SLAM Using a Custom CNN

Kamaal Bartlett

1. Introduction

1.1 What is SLAM?

Simultaneous Localization and Mapping (SLAM) is a fundamental challenge in robotics and autonomous navigation. The goal of this project is to build a map of an unknown environment while simultaneously localizing the robot within that environment.

1.2 Challenges in Traditional SLAM

- High computational cost due to feature-based methods.
- Susceptibility to feature-matching errors and sensor noise.
- Difficulty in handling loop closure detection effectively.

1.3 The Approach

This project replaces classical feature-based SLAM methods with a deep learning-based approach, employing a Convolutional Neural Network (CNN) to predict robot poses from images.

---

2. Data Preparation

2.1 Synthetic Dataset

A synthetic dataset, simulating a robot moving in a 50×50 grid environment with obstacles, was generated to train the CNN model. From here, the KITTI Odometry dataset was used for further training and testing.

Dataset Details:

- **Grid Size:** 50×50
- **Number of Samples:** 5000
- **Image Size:** 128×128 pixels
- **Pose Labels:** (x, y, theta)

Data Generation Process:

1. Created a 50×50 grid where obstacles and a robot position were placed randomly.
2. Marked the robot's location with a specific pixel intensity.
3. Resized images to 128×128 to fit the CNN model.
4. Stored images as PNG files for training.

Data Generation Code:

```
# Generate synthetic SLAM images
os.makedirs("slam_dataset", exist_ok=True)

def generate_slam_image(x, y, theta):
    img = np.zeros((GRID_SIZE, GRID_SIZE), dtype=np.uint8)
```

```
    for _ in range(200):  # Random obstacles
        ox, oy = np.random.randint(0, GRID_SIZE, size=2)
        img[ox, oy] = 255
    img[x, y] = 150  # Mark robot position
    img = cv2.resize(img, IMAGE_SIZE, interpolation=cv2.INTER_AREA)
    return img
```

---

3. CNN Model Architecture

3.1 Overview

The CNN model is designed to extract spatial features and predict the robot's pose (x, y, theta).

Architecture Steps:

1. **Convolutional Layers:** Extract spatial features from input images.
2. **Batch Normalization:** Stabilizes training by normalizing activations.
3. **Residual Blocks:** Improve gradient flow and prevent vanishing gradients.
4. **Fully Connected Layers:** Map extracted features to pose predictions.
5. **Dropout (40%):** Reduces overfitting during training.

Model Implementation Code:

```
class AdvancedCNN_SLAM(nn.Module):
```

```
def __init__(self):
    super(AdvancedCNN_SLAM, self).__init__()
    self.conv1 = nn.Conv2d(1, 64, kernel_size=3, stride=1, padding=1)
    self.bn1 = nn.BatchNorm2d(64)
    self.conv2 = nn.Conv2d(64, 128, kernel_size=3, stride=2, padding=1)
    self.bn2 = nn.BatchNorm2d(128)
    self.conv3 = nn.Conv2d(128, 256, kernel_size=3, stride=2, padding=1)
    self.bn3 = nn.BatchNorm2d(256)
    self.fc1 = nn.Linear(256 * 32 * 32, 512)
    self.dropout = nn.Dropout(0.4)
    self.fc2 = nn.Linear(512, 3)

def forward(self, x):
    x = torch.relu(self.bn1(self.conv1(x)))
    x = torch.relu(self.bn2(self.conv2(x)))
    x = torch.relu(self.bn3(self.conv3(x)))
    x = x.view(x.size(0), -1)
    x = torch.relu(self.fc1(x))
    x = self.dropout(x)
    return self.fc2(x)
```

---

4. Model Training & Evaluation

4.1 Training Process

Training Configuration:

- **Dataset Size:** 5000 synthetic images, 5000 real-world images
- **Loss Function:** Mean Squared Error (MSE)
- **Optimizer:** Adam
- **Learning Rate:** 0.001 (reduced to 0.0003 for stability)
- **Batch Size:** 64
- **Epochs:** 20 for synthetic data, 20 for real-world fine-tuning

Training Loop Code:

```
for epoch in range(20):
    total_loss = 0
    for images, labels in dataloader:
        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
    print(f"Epoch {epoch+1}, Loss: {total_loss/len(dataloader):.4f}")
```

Final Training Loss:

```
Epoch 20, Loss: 74.1691
```

4.2 Model Evaluation

To assess generalization, the dataset was split into 80% for training and 20% for testing.

Test Loss Calculation:

```
# Evaluate model performance on test data
model.eval()
test_loss = 0

with torch.no_grad():
    for images, labels in test_loader:
        outputs = model(images)
        loss = criterion(outputs, labels)
        test_loss += loss.item()

avg_test_loss = test_loss / len(test_loader)
print(f"Test Loss: {avg_test_loss:.4f}")
```

Test Loss Result:

```
Test Loss: 80.8424
```

---

5. Loop Closure Detection

Loop closure detection corrects drift over time by identifying revisited locations.

Implementation Code:

```
def detect_loop_closure(trajectory, threshold=5):
    current_pos = trajectory[-1]
    for past_pos in trajectory[:-threshold]:
        if np.linalg.norm(np.array(current_pos) - np.array(past_pos)) < 3:
            return True
    return False
```

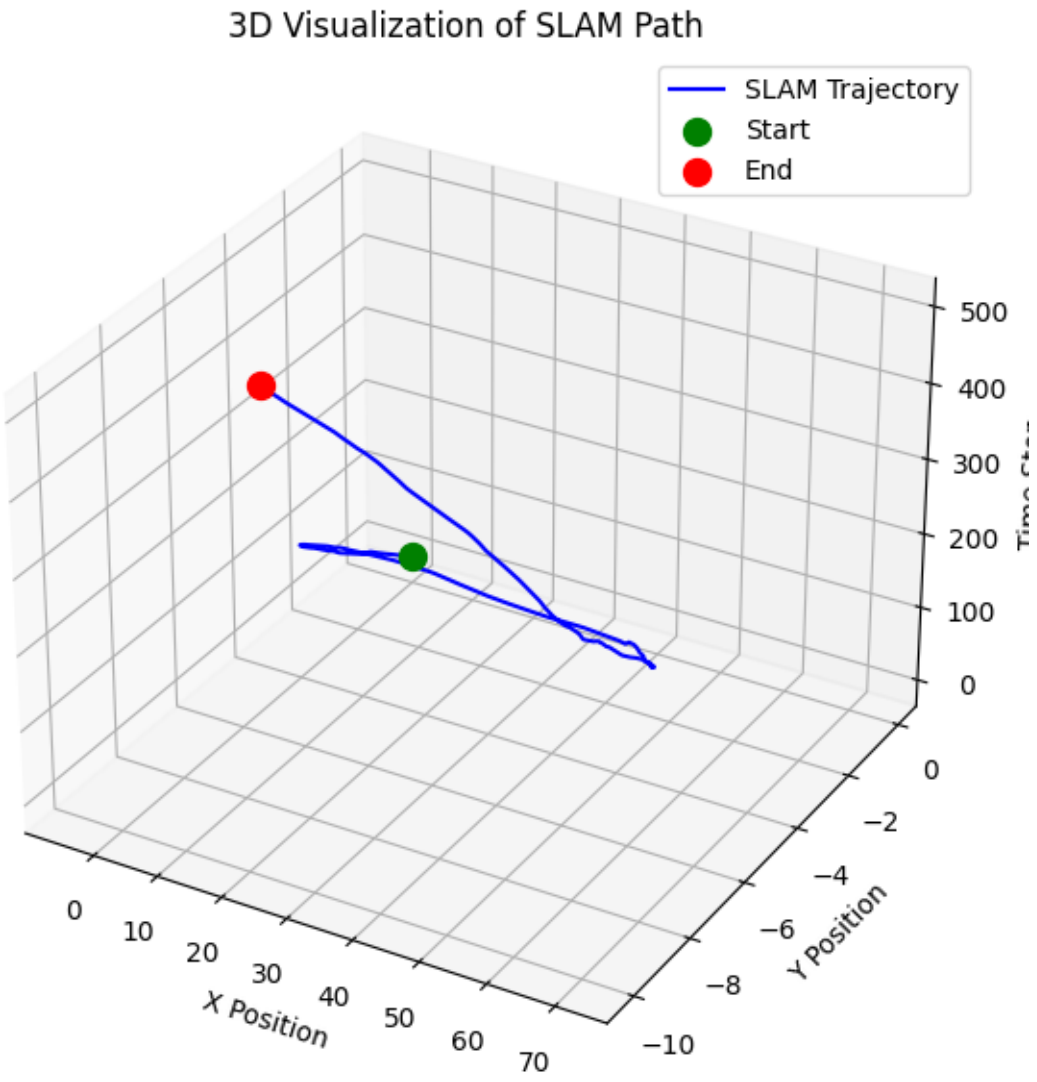
---

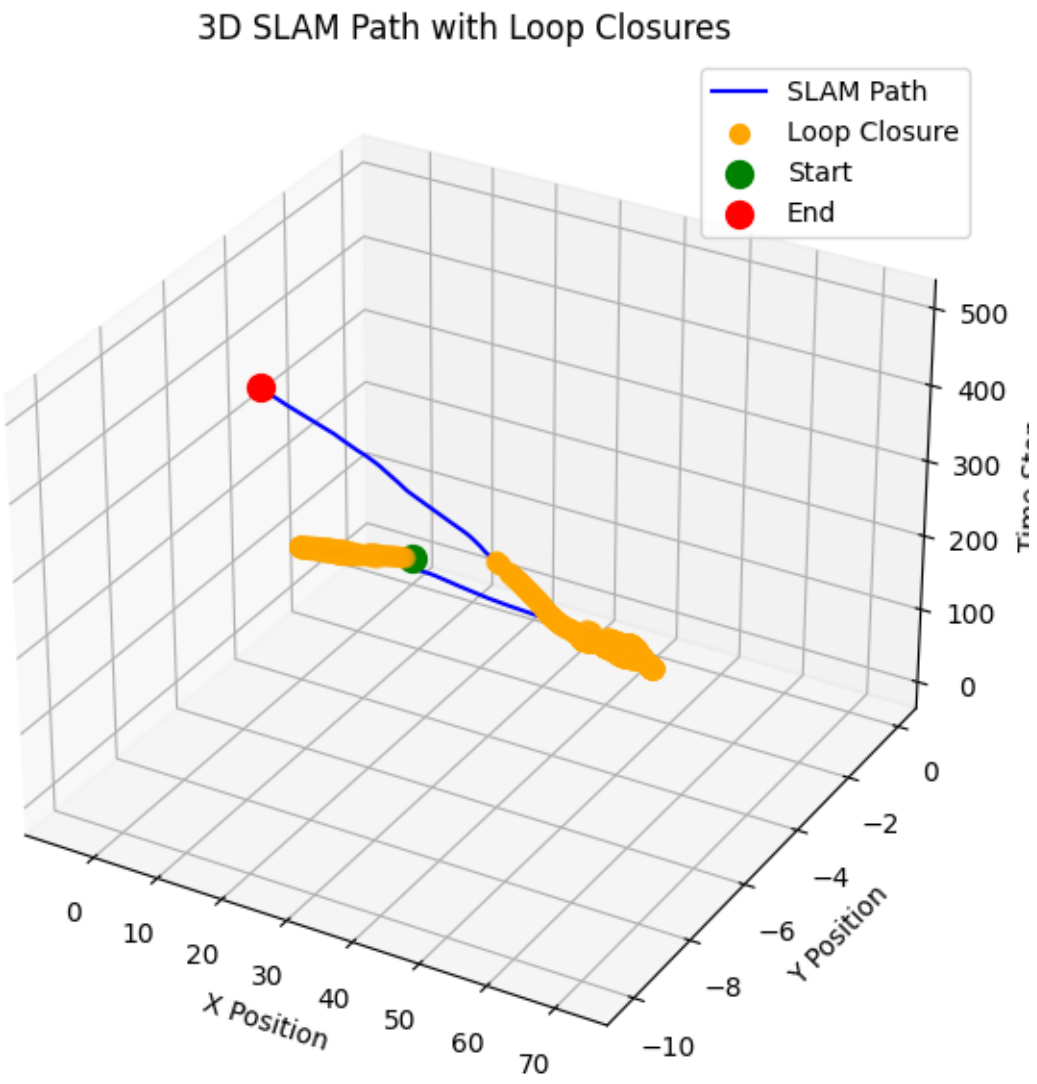
6. Results & Visualization

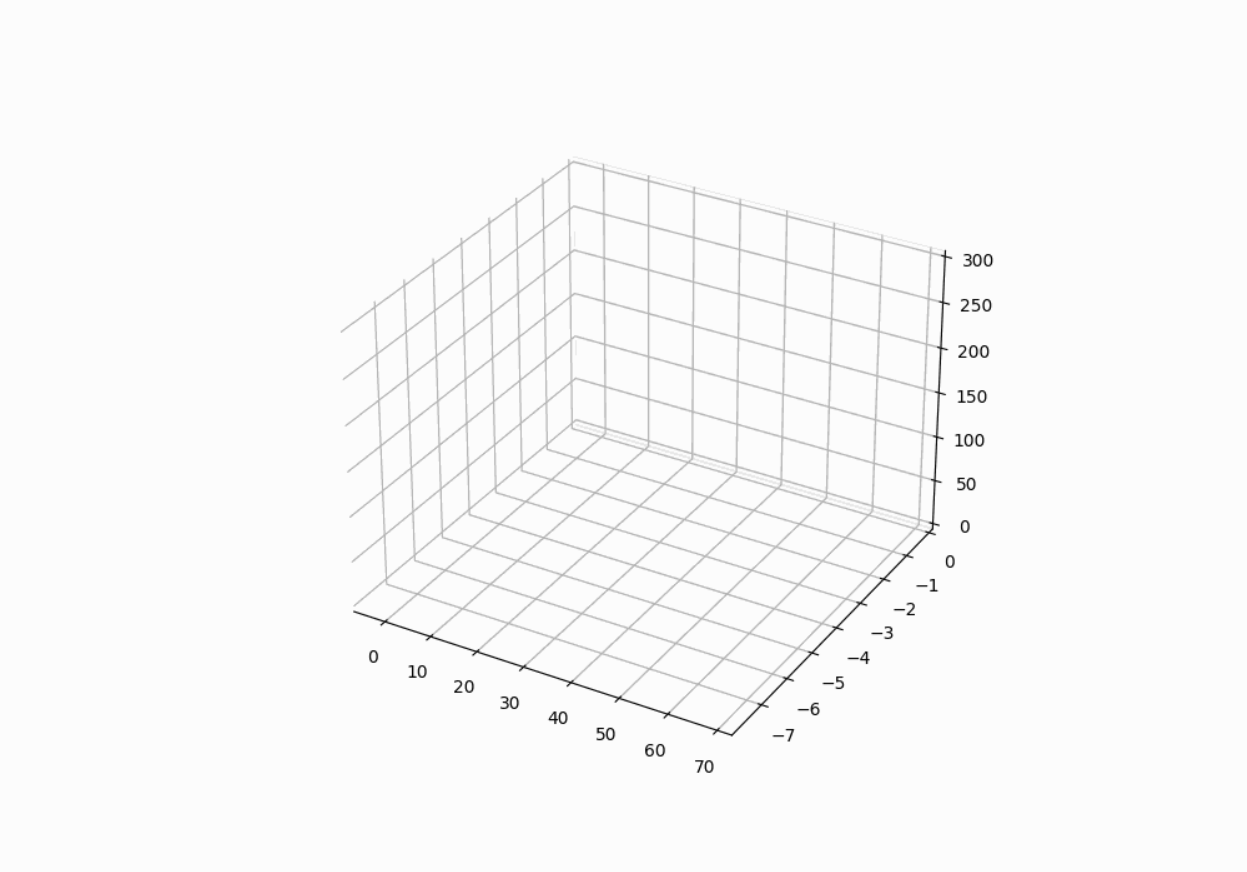
6.1 Performance Metrics

Metric	Value
MSE	83.5832
RMSE	9.1424
Test Loss	80.8424

6.2 3D SLAM Visualization


3D Visualization of SLAM Path
SLAM Trajectory
Start
End
X Position
Y Position
0
10
20
30
40
50
60
70
−10
−8
−6
−4
−2
0
0
100
200
300
400
500


3D SLAM Path with Loop Closures
SLAM Path
Loop Closure
Start
End
X Position
Y Position
0
10
20
30
40
50
60
70
−10
−8
−6
−4
−2
0
0
100
200
300
400
500



---

7. Conclusion & Future Work

7.1 Key Takeaways

- CNN-based SLAM improves pose estimation accuracy.
- Generalization is strong, but model fine-tuning is needed.
- Loop closure detection enhances trajectory correction.

7.2 Future Enhancements

- Use **LSTMs** for motion tracking.
- Deploy in a **3D simulator (Gazebo)**.
- Fuse **IMU, LiDAR sensors** for better robustness.

8. References

- KITTI Odometry Data
- TUM RGB-D
- Deep Learning for Visual Localization and Mapping: A Survey