Real-Time Monitoring of Crowd Panic Based on Biometric and Spatiotemporal Data

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Abstract: Panic is one of the most important indicators when it comes to Emergency Response Systems (ERS). Until now, panic events of any cause tend to be treated in a local manner based on traditional methods such as visual surveillance technologies and community engagement systems. This paper aims to present an approach for crowd panic event detection that takes advantage of wearable devices tracking real-time biometric data that are combined with location information. The real-time biometric and spatiotemporal nature of the data in the proposed approach is spatially unrestricted and information is flawlessly transmitted right from the source of the event, the human body. First, a machine learning classifier is demonstrated that successfully detects whether a subject has developed panic or not, based on its biometric and spatiotemporal data. Second, a real-time analysis model is proposed that uses the geospatial information of the labeled subjects to expose hidden patterns that possibly reveal crowd panic. The experimental results demonstrate the applicability of the proposed method in detecting and visualizing in real-time areas where an event of abnormal crowd behavior occurs.

1 INTRODUCTION

Emergency response systems (ERS) are integrated solutions that handle urgent and severe events (Bui and Sankaran, 2006). They have benefited from the evolution of information technology, which has resulted in increased responsiveness and effectiveness (Li et al., 2014). The wide range of online available sensors allows scientific decisions to be made regarding emergencies based on real-time data. When it comes to the use of such systems, one of the most common indicators is panic. It serves as a major cause of unpleasant events mostly when it develops simultaneously among a group of people, as it prevents those who are affected from verbally disseminating urgent information. This indicates that the proper detection of panic at a crowd level is an application field that undoubtedly would benefit from ERSs. Attempts to model and analyze panic behavior to detect, for example, crowd escape patterns, date back to 2000 when, for instance, (Helbing et al., 2000) used a model of pedestrian behavior to investigate the mechanisms of (and preconditions for) panic and jamming by uncoordinated motion in crowds.

Until now, panic events of any cause tend to be treated in a local manner. Various attempts to detect such events have been proposed based on traditional methods such as visual surveillance technologies and community engagement systems. However, panic events detected by visual surveillance technologies are spatially limited by the range of the visual equipment while during an emergency it is highly unlikely that people will give priority to reporting the event to an engagement system, instead of running away.

While the use of ERS is increasingly adopted across many aspects of everyday life, the combination of them with real-time biometric data and time-enabled location information appears to provide a different perspective. In this paper a new data model is proposed that takes advantage of wearable devices tracking real-time biometric data and combines them with location information. This blend of information is used to predict the current panic state of a subject in real-time. For this purpose, a machine learning classifier is involved that has been previously trained on a dataset of similar biometric and spatiotemporal information gathered by monitoring several subjects in various activities. The classifier characterizes each

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subject as being either in calm or in panic state. Thus, a classifier well-trained on a careful selection of appropriate data can be the basis for a real-time panic prediction system. The proposed data model transforms the gathered measurements (biometric and spatiotemporal data) into valuable information to expose hidden patterns that possibly reveal panic behavior. For this purpose, the several entities of the proposed data model are described in detail in order to highlight their contribution in the ability of the system to scale the panic phenomenon examination to a crowd level. The experimental results demonstrate the applicability of the proposed method in detecting and visualizing in real-time areas where an event of abnormal crowd behavior occurs. The real-time biometric and spatiotemporal nature of the data in the proposed approach is spatially unrestricted and information is flawlessly transmitted right from the source of the event, the human body. This is moving towards the creation of a smart geo-referenced ERS that could be used to inform the authorities regarding a potentially unpleasant event by detecting possible crowd panic patterns and helping to act accordingly.

2 RELATED WORK

Panic is a phenomenon generally studied in psychology and human sciences and often identified by its consequences. It is triggered whenever a situation of tension worsens, slips or escapes from human control. Panic is defined as an intense fear triggered by the occurrence of a real or imaginary danger felt simultaneously by all individuals in a group, a crowd, or population, characterized by the regression of mentalities to an archaic and gregarious level, leading to primitive reactions of hopeless jumps, indiscriminate agitation of violence or collective suicide (Lin et al., 2016). Mass Panic is type of anomaly in a human crowd, which appears when a group of people start to move faster than the usual speed. Such situations can arise due to a fearsome activity near a crowd such as stampede, fire, fight, robbery, riot, etc. (Kumar, 2012).

In the recent literature, there are numerous studies as well as systems in production that deal with panic detection based on CCTV (Closed Circuit Television) technologies. They involve surveillance techniques that collect visual data in terms of still images and/or video sequences in order to analyze human behavior either of individuals or groups of people. For instance, (Hao et al., 2016) propose an approach to detect crowd panic behavior based on optical flow features. In another view, (Ammar et al., 2021) describe an online and continuous surveillance system of a particular public place using a fixed camera on the one hand, and a methodology for real-time analysis of the captured images on the other hand.

Another category of such systems is based on the user's intervention (community engagement) in the reporting of an emergency event, as a disaster preparedness enhancement (Sufri, 2020). It has been observed that, all over the globe, nations are encouraged to plan accordingly in order to be prepared to disrupt entire communities in the occurrence of an unpleasant event that will inevitably happen (Andrulis, 2011).

Conventional approaches for data acquisition and distribution are clearly not able to provide the experts with sufficient on-site and real-time data, which may cause potential safety hazards especially when crises are highly time-sensitive (Li et al., 2014). Internet of Things (IoT) provides a vital solution to acquire real-time data about any objects and transmit the data to experts promptly for decision-making. Various studies use wearable devices and IoT to collect biometric data and analyze them for stress detection. Regarding the wearables and IoT sector, it exponentially gains considerable interest due to the technological evolution and progress of the related technologies that involve sensors and chips. It exists for many years already but nowadays has matured and belongs among the most invaluable sources of real-time data. As a result, such information can be further paired with 5G smartphone capabilities providing real-time sensor data.

Recent studies conclude that research on systems, quantitative analysis, and visualization studies on crowd evacuation is still a developing field (Li, 2020), (Lin et al., 2012), (Xu, 2013), (Xu, 2020), and (Xu et al, 2016). In (Tsai, 2022) wearable data are used for panic attack disorder prediction based on time-series. This way they provide a panic attack prediction model that relates a panic attack to various features, such as physiological factor, and air quality. Next, (Kutsarova and Matskin, 2021) combine mobile crowdsensing and wearables to produce alarms based on CrowdS, an existing crowdsensing system. In this approach, smartwatch sensors detect abnormal events. Then they integrate the smartwatch with the CrowdS platform either through a direct internet connection, or a connection through a smartphone by pairing it via Bluetooth with the smartwatch. Lastly, (Alsalat, 2018) uses machine learning to detect human panic based on wearables and classify them between stressed and calm.

3 PROPOSED METHODOLOGY

3.1 System Workflow

The scope of the proposed crowd panic detection system is to transform the gathered measurements (biometric and spatiotemporal data) into valuable information to expose hidden patterns that possibly reveal panic behavior in crowd level. Figure 1 illustrates the main modules of the proposed scheme. Starting from the user's endpoint, the workflow begins from the wrist where an application running on the wearable device monitors the real-time biometric footprint regarding data such as heart rate and heart rate variability. At the same time, a paired application running on an Android smartphone collects GPS location coordinates (longitude, latitude), time data, user activity, speed, and steps. Following a time interval of one second, all this information is bundled together into a single UDP packet and is sent encrypted to a server through the GSM network. On the server side, a Java code receives the UDP packets, decrypts the information, and constructs points having all the above-referenced characteristics as attributes. This procedure enables the collection of real-world biometric and spatiotemporal data. The real-time server is designed to receive a large amount of data that is analyzed for possible patterns of crowd panicking.

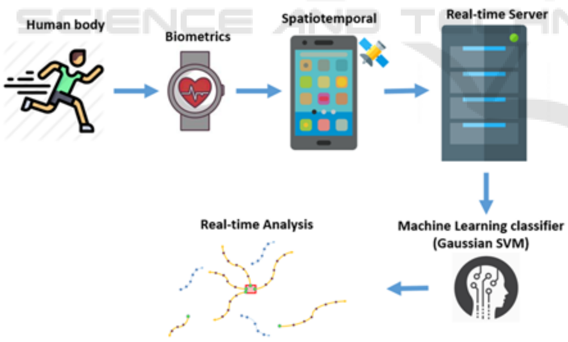

Figure 1: System workflow.

3.2 Panic State Classification

An important part of the proposed methodology is the characterization of a subject as being in a clam or in a panic state. For this purpose, a classifier is involved whose input are various biometric and geospatial data gather by the wearable devices while its output is the panic state of the subject. The efficiency of various machine learning classifiers was tested in order to choose the most appropriate one. The training of the classifiers is performed in advance and is based on a dataset that consists of 27 different subjects that are monitored during a short time frame (Lazarou et al., 2022). Two of the 27 subjects are actual humans that used the wearable and the smartphone and captured real-world data using the accompanying applications. The data regarding the rest of the subjects were artificially produced. Their biometric and geospatial data are gathered per second for a period of 10 minutes resulting in a set of 600 measurements per subject. In most cases, a panic event is simulated that affects these measurements. However, in three out of the 27 subjects, there is no panic event. This is in purpose examined in order to capture the variability of the observed data in both calm and stressed states.

For the collection of the raw biometric and positional data, a Samsung Galaxy Watch wearable, as well as a Samsung Galaxy A70 smartphone were used. The biometric and spatiotemporal features of the dataset are divided into four categories, namely i) biometric data (from wearable) including heart rate and heart rate variability; ii) spatiotemporal data (from the smartphone) that provide location coordinates, type of activity, the subject's speed and the number of steps performed iii) descriptive data (from wearable) regarding the gender, age and weight of the subject; and iv) the secure ID (from the smartphone) which provides a unique identification code for each subject.

The values of the several features are determined by studies that provide such relevant information. For instance, normal heart rate for ages 10 and above reaches 60 to 100 beats per minute (bpm) while athletes belong to a separate category with a range of 40 to 60 bpm (Forbes Health). On the other hand, the target heart rate during activities of moderate intensity is about 50–70% of the maximum heart rate, while during vigorous physical activity it is about 70–85% of the maximum (Centers for Disease Control).

In addition to the above raw data, a feature named heart rate moving average deviation (HRMAD) is also derived. It encloses a temporal effect on the dataset that is based on a time window regarding heart rate values of the past. It acts as an indicator that a subject has suddenly developed high measurements of the heart rate which could imply sudden panic conditions.

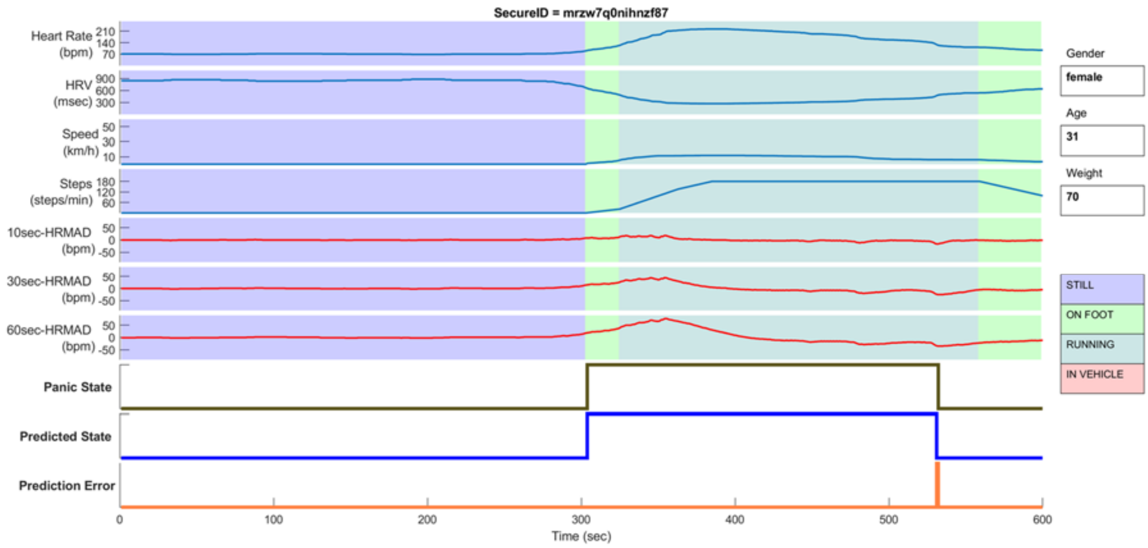

Figure 2: Panic prediction example.

Typically, the mean value of the last minute's heart rate should be around 5–10 bpm based on the assumption that it slightly varies from the resting heart rate levels. In contrary, a sudden event that causes panic would exaggerate the heart rate possibly beyond 150 bpm denoting a remarkable difference from the previous measurements. Three different time windows of 10, 30, and 60 seconds are provided in the dataset namely HRMAD10, HRMAD30, and HRMAD60, respectively. They indicate how much the current heart rate measurement deviates from a moving average of a specific time window in the past. The time window acts as a smoothing technique where potential residuals and deviations are absorbed by the averaging process.

Figure 2, depicts an example of a subject (female, aged 31, 70 kg weight) which iterates through several states starting from a still position, then walking, running, and walking again. Her biometric and positional data vary significantly during these state transitions. For instance, her heart rate ranges from 70 to 186, her HRV ranges from 323 to 909, speed is up to 9.6 and her steps are approaching 120 steps per minute. Finally, the calculated HRMAD60 values are in the range of 55 to −33. It can be seen that, even though the feature values vary significantly, the classifier accurately detects the panic state showing only a negligible error at the end of the stress period.

The aforementioned dataset is used to train machine learning models in order to correctly distinguish panic states from normal behavior. A variety of models are examined, namely, decision trees (Loh, 2014), logistic regression (Hosmer et al., 2013), Gaussian and kernel naïve Bayes (Ren et al., 2009), Gaussian SVM and SVM kernel (Keerthi and Lin, 2003), and boosted trees (Elith et al., 2008). The cross-entropy is used as the cost function for the classification tasks. The Gaussian SVM classifier in accordance with the HRMAD60 feature achieved the highest accuracy, as shown in Table 1.

Table 1: Classification results using a combination of raw features and the HRMAD60 feature.

Classifier	Accuracy
Decision Tree	92.8%
Logistic Regression	89.5%
Gaussian Naïve Bayes	81.3%
Kernel Naïve Bayes	85.3%
Gaussian SVM	**94.5%**
SVM Kernel	94.1%
Boosted Trees	93.9%

3.3 Real-Time Analysis Model

To support the real-time analysis, a data model whose graphical representation is shown in Figure 3, has been created. Initially, the streaming of the points that encapsulate all the spatiotemporal and biometric information collected from the wearable and the smartphone, is consumed by the Gaussian SVM machine learning classifier that distinguishes normal behavior from panic conditions, assigning values of 0 and 1, accordingly.

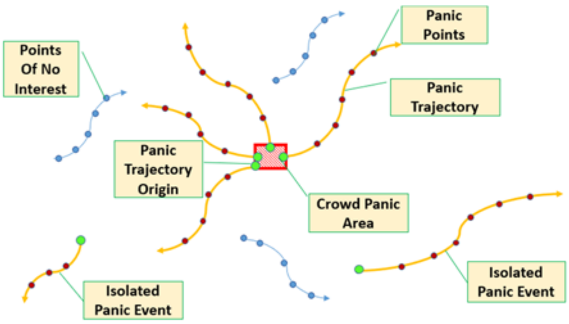

Figure 3: Graphic representation of the data model entities.

This kind of labeling is introduced in this paper as the Stress Profile Index (SPI) and categorizes the data into Points of No Interest and Panic Points. The main entities of the data model are:

Point of No Interest: These are the points that have been assigned an SPI of 0. These points indicate that the subject behaves normally, so there is no need to be further monitored. Their only use is to signal the end of a sequence of Panic Points.

Panic Point: These are points that contain biometric information indicating a highly stressed profile, having an SPI of 1. If this is an isolated incident after which a Point of No Interest is received then this is a no-action event, but if there are consequent PPs this leads to the formation of a Panic Trajectory.

Panic Trajectory: It is a line whose vertices consist of consequent Panic Points for a given subject. Such a line is terminated only when a Point of No Interest breaks the sequence of Panic Points.

Figure 4: Image showing multiple Panic Trajectory Origins (green) along with their Panic Trajectories.

Panic Trajectory Origin: It is the very first point of a Panic Trajectory. Figure 4 depicts an example of Panic Trajectories that correspond to four subjects. The brown dots represent Panic Points as spatiotemporal data (locations in time). The Panic Trajectory Origins (green dots) of the various subjects are examined by the algorithm to decide whether there is a spatiotemporal correlation between them. If this is true, then this triggers the creation of a Crowd Panic Area.

Crowd Panic Area: The Crowd Panic Area denotes the origin of Panic Trajectories whose starting points are spatially correlated, that is, they are located within a short distance from each other. It represents the spatial extent of a potentially stressful event that is happening, and it is depicted as an area on the map, as shown in red in Figure 5.

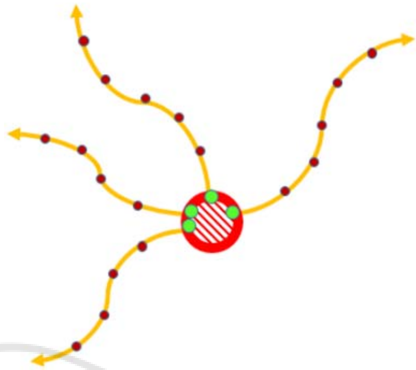

Figure 5: Image showing multiple Panic Trajectories that are spatially correlated. The red circle shows the Crowd Panic Area.

4 EXPERIMENTAL RESULTS

For the proof of concept, an experiment involving real people took place. This group followed a specific scenario to simulate the gradual development of panic conditions at a crowd level. Following the development of the current state of the data model, their data were used as input in order to create the Panic Trajectories, the Panic Trajectory Origins, and the Crowd Panic Areas. In our experiments, six people were monitored wearing the Samsung Galaxy Watch and also having the smartphone app on their mobile device. The participants were acting on the street starting from relatively the same location of a common neighborhood as it is presented in the following paragraphs. The goal was to collect and analyze their biometric and spatiotemporal data in real-time to produce the Crowd Panic Area.

The real-time server collected their data successfully over a UDP connection and transformed them into points carrying all the appropriate spatiotemporal and biometric information as attributes. Consequently, the point data were analyzed and produced the data model objects, leading to the creation of the Crowd Panic Area around the location where all the actions were initiated.

Figure 6 depicts the crowd in their origin locations, being in a calm state (green dots, SPI = 0). At this stage all subjects are considered as Points of No Interest.

Figure 6: Sample crowd in a calm state.

Next, Figure 7 shows that two of the subjects have been suddenly stressed and this is depicted in their SPI that has changed to 1. At the same time, their symbol on the map changes to a red circle and these two points are now considered as Panic Points.

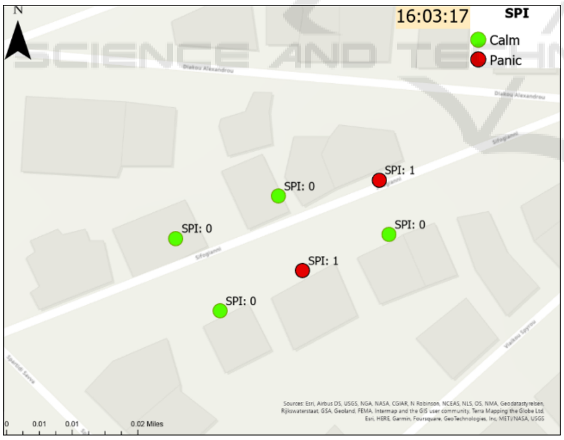

Figure 7: Two of the subjects switch to a stressed state.

Moving on, Figure 8 reveals that a few seconds later the two subjects keep showing stressed conditions and attempt to escape. Once this happens the system detects that they are moving, still in a stressed state, which consequently, creates their Panic Trajectories (red arrowed lines) and Panic Trajectory Origins (green flags). Also, the initial Crowd Panic Area comes up as a Minimum Bounding Polygon (red dashed rectangle).

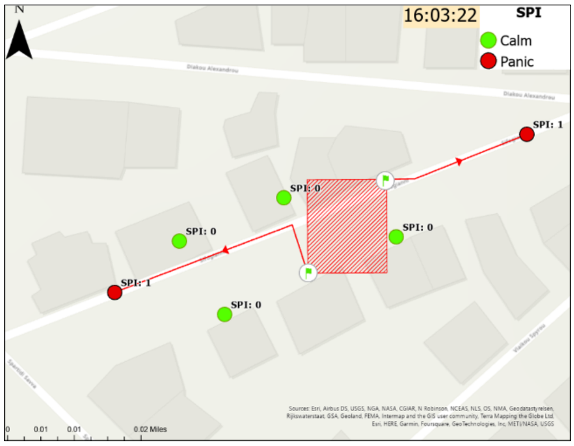

Figure 8: Stressed subjects attempt to escape. Origins (green flags) are created and trigger the creation of an initial Crowd Panic Area.

In Figure 9 the rest of the crowd are also in a panic state (all SPIs are 1), and their Panic Trajectories and the Origins are created as well. As a result, the initial Crowd Panic Area updates its boundaries to reflect the new conditions.

Figure 9: The Crowd Panic Area is updated in order to include all the Panic Trajectory Origins.

The above scenario demonstrates how the system reacts and operates in real-time detecting abnormal crowd behavior regarding the Stress Profile Index of the participants, and how it processes the multimodal data it receives to produce a well-formed result.

5 CONCLUSIONS

In this paper a real-time monitoring system is proposed that allows crowd panic detection taking advantage of wearable devices that track real time biometric data in accordance with location information. The proposed approach creates real-time trajectories of moving objects that are in panic state and analyzes them to come up with the detection of potential crowd panic event areas. Future work includes the examination of alternative classification strategies that would increase the panic state determination accuracy as well as the extension of the real-time analysis model in order to efficiently process simultaneously appearing panic events in spatially distributed groups of subjects.

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