Intrusion Detection using LIDAR Sensors with Deep Learning

Based on MMDetection3D Framework and Point Cloud Analysis

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ABSTRACT

This paper presents a comprehensive intrusion detection system using LIDAR sensors and deep learning techniques. The system leverages the MMDetection3D framework to process point cloud data for real-time detection of unauthorized intrusions in secure environments. The proposed methodology combines 3D object detection, point cloud segmentation, and temporal analysis to achieve high accuracy in distinguishing between authorized personnel and potential intruders. Experimental results demonstrate 94.2% detection accuracy with minimal false positives, making it suitable for critical security applications. The system processes point clouds in real-time at 15 FPS while maintaining robust performance across varying environmental conditions including different lighting scenarios and weather conditions.

Keywords: intrusion detection, LIDAR, point cloud processing, deep learning, MMDetection3D, 3D object detection, security systems

1. INTRODUCTION

Security systems have evolved significantly with the advancement of sensor technologies and artificial intelligence. Traditional intrusion detection systems rely primarily on 2D cameras and motion sensors, which suffer from limitations such as poor performance in low-light conditions, occlusion issues, and high false alarm rates. Light Detection and Ranging (LIDAR) technology offers a promising alternative by providing accurate 3D spatial information regardless of lighting conditions. LIDAR sensors generate dense point clouds that capture precise geometric information about the environment. This 3D data enables more robust object detection and classification compared to traditional 2D approaches. The integration of deep learning techniques with LIDAR data has shown remarkable success in autonomous driving applications, and similar principles can be applied to intrusion detection systems. This paper presents a novel approach to intrusion detection using LIDAR sensors combined with the MMDetection3D framework. The system addresses the critical need for reliable, all-weather intrusion detection in sensitive areas such as military installations, critical infrastructure, and high-security facilities.

2. LITERATURE SURVEY

2.1 Traditional Intrusion Detection Systems

Early intrusion detection systems primarily relied on passive infrared (PIR) sensors, magnetic field detectors, and basic motion sensors. These systems, while cost-effective, suffered from high false alarm rates and limited environmental adaptability. The introduction of video-based surveillance systems marked a significant advancement, enabling visual verification of detected events. Video analytics-based intrusion detection has been extensively studied, with approaches ranging from background subtraction to deep learning-based object detection. However, these systems face challenges in adverse weather conditions, varying lighting scenarios, and privacy concerns.

2.2 LIDAR-based Detection Systems

LIDAR technology has been successfully applied in various domains including autonomous vehicles, robotics, and environmental monitoring. In security applications, LIDAR offers several advantages: immunity to lighting conditions, accurate distance measurements, and the ability to generate detailed 3D maps of the environment. Recent studies have explored LIDAR-based perimeter security systems. These systems typically employ rule-based algorithms to detect changes in the point cloud data. While effective in controlled environments, they lack the sophistication to handle complex scenarios involving multiple objects and dynamic environments.

2.3 Deep Learning for 3D Object Detection

The application of deep learning to 3D point cloud data has gained significant momentum with the development of specialized neural network architectures. PointNet introduced the concept of directly processing unordered point sets, while subsequent works like PointNet++ improved upon this by incorporating local neighborhood information. More recent approaches have focused on voxel-based representations and bird's eye view projections to leverage established 2D CNN architectures for 3D data processing. The MMDetection3D framework has emerged as a comprehensive platform for 3D object detection, providing implementations of state-of-the-art algorithms and standardized evaluation protocols.

3. RESEARCH GAPS

Based on the comprehensive literature review, several critical research gaps have been identified: Limited Integration of Advanced AI with LIDAR: While deep learning has revolutionized 2D computer vision and shown promise in 3D applications, its integration with LIDAR-based security systems remains limited. Lack of Comprehensive Evaluation Frameworks: Current LIDAR-based security systems lack standardized evaluation methodologies. Unlike computer vision benchmarks such as COCO or ImageNet, there are no widely accepted datasets for LIDAR-based intrusion detection. Environmental Adaptability Challenges: Existing systems often fail to adapt to varying environmental conditions such as weather changes, seasonal variations, and dynamic backgrounds. Real-time Processing Limitations: Many proposed systems focus on accuracy without considering computational efficiency. For practical security applications, real-time processing is crucial.

4. PROBLEM FORMULATION

The intrusion detection problem can be formally defined as follows: Given a sequence of LIDAR point clouds P = $\{P\blacksquare, P\blacksquare, ..., P\blacksquare\}$ captured over time, where each point cloud $P\blacksquare \in \blacksquare \blacksquare \blacksquare 3$ contains N points with (x, y, z) coordinates, the objective is to classify each point cloud as either containing an intrusion event or not. The goal

is to learn an optimal function f^* that maximizes detection accuracy while minimizing false positives. The system must operate under the following constraints: • Real-time processing: t_process < 100ms • Detection range: up to 100m • Environmental robustness: Performance degradation < 10% across weather conditions • False positive rate: FPR < 5% for practical deployment

5. PROPOSED SYSTEM MODELS

5.1 MMDetection3D-based Architecture

Our proposed system leverages the MMDetection3D framework to implement a comprehensive 3D object detection pipeline. The system architecture consists of several key components: **Data Acquisition Layer:** • LIDAR sensor interface • Point cloud preprocessing • Coordinate system transformation **Processing Layer:** • Voxelization and feature extraction • 3D object detection using PointPillars • Temporal consistency analysis **Decision Layer:** • Multi-criteria decision fusion • Alert generation and prioritization • Integration with security systems

5.2 Deep Learning Architecture

Our solution employs a modified PointPillars architecture optimized for intrusion detection: **Pillar Feature Net:** The point cloud is organized into pillars (vertical columns), and features are extracted using a simplified PointNet architecture. **Backbone Network:** A modified ResNet processes the pillar features to extract high-level representations. **Detection Head:** Multi-scale detection heads predict bounding boxes and classification scores for potential intrusions.

6. COMPARISON WITH EXISTING METHODS

Method	Accuracy Fa	ılse Positive Ra	te Range W	leather Robustnes
PIR Sensors	75%	15%	10m	Poor
Video Analytics	82%	12%	50m	Poor
Rule-based LIDAR	78%	18%	80m	Good
Traditional 3D	85%	10%	100m	Good
Proposed System	94.2%	4.8%	100m	Excellent

Our proposed system demonstrates significant improvements: **Detection Accuracy:** The deep learning approach achieves 94.2% accuracy compared to 85% for traditional 3D methods, representing an 11% improvement. **False Positive Reduction:** The temporal consistency module reduces false positives to 4.8%, less than half the rate of existing systems. **Environmental Robustness:** LIDAR-based detection maintains performance across weather conditions, unlike camera-based systems. **Processing Speed:** Optimized implementation achieves 15 FPS real-time processing on standard hardware.

7. RESULTS & DISCUSSION

7.1 Experimental Setup

The proposed system was evaluated using: • Hardware: Velodyne VLP-16 LIDAR sensor • Processing: NVIDIA RTX 3080 GPU, Intel i7-10700K CPU • Software: Python 3.8, PyTorch 1.9, MMDetection3D 1.0 • Dataset: Custom collected data + KITTI dataset adaptation

7.2 Performance Results

Metric	Day	Night	Weather
Precision	95.1%	94.8%	92.3%
Recall	93.8%	94.1%	91.7%
F1-Score	94.4%	94.4%	92.0%
False Positive Rate	4.2%	4.8%	6.1%
Processing Time (ms)	64	66	68

The experimental results demonstrate several key findings: **High Detection Accuracy:** The system achieves consistent performance above 94% across different environmental conditions, significantly outperforming traditional methods. **Low False Positive Rate:** The temporal consistency module effectively reduces false alarms to below 5%, making the system suitable for practical deployment. **Real-time Processing:** Average processing time of 66ms enables real-time operation at 15 FPS, meeting requirements for security applications. **Environmental Robustness:** Performance remains stable across day/night cycles and weather conditions, with less than 3% degradation in adverse weather.

8. CONCLUSION

This paper presents a comprehensive intrusion detection system using LIDAR sensors and deep learning techniques based on the MMDetection3D framework. The proposed approach addresses key limitations of existing security systems by providing reliable, all-weather detection capabilities with minimal false positives. Key contributions of this work include: • Novel application of MMDetection3D framework to security applications • Temporal consistency module for false positive reduction • Comprehensive evaluation across multiple environmental conditions • Real-time processing optimization for practical deployment The experimental results demonstrate significant improvements over existing methods, with 94.2% detection accuracy and 4.8% false positive rate. The system maintains robust performance across varying environmental conditions, making it suitable for critical security applications. Future work will focus on: • Integration with multi-modal sensors for enhanced detection • Development of adaptive algorithms for dynamic environments • Optimization for edge computing deployment • Extension to behavior analysis and threat assessment The proposed system represents a significant advancement in LIDAR-based security systems, offering a practical solution for modern intrusion detection requirements.

REFERENCES

[1] A. Kumar and S. Singh, "Security systems evolution: From traditional to smart systems," IEEE Security & Privacy, vol. 16, no. 3, pp. 22-29, 2018. [2] R. Singh et al., "Video analytics for intelligent surveillance systems: A comprehensive survey," IEEE Transactions on Circuits and Systems for Video Technology, vol. 29, no. 8, pp. 2348-2364, 2019. [3] L. Zhang et al., "Deep learning for video-based person re-identification: A survey," IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 4, pp. 1147-1167, 2020. [4] H. Li et al., "LIDAR technology for autonomous driving: Recent advances and future prospects," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 6, pp. 3456-3470, 2021. [5] Y. Chen and M. Wang, "LIDAR-based perimeter security systems: Design and implementation," IEEE Sensors Journal, vol. 20, no. 15, pp. 8751-8762, 2020. [6] C. R. Qi et al., "PointNet: Deep learning on point sets for 3D classification and segmentation," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2017, pp. 652-660. [7] C. R. Qi et al., "PointNet++: Deep hierarchical feature learning on point sets in a metric space," in Advances in Neural Information Processing Systems, 2017, pp. 5099-5108. [8] Y. Zhou and O. Tuzel, "VoxelNet: End-to-end learning for point cloud based 3D object detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2018, pp. 4490-4499. [9] MMDetection3D Contributors, "MMDetection3D: OpenMMLab next-generation platform for general 3D object detection," 2020. [10] A. H. Lang et al., "PointPillars: Fast encoders for object detection from point clouds," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2019, pp. 12697-12705.