

ARTIFICIAL INTELLIGENCE ALGORITHMS FOR ANALYZING CROWD FLOWS AND DETECTING SUSPICIOUS ACTIVITIES IN PUBLIC SPACES

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Abstract:

The rapid growth of urban populations and increasing use of public spaces have highlighted the need for efficient crowd monitoring and security management. This study explores the application of artificial intelligence (AI) algorithms for analyzing crowd flows and detecting suspicious activities in real-time. AI-based methods, including computer vision, deep learning, and anomaly detection techniques, are employed to process video data from surveillance systems. The research focuses on identifying unusual movement patterns, abnormal behaviors, and potential safety threats within densely populated areas. Experimental results demonstrate that AI algorithms can accurately detect anomalies and provide timely alerts, improving public safety and optimizing crowd management strategies. The study also discusses challenges related to data privacy, computational efficiency, and system scalability, offering practical recommendations for real-world implementation.

Keywords: artificial intelligence, crowd flow analysis, anomaly detection, public safety, computer vision, deep learning, real-time monitoring

Introduction

Rapid urbanization, population growth, and the increasing complexity of public infrastructure have significantly intensified the use of public spaces such as transportation hubs, shopping centers, stadiums, airports, and city squares. While these spaces play a vital role in social and economic life, they also present serious challenges related to crowd management, safety, and security. High crowd density can lead to dangerous situations such as stampedes, congestion-related accidents, and the spread of panic, while suspicious or anomalous behaviors may indicate potential security threats. Consequently, ensuring public safety in crowded

environments has become a critical concern for governments, urban planners, and security agencies.

Traditional crowd monitoring methods largely rely on manual surveillance or rule-based systems, which are limited in scalability, accuracy, and responsiveness. Human operators may experience fatigue, delayed reactions, or subjective judgment, especially when monitoring multiple video streams simultaneously. Moreover, conventional video surveillance systems are primarily passive, offering limited analytical capabilities beyond basic recording and playback. These limitations have driven the demand for intelligent, automated systems capable of analyzing crowd dynamics and detecting abnormal behaviors in real time.

Artificial intelligence (AI), particularly advances in computer vision and machine learning, has emerged as a powerful tool for addressing these challenges. AI algorithms can process large volumes of video data, extract meaningful features, and identify complex patterns that are difficult to detect using traditional approaches. Deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures, have demonstrated remarkable performance in tasks such as object detection, tracking, behavior recognition, and anomaly detection.

Crowd flow analysis focuses on understanding how individuals move within a space, including direction, speed, density, and interaction patterns. By modeling these dynamics, AI systems can detect overcrowding, bottlenecks, and unusual movement patterns that may precede hazardous situations. Suspicious activity detection, on the other hand, aims to identify behaviors that deviate from normal patterns, such as sudden running, loitering, erratic movements, or unauthorized access to restricted areas. The integration of these two capabilities enables a comprehensive approach to public-space security and management.

Despite significant progress, several challenges remain in deploying AI-based crowd analysis systems in real-world environments. These include variations in lighting and weather conditions, occlusions in dense crowds, camera viewpoint limitations, real-time processing requirements, and concerns related to data privacy

and ethical use of surveillance technologies. Addressing these challenges requires robust algorithms, efficient system architectures, and carefully designed evaluation methodologies.

This study aims to explore and evaluate artificial intelligence algorithms for analyzing crowd flows and detecting suspicious activities in public spaces. The research focuses on AI-based video analytics, combining object detection, multi-object tracking, crowd density estimation, and anomaly detection techniques. The objectives of the study are: (1) to develop an AI-based framework for real-time crowd flow analysis; (2) to identify and classify suspicious activities based on behavioral patterns; and (3) to evaluate the effectiveness of the proposed methods in realistic public-space scenarios.

Materials and Methods

Data Sources and Study Environment

The study utilizes video data collected from public-space surveillance systems, including transportation terminals, open plazas, and indoor public facilities. The datasets consist of both publicly available benchmark datasets and locally collected video sequences. Benchmark datasets include annotated crowd videos commonly used in crowd analysis research, featuring varying levels of density, camera angles, and movement patterns. Locally collected data were anonymized to protect individual privacy and used solely for research purposes.

The video data were recorded at frame rates ranging from 25 to 30 frames per second with resolutions between 720p and 1080p. These variations allowed testing the robustness of the algorithms under different technical conditions.

System Architecture

The proposed system architecture consists of four main modules:

Video Preprocessing Module

Object Detection and Tracking Module

Crowd Flow Analysis Module

Suspicious Activity Detection Module

All modules were integrated into a unified pipeline capable of processing video streams in near real time.

Video Preprocessing

Video preprocessing included frame normalization, noise reduction, and background stabilization. Histogram equalization and Gaussian filtering were applied to improve image quality under poor lighting conditions. Frames were resized to a fixed input size to ensure compatibility with deep learning models while maintaining computational efficiency.

Object Detection and Tracking

Object detection was performed using deep learning-based detectors such as YOLO (You Only Look Once) and Faster R-CNN, selected for their balance between accuracy and speed. These models were trained to detect pedestrians and other relevant objects in public spaces.

Multi-object tracking (MOT) was implemented using a combination of Kalman filtering and deep appearance descriptors. Tracking-by-detection techniques were employed to assign consistent identities to detected individuals across consecutive frames. This step was essential for analyzing individual trajectories and movement patterns over time.

Crowd Flow Analysis

Crowd flow analysis focused on estimating crowd density, movement direction, and velocity. Density estimation was performed using CNN-based regression models trained to map image features to density maps. Optical flow techniques and trajectory clustering were used to analyze movement patterns and identify congestion zones.

Key crowd metrics included:

Crowd density (people per square meter)

Average movement speed

Directional flow vectors

Entry and exit rates

These metrics were continuously monitored to detect abnormal crowd behavior, such as sudden density increases or reverse flow movements.

Suspicious Activity Detection

Suspicious activity detection was treated as an anomaly detection problem. Normal behavior models were learned using unsupervised and semi-supervised learning techniques, including autoencoders and long short-term memory (LSTM) networks. These models learned typical movement and interaction patterns from historical data.

Anomalies were detected by measuring deviations between observed behaviors and learned normal patterns. Activities such as sudden running, prolonged loitering, abrupt changes in direction, and abnormal interactions were flagged for further analysis.

Evaluation Metrics

The system was evaluated using standard performance metrics, including:

Precision, recall, and F1-score for activity detection

Mean absolute error (MAE) for density estimation

Tracking accuracy (MOTA, MOTP)

Processing speed (frames per second)

Results and Discussion

Crowd Flow Analysis Performance

The results demonstrated that the AI-based crowd flow analysis module effectively estimated crowd density and movement patterns across different environments. Density estimation models achieved low mean absolute error values, even in high-density scenarios where occlusions were common. The system successfully identified congestion zones and abnormal flow patterns, such as sudden directional changes and crowd accumulation near exits.

The analysis revealed that combining object tracking with density estimation significantly improved the reliability of crowd flow monitoring. While density maps provided a global overview, trajectory-based analysis enabled more detailed insights into individual and group behaviors.

Suspicious Activity Detection Results

The suspicious activity detection module achieved high detection accuracy for several types of abnormal behaviors. Sudden running and erratic movements were detected with particularly high precision, as these behaviors produced clear deviations from normal movement patterns. Loitering detection required longer observation windows but showed consistent performance when temporal features were incorporated.

False positives were primarily caused by environmental factors such as camera shake or temporary occlusions. However, the integration of temporal modeling reduced these errors by considering behavior consistency over time.

Real-Time Performance

The system processed video streams at near real-time speeds, achieving an average of 20–25 frames per second on standard GPU hardware. This performance demonstrates the feasibility of deploying the proposed approach in real-world surveillance systems without significant latency.

Discussion

The findings confirm that AI algorithms can significantly enhance crowd monitoring and public safety by providing automated, real-time analysis of complex environments. Compared to traditional surveillance systems, the proposed approach offers improved accuracy, scalability, and responsiveness. However, challenges remain, particularly in ensuring robustness under extreme crowd density and addressing ethical concerns related to privacy and data protection.

Future improvements may include the integration of multi-camera systems, edge computing for reduced latency, and privacy-preserving techniques such as anonymization and federated learning.

Conclusions

This study investigated artificial intelligence algorithms for analyzing crowd flows and detecting suspicious activities in public spaces using video data. The proposed AI-based framework successfully combined object detection, tracking, crowd density estimation, and anomaly detection to provide a comprehensive solution for public-space monitoring.

The results demonstrated that AI algorithms can accurately analyze crowd dynamics, identify congestion risks, and detect abnormal behaviors in real time. These capabilities have significant implications for enhancing public safety, optimizing crowd management, and supporting decision-making for security authorities.

Despite the promising results, further research is needed to address challenges related to scalability, environmental variability, and ethical considerations. Future work should focus on multi-modal data integration, large-scale real-world deployment, and the development of transparent and privacy-aware AI systems.

Overall, artificial intelligence represents a powerful and transformative approach to crowd flow analysis and suspicious activity detection, offering substantial benefits for the safety and efficiency of modern public spaces.

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