Synthetic Dataset for Panic Detection in Human Crowded Scenes

J. Calle[1], P. Leskovsky[1], J. Garcia[1], M. Sanchez[1]

[1] Fundación Vicomtech, Basque Research and Technology Alliance (BRTA), Donostia-San Sebastián, 20009, Spain

Abstract

AI is increasingly being used in public protection by using crowd anomaly detection. This is useful for identifying panic events enabling control forces to act faster. A significant challenge in this field is the lack of data for training these algorithms. Recreating panic events with big crowds can be both expensive and hazardous. To address this issue, this paper proposes the creation of a synthetic dataset for crowd panic behaviour. The process involves defining the scenario and setting up the appropriate CCTV cameras. Many scenarios are prepared, including variations in weather conditions. Next is the scene population with pedestrians and vehicles, with different crowd sizes and vehicle trajectories. To recreate panic, the behaviour of each person is programmed. The final videos show normality situations before the panic events start. Finally, we achieved 1717 simulations.

CCS Concepts

• ***Computing methodologies*** → *Image and video acquisition; Computer graphics;*

1. Introduction

Analyzing footage from multiple CCTV cameras in public spaces in real-time presents a significant challenge. Artificial intelligence (AI) methods are employed to detect abnormal situations rapidly. However, collecting real data for AI can be difficult and expensive due to privacy concerns or people's usage, especially with big crowds. Also, it is necessary to have different weather conditions, scenarios and points of view. We have created a synthetic dataset using CARLA simulator [DRC*17] to solve these problems.

This document describes our dataset, explaining why it has been created. It begins by defining a panic event and then delves into the steps involved in its creation. These steps include scene generation, weather options, camera placement, labelling and pedestrian control. Additionally, it covers other important aspects, such as vehicle traffic or a variety in the spawned pedestrians.

2. State of the art

The main public datasets for panic events analysis consist of a group of 10 to 20 people walking around until the panic begins. These datasets are **UMN** [LLC] and **MED** [RHM*16]. Another approach is to use a synthetic dataset for pedestrian action detection. In [LGWL21], a synthetic dataset is created to analyse abnormal events using **Grand Theft Auto** (GTA) video game. It is not available or usable commercially. An alternative is to use **CARLA simulator**, such as in [AMF*22], where the pedestrian trajectories are analyzed from a vehicle point of view. Also, CARLA offers a commercial license.

3. Simulation of panic events

CARLA is a versatile platform designed for training autonomous driving systems that offers control over all actors within the simulation. It allows AI models to be trained without relying solely on real-world data. Their latest updates have improved the intelligence of pedestrians, making it an ideal choice for making a panic dataset.

The first step is to **understand** what constitutes a **panic event**. In this work, a panic event is defined as people fleeing in different directions after a period of normality. People escape from the location using different escape paths. Simulations with high-density crowds may be perceived as abnormal, but in this dataset, they are regarded as normal due to the absence of panic behaviour.

3.1. Scenario creation and camera location

The next step was to select the scenarios. We found six locations of interest in the official CARLA simulator maps, see Figure 1.The locations needed to be outdoors, with different options to run away (such as parking lots, squares or gas stations).

To maximize diversity, we ran simulations for all the scenarios under various weather conditions, including clear skies, cloudiness and different intensities of rain, such as heavy, moderate and light. Additionally, simulations were run at different times of the day, including night, noon and sunset. **Cars driving** on roads were included to increase realism.

Once the scenarios were identified, it was necessary to **determine the location of the cameras** within them. The same simulation was recorded from different viewpoints of a potential CCTV

DOI: 10.2312/egp.20231026

camera. Each camera position was selected manually to simulate real CCTV camera positions, as in Figure 2 and randomized in each simulation to get different points of view. This resulted in a large number of different viewpoints for each simulation, reducing the number of executions and producing variety in the dataset.

Figure 1: *Different scenarios: a. Terrace (top left), b. Gas station (top centre), c. Small parking (bottom left), d. Square (bottom centre), e. Stairs (bottom right)*

3.2. Pedestrian control and panic generation

Programming panic behaviour in crowds is challenging because it is not feasible to manually control each pedestrian's direction. Instead, it is necessary to use Carla's Pedestrian Navigation system to adjust each route dynamically. This algorithm selects the best path to arrive at a destination, avoiding obstacles (such as static or dynamic objects) and walking through the navigable meshes.

This dataset is a set of sequences where a crowd is spawned in a certain area to analyze their behaviour. The crowd has pedestrians with different characteristics such as age, gender, physical aspect or clothing. Each pedestrian has its own movement velocity, and direction pattern, creating a more realistic simulation. Also, the position and number of pedestrians are different for each simulation.

The simulations begin with a period of normality, where the pedestrians walk calmly in the area. After 250 frames of normality, panic begins. In this step, the pedestrians change their path and velocity to flee the scene. The simulation ends after 125 frames of panic.

There are three kinds of simulations in terms of pedestrians' numbers to represent different densities of crowds: low (approx 25 pedestrians), medium (approx 75 pedestrians), and high (approx 150 pedestrians). The scenes shown in Figure 1 and Figure 2 were simulated for medium density.

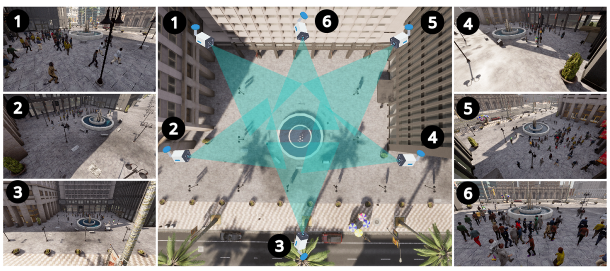

Figure 2: *Camera location*

3.3. Labelling

For each simulation, the frames from the available CCTV cameras are captured and temporarily labelled using frame intervals, identifying the simulation status (normal or panic event).

3.4. Dataset statistics

The table below shows the number of sequences and cameras for each scenario. As can be seen, there are some differences in the number of sequences between scenarios. This is because some were discarded due to the gap with the real world. Counting the different camera viewpoints, we have 1717 sequences in total. Each sequence contains 250 frames of normality and 125 frames of panic saved at 25 fps and stored with a resolution of 1920x1080.

Scene name	nº cameras	High density	Mid density	Low density	Total sim	Total sequences
Terrace	4	12	20	20	52	208
Gas station	4	20	20	18	58	232
Small parking	4	19	20	20	59	236
Big parking	10	20	20	20	60	600
Square	6	16	20	20	56	336
Stairs	3	12	11	12	35	105
						1717

4. Conclusions

CARLA is a powerful 3D software simulator with applications beyond driving contexts. One of its strengths is the ability to generate synthetic data, which can be a valuable alternative when there is a lack of real-world data or when it is difficult to recreate certain scenarios. However, there may be some issues with realism and discrepancies between synthetic data and reality that need to be taken into account for training a model.

5. Acknowledgments

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101021981, APPRAISE project.

References

[AMF*22] ACHAJI L., MOREAU J., FOUQUERAY T., AIOUN F., CHARPILLET F.: Is attention to bounding boxes all you need for pedestrian action prediction? In *2022 IEEE Intelligent Vehicles Symposium (IV)* (2022), pp. 895–902. doi:10.1109/IV51971.2022.9827084. 1

[DRC*17] DOSOVITSKIY A., ROS G., CODEVILLA F., LOPEZ A., KOLTUN V.: CARLA: An open urban driving simulator. In *Proceedings of the 1st Annual Conference on Robot Learning* (2017), pp. 1–16. 1

[LGWL21] LIN W., GAO J., WANG Q., LI X.: Learning to detect anomaly events in crowd scenes from synthetic data. *Neurocomputing 436* (01 2021). doi:10.1016/j.neucom.2021.01.031. 1

[LLC] LLC M.:. Unusual crowd activity dataset of university of minnesota [online]. URL: http://mha.cs.umn.edu. 1

[RHM*16] RABIEE H., HADDADNIA J., MOUSAVI H., KALANTARZADEH M., NABI M., MURINO V.: Novel dataset for fine-grained abnormal behavior understanding in crowd. In *2016 13th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)* (2016), pp. 95–101. doi:10.1109/AVSS.2016.7738074. 1