



Crowd-Motion Analysis for Disaster Prediction: A Review of Computer Vision Approaches

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Abstract. Crowd disasters in large public gatherings pose a major challenge to public safety, particularly in dense and dynamically changing environments where manual surveillance becomes inefficient, error-prone, and difficult to scale. Computer vision has emerged as a promising tool for automated crowd understanding, enabling the analysis of motion patterns, abnormal behavior, and scene dynamics from surveillance videos. This paper presents a comprehensive review of computer vision-based methods for crowd-motion behavior analysis with emphasis on their relevance to crowd disaster prediction and prevention. The survey examines key research directions, including abnormal behavior detection, crowd-motion pattern analysis, and benchmark video datasets commonly used for evaluation. It further analyzes the strengths and limitations of existing approaches in the context of real-world crowded scenes, where challenges such as severe occlusion, limited field of view, track fragmentation, and high crowd density significantly affect performance. In addition, the paper reviews the characteristics of available datasets and highlights the limited availability of multi-camera benchmark data for realistic crowd analysis. The study identifies important research gaps in real-time crowd disaster prediction and argues that more robust, scalable, and multi-view vision frameworks are needed to support intelligent surveillance in high-density public events.

Keywords: Crowd Disaster Prediction, Abnormal Crowd Behavior Detection, Multi-Camera Surveillance

1 Introduction

Disaster management not only relates to the prediction of the course and consequences of disasters, but also to mitigate their unwanted consequences. This is undoubtedly a very challenging task and even more due to time constraint. During natural or human-induced emergencies a series of carefully chosen decisions are important to mitigate the casualties caused by the disaster. In such

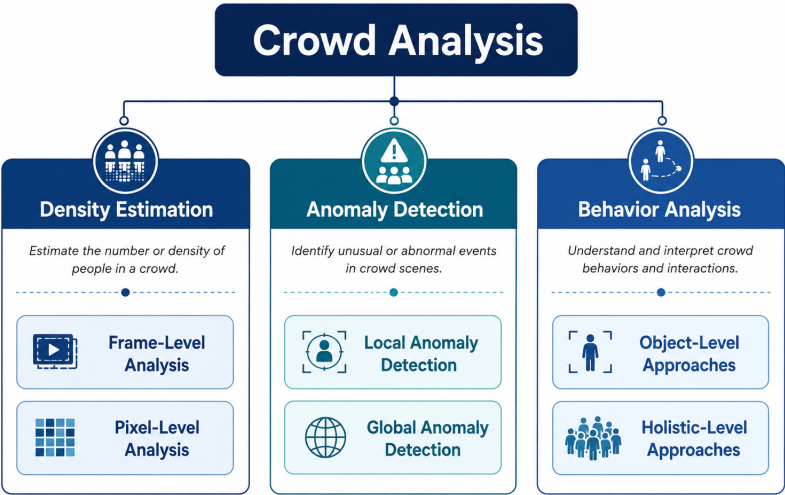


Fig. 1. Major research directions in crowd analysis, including density estimation, anomaly detection, and behavior analysis with their representative subcategories.

situations, computer vision (CV) algorithms can be helpful to solve various problems of disaster mitigation and management (such as, automatic video analysis, crowd behavior and motion analyses, etc.).

In recent years, crowded scenes have become increasingly common due to population growth, urbanization, and the rising frequency of large-scale public events. Whether the crowd comes together to protest or just to entertain themselves at a party, such gatherings can rapidly become hazardous under conditions of overcrowding, panic, or poor crowd management. Hence, it is essential to carefully analyze the crowd to nullify the bad effects of such deadly events.

Crowd disaster analysis is an active research area in video surveillance. Crowd disaster analysis problem is divided into four sub problems. These includes crowd behavior analyses, density estimation, anomaly detection and crowd-motion pattern analysis. Fig. 1 summarizes the major research directions commonly explored in crowd analysis studies. Density estimation focuses on understanding crowd concentration at frame and pixel levels, while anomaly detection identifies unusual patterns at local and global scales. Behavior analysis captures crowd dynamics through object-level and holistic-level approaches, providing a structured view of key problem areas in the field. The application of computer vision (CV) in crowd behavior analysis has gained significant attention because it enables systematic, scalable, and objective interpretation of crowd scenes. Unlike manual monitoring, CV-based methods can process large volumes of visual data, detect subtle movement patterns, and support timely decision-making in complex public environments. Its key advantages include:

Table 1. Representative crowd crush incidents and their characteristics.

S. No.	Year	Place	Crowd Type	Density Level
1	2010	Love Parade, Germany	Unstructured	High
2	2013	Madhya Pradesh, India	Structured	High
3	2014	Patna, India	Unstructured	High
4	2014	Black Friday, USA	Unstructured	High
5	2015	Mina, Saudi Arabia	Structured	High
6	2015	Puri, India	Unstructured	High
7	2015	Rajahmundry, India	Unstructured	High
8	2016	Ethiopia, Africa	Unstructured	High
9	2017	Mumbai, India	Unstructured	Medium
10	2019	Rave Party, Los Angeles, USA	Unstructured	High
11	2019	Los Angeles, USA	Unstructured	Medium

- Reducing the time required for crowd monitoring and improving the overall effectiveness of surveillance and decision-support systems.
- Enabling more precise analysis of specific crowd events, movement patterns, abnormal behaviors, and scene-level dynamics.
- Minimizing human intervention by supporting automated detection, tracking, and interpretation of crowd activities.
- Improving consistency in analysis by reducing subjective bias associated with manual observation.
- Supporting real-time or near real-time responses in safety-critical environments such as public gatherings, transport hubs, stadiums, and religious events.

Table 1 shows the most recent crowd crushes with their details. It is clear from the table that crowd management and early detection of abnormal crowd-motion is an important task. It should be done in real time. The aforementioned benefits motivate the application of CV algorithms to analyse the crowd motion behavior. According to the crowd-motion movement pattern the crowd can be categorized into two classes [24]: structured and unstructured. When crowd moves in well defined common direction, the motion of the crowd is said to be structured motion, whereas if individual in the crowd is moving in any direction then the crowd type is unstructured [27]. Fig. 2(a) and Fig. 2(b), shows the structured and unstructured crowd-motion respectively.

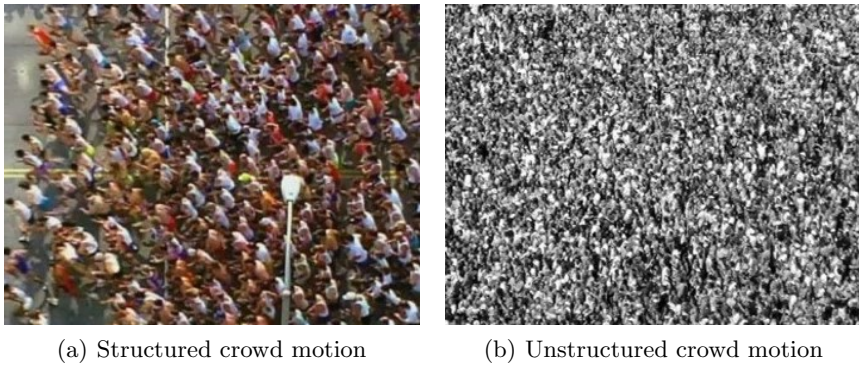


Fig. 2. Crowd type based on the direction of crowd movement.

The mass gathering can be of two types, planned and unplanned. Planned events are held at particular place for certain time period and that make every effort for adequate planning and response process. Conversely, unplanned events are those where the density of crowd is unpredictable and unhampered. Risk associated with crowd disasters in public gatherings can be reduced by considering a series of safety measures. Firstly, the infrastructure must be sufficient for public gatherings with sufficient capacity and no bottlenecks or compression points. Secondly, there should be emergency plans, like evacuation plan in case of any mishappening. Before any public gathering careful identification of all the factors that provoke the risks that lead to a miss-happening in a crowd is necessary.

1.1 Scope and Contributions of This Review

This review focuses on computer vision-based crowd-motion behavior analysis from the perspective of crowd disaster prediction and prevention. Unlike general surveys on crowd analysis, this paper emphasizes the relationship between abnormal crowd motion, high-density crowd scenarios, real-time monitoring, and disaster-risk indicators. The major contributions of this review are:

- To classify existing crowd analysis approaches into density estimation, anomaly detection, and behavior analysis.
- To examine the relevance of these approaches for early detection of crowd disasters.
- To summarize commonly used crowd video datasets and their suitability for disaster-oriented research.
- To identify key challenges such as occlusion, limited camera coverage, track fragmentation, and the scarcity of realistic multi-camera datasets.
- To highlight future research directions for real-time, scalable, and multi-view crowd disaster prediction systems.

2 Computer Vision Approaches for Crowd-Motion Behavior Analysis

Computer vision-based crowd-motion behavior analysis aims to understand the spatial and temporal dynamics of people in crowded environments using visual data. In the context of crowd disaster prediction, this task is particularly important because unsafe crowd conditions are often preceded by observable visual cues such as rapid density variation, sudden changes in flow direction, local congestion, bottleneck formation, panic-driven motion, and irregular collective behavior. Therefore, crowd-motion analysis is not only a surveillance problem but also an important component of early warning and disaster-prevention systems.

Several studies have addressed crowd-motion behavior analysis and abnormal behavior detection using computer vision techniques [5–7, 9, 17, 20, 21, 30, 32]. Broadly, existing methods can be studied from two complementary perspectives. The first perspective is based on the type of visual representation used, such as hand-crafted features or deep learned features. The second perspective is based on the task being addressed, such as density estimation, anomaly detection, behavior analysis, and multi-camera crowd understanding. This section reviews these approaches with emphasis on their relevance to crowd disaster prediction.

2.1 Positioning of Existing Surveys

A number of survey papers have reviewed crowd analysis from different viewpoints. Li et al. [13] presented a survey on crowded scene analysis with emphasis on crowd detection, motion-pattern analysis, and behavior understanding. Zhan et al. [35] reviewed crowd analysis from the perspective of pedestrian detection and tracking in severely occluded scenarios. Yogameena et al. [31] discussed computer vision-based crowd disaster avoidance systems and covered multiple dimensions of crowd analysis. Afq et al. [3] reviewed abnormal behavior classification techniques for video surveillance, whereas Zitouni et al. [37] surveyed visual crowd analysis and crowd modeling techniques.

Although these surveys provide useful foundations, many of them focus either on general crowd monitoring, pedestrian tracking, activity recognition, or abnormal-event detection [11]. Comparatively less attention has been given to the direct connection between crowd-motion behavior analysis and real-time crowd disaster prediction, especially under high-density, multi-camera, and dynamically changing surveillance environments. This gap is important because disaster-oriented crowd analysis requires not only detecting abnormal behavior after it occurs, but also identifying early motion cues that may indicate the possibility of crowd crush, panic propagation, or unsafe crowd compression.

2.2 Hand-Crafted Feature-Based Approaches

Early methods for crowd-motion analysis largely relied on hand-crafted visual descriptors. These approaches used optical flow, particle advection, trajectory in-

formation, social-force models, spatio-temporal gradients, local texture descriptors, and motion histograms to represent crowd dynamics [15, 18, 19]. For example, social-force-based methods model abnormal crowd behavior by analyzing interaction forces among moving individuals, while optical-flow-based methods capture dominant motion direction and speed variation in the scene.

Hand-crafted approaches are useful because they are relatively interpretable and often require less training data. They can provide meaningful motion cues in controlled or moderately crowded scenarios. However, their performance is strongly dependent on the quality of manually designed features. In highly dense scenes, where individual boundaries are unclear and occlusion is severe, such methods may fail to capture complex crowd dynamics. Their generalization capability is also limited when applied to scenes with varying camera viewpoints, illumination conditions, density levels, and movement patterns.

2.3 Deep Learning-Based Approaches

With the increasing availability of video data and computational resources, deep learning-based methods have become popular for crowd-motion analysis, abnormal event detection, crowd counting, and behavior recognition. Unlike hand-crafted methods, deep neural networks can automatically learn discriminative appearance and motion representations from video frames. Convolutional neural networks (CNNs), auto-encoders, recurrent networks, and hybrid deep architectures have been used for anomaly detection, density classification, crowd counting, and scene-level behavior understanding [14, 17, 30].

Xu et al. [30] used a stacked denoising auto-encoder framework to learn deep representations for anomalous event detection. Zhai et al. [34] proposed a preference distribution model for crowd behavior recognition. Ravanbakhsh et al. [23] used CNN-based representations to extract temporal motion features from crowd videos, while another work by Ravanbakhsh et al. [22] explored deep generative modeling for abnormal event detection. Zhang et al. [36] used shift features as motion information for abnormal crowd-motion detection. These studies show the increasing role of learning-based models in crowd video analysis.

Deep models generally provide stronger feature representation than traditional methods. However, they also have important limitations. They require large and diverse annotated datasets, which are not always available for crowd disaster scenarios. Many models are trained and tested on limited benchmark datasets, and their performance may degrade when deployed in unseen real-world environments. Moreover, disaster prediction requires real-time or near real-time response, whereas many deep models remain computationally expensive or insufficiently validated for practical deployment.

2.4 Density Estimation for Crowd Risk Assessment

Density estimation is an important task in crowd disaster prediction because high local density, crowd compression, and sudden accumulation of people are closely related to crowd safety risks. Density estimation methods generally operate at

two levels. Frame-level methods estimate the overall crowd count or density category for an entire image or video frame. Pixel-level methods generate density maps that show local crowd concentration in different regions of the scene.

Frame-level density estimation is useful for broad monitoring and high-level decision support. However, it may not identify localized danger zones within a scene. Pixel-level density estimation is more useful for disaster prediction because it can highlight spatially concentrated regions where crowd pressure, congestion, or bottleneck formation may occur. Nevertheless, density estimation remains challenging under severe occlusion, perspective distortion, low image quality, and irregular camera placement.

2.5 Anomaly Detection in Crowd Videos

Anomaly detection focuses on identifying unusual motion patterns or abnormal events that deviate from normal crowd behavior. In crowd disaster scenarios, anomalies may include sudden running, abrupt dispersal, flow reversal, panic movement, crowd turbulence, or unexpected stoppage. Many existing anomaly detection methods learn normal crowd behavior and then detect deviations from the learned pattern.

Anomaly detection is highly relevant to crowd disaster prediction because abnormal motion may act as an early warning signal. However, the definition of anomaly is often dataset-dependent. A movement pattern considered abnormal in one scene may be normal in another. For example, sudden running may be abnormal in a railway platform but expected in a sports event. Therefore, context-aware anomaly detection remains an important research challenge.

2.6 Object-Level and Holistic-Level Behavior Analysis

Crowd behavior analysis can be broadly categorized into object-level and holistic-level approaches. Object-level approaches detect, track, and analyze individuals or small groups within a crowd. These methods provide fine-grained information such as trajectories, interactions, speed variation, and person-level movement patterns. They are useful in sparse or moderately crowded scenes where individual people can be reliably detected and tracked.

However, in highly dense crowd scenarios, object-level approaches often suffer from occlusion, identity switching, and track fragmentation. As a result, holistic-level approaches become more practical. Holistic methods treat the crowd as a collective entity and analyze global motion patterns, optical-flow fields, crowd texture, or scene-level dynamics. These methods are useful for identifying collective abnormal motion and large-scale crowd behavior. However, they may miss small localized anomalies that occur in a limited region of the scene.

2.7 Multi-Camera and Multi-View Crowd Analysis

Most existing crowd analysis methods rely on single-camera video. However, single-camera surveillance has several limitations, including restricted field of

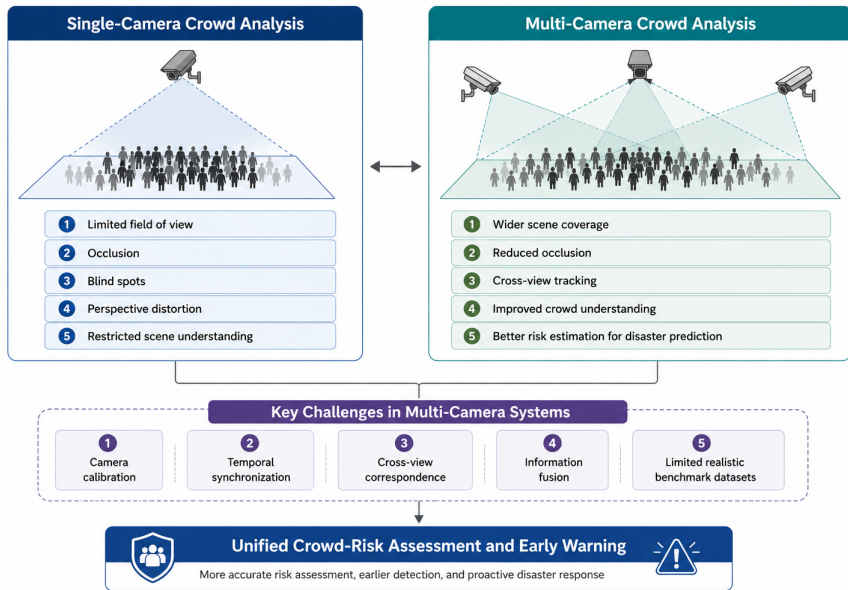


Fig. 3. Single-Camera vs Multi-Camera Crowd Analysis for Disaster Prediction.

view, occlusion, blind spots, and poor visibility in dense scenes. Multi-camera and multi-view analysis can overcome some of these limitations by combining information from different viewpoints. Such methods can improve scene coverage, support cross-view tracking, reduce occlusion-related errors, and provide a more complete understanding of crowd dynamics. Fig. 3 compares single-camera and multi-camera crowd analysis frameworks for disaster prediction in intelligent surveillance systems. Single-camera approaches are limited by restricted field of view, occlusion, blind spots, and perspective distortion, which can reduce the reliability of crowd understanding and risk estimation. In contrast, multi-camera systems provide wider scene coverage, cross-view tracking, reduced occlusion, and improved analysis of complex crowd dynamics, thereby enabling more accurate crowd-risk assessment and early warning generation. However, multi-camera frameworks also introduce additional technical challenges, including camera calibration, temporal synchronization, cross-view correspondence, information fusion, and the scarcity of realistic benchmark datasets. Collectively, the figure highlights the growing importance of multi-camera surveillance architectures for robust and scalable crowd disaster prediction.

Despite these advantages, multi-camera crowd analysis remains challenging. It requires camera calibration, temporal synchronization, view correspondence, and effective fusion of information across cameras. Moreover, realistic multi-camera benchmark datasets for high-density crowd disaster prediction are lim-

Table 2. Comparison of major computer vision approaches for crowd-motion behavior analysis.

Approach	Core Idea	Relevance to Crowd Analysis	Key Limitations
Hand-crafted feature-based methods	Use manually designed descriptors such as optical flow, trajectories, spatio-temporal features, particle advection, or social-force models.	Useful for motion pattern analysis, abnormal behavior detection, and crowd flow modeling.	Limited generalization in dense, occluded, and dynamically changing scenes.
Deep learning-based methods	Learn appearance and motion representations automatically using CNNs, auto-encoders, recurrent networks, or hybrid architectures.	Applied in anomaly detection, crowd counting, density classification, and behavior recognition.	Require large annotated datasets and may suffer from poor cross-scene generalization.
Density estimation methods	Estimate the number of people or local density distribution in a frame or scene.	Useful for crowd counting, congestion detection, and identification of high-risk dense regions.	Performance may degrade under severe occlusion, perspective distortion, and illumination variation.
Anomaly detection methods	Identify motion patterns or events that deviate from normal crowd behavior.	Useful for detecting panic movement, sudden dispersal, flow reversal, and abnormal collective motion.	The definition of anomaly is often scene-dependent and may not generalize across events.
Object-level behavior analysis	Detect, track, and analyze individuals or small groups within a crowd.	Supports trajectory analysis, person-level motion understanding, and interaction modeling.	Difficult to apply in highly dense crowds due to occlusion, identity switching, and track fragmentation.
Holistic-level behavior analysis	Treat the crowd as a collective entity and analyze global motion, flow fields, or scene-level dynamics.	Useful for crowd flow analysis, abnormal collective motion detection, and scene-level behavior recognition.	May miss localized abnormal events or small-scale behavioral changes.
Multi-camera and multi-view methods	Combine information from multiple camera views to improve scene coverage and continuity.	Useful for large-area monitoring, cross-view tracking, and crowd disaster-risk assessment.	Require camera calibration, synchronization, and realistic multi-view datasets.

ited. Therefore, multi-view crowd analysis remains an important future direction for practical crowd safety systems.

Table 2 summarizes the major computer vision approaches used for crowd-motion behavior analysis and their relevance to crowd disaster prediction. Table 3 summarizes representative studies on crowd-motion behavior analysis by comparing their merits, limitations, datasets, and crowd density levels. The comparison shows that although several methods perform well in sparse to moderately dense scenes, robust analysis of highly dense and disaster-prone crowd scenarios remains a major research challenge.

From the perspective of crowd disaster prediction, no single computer vision approach is sufficient in isolation. Hand-crafted methods provide interpretability but often struggle in complex and dense scenes. Deep learning-based methods improve representation learning but require diverse and well-annotated datasets. Density estimation helps identify overcrowded regions, whereas anomaly detection and behavior analysis help interpret irregular movement patterns. Object-level methods are useful in sparse or moderately crowded scenes, while holistic-level methods are more suitable for high-density crowd conditions. Similarly, multi-camera analysis can improve coverage and robustness but introduces additional challenges related to calibration, synchronization, and dataset availability. Therefore, future crowd disaster prediction systems should integrate density estimation, anomaly detection, behavior analysis, and multi-view reasoning into a unified real-time framework.

2.8 Challenges in Crowd-Motion Behavior Analysis

Despite significant progress, crowd-motion behavior analysis remains challenging in real-world public gatherings. The difficulty increases when the crowd becomes dense, unstructured, and visually complex. Some of the major challenges are discussed below.

- **Occlusion:** In dense crowds, individuals are frequently hidden by other people or objects. This reduces the reliability of detection, tracking, and individual-level behavior analysis.
- **Limited field of view:** A single camera can monitor only a restricted portion of the scene. Important crowd activities may occur outside the visible region or at locations where visual details are poor.
- **Track fragmentation:** Tracking continuity is often lost when a person is temporarily occluded or when multiple people move closely together. This affects trajectory-based behavior analysis.
- **High crowd density:** In very dense scenes, individual boundaries become difficult to distinguish. As a result, object-level methods become less reliable and holistic or density-based approaches become more suitable.
- **Scene variability:** Changes in illumination, camera viewpoint, perspective distortion, weather conditions, and background clutter can significantly affect the performance of computer vision models.
- **Real-time processing requirement:** Crowd disaster prediction requires timely detection of unsafe conditions. Therefore, methods must not only be accurate but also computationally efficient enough for real-time or near real-time deployment.
- **Limited benchmark datasets:** Many available datasets are designed for anomaly detection, crowd counting, or behavior recognition, but only a few represent realistic high-density, multi-camera, disaster-like scenarios. This limits the evaluation of practical crowd disaster prediction systems.

These challenges indicate that crowd-motion behavior analysis should move beyond isolated anomaly detection and toward integrated, real-time, and context-aware crowd safety frameworks. In particular, multi-view analysis, robust density

Table 3. Overview of selected crowd analysis methods with their merits, limitations, datasets, and density levels.

Year and Ref.	Merits	Limitations	Dataset Used	Density Level
2008 Zhan et al.	Presented a survey of CV-based crowd analysis methods and discussed crowd-motion analysis from sociology, psychology, and computer graphics perspectives.	Did not sufficiently address the development of intelligent video surveillance systems using computer vision approaches.	N/A	N/A
2009 Mehran et al.	Detected and localized abnormal crowd behavior without individual object tracking or segmentation.	May fail when anomalies do not occur in regions of strong social interaction.	UMN and UCF Behavior	Moderate to high
2010 Mahadevan et al.	Localized anomalies and showed robustness under perspective distortion.	Computational cost is relatively high.	UCSD	High
2011 Emonet et al.	Jointly processed and handled information from multiple cameras.	Mainly effective in indoor environments.	Real-time dataset	Sparse
2015 Li et al.	Reviewed state-of-the-art crowd analysis methods, including motion pattern analysis, crowd detection, and crowd behavior analysis.	Did not cover deep learning-based crowded scene analysis.	N/A	N/A
2015 Mousavi et al.	Proposed trajectory-based anomaly detection for crowded scenarios.	Used standard classifiers and did not combine multiple descriptors.	UCSD	High
2016 Rabiee et al.	Classified crowd behavior while also considering emotional attributes.	Did not automatically recognize crowd behavior.	Real-time dataset	Sparse to moderate
2016 Zhang et al.	Addressed the problem of limited training data.	Did not predict unusual crowd behavior in advance.	UMN and real-time dataset	Sparse to moderate
2016 Zitouni et al.	Surveyed crowd behavior analysis in the context of crowd modeling studies.	Did not focus on real-time crowd behavior analysis.	N/A	N/A
2016 Kok et al.	Reviewed crowd behavior analysis methods from physics and biology perspectives.	Did not cover deep learning-based crowd behavior analysis methods.	N/A	N/A

estimation, abnormal motion detection, and early-warning indicators should be jointly considered for practical crowd disaster prediction.

3 Crowd Video Datasets

This section describes some existing datasets used for crowd-motion analysis. Table 4 lists the available datasets of crowd video with their details.

- UCF [4]: This dataset having crowd videos and other high density moving objects. All videos of this dataset are collected from the BBC Motion Gallery

Table 4. Summary of publicly available datasets for crowd-motion behavior analysis.

Sl. No.	Dataset	Description	Size (# videos or frame sequences)	Labels
1	UCF [4]	Contains videos of crowd and vehicle flows.	38	Partial
2	UMN [1]	Contains videos captured from three different indoor and outdoor scenarios.	11	All
3	UCSD [16]	Includes two subsets. Subset 1 contains 34 training and 36 testing videos, while Subset 2 contains 16 training and 12 testing videos.	98	All
4	CUHK [29]	Contains crowd and traffic videos for activity and behavior analysis.	2	Partial
5	WWW [26]	Contains crowd videos collected from 8,257 diverse scenes.	10,000	All
6	PETS2009 [10]	Contains videos of different crowd activities captured using multiple sensors.	8	All
7	Violent-Flows [12]	A crowd violence dataset containing violent and non-violent crowd video clips.	246	Partial
8	Data-Driven Crowd [25]	Contains crowd videos with labeled object trajectories.	520	Partial
9	UCF Behavior [28]	Contains labeled crowd videos for normal and abnormal behavior analysis.	20	All
10	Subway dataset [2]	Contains CCTV videos captured at subway station entry and exit points.	2	All
11	Train dataset [33]	Contains frame sequences of moving people inside a train environment.	19,218	All
12	Crowd-11 [8]	Contains 11 classes of crowd behavior with more than 6,000 crowd videos.	6,272	All

and Getty Images website. The most striking feature is the variation in lighting that can facilitate the performance analysis of algorithms designed for crowded scenes.

- UMN [1]: It is also a publicly available dataset. This dataset having normal and abnormal crowd videos from the University of Minnesota. This is mainly used for anomaly detection in a crowd. The anomaly event can be crowd running or crowd dispersing.
- UCSD [16]: This dataset having two sets of video named as ped1 and ped2. These two sets represents the pedestrian movement with respect to the camera location. All videos in which people walking towards or away from the camera are club into the ped1. Ped2 contains the video clips in which pedestrians moving parallel to the camera plane. This dataset was created with a

stationary camera located at an elevation, overlooking pedestrian walkways. The crowd density in the walkways ranges from sparse to very crowded.

- CUHK [29]: This dataset can be applied for crowd behavior analysis in challenging environment. It considers illumination changes, occlusions, indoor and outdoor environment constraint, etc. It contains two subsets: a traffic dataset (MIT traffic) and a pedestrian dataset. The traffic dataset contains a 90 min long traffic video clip. The pedestrian dataset contains a 30 min long video clip of pedestrians.
- WWW [26]: This dataset having 10,000 videos with more than 8 million frames. It consists videos that cover 8,257 diverse scenes. However, this dataset comprised many crowd behaviors but all videos are associated to one of the label: outdoor, street, newly-wed, couple and walk. Thus, this labeled dataset is not useful for understanding the crowd-motion behavior analysis.
- PETS2009 [10]: This dataset comprises multi-sensor sequences of different crowd activities. It is made up of five subsets: calibration, training data, People tracking data, people count (density estimation) data and flow analysis (event recognition) data. However, each subsets consists several sequences of different views but still there is a scarcity of variety in appearance.
- Violent-Flows [12]: This dataset have two classes, violent and non-violent. It can be used to detect violence outbreak and scenes classification as violent/non-violent. All the videos were downloaded from YouTube, and the average length of a video clip is 3.60 s.
- Data-Driven Crowd [25]: This dataset contains 520 crowd videos of length 2-5 minutes. All videos of this dataset were collected by crawling and downloading videos from search engines and stock footage websites (e.g., Getty Images and YouTube). In addition to the crowd videos, the dataset also contains ground truth trajectories for 100 individuals, which were selected randomly from the set of all moving people.
- UCF Behavior [28]: This dataset contains the labeled videos of crowd normal and abnormal behavior. This dataset mainly designed for crowd-motion analysis.
- Subway Dataset [2]: This dataset contains two videos that were collected using CCTV cameras. These videos are corresponding to the entry and exit point of two different subway station. In the entrance and exit subset, there are 66 and 19 abnormal events respectively. People moving in a wrong direction, sudden stopping or running, etc., are considered as abnormal events.
- Train Dataset [33]: The Train dataset focuses on moving people inside a train. This dataset consists of 19,218 frames sequences. In this dataset the unusual movements of people are considered as abnormal event. Dynamic illumination changes and camera motion make this dataset a challenging abnormal event detection dataset.
- Crowd-11 [8]: This dataset composed of 11 different crowd motion pattern classes with more than 6000 videos. This dataset mainly focuses on the two types of crowds. First, structured and dense crowds and second, unstructured crowds.



Fig. 4. Snapshots of some crowd disasters. (a) Love parade stampede, Germany, 2010, (b) Pushkar festival stampede, India, 2015, (c) Mumbai stampede, India, 2017 and, (d) Black Friday stampede, USA, 2018.

4 Evaluation Metrics Used in Crowd-Motion Analysis

The performance of crowd-motion analysis methods is generally evaluated using task-specific metrics, as different sub-problems such as anomaly detection, density estimation, crowd counting, tracking, and disaster prediction require different forms of assessment. In the context of crowd analysis, the choice of evaluation metric is important because a method that performs well in general classification may not necessarily be suitable for real-time disaster prediction, where early detection, low false alarm rate, and computational efficiency are equally critical.

For abnormal crowd-motion detection and anomaly detection, commonly used evaluation metrics include accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC), false alarm rate, and detection delay. Accuracy indicates the overall correctness of the model by measuring the proportion of correctly classified normal and abnormal events. However, accuracy alone may not be sufficient, especially when abnormal events are rare

compared to normal crowd behavior. In such cases, precision and recall provide a more meaningful evaluation. Precision measures how many detected abnormal events are actually abnormal, whereas recall measures the ability of the model to correctly identify actual abnormal events. The F1-score provides a balanced measure by combining precision and recall, making it useful when there is an imbalance between normal and abnormal samples.

In crowd disaster prediction, recall is particularly important because missing a true abnormal or hazardous event may result in delayed response and serious consequences. At the same time, a very high false alarm rate may reduce the practical usability of the system, as frequent incorrect warnings can lead to alarm fatigue among surveillance operators. Therefore, a reliable crowd disaster prediction framework should maintain a suitable balance between high detection sensitivity and low false alarm rate. AUC is also widely used to evaluate the discriminative ability of anomaly detection models across different threshold settings. In addition, detection delay is an important metric because the usefulness of a prediction system depends not only on whether it detects an abnormal event, but also on how early it detects the event before the situation becomes uncontrollable.

For density estimation and crowd counting, error-based metrics such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) are commonly used. These metrics measure the difference between the estimated crowd count or density and the ground truth value. MAE provides an average absolute deviation and is easy to interpret, while MSE and RMSE penalize larger errors more strongly. These metrics are especially relevant in dense crowd scenarios, where even small errors in density estimation may affect the assessment of risk levels. In crowd disaster prediction, density estimation should not only provide the total number of people present in a scene, but should also identify local high-density regions where crowd pressure, congestion, or bottlenecks may develop.

For tracking-based crowd analysis approaches, metrics such as multiple object tracking accuracy (MOTA), multiple object tracking precision (MOTP), identity switches, missed detections, false positives, and track fragmentation are commonly used. These metrics evaluate how consistently individuals or groups are detected and tracked over time. In dense crowds, tracking becomes difficult due to severe occlusion, overlapping bodies, changing viewpoints, and frequent merging and splitting of trajectories. Identity switches and track fragmentation are particularly important because unstable tracks may lead to incorrect interpretation of crowd flow and movement direction. However, in extremely dense crowd scenes, individual-level tracking may become unreliable, and therefore group-level or scene-level motion analysis is often more practical.

In addition to conventional performance metrics, disaster-oriented crowd analysis requires deployment-level evaluation measures. These include computational time, frame processing rate, real-time latency, robustness under occlusion, scalability to multiple cameras, and early-warning lead time. Real-time latency measures the delay between the occurrence of an abnormal visual cue and the

generation of an alert. Early-warning lead time refers to the time gap between the system warning and the actual development of a dangerous crowd condition. A longer and reliable lead time can provide authorities with more opportunity to initiate crowd control, rerouting, evacuation, or emergency response measures. However, many existing datasets and studies do not report such disaster-specific metrics, which limits the practical comparison of existing methods for real-world crowd disaster prediction.

Thus, evaluation of crowd-motion analysis systems should not be limited to classification accuracy or counting error alone. A comprehensive evaluation framework should consider detection reliability, localization capability, false alarm behavior, processing speed, robustness in dense scenes, and the ability to provide timely warnings. This is especially important for public safety applications, where the ultimate objective is not merely to classify crowd behavior but to support early intervention and prevent crowd-related disasters.

5 Visual Indicators for Crowd Disaster Prediction

Crowd disaster prediction depends on the timely identification of visual indicators that appear before or during the development of hazardous crowd conditions. In large public gatherings, disasters rarely occur instantaneously; they are often preceded by changes in crowd density, movement direction, flow stability, and local crowd behavior. Computer vision-based systems can play an important role in identifying such early warning cues from surveillance videos and assisting authorities in taking preventive action before the situation escalates into a crowd crush, stampede, or panic-driven emergency.

One of the most important visual indicators is a rapid increase in local crowd density. A crowd may appear manageable when viewed at a global level, but specific regions such as entry gates, exits, narrow corridors, staircases, barricades, or turning points may experience sudden local congestion. Such high-density pockets can create excessive physical pressure and restrict individual movement. Therefore, density estimation at the local region level is more useful for disaster prediction than only estimating the total crowd count in the scene. A sudden rise in density in confined area indicate the early formation of a hazardous zone.

Another important indicator is the formation of bottlenecks. Bottlenecks occur when a large number of people attempt to pass through a narrow passage or restricted area. In video sequences, bottlenecks can be observed through reduced movement speed, increased crowd accumulation, and irregular motion near the constrained region. If not addressed in time, bottlenecks may lead to crowd compression and loss of individual control. Computer vision methods can help detect such situations by analyzing crowd flow, movement speed, and spatial distribution of people across the scene.

Sudden changes in crowd flow direction also serve as significant warning cues. In normal conditions, crowd movement usually follows a relatively stable direction, especially in structured environments such as walkways, corridors, transport stations, or event entry routes. However, abrupt flow reversal, crossing

movement, random dispersal, or opposing flows may indicate panic, confusion, obstruction, or an emerging threat. Such changes can be detected through motion vectors, optical flow patterns, trajectory analysis, or deep spatio-temporal representations. Detecting these deviations at an early stage can help identify abnormal crowd behavior before it becomes dangerous.

Stop-and-go waves are another visual pattern associated with unstable crowd motion. These waves occur when people alternately stop and move due to congestion, pressure, or restricted movement ahead. In dense crowds, such waves can propagate backward and create instability in the crowd structure. From a computer vision perspective, stop-and-go movement can be observed as repeated changes in local velocity, temporary freezing of motion, and sudden acceleration in specific regions. The presence of such patterns may indicate that the crowd is approaching an unsafe density level.

Crowd turbulence is a more serious visual indicator and is often associated with highly dense and unstable crowd conditions. It refers to irregular, uncontrolled, and multidirectional movement of people caused by physical pressure and lack of free space. Unlike normal crowd flow, turbulent motion does not follow a stable direction and may appear as random oscillations, sudden lateral movement, or chaotic displacement of individuals or groups. Detecting crowd turbulence is important because it may indicate that individuals are no longer moving voluntarily but are being pushed by surrounding crowd forces.

Panic-driven motion and abnormal dispersal are also relevant indicators for disaster prediction. Panic may be reflected through sudden running, rapid scattering, unusual acceleration, or abrupt movement away from a particular region. Similarly, abnormal dispersal may occur when a crowd suddenly breaks its normal movement pattern due to fear, obstruction, or perceived danger. These patterns are especially important in public gatherings, transport hubs, stadiums, and religious events, where a sudden behavioral shift can quickly spread across the crowd.

High compression zones are another critical visual cue. These zones appear when people are tightly packed and movement becomes extremely restricted. Although such compression may not always be visible at the individual level due to occlusion, it can often be inferred from density maps, reduced optical flow magnitude, low movement freedom, and accumulation near physical barriers. Identifying such zones is important because crowd crush incidents are closely associated with excessive local pressure rather than only panic or running behavior.

Overall, visual indicators for crowd disaster prediction can be grouped into density-based indicators, motion-based indicators, flow-based indicators, and behavior-based indicators. Density-based indicators include local overcrowding and high compression regions. Motion-based indicators include sudden acceleration, irregular movement, stop-and-go waves, and turbulence. Flow-based indicators include bottleneck formation, flow reversal, and opposing movement streams. Behavior-based indicators include panic running, abnormal dispersal,

and sudden collective movement changes. A robust computer vision system should ideally combine these indicators rather than relying on a single cue.

Therefore, the role of computer vision in crowd disaster prediction is not limited to detecting an abnormal event after it has occurred. Its greater value lies in continuously monitoring visual patterns, identifying early signs of risk, and generating timely alerts for decision-makers. By integrating density estimation, motion analysis, anomaly detection, and scene-level behavior understanding, computer vision-based systems can support proactive crowd management and contribute to the prevention of large-scale crowd disasters.

6 Relevance of Existing Research to Crowd Disaster Prediction

Research on crowd disaster prediction has gained considerable importance due to the increasing frequency of large-scale public gatherings and the serious risks associated with dense crowd formations. Ineffective crowd management can lead to severe consequences such as crowd crushes, stampedes, panic propagation, and coordination failure. These risks highlight the need for intelligent and automated systems capable of continuously monitoring crowd behavior and identifying hazardous situations at an early stage.

Existing work in crowd analysis provides an important foundation for the development of such systems. Over the years, computer vision-based approaches have contributed significantly to the understanding of crowd dynamics by enabling the analysis of motion patterns, abnormal activities, crowd density, and behavioral changes from surveillance videos. These studies have demonstrated that video-based crowd monitoring can support faster and more reliable assessment than manual surveillance, particularly in environments where constant human observation is difficult to maintain.

The relevance of prior research becomes even more evident in highly dense crowd scenarios. In such situations, traditional surveillance practices are often insufficient because of severe occlusions, limited visibility, and the practical difficulty of monitoring multiple camera feeds simultaneously. As crowd density increases, the possibility of missing critical behavioral cues also rises. Existing computer vision methods attempt to address these limitations by automatically detecting irregular motion, unusual crowd flow, and sudden changes in behavior that may indicate the onset of a dangerous event. This makes previous research highly valuable for designing proactive crowd safety frameworks.

Another important contribution of existing studies lies in establishing the relationship between abnormal crowd-motion behavior and disaster situations. In many real-world events, unusual movement patterns may act either as an early warning sign of an impending disaster or as an immediate consequence of a hazardous incident already taking place. Therefore, methods developed for anomaly detection, crowd-motion analysis, and behavior understanding are directly relevant to crowd disaster prediction. By identifying the nature and direction of crowd movement in real time, such approaches can help authorities

respond more effectively and reduce the likelihood of large-scale casualties. Fig. 4 presents representative crowd disaster incidents, demonstrating that regardless of location or event type, crowd disasters are often associated with sudden disruption in normal crowd motion. This underscores the importance of computer vision-based systems for early detection of abnormal behavior and timely crowd disaster prevention.

Furthermore, the existing body of work helps identify current limitations and future research needs. While substantial progress has been made, many approaches still struggle in extremely dense and complex environments. This indicates that further research is required to build more robust, scalable, and real-time systems for practical deployment. Hence, the existing literature is not only useful from a methodological perspective but also essential for guiding future innovations in intelligent surveillance and crowd disaster prevention.

7 Research Gaps and Future Directions

Despite steady progress in computer vision-based crowd-motion analysis, reliable crowd disaster prediction remains an open and practically demanding research problem. Existing studies have advanced crowd-density estimation, anomaly detection, motion-pattern analysis, and behavior understanding. However, much of the current literature is still oriented toward detecting or classifying crowd events under benchmark conditions, rather than forecasting hazardous crowd states in real-world, high-density public gatherings. This gap between controlled experimental performance and operational disaster-prevention capability remains one of the central limitations of the field.

A key research direction is the transition from *abnormal event detection* to *early risk prediction*. Many existing methods identify abnormal crowd behavior only after visible deviations have already occurred. In disaster-prevention scenarios, however, the objective is to detect risk indicators before the situation becomes critical. Visual cues such as rapid local density growth, bottleneck formation, crowd compression, stop-and-go waves, flow reversal, abnormal dispersal, and crowd turbulence should therefore be treated as early predictive signals rather than only as post-event anomalies. Future systems should model the temporal evolution of such cues and estimate the likelihood of crowd-risk escalation with sufficient lead time for preventive intervention.

Another important challenge is the analysis of highly dense crowd scenes. Object-level methods based on person detection, tracking, and trajectory modeling are useful in sparse or moderately crowded environments, but their reliability decreases sharply when occlusion, body overlap, and track fragmentation become severe. Since crowd disasters are often associated with collective instability rather than isolated individual actions, future research should place greater emphasis on group-level and scene-level representations. Density maps, motion fields, flow-consistency measures, congestion maps, crowd-pressure indicators, and spatio-temporal risk maps may provide more robust descriptions of hazardous crowd dynamics in dense environments.

Dataset limitations also remain a major bottleneck. Existing crowd datasets are valuable for tasks such as anomaly detection, behavior recognition, crowd counting, and violence detection, but they do not fully capture the complexity of disaster-prone public gatherings. In particular, there is a lack of large-scale datasets containing high-density scenes, multi-camera coverage, long-duration crowd evolution, realistic bottleneck situations, and progressive risk development. Moreover, many datasets use broad labels such as normal, abnormal, violent, non-violent, or density level. Such labels are insufficient for training models to understand disaster-risk progression. Future benchmark datasets should include fine-grained annotations for local overcrowding, flow instability, compression zones, panic-driven motion, bottleneck formation, crowd turbulence, and early-warning intervals.

Multi-camera and multi-view crowd understanding is another critical direction for future work. Single-camera systems are inherently limited by restricted field of view, blind spots, perspective distortion, and occlusion. These limitations are particularly serious in large public events, where crowd movement often extends across multiple connected regions. Multi-view systems can provide wider spatial coverage and more complete interpretation of crowd dynamics, but they introduce additional challenges such as camera calibration, temporal synchronization, cross-view correspondence, and information fusion. Future research should focus on scalable multi-camera architectures that can integrate observations from different viewpoints and generate a unified estimate of crowd-risk levels across large surveillance areas.

Generalization across diverse crowd environments is another unresolved issue. Crowd behavior varies across railway stations, stadiums, religious gatherings, festivals, public rallies, transport hubs, and evacuation routes. Models trained on one scene may fail in another due to differences in camera viewpoint, illumination, scene geometry, density distribution, crowd culture, and movement pattern. Future work should therefore explore domain adaptation, self-supervised learning, transfer learning, and scene-adaptive modeling to improve robustness in unseen environments. This is particularly important because collecting large, well-annotated datasets for every deployment location is often impractical.

Overall, future crowd disaster prediction systems should move toward integrated, real-time, multi-view, and context-aware frameworks. Density estimation can identify overcrowded regions, anomaly detection can capture unusual motion, behavior analysis can interpret collective movement, and multi-camera reasoning can improve spatial coverage. A unified system that combines these complementary cues can provide a more reliable understanding of evolving crowd risk. The long-term goal should not be limited to detecting abnormal behavior, but should extend to forecasting hazardous crowd conditions early enough to support timely decision-making, crowd-flow regulation, evacuation planning, and disaster prevention.

8 Conclusion

This paper reviewed computer vision-based approaches for crowd-motion behavior analysis with emphasis on crowd disaster prediction and prevention. The review covered key directions such as density estimation, anomaly detection, motion-pattern analysis, behavior understanding, multi-camera analysis, benchmark datasets, evaluation metrics, and visual indicators of hazardous crowd conditions. The discussion shows that computer vision can significantly support automated crowd monitoring and reduce dependence on manual surveillance in dense public environments. However, crowd disaster prediction remains a challenging problem. Existing methods often perform well on benchmark datasets but show limitations in highly dense, occluded, unstructured, and large-scale real-world scenarios. The lack of realistic multi-camera datasets, disaster-specific annotations, and early-warning evaluation protocols further restricts practical deployment.

Future research should focus on real-time, scalable, and multi-view frameworks that jointly model crowd density, motion, behavior, and scene-level risk progression. Such systems can help detect early warning indicators such as overcrowding, bottleneck formation, flow instability, crowd turbulence, and abnormal dispersal, thereby supporting timely crowd-management decisions and disaster prevention.

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