We assumed the grids, where the two endpoints of the line feature $l_i$ in the left image were located $(a_x, b_x)$ and $(a_y, b_y)$, then we selected the line features to be matched within the corresponding grid range in the right image, and only the line $l_r$ meet the line matching rule will be selected as the candidate line of $l_i$, as depicted in Figure 1 A mutual consistency check was again performed, i.e. the best-left match must correspond to the best right match, and only these matches that meet the above requirements can participate in the follow-up work.

As shown in Figure 2, for the dynamic line features tracking process between adjacent frames, we used the re-projection error between the estimated line midpoint $p_{en}$ and the matched line midpoint $p'_{en}$ as the judgment basis. Once the value exceeded the preset threshold, we determined that the line feature was a dynamic line feature and removed it.

**B. Representation of Line Features**

A 3D point can be represented by Euclidean spatial coordinates. However, the representation of line features in space is a challenging task. We assumed the homogeneous coordinates of line endpoints are $X_l(x_1, y_1, z_1, w_1)$ and $X_r(x_2, y_2, z_2, w_2)$, respectively, while their inhomogeneous coordinates were represented as $X_s, X_e$. Then the Plücker coordinates of the line $L$ can be constructed as follows:

$$L = \begin{bmatrix} X_s \times X_e \\ w_2X_s - w_1X_e \end{bmatrix} = \begin{bmatrix} n \\ d \end{bmatrix} \in \mathbb{R}^6$$

where $n$ and $d$ are 3-dimensional vectors, $d$ is the direction vector of the line and $n$ is the normal vector of the plane determined by the line and the origin, i.e. $n^T \times d = 0$. The Plücker coordinates $L$ can also be extracted from the dual Plücker matrix $T^*$. The dual plucker matrix can be defined as follows:

$$T^* = \begin{bmatrix} d^T & n \\ -n^T & 0 \end{bmatrix}$$

The representation of Plücker coordinates is convenient for both line feature projection and transformation.

In a nutshell, in the proposed visual odometry system, we used the motion model to find the dynamic features, and we used Plücker coordinates to parameterize the line features. In addition, a simple and effective Jacobian matrix perfectly solved the over-parameterized problem of the Plücker coordinates.

**IV. Motion Estimation**

In this section, we presented in detail how the point and line measurements were introduced in our system and motion estimation were performed. In addition, we derived the analytical Jacobians of re-projection error with respect to point and line feature parameters.

**A. Problem Statement**

We had obtained the point and line features in a sequence of images and their plural positions in camera frames. The problem to be solved is how to find the optimal transformation that satisfies projection constraints of the corresponding features as much as possible. This can be solved by a non-linear least-square equation formed by the projection constraints of
the corresponding features in the previous frame and current frame. Different from other point-line VO/vSLAM systems with the re-projection error of point features and vertical re-projection error of line features, the proposed method not only retained the above two kinds of re-projection error but also introduced the horizontal re-projection error of line features into the motion estimation. This can make full use of the structural characteristics of the line features and improve system robustness and accuracy. So the non-linear least-square equation of our approach as shown in (3).

\[ \xi^* = \arg\min_\xi \left[ \sum_{i=1}^{m} e^i_p(\xi)^T \Sigma^{-1}_{e_p} e^i_p(\xi) + \sum_{j=1}^{n} e^j_{l}(\xi)^T \Sigma^{-1}_{e_{l_x}} e^j_{l_x}(\xi) + \sum_{k=1}^{q} e^k_{l_h}(\xi)^T \Sigma^{-1}_{e_{l_h}} e^k_{l_h}(\xi) \right] \]

where \( m, n \) and \( q \) denote the number of points, all lines and the lines complete in image, respectively. It consisted of the point re-projection error \( e^i_p \), vertical and horizontal re-projection error of line feature \( e^j_{l_x}, e^k_{l_h} \). The matrices \( \Sigma^{-1} \) in (3) represent the inverse covariance matrices related to the uncertainty of each re-projection error.

The re-projection error of points were defined as the distance between the projected point features from the previous frame to the detected point features in the current frame:

\[ e^i_p = p_i - p'_i(\xi) \]

where \( p_i, p'_i(\xi) \) represent point detected from current frame and point projected from the previous frame into current frame, respectively.

Compared with point features, it is a challenging task to introduce the re-projection error of line features in optimization. In most methods, only the vertical re-projection errors of the line features were introduced into the motion estimation, i.e. the distance from the endpoints of the detected line features to the projected infinite line features, shown as

\[ e^j_{l_x} = \left\| \left( l_{j_x}(p_j(\xi)) \right) - \left( l_{j_x}(p'_j(\xi)) \right) \right\| \]

where \( p_j' \) and \( p_j \) denote the endpoints of the line features and \( d(\cdot) \) represent the distance function from point to line.

In our method, the horizontal re-projection error of the line features was introduced into the optimization part by using the re-projection error of the midpoints of the line features:

\[ e^k_{l_h} = p_{i,m} - p'_{i,m}(\xi) \]

where \( p_{i,m}, p'_{i,m}(\xi) \) represent midpoint of the line detected from current frame and projected from previous frame, respectively.

The pose optimization problem in (3) can be iteratively solved using the Gauss-Newton and Levenberg-Marquardt algorithm. To do this, we need to derive the Jacobian of the point and line feature re-projection errors. In the next section, we will illustrate the Jacobian of the three above-mentioned re-projection errors of point and line features.

### B. Jacobian Matrix of Point and Line Re-Projection Errors

In order to derive the Jacobian of feature re-projection error, we converted the pose transformation to Lie algebra form, i.e. using six-dimensional vectors \( \xi \in SE(3) \) to represent the pose transformation matrix \( T \in SE(3) \). So the Jacobian of a point features can be expressed as:

\[ J_p = \frac{\partial e^p}{\partial \xi} = \frac{\partial e^p}{\partial P'} \frac{\partial P'}{\partial \xi} \]

where \( P' \) represent 3D point of matched point feature from previous frame to current camera frame. The above Jacobian can be divided into two parts by the chain rule. The first part can be expressed by the camera projection principle as the following equation:

\[ \frac{\partial P'}{\partial \xi} = - \left[ \begin{array}{ccc} 0 & \frac{f_X}{Z} & \frac{f_{X,Y}}{Z^2} \\ \frac{f_X}{Z} & 0 & \frac{f_{X,Y}}{Z^2} \\ \frac{f_{X,Y}}{Z^2} & \frac{f_{X,Y}}{Z^2} & 1 \end{array} \right] \]

For the second part, we can obtain the following results through the Lie algebra perturbation model:

\[ \frac{\partial P'}{\partial \delta\xi} = \frac{\partial TP}{\partial \delta\xi} \Rightarrow \left[ I \ -P'^\wedge \right] \]

where \( [\cdot]^\wedge \) denotes the skew-symmetric matrix of a vector. So, the Jacobian of point re-projection error can be constructed as (10).

\[ J_p = \frac{\partial e^p}{\partial \delta\xi} = \frac{\partial e^p}{\partial P'} \frac{\partial P'}{\partial \delta\xi} \]

\[ = - \left[ \begin{array}{ccc} -\frac{f_{X,Y}}{Z^2} & \frac{f_{X,Y}}{Z^2} & \frac{f_{X,Y}}{Z^2} \\ \frac{f_{X,Y}}{Z^2} & -\frac{f_{X,Y}}{Z^2} & \frac{f_{X,Y}}{Z^2} \\ \frac{f_{X,Y}}{Z^2} & \frac{f_{X,Y}}{Z^2} & -\frac{f_{X,Y}}{Z^2} \end{array} \right] \]

More detailed information can be found in [3] [16].

We divided the re-projection error of line features \( e_l \) into horizontal \( e_{l_h} \) and vertical \( e_{l_v} \), i.e. \( e_l = e_{l_h} + e_{l_v} \). Vertical re-projection error is similar to the expression in [15] [27], and can be defined as [5]. Firstly, we converted the 3D line \( L_w \) from the world frame to the current camera frame as follows:

\[ L_c = \begin{bmatrix} n_c \\ d_c \end{bmatrix} = T_{cw} L_w = \begin{bmatrix} R_{cw} & (t_{cw})^\wedge R_{cw} \\ 0 & R_{cw} \end{bmatrix} L_w \]

where the \( R_{cw} \) and \( t_{cw} \) represent the rotation matrix and translation vector from the world frame to the camera frame, respectively.

Then, the 3D line was projected into the image and described as \( \ell \), according to the known intrinsic parameter matrix of the camera, the projection of 3D line \( L_c \) from the camera frame to normalize image plane can be shown as follows:

\[ \ell' = KL_c = \begin{bmatrix} f_y & 0 & 0 \\ 0 & f_x & 0 \\ -f_y c_x & -f_x c_y & f_x f_y \end{bmatrix} \begin{bmatrix} l_1 \\ l_2 \\ l_3 \end{bmatrix} \]

where \( K \) represents the projection matrix of the line. Note that the coordinates of the segment projected by the 3D line is only related to the normal vector \( n_c \). Since we projected the line features into the image as an infinite line, so only normal
components \( n_c \) in the Plücker coordinates \( L_c \) can provide meaningful information in the projection.

The vertical re-projection error of the line features can be expressed as follows, as mentioned in Section IV-A.

\[
e^{l}_v = \begin{bmatrix} d_s \\ d_c \end{bmatrix} = \begin{bmatrix} \frac{p_{1l}}{\sqrt{t^2_{1l}+l^2}} \\ \frac{p_{2l}}{\sqrt{t^2_{2l}+l^2}} \end{bmatrix}
\]

(13)

We assumed \( l = \sqrt{t^2_{1l}+l^2} \) and \( d = \frac{p_{2l}}{l} \). So the Jacobian of vertical re-projection error of line feature can be expressed as:

\[
\frac{\partial d}{\partial \delta \xi} = \frac{\partial \frac{p_{2l}}{l}}{\partial \delta \xi} = \frac{\partial (u_1 + v l_2 + l_3)}{\partial \delta \xi} \frac{1}{l}
\]

(14)

\[
\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 1 & 1 \end{bmatrix} \frac{\partial \frac{p_{2l}}{l}}{\partial \delta \xi} \frac{1}{l}
\]

The following equation can be found using the chain rule:

\[
\begin{bmatrix} d_s \\ d_c \end{bmatrix} = \frac{\partial \frac{p_{2l}}{l}}{\partial \delta \xi} \frac{1}{l}
\]

(15)

Finally, the Jacobian of the vertical re-projection error of the line features can be found by referring to the \([10]\) as follows:

\[
\frac{\partial d}{\partial \delta \xi} = - \begin{bmatrix} 1 & 1 \end{bmatrix} \frac{\partial \frac{p_{2l}}{l}}{\partial \delta \xi} \frac{1}{l}
\]

(16)

\[
J_v = d_s \frac{\partial d_s}{\partial \delta \xi} + d_c \frac{\partial d_c}{\partial \delta \xi}
\]

(17)

Compared to the methods of directly deriving the Lie algebra of the transformation in \([3] [16]\), obtaining the Jacobian of vertical re-projection of the line features is more efficient and convenient using the derivation result of the endpoints of the line.

The Jacobian derivation of the horizontal re-projection errors of the line feature was similar to the expression above. We defined the re-projection error of the matched and projected line midpoints as the cost function of line horizontal re-projection error. The result was shown as the following:

\[
\begin{bmatrix} e^{h}_{k} \\ e^{h}_{c} \end{bmatrix} = \begin{bmatrix} e^{h}_{k} \\ e^{h}_{c} \end{bmatrix} \begin{bmatrix} \frac{p^{'l}_{mk}}{m} \end{bmatrix} \frac{\partial \delta \xi}{\partial \delta \xi}
\]

(18)

where \( P'_m \) represent 3D midpoint of matched line feature from previous frame to current camera frame.

Referring to \([10]\), we can obtain the Jacobian of line feature horizontal re-projection error as follows:

\[
J_h = \frac{\partial e^{h}_{k}}{\partial \delta \xi}
\]

\[
= \begin{bmatrix} f_x & 0 & -f_x X'_m \frac{y'_m}{z'_m} & -f_x X'_m \frac{y'_m}{z'_m} & f_x + f_x X'_m \frac{y'_m}{z'_m} \\ 0 & f_y & -f_y Y'_m \frac{z'_m}{y'_m} & f_y + f_y Y'_m \frac{z'_m}{y'_m} & -f_y Y'_m \frac{z'_m}{y'_m} \end{bmatrix}
\]

(19)

So far, the Jacobians of all feature re-projection errors had been obtained, and we can obtain the pose transformation between adjacent frames by solving the non-linear least-square equation by Levenberg-Marquard algorithm.

V. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we evaluated the proposed method on the public KITTI dataset \([33]\) and EuRoC MAV dataset \([34]\). To verify the performance of our method, we compared the accuracy of our algorithm with the state-of-the-art VO systems that can run with stereo RGB data. The selected methods were stvo_pl \([27]\), ORB_SLAM2 \([6]\) and BoPLW \([35]\). In order to fairly compare all methods, we only kept the front end of ORB_SLAM2 and BoPLW to form VO systems. In addition, to illustrate the benefits of the line feature horizontal re-projection error on the accuracy of motion estimation, we showed the results of our proposal with only horizontal or vertical re-projection errors. Finally, we evaluated the ability of dynamic grids to cope with dynamic scenes on highly dynamic sequences. For that, we estimated the trajectory of a stereo camera in several video sequences with moving objects.

All the experiments had been run on an Intel Core i5-4210U CPU @ 1.70GHz × 4 and 16 GB RAM without GPU. In the evaluation of the system’s ability to deal with dynamic environmental issues, since there are no dynamic objects in the EuRoC MAV dataset, the effect of the dynamic grid method is limited, and the dynamic grids to improve the system to cope with dynamic environments cannot be well demonstrated. So, we only estimated the trajectory of our method with or without dynamic grids in the KITTI dataset.

A. KITTI

We had tested the proposed method on the well-known KITTI dataset, which provided ground truth trajectories based on a 64 channels Velodyne LiDAR sensor and a GPS localization system. The stereo images were captured by two grayscale cameras(FL2-14S3M-C) attached to the top of a car. Since this dataset has highly textured urban scenes with light changes, it is closer to the real autonomous driving scenes, and the dynamic scenes containing moving objects like cars and pedestrians in some image sequences have a great impact on the performance of the VO/vSLAM systems. To verify that the proposed method has an outstanding performance on accuracy, we showed both absolute pose error in table I and relative pose error in table II compared to three other systems, i.e. stvo_pl, ORB_SLAM2 front end, and BoPLW front end. On one hand, in table II with absolute pose error comparisons, we listed the root-mean-square error (RMSE) of absolute translation errors.
and rotation errors for the proposed method and the compared approaches, where our method had a better performance than other methods in 9 sequences and the proposed approach enhances 24.8% accuracy compared to traditional approaches in same experimental sequence. The result showed that our method presented better accuracy performance in terms of motion estimation in most sequences, especially in the dynamic ones. On the other hand, in table I with relative pose errors comparisons, the result showed that our system achieves more accuracy than other comparative experimental systems in most scenes. Figure 3 showed the reconstruction of the path from our algorithm, stvo_pl and ORB_SLAM2 front end. The ground truth is represented with blue lines, the green lines represent the estimation of our method, the red lines represent the estimation of stvo_pl, the path provided by ORB_SLAM2 and BoPLW are plotted with purple and brown lines, respectively. (a) Top view of the Sequence 00 path. (b) Top view of the Sequence 05 path. (c) Top view of the Sequence 08 path.

Finally, we also did an ablation study on different directions of line features in our system, yielding the results presented in table III. We can observe that the system with only the horizontal error has a more accurate result than only with the vertical error in almost all sequences of the KITTI dataset, especially on relative errors. The horizontal re-projection error achieves more accuracy in 10 sequences than the system with-

| Seq. | t_m | R_deg | t_m | R_deg | t_m | R_deg | t_m | R_deg | BoPLW front end | t_m | R_deg |
|------|-----|-------|-----|-------|-----|-------|-----|-------|---------------|-----|-------|
| 00   | 6.091 | 1.788 | 7.426 | 2.105 | 14.076 | 3.461 | 7.551 | 1.519 |
| 01   | 172.302 | 8.910 | 371.245 | 12.212 | - | - | - | - |
| 02   | 21.653 | 4.423 | 8.167 | 1.505 | 14.187 | 2.615 | 11.276 | 2.350 |
| 03   | 6.077 | 4.308 | 6.030 | 3.310 | 2.317 | 1.511 | 3.018 | 1.466 |
| 04   | 2.100 | 29.944 | 2.216 | 34.067 | 2.655 | 49.025 | 2.550 | 38.861 |
| 05   | 4.097 | 1.598 | 6.506 | 2.695 | 11.755 | 4.217 | 8.750 | 3.641 |
| 06   | 4.113 | 2.927 | 5.564 | 6.305 | 4.219 | 1.518 | 4.120 | 2.364 |
| 07   | 5.216 | 1.957 | 3.028 | 2.165 | 14.155 | 5.698 | 15.512 | 6.957 |
| 08   | 7.202 | 3.019 | 10.054 | 3.254 | 24.796 | 6.134 | 17.134 | 3.302 |
| 09   | 4.729 | 1.465 | 12.205 | 2.454 | 18.387 | 3.718 | 24.154 | 4.288 |
| 10   | 2.064 | 1.831 | 2.649 | 1.155 | 3.823 | 2.081 | 4.992 | 1.823 |
Table II
Mean Relative Pose Errors on the KITTI Dataset, Note that the dash indicates that the experiment failed.

| Seq. | Ours w/line error | Ours w/vertical error | Ours w/horizontal error | ORB_SLAM2 front end w/line error | ORB_SLAM2 front end w/vertical error | ORB_SLAM2 front end w/horizontal error |
|------|-------------------|-----------------------|------------------------|---------------------------------|--------------------------------------|---------------------------------------|
|      |                 |                       |                        |                                 |                                      |                                       |
| 00   | 1.569 0.443      | 1.607 0.405           | 1.424 0.590           | 1.137 0.366                     |                                      |                                       |
| 01   | 21.339 1.402     | 43.723 1.939          | -                      | -                               | -                                    |                                       |
| 02   | 1.733 0.517      | 1.738 0.344           | 1.621 0.508           | 1.581 0.433                     |                                      |                                       |
| 03   | 3.604 1.637      | 3.467 1.260           | 2.447 0.498           | -                               | -                                    |                                       |
| 04   | 1.907 0.424      | 2.023 0.282           | 2.649 0.754           | 2.405 0.609                     |                                      |                                       |
| 05   | 1.007 0.375      | 1.412 0.493           | 1.974 0.524           | 1.761 0.567                     |                                      |                                       |
| 06   | 1.898 0.582      | 2.372 0.506           | 4.658 2.138           | 5.067 2.542                     |                                      |                                       |
| 07   | 2.051 0.879      | 1.725 1.047           | 3.121 0.959           | 2.642 0.608                     |                                      |                                       |
| 08   | 1.279 0.453      | 1.670 0.468           | 3.422 1.044           | 4.388 0.933                     |                                      |                                       |
| 09   | 1.486 0.353      | 2.129 0.465           | 1.693 0.716           | 1.903 0.566                     |                                      |                                       |
| 10   | 1.204 0.572      | 1.032 0.337           | 2.129 0.465           | 1.903 0.566                     |                                      |                                       |

Fig. 4. Picture from KITTI-01. The green points represent point features and green lines represent line features. There are many features attached to the moving cars which will reduce the robustness of the result, even failed.

Fig. 5. The matching results of line features between adjacent frames in challenging scenes on KITTI-03. The line features are represented with green lines and the match lines are represented with red lines. There are still enough stable line features in challenging scenes for horizontal re-projection errors to improve pose estimation.

out line error and improves average 49.1% accuracy compared to the vertical re-projection error in the KITTI dataset. Figure 5 depicted the matching results of line features between adjacent frames in the sequence KITTI-03. It can be noted that there are still enough stable line features in challenging scenes. The numerous short lines show more superior characteristics in horizontal re-projection errors than vertical. Therefore, the system with horizontal re-projection errors can have a better performance in most sequences, especially in relative errors.

B. EuRoC MAV

The EuRoC MAV dataset, which was collected by a micro aerial vehicle (MAV), including 11 sequences in two indoor scenes. The dataset contains stereo images from a global shutter camera (Aptina MT9V034 global shutter, WVGA monochrome, and 20 FPS) and synchronized inertial measurement unit (IMU, ADIS16448, 200 Hz) [2]. Note that the dataset is an indoor dataset with large rotation movements of drones, and there are a lot of line features in the indoor environment for motion estimation. We ran our method and stvo_pl for comparison. In addition, to verify that the horizontal re-projection errors of the line features have an optimized effect on estimation accuracy, we also ran the method only with horizontal and vertical re-projection errors, respectively, on the EuRoC MAV dataset.

As an example, Figure 6(a) showed the line features extraction in the V2_01_easy sequence, Figure 6(b) and 6(c) respectively showed the line features before and after the optimization process in the motion estimation. There are a large amount of short but complete lines in the scene, as mentioned above, horizontal re-projection errors show more superior characteristics in this case than vertical re-projection errors. At the same time, we observed good performance of all line features pose optimization by minimizing re-projection errors. Table IV shows that the systems with horizontal re-projection error, i.e. our system and the system with only horizontal error, provided more accurate results in 9 experimental scenes of the EuRoC MAV dataset, even in the indoor and static environment, the ablation study shows that the horizontal error plays a more important role than the vertical error in most sequences, and our proposed method also had higher accuracy than stvo_pl, such as MH_01_easy, MH_04_different etc. The reasons are that there are many short but complete lines in
Fig. 6. The tracking of line features in the process of motion estimation. (a) The result of features detection on V2_01_easy. (b) Showed the line features before pose optimization, the green lines represent detected line segments from the current frame, and the red lines represent re-projected line segments from the previous frame. (c) Showed the result of motion estimation. There are also numerous stable short line features in indoor scenes, which can be efficient for optimization by horizontal re-projection errors.

The table below shows the mean relative RMSE on the EUROC MAV dataset:

| Sequence   | stvo pl | Ours | ours w/vertical error | ours w/horizontal error |
|------------|---------|------|------------------------|-------------------------|
| MH_01_easy | 0.033349| **0.033276** | 0.033294               | 0.03358                 |
| MH_02_easy | 0.032896| 0.032547 | 0.032501               | **0.032016**            |
| MH_03_med  | 0.073692| 0.072181 | 0.071908               | **0.071196**            |
| MH_04_diff | 0.103936| **0.103109** | 0.103346               | 0.103473                |
| MH_05_diff | 0.095603| **0.094194** | 0.094640               | 0.094608                |
| V1_01_easy | **0.048642** | 0.049194 | 0.049011               | 0.04927                 |
| V1_02_med  | 0.102017| 0.102235 | 0.102260               | **0.101900**            |
| V1_03_diff | 0.098576| 0.101252 | 0.101670               | **0.097804**            |
| V2_01_easy | 0.037155| **0.032626** | 0.032655               | 0.032629                |
| V2_02_med  | 0.074001| 0.071558 | 0.073592               | **0.071348**            |

The sequences and the use of horizontal re-projection errors in our method help improve the performance. This experiment proved that the horizontal re-projection errors have a good performance in motion estimation, even better than the vertical re-projection errors. Besides, our proposed approach can also provide a good result in a static environment.

C. Evaluation of the ability of dynamic grids to cope with dynamic scenes.

By combining the dynamic grid method with the VO system, the ability of the system to deal with dynamic scenes can be improved. To further verify the effect of dynamic grids on dynamic scenes during motion estimation, a comparative analysis was done to determine the improvement of dynamic grids in a series of dynamic sequences. There are moving objects like cars and people in the KITTI dataset. As Figure 7(a) and Figure 7(b) shown, regardless of whether the scene contains rich structural information, the dynamic grids can identify vehicles traveling at high speeds in different directions. In addition, for dynamic objects that move slowly, such as pedestrians, the dynamic grids can still eliminate dynamic features through the complete market area(see Figure 7(c) and (d)). It verified that the dynamic grids can accurately identify the dynamic regions to avoid the influence of dynamic features on the accuracy, and our proposed method was robust in dynamic scenes. To represent the error in the quantitative analysis, we compared the absolute and relative root-mean-square error (RMSE) with and without dynamic grid approaches in the KITTI dataset. And the result showed in Table V for each of the tested datasets. It can be noticed that the system with the dynamic grid method has a more accurate estimation in 8 sequences and enhances about 15% accuracy compared to the traditional approaches. Especially, the dynamic grid method worked well in sequences (such as KITTI-01,05,09) with highly dynamic scenes, even improved accuracy more than 30%. However, when there are large numbers of unstable scenes in the surrounding environment, such as the KITTI-02 with the presence of a large number of non-artificial environments and the lack of dynamic objects, the accuracy of the results was estimated by our method degrades. The main reason is that the dynamic grids mark some unstable positions like leaves as dynamic regions, which reduce the number of features involved in motion estimation and decrease the accuracy of the results. The results proved that our method gave much stable and higher accuracy motion estimation in a dynamic environment.

VI. Conclusions

In this paper, a robust RGB stereo visual odometry method using both point and line features was proposed mainly in dynamic scenes. In order to cope with the reduction of robustness and accuracy of visual odometry systems by dynamic objects, the dynamic grid method that can efficiently mark dynamic regions and remove point features on dynamic objects without depth information and other sensors was proposed. In addition, to make full use of the structural information of line features, the horizontal re-projection error of the line features was introduced into the cost function to further improve the motion estimation accuracy. Finally, the proposed method had been compared with three different systems, such
Fig. 7. Dynamic scenes on the KITTI dataset and the effect of dynamic grids on dynamic regions. The blue boxes represent the dynamic grids. (a) Moving cars in KITTI-01. (b) Moving car in KITTI-06. (c) The person riding a bike in KITTI-06. (d) The pedestrian in KITTI-09.

| Seq. | ours w/dynamic grid | ours wo/dynamic grid |
|------|---------------------|----------------------|
|      | APE                 | RPE                  | APE                 | RPE                  |
| 00   | 11.221715           | 0.040752             | 13.236462           | 0.038351             |
| 01   | 182.531449          | 1.019784             | 319.707988          | 1.306922             |
| 02   | 21.654051           | 0.064572             | 10.960957           | 0.055898             |
| 03   | 6.094158            | 0.032278             | 5.946504            | 0.031802             |
| 04   | 2.207623            | 0.054315             | 2.015523            | 0.052209             |
| 05   | 4.403628            | 0.019534             | 2.015523            | 0.052209             |
| 06   | 4.428359            | 0.044869             | 4.40736            | 0.056673             |
| 07   | 5.216922            | 0.062928             | 4.725139            | 0.064978             |
| 08   | 7.443639            | 0.043877             | 12.509229           | 0.042731             |
| 09   | 4.823906            | 0.064949             | 13.612393           | 0.070549             |
| 10   | 2.282632            | 0.032286             | 2.786268            | 0.033558             |

as stvo_pl, ORB_SLAM2 front end, and BoPLW front end on two different datasets like KITTI and EuRoC MAV. The experimental result showed that our proposal can produce a more robust and accurate result in most scenes, especially in dynamic ones.

Future work will focus on introducing features with more geometric information, such as planes and cubes, into the system to further improve the accuracy of estimation and create a more informative map. In addition, using deep learning to improve the ability of the system to deal with dynamic scenes is also a meaningful research direction.

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