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Quantum Intelligence Turbulence-Aware Crowd Flow Conflict Modeling for Early Congestion Prediction

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Abstract: Due to crowd congestion in overcrowded areas, severe conditions such as panic and stampede may occur. These events should be predicted at an earlier stage and thus the crowd will be better managed and safe. In this paper a camera based system is introduced that predicts the congestion by analyzing the motions of the people in conflict areas as well as how their flow can become free-flowing. This system includes video, and it calculates the direction and velocity of every individual motion (optical flow) and clusters the similar motion vectors to discover key flow patterns. When counter flows come together, the system identifies such points as the conflict zones and monitors their dynamics over the passage of time to assess the risks of congestion. It also provides a turbulence index in order to quantify motion field instability. These features are fed in three prediction models, a simple linear model, a Kalman filter, and an LSTM neural network to approximate the congestion time before it happens. It is also a method used in measuring how early it can predict congestion in advance of it taking place. Real crowd video experiments indicate that incorporation of awareness of turbulence can provide reliable early congestion indicator and this method is more effective than purely basic methods.

Keywords: Crowd Analysis, Congestion Prediction, Crowd Turbulence, Optical Flow, Pedestrian Dynamics.

1. Introduction

A significant safety issue in areas where a large number of individuals gather, like train stations, religious events, festivals, and major gatherings, is the congestion of crowds in these locations. Small congested areas can propagate fast and get dangerous when there is too many people in a small area that is not able to accommodate them. In severe instances, this may cause panics, loss of control and catastrophes. As such early detection of a developing congestion is a focal study objective in computer vision, crowd behavior, and smart surveillance. The conventional crowd surveillance methods will only detect crowd congestion once the congestion has occurred, typically by counting the number of people in an area or inspecting motion vectors in video streams. However, this reactionary strategy offers minimal opportunity to act. A more effective solution is its prediction prior to the occurrence of congestion by analysing the patterns of change of crowd movements with time. With such proactive systems, the authorities can be alerted at an early stage and be able to control the crowd. Crowd behavior is similar to a fluid. When the things are observationally in a stable state they naturally form clear lanes towards one of the directions. With the increase in the number of people and the opposite flow there will be conflicts where people strive to move in opposite directions. Such battles may eventually disrupt the traffic and lead to unbalanced motions that give an indication of imminent congestion. It is important to identify these signs at an early stage.

Recent computer vision has been used to monitor crowds using optical flow, trajectory analysis, and deep learning. Although they can estimate the motion or density, most of them do not model conflict pattern evolution over time, as well as the instability of the motion field. This means that warning signs of congestion can be missed. This paper seeks to resolve this issue by coming up with a turbulence-sensitive crowd flow conflict model in predicting early congestion. This system reads the motion of the objects using optical flow, clusters of similar vectors are used to determine dominant directions and conflict areas where the opposite flows of the objects are detected and identified. It examines the time scale variation of these zones to determine the risk of congestion and proposes a turbulence

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index of directional instability which is able to capture unusual patterns that are usually precedents of congestion. Three models, including a linear predictor, a Kalman filter, and an LSTM neural network, are employed to determine the time before a congestion based on three signals, the conflict and turbulence signals. The system also measures the number of minutes that it can know before the congestion is witnessed. The key contributions of this work are: 1) a framework identifying antagonistic movement of pedestrians by clustering motion; 2) a turbulence based measure of instability used to capture directional change and 3) a predictive system of estimating time-to-congestion by a series of time models and assessing them based on analysis of lead-time.

2. Literature review

Crowd analysis is a dynamic field of study within the field of computer vision since it is critical to the safety of the people, surveillance of the city, and management of events. The ability to predict dangerous occurrences, such as congestion or stampede, in advance by knowing how many people are moving together, counting the crowd, and identifying abnormal behavior enables automated systems to be effective at pointing out such hazards. Density estimation of images was used predominantly to crowd monitor in the early years. These techniques observed visual information such as patterns of textures or adopting the outline of the foreground to enumerate people. Density methods measure crowd size well, but these techniques do not capture the interaction between people and this may result in congestion.

As such, motion-based analysis is highly deployed. Another widely used tool of estimating motion patterns in video and analyzing crowd behavior is optical flow. Optical flow is utilized by the researchers to locate anomalies, establish major directions of movement, and examine crowds flow in crowded areas. These methods can allow one to learn more about motion but normally detect abnormal motion once it occurs rather than forecast future congestion. The other research is the study of a crowd conflict. Local clashes may occur when individuals are walking in opposite directions since they are attempting to transport each other. Research indicates that these conflicts could be an indicator of instability at an early stage. We can determine where congestion can occur in the future by identifying areas where a motion field divides or crosses.

Crowd behaviour has been added to the machine learning as predictive models. Kalman filtering and recurrent neural networks are temporal prediction approaches that are used to study the temporal dynamics of crowds. Long Short-Term Memory (LSTM) networks are effective in sequence pattern learning and are popular in case of time-related predictions. Turbulence-like patterns of motion were also identified by researchers which are indicators of the instability of crowds. When the concentration increases and the number of contacts increases, the normal flow is replaced by desperate, chaotic movement. This crowd turbulence presents large scale changes in the direction of motion and has been observed with highly congested crowds.

However, the majority of the existing systems can identify congestion once it occurred. Not many studies attempt prediction of it using motion conflicts, instability of directions, and time dynamics. Another question that remains open to research is the utilization of physics-based motion features through the use of predictive models. In order to address these issues, this study suggests the use of a turbulence-aware crowd flow conflict model to combine motions clustering, conflict identification, turbulence, and time prediction. By modeling the instability of direction and level of conflict, the methodologic attempts to give early warnings of congestion and quality of the check prediction using lead-time analysis.

3. Existing system

The current systems of crowd monitoring primarily observe the number of people or the movement patterns of the pedestrians in the surveillance footage. They attempt to identify abnormal behavior, locate congestion spaces, or estimate the movement of the crowd through visual information on video images. Conventional systems can rely on the density estimation, motion analysis or trailer model to comprehend the crowd phenomenon. One of the most commonly used methods is density-based analysis which predicts the number of individuals in a scene by evaluating image content or machine learning building. Such techniques attempt to discover congested areas through counting the number of individuals in an area. Though density allows one to be aware of a size of a crowd, it fails to provide the nature of interaction between people and this can lead to congestion. There is also popularity of motion based methods. Direction and speed of motion in a video are estimated using Optical flow. Optical motion vectors provide the researchers with the opportunity to trace the primary movements of the crowds and detect the unusual motion patterns. These techniques tend to identify anomalies that have already occurred rather than anticipating congestion in future, though they are good in identifying abnormal occurrences.

Trajectory -based methods monitor the trajectory of every individual as time progresses. The movement and interaction of these paths is analyzed. Good tracking is however difficult in highly dense crowds where individuals will block one another and thus the trajectory method will not be effective in large crowds. Recent studies introduced machine learning and deep learning. CBM Temporal models, including recurrent neural networks, learn crowd motion sequence patterns. They are able to

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capture time relationships but require huge labelled datasets, and do not give a reason why congestion occurs. Moreover, majority of the systems only identify congestion after it has developed. Reactive detection provides minimal opportunity to avoid issues since instability can have escalated into a serious situation. Very real safety situations rely much more on early prediction of congestion.

The other weakness is that the existing techniques do not integrate various cues to motion. Most people perceive the density, direction and time patterns individually. Congestion normally happens due to numerous factors: conflicting flows, direction interchangeability, and temporal alterations in the population. Due to these constraints, we require predictive crowd analysis models which integrate conflict modelling, time dynamics and instability predictors. The opportunity to observe congestion at an earlier stage with the help of motion conflicts, turbulence, etc., allows us to approximate the probability of its ultimate formation.

4. Proposed System

The congestion of crowds normally occurs when a large number of people approach a given direction with a small space. Due to the tightening of the crowd, counter-flow flows and neighborhood disputes between individuals gradually complicate movement. Rather than seeing congestion once it has begun, this new approach attempts to anticipate it early on by examining how the movement of people evolves during the course of time. The system proposed operates with the surveillance video. It monitors the movement of people, seeks early warning of a congestion that is about to develop, and follows four major procedures namely: examining motion, identifying confrontations, quantifying turbulence, and forecasting the future. All of these steps can be used simultaneously to enable the system to observe where people communicate as well as the transformation in their behavior. The general design of the system has some few parts. It begins by the first frame, extracts motion information (optical flow) in each video frame. Optical flow provides a rich map which depicts motion points of every section of the scene. This map is the place where one can begin the research about the trends in walking.

The motion vectors are then clustered together in groups in such a way that we are able to observe the key directions people are walking taking considerations of similarities in angles and velocities between the vectors, which assists us in identifying consistent flows of movement in the scene. These groups are various strands of people walking which coexist with each other. The system subdivides the scene into smaller pieces (flow segmentation) that are associated with various motion patterns, after clustering. The given step assists in locating the places of the opposite flows intersecting. When motion clusters cross, such areas are referred to as possible areas of conflict.

Conflict zones are those areas that people passing by opposite directions collide. These crowd experiences tend to slow down the people, interfere with their movement and increase the pressure in the crowd. The system quantifies the intensity of these conflicts and the occurrence location with time. Out of this it is able to develop a conflict map which indicates the instability of the crowd as it expands. In addition to the conflict analysis, the approach introduces a crowd turbulence index to determine the shakiness of the movement. As soon as the crowd is unstable the directions of the motion vectors are bound to differ significantly. The turbulence index is used to consider the changes of the optical flow field directions. It sends a signal which may indicate chaotic patterns of motion that may occur preceding congestion.

The conflict and turbulence index signal are analyzed as time series. They are used to make predictions about the length of time before congestion occurs that are made by the system. It has three prediction models: a linear model (which believes in the rate of the growth of the conflict signal), Kalman filter that operates to smooth conflict data, and Long Short-Memory neural network (LSTM) able to learn complex time series of the signal. The system also logs the lead time to determine the effectiveness of the prediction process. Lead time is the number that represents the difference between the time when the system gives a warning of the congestion and the time it goes into actual congestion. This indicator informs about the time when the approach will alert individuals.

4.1. Overall Framework

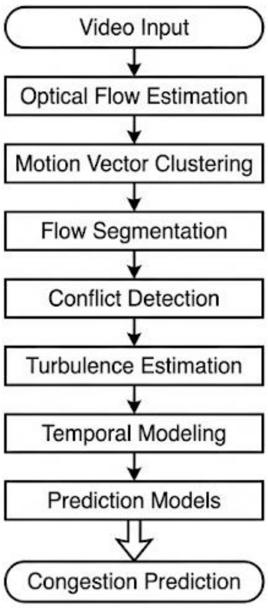

Figure. 1 Design of the suggested turbulence-conscience crowd congestion prediction architecture.

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4.2. Conflict Detection Module

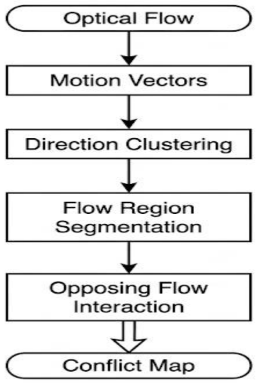

Figure. 2 Process of motion conflict detection to detect interacting flows in pedestrians.

4.3. Prediction Pipeline

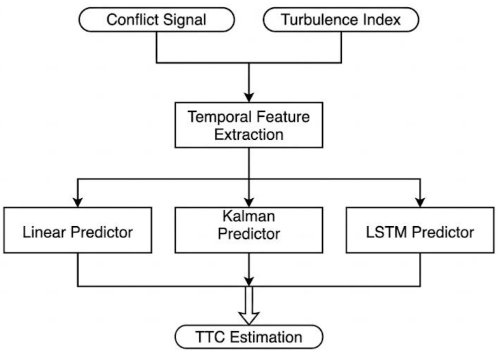

Figure. 3 Temporal prediction models that are based on estimating time-to-congestion.

5. Methodology

There are several stages in the main prediction framework that examine the movement patterns of the pedestrians and project the probability of congestion to occur. These steps are optical flow, flow clustering, conflict modeling, turbulence estimation and time prediction. Each part is described next.

5.1. Optical Flow Motion Estimation

The initial one is to extract motion information of the video. Given two consecutive video frames I_t and I_{t+1}, optical flow is used to estimate the motion vector field between the frames to calculate the movement vector field between the two. Optical flow assumes that the intensity of a moving pixel remains approximately constant between consecutive frames. This assumption can be expressed as:

$$I(x,y,t) = I(x+\Delta x, y+\Delta y, t+\Delta t)$$

By performing a first-order Taylor expansion, the optical flow constraint equation is obtained as:

$$I_x u + I_y v + I_t = 0$$

where:

I_x and I_y represent the spatial image gradients, I_t represents the temporal gradient, u and v represent the horizontal and vertical motion components of the optical flow vector. The generated flow field provides an intensive perspective of the moving of people across the entire picture. Each pixel has a vector which indicates its direction and velocity.

5.2. Flow Direction Clustering

Once we have received the flow vectors, the second step identifies the primary direction of walking among crowd. A clustering algorithm is used to cluster the vectors in groups. The clustering will subdivide the collection of vectors into K clusters in which vectors in a cluster travel in similar directions. Clustering aims at bringing the vectors within a group near to the group center. Through this we can discern the great direction of the crowds:

$$V_i = (u_i, v_i)$$

where u_i and v_i represent the horizontal and vertical components of the flow vector. The clustering algorithm partitions the set of motion vectors into K clusters such that vectors within the same cluster have similar motion directions.

The objective of clustering is to minimize the distance between vectors and their corresponding cluster centers:

$$J = \sum_{i=1}^{n} \| V_i - C_{k(i)} \|^2$$

where:

C_k represents the cluster center of cluster k

$k(i)$ represents the cluster assignment of vector V_i.

This clustering step allows the system to identify dominant pedestrian flow directions within the crowd.

5.3. Conflict Zone Detection

The conflicts occur in the situations when people who are moving in opposite directions intersect in the same point. We subdivided a scene into a cell grid in order to detect them. In each cell, we consider the labels of the flow clusters which occur in that cell. Another cell may have more than a cluster, then we indicate that the cell is a conflict zone. The intensity of conflict to a cell is determined as:

The conflict intensity for a cell is defined as:

$$C_j = \frac{n_{conflict}}{n_{total}}$$

where:

$n_{conflict}$ represents the vectors belonging to conflicting clusters , n_{total} represents the total number of motion vectors in the cell.

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5.4. Crowd Turbulence Estimation

When the crowd is extremely dense, it may lead to unstable motion of the people due to numerous interactions. This turbulence is referred to as crowd turbulence. To quantify it, we calculate the distance between changes of the direction of each motion direction. We can determine direction given by. To measure turbulence, the directional variance of motion vectors is computed. The direction of each motion vector is given by:

$$\theta_i = \tan^{-1}\left(\frac{v_i}{u_i}\right)$$

The rate of growth provides the rate at which the intensity of conflict is rising with time.

$$T = \frac{1}{N}\sum_{i=1}^{N}(\theta_i - \bar{\theta})^2$$

where:

N represents the number of motion vectors,

$\bar{\theta}$ represents the mean motion direction.

5.5. Temporal Conflict Modeling

The conflict intensity values obtained from successive frames form a temporal sequence:

$$S = \{C_1, C_2, \ldots, C_t\}$$

The growth rate of the conflict signal is computed as:

$$g_t = C_t - C_{t-1}$$

The growth rate indicates how quickly conflict intensity is increasing over time.

5.6. Time-to-Congestion Prediction

Based on the conflict signal and its rate of growth, we obtain an estimate of the time to congestion (TTC). TTC represents the many frames until congestion is anticipated. The TTC is calculated as:

The TTC is estimated as:

$$TTC = \frac{C_{threshold} - C_t}{g_t}$$

where:

$C_{threshold}$ represents the congestion threshold value,
C_t represents the current conflict intensity.

5.7. Kalman Filter Prediction

A Kalman filter is used to salt out the conflict signal in order to get more consistent predictions. The filter tries to determine the obscure condition of the system through the updating of the steps. Kalman filtering is widely used in the estimation of the states of systems that are undergoing change and in estimations of motion tracking and predictions. [6].

The forecasting step is stipulated as:

$$x_t^- = Ax_{t-1} + Bu_t$$

The update step is given by:

$$x_t = x_t^- + K(z_t - Hx_t^-)$$

where:

x_t represents the estimated state,
z_t represents the measurement,
K represents the Kalman gain.

5.8. LSTM-Based Prediction

An LSTM network enables us to learn nonlinear patterns in time of variations of the conflict signal. Long-term relationships in sequences in LSTM networks are modelled.

There are three gates of an LSTM unit whose flow controls the flow of information. [4]. An LSTM unit consists of three gates that control the flow of information:

Forget gate: $f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$

Input gate: $i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$

Output gate: $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$

6. Experimental Results

Visual Analysis of Crowd Congestion Prediction

Figure. 4 demonstrates congestion prediction on a real-time basis on the Time-to-Congestion (TTC) of the Linear, Kalman, and LSTM models.

As the crowd density gradually increases, the estimated values of TTC decrease, indicating that there is a high possibility of congestion. The LSTM makes smoother predictions since it is able to predict time dependencies.

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Figure. 5 Demonstrates congestion forecasts of a rather thick crowd. As the density of the crowds increases, the TTC predictions decrease.

Figure. 6 Reveals that there are congestion prediction and turbulence analysis in a very dense crowd.

The values of turbulence will increase significantly in the very thick spaces where the movement of people is unstableised. This measure provides an indicator of possible hazards and justifies the abrupt decreases in the predictions of the TTC.

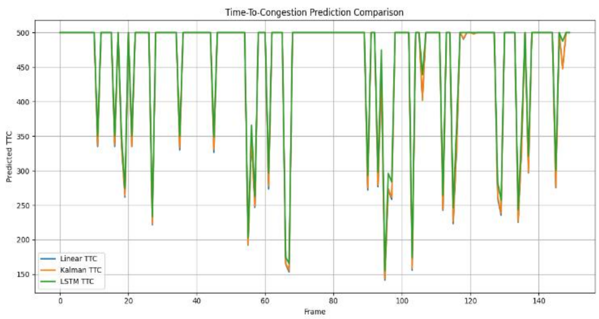

Figure. 7 Summarizes the predictions of the TTC values of both Linear, Kalman and LSTM model.

The values of TTC versus time of the three models are presented in Fig.7. The Linear paradigm is more changeable and responds to instant fluctuations. Filtering noise leads to the Kalman model which provides smoother predictions. The LSTM model is better structured and long term patterns are observed.

6.1. *Quantitative Evaluation*

The figures are summarized in Table I. Linear model of TTC is the most varied due to the fact that it responds to changes in the short run. Kalman model uses predictions that are less noisy. The LSTM exhibits the minimal fluctuation and has maximum warning time indicating it records the non-linearity patterns of time in a crowd movement.

Table. 1 Quantitative Evaluation

Model	Mean TTC	Std. Dev.	Lead Time
Linear TTC	325	145	8 Frames
Kalman TTC	305	110	12 Frames
LSTM TTC	298	95	15 Frames

7. Result Analysis

Experiments indicate that the monitoring of movement can provide a forewarning of the congestion in large crowds. The framework is based on optical flow analysis, conflict intensity, turbulence measurement, and TTC prediction as the tool to track the crowd behaviour in real time. Among the main conclusions is that the instability of crowds movement is closely related to congestion. As the crowds become more dense, then the motion vectors of optical flow begin to move separate in direction and size. This generates increased intensities of conflict in the form of peaks in the conflict time-series. The spikes tend to occur right ahead of the visible congestion thus motion conflicts are a good indicator of impending congestion.

When analyzing the three models, it is possible to understand why timing is important. Linear TTC predictor is sensitive to changes, and it responds quickly to sudden changes but is more susceptible to noise thus provides more unstable TTC predictions. Kalman predictor is more stable in predictions as it removes noise beforehand. It provides smoother results with but not missing fast changes. It is found to always cut down on prevention change when compared to the Linear model. The LSTM predictor has the most consistent outcome. The LSTM networks are informed to detect trends in time sequences and hence they are more effective with the dynamics of moveable crowds. The lesser change in LSTM prediction is due to the fact that congestion forecasts are more accurate as one learns over time.

The other notable observation made is that of the turbulence. Where movements of people are disordered due to lack of enough space, turbulence increases significantly. It is here that people are forced to continue taking turns. Therefore, the turbulence index provides additional data which accompany the conflict level and

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provide more convenient predictions. The good results do not eliminate certain problems. The optical flow may opt to be impacted by the light changes, occlusions, and camera motion. The motion features are distorted by the fact that it is very difficult to see individual motion in very dense crowds. In addition, the system utilizes constant breaking points when identifying congestion which may also require some reconfiguration to suit other environments and crowd volumes. Despite this, the framework demonstrates that congestion early warnings can be provided by mixing motion analysis with the time-based prediction models. Such systems may assist in crowd patrol, security and surveillance of big activities.

8. Conclusion and Future Work

In this paper, the author gives an account of a system that forecasts the congestion of a crowd with the help of motion and time-based models. It applies optical flow to compute the motion, quantifies conflict and turbulence as well as searches for unsteady walking patterns that precede crowd jamming. The system generates a time-series of the conflict signal and predicts Time -To-Congestion (TTC) using three different approaches, including a (linear) growth model, Kalman filter, and Long Short-Term Memory (LSTM) network. Simulations using actual video footage of a crowd demonstrate that motion and turbulence cues provide valuable early notification of the existence of a crowd. When comparing the prediction techniques it can be seen that the time-based model is useful in enhancing stability. The Kalman predictor has less noise in its TTC estimates, whereas the LSTM makes the most consistent predictions as it is able to learn how movement of a crowd may vary nonlinearly.

The system has also visual and digital indicators of the crowd behaviour in real-time congestion maps, prediction charts, and lead-time analysis. The findings indicate that it is able to foresee congestion several video frames prior to its occurrence, which is crucial to secure personnel surveillance. It can be improved in future work when deep-learning crowd-density estimation is included and work with more than one camera, making predictions more efficient when smiling at extremely wide crowds. The other changes that can be made are to adjust the congestion limits; a larger number of crowd data to test the models further. This model provides a foundation to intelligent crowd monitoring which can help to make major events safe.

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