A Project Report

on

Anomalous Human Activity Detection

carried out as part of the course CSE CS3270 Submitted by

Sumit Kumar & Vaibhav Kumar Goel

219301597, 219301152

VI-CSE

in partial fulfilment for the award of the degree

of

BACHELOR OF TECHNOLOGY

In

Computer Science and Engineering

MANIPAL UNIVERSITY JAIPUR

(University under Section 2(f) of the UGC Act)

Department of Computer Science and Engineering,
School of Computer Science and Engineering,
Manipal University Jaipur,

JAN-MAY 2024

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Student Signature

Student Name : Sumit Kumar & Vaibhav Kumar Goel
Registration No. : 219301597 & 219301152

MANIPAL UNIVERSITY
JAIPUR
(University under Section 2(f) of the UGC Act)

Department of Computer Science and Engineering
School of Computer Science and Engineering

Date: March 29, 2024

CERTIFICATE

This is to certify that the project entitled "**Anomalous Human Activity Detection** " is a bonafide work carried out as ***Minor Project Midterm Assessment (Course Code: CS3270)*** in partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science and Engineering, by ***Sumit Kumar & Vaibhav Kr Goel*** bearing registration number ***219301597 & 219301152***, during the academic semester *VI of year 2023-2024.*

Signature of the project guide: ______________________

Name of the project guide: **Dr. Sandeep Chaurasia**

Place: Manipal University Jaipur, Jaipur

Contents

INTRODUCTION

1.1 OBJECTIVES OF THIS PROJECT:

The primary objective of our project is to tackle the escalating concern over security breaches and anti-social activities within various environments. Traditional methods of surveillance often rely on manual monitoring, which is both labor-intensive and prone to oversight. Recognizing the limitations of human surveillance, our goal is to develop an advanced surveillance system capable of autonomously detecting and flagging unusual or abnormal activities in video footage.

To achieve this objective, our project focuses on the development of a sophisticated model equipped with artificial intelligence and computer vision algorithms. This model will be trained to analyze motion characteristics and patterns within crowd scenes, enabling it to identify deviations from normal behavior effectively. By implementing a combination of local and global detection techniques, our system aims to provide comprehensive coverage and accurate identification of abnormal events.

Ultimately, our project seeks to offer organizations and security agencies a powerful tool for enhancing surveillance capabilities, mitigating risks, and ensuring the safety and security of various environments.

1.2 DESCRIPTION OF THIS PROJECT:

In today's world, security concerns have escalated due to the increasing prevalence of anti-social activities. To address this, organizations have turned to constant monitoring through the deployment of Closed-Circuit Television (CCTV) systems. However, the sheer volume of data generated by these systems makes it impractical for human operators to manually analyze and identify abnormal events. This presents a significant challenge as timely detection of such events is crucial for ensuring public safety and security.

Our project aims to tackle this challenge by developing an intelligent surveillance system capable of automatically detecting unusual or abnormal activities in crowded scenes captured by CCTV cameras. The system leverages advanced computer vision techniques to analyze motion characteristics and identify patterns indicative of abnormal behavior. By automating the surveillance process, our system reduces the burden on human operators and enables timely intervention in potentially threatening situations.

One of the key features of our system is its ability to provide accurate detection and localization of abnormal activities within crowded scenes. By analyzing motion patterns and spatial relationships between objects in the scene, the system can identify deviations from normal behavior and flag them as potential security threats. This granular level of analysis allows for targeted intervention and response, enhancing overall security measures.

To achieve this, we employ a generalized framework that combines local and global approaches to anomaly detection. This framework enables the system to adapt to diverse environments and scenarios, ensuring robust performance across different settings. Additionally, we utilize advanced machine learning algorithms to continuously refine and improve the system's performance over time.

Our project has the potential to revolutionize the field of video-based surveillance by providing organizations with a powerful tool for enhancing security and public safety. By automating the detection of abnormal activities, our system enables proactive intervention and response, mitigating potential risks and ensuring a safer environment for all.

In summary, our project aims to develop an intelligent surveillance system that can automatically detect and localize abnormal activities in crowded scenes captured by CCTV cameras. By leveraging advanced computer vision and machine learning techniques, we seek to enhance security measures and ensure timely intervention in potentially threatening situations.

1.3 TECHNOLOGY USED

1.3.1 Hardware Requirements:

- CPU: Intel Core i3 or equivalent
- GPU: NVIDIA GeForce GTX 1050 or higher
- Storage: Minimum 500GB HDD/SSD
- RAM: 8 GB or higher
- Camera: High-resolution CCTV cameras compatible with the system
- Network: Stable internet connection for data transfer and remote access

1.3.2 Software Requirements:

- Python: Version 3.11 or higher
- PyTorch: Version 1.7 or higher
- OpenCV: Required for Computer Vision tasks.
- Version Control: Git for collaborative development
- Visualization: Matplotlib, Seaborn for data visualization
- Deployment: Docker for containerization, Kubernetes for orchestration
- Miscellaneous: Image processing libraries (e.g., PIL), video editing tools

DESIGN DESCRIPTION

2.1 FLOWCHART:

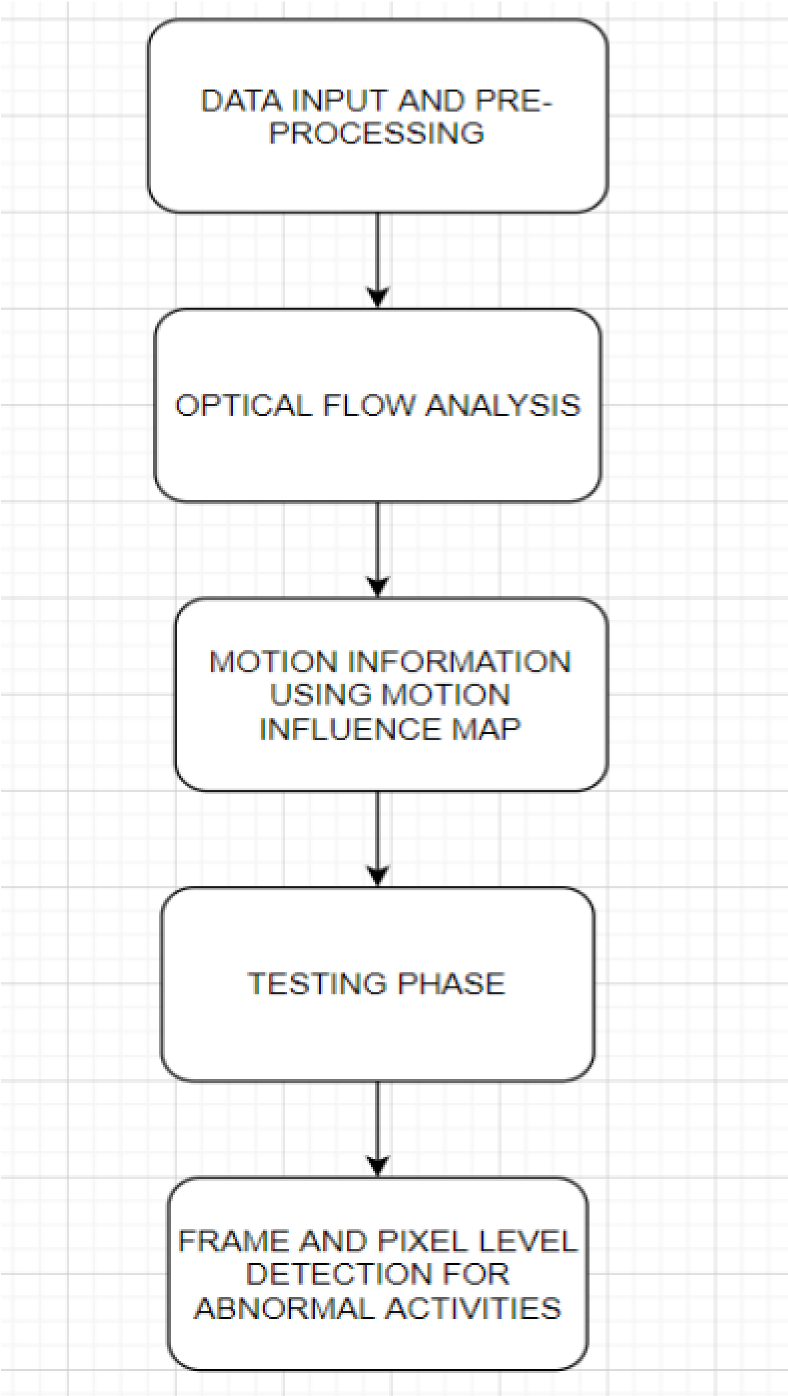


Fig. Control Flow Diagram

2.2 SEQUENCE DIAGRAM:

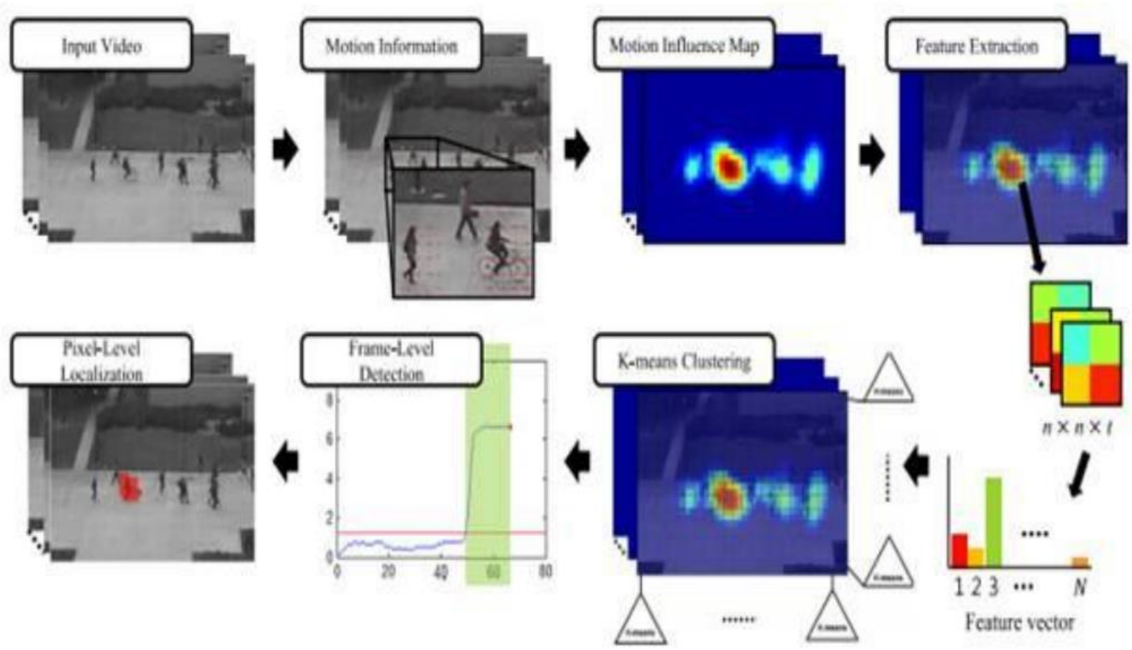


Fig. Sequence Diagram - 1

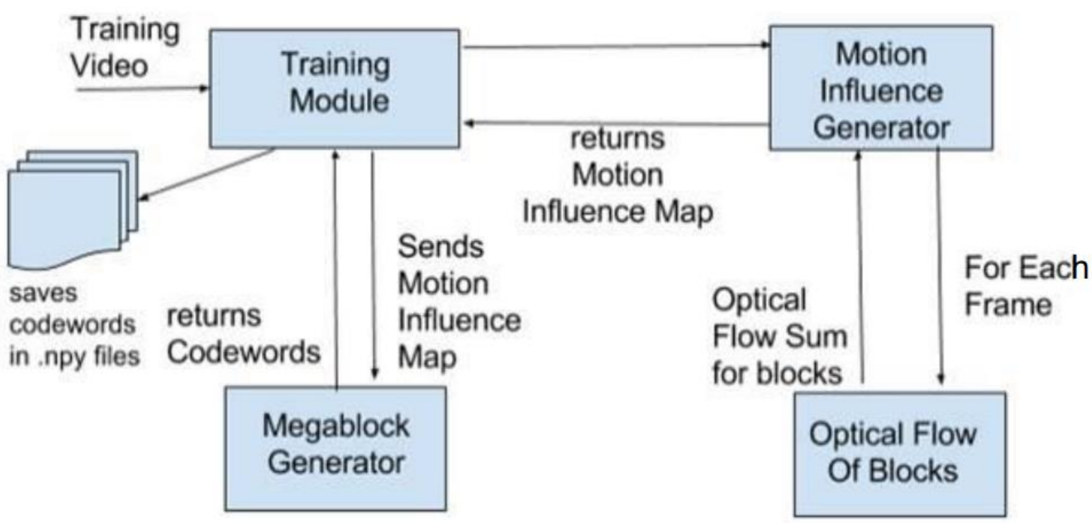


Fig. Sequence Diagram – 2

PROJECT DESCRIPTION

3.1 DATABASE:

The database infrastructure in the Abnormal Human Activity Detection System is meticulously designed to efficiently manage the diverse range of data generated and processed during surveillance activities. It encompasses data modeling to define tables and relationships, storage structures for optimal data organization, indexing for fast data retrieval, and normalization to minimize redundancy. Optimization techniques are applied to enhance performance, including query optimization and database tuning. Regular backups and recovery mechanisms safeguard against data loss, while security measures such as access control and encryption ensure data confidentiality and integrity. Overall, the database architecture provides a robust foundation for storing, accessing, and analyzing video files, frames, abnormal events, and other relevant data, supporting the system's surveillance objectives effectively and reliably.

3.2 TABLE DESCRIPTION:

The database consists of several tables designed to organize and manage different types of data effectively. These tables include:

1. VideoData: This table stores information about the input video files, including metadata such as filename, duration, resolution, and format.

2. FrameData: This table contains details about individual frames extracted from the input videos. Each record includes frame number, timestamp, and associated video file.

3. AbnormalFrames: This table records abnormal frames detected during the analysis process. It stores frame identifiers along with timestamps and corresponding abnormality scores.

4. MotionInfluenceMap: This table holds data related to motion influence maps generated for each frame. It includes motion vectors, block-wise motion influence values, and other relevant attributes.

5. FeatureVectors: This table stores feature vectors extracted from frames for further analysis. It includes information about feature extraction methods, dimensions, and associated frames.

6. Codewords: This table contains codewords generated during the training phase for normal activity patterns. It stores information about codeword identifiers, corresponding feature vectors, and clustering results.

3.3 File/Database Design:

The file/database design encompasses the structure and organization of data within the database system. It includes considerations for data storage, indexing, retrieval mechanisms, and optimization strategies to ensure efficient data handling and processing.

- Storage Structure: Data is stored in relational tables using appropriate data types and constraints to maintain data integrity and consistency.

- Indexing: Indexes are created on key columns to improve query performance and facilitate fast data retrieval operations.

- Normalization: The database schema is normalized to reduce redundancy and minimize data anomalies, ensuring data integrity and efficient storage utilization.

- Optimization: Optimization techniques such as query optimization and database tuning are applied to enhance system performance and responsiveness.

- Backup and Recovery: Regular backups are performed to safeguard against data loss, with mechanisms in place for data recovery in case of system failures or errors.

- Security: Access control mechanisms and encryption techniques are implemented to secure sensitive data and prevent unauthorized access or tampering.

<u>Input/Output Form Design</u>

4.1 INPUT FORM:

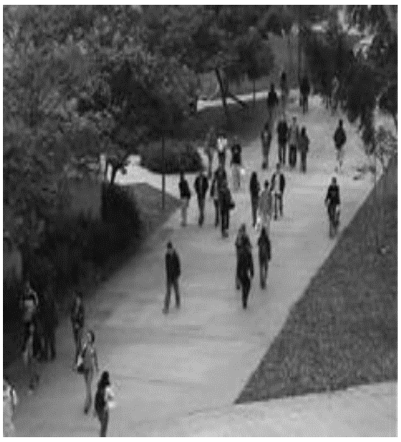


Fig Input Data Scene – 1

Fig Input Data Scene – 2

Fig RGB and Gray Scale of Input Data Scene

4.2 OUTPUT FORM:

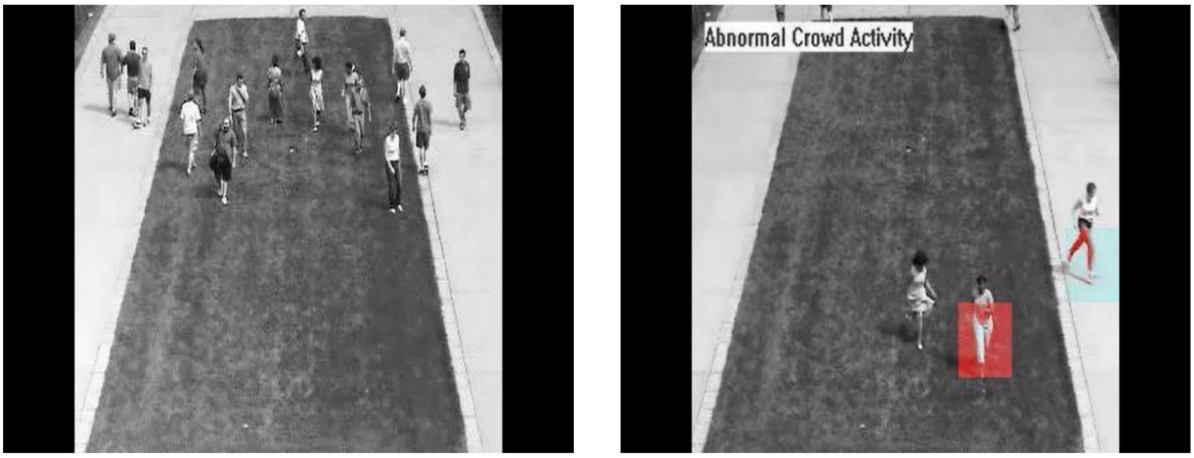


Fig Output- Abnormal Crowd Detected(A person Suddenly Starts Running)

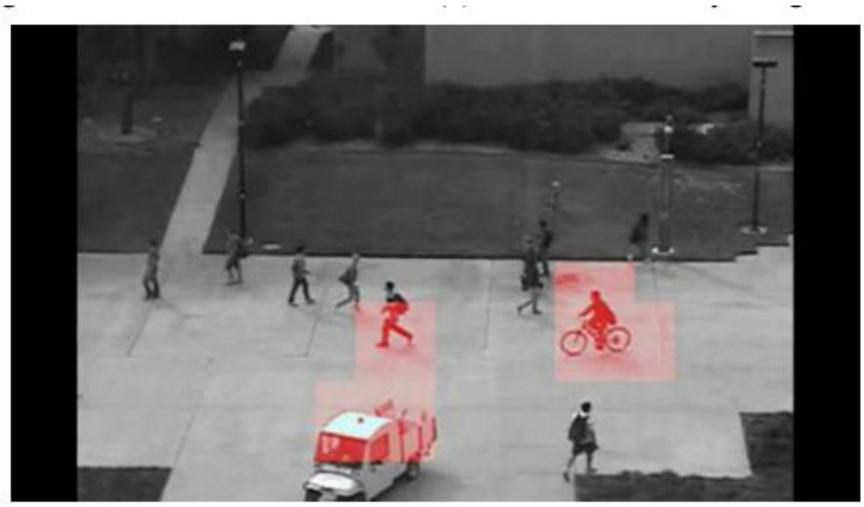


Fig Abnormal Activity Detected(Vehicle in Walking Area)

<u>TESTING CASES</u>

Software quality robustness and testing are crucial aspects of any software program, enhancing its overall quality and performance. Various factors contribute to ensuring the robustness and quality of a software product:

Completeness: Ensuring that all constituent parts of the software are fully developed and present.

Conciseness: Minimizing excessive or redundant information or processing within the software.

Portability: The ability of the software to run effectively on multiple computer configurations, including different hardware setups.

Testability: Building in support for acceptance criteria and evaluation of performance during the design phase to ensure easy testability.

Usability: Ensuring convenience and practicality of use, which includes factors such as the human-computer interface.

Reliability: The software's ability to perform its intended functions satisfactorily over a period of time, implying a certain level of consistency and stability.

Efficiency: Fulfilling the software's purpose without wasting resources like memory, space, processor utilization, network bandwidth, and time.

Security: Protecting data against unauthorized access and withstanding malicious or inadvertent interference with its operations.

Testing Plan

The testing phase commenced with comprehensive unit testing across the entire project. Subsequently, integration testing was applied to ensure seamless functioning while integrating different modules. This approach aimed to identify and address any bugs or issues that might arise when using functions from one module while calling from another.

Limitations of the Solution

The proposed method for abnormal activity detection via motion influence mapping exhibits certain limitations. One notable limitation arises when there is strong perspective distortion in the input video, affecting the accuracy of the motion influence map. Additionally, the method's applicability is restricted to fixed viewpoints, posing challenges for surveillance cameras with pan, zoom, or tilt functionality.

While the approach primarily targets detecting unusual activities within crowded scenes, it may encounter difficulties with large scaling changes or significant alterations in the scene's perspective. However, there is potential for extending the method to accommodate PTZ cameras using localization results, mitigating some of these limitations.

Completeness:

Verifying that the system processes the entire video for abnormalities detection, marking each abnormal frame.

Ensuring that the abnormal frames are correctly flagged and marked for further analysis.

Conciseness:

Checking for any redundant processing that may impact the efficiency of abnormality detection.

Verifying that the marking of abnormal frames is concise and does not interfere with the clarity of the video.

Portability:

Testing the system's ability to detect abnormalities in videos captured by different CCTV cameras with varying resolutions and frame rates.

Ensuring that the abnormality detection mechanism remains effective across different input video formats and configurations.

Testability:

Developing test cases to evaluate the system's performance in detecting abnormalities under various scenarios, including different crowd densities and movement patterns.

Verifying that the abnormal frames are consistently marked and easily identifiable for further review.

Usability:

Assessing the user interface for ease of understanding and navigation during abnormality detection.

Ensuring that the marking of abnormal frames is intuitive and does not require additional training or expertise.

Reliability:

Conducting extensive testing with diverse datasets to validate the system's reliability in accurately detecting abnormalities.

Verifying that the marking of abnormal frames is reliable and consistent across different videos and scenarios.

Efficiency:

Measuring the system's efficiency in processing video frames and detecting abnormalities within a reasonable timeframe.

Optimizing resource utilization to ensure efficient marking of abnormal frames without causing significant overhead.

Security:

Ensuring that the marking of abnormal frames does not compromise the security or integrity of the surveillance system.

Implementing access control mechanisms to prevent unauthorized manipulation of abnormality detection results.

IMPLEMENTATION AND MAINTENANCE

Requirement Analysis

Functional Requirements

The system must handle images in various formats (jpg, png, bmp, tif) and should accurately detect abnormal frames, displaying the precise time from the video's start when an abnormal event occurs. There is no set limit on the length of the test video. In case of no abnormalities, a message indicating the normalcy of the video should be displayed. Upon processing the entire video, users should have the option to view the portion where abnormal events were detected, playing only the suspected abnormal frames. Users should be able to access the abnormal portion of the video multiple times.

Non-Functional Requirements

- Usability: The system should be easy to train and test, navigating efficiently with minimal delay. It should support parallel computation for high frame rates, enabling easy addition of frames by users for testing.

- Assumption: Test frames are assumed to be in .tif, .jpg, .png, or .bmp formats, with each frame representing one second of the video. Specific parameters for training and testing are predefined.

- Performance: The system should analyze pre-captured video frames rapidly, while real-time capturing may extend processing time. Abnormality detection should occur at a rate of 150fps using parallel processing, achieving 90% accuracy.

- Reliability: Extensive testing with various datasets confirms the system's reliability, provided all assumptions are met.

Experimental Work

The dataset comprises videos showcasing normal and abnormal scenarios, divided into distinct scenes. Each scene presents unique challenges for abnormal activity detection, with varying crowd densities and movement patterns.

Solution Approach

The Abnormal Human Activity Detection System utilizes computer vision for intelligent surveillance. The implementation involves thorough research to ensure accuracy and efficiency.

Data Input and Pre-processing

The input video undergoes preprocessing within the system. It is segmented into a sequence of images, commonly referred to as frames, and processed sequentially. Each RGB frame is then converted to grayscale, preserving only intensity details while eliminating apparent colors. Unlike the three-dimensional RGB vector, the grayscale vector is one-dimensional, representing intensity values without color components.

Fig RGB to Gray Scale

Optical Flow Analysis

Following the preprocessing stage conducted for each frame in the given video, the subsequent step involves Optical Flow analysis using the FreneBack algorithm to determine motion for every pixel. Optical flow refers to the clear movement of objects, surfaces, and edges in a visual scene resulting from the overall movement between an observer and the scene. The optical flow vector, denoted as (r, θ), represents the magnitude (r) and direction (θ) of movement for each pixel relative to its corresponding pixel in previous frames. Gunnar Farneback's algorithm, implemented through the calcOpticalFlowFarneback() function in OpenCV, computes dense optical flow. After calculating optical flow for each pixel, the frame is partitioned into blocks of size M x N. Optical flow for each block is then determined as the average of the optical flow values of all pixels within that block. This division into blocks allows us to assess the magnitude and direction of movement for each frame compared to previous frames using the optical flow vector (r, θ) of the block.

Fig Image divided blocks

Motion Information Using Motion Influence Map

The direction of motion for an individual amidst a crowd may be influenced by various factors, such as obstacles, nearby pedestrians, and moving vehicles. This interplay of factors is referred to as motion influence. We acknowledge that the areas influenced by the movement of an object are determined by two main components:

1. The direction of the movement.

2. The speed of the movement. The faster an object moves, the more adjacent blocks it affects. Blocks closer in proximity have a greater impact compared to those farther away.

Feature Extraction:

Within the motion influence map, the process of feature extraction involves identifying blocks where unusual activity occurs, along with their neighboring blocks, which exhibit distinct vectors of motion influence. Additionally, since motion is captured across consecutive frames, we extract a feature vector from a cuboid defined by n × n blocks over the most recent t frames.

To create Mega blocks, frames are divided into non-overlapping mega blocks, each comprising a combination of various motion influence blocks. The Motion Influence estimation of a Mega block is determined by summing up the motion influence estimations of smaller blocks that constitute the larger block. Features are extracted after processing the ongoing 't' number of frames, where for each mega block, an 8 × t-dimensional connected component vector is derived from all the frames.

Fig Motion Influence Map

Clustering

Cluster analysis is conducted on each mega block, utilizing the spatio-temporal features to establish centroids as codewords. During the training phase, only video clips depicting normal activities are employed. Consequently, the codewords of a mega block represent typical activity patterns characteristic of the respective area.

Testing Phase

Following the creation of codewords for normal activities, we proceed to the testing phase. This involves evaluating the model we've developed using a dataset comprising both normal and abnormal activities. Subsequently, after extracting the feature vector of spatio-temporal data for each mega block, we construct a minimum distance matrix (E) above each mega block. This matrix estimates the component based on the Euclidean distance between a vector element of the current test scenario and the codewords in the corresponding mega block.

Frame and Pixel Level Detection for Abnormal Activities

Observation at the frame level regarding anomalies involves analyzing a minimum distance matrix. A smaller estimation of an element within the matrix suggests a lower likelihood of irregular movement occurring within the individual block. Conversely, the presence of higher values in the minimum-distance matrix across t consecutive frames indicates abnormal activities. Subsequently, we identify the highest value in the minimum-distance matrix as the characteristic feature value for the frame. If this highest value exceeds the threshold, we classify the current frame as abnormal.

Identification of abnormal activities at the pixel level entails examining the estimation of the minimum-distance matrix for each mega block against the threshold value.

Deployment Guide:

Hardware Requirements:

Ensuring that the hardware meets the specified requirements for processing video data and generating alerts.

Software Requirements:

Installing the necessary software components for abnormality detection, including Python, PyTorch, OpenCV, and visualization libraries.

Abnormality Detection Process:

Configuring the system to analyze video frames and detect abnormalities using computer vision algorithms.

Implementing mechanisms to mark abnormal frames and generate alerts at the top-left corner of the video display.

Testing and Validation:

Conducting thorough testing to verify the accuracy and reliability of abnormality detection.

Validating the marking of abnormal frames and the generation of alerts under different scenarios and input conditions.

Deployment and Monitoring:

Deploying the system in production environments and integrating it with existing surveillance infrastructure.

Monitoring the system's performance and alert generation process to ensure timely intervention in case of abnormalities.

FUTURE SCOPE

There is a lot of room for future growth and application for the helmetless cyclist object detection project. Here are a few possible directions for further expansion:

1. **Framework Expansion:** Our primary objective is to extend the current motion influence map framework to cater to a broader range of video applications. By doing so, we aim to enhance its versatility and applicability across various environments and scenarios.

2. **Detection of Different Abnormalities:** We intend to incorporate additional features into the model to facilitate the detection of various types of abnormal events. This includes exploring methods to identify suspicious objects such as knives or guns, thereby improving the system's ability to recognize potential threats.

3. **Integration with Audio Interfaces:** One avenue of future work involves integrating the model with audio interfaces to address specific challenges. For instance, analyzing audio data could enable the detection of anomalies like a person shouting for help, complementing the system's visual detection capabilities.

4. **Facial Recognition Integration:** We plan to integrate the model with facial recognition systems to aid in criminal identification. This integration would enable the system to identify individuals involved in abnormal activities captured by surveillance footage, thereby enhancing security measures and law enforcement efforts.

5. **Real-Time Implementation:** One crucial aspect of future work involves refining the model for real-time implementation. This entails optimizing algorithms and hardware configurations to ensure efficient processing of video streams in real-time, enabling instantaneous detection and response to abnormal events as they occur.

6. **Enhanced Parallel Processing:** Further exploration will focus on identifying and leveraging opportunities for enhanced parallel processing within the algorithm. By refining parallelization techniques and optimizing computational resources, we aim to achieve higher efficiency and accuracy in abnormal event detection, especially in scenarios with large-scale surveillance systems.

7. **Integration with IoT Devices:** Another promising direction is the integration of the model with Internet of Things (IoT) devices for comprehensive environmental monitoring. By incorporating data from IoT sensors, such as motion detectors or environmental sensors, the system can enhance its situational awareness and provide more contextually rich insights into abnormal activities, contributing to improved security and safety measures.

In general, the future work entails expanding the motion influence map framework to diverse video applications, enhancing parallel processing capabilities, and integrating the model with IoT devices for real-time monitoring. Additional efforts include extracting new features for detecting various abnormalities, integrating audio interfaces for enhanced detection, and incorporating facial recognition systems for improved criminal identification.

CONCLUSION

In conclusion, our abnormal event detection method utilizing motion influence maps offers a groundbreaking approach to enhance surveillance systems' efficiency. By directly learning motion influence characteristics, our method significantly accelerates testing speed without compromising accuracy. Achieving state-of-the-art results across various datasets underscores the effectiveness of our approach, which differs substantially from traditional subspace clustering methods.

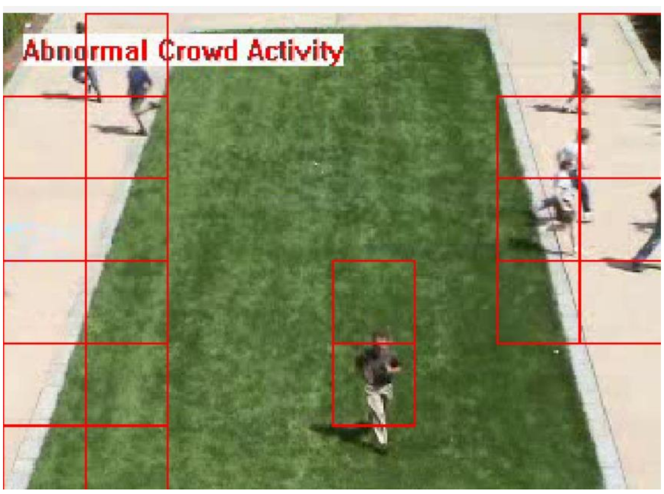
In today's pervasive surveillance landscape, the need for rapid and intelligent abnormal event detection is paramount. Our method addresses this need by providing a fast and effective means of monitoring surveillance cameras for potential threats or emergencies. By automating the detection process, our system alleviates the burden on human operators, enabling quicker responses to abnormal activities through integrated alarm systems and timely intervention protocols.

With a frame rate capability of 100 frames per minute, our method facilitates automatic abnormality detection in real-time surveillance footage. This capability is essential for enhancing security measures and public safety, allowing for swift identification and response to anomalous events. By leveraging the signals generated by our system, authorities can implement proactive measures to mitigate risks and ensure timely interventions when abnormal activities are detected.

Looking ahead, future work will focus on expanding the application of our motion influence map framework to other video-based scenarios and integrating additional features such as object detection and audio analysis. By further enhancing the capabilities of our system and integrating it with complementary technologies like facial recognition, we can continue to advance the state-of-the-art in abnormal event detection and contribute to the development of more intelligent and effective surveillance systems.

COURSE OUTCOME

The final outcome of our project is the successful detection of anomalous human activity.
It functions effectively, particularly in crowded environments.
When it detects any anomalous human activity, it will generate a tag on the screen.



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