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Optical Flow Approach for Real-Time Crowd Activity Identification Using Segmentation

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Abstract—This research introduces an optical flow approach for real-time crowd activity identification using segmentation methods. The methodology focuses on utilizing the optical flow field to analyze motion patterns within crowd scenes, thereby segmenting the scene into coherent motion regions for activity identification. Through clustering of optical flow vectors, distinct motion regions are delineated, facilitating the identification of various crowd activities such as walking, running, and gathering.Efficient algorithms for optical flow computation and segmentation are implemented to ensure real-time performance. The research is validated through implementation and testing on diverse crowd scenes, demonstrating its efficacy in accurately identifying different crowd activities in real time. Experimental results showcase the superiority of the optical flow-based segmentation method over traditional techniques in terms of accuracy and computational efficiency, thus presenting a promising solution for real-time crowd activity identification systems.

Keywords:Optical Flow, Real-Time, Crowd Activity Identification, Segmentation, Motion Patterns, Clustering.

I. Introduction

Crowd activity identification in real-time scenarios is a critical aspect of modern surveillance and security systems. Understanding the dynamics of crowd behavior can aid in various applications, including crowd management, event monitoring, and public safety. Traditional methods for crowd activity analysis often rely on manual observation or simplistic algorithms that struggle to cope with the complexity and rapid changes inherent in crowded environments. As such, there is a growing need for robust and efficient techniques that can accurately identify and classify crowd activities in real-time.

This paper introduces an innovative approach leveraging optical flow and segmentation techniques for real-time crowd activity identification. Optical flow, which captures the apparent motion of objects in a scene, provides a rich source of information about crowd dynamics. By analyzing the optical flow field and segmenting the scene based on motion patterns, our method aims to automatically detect and categorize various crowd activities such as walking, running, and gathering. This

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approach not only enhances the accuracy of activity recognition but also ensures timely responses in dynamic crowd settings.

The integration of segmentation algorithms with optical flow analysis is a key strength of our proposed method. Segmentation allows us to partition the crowd scene into coherent motion regions, enabling more precise activity identification. Moreover, our emphasis on real-time performance ensures that the system can handle streaming video feeds efficiently, making it suitable for applications requiring immediate feedback and decision-making. In this paper, we present the details of our optical flow-based approach, discuss the implementation challenges, and showcase experimental results that demonstrate its effectiveness in real-world crowd monitoring scenarios.

II. Literature Study

Crowd management and surveillance have become paramount in ensuring public safety and security, particularly with the advancements in technologies like computer vision, deep learning, and edge computing. Various research works have contributed significantly to this domain, addressing challenges such as anomaly detection, crowd behavior analysis, and activity recognition. Here, we delve into a comprehensive literature review of selected papers that have made notable contributions to the field of crowd management and surveillance.

W. Halboob et al. [1] proposed a Crowd Management Intelligence Framework, focusing on the Umrah use case, leveraging technologies to enhance crowd control and safety during mass gatherings. L. Wang et al. [2] introduced a new dataset for crowd scenes, crucial for training and evaluating models for tasks like image captioning in crowded environments.

S. Jiao et al. [3] presented a method for abnormal crowd behavior detection by fusing macro and micro features, enhancing the accuracy of anomaly detection systems. R. Wang et al. [4] developed the Limo-Powered Crowd Monitoring System, integrating deep learning for dynamic crowd modeling and edge-based information processing.

M. Mentari et al. [5] explored crowd counting during a pandemic using deep learning, shedding light on community responses to activity restriction policies. A. Xing and H. Sun [6] proposed a crowd equivalence-based model generation method, contributing to crowd science simulations and understanding collective behaviors.

X. Fu et al. [7] introduced a spatial-temporal convolutional model for urban crowd density prediction based on mobile phone signaling data, facilitating crowd management in urban environments. S. Song and H. Bae [8] presented a self-conditional crowd activity detection network with multi-label classification, improving the accuracy of activity recognition systems.

P. Liyanage and P. Fernando [9] explored suspicious human crowd behavior detection using transfer learning approaches, vital for security applications. L. Rajendran and R. S. Shankaran [10] developed a real-time crowd surveillance system enabled by big data analytics and deep learning techniques.

Y. Zhao et al. [11] contributed an indoor crowd movement trajectory benchmark dataset, essential for evaluating trajectory prediction models in indoor environments. N. A. Pham et al. [12] introduced a socially aware robot navigation framework, focusing on social activities recognition using deep learning.

Additionally, research works such as those by A. K. Jhapate et al. [13] and A. Chattoadhyay and A. Tripathy [14] addressed unusual crowd activity detection using computer vision techniques and edge devices. F. Fereidoonian et al. [15] explored human activity recognition from sensors to applications, highlighting the significance of sensor-based systems in understanding human behaviors.

Collectively, these studies underscore the diverse approaches and technologies employed in crowd management, surveillance, anomaly detection, and activity recognition, contributing to advancements in public safety and security.

III. Proposed Methodology

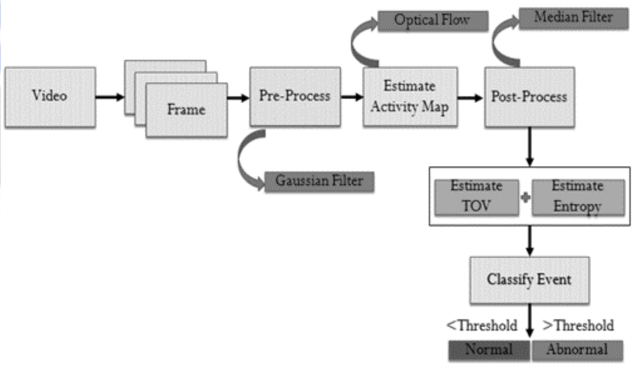

Figure 1. Proposed Methodology

The detailed description of each step in the algorithm for real-time crowd activity identification using segmentation and optical flow techniques.

A. GUI Design and Video Upload

The first step involves designing and developing a Graphical User Interface (GUI) tailored to the project's requirements. This GUI serves as the user-friendly platform for uploading videos intended for analysis. It should include features such as file upload functionality, progress indicators, and options for initiating the analysis process.

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B. Frame Extraction

Upon video upload, the system extracts frames from the video stream. This step is crucial as it prepares the individual frames for subsequent processing and analysis. Each frame represents a snapshot of the crowd scene at a specific moment in time.

C. Pre-processing with Gaussian Filter

Pre-processing is essential for enhancing the quality of frames and reducing noise. A Gaussian filter is applied to each extracted frame to achieve these objectives. This filtering technique smooths out pixel intensities, leading to cleaner and more refined images, which are conducive to accurate analysis.

D. Activity Map Estimation with Optical Flow

Next, a code module is developed to estimate the Activity Map using Optical Flow techniques. Optical flow analyzes the motion patterns of objects within the frames between consecutive time intervals. It calculates the displacement vectors of pixels, depicting the movement of objects in a 2D vector field. This step is fundamental in understanding crowd dynamics and identifying various activities such as walking, running, or gathering.

E. Post-processing with Median Filter

Following the Optical Flow analysis, a post-processing step is implemented. A Median filter, known for its noise reduction capabilities while preserving edges, is applied to refine the Activity Map obtained from Optical Flow. This filtering helps in smoothening out any artifacts or irregularities, resulting in a more accurate representation of crowd activities.

F. TOV and Entropy Estimation

Subsequently, additional code modules are developed to estimate Temporal Occupancy Variation (TOV) and Entropy from the processed frames. TOV focuses on identifying differences between consecutive Activity Maps, highlighting areas of significant motion or change. Entropy, on the other hand, quantifies the uncertainty or randomness in pixel intensities, providing insights into motion intensity variation across frames.

G. Classify Event and Thresholding

The Classify Event algorithm is utilized to analyze the movement behavior captured in the processed frames. It categorizes events based on predefined criteria, such as the magnitude of motion or changes in activity intensity. Thresholding mechanisms are then applied to determine normal and abnormal behavior. If the TOV or Entropy levels exceed a specified threshold, it indicates an abnormality or potential alarm situation, prompting further action or alert generation.

H. Video Division for Enhanced Detection

To enhance the accuracy of crowd behavior detection, the video is divided into multiple frames. This division allows for finer-grained analysis and detection of subtle changes in crowd activity, improving the system's overall performance and reliability.

I. Dataset and Optical Flow

For the input dataset, the UMN dataset is utilized, comprising various scenes such as Lawn, Indoor, and Plaza, each containing multiple videos. Optical Flow plays a pivotal role in this process, capturing the motion patterns between frames and providing valuable insights into crowd behavior and dynamics.

In conclusion, this detailed algorithmic approach integrates GUI design, frame extraction, pre-processing, optical flow analysis, post-processing, event classification, and thresholding to achieve real-time crowd activity identification using segmentation and motion analysis techniques. Each step contributes to the system's robustness, accuracy, and efficiency in detecting and categorizing crowd activities, making it suitable for applications in surveillance, security, and crowd management.

IV. RESULTS

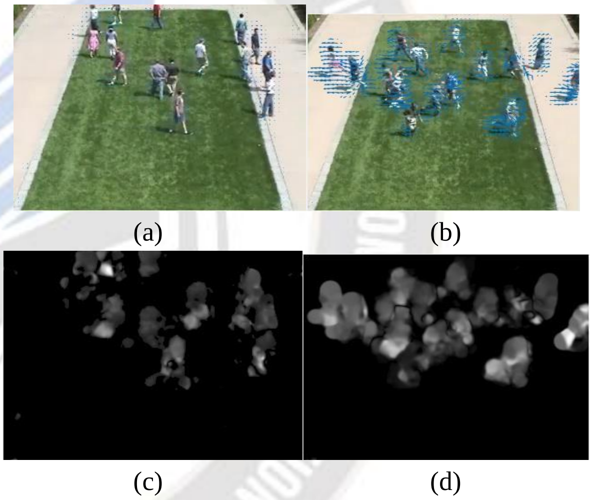

Figure 2. (a) Normal Frame (b) Abnormal Frame (c) Activity map Normal Frame (d) Magnitude of Normal Frame

Figure 3. Final Lawn Result with Alarm indication

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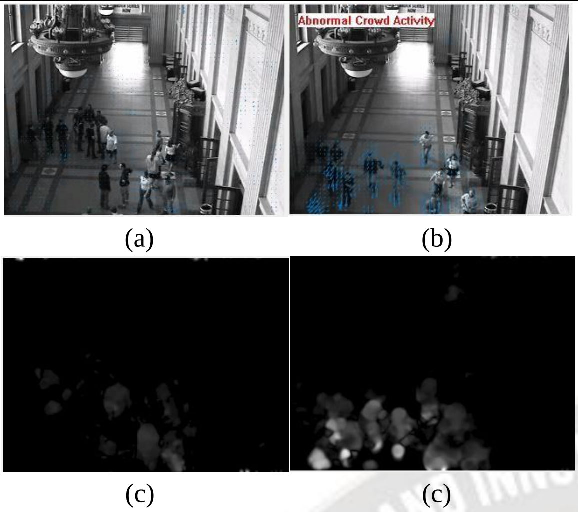

Figure 4. (a) Normal Frame (b) Abnormal Frame (c) Activity map Normal Frame (d) Magnitude of Normal Frame

Figure 5. Final Indoor Result with Alarm indication

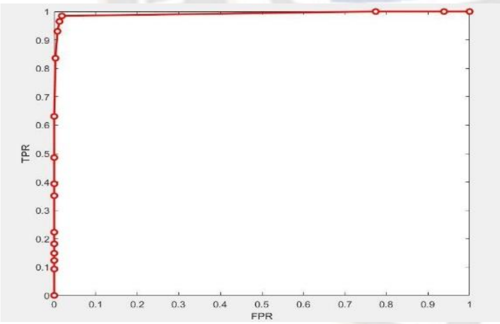

Figure 6. ROC of Result

COCNLUSION

In this research, our primary goal was to develop a method that utilizes TOV and Entropy metrics to detect anomalies within image sequences captured by surveillance cameras. Given the escalating safety concerns in today's society, such detection mechanisms hold immense importance. By harnessing optical flow calculations, we were able to construct activity maps that capture fluctuations in optical flows over specified time intervals. The subsequent computation of TOV metrics revealed notable distinctions between normal and abnormal scenes. Our evaluation, as evidenced by ROC plots, showcased an impressive classification performance averaging around 99% across all datasets.

Looking forward, there is an exciting prospect of integrating changes in entropy and TOV for more nuanced video frame classification as either normal or abnormal. This combined approach has the potential to significantly enhance classification accuracy, thereby fortifying surveillance systems and advancing real-time anomaly detection capabilities. These developments are pivotal in augmenting safety measures and bolstering security protocols across a spectrum of applications.

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