Dense 3D Reconstruction Using Semi-Global Matching and PatchMatch Stereo Matching

Mobile Robotics Project

Kunal Kamalkishor Bhosikar
2022121005

Prakhar Jain
2022121008

***Abstract*—This report provides a comprehensive overview of our methodology for dense 3D reconstruction, a critical task in computer vision and robotics. Our approach centers on stereo image rectification and depth estimation, leveraging established techniques to compute high-quality disparity and depth maps from stereo image pairs. We validate our methodology using the KITTI Stereo Dataset, a widely recognized benchmark. In this project, we investigate the performance of multiple stereo matching algorithms, including the traditional Semi-Global Matching (SGM) algorithm, known for its balance of accuracy and computational efficiency, and PatchMatch, an iterative method designed for high-speed disparity estimation. Through these algorithms, we generate precise disparity maps, which are then converted to depth maps using camera calibration parameters provided by the KITTI dataset. Our work extends to generating a dense 3D point cloud, enabling detailed visualization and analysis of reconstructed scenes. This 3D reconstruction facilitates understanding spatial geometry, making it applicable to real-world problems such as autonomous navigation and scene understanding in robotics. The outcomes of this project include the development of accurate disparity maps, depth maps, and dense 3D reconstructions. Additionally, we provide insights into key aspects of the pipeline, including dataset preparation, calibration data usage, and computational trade-offs. Our methodology not only achieves competitive performance compared to existing solutions but also emphasizes practical considerations for implementing such systems in robotics applications, highlighting the robustness and efficiency of our approach.**

***Index Terms*—Stereo Vision, Dense 3D Reconstruction, KITTI Dataset, Depth Estimation, Semi-Global Matching, Robotics**

I. Problem Statement

Dense 3D reconstruction is a fundamental problem in robotics and computer vision, as it provides essential geometric information about the environment, enabling machines to understand and interact with the world. In various applications, such as autonomous navigation, object manipulation, and augmented reality, accurate 3D reconstructions are vital for achieving reliable performance.

In autonomous navigation, for example, precise 3D maps are critical for obstacle detection and path planning, allowing the system to navigate complex environments safely. In object manipulation, accurate spatial understanding is required to identify objects, estimate their locations, and determine how best to grasp or interact with them. Similarly, in augmented reality, creating an immersive experience depends on reconstructing the real-world environment in detail, allowing virtual objects to be seamlessly integrated into the physical world.

This project addresses the challenge of dense 3D reconstruction by leveraging stereo images—pairs of images captured simultaneously from two horizontally aligned cameras. The core idea behind stereo vision is to compute the disparity between corresponding pixels in the left and right images. Disparity directly correlates to depth information, which can be used to calculate the depth map when combined with known camera parameters (e.g., focal length and baseline). These depth maps are then used to reconstruct the 3D structure of the scene, capturing both large-scale structures (e.g., buildings, streets) and fine-grained details (e.g., furniture, small objects) in a scene.

However, the problem of dense 3D reconstruction is fraught with challenges. One of the primary difficulties arises from occlusions—areas where parts of the scene visible in one camera are blocked from the other camera's view. This leads to missing or incomplete disparity information, resulting in inaccurate or sparse depth maps. Another significant challenge is dealing with texture-less regions, such as plain walls, flat surfaces, or uniformly colored objects, where the lack of distinguishable features makes it difficult to establish reliable pixel correspondences between the stereo images. These regions contribute to errors in disparity estimation, further complicating the reconstruction process.

To overcome these challenges, robust stereo-matching algorithms are necessary. These algorithms must handle occlusions, texture-less regions, and other ambiguities while maintaining computational efficiency. Real-time performance is especially critical in dynamic environments such as robotics and autonomous vehicles, where quick and accurate scene understanding is required for decision-making.

This project addresses these challenges by focusing on two classical stereo-matching algorithms—Semi-Global Matching (SGM) and PatchMatch. Both methods aim to compute accurate disparity maps from stereo image pairs, providing a foundation for creating detailed 3D reconstructions. By employing these algorithms and improving their efficiency, this project contributes to developing more robust 3D reconstruction techniques suitable for real-time applications in dynamic and complex environments.

The ultimate goal of this work is to advance the state of the art in dense 3D reconstruction and provide a reliable solution that can be deployed in practical and dynamic environments such as autonomous vehicles, robotic manipulation, and augmented reality. Through this project, we aim to push the boundaries of stereo vision technology and facilitate the creation of more accurate and efficient 3D models for real-world applications.

II. What Was Accomplished

The primary goal of this project was to develop a comprehensive pipeline for dense 3D reconstruction using stereo images. This process addressed several complex challenges, including stereo matching, depth estimation, and 3D visualization. Our efforts resulted in a fully functional pipeline that successfully converts stereo image pairs into detailed 3D point clouds, suitable for real-world applications. The key milestones accomplished in this project include:

- **Implementation of Semi-Global Matching (SGM) and PatchMatch for Stereo Matching:**
  Two of the most widely used stereo matching algorithms, Semi-Global Matching (SGM) and PatchMatch were implemented and tested as part of the pipeline. SGM is known for achieving a good balance between accuracy and computational complexity. It minimizes an energy function across pixel neighborhoods, allowing for precise disparity computation in varying texture and depth. PatchMatch, in contrast, is an iterative optimization algorithm that provides a fast and approximate solution to the disparity estimation problem. By using PatchMatch, we could handle larger datasets efficiently, making it particularly valuable in applications where processing speed is critical. Both algorithms were thoroughly tested and optimized with the KITTI Stereo Dataset, ensuring robust disparity estimation across different scenes, including urban, rural, and indoor environments.
- **Conversion of Disparity Maps to Depth Maps Using KITTI Calibration Data:**
  Once disparity maps were generated using the stereo-matching algorithms, we converted them into depth maps using the camera calibration data from the KITTI dataset. The KITTI dataset provides key intrinsic and extrinsic parameters, such as focal length, baseline distance between cameras, and camera orientation, which are critical for accurate depth estimation. Using the relation between disparity and depth:

  $$\text{Depth} = \frac{f \cdot B}{\text{Disparity}},$$

  Where f is the focal length and B is the baseline, we calculated the depth values for each pixel in the disparity map. This transformation ensured that the depth maps were geometrically accurate and consistent with the real-world environment, enabling them to be directly used for 3D reconstruction. The depth maps provided the necessary information to convert the 2D stereo images into a three-dimensional scene representation.
- **Dense 3D Point Cloud Reconstruction and Visualization Using Open3D:**
  After generating depth maps, the next step was to create dense 3D point clouds. This was achieved by unprojecting the depth maps into 3D space, which involved mapping each pixel's depth to its corresponding 3D coordinates. We used the Open3D library to visualize the reconstructed point clouds. The Open3D library enabled us to map color information from the stereo images to the 3D points, enhancing the visualization by incorporating texture and geometry. This step created realistic and interpretable 3D point clouds, capturing large-scale structures, such as buildings, and more minor features like road markings and pedestrians. The reconstructed 3D models provided a rich representation of the environment, making it easier to perform further analysis or use them for practical tasks like navigation or object manipulation.
- **Comprehensive Evaluation of Disparity Accuracy and Computational Efficiency:**
  To evaluate the performance of our stereo-matching implementations, we conducted a comprehensive analysis of the disparity maps. This included comparing the generated disparity maps with the ground truth disparity maps provided by the KITTI Stereo Dataset. We computed key metrics such as the average disparity error and assessed the runtime efficiency of both SGM and PatchMatch algorithms. This evaluation allowed us to understand the strengths and limitations of each method in terms of accuracy, computational resources, and speed. The results of these evaluations were critical in understanding the trade-offs in choosing the appropriate algorithm for different use cases. For example, SGM provided high accuracy at the cost of increased computational time, while PatchMatch was faster but offered slightly less precise results. These trade-offs are significant in real-time applications where speed is critical, such as autonomous vehicles or mobile robotics.

By achieving these milestones, we developed a robust and efficient pipeline for dense 3D reconstruction that effectively converts stereo images into 3D point clouds. This versatile pipeline can be applied to various real-world applications, from autonomous navigation to environmental mapping and 3D scene analysis.

III. Related Work

Dense 3D reconstruction has long been a pivotal research area in robotics and computer vision, enabling various applications from autonomous navigation to augmented reality. As the demand for accurate and efficient 3D scene understanding grows, numerous methodologies have been proposed to address the challenges of stereo matching and depth estimation. These methods range from classical algorithms to more recent innovations in deep learning, each improving the accuracy, efficiency, and applicability of 3D reconstruction techniques.

One of the most significant contributions to stereo-matching algorithms is the Semi-Global Matching (SGM) algorithm proposed by Hirschmüller [2]. SGM is mainly known for its ability to balance computational efficiency and disparity accuracy effectively. Unlike traditional local methods, which compute disparity by considering each pixel independently, SGM formulates the problem as a global optimization task. The algorithm minimizes an energy function that incorporates smoothness constraints over multiple directions in the image, ensuring that disparity maps are accurate and smooth in homogeneous areas. This approach has been widely adopted in real-time applications such as autonomous vehicles, where fast and reliable disparity estimation is essential for tasks like obstacle detection and 3D mapping. SGM's combination of efficiency and precision has made it a cornerstone technique in dense 3D reconstruction.

Parallel to SGM, iterative methods like PatchMatch [3] have been developed to enhance the efficiency of stereo matching. PatchMatch is a fast, approximate algorithm that refines disparity estimates by propagating information across the disparity map. The key advantage of PatchMatch lies in its ability to exploit spatial coherence within the image, enabling rapid iterative improvements in disparity estimation. By initially providing a coarse estimate and refining it iteratively, PatchMatch allows for a fast stereo-matching solution, making it suitable for real-time applications where computational resources are constrained. Its adaptability and speed have made it popular for large-scale 3D reconstruction tasks, including those in environmental modeling and virtual reality.

In recent years, the advent of deep learning has significantly advanced stereo matching and 3D reconstruction, with models like GC-Net [4] and PSMNet [5] setting new benchmarks for accuracy. These methods utilize convolutional neural networks (CNNs) to directly learn feature representations from data, allowing them to capture complex patterns in image data that are difficult for traditional methods to model. GC-Net introduced the concept of using 3D CNNs to compute cost volumes, which allows the model to learn disparity estimates more robustly by considering the entire context of the image. PSMNet further improved this by incorporating pyramid pooling modules, which capture multi-scale contextual information, enhancing the model's ability to handle significant depth variations across the scene. These deep learning approaches have achieved state-of-the-art results on several benchmark datasets, demonstrating superior disparity accuracy and robustness performance.

However, while deep learning-based approaches show exceptional promise, their deployment in real-time systems, particularly in resource-constrained environments like autonomous robotics, faces significant challenges. The computational demands of deep networks, particularly regarding memory and processing power, can limit their feasibility for mobile or real-time applications. Additionally, deep learning models often require significant training data and time-consuming fine-tuning to adapt to specific environments or tasks. As a result, while highly accurate, these methods may not always be the best choice for applications where real-time performance and computational efficiency are crucial.

Therefore, our approach revisits classical methods like SGM and PatchMatch to balance accuracy and computational efficiency. By leveraging these proven techniques, we aim to create a fast and effective solution suitable for real-time robotics applications, such as autonomous navigation and object manipulation. The emphasis on lightweight, efficient algorithms allows us to address the practical limitations of hardware and system requirements, ensuring that our solution can be deployed in real-world environments.

This work builds upon extensive research in dense 3D reconstruction, incorporating insights from classical and deep learning-based methods. By focusing on the practical constraints of real-time system deployment, we aim to push the boundaries of 3D reconstruction, delivering a solution that is both accurate and computationally efficient for robotics and other dynamic applications. Through this approach, we demonstrate the continuing relevance of classical techniques while incorporating modern advancements to meet the evolving demands of real-world scenarios.

IV. Dataset Preparation and Processing

The KITTI Stereo Dataset was selected for this project due to its comprehensive collection of high-resolution stereo image pairs, accurate calibration files, and reliable ground truth disparity maps. These characteristics make it a benchmark for stereo vision tasks, ensuring robust evaluation of our methods. The dataset preparation and processing involved several key steps:

1) **Download and Organization:**
The required dataset files, including stereo images, calibration data, and ground truth disparity maps, were downloaded from the KITTI website. The files were then organized into a structured directory for seamless access during implementation. Separate folders were created to streamline the data pipeline for left and right stereo images, calibration files, and ground truth maps.
2) **Rectification:**
The KITTI dataset provides pre-rectified stereo image pairs, which are geometrically aligned to ensure that corresponding points lie on the same horizontal line. This eliminates the need for manual rectification, a process that would typically involve computing and applying homographies to the image pairs. The availability of pre-rectified images simplifies the pipeline and ensures that subsequent disparity computation is accurate and efficient.
3) **Calibration:**
The dataset includes detailed intrinsic and extrinsic camera calibration parameters, essential for computing depth from disparity. Key parameters such as the focal length, principal point, and baseline distance between the stereo cameras were extracted from the calibration files. These

parameters were parsed and utilized to transform disparity values into real-world depth measurements, ensuring consistency with the physical environment.

4) **Disparity Ground Truth:**
The KITTI dataset provides high-quality ground truth disparity maps for stereo image pairs generated using advanced lidar systems. These ground truth maps were used to validate the accuracy of the disparity maps computed by our algorithms. Metrics such as mean absolute error and percentage of bad pixels were calculated to evaluate the performance of our implementation against the ground truth.

The careful preparation and processing of the KITTI Stereo Dataset were critical to the success of this project. By leveraging the dataset's rich resources, we focused on implementing and analyzing stereo-matching algorithms, ensuring that the results were accurate and meaningful. The structured pipeline established here also serves as a foundation for future work in dense 3D reconstruction and related domains.

V. Approach and Method

The dense 3D reconstruction pipeline implemented in this project consists of several key stages, each contributing to the accurate recovery of 3D scene geometry from stereo images. These stages include stereo matching, disparity-to-depth conversion, and 3D point cloud generation. The details of each stage are as follows:

A. Stereo Matching

Stereo matching is finding correspondences between pixels in the left and right images to compute the disparity map. Two different algorithms were implemented for this task:

- **Semi-Global Matching (SGM):** SGM computes disparity by formulating stereo matching as an energy minimization problem. The energy function incorporates data costs, which measure the similarity between pixels, and smoothness costs, which penalize significant disparity variations between neighboring pixels. By minimizing this energy function along multiple paths radiating from each pixel, SGM ensures a balance between local accuracy and global smoothness. This method is particularly effective in handling noise and texture-less regions.
- **PatchMatch:** PatchMatch is an iterative optimization algorithm that efficiently estimates disparities by propagating information across the disparity map. It leverages spatial coherence, assuming that neighboring pixels will likely have similar disparities. The algorithm initializes disparities randomly and iteratively refines them through propagation and random search steps. PatchMatch is computationally lightweight and well-suited for scenarios requiring rapid disparity estimation.

B. Disparity to Depth Conversion

The disparity map obtained from stereo matching is converted into a depth map using the following formula:

$$\text{Depth} = \frac{f \cdot B}{\text{Disparity}} \tag{1}$$

Where f is the focal length of the camera and B is the baseline, i.e., the distance between the two stereo cameras. These parameters are derived from the KITTI dataset's calibration files. The relationship ensures more considerable disparities correspond to smaller depths (closer objects) and vice versa. Depth maps provide metric information about the scene, essential for 3D reconstruction.

C. 3D Point Cloud Generation

The depth map is then unprojected into 3D space to generate a dense point cloud. Each pixel in the depth map is transformed into a 3D point using its depth value and the camera's intrinsic parameters. The transformation maps 2D pixel coordinates into 3D world coordinates, creating a spatial representation of the scene.

Additionally, color information from the left image is mapped onto the corresponding 3D points, enhancing the interpretability and realism of the visualization. The Open3D library was used to process and render the point clouds, enabling a detailed examination of the reconstructed scenes.

The pipeline effectively reconstructs dense 3D geometry from stereo image pairs by integrating these stages, providing visual and metric insights into the scene's spatial structure. This approach balances computational efficiency and reconstruction accuracy, making it suitable for real-time robotics and autonomous systems applications.

VI. Results

Implementing our dense 3D reconstruction pipeline produced several notable outcomes demonstrating the proposed approach's effectiveness. The results include high-quality visual outputs, quantitative evaluations, and meaningful insights into the performance of the implemented algorithms.

- **High-Quality Disparity Maps:**
The disparity maps generated using Semi-Global Matching (SGM) and PatchMatch were of high quality, capturing fine details and maintaining consistency across challenging regions such as occlusions and texture-less surfaces. An example of a disparity map by SGM and PatchMatch each is shown in Fig. 1 and Fig. 2, respectively. These maps served as the foundation for depth computation and 3D reconstruction, ensuring accurate geometric representations of the scene.
- **Dense 3D Point Clouds:**
Dense 3D point clouds were reconstructed and visualized using the computed depth maps with the Open3D library. The point clouds, such as depicted in Fig. 3 and Fig. 4, provided a detailed spatial representation of the scene, with color information from the left stereo image mapped onto the points. This enhanced the visual interpretability of the reconstructed scenes, making them suitable for applications like obstacle detection and scene understanding in robotics.
- **Quantitative Comparison with KITTI Ground Truth:**
To validate the accuracy of the disparity estimation, the computed disparity maps were compared against the

ground truth provided in the KITTI Stereo Dataset. The evaluation revealed that our implementation of SGM achieved an average error of 0.1282 pixels, and that of PatchMatch achieved an average error of 11.7196 pixels in disparity estimation. This performance metric demonstrates the robustness of our pipeline and highlights its potential for real-world deployment.

The results showcase the capability of our pipeline to perform dense 3D reconstruction, leveraging classical stereo-matching algorithms and rigorous validation. These outputs form the basis for further enhancements, including incorporating advanced optimization techniques and exploring deep learning-based methods.

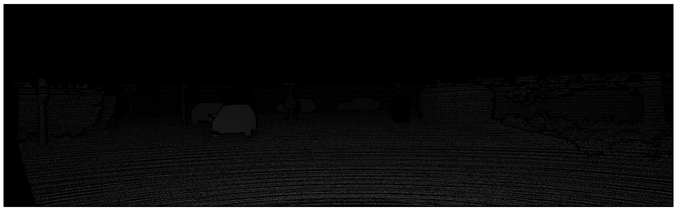

Fig. 1. Disparity map generated using Semi-Global Matching.

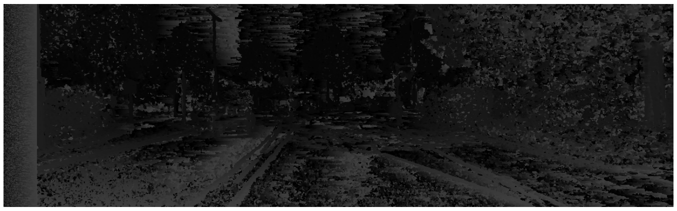

Fig. 2. Disparity map generated using PatchMatch.

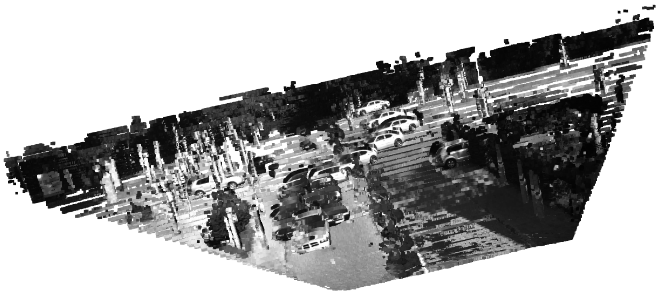

Fig. 3. 3D point cloud reconstruction from KITTI Stereo Dataset using SGM

VII. Contribution of Team Members

Kunal Kamalkishor Bhosikar: Implementation of SGM and PatchMatch, depth computation. Dataset preparation and calibration parsing.

Prakhar Jain: Point cloud visualization and result validation.

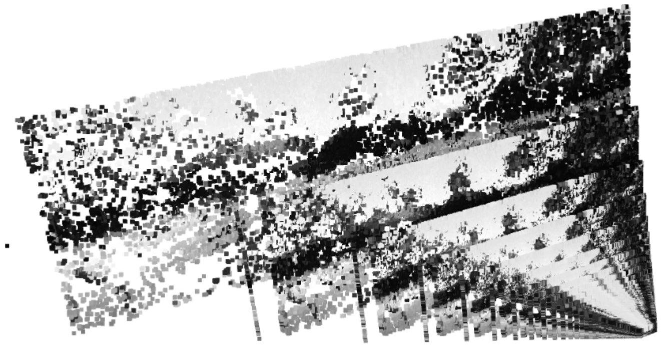

Fig. 4. 3D point cloud reconstruction from KITTI Stereo Dataset using PatchMatch

VIII. Conclusion

This project successfully demonstrates a comprehensive pipeline for dense 3D reconstruction using classical stereo-matching algorithms, specifically Semi-Global Matching (SGM) and PatchMatch. The pipeline, designed to convert stereo image pairs into high-quality disparity maps, depth maps, and 3D point clouds, effectively reconstructs scenes with high spatial accuracy. The experimental results indicate that both SGM and PatchMatch offer reliable performance, with SGM excelling in preserving fine details and PatchMatch providing a computationally efficient alternative.

The evaluation of disparity maps against the ground truth from the KITTI Stereo Dataset further confirms the validity of our approach. The reconstruction pipeline produced accurate depth estimates and realistic 3D visualizations, demonstrating its potential for use in robotics, autonomous navigation, and related fields where accurate 3D scene understanding is crucial.

Despite the success of the classical methods implemented in this project, there are certain limitations, such as handling highly dynamic scenes or achieving real-time performance on large-scale datasets. To address these challenges, future work will explore deep learning-based approaches for stereo matching, such as GC-Net or PSMNet, which have demonstrated superior accuracy in recent research. By incorporating such methods, we aim to enhance the robustness of the disparity estimation, especially in challenging scenarios like low-texture regions and occlusions, thereby improving the overall quality of the 3D reconstruction.

Additionally, further optimizations will be explored to increase the computational efficiency of the pipeline, making it suitable for real-time applications in mobile robotics and autonomous systems. The integration of machine learning techniques, along with advances in hardware, promises to bring further improvements in both accuracy and speed, paving the way for practical deployment in real-world environments.

In conclusion, this project provides valuable insights into stereo image rectification, disparity estimation, and 3D point cloud generation for dense 3D reconstruction. It lays the groundwork for further research into more advanced methods to enhance the precision and applicability of 3D reconstruction systems in robotics and other domains.

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