Real-Time Detection and Mapping of Crowd Panic Emergencies

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Abstract: We present a real-time system that uses machine learning and georeferenced biometric data from wearables and smartphones to detect and map crowd panic emergencies. Our system predicts stress levels, tracks stressed individuals, and introduces the CLOT parameter for better noise filtering and response speed. We also introduce the DEI metric to assess panic severity. The system creates dynamic areas showing the evolving panic situation in real-time. By integrating CLOT and DEI, emergency responders gain insights into crowd behaviour, enabling more effective responses to panic-induced crowd movements. This system enhances public safety by swiftly detecting, mapping, and assessing crowd panic emergencies.

1 INTRODUCTION

Crowd panic emergencies are a significant public safety concern, particularly in densely populated areas like cities, sports events, concerts, and festivals. These incidents can result in injuries, fatalities, and property damage, often triggered by perceived threats, rumors, or stampedes. Real-time detection and mapping of such emergencies are vital for swift response and evacuation.

Recent advancements in machine learning and wearable technology offer new opportunities for real-time detection and mapping. Our system utilizes georeferenced bio-metric data from wearables and smartphones, providing more accurate insights into stress levels and movement patterns. It employs a Gaussian SVM machine learning classifier to identify stressed individuals. We introduce the Classifier Level of Trust (CLOT) as a parameter to balance detection speed and noise filtering.

Once a stressed individual is detected, the system conducts real-time spatial analysis to track their movement and identify nearby stressed individuals. It creates dynamic areas based on trajectories and adjacency. The system also introduces the Domino Effect Index (DEI) to assess the severity of the emergency by considering factors like panic transmission rate, panicked crowd density, and alignment with road networks.

Incorporating DEI enhances emergency detection and response, ensuring public safety in densely populated areas. Emergency responders can use this information to de-ploy resources, evacuate affected areas, and prevent escalation. The system's components, including the machine learning classifier and georeferencing, are detailed in subsequent sections, along with an evaluation of its effectiveness and potential applications. We also outline future research directions in this field.

2 RELATED WORK

Panic, extensively studied in psychology and human sciences, involves intense fear resulting from real or perceived danger. It often occurs in groups or crowds, leading to regressive behaviors like violence, jumps, or collective suicide. Mass panic is an abnormal response where a group moves faster than usual due to alarming events like stampedes, fires, fights, robberies, or riots.

In recent literature, several studies and systems have concentrated on panic detection through the utilization of Closed Circuit Television (CCTV) technology. These surveillance methods scrutinize human behavior by analyzing both still images and video sequences of individuals or groups. For instance, Hao et al. (Hao, 2016) have presented an approach based on optical flow features to identify crowd panic behavior, while Ammar et al. (Ammar, 2021) have outlined a continuous surveillance system for a particular public location, employing a stationary camera and a methodology for real-time analysis of captured images.

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Another approach to panic detection systems involves user intervention and community engagement in reporting emergency events. While disaster preparedness plans are crucial for community safety, traditional methods of data acquisition and distribution fall short, especially during time-sensitive crises.

The Internet of Things (IoT) technology emerges as a solution to acquire real-time da-ta and promptly transmit it to experts for decision-making. Wearable devices and IoT play a pivotal role in collecting biometric data and conducting stress detection. The wearables and IoT sector has seen exponential growth, thanks to technological advancements in sensors and chips. This growth allows real-time sensor data to be combined with the capabilities of 5G smartphones, providing essential information for decision-making.

Recent research shows that the field of crowd evacuation systems, quantitative analysis, and visualization is still evolving. Notable contributions include Tsai's work (Tsai, 2022), which uses wearable data to predict panic attack disorders based on time series data, incorporating physiological factors and air quality into a prediction model.

Kutsarova and Matskin (Kutsarova, 2021) employ mobile crowdsensing and wearables on the CrowdS platform, utilizing smartwatch sensors to detect abnormal events and trigger alarms. Alsalat's research (Alsalat, 2018) focuses on using machine learning with wearables to classify individuals as stressed or calm during panic situations.

Sun et al. (Sun, 2021) address crowd behavior during emergencies, particularly in earthquake evacuations. They conducted an evacuation drill experiment to analyze evacuation processes, participation ratios, and behavior characteristics. Their study includes a computer-aided quantitative simulation, establishing a response rule equation for crowds in emergencies, exploring panic behavior, exit familiarity, and the relationship between training time and exit familiarity. The study aims to optimize the efficiency of evacuation processes and prevent congestion and stampede accidents.

These studies collectively contribute to our understanding of crowd panic and emergency response, pushing the boundaries of current research in this field.

In a related study, Zhang et al. (Zhang, 2023) address the challenges of urban security and management concerning crowd gatherings in large public spaces like shopping malls, stations, and entertainment venues. They propose a Crowd Density Estimation Model (CDEM-M) that utilizes deep learning and Geographic Information System (GIS) technology. This model surpasses the limitations of traditional crowd density estimation methods that rely on human head features, which can be problematic in high-altitude scenes or when head information is obscured. The CDEM-M provides a comprehensive solution by integrating GIS, offering a unified map visualization interface for accurate crowd area extraction through semantic segmentation. It considers various aspects, including crowd information extraction, geographic mapping, number estimation, and map visualization.

Another study by Albarakt et al. (Albarakt, 2021) explores the role of public spaces in cities, focusing on their political, social, economic, and sustainability aspects. The research investigates how streets, commercial centers, squares, and cafes either support or restrict public engagement. It also delves into the evolving political use of public spaces, the contestation over space, and the competition among various stakeholders for dominance. Using examples from the Middle East and ArcGIS mapping, the study examines visual and verbal narratives of protest events in contested public spaces. The findings have potential implications for urban planning and management strategies related to public spaces.

In conclusion, these studies illustrate the potential of utilizing machine learning and sensor data for real-time detection and mapping of crowd panic emergencies. Each paper offers a distinct approach, utilizing various data types and machine learning algorithms.

Our proposed system builds upon this prior research by leveraging georeferenced biometric data from wearable devices and smartphones, employing a Gaussian SVM machine learning classifier for the real-time detection and mapping of crowd panic emergencies.

This represents a significant advancement, as it utilizes precise data, offering a more accurate assessment of stress levels and panic behavior compared to traditional data sources like GPS or video. Additionally, our system conducts real-time spatial analysis to monitor the movement of stressed individuals and generate dynamic areas, providing emergency responders with accurate, up-to-date information about the situation.

In essence, our research takes a comprehensive and precise approach to the real-time detection and mapping of crowd panic emergencies, enabling emergency responders to make faster, more informed decisions that mitigate risks and ensure public safety.

3 METHODOLOGY

3.1 Workflow Process

Our crowd panic detection system aims to extract insights from collected biometric and spatiotemporal data to identify panic patterns in crowds, as shown in Figure 1. The process begins with a wearable device monitoring biometric data, while an Android smartphone collects GPS coordinates, time, activity, speed, and step data. This information is compiled into encrypted UDP packets and sent to a server over the GSM network. The server decrypts and processes the data to identify panic patterns, handling a significant volume of real-time data.

3.2 Stress Profile Index (SPI) Classification

The proposed method characterizes an individual as calm or in a panic state using a classifier that takes various biometric and geospatial data from wearable devices as input, as described in (Lazarou, 2022). To select the most suitable machine learning classifier, several classifiers were assessed with a dataset comprising of 27 subjects. This dataset includes biometric information such as heart rate, heart rate variability, spatiotemporal data including location coordinates, activity type, subject speed, step count, and descriptive data like gender, age, weight, and a unique identification code for each subject.

The biometric and spatiotemporal attributes in the dataset are categorized into four groups, with values informed by relevant studies: i) biometric data from wearables, including heart rate and heart rate variability; ii) spatiotemporal data from smartphones, which includes location coordinates, activity type, subject velocity, and step count; iii) descriptive data from wearables, encompassing subject gender, age, and weight; and iv) the unique ID assigned to each subject from smartphones. Additionally, a feature called "heart rate moving average deviation" (HRMAD) is introduced to detect sudden panic conditions based on heart rate values.

Machine learning models are trained on this dataset to differentiate between panic states and normal behavior. Various classifiers, including decision trees, logistic regression, Gaussian and kernel naïve Bayes, Gaussian SVM, SVM kernel, and boosted trees, were examined. The Gaussian SVM classifier yielded the highest accuracy, especially when using the HRMAD60 feature. Consequently, the Stress Profile Index (SPI) is introduced as a binary index, indicating a Calm state (value 0) or a Stressed state (value 1) based on the classifier's output (Lazarou, 2022)

3.3 Real-Time Analysis of Spatial Patterns

The purpose of real-time spatial analysis in monitoring panic conditions is supported by a data model as in (Lazarou, 2023), represented in Figure 3. This model processes streaming data containing spatiotemporal and biometric information collected from wearable devices and smartphones. As stated in the previous section, a Gaussian SVM machine learning classifier is utilized to distinguish between normal behavior and panic conditions, assigning the SPI values of 0 and 1, respectively. The resulting categorization labels the data as either Points of No Interest or Panic Points.

Real-time spatial analysis for panic monitoring relies on a data model, as illustrated in Figure 3 and detailed in (Lazarou, 2023). This model processes streaming data, combining spatiotemporal and biometric information from wearables and smartphones. A Gaussian SVM classifier discerns normal behavior from panic, assigning SPI values of 0 and 1, respectively. The data is categorized as "Points of No Interest" (SPI 0), marking the end of a sequence of "Panic Points" (SPI 1) representing highly stressed profiles. If isolated Panic Points are followed by a Point of No Interest, no further action is taken. However, consecutive Panic Points form a "Panic Trajectory" with an associated "Panic Trajectory Origin."

A Panic Trajectory is a continuous sequence of Panic Points linked to a subject, ending with one or more Points of No Interest. The initiation of a Panic Trajectory can depend on a single or multiple panic points, with the required initiation and termination points determined by the "Classifier Level of Trust" (CLOT).

In Section 4, we delve into various start and end-point scenarios for Panic Trajectories, exploring variations where two or more Points of No Interest are needed to conclude a Panic Trajectory. We also examine scenarios requiring two or more Panic Points for initiation. Once a Panic Trajectory begins, the first point becomes the "Panic Trajectory Origin." We use the DBSCAN algorithm to identify spatiotemporal correlations among these origins. This algorithm works within a 100-meter radius and a 10-second timeframe, aiding our understanding of panic behavior patterns.

Meeting specific conditions triggers the creation of "Crowd Panic Areas," comprising the "Origin

Crowd Panic Area" and the "Current Location Crowd Panic Area." The Origin CPA traces the origin of correlated Panic Trajectory starting points, while the Current Lo-cation CPA relies on the most recent points of ongoing correlated Panic Trajectories.

Additionally, the "Domino Effect Index," introduced later, assesses the severity of panic-induced crowd behavior during emergencies.

3.4 Classifier Level of Trust (CLOT)

CLOT, a numerical parameter from 0 to 10, indicates the system's confidence in the classifier's output. Lower CLOT values prioritize fast detection with less noise reduction, while higher values filter out more noise, reducing false positives but slowing detection.

In essence, adjusting CLOT balances detection speed and noise filtering, enabling performance testing under different settings and noise levels.

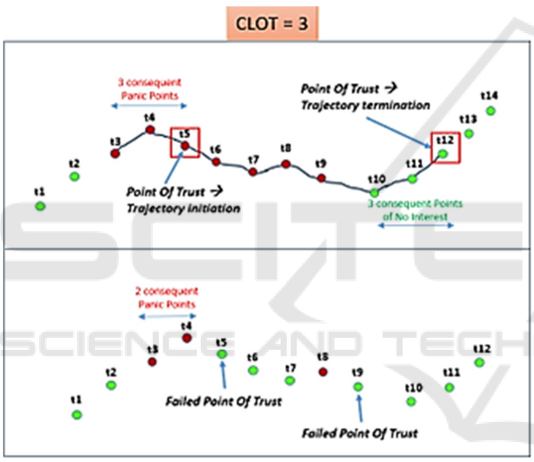

Figure 1: Example of CLOT = 3.

In Figure 1, two examples highlight the influence of a CLOT value set at 3. On the top, a subject initially exhibits calmness with two Points of No Interest. Then, a sequence of Panic Points unfolds, triggering the system to mark the third successive Panic Point as the Point of Trust (POT), initiating a Panic Trajectory. If the sequence continues uninterrupted, the trajectory extends. Points of No Interest eventually appear, and the system assesses if at least three consecutive Points of No Interest are present to end the Panic Trajectory. In the bottom example, another subject remains composed, and the subsequent Panic Points don't surpass the CLOT threshold of 3. As a result, the system classifies them as noise, leading to no trajectory formation.

3.5 Domino Effect Index (DEI)

The DEI assesses panic severity by considering factors such as panic transmission rate, panicked population density, new panic origins, convex hull area change rates, and alignment with the road network. It's rated from 0 to 5, with higher values indicating more severe panic. This scale has five levels, with DEI scale 1 being the lowest severity, and DEI scale 5 indicating the highest severity. By incorporating various factors contributing to the domino effect, DEI offers a dependable evaluation of crowd panic, aiding decision-makers in shaping effective emergency response strategies. Methodologically, DEI is determined by a combination of weighted and normalized factors influencing panic propagation, detailed in Table 2 below:

Table 1: DEI contributing factors.

Factor	Description
Rate of panic transmission (f_1)	**The rate at which panic spreads among the crowd**
Number of new panic origins within the panic origin convex hull (f_2)	**The distribution of new panic origins within the area where panic first emerged**
Density of panicked people (f_3)	**The concentration of panicked individuals within the current location convex hull**
Area change rate of the panic origin convex hull (f_4)	**The rate at which the area of the panic origin convex hull changes over time**
Area change rate of the current location convex hull (f_5)	**The rate at which the area of the current location convex hull changes over time**
Number of aligned clusters (f_6)	**The count of panic clusters aligned with the road network, which might indicate the crowd's tendency to use streets for escape**

Each factor is normalized between 0 and 1, and then multiplied by a weight that reflects its importance in contributing to the domino effect. The DEI is then calculated as the sum of these weighted factors:

$$\mathrm{DEI} = \sum w_i f_i \text{ for i =1…6}$$

where f_i and w_i denote the i-th factor and the corresponding weight, respectively.

To normalize the contributing factors for DEI, each factor is scaled between 0 and 1, ensuring fair comparisons and combining different numerical values. This process involves three steps. First, determining the factor's minimum and maximum values to set its range. Second, scaling the current factor value at a time step to a normalized value within 0 to 1 by subtracting the minimum and dividing by the range between the maximum and minimum values.

normalized_value = (current_value - min_value) / (max_value - min_value)

To compute DEI, normalization ensures that various factors, regardless of their original scales, are equitably assessed for their collective influence on the domino effect's severity. Normalized values are then weighted by user-defined weights and summed to determine the final DEI value. This quantifies the potential panic propagation extent in a crowd and aids in intervention prioritization. The DEI value is classified into five intervals (0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1), with each interval corresponding to DEI scales from 1 to 5, as shown in Table 3.

Table 2: DEI scales.

DEI Scale	DEI value
1	0-0.2
2	0.2-0.4
3	0.4-0.6
4	0.6-0.8
5	0.8-1

DBSCAN clustering is employed to identify panicked individual clusters based on their alignment with the road network. DBSCAN, a widely used density-based clustering algorithm, identifies dense regions in datasets. Each cluster is enclosed by a minimum area bounding rectangle (MABR), and the axis ratio is calculated. If the axis ratio is below a certain threshold (e.g., 0.5), it is deemed an aligned cluster. This information is valuable, suggesting that panic transmission is more likely when a significant portion of a panicked crowd flees through the streets. The DEI metric and its scale are valuable for assessing panic severity in real-world scenarios like evacuations, natural disasters, or terrorist attacks. By quantifying the domino effect and categorizing it into five severity levels, emergency planners and responders can better understand crowd behavior and develop more effective response strategies to mitigate risks associated with panic-induced crowd movements.

4 EXPERIMENTAL SETUP AND RESULTS

We conducted a proof of concept in Syntagma Square, Athens, testing three unique crowd panic scenarios: ESCAPE, SHRINK, REPULSION. These scenarios were designed to examine different crowd panic behaviors and DEI dynamics.

In these scenarios, the crowd responds to aversive events by dispersing (ESCAPE), contracting towards the center (SHRINK), or reacting to repulsive forces (REPULSION). Weight variations in each scenario were applied to analyze the DEI factors' impact on crowd behavior, contributing to a better understanding of panic propagation.

Regarding the ESCAPE scenario that will be presented in this paper, approximately 30 individuals from diverse backgrounds gather in a controlled environment, initially in a calm state, engaging in various activities. At a predetermined moment, an unpleasant event is deliberately introduced, causing a sudden onset of stress and panic among some participants. This event triggers physiological symptoms like increased heart rate and rapid breathing. As panic spreads, individuals' emotions influence each other, resulting in a chain reaction of stress and anxiety. This phenomenon is known as emotional contagion, where emotions transfer between people through nonverbal cues and social interactions. Those initially calm also become stressed as they observe the panic. As the situation unfolds, panic continues to propagate, with individuals instinctively seeking escape in various directions. This amplifies the scale and magnitude of the event.

In Figures 2, 3, and 4, the maps illustrate the progression of the phenomenon over time. Panic points are depicted as red dots, calm points as green dots, and recovered points as blue dots. Panic trajectories are represented by red lines, while the origins of these trajectories are marked by green flags. The shaded orange region denotes the Origin CPA (Common Panic Area), and the hollow red region indicates the Current Location CPA.

Figure 2: Initial expansion.

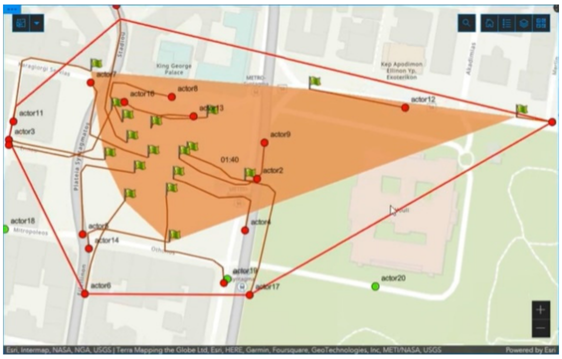

Figure 3: Panic starts to spread widely.

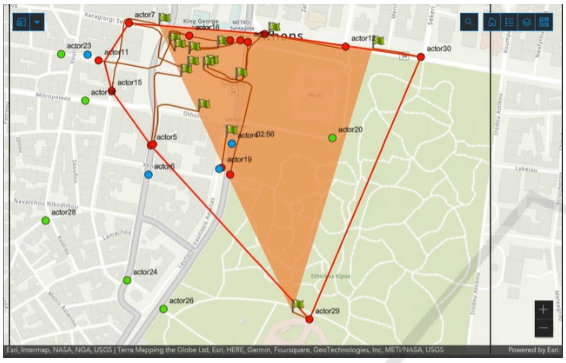

Figure 4: After some time it still expands but some subjects tend to recover (blue dots).

Figures 5, 6, 7, and 8, depict real-time counts of individuals categorized as stressed, calm, and recovered. These visualizations facilitate the effective monitoring of emotional distribution within the group. Real-time charts graphically represent emotional trends for each category, helping identify influencing factors and individual transitions between emotional states.

Furthermore, the Panic Transmission and Recovery Rate Charts offer insights into the speed of panic propagation and recovery rate, providing valuable information about the effectiveness of interventions and the overall resilience of the group. Additionally, the DEI Current Value offers real-time insights into the collective emotional state, reflecting stress and anxiety levels. The DEI Progress Diagram tracks the evolution of the emotional state over time, providing valuable information about its progression throughout the scenario.

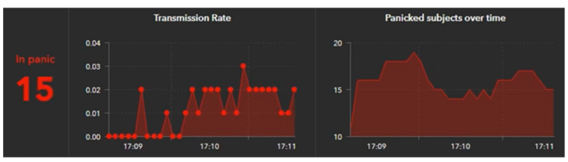

Figure 5: Transmission rate and panicked population.

The count of recovered individuals demonstrates a progressive increase after a certain period, as evidenced by the recovery rate. Simultaneously, the number of calm individuals exhibits a noticeable decline, gradually approaching zero.

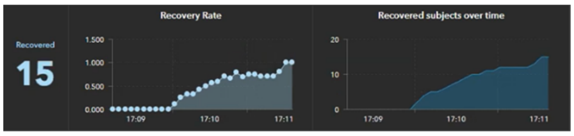

Figure 6: Recovery rate and recovered population.

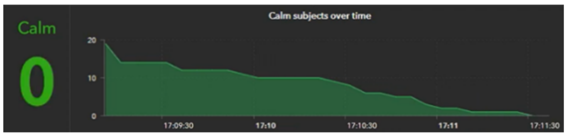

Figure 7: Calm population.

Ultimately, the comprehensive evaluation of the DEI reveals that, in this particular scenario, the phenomenon only marginally surpasses the threshold of 0.40, resulting in a DEI scale of 2.

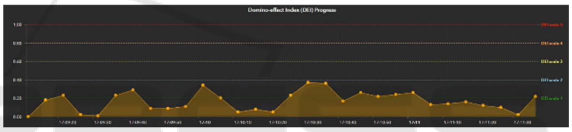

Figure 8: Evolution of DEI.

In Figure 9, it is evident that the population of panicked individuals exhibits considerable fluctuations over time, indicating the arbitrary nature of the phenomenon's expansion and its variable impact on different individuals. During the initial minutes, the transmission rate remains predominantly low, as the panic has yet to propagate to a wider population. However, in subsequent stages, the transmission rate reaches higher values, signifying the widespread dissemination of panic.

Figure 9: Final state where the event has spread significantly, and multiple subjects are now in the recovery phase.

5 CONCLUSIONS AND FUTURE WORK

In our experiments, we closely monitored participants to understand panic behavior in groups. We used a digital map to visualize how panic evolves, identifying clusters of stressed individuals and support networks. The Domino Effect Index (DEI) is a vital tool for assessing emergency severity. It considers panic speed, density, and road alignment. The Classifier Level of Trust (CLOT) balances noise filtering and quick detection. Our research can shape interventions for managing panic in real-life situations, reducing negative consequences. In conclusion, our real-time spatial analysis, using wearables and smartphones, advances crowd panic monitoring. serves as a valuable index for prioritizing interventions in scenarios characterized by concurrent multiple events. Empirical validation of this approach has been substantiated through rigorous experimental investigations. Future work will delve into bio-algorithms and mathematical models to better understand panic spread, refining our approach in crowd safety and security.

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