ITAI 3377

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Case Study Analysis

**A. Introduction and Objectives**

A project in Liverpool, Australia, received funding from the Australian government to develop new ways of collecting data to help with city planning. Liverpool is a suburb of Sydney that's experiencing rapid growth, which has led to challenges in planning for the increasing number of pedestrians and vehicles. The city's downtown area is being redeveloped, and it's expected that this will bring an additional 30,000 pedestrians into the area every day. Because of this, the project aimed to improve real-time traffic monitoring. A key part of the project was figuring out how to track pedestrians, cyclists, and vehicles using existing security camera systems, but in a way that respects people's privacy. The project also needs to make sure that the system could be expanded in the future and could work with other systems (Barthelemy et al., 2019).

**B. Methodology**

This project used a step-by-step approach, starting with meetings with the community to figure out what was needed. People wanted the system to protect their privacy, be able to grow as the city grows, and use the cameras that were already in place. The project team built a small computer (using an NVIDIA Jetson TX2 processor) that could be attached to the existing security cameras and analyze the video in real-time. They tested this system using a set of video data called the Oxford Town Center dataset to make sure it was accurate and worked well. The system was designed to process the video locally, rather than sending it to a central server, to save bandwidth and protect people's privacy (Barthelemy et al., 2019).

**C. Technology and Implementation**

The project used a small, powerful computer (NVIDIA Jetson TX2) to process video quickly and efficiently without using much power. They used a computer vision program called YOLO V3 to spot objects like people and cars in the video, because it's both fast and accurate. Another program, SORT, was used to track those objects as they moved from frame to frame. Because the processing happened right there at the camera (called "edge computing"), the system didn't need to send huge amounts of data to a central computer, which made it faster, cheaper, and more secure. A special framework called Agnosticity helped collect and store the data, and made sure the system could work with different types of sensors and communication methods (Barthelemy et al., 2019).

**D. Validation and Performance**

Tests were done to check how accurate, fast, and efficient the system was. They used a set of video data called the Oxford Town Center dataset to see how well it could spot pedestrians. The system was correct about 69% of the time but sometimes missed people in big crowds when they were blocked from view. It processed video at about 20 frames per second, which is fast enough to work in real-time. Tests also showed that the computer parts (CPU and GPU) were used steadily, and the network was efficient because only small amounts of data (not the whole video) were sent (Barthelemy et al., 2019).

**E. Real-World Applications**

Two real-world applications were tested:

1. **Indoor Deployment:** The sensor was deployed inside a building during an emergency evacuation. The system successfully tracked pedestrian movements, demonstrating its potential for monitoring emergency responses and ensuring crowd safety.
2. **Outdoor Deployment in Liverpool:** The sensor network monitored traffic flow at a busy intersection. Data analysis revealed daily pedestrian and vehicle activity trends, with peak traffic observed during business hours. These insights provided urban planners with valuable information to optimize traffic management and pedestrian infrastructure (Barthelemy et al., 2019).

**F. Challenges and Future Work**

Several challenges were encountered:

* **Occlusion and Underestimation:** The system struggled with detecting pedestrians in dense crowds due to overlapping bounding boxes.
* **SORT Algorithm Limitations:** The tracking algorithm did not leverage GPU acceleration, creating a processing bottleneck.
* **Hardware Constraints:** The NVIDIA Jetson TX2, while efficient, limited performance in high-traffic scenarios.

Future improvements include:

* Implementing alternative tracking algorithms optimized for GPU acceleration.
* Exploring newer hardware such as the NVIDIA Xavier for improved computational efficiency.
* Enhancing detection accuracy through additional training on diverse datasets.
* Investigating recent advancements in AI, such as Transformer-based object detection models, to improve real-time tracking.
* Utilizing 5G and edge AI developments to enhance data transmission efficiency and real-time processing capabilities (Barthelemy et al., 2019).

**G. Personal Evaluation**

The Liverpool project showed that it's possible to use small, local computers to track traffic in real-time in cities. Using existing security cameras made it a cost-effective solution. While the system wasn't perfect, and there were some issues with accuracy and the hardware, it's a good starting point for future improvements. Better AI and tracking software could make it even better. Overall, this project is a big step forward for planning how people move around cities and for developing smart cities.

**References**

Barthelemy, J., Verstaevel, N., Forehead, H., & Perez, P. (2019). Edge-computing video analytics for real-time traffic monitoring in a smart city. *Sensors, 19*(9), 2048. https://doi.org/10.3390/s19092048