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A Review on Recognition of Motion Pattern from Crowd Scene

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ABSTRACT

In the epoch of video surveillance, crowd management, and crowd video control received a substantial amount of attention. These systems are primarily used for monitoring and security. Monitoring of crowd in public places is the most demanding endeavor to accomplish. However, occlusion in visual, low resolution, cluttering, and complex behaviors in the scene make more challenging crowd management. A growing requirement for a sophisticated surveillance system of private and public space using different crowded scene analyses that covers a range of issues, such as crowd motion-pattern recognition, normal and abnormal crowd behavior and the activity evaluation, as well as crowd anomalies identification. The main purpose of this study is to discuss the background awareness of crowded situations and the elements that are offered. Then, existing models, popular algorithms with different environment scenarios to find motion pattern from crowded scenes, also, discussed several datasets used for the crowd analysis.

Keywords: *Crowd Behavior, Motion Pattern, Pedestrian, Fountainhead, Bottleneck.*

1. INTRODUCTION

As the world's population grows, crowd control and video monitoring become more important. As a result, public security and safety have become a serious source of concern in public places such as shopping centers, stations, as well as the road. So we discuss here the recent work related to the crowd analysis of motion pattern recognition and behavior detection. Nowadays, due to the increment in a crowd scene in the real world, crowd analysis becomes a very attractive topic. If we extract the motion pattern information from crowd scene manually then we know that human has the strength of doing this but due to very high dense crowd human eyes and his experience is not sufficient to do manually, it is proved by the psychological researches that humans have the limitations on monitoring simultaneously signals [8]. High dense crowd area required multiple numbers of monitoring individuals that is a big challenge for the human observer, so that's why we use computer vision approaches to monitor high dense crowd area with visual surveillance [3]. So we have a massive amount of approaches that are related to pattern recognition, anomaly detection, tracking, behavior understanding, activity analysis, and identification in which different researchers provide several methodologies to accomplish the demands of crowd analysis for behavior recognition. The methodology used by the researcher is depending upon what kind of our requirements is after that a researcher applies a suitable approach to this. During the previous few years, research on detecting motion pattern behavior of pedestrian has actively evolved using recent advancements in certain connected fields such as Digital Image Processing (DIP) Computer Vision (CV), Pattern Recognition (PR), Neural Network (NN), Fuzzy Logic (FL), Soft Computing (PR), Mathematical_Modeling (MM), Biomedical_Information (BI), Image_Signal Processing (ISP), Data_Mining (DM), Computational_Intelligence (CI), and Artificial_Intelligence (AI). Since 2008, an overview of the relevant improvements in the field of pedestrian motion-pattern detection in a crowd setting has been presented in this work.

This paper's flow is like this: Section 2 explains the brief knowledge about a crowd that will enhance the better understanding of the motion behavior of the crowd that introduces the brief history of crowd analysis and their subparts to illustrate their working areas. In section 3 we describe the various types of applications related to crowd analysis. In section 4 we explain the overview and also provide a literature survey of related research works of motion pattern recognition from crowded video. In section 5, here we provide huge information of different types of the dataset which helps in crowd analysis research work. We conclude this paper in section 6.

2. CROWD ANALYSIS

Nowadays the in the actual world, crowds are growing and crowd analysis becomes more popular in the field of image-processing and computer-vision. Typically, a crowd is a unique group of individuals or a collection of individuals who are gathered together for a purpose. We have several places that have a high volume of a dense crowd like as railway stations, Shopping malls, airports, traffic on streets, and festivals influence a big focus on public security and transportation efficiency. In computer vision, we employ a variety of methods to do analysis, but we mostly use three approaches. In-crowd analysis that is applicable and very suitable in detection and understanding the behavior of crowd scene, these approaches is general methodology is performed crowd analysis and wildly used by most of the researchers. Object detection consists of; optical flow, background subtraction, Spatio-Temporal filtering technique. Object tracking consists of; point tracking, silhouette tracking, and kernel tracking. Behavior analysis consists of; holistic method and object method.

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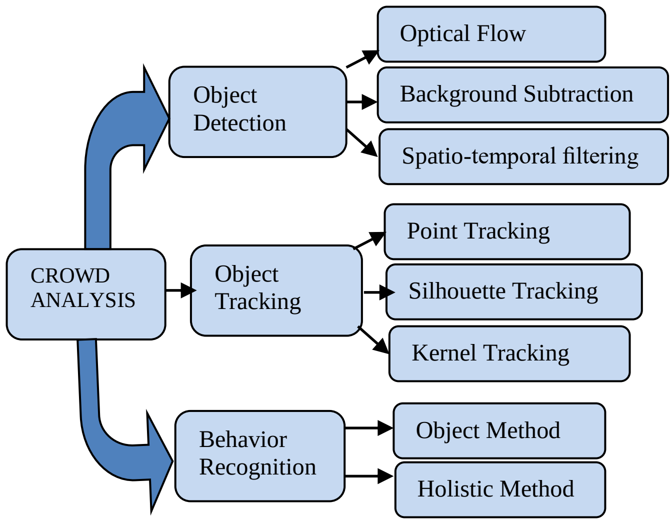

Fig.1: Crowd analysis approaches [3].

2.1 OBJECT DETECTION

The very first step of any surveillance system is to accurate identification of active objects in a crowded scene. We have several types of methodology for object detection from a crowd scene.

2.1.1 OPTICAL FLOW

Optical flow is the most famous approach for motion estimation. Optical_flow is the method to evaluate the motion of any object in a visual scenario due to comparative motion among a scene and the observer. We have some very famous methods to find the optical flow, they are:

- **Horn-Schunck Approach**
- **Lucas-Kanade Approach**
- **Fleet and Jepson**
- **Heeger**

2.1.2 BACKGROUND SUBTRACTION

Background subtraction is considered one of the oldest methods in computer vision which gives the distinction between the previous frame and an image of the scene.

2.1.3 SPATIO-TEMPORAL FILTERING

It uses statistical characteristics of each pixel to overcome the drawback of background subtraction.

2.2 OBJECT TRACKING

In the discipline of computer vision object-tracking is a crucial step. Object tracking in the video clip is a method to point an object that is in motion (or different objects) at a particular time via using a camera. It has a huge collection of applications, these are surveillance and security, monitoring of traffic, medical imaging, and video editing. We have some category of tracking these are:

- **Point tracking:** Point tracking, we locate the pointed person in successive frames from the video.
- **Silhouette Tracking:** Through this we track the object in consecutive frames with the help of object shape.
- **Kernel Tracking:** This tracking method computes the motion of an object from one to next frame of video.

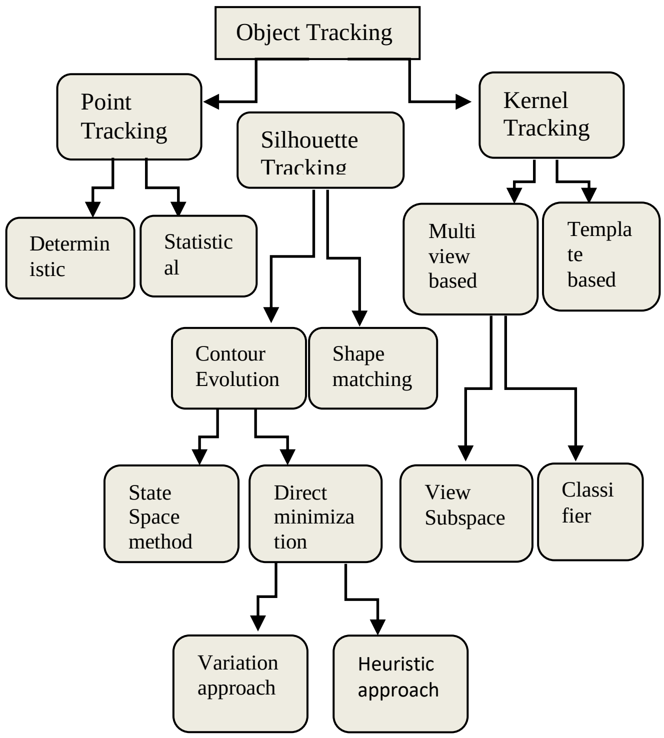

Fig.2: Taxonomy of object tracking [2].

2.3 BEHAVIOR RECOGNITION

In computer vision, we use the concept of behavior recognition to understand and detect that what kind of crowd is this i.e., that normal or abnormal with the help of action recognition and pattern recognition among object and pedestrians in a visual scene. Video surveillance is most of the common approaches to detect this activity in a particular area. The crucial issue related to this scenario is a high density of the crowd and occlusion in a scene, so with the help of a multi-camera approach, we solve these problems. Behavior understanding is quite easy for humans in comparison to computers because they have knowledge and experience about it, but for the computer system, they don't have any experience and learning for this we have to create learning for this to make it understandable. But this task involves lots of issues and challenges. Some of them are described here.

- **Human Identification:** Person should be recognized correctly.
- **Occlusion:** When more than one object overlapped each other.

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- **Human Modeling:** Projection of object recognize should be correctly.
- **Scene Modeling:** Correctly modeling between 2D image and 3D model to better visualization.

For recognizing the behavior of the crowd we have two very famous methods. These are:

- **Object Based Approach**
- **Holistic Based Approach**

When we are going to recognize the behavior pattern of any crowd scene then so it is much difficult due to the crowd. Sometimes we have the normal type of crowd so we can easily extract that behavior from the crowd scene but if the abnormal type of crowd has then it is quite tough to extract the behavior of the crowd. Here we have some classification of crowd base on crowd situation.

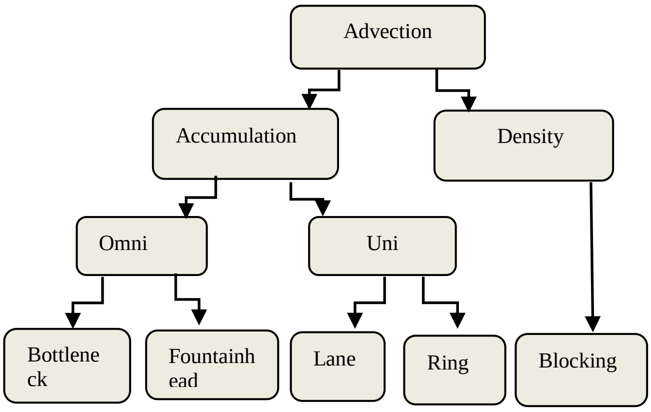

Fig.3: Decision tree for behavior selection [5].

2.3.1 FOUNTAINHEAD

Fountainhead is considered one of the pedestrian behaviors in a crowd where all the pedestrians emerge from one direction and spread over different directions just like a fountain.

(a) (b)

Fig.4: Frame (a) showing the output Fountainhead behavior [32]. (b) Green lines showing the of Fountainhead behaviors [54].

2.3.2 BOTTELNECK

In bottleneck behavior, pedestrians or object originated from a different direction and assemble at one point e.g. exit door.

(a) (b)

Fig.5: (a) Red lines showing the Bottleneck behaviors [54]. (b) Showing the output of bottleneck behavior [32].

2.3.3 LANE

Lane behavior shows that objects or pedestrians moving parallel to one another with the same speed.

(a) (b)

Fig.6: Frames which showing the lane behaviors [41] [9].

2.3.4 RING

In ring type of behavior, objects are moving in a clockwise direction or counterclockwise.

(a) (b)

Fig. 7: (a) Frame showing the Ring behaviors [41]. (b) Showing the output of Ring behavior [32].

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2.3.5 BLOCKED

In blocked behavior, objects are can't move towards the same direction due to some obstacle, they begin to settle in a random direction.

(a) (b)

Fig.8: (a) Showing the behavior of blocking [9]. (b) Showing the output result of blocking behavior [32].

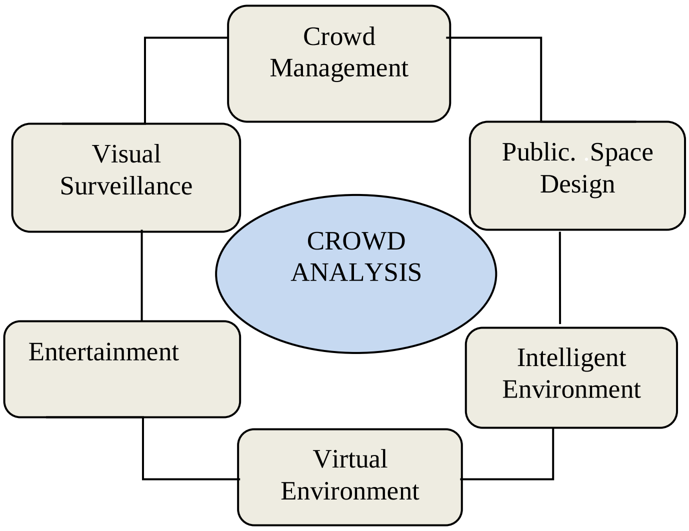

Fig.9: Crowded analysis in different fields.

3. CROWD ANALYSIS APPLICATION

Crowd analysis in computer_vision and pattern _recognition has become a very trendy and attractive research area. As we know that rapid growth in the crowd and concerning crowd security gives a huge opportunity for several applications such as public space design, crowd management, intelligent environment, visual surveillance, and virtual environment.

We have a series of applications developed by B. Zhan et al [7] to present automatically crowd monitoring:

3.1 MANAGEMENT OF CROWD

There could be a serious risk of an unusual and dangerous situation arising from large dense crowds gathering, such as the mob at Mecca, etc., therefore there could be a high likelihood of unavoidable occurrence due to oppression and rushing. Consequently,, crowd management is critical to minimize unavoidable incidents and disasters, as well as to improve public security.

3.2 DESIGN OF PUBLIC SPACE

It is defined by a set of regulations and norms for public space design like designing the space usage of such places like an apartment, retail mall, etc. Understanding crowd behaviour is critical to the final design.

3.3 VISUAL SURVEILLANCE

It is a prominent and fascinating application of computer_vision. Visual surveillance has grown very popular as a result of the hasty proliferation of digital_cameras and crowds. For public safety, visual surveillance is implemented to identify inconsistencies in the mob as well as some mob behavior.

3.4 ENVIRONMENTAL INTELLIGENCE

It comprises the steps of supporting the mob and how to lead the crowd in an intelligent setting. For example, if there is a large crowd at a sporting event or a festival, it becomes difficult to deflect it and assist in crowd management.

3.5 ENTERTAINMENT

The application of a mathematical approach to crowd analysis could give accurate simulations, which could be used in video games, movies, and television [3].

3.6 VIRTUAL ENVIRONMENT

Virtual environments having mathematical models of crowds to enhance the simulation of crowd behavior. The virtual environment is the study part of computer graphics.

4. OVERVIEW OF MOTION PATTERN RECOGNITION FROM CROWDED VIDEO

Crowd Analysis has evolved into a specialized, popular subject in recent years as the number of individuals in the real world has increased. If we manually retrieve activity information from a crowd scene, we know that humans are capable of doing so, but large masses of the crowd, human eyes, and expertise are insufficient to do so. According to psychological research, humans have limitations on simultaneously monitoring signals [8]. Since monitoring a high-density crowd area with visual surveillance necessitates an ample amount of monitoring individuals, which is difficult for a human observer, we use computer vision approaches to track high-density crowd areas [3]. Visual surveillance is becoming more common in this era as a result of public security concerns. As a result, we have a vast number of methods for anomaly detection, monitoring, behavior analysis,

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access control, and recognition. Similar types of events and requirements are treated differently by researches.

The methodology is influenced by the nature of our criteria, after which a researcher employs the most appropriate approach. We'll go over some of the work that's been performed in the realm of recognizing crowd behavior and motion pattern analysis.

A dense crowd, which generates occlusion and clutter, is the main problem with motion pattern retrieval. When more than one entity or pedestrians overlap one other, an occlusion occurs, and it is not immediately apparent what the object behavior is under surveillance and the second factor is cluttering, which occurs when the scene density is increased with multiple types of objects (automobiles, pedestrians, and animal species) going fast into different directions, causing the crowd scene to become cluttered, making it difficult to recognize the objects and their behavior.

In the last several years, there have been a lot of studies in the concern of motion pattern recognition in crowded scenes. Table 1 summarizes several approaches used by various researchers in the sector of motion behavior recognition. The review lasted from 2008 to 2020.

Table 1. Publications on Motion Pattern and Behavior Recognition from crowded scenes

Year	Author	Publications
2008	Ermish et al.	29
2008	Hu et al.	10
2008	Ali et al.	30
2009	Rodriguez et al.	15
2009	Mehran et al.	2
2010	Pathan et al.	18
2010	Dee et al.	20
2011	Srivastava et al.	38
2012	Ren et al.	16
2012	Zhou et al.	40
2012	He et al.	43
2012	Zhang et al.	39
2012	Solmaz et al.	9
2013	Alqaysi et. al	19
2013	Wang et al.	21
2013	Chongjing et al.	33
2015	Yi et al.	34
2016	Ullah et al.	23
2016	Teja et al.	4
2017	Zaki et al.	36
2017	Wu et al.	32
2017	Wu et al.	1
2017	Lu et al.	42
2018	Heldens et al.	24
2018	Hassanein et al.	25
2018	Xie et al.	31
2019	Marčetić et al.	22
2020	Basalamah et al.	26
2020	Singh et al.	41
2020	Yao et al.	37

Table 2. Comparative analysis of previous work

Year	Authors	Title	Methodology	Strength	Limitation
2020	Yao et al [37]	**Learning Crowd Behavior From Real-Data: A Residual-Network. Method for Crowd-Simulation**	Residual_Network Based Scene Independent Crowd Simulation (Resnet_SICS) + Residual_Network For Crowd Behavior Properties Learning(Resnet_CBPL) + Data_Driven Crowd Properties Quantization (DCPQ) + Tracking Learning Detection (TLD)	Provide more realistic, accurate motion patterns of mob and uses the real crowd data for learning actual motion pattern.	Computation cost is high and due to the ResNet training method for crowd data-poor performance is attained.
2020	Basalamah et al [26]	**Pedestrian_Crowd Detection and Segmentation using Multi_Source Feature Descriptors**	Local_BinaryPattern (LBP) + Fourier_Analysis + Graylevel Co_occurrence Matrix + SVM	Automatically identify crowd segment as a Region of interest from crowded scene, due this computation cost is decreases.	The approach is detecting crowd segment as ROI from only one image instead of the whole video.
2020	Singh et al[41]	**Motion_Pattern Recognition From Crowded Video**	Social_Force Model + Optical_Flow + K_ Means Clustering + Jacobian_Matrix	Deal with the following five categories of behaviour: lane, ring, bottle-neck, fountain-head, and block.	The technique detects the abnormal behavior on the basis of the behavior of all objects, not detect the behavior on the basis of category wise.
2019	Marčetić et al [22]	**Crowd Motion_Pattern Detection at the Microscopic Level**	Fuzzy Predicate + Fuzzy Knowledge-Based Methods.	Unique idea to recognize motion pattern from Fuzzy Logic.	The proposed approach does not work well on the multi-object scenes, medium to the dense types of the crowd, and not for complex motion patterns of crowds.
2018	Xie et al [31]	**Video_Crowd Detection and Abnormal_Behavior Model Detection Based on Machine_Learning Method**	Optical flow via LK + Social Force Model + Machine learning	Overcome the challenge of user behaviour pattern representation flexibility and agility.	Not suitable if behavior sequence increases then approach result may be different.
2018	Heldens et al[24]	**Scalable_Detection of Crowd Motion Patterns**	Proximity Graph + Spatial Clustering + Temporal Clustering	Proximity graphs gives a number of benefits in compression of other crowd monitoring methods, like video surveillance or GPS receivers. i.e. less expensive, scalable, low in cost etc.	Instead of having lots of advantages of using Proximity Graphs it has some disadvantages too i.e., it needs proximity sensors equipped device. In a close environment, it's ok but not ok in an open environment.

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ITEE Journal
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2018	Hassanein et al [25]	**Identifying Motion_Pathways in Highly Crowded Scenes: A Non_Parametric Tracklet Clustering Approach**	Distance_ Dependent Chinese Restaurant Process (DD_CRP)	It performs well in gradient orientation issues for distinguishing between aberrant and normal behavior classes due to HOG.	There is no detection of crowd-related events, such as congestion at the scene's entrance point and the influence of this congestion on the crowd's behaviour.
2017	Wu et al [32]	**Motion _SketchBased Crowded Video Retrieval**	Motion_Structure Coding+ CDT Descriptor + Motion_Vector Field.	An innovative method of retrieving motion patterns from a hand-drawn sketch query.	It is time-consuming and does not consider another type of path than these four (Lane, ring, fountain-head, and bottle-neck).
2017	Lu et. al[42]	**Trajectory-Based Motion-Pattern Analysis of Crowds**	Fuzzy c-means (FCM) + Local_outlier factor (LOF)	Find spatiotemporal statistical properties of pedestrians	Time consuming and misclassification problem.
2017	Zaki et al [36]	**Automated Analysis of Pedestrian Group Behavior in Urban Settings**	MMTrack Algorithm + Homography matrix.	The method can count the count of people in a group and distinguish the walking behaviour of people in the same or distinct groups.	Group detection was only done in low to moderately dense pedestrian environments, not in crowded pedestrian environments.
2017	Wu et al [1]	**Crowd_Behavior Analysis Via Curl & Divergence of Motion_ Trajectories**	Optical Flow + Curl & Divergence of Motion. Trajectories + SVM.	Quantitatively and globally, assess collective motion patterns.	The proposed approach does not work on blocking patterns for crowd behavior evaluation and is a time-consuming approach. .
2016	Ullah et al [23]	**Crowd Behavior Identification**	Thermal_Diffusion Process (TDP) + Modified _Social Force Model (MSFM) + Optical Flow Technique	M-SFM is used to extract and filter out particles that aren't useful in the behaviour detection process. As opposed to the traditional Social Force Model.	It is not appropriate work to prevent such behavior.
2016	Teja et al[4]	**Crowd Behavior Detection Using Optical_Flow & Clustering**	Optical_Flow + K_ Mean Clustering + Jacobian _Matrix.	Reduce computing costs by addressing the issue of occlusion and cluttering.	It is not applicable to abnormal types of behavior.
2015	Yi et al [34]	**Understanding Pedestrian Behaviors from Stationary Crowded Group**	General _Energy Map + Scene_Layout (SL) + Moving_Pedestrians (M P) + Stationary_Groups (SG)	Proposed an innovative approach to stationary crowd groups with pedestrian behavior and they also built a large pedestrian walking dataset.	In spite of having good path prediction for pedestrians, it is not well defined for different types of path.
2013	Chongjing et al [33]	**Analyzing Motion Patterns in Crowded Scenes Via Automatic_Tracklets Clustering**	LK Optical Flow + Hierarchical Clustering Algorithm	Finding motion patterns in dynamic, crowded scenes using an unsupervised approach. .	The suggested approach is not applicable to acquiring the long-term motion of the scene to gain a deeper understanding the behavior

					of the crowd.
2013	Alqaysi et al[19]	**Detection of Abnormal Behavior in Dynamic-Crowded Gatherings**	Motion_History Image (MHI) + Optical_Flow via Lucas_ Kanade + Histogram	Improved accuracy, reduced response time, and noise sensitivity. Early detection of congestion and overpopulation.	It has not been thoroughly tested on large or realistic crowd videos.
2013	Wang et al[21]	**Motion_Pattern Analysis in Crowded Scenes Based on Hybrid _GenerativeDiscriminative Feature Maps**	Dense Points Tracking with LK-optical flow method, Hidden Markov model, Hierarchical clustering algorithms.	Accurate and dense tracking solves the issue of occlusion.	This approach is inefficient.
2012	Solmaz et al [9]	**Identifying Behavior in Crowd using Stability _Analysis**	Jacobian Matrix + Linear _Dynamical System.	No need for training, or detection and tracking.	When there is a considerable overlap of the motion pattern in the scene, or when a consistent characteristic flow is missing, the approach cannot be applied.
2012	Ren et al[16]	**Abnormal Crowd Behavior Detection using Behavior Entropy_Model**	Behavior Entropy Model + Behavior certainty (BC) + Behavior entropy (BE).	The Behavior Entropy Model is successful and popular due to its exorbitant performance in recognising and locating abnormal events. However, the most crucial factor is to create a consistent framework that targets a variety of anomalies.	It does not apply to videos that are extremely dense and crowded.
2012	He et al[43]	**Motion_Pattern Analysis in Crowded Scenes by using Density_Based Clustering**	Density based clustering (DBSCAN) + Motion flow field.	In congested scenes, motion patterns are well detected.	Clustering is time-consuming and inefficient.
2012	Zhang et al [39]	**Abnormal_Crowd Behavior Detection Based on Social_Attribute Aware Force Model**	Social _AttributesAware Force Model (SAFM) + Particle_ Advection + Disorder_Attribute + Congestion_Attribute	Overcome the problem of the conventional social-force model.	With the social force's appr oach, the model needs to be improved. Despite the fact that this method produces g ood outcomes, it is an offli ne method.
2012	Zhou et al [40]	**Understanding Collective Crowd Behaviors: Learning A Mixture Model of Dynamic Pedestrian Agents**	Mixture Model Of Dynamic Pedestrian-Agents (MDA) + KLT Tracker	Method classified collective behaviors and also predicted collective crowd behaviors.	The proposed method is scene-specific. That’s why we can’t apply this to another type of scene.

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2011	Srivastava et al[38]	**Crowd Flow_Estimation using Multipl_Visual Features for Scenes with Changing_Crowd Densities**	Graylevel Co_Occurrence Matrix (GLCM) + Texture. Features + Scaling Factors	The method can calculate the total count of persons crossing through a specific area, deal with occlusion, and performs best in dense crowds.	An ample amount of occlusions can be an issue in the foreground pixel_based counting for recognizing the actual counting of pedestrians in the scene.
2010	Pathan et al[18]	**Crowd Behavior Detection by Statistical_ Modeling of Motion_ Patterns**	Gaussian Mixture Model(GMM) + K-Means clustering + Spatio-Temporal Block-clips + Conditional_ Random Field (CRF)	Automatic detection and localization of crowd behaviors, with the goal of overcoming the problem of spatial localization caused by block-clips.	Because of the offline nature of this approach, the model is complex and slow, and it is not sufficient when pedestrian density is critically high.
2010	Dee et al[20]	**Crowd_Behavior Analysis using Histograms of Motion_Direction**	HOG_based. Pedestrian Detector + Viola_Jones FaceDetector + KLT Tracker + Histograms of Motion_Direction (HMDs)	It requires little training data and performs admirably in detecting a huge range of events in a publicly available crowd_dataset.	The notion that the motion in the scene will be steady is the flaw in this strategy.
2009	Mehran et al [2]	**Abnormal_Crowd Behavior Detection using Social_Force Model**	Optical flow + Social Force Model + K Means Clustering	Not dependent on tracked objects in the analysis of crowd behavior.	It necessitates a set of objectives for the scene.
2009	Rodriguez et al [15]	**Tracking in Unstructured_Crowded Scenes**	Correlated_Topic Model (CTM) + Scene_ Codebook + Kalman_ Tracker + EM Algorithm	The model may capture both the association bet ween diverse patterns of behaviour as well as the multi-modal nature of dense, u nstructured settings.	Despite advancements in sp ecific tracking in crowded crowds, the automated startup of each t rack remains a hurdle.
2008	Ali et. al [30]	**Floor_Fields for Tracking in High_Density Crowd**	Dynamic_Floor Field (DFF) + Static_Floor Field (SFF) + Boundary _Floor Field (BFF)	Think about the group flow and scene design for the following and provide the briefest separation from a sink for every area.	The dynamic floor field generates mistakes when interference occurs and noise occurs from another object in the scene.
2008	Ermish et al [29]	**Motion_Segmentation and Abnormal_Behavior Detection Via Behavior _Clustering**	Busy-Idle Rate Statistics + Random Projections + k-Means Clustering	Even when there are onl y a few busy-idle-rate examples, it works nicely.	There is no path identificati on or tracking in this strate gy. Only a few busy-idle rate samples per pixel are used in the suggested st rategy.
2008	Hu et al [10]	**Learning Motion Pattern in Crowded Scenes using Motion_Flow Fields**	Agglomerative clustering + Motion Flow Fields	No affection for the object's density within the image.	The method has a misclassification issue. .

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5. DATASET FOR CROWDED VIDEO ANALYSIS

In addition to research in the domain of crowd analysis and surveillance video, a lot of progress is also being done in the field of datasets. We can't deny that in the sector of the crowd_analysis and video_surveillance, the dataset is necessary as much as methods and technologies used in research. That is why, in this area, a lot of novel work is being done from time to time to make the dataset more advance and suitable. These are some of the datasets whose contribution in the field of Crowd Analysis has been commendable.

5.1 PETS 2009 DATASET [45]

This dataset includes several multi_sensor patterns of distinct crowd behaviors. There are four sections to the PETS_2009 data set. These are the:

- **S0_Training dataset:** Background Range, City-Center, and Routine-Flow are the three training sets in this dataset.
- **S1_Person Count & Density Estimation:** This L1_walking, L2_walking, and L3_running are three members of a dataset dedicated to Pedestrian count and density estimation of the crowd. L1_Walking and L3_Running are moderately crowded images, while L2_Walking is extremely dense.
- **S2 People Tracking:** This dataset was used to monitor all of the people in Sequence, which was split into three sections. L1_Walking shows a sparse mob, L2_Walking shows a medium-density crowd and L3_Walking shows a dense crowd.
- **S3 Flow Analysis & Event recognition:** Multiple Flow and Event Recognition are the two subsets of this dataset. The Flow of Multiples Detect and estimate multiple flows in the given sequences, while event identification includes a variety of crowd behaviors, and each of the walkings, running, scattering, crowd formation, and crowd separation occurrences is given a probability value.

5.2 CUHK DATASET [51]

This dataset is one of the most well-known datasets used in crowd analysis studies. Out of 215 crowded scenes, there are 474 videos in the entire dataset. This CUHK dataset is split into two parts: a pedestrian path and a traffic dataset (MIT_traffic). The pedestrian dataset, also known as the Grand Central Station dataset, contains 33 minutes and 20 seconds of footage, while the traffic dataset contains a 90-minute video.

5.3 UCF CROWD BEHAVIOR DATASET [50]

It is a publicly accessible dataset that only contains image sequences, not recordings, and can be obtained from the BBC_Motion Gallery and Getty_Images websites, along with all ground truth marks. This dataset is specifically built for crowd flow activities such as fountain_heads, bottle_necks, rings, and blocking, but it does not cover unusual activity.

5.4 COLLECTIVE MOTION DATASET [54]

Zhou et al [35] proposed this Collective Motion Dataset to find collective motions from random crowd motions. It includes 413 video from 62 crowded scenarios, each with approximately 1000 frames and trajectories, but it focuses on a single action and panic gestures. It only has three scenes, each with a few images, which is much too limited.

5.5 UMN DATASET [44]

This dataset was created by the University of Minnesota and is open to the public. It contains many crowded videos of irregular and natural crowds in fields such as action recognition, event detection, real-time monitoring, pattern learning from video sequences, and many others.

5.6 UCFF_CROWD DATASET [51]

The BBC_Motion Gallery and Getty_Images both have this crowd. dataset available for download, which have 38 publically available video clips of the crowd scene, vehicle traffic, and extremely dense moving objects.

5.7 UCSD ANOMALY-DETECTION DATASET [49]

This crowd dataset can be downloaded from the BBC Motion Gallery and Getty Images, which both include 38 publicly available video clips of crowds, traffic, and incredibly dense moving objects. It covers both standard crowd footage in which a pedestrian is the only person in the scene and odd crowd videos in which non-pedestrian objects cross the sidewalk or pedestrian motion patterns are unclear. The dataset is categorized into two parts, each of which is called a subset.

- **Peds_1:** There are a total of 34 instructional video clips and 36 research sample clips showing people walking around the camera.
- **Peds_2:**There are 16 training videos and 12 resear ch sample videos showing people travelling exactl y the same way as the camera.

5.8 VIOLENT_FLOWS DATASET [46]

A real_world footage of crowd_violence is included in the Violent Flows Crowd Violence and Non-violent Dataset, as well as typical benchmark techniques for assessing violent/non-violent classification and identifying violence breakouts. There are 246 videos in the data collection. All of the video snippets were discovered on YouTube. The least footage is 1.04 seconds long, the widest is 6.52 seconds long, and the cumulative video clip length is 3.60 seconds.

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5.9 RODRIGUEZ'S WEB_COLLECTED DATASET

Rodriguez compiled his own dataset by uploading and crawling video clips from Getty Images and YouTube, among other sources. There are 520 video clips available, ranging in length from 2 to 5 minutes and resized to 720x480 resolutions. This dataset isn't open to the general public [27].

5.10 QMUL DATASET [53]

QMUL_Junction Dataset, QMUL_Junction2 Dataset, and QMUL_Roundabout Dataset are the three classifications of this dataset. QMUL_Junction has a nearly 1 hour long footage with 90000 frames, QMUL_Junction2 has a 52-minute long footage with 78000 frames, and QMUL_Roundabout has a 93500 frame video clip. It's a dataset that's open to the public.

5.11 NOVEL MULTI_CLASS CROWD DATASET

Rabiee et al. [54] added a new dataset contains 31 video sequences in all, or approximately 44,000 regular and abnormal video clips. The videos were shot at a resolution of 554 x 235 at 30 frames per second using a fixed video camera positioned at a particular height overlooking individual walkways. The scene's crowd density fluctuated from sparse to dense [53].

Table 3 discusses several aspects of the dataset, such as the type of dataset (video or image), the resolution of the video or image series, whether it is publicly accessible or not, and which researcher used the data in his or her work

In Table 4, we have shown some sequences related to the dataset so that the working area and the crowd scene of the dataset can be better understood.

Table 3. Comparative analysis of previous work

Reference	Dataset	Resolution	Category	Number of Videos	Availability
1. Dee et al. [20] 2. Pathan et al. [18]	PETS 2009	768x576 and 720x576	Image sequence	8	Public
1. Basalamah et al. [26] 2. Wang et al. [21] 3. Wu et al. [32]	UCF Crowd Dataset	Multiple	Video	38	Public
1. Hassanein et al. [25] 2. Wu et al. [32] 3. Yi et al. [34] 4. Zhou et al. [40] 5. Wu et al. [1]	CUHK Dataset	Multiple	Video	2	Public
1. Ali et al. [30] 2. Xie et al. [31] 3. Chongjing et al. [33]	UCF Crowd Behavior Dataset	Multiple	Video	68	Public
1. Ren et al.[16] 2. Pathan et al. [18] 3. Zhang et al. [39]	UMN Dataset	320 × 240	Video	11	Public
1. Zhou et al. [35]	Collective Motion Dataset	Multiple	Video	413	Public
1. Zhang et al. [39] 2. Srivastava et al. [38]	UCSD Anomaly-Detection Dataset	238x158	Image sequence	98	Public

ITEE Journal
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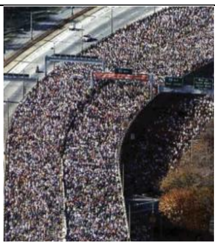
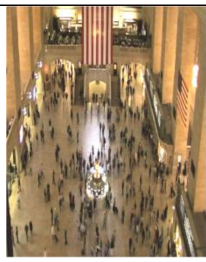
1. Hassner et al. [17]	Violent-Flows Dataset	320 × 240	Video	246	Public
1. Rodriguez et al. [27]	Rodriguez's Web-Collected Dataset	720x480	Video	520	Private
1. Loy et al. [52]	QMUL Dataset	360x288	Video	3	Public
1. Rabiee et al. [53]	Novel Multi-Class Crowd Dataset	554 x 235	Video	30	Private

Table 4. Comparative analysis of previous work

Dataset	**Snap 1**	**Snap 2**	**Snap 3**	**Snap 4**	**Snap 5**
PETS 2009					
UCF Crowd Dataset					
CUHK Dataset					
UCF Crowd Behavior Dataset					
UMN Dataset					

ITEE Journal
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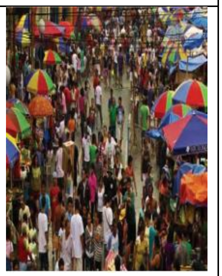
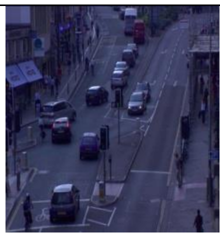
Collective Motion Dataset					
UCSD Anomaly Detection Dataset					
Violent-Flows Dataset					
Rodriguez's Web-Collected Dataset					
QMUL Dataset					
NOVEL MULTI-CLASS CROWD DATASET					

6. CONCLUSION

In this article, we concentrated on the review concept of crowd motion patterns, where we can find a wealth of knowledge about crowd movement patterns. This paper discusses a vast amount of information about crowd analysis, its applications, and emerging crowd motion pattern recognition technologies, as well as their benefits and drawbacks, various forms of crowd activity, and various types of datasets used in the realm of crowd motion pattern recognition.

We can see from the literature review that there has been a lot of work done in the realm of crowd behavior recognition. Various researchers have suggested various methods for archiving their targets. Some researchers achieved their goal with high precision, but their

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computational cost and complexity of the solution increased, while other researchers' complexity and computational cost did not increase, but their accuracy and the desired goal did not.

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