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Real - time Anomaly Target Detection and Recognition in Intelligent Surveillance Systems based on SLAM

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Abstract: ***This paper introduces the application of Simultaneous Localization and Mapping (SLAM) technology in intelligent monitoring system. Traditionally, intelligent surveillance systems utilize image processing, pattern recognition, and computer vision technologies to filter out irrelevant information and automatically identify objects of interest. However, by incorporating SLAM technology into these systems, we are taking their capabilities to the next level. SLAM is a powerful tool that enables real-time spatial perception and mapping in dynamic environments. By applying SLAM technology to intelligent monitoring systems, we can improve the system's situational awareness, automate scene analysis, and realize the precise location of events. The combination of SLAM and intelligent surveillance systems enables these systems to autonomously identify and analyze critical information from surveillance video, effectively locate accident scenes, and detect anomalies with unprecedented speed and accuracy. At the same time, we also analyze the challenges and opportunities of integrating SLAM into these systems, and the direction of future research and development. Through comprehensive analysis, we aim to shed light on the transformational impact of SLAM technology on the capabilities of intelligent surveillance systems, as well as on the ability to drive real-time, round-the-clock surveillance.***

Keywords: Intelligent monitoring system; SLAM technology; Anomaly detection; Target recognition.

1. INTRODUCTION

The integration of SLAM technology into intelligent monitoring systems revolutionizes the way we perceive and interact with surveillance data. Traditionally, intelligent monitoring systems leverage image processing, pattern recognition, and computer vision technologies to filter out irrelevant information and automatically identify objects of interest. However, by incorporating SLAM technology into these systems, we elevate their capabilities to a new level of sophistication and efficiency.

SLAM, or Simultaneous [1] Localization and Mapping, is a powerful tool that enables real-time spatial awareness and mapping in dynamic environments. By adding SLAM to intelligent monitoring systems, we harness its ability to enhance situational awareness, automate scene analysis, and enable precise localization of events.

The marriage of SLAM with intelligent monitoring systems empowers these systems to autonomously identify and analyze critical information within surveillance footage, effectively locating accident scenes, and detecting abnormal situations with unprecedented speed and accuracy [2]. Moreover, SLAM facilitates seamless integration with other advanced technologies, such as machine vision AI target recognition and detection.

In this paper, we delve into the utilization of SLAM technology in intelligent monitoring systems, exploring its role in enhancing anomaly detection, target recognition, and overall system performance. We also examine the challenges and opportunities associated with integrating SLAM into these systems, as well as future directions for research and development in this rapidly evolving field. Through a comprehensive analysis, we aim to shed light on the transformative impact of SLAM technology on the capabilities of intelligent monitoring systems and its implications for advancing real-time, all-weather surveillance capabilities.

2. RELATED WORK

2.1 SLAM in Surveillance Systems

SLAM(Simultaneous Localization and Mapping) simultaneous localization and map construction, a technology that simultaneously realizes the localization of the device itself and the construction of the environment map. The principle is to use sensors such as cameras, liDAR, and inertial measurement units to collect environmental information, and then use algorithms to fuse this information to determine the location of the device in an unknown environment and build a map of the environment.

SLAM includes the following aspects:

(1) Sensors: LiDAR, camera, Inertial Measurement Unit (IMU), odometer, etc [3]. These sensors can provide the information required by the device in the process of motion, such as distance, Angle, speed, direction, etc.

(2) Device motion model: Motion model is used to estimate the posture of the device, such as odometer model, speed model, acceleration model, etc.

(3) Visual algorithm: Visual algorithm is mainly used for the perception and positioning of the device in the environment, such as feature extraction, feature matching, image registration, etc.

(4) Filter algorithm: Filter algorithm is used to estimate the pose of the device and the probability distribution of different positions in the map, such as Kalman filter, particle filter, etc.

(5) Optimization algorithm: Optimization algorithm is used to optimize the pose and map of the device, such as extended information filter and pose map optimization.

(6) Map representation: Map representation can have a variety of ways, such as raster maps, topological maps, point cloud maps, etc.

Therefore, in the field of monitoring, the application of SLAM technology can significantly improve the performance and function of intelligent monitoring systems [4]. Through SLAM, the monitoring system can sense the environment of the monitoring area in real time and build a scene map to achieve accurate positioning of the monitoring area and real-time spatial perception. This spatial perception can not only help the system analyze and understand the monitoring picture more accurately, but also realize the position tracking and motion trajectory prediction of the target in the monitoring area, thus enhancing the system's overall grasp of the monitoring scene.

The integration of SLAM technology with artificial intelligence (AI) further enhances the capabilities of surveillance systems. AI algorithms can use the real-time map constructed by SLAM for intelligent analysis and decision-making, so as to realize intelligent perception and behavior recognition of monitoring scenes. For example, combined with AI's target detection and recognition algorithm, the monitoring system can automatically identify different objects in the monitoring screen and analyze their [5] behavioral characteristics, so as to find anomalies or potential security threats in time. In addition, through machine learning technology, the monitoring system can also continuously optimize its own performance and accuracy, and gradually improve the ability to respond to complex monitoring scenarios.

Overall, the integration of SLAM technology with AI has led to a breakthrough in intelligent surveillance systems, enabling more accurate and intelligent monitoring and analysis capabilities. This combination provides a solid foundation for the real-time, accuracy and intelligence of the monitoring system, and is expected to play an important role in a variety of monitoring scenarios, including but not limited to public safety, traffic monitoring, industrial production and other fields.

2.2 Anomaly Target Detection

Aiming at the problem that traditional semantic real-time localization and mapping (SLAM) algorithm can eliminate too many feature points in dynamic environment, a visual semantic SLAM algorithm based on case segmentation and optical flow is proposed. SLAM [1] estimates robot pose and builds a world map to obtain location and environmental information. In recent years, visual-based SLAM algorithm has been widely studied and made great progress [6]. Mature visual SLAM algorithm has been proposed constantly [7], and its positioning accuracy has reached the centimeter-level, and it can build large-size 3D maps . However, the above mature visual SLAM algorithms are all based on the strong assumption of rigid scenes, which makes the application of visual SLAM algorithms in dynamic scenes have great limitations.

In the real world, high-value use cases for AI anomaly detection have grown significantly in recent years and are expected to continue their growth momentum. Advances in artificial intelligence (AI) are revolutionising the field of anomaly detection. It improves detection accuracy, speeds up detection, reduces false positives, and achieves scalability and cost-effectiveness. This article describes how to implement such a solution, and provides some use cases for illustration. Many of the anomalies we encounter today are not just accidental, but may be malicious, man-made phenomena. For example, social media is flooded with fake and deepfake images and videos. Advanced graphics and video production and processing technologies make this possible.

Early on, researchers identified dynamic objects through geometric methods [7] and used an improved random sampling consistency algorithm (RANSAC) to remove dynamic feature points [8]. This method is difficult to accurately identify object contours and is not suitable for scenes with many dynamic objects.

Recently, with the development of machine learning, dynamic environment SLAM algorithms have begun to be combined with semantic segmentation or object detection algorithms to directly segment and delete dynamic objects from images. Dyna-SLAM[11] combines semantic segmentation algorithms with geometric methods to identify and delete dynamic objects in images. DM-SLAM[12] uses semantic segmentation information and optical flow information to eliminate the influence of dynamic objects in the scene. Detect-SLAM[13] uses an object detection algorithm to identify dynamic feature points and transfer the motion information of feature points through motion probability. DS-SLAM[14] uses the SgeNet semantic segmentation algorithm to segment the dynamic object region. If there are dynamic feature points in the region, all feature points in the region will be deleted.

2.3 Target Recognition

There are a large number of high-definition camera monitoring devices distributed in the city, however, most of the monitoring equipment only plays the role of recording, and can not be a system alarm for abnormal behavior [9-11]. Traditional camera monitoring equipment based on manual operation, can not achieve long-term monitoring of abnormal behavior, and this equipment for the waste of resources is very serious, can not do the monitoring behavior analysis and processing, in terms of use has great limitations.

Relevant experts and scholars have conducted in-depth research on abnormal behavior detection and recognition methods in video surveillance systems, and are committed to improving the problem of low detection rate and long working time. Li Ming et al. proposed a laboratory abnormal behavior detection method based on video image processing, that is, the multi-frame video images in the video surveillance system are continuously captured first, the background image is constructed by filtering method, and an improved background difference algorithm is introduced to the background image to extract the complete target contour, and then the contour features are integrated according to the linked list method. The object anomaly detection intelligent monitoring system SLAM is used to detect abnormal behavior [12]. Therefore, to solve the problems of low detection efficiency and long working time in the traditional abnormal behavior detection and recognition method, a new abnormal behavior detection and recognition method in the video surveillance system is proposed. In this method, the video image noise filtering, image gray correction, binary processing, image edge detection are four steps to complete the image preprocessing. Then, on the basis of defining the characteristics of the abnormal target in the image, the key frame of the moving abnormal target image is detected and the data is dissected to complete the abnormal behavior detection of the video surveillance system [13]. Finally, the law of video image is analyzed by adaptive algorithm, and the abnormal behavior of video surveillance system is identified by the principle of computer visual detection with the change of scene environment. In order to detect the effect of the method, a comparative experiment is set up, and the experimental results show that the new method can accurately detect abnormal behavior in a short time, and the working ability is strong.

The integration of SLAM (Simultaneous Localization and Mapping) technology with artificial intelligence (AI) has led to significant advancements in intelligent surveillance systems [14]. SLAM enables real-time environment mapping and precise device localization, enhancing spatial perception and monitoring capabilities. AI algorithms, combined with SLAM-generated maps, enable intelligent analysis, behavior recognition, and anomaly detection in monitoring scenes. Additionally, advancements in anomaly detection, such as dynamic environment SLAM algorithms combined with semantic segmentation or object detection, further enhance surveillance systems' ability to identify and respond to abnormal behavior. Moreover, researchers are developing new methods for target recognition in video surveillance systems to improve detection efficiency and accuracy, utilizing techniques such as video image processing, anomaly detection, and computer visual detection.

3. METHODOLOGY

3.1 Experimental design

In this section, we introduce a new goal-aware dynamic SLAM system that robustly estimates the motion of the camera and the target, as well as the static and dynamic structure of the environment. The whole system, as shown in Figure 1, consists of four main parts: image preprocessing, tracking, mapping and monitoring and detection.

Inputs to the system can be binocular images or RGB-D [15] images. For binocular images, we first adopted the binocular depth estimation method described by Yamaguchi et al. (2014), extracted the depth information and generated the depth map, and finally converted it into RGB-D form.

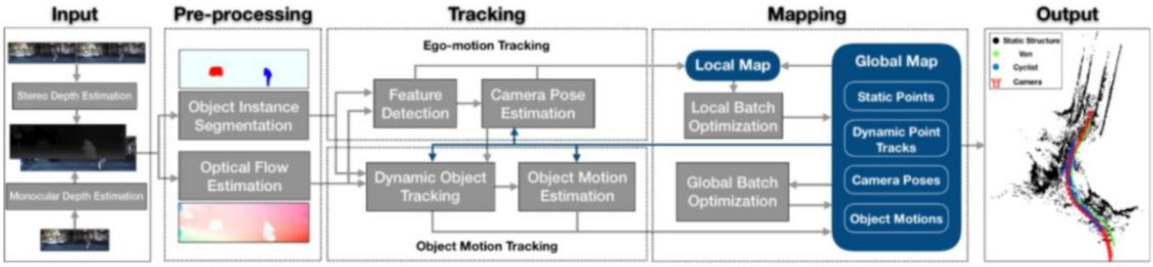

Figure 1: Overview of the VDO-SLAM system

Firstly, the input image is preprocessed to generate instance-level pose segmentation and dense optical flow. Then, the static background structure and dynamic pose characteristics of the preprocessed images are tracked.

Although originally designed as an RGB-D system, in order to make full use of image-based semantic information, we use single-image depth estimation from a monocular camera to obtain depth information. Our "learn-based monocular" system is single-purpose because the system only uses RGB images as input, whereas the estimation problem uses [16] RGB-D data, and the depth of the image is estimated from the depth of a single image.

In the monitoring and detection part, the system will use the environment map and target motion information generated by SLAM, combined with the target detection and tracking algorithm, to realize the real-time detection and recognition of abnormal behaviors and targets in the monitoring scene. In this way, the system can not only complete the spatial perception and motion estimation of the environment, but also carry out intelligent analysis and behavior recognition of the monitoring area, so as to achieve timely response and processing of abnormal situations.

3.2 Pretreatment and feature engineering

In the preprocessing module, we face two challenges: how to robustly separate the static background from the (dynamic) target, and how to ensure the long-term tracking of the dynamic target [17]. To solve these problems, we utilize the latest techniques in computer vision, such as horizontal semantic segmentation and dense optical flow estimation, to ensure efficient target motion segmentation and robust target tracking.

In the aspect of object instance segmentation, we use the case level semantic segmentation technique to segment and identify the potential movable pose in the scene. Semantic information is an important priori to distinguish between static and moving objects, for example, buildings and roads are usually static, while cars can be static or dynamic. With instance segmentation, we are able to further divide the semantic foreground into different instance masks, making it easier to track each individual pose. In addition, the segmentation mask provides a "precise" target boundary to ensure robust tracking of points on the target.

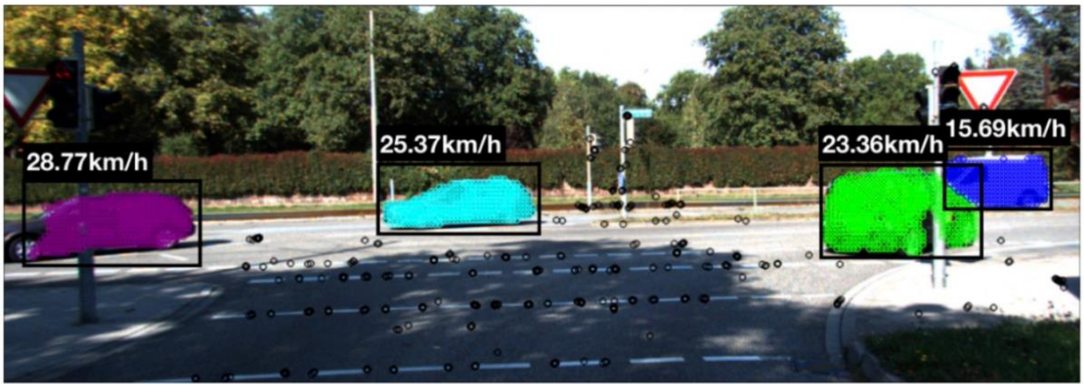

Figure 2: Results of the VDO-SLAM system

On the other hand, using dense optical flow estimation can maximize the number of points on tracking moving targets. Since most moving objects occupy only a small part of the image, it is difficult to ensure robustness and long-term feature tracking using sparse feature matching. Our method utilizes a dense optical flow to significantly increase the number of points for the target (for motion) by sampling all points within the semantic mask [18]. Dense optical flow can also continuously track multiple poses by assigning a unique identifier to each point of the target mask. In the case of semantic segmentation failure, our system can recover the target mask, which is difficult to achieve with sparse feature matching.

We first perform feature detection, detecting a set of sparse corner features and tracking them using optical flow. Within each frame, only the inner points that fit the camera motion estimate are saved to the map for tracking the corresponding points in the next frame. If the number of internal points tracked falls below a certain threshold, the system detects and adds new features. In particular, in the sparse features detected in the static background, the image region does not include the segmented target pose.

Next, we perform camera pose estimation. For all the detected 3D-2D corresponding static points, we calculate the camera pose using DVO-SLAM. In order to ensure the robustness of the estimation, the system uses motion model generation method to initialize the data. Specifically, the method generates two models based on reprojection errors and compares the interior points of the two models. One of the models was generated by calculating the previous motion of the camera, and the other was generated by calculating a new motion transformation using RANSAC's P3P algorithm. The system selects the motion model with more internal points for initialization.

After completing the camera pose estimation, we need to carry out dynamic target tracking. The process is divided into two steps: First, the segmented target is divided into static target and dynamic target; Dynamic targets are then associated through successive frames. Instance level object segmentation allows us to separate objects from the background and realize dynamic object identification effectively through scene flow estimation. Specifically, after obtaining the camera pose, the scene flow quantity that describes the motion of a three-dimensional point between K-1 and k frames can be calculated.

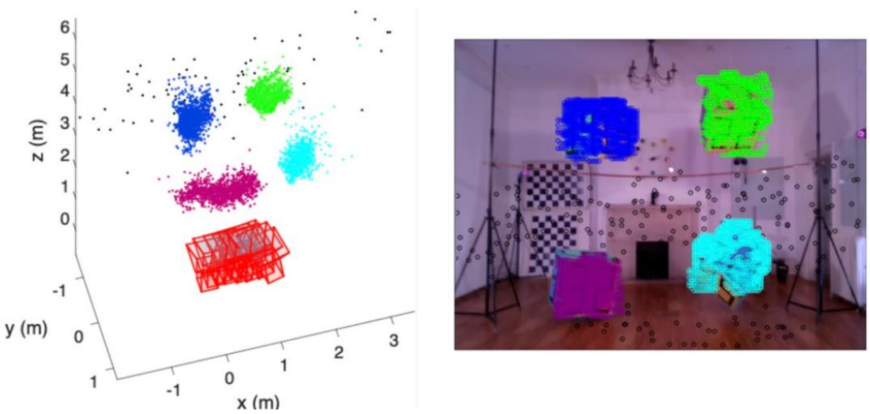

Figure 3: Qualitative results of motion data sets

3.3 Computational analysis

Finally, we provide the calculation and analysis results of DVO-SLAM system. The experiment was conducted on an Intel Core i7 2.6GHz laptop with 16GB of RAM. The computational time for semantic segmentation and dense optical flow depends on the GPU performance of the computer and the complexity of CNN model. Many of the latest algorithms can run in real time (Bolya et al. (2019); Hui et al. (2020). In this paper, semantic segmentation and optical flow results are generated offline and input into the system. The entire SLAM system is implemented in c++ on the CPU, using modified g2o as its backend (K ¨ ummerleet al. (2011)). We show the computation time of DVO-SLAM on the two data sets in Table 5. In local batch optimization, the window size is set to 20 frames with an overlap of 4 frames. The time cost of each system component is averaged across all frames and sequences. Overall, the tracking part of our proposed system can run at a frame rate of 5-8 frames per second depending on the number of moving objects detected, with the use of parallel computing to further improve performance. The run time of global batch optimization is largely determined by the number of camera poses (frames) in the scene and the target density (calculated from the number of dynamic targets observed per frame).

3.4 Result Discussion

In this article, we introduced VDO-SLAM. This is a novel SLAM system based on dynamic features and image semantic information in the scene, which can realize synchronous localization, mapping and tracking of dynamic targets without additional target pose or geometry information [19-23]. The system achieves globally consistent robust and accurate results in both indoor and challenging outdoor data sets, and can demonstrate its superior performance in target motion estimation. We believe that the high precision results in target motion estimation are due to the fact that our system is a feature-based system. Feature points are still the easiest to detect, track, and integrate in SLAM systems, without requiring the front end to provide any additional information about the target model.

How to reduce the computational complexity of SLAM for dynamic targets is an important topic. In the long run, different techniques can be applied to limit the growth of the number of images (Strasdat et al. (2011); Ila et al.(2010). In fact, summarizing/deleting map points associated with dynamic objects observed long ago seems to be a natural way for long-term SLAM systems to adapt to highly dynamic environments.

4. CONCLUSION

In summary, the application of SLAM technology has brought revolutionary changes to intelligent monitoring systems, and has shown great development potential in the context of artificial intelligence. Traditional intelligent surveillance systems rely on image processing, pattern recognition, and computer vision techniques to filter out irrelevant information and automatically identify objects of interest. However, by incorporating SLAM technology into these systems, we are taking their capabilities to the next level. SLAM is a powerful tool that enables real-time spatial awareness and map construction in dynamic environments. The application of SLAM technology in intelligent monitoring system can improve the situational awareness of the system, automate the scene analysis, and realize the accurate location of events [24-25]. The combination of SLAM and intelligent surveillance systems enables these systems to autonomously identify and analyze critical information from surveillance video, effectively locate accident scenes, and detect anomalies with unprecedented speed and accuracy. In addition, SLAM facilitates seamless integration with other advanced technologies such as machine vision AI object recognition and detection. In summary, the combination of SLAM technology and artificial intelligence has brought breakthrough progress to the intelligent monitoring system, achieving more accurate and intelligent monitoring and analysis capabilities, and providing a solid foundation for real-time, all-weather monitoring. Looking forward to the future, with the continuous progress and development of technology, SLAM technology will have a broader application prospect in the field of intelligent monitoring, and is expected to play an important role in public safety, traffic monitoring, industrial production and other fields.

One of the directions of future research is to further optimize SLAM technology to cope with more complex and dynamic monitoring environments and improve the robustness and stability of the system [26]. On the other hand, artificial intelligence technologies such as deep learning and augmented learning are combined to further improve the perception ability and decision-making ability of intelligent monitoring systems, so that they can more accurately identify and respond to abnormal situations in various monitoring scenarios. In addition, it is also necessary to strengthen the verification and testing of SLAM technology in practical applications, and promote its wide application and promotion in the field of intelligent monitoring. Through continuous innovation and exploration, SLAM technology will provide strong support for the development and popularization of intelligent monitoring systems, and provide more reliable and efficient monitoring solutions for social security and public management.

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