Traditional Visual Simultaneous Localization and Mapping

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Simultaneous Localization and Mapping (SLAM) was first applied in the field of robotics. Its goal is to build a real-time map of the surrounding environment based on sensor data without any prior knowledge, and at the same time predict its own location based on the map. SLAM has attracted extensive attention from many researchers since it was first proposed in 1986 and is now a necessary capability for autonomous mobile robots.

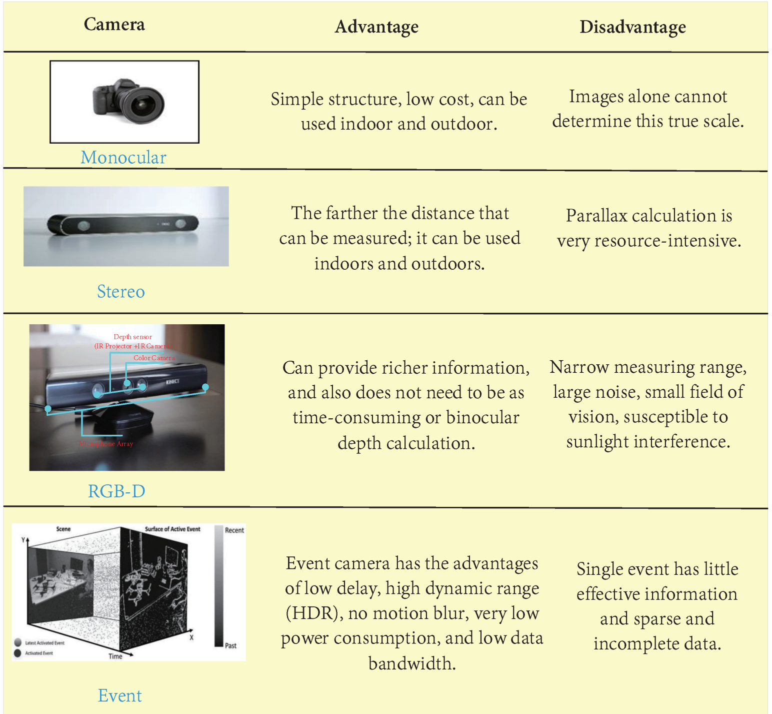
Keywords: SLAM ; computer vision ; Robot ; Environmental awareness

1. Introduction

SLAM [1] (Simultaneous Localization and Mapping), which enables localization and mapping in unfamiliar environments, has become a necessary capacity for autonomous mobile robots. Since it was first proposed in 1986, SLAM has attracted extensive attention from many researchers and developed rapidly in robotics, virtual reality, and other fields. SLAM refers to self-positioning based on location and map, and building incremental maps based on self-positioning. It is mainly used to solve the problem of robot localization and map construction when moving in an unknown environment [2].

2. Sensors Commonly Used in VSLAM

The sensors used in the VSLAM typically include the monocular camera, stereo camera, and RGB-D camera. The monocular camera and the stereo camera have similar principles and can be used in a wide range of indoor and outdoor environments. As a special form of camera, the RGB-D camera can directly obtain image depth mainly by actively emitting infrared structured light or calculating time-of-flight (TOF). It is convenient to use, but sensitive to light, and can only be used indoors in most cases [3]. Events camera as appeared in recent years, a new camera sensor, a picture of a different from the traditional camera. Events camera is “events”, can be as simple as “pixel brightness change”. The change of events camera output is pixel brightness, SLAM algorithm based on the event camera is still only in the preliminary study stage [4]. In **Figure 1**, researchers compare the main features of different cameras.



Camera	Advantage	Disadvantage
Monocular	Simple structure, low cost, can be used indoor and outdoor.	Images alone cannot determine this true scale.
Stereo	The farther the distance that can be measured; it can be used indoors and outdoors.	Parallax calculation is very resource-intensive.
RGB-D	Can provide richer information, and also does not need to be as time-consuming or binocular depth calculation.	Narrow measuring range, large noise, small field of vision, susceptible to sunlight interference.
Event	Event camera has the advantages of low delay, high dynamic range (HDR), no motion blur, very low power consumption, and low data bandwidth.	Single event has little effective information and sparse and incomplete data.

Figure 1. Comparison between different cameras.

An event camera is not a specific type of camera, but a camera that can obtain "event information". "Traditional cameras" work at a constant frequency and have natural drawbacks, such as lag, blurring, and overexposure when shooting high-speed objects. However, the event camera, a neuro-based method of processing information similar to the human eye, has none of these problems.

3. Traditional VSLAM

Cadena et al. [5] proposed a classical VSLAM framework, which mainly consists of two parts: front-end and back-end, as shown in **Figure 2**. The front end provides real-time camera pose estimation, while the back end provides map updates and optimizations. Specifically, mature visual SLAM systems include sensor data collection, front-end visual odometer, back-end optimization, loop closure detection, and map construction modules [6].

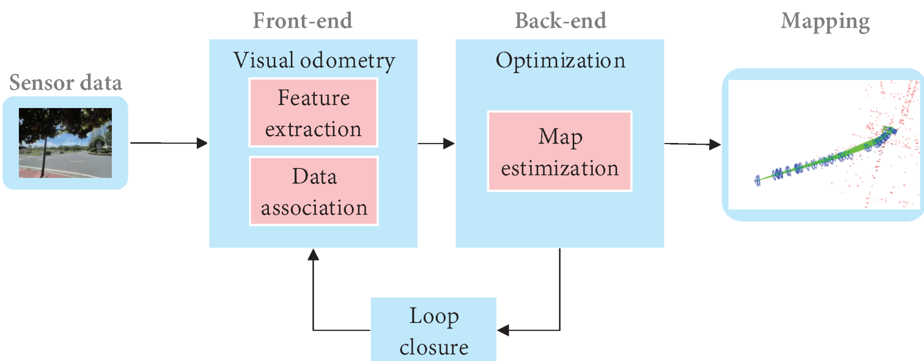
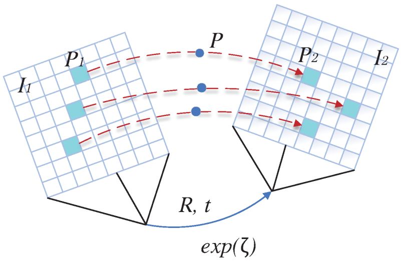


Figure 2. The typical visual SLAM system framework.

3.1 VSLAM Based on the Feature-Based Method

The core of indirect VSLAM is to detect, extract and match geometric features(points, lines, or planes), estimate camera pose, and build an environment map while retaining important information, it can effectively reduce calculation, so it has been widely used [7]. The VSLAM method based on point feature has long been taken into account as the mainstream method of indirect VSLAM due to its simplicity and practicality [8].

Different from feature-based methods, the direct method operates directly on pixel intensity and can retain all information about the image. Furthermore, the direct method cancels the process of feature extraction and matching, so the computational efficiency is better than the indirect method. Furthermore, it has good adaptability to the environment with complex textures. It can still keep a good effect in the environment with missing features. The direct method is similar to the optical flow, and they both have a strong assumption: gray-level invariance, the principle of which is shown in **Figure 3**.



P1 and P2 are the pixel coordinates of point P on the two images. Using the first camera as a reference frame, the rotation and translation of the second camera are R, t（the corresponding lie group is T）.

The brightness error of two pixels of space point P is:

$$e = I_1(p_1) - I_2(p_2)$$

Here e is a scalar. The optimization objective is the binary norm of the error, and the unweighted form is temporarily taken.

$$\min_T J(T) = \|e\|^2$$

If there are multiple points Pi in the space, the whole camera pose estimation problem becomes :

$$\min_T J(T) = \sum_{i=1}^{N} e_i^T e_i,$$

$$e_i = I_1(p_{1,i}) - I_2(p_{2,i}).$$

Figure 3. Schematic diagram of the direct method.

3.2. RGB-D SLAM

An RGB-D camera is a visual sensor launched in recent years. The RGB-D camera, as a special camera, can gain three-dimensional information in space more conveniently. So it has been widely concerned and developed in three-dimensional reconstruction [9]. Although the RGB-D camera is more convenient to use, the RGB-D camera is extremely sensitive to light. Furthermore, there are many problems with narrow, noisy, and small horizons, so most of the situation is only used in the room. In addition, the existing algorithms must be implemented using GPU. So the mainstream traditional VSLAM system still does not use the RGB-D camera as the main sensor.

3.3. Visual-Inertial SLAM

IMU is considered to be one of the most complementary sensors to the camera. It can obtain accurate estimation at high frequency in a short time, and reduce the impact of dynamic objects on the camera. In addition, the camera data can effectively correct the cumulative drift of IMU [10]. At the same time, due to the miniaturization and cost reduction of cameras and IMU, visual-inertial fusion has also achieved rapid development. Nowadays, visual-inertial fusion can be divided into loosely coupled and tightly coupled according to whether image feature information is added to the state vector [11]. Loosely coupled means the IMU and the camera estimate their motion, respectively, and then fuse their pose estimation. Tightly coupled refers to the combination of the state of IMU and the state of the camera to jointly construct the equation of motion and observation, and then perform state estimation [12].

3.3.1. Loosely Coupled Visual-Inertial

The loosely coupled core is to fuse the positions and poses calculated by the vision sensor and IMU, respectively. The fusion has no impact on the results obtained by the two. Generally, the fusion is performed through EKF. The loose-coupling implementation is relatively simple, but the fusion result is prone to error and there has been little research in this area.

3.3.2. Tightly Coupled Visual-Inertial

The core of the tightly coupled is to combine the states of the vision sensor and IMU through an optimized filter. It needs the image features to be added to the feature vector to jointly construct the motion equation and observation equation [13]. Then perform state estimation to obtain the pose information. Tightly coupled needs full use of visual and inertial measurement information, which is complicated in method implementation but can achieve higher pose estimation accuracy. Therefore, it is also the mainstream method, and many breakthroughs have been made in this area.As a supplement to cameras, inertial sensors can effectively solve the problem that a single camera cannot cope with. Visual inertial fusion is bound to become a long-term hot direction of SLAM research [14].

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