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Minor Project-2 Report
on

# Simultaneous Localisation and Mapping (SLAM) Based Scene Reconstructions

by:

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SCHOOL OF ELECTRONICS AND COMMUNICATION ENGINEERING

## CERTIFICATE

This is to certify that project entitled **"SLAM Based Scene Reconstructions"** is a bonafide work carried out by the student team of **"Shyam Desai (01FE21BEC110), Shridhar Naragund (01FE21BEC116), Vinayak Nayak (01FE21BEC305)"**. The project report has been approved as it satisfies the requirements with respect to the minor project-2 work prescribed by the university curriculum for BE (VI Semester) in School of Electronics and Communication Engineering of KLE Technological University for the academic year 2023-2024

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**by:**

**Project Team**

## ABSTRACT

ORB-SLAM is a new real-time system that builds a 3D map of its surroundings (SLAM) using a single camera. It works well in various environments, indoors and outdoors, even with significant movement. The system can automatically initialize, track its location, and relocate itself, all while using the same features for different tasks.We demonstrate the proposed system on a low memory embedded system, the ARM Cortex A53 board (Rasp berry Pi 3 Model B). The proposed system enables faster, low memory relocalization with improved memory usage.ORB-SLAM achieves unprecedented performance with respect to otherstate-of-the-art monocularSLAMapproaches.For the benefit of the community, we make the source code public.

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# Chapter 1

# Introduction

Simultaneous Localization And Mapping (SLAM) is very important task for mobile robotics. For a robot in motion, it is always required to know its location and the surroundings. “Localization” and “Mapping” are two components of SLAM. Precisely, the challenge can be described as follows. When a mobile robot is placed at an unknown location and environment, it will have to build a map of the environment incrementally and determine its own location within that map. Both the tasks go on simultaneously.As described earlier, The major components of SLAM are “localization” and “mapping”, Combining localization and mapping allows the robot to build a map of an unknown environment while simultaneously determining its location within that map. This process is iterative and requires robust algorithms to handle uncertainties and dynamic changes in the environment. an overview of different components of a SLAM are described as follows.

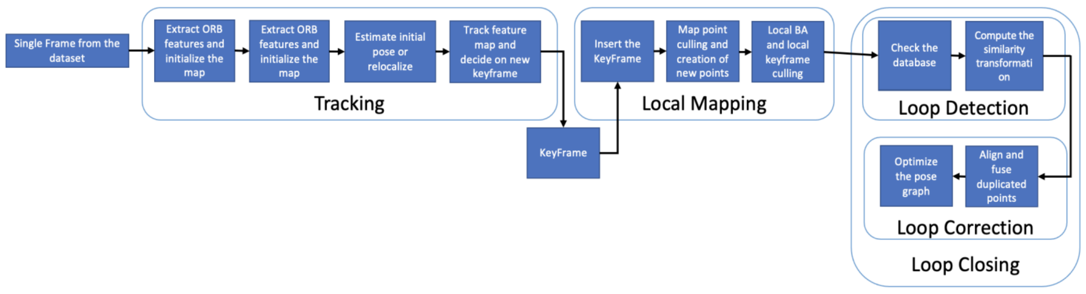

Single Frame from the dataset
Extract ORB features and initialize the map
Extract ORB features and initialize the map
Estimate initial pose or relocalize
Track feature map and decide on new keyframe
Tracking
KeyFrame
Insert the KeyFrame
Map point culling and creation of new points
Local BA and local keyframe culling
Local Mapping
Check the database
Compute the similarity transformati on
Loop Detection
Optimize the pose graph
Align and fuse duplicated points
Loop Correction
Loop Closing

Figure 1.1: Block Diagram of ORB-SLAM with its three parallel Modules.

Localization refers to the process of determining the position and orientation of a robot within a known environment. The goal of localization is to find the location of the robot relative to a reference. It involves estimating the robot’s pose (its location and direction) using sensor data. Accurate localization is crucial for the robot to navigate effectively and avoid obstacles. The problem of Mapping deals with creating a representation of the environment that the robot can use for navigation and decision-making. This map can be a 2D grid map, a 3D point cloud, or other formats.

## 1.1 Motivation

**Real-time 3D Understanding**: Enable robots and vehicles to build a 3D understanding of their surroundings for tasks like navigation and interaction with the environment.

**Low-Cost 3D Reconstruction**: Offer an affordable and accessible way to reconstruct 3D scenes using cameras, promoting applications like rapid prototyping or cultural heritage preservation.

## 1.2 Objectives

- Setup a ORB Based SLAM for Real time Scene Reconstruction..
- Extract reconstructed 3D scene.
- Camera Calibration and Real time scene reconstruction.

The implementation of SLAM Based Scene Reconstruction using embedded systems technology for Industry, Innovation, and Infrastructure, focuses on fostering sustainable industrialization, promoting innovation, and building resilient infrastructure. It aims to support inclusive economic growth, enhance productivity, and create job opportunities, particularly in developing countries.

## 1.3 Literature survey

### 1.3.1 3-D Reconstruction System Based on Multi Sensor

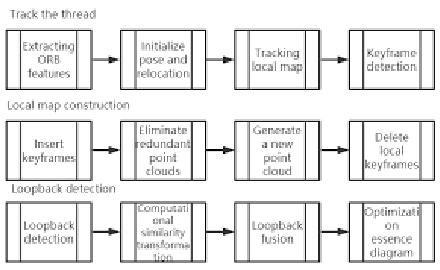


Figure 1.2: Overview of ORB-SLAM.

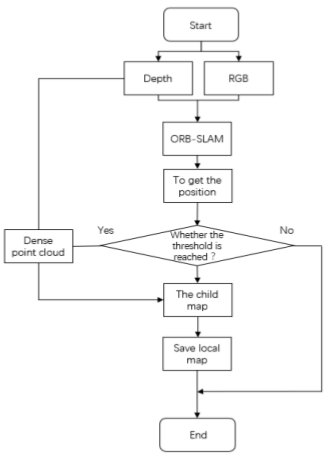


Figure 1.3: ORB-SLAM algorithm flow.

- The research presents a 3D reconstruction system for indoor scene mapping by mobile robots, utilizing the ORB-SLAM algorithm with depth and inertial sensors to enhance accuracy and efficiency

- Integration of depth and inertial sensor data with visual information enables precise positioning, real-time 3D reconstruction, and dense map construction, improving robot navigation and scene understanding in complex environments.
- A method developed to construct dense 3D maps using only CPU resources and eliminating the need for GPU parallel computing. This method aim to reduce map construction time and improve overall performance.
- ORB-SLAM2 originally creates a sparse point cloud map by retaining ORB features. Enhancements include adding a dedicated thread for dense point cloud construction, leaving key frames generated by ORB-SLAM2.
- An improved ORB-SLAM framework for dense 3D mapping enables robots to perform high-precision positioning and reconstruction in both large and small unknown environments. This is achieved by converting sparse maps to dense 3D point clouds.
- The enhanced ORB-SLAM2 was tested using open datasets from the Technical University of Munich (TUM), showcasing the transition from sparse to dense reconstructions and validating the system reliability in real-world indoor mobile robot applications.

### 1.3.2 ORB-SLAM: A Versatile and Accurate Monocular SLAM System

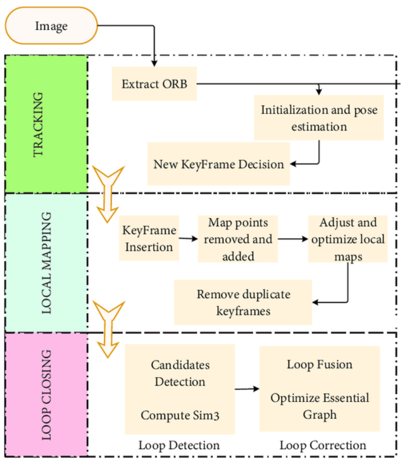


Figure 1.4: ORB-SLAM system overview.

- ORB-SLAM uses the features for tracking, mapping, relocalization, and loop closing, employs a strategy to select points and keyframes. This ensures robustness and creates a compact, trackable map.
- ORB-SLAM was exhaustively evaluated on 27 sequences from popular datasets, demonstrating unprecedented performance compared to other state-of-the-art monocular SLAM approaches.
- The ORB-SLAM system was tested across multiple datasets to assess general performance, localization accuracy, relocalization capabilities, and efficiency in real-time, large-scale operations. The experiments were performed on the NewCollege dataset, TUM RGB-D benchmark, and KITTI dataset.

### 1.3.3 Re-localization of Camera in a 3D Map on Memory Restricted Devices

- The paper discusses the distinction between landmark-based SLAM, which uses range measuring devices like LiDar, and visual SLAM, which relies on raw data from cameras, highlighting the advantages of visual SLAM in providing texture and visual information of surroundings without constraints of planar movements

- Various relocalization methods are explored,place recognition using bag of binary words, real-time relocalization for keyframe-based mapping, and a convolutional neural network approach for camera relocalization, each addressing the need for accurate camera pose recovery in SLAM systems.

## 1.4 Problem statement

Simultaneous Localisation and Mapping (SLAM) Based Scene Reconstructions

- Exploration and Mapping of Unknown Areas: In scenarios where robots are exploring unknown or partially known environments, they cannot rely solely on pre-existing maps

- Real maps may not always provide precise localization information, especially in complex indoor environments with limited GPS signal availability.

# Chapter 2

# System design

In this chapter, we will be looking towards the functional block diagram, the design alternatives and also about the final design which is being implemented.

## 2.1 Design alternatives

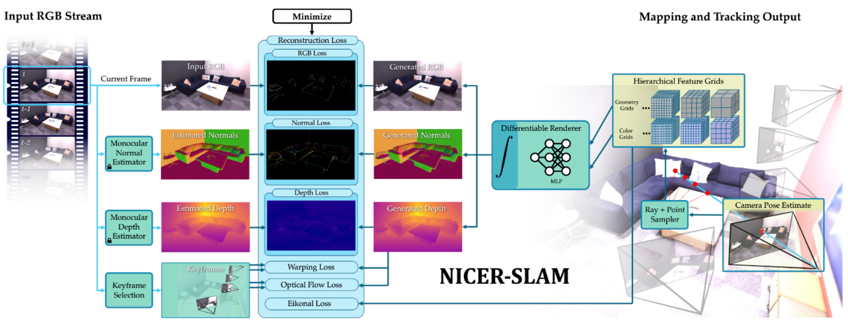


Figure 2.1: Overview of NICER-SLAM(Neural Implicit Scene Encoding for RGB SLAM).

- Neural implicit representations have become increasingly popular in simultaneous localization and mapping (SLAM), particularly in dense visual SLAM applications. Existing approaches either utilize RGB-D sensors or depend on a separate monocular SLAM system for camera tracking.

## 2.2 Overview of ORB-SLAM

This is the overview of ORB-SLAM, It has three modules that works simultaneously they are Tracking, Local Mapping, Loop Closure.
Basically ORB-SLAM starts with the Initializing the map of 3-D points from frames. Once a map is Initialized, the Tracking components are responsible for the real time camera pose estimation. For each new frame the camera pose is estimated by matching features in the current frame to last key frame. The Local mapping manages the both keyframe and map points, Keyframe are subset of video frames that contains the information about the localization and mapping, while map points are list of 3-D points that represent the map of the environment. Loop Closing detects and corrects loops in the trajectory and recognizes previously visited locations.

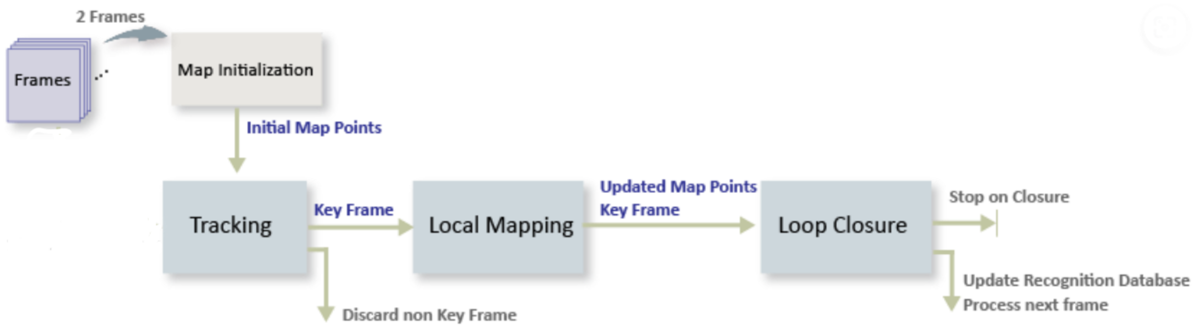


Figure 2.2: ORB-SLAM system overview, showing all the steps performed by the tracking, local mapping, and loop closing threads.

## 2.3 Flowchart

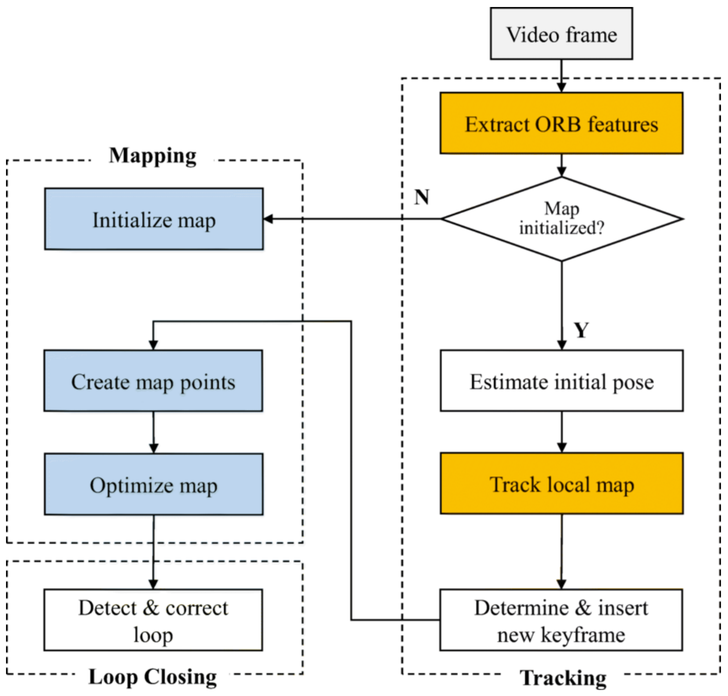


Figure 2.3: Flowchart of the ORB-SLAM

# Chapter 3

# Implementation details

## 3.1 Specifications

### 3.1.1 Hardware Requirements

- **Camera:**
  - **Monocular:** A single RGB camera with high frame rate and resolution.
  - **Stereo:** A pair of synchronized RGB cameras.
  - **RGB-D:** A depth sensor (e.g., Microsoft Kinect, Intel RealSense).
- **Processing Unit:**
  - **CPU:** Multi-core processor.
  - **GPU:** (optional but recommended for speed) NVIDIA CUDA-enabled GPU.
  - **RAM:** At least 8 GB, preferably 16 GB or more.
- **Storage:** SSD with sufficient space for storing video data and map data.
- **IMU:** (optional but recommended for improved accuracy) An inertial measurement unit for better pose estimation.

### 3.1.2 Software Requirements

- **Operating System:**
  - Linux (Ubuntu is commonly used for ROS compatibility).
- **Dependencies:**
  - **ROS (Robot Operating System):** Provides the framework for robot software development.
  - **OpenCV:** For computer vision operations.
  - **Pangolin:** For 3D visualization.
  - **Eigen:** For linear algebra.
  - **DBoW2:** For place recognition.
- **CMake:** For building the software.

## 3.2 Final System Architecture

### 3.2.1 Data Acquisition

- **Camera Input:** Video stream from monocular, stereo, or RGB-D camera.
- **IMU Input:** (if available) provides orientation and acceleration data.

### 3.2.2 ORB-SLAM System

- **Tracking:**
  - Extract ORB features from each frame.
  - Match features with previous frames to estimate camera pose.
  - Utilize IMU data to enhance pose estimation (if available).
- **Mapping:**
  - Construct a sparse 3D map using keyframes.
  - Detect loop closures and correct map using pose graph optimization.
- **Relocalization:**
  - Detect previously visited places and relocalize the camera if tracking is lost.

### 3.2.3 Back-End

- **Local Mapping:** Incrementally build and refine local map sections.
- **Global Mapping:** Maintain global consistency by optimizing the entire map when loops are detected.

### 3.2.4 Visualization and User Interface

- **Pangolin Viewer:** Real-time 3D visualization of camera trajectory and map points.
- **ROS Nodes:** Interface with other ROS components for integration into broader systems (e.g., robot navigation).

## 3.3 Implementation Steps

1. **Install Dependencies:**
   - Install ROS, OpenCV, Eigen, Pangolin, and DBoW2.
2. **Build ORB-SLAM:**
   - Clone the ORB-SLAM repository.
   - Use CMake to configure and build the project.
3. **Configure Camera:**
   - Calibrate the camera and configure the input source (camera or video file).

4. **Run ORB-SLAM:**
    - Launch the ORB-SLAM node with appropriate configuration files for the chosen camera type (monocular, stereo, or RGB-D).
5. **Visualization:**
    - Use the provided visualization tools to view the reconstructed scene and camera trajectory.

## 3.4 Algorithm

- **Feature Extraction and Description:**
  - Key Points: Extract distinctive local features from images, representing points of interest in the environment.
  - Descriptors: Describe these key points using descriptors such as ORB (Oriented FAST and Rotated BRIEF), which provide compact representations of the local image patches surrounding the key points.
- **Camera Pose Estimation (Localization):**
  - Tracking: Continuously estimate the camera's pose (position and orientation) relative to the environment by matching the extracted features between consecutive frames.
  - Local Mapping: Simultaneously build a local map of the environment using the detected key points and their descriptors. This map consists of keyframes (selected frames with high-quality localization) and the associated 3D map points.
- **Loop Closure Detection:**
  - Identify loop closures, which occur when the camera revisits a previously visited location. Loop closure detection aims to recognize these revisits and correct accumulated errors in the estimated camera trajectory.
- **Scene Reconstruction:**
  - Once the SLAM system has operated for a sufficient duration or has covered a significant area, the reconstructed 3D scene can be extracted from the accumulated map.
  - The reconstructed scene consists of a dense 3D point cloud representing the environment's geometry and texture.
- **Camera Calibration:**
  - Ensure accurate camera calibration to correctly interpret the observed scene geometry and texture.
  - Calibrate the camera parameters such as focal length, principal point, and distortion coefficients

**Algorithm 1** ORB-SLAM Algorithm for 3D Reconstruction

```
Initialize ORB features and camera parameters
Initialize map $M$ and camera trajectory $T$
while frames available do
    Receive new frame $F$
    Extract ORB features from $F$
    Match ORB features with map $M$
    Estimate camera pose relative to map $M$
    if camera tracking succeeds then
        Update map $M$ with new frame $F$ and camera pose
        Optimize map $M$ and camera trajectory $T$
    else
        Perform relocalization using ORB features
    end if
end while
```

# Chapter 4

# Results and Discussions

## 4.1 Datasets

### KITTI Odometry Dataset

The KITTI Odometry Dataset is a comprehensive collection of data designed for evaluating visual odometry algorithms. It includes grayscale images captured from a moving platform under varying environmental conditions, such as different weather and lighting conditions. This dataset is widely used in research and development of techniques for estimating the motion trajectory (odometry) of a camera in 3D space. It provides ground truth poses and can be utilized for tasks such as camera calibration, feature tracking, and motion estimation.

### TUM Dataset

The TUM Dataset is a popular benchmark in computer vision and robotics research, particularly for visual SLAM (Simultaneous Localization and Mapping). It includes RGB-D (color and depth) sequences captured in indoor environments using handheld cameras or mobile devices. The dataset is annotated with camera poses and 3D reconstruction of scenes, making it suitable for evaluating algorithms related to scene understanding, depth estimation, and 3D mapping. Researchers often use the TUM Dataset for developing and testing SLAM algorithms under controlled indoor conditions.

## 4.2 Evaluation Metrics

Evaluating the performance of a SLAM-based scene reconstruction system involves various metrics that assess different aspects of the system's accuracy, efficiency, and robustness. Below are the key evaluation metrics commonly used:

### 4.2.1 Trajectory Accuracy

- **Absolute Trajectory Error (ATE):** Measures the absolute distance between the estimated trajectory and the ground truth trajectory. It provides an overall indication of the global consistency of the SLAM system.

$$ATE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|\mathbf{p}_i^{est} - \mathbf{p}_i^{gt}\|^2} \tag{4.1}$$

  where $\mathbf{p}_i^{est}$ and $\mathbf{p}_i^{gt}$ are the estimated and ground truth positions at time step $i$, respectively, and $N$ is the total number of time steps.

- **Relative Pose Error (RPE):** Measures the local accuracy of the trajectory over short time intervals. It evaluates how well the SLAM system can estimate the motion between consecutive frames.

$$RPE = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} \|(\mathbf{p}_{i+1}^{est} - \mathbf{p}_i^{est}) - (\mathbf{p}_{i+1}^{gt} - \mathbf{p}_i^{gt})\|^2} \tag{4.2}$$

### 4.2.2 Map Quality

- **Map Accuracy:** Evaluates the accuracy of the reconstructed 3D map by comparing the reconstructed points with ground truth points. This can be done using metrics such as Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \|\mathbf{m}_j^{est} - \mathbf{m}_j^{gt}\|^2} \tag{4.3}$$

  where $\mathbf{m}_j^{est}$ and $\mathbf{m}_j^{gt}$ are the estimated and ground truth map points, respectively, and $M$ is the total number of map points.

- **Map Completeness:** Measures the completeness of the map by comparing the number of correctly reconstructed points to the total number of ground truth points.

$$Completeness = \frac{NumberofCorrectlyReconstructedPoints}{TotalNumberofGroundTruthPoints} \tag{4.4}$$

### 4.2.3 Computational Efficiency

- **Processing Time:** Measures the time taken by the SLAM system to process each frame. This includes feature extraction, matching, pose estimation, and map updating.

$$AverageProcessingTimeperFrame = \frac{1}{N} \sum_{i=1}^{N} t_i \tag{4.5}$$

  where $t_i$ is the processing time for frame $i$.

- **Memory Usage:** Evaluates the memory consumption of the SLAM system during operation, which includes storing the map, keyframes, and other relevant data structures.

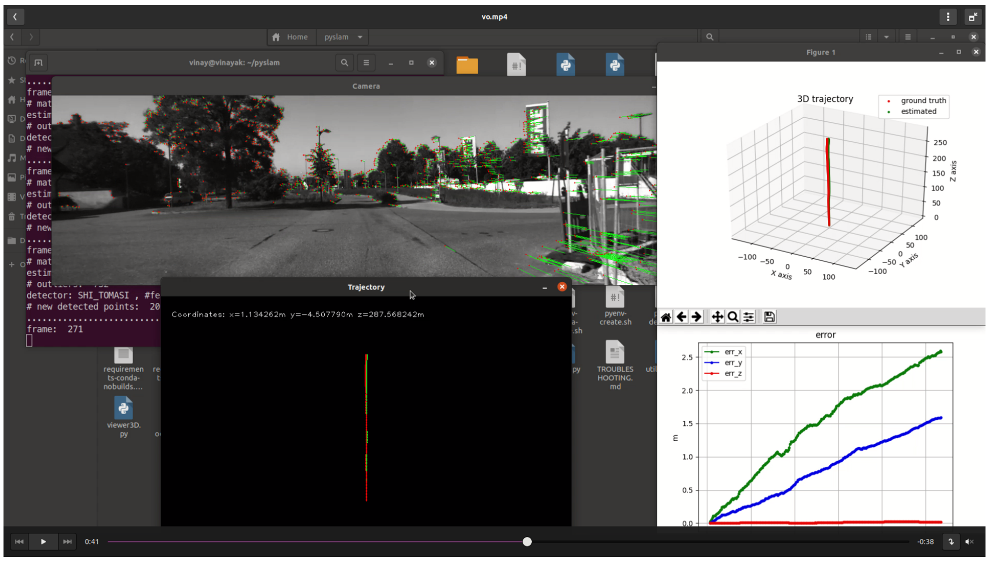
### 4.2.4 Robustness

- **Tracking Robustness:** Assesses the system's ability to maintain accurate tracking in challenging scenarios such as dynamic environments, illumination changes, and motion blur. This can be measured by the percentage of frames where tracking is successfully maintained.

$$TrackingSuccessRate = \frac{NumberofSuccessfullyTrackedFrames}{TotalNumberofFrames} \times 100\% \tag{4.6}$$

- **Failure Recovery:** Evaluates the system's capability to recover from tracking failures, typically measured by the time or number of frames required to relocalize after a tracking loss.

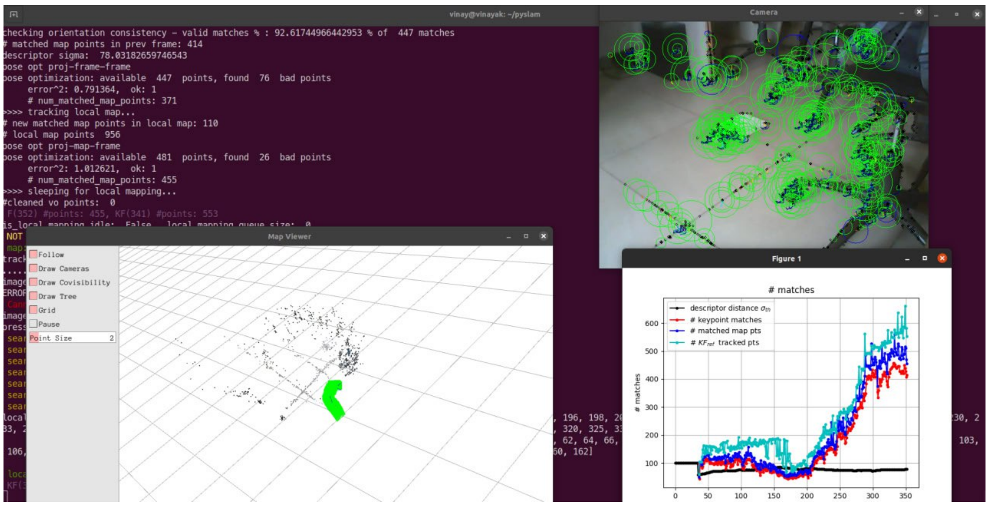
## 4.3 Experimental Results



```
detector: SHI_TOMASI , #fe
# new detected points: 20
..........................
frame: 271
```

```
Coordinates: x=1.134262m y=-4.507790m z=287.568242m
```

Figure 4.1: Results of VISUAL ODOMETRY



```
checking orientation consistency - valid matches % : 92.61744966442953 % of  447 matches
# matched map points in prev frame: 414
descriptor sigma:  78.03182659746543
pose opt proj-frame-frame
pose optimization: available  447  points, found  76  bad points
     error^2: 0.791364,  ok: 1
     # num_matched_map_points: 371
>>>> tracking local map...
# new matched map points in local map: 110
# local map points  956
pose opt proj-map-frame
pose optimization: available  481  points, found  26  bad points
     error^2: 1.012621,  ok: 1
     # num_matched_map_points: 455
>>>> sleeping for local mapping...
#cleaned vo points:  0
 F(352) #points: 455, KF(341) #points: 553
```

Figure 4.2: Results of 3-D Reconstruction using ORB-SLAM

# Chapter 5

# Conclusions and future scope

## 5.1 Conclusion

- Our project demonstrates real-time 3D scene reconstruction using SLAM algorithms, offering practical applications and accessibility.
- SLAM's future lies in semantic scene understanding and multi-sensor fusion for richer contextual understanding and enhanced robustness

SLAM's future lies in semantic scene understanding and multi-sensor fusion for richer contextual understanding and enhanced robustness

## 5.2 Future scope

The field of SLAM-based scene reconstruction is rapidly evolving, with numerous opportunities for advancement and innovation. Below are several potential directions for future research and development:

### 5.2.1 Improved Robustness and Accuracy

- **Enhanced Feature Extraction:** Developing more robust and discriminative feature extraction methods that can handle varying lighting conditions, motion blur, and dynamic scenes can significantly improve SLAM performance.
- **Fusion with Additional Sensors:** Integrating data from additional sensors such as LiDAR, GPS, and barometers can enhance the accuracy and robustness of the SLAM system, particularly in challenging environments.
- **Machine Learning Integration:** Leveraging machine learning techniques for tasks such as feature extraction, matching, and loop closure detection can improve the overall performance and adaptability of SLAM systems.

### 5.2.2 Scalability and Efficiency

- **Optimized Algorithms:** Developing more efficient algorithms for feature extraction, matching, and optimization can reduce the computational load and improve real-time performance.

- **Distributed SLAM:** Exploring distributed SLAM approaches where multiple agents (robots, drones, etc.) collaborate and share their map data can enhance scalability and coverage in large-scale environments.
- **Cloud-based SLAM:** Implementing cloud-based SLAM solutions that offload heavy computations to cloud servers can enable real-time processing on resource-constrained devices.

### 5.2.3 Map Representation and Utilization

- **Semantic Mapping:** Integrating semantic information into the maps (e.g., recognizing objects, structures, and their relationships) can make the maps more informative and useful for high-level tasks.
- **Dense Mapping:** Developing methods for real-time dense mapping that can generate detailed 3D reconstructions can benefit applications in virtual reality, augmented reality, and robotics.
- **Long-term Mapping:** Addressing the challenges of long-term mapping, such as handling map changes over time and ensuring map consistency, is crucial for applications in dynamic environments.

### 5.2.4 Application-Specific Adaptations

- **Autonomous Vehicles:** Tailoring SLAM algorithms to meet the specific requirements of autonomous vehicles, such as high-speed operation and safety-critical environments, can enhance their reliability and performance.
- **Augmented Reality:** Improving SLAM for augmented reality applications, where precise and real-time localization and mapping are critical, can provide more immersive and interactive user experiences.
- **Robotics:** Adapting SLAM systems for various robotic applications, including warehouse automation, agriculture, and healthcare, can expand their usability and impact.

### 5.2.5 User Interaction and Interfaces

- **User-friendly Interfaces:** Developing intuitive user interfaces that allow non-experts to easily set up, configure, and monitor SLAM systems can broaden their accessibility and adoption.
- **Visualization Tools:** Enhancing visualization tools for real-time monitoring and analysis of SLAM performance can aid in debugging and improving system reliability.

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