BICYCLE THEFT DETECTION

Dima Damen, David Hogg

School of Computing, University of Leeds, LS2 9JT, Leeds dima@comp.leeds.ac.uk, dch@comp.leeds.ac.uk

Keywords: Surveillance, Theft Detection, Clothing Colour Comparison, Event Recognition.

Abstract

We outline a method for detecting bicycle thefts from CCTV and give preliminary experimental results, including indicative failure modes.

1 Introduction and Background Review

Reports in the UK show that around 500,000 bicycles are stolen annually [5]. In Greater London, only 5% of stolen bicycles were returned to their owners in 2005 [6]. Despite available guidelines for safe locking of bicycles, leaving a bicycle locked onto a public rack is still a major concern for the bicycle's owner. Due to the vast number of CCTV cameras, a monitoring teams' duty seems daunting. Not only is it impossible for the monitoring staff to watch the camera input all the time, but also it is impossible to monitor more than one camera simultaneously.

An increasing number of studies have sought to use computer vision technology to enhance the use of CCTV, particularly within the transport infrastructure. Such studies have covered raising warnings when pedestrians try to tamper with ticket machines in metro stations or enter the rail area [4], when suspicious people walk through security gates at airports [2], or when a piece of baggage is left unattended in a public area [1]. A general review of academic and commercially successful projects for surveillance was provided by Valera and Velastin [3]. Their paper covers both the hardware and software aspects of such systems.

2 Outline of the method

Our method is designed to associate people depositing bikes with those who collect them later. With this association, we can detect thefts when the individuals do not look alike.

People in motion can be detected and tracked with reasonable certainty using current computer vision methods, albeit with occasional errors. By comparing images before and after someone (or a group of people) enter the vicinity of a rack, we can estimate the positions and appearances of any bikes that are dropped off or picked up.

By comparing appearance, we can identify the bicycle between being dropped and being picked up again. Unfortunately, the association between people and bikes is uncertain and a simple-minded strategy for matching the two is too unreliable. We resolve this problem by searching for a globally optimal assignment of people to bikes that satisfies the constraint that each person entering the rack can only drop off or pick up one bike, or may pass through without doing either. The optimisation balances the evidence linking people to bikes, and incorporates a preference for bikes being both dropped off and picked up again during the period under study.

3 Experiments and Performance Evaluation

Three Experiments were conducted using a colour CCTV camera overlooking a bicycle rack. Figure 2 shows the viewpoint utilized in recording 11 hours of cyclists dropping their bicycles and picking them up. The experiments included both short term and long term parking.



Figure 2: The CCTV camera viewpoint overlooking the bicycle racks

Confusion matrices from the three experiments are shown in Tables 1-3

	Predicted	
Actual	Thief	Non-Thief
Thief	5	2
Non-Thief	6	45
la 1. Eventim	ant 1 (1 hour)	Confusion M

Table 1: Experiment 1 (1 hour) Confusion Matrix

Predicted	
Thief	Non-Thief
0	1
4	23
	Pred Thief 0 4

Table 2: Experiment 2 (50 minutes) Confusion Matrix

	Predicted	
Actual	Thief	Non-Thief
Thief	4	2
Non-Thief	6	116

Table 3: Experiment 3 (9 hour and 40 mins) Confusion Matrix

As the results show, a warning was raised for 9 out of the 14 theft cases. The system raised 16 false warnings, of which 4 were people returning with different clothing – this is expected because the method is dependent on clothes colouring for comparison.

Five theft cases were undetected by the system: One was not tracked properly. The second was detected as a drop (instead of a pick-up) event. The last two were falsely connected to previous drop-offs that matched in colour. We believe such false connections were generated because of the high number of staged thefts in the experimental data.

In analyzing how theft cases could go undetected, it is apparent that there are several ways to fool the system. Some of these ways are caused by technical characteristics of the tracker; others are based on understanding how the system decides on raising warnings:

- The thief could wear exactly the same clothing colours as the person who dropped the bicycle earlier.
- The thief drops another bicycle and picks a better one at the same time. The system would be unable to detect a drop or pick event and the theft case would go undetected.
- The tracker loses track of people as they pause. If someone pauses for several minutes every few steps, the tracker would detect the trajectory as noise, and the person would go undetected
- Theft cases of parts of the bicycle (like tyres or seats) can not be detected by this application.

Acknowledgements

The blob tracker utilized in the experiments had been developed by Dr. Derek Magee at the school of computing, university of Leeds

References

- [1] Ferryman, J., Ed. Ninth IEEE International Workshop on Performance Evaluation of Tracking and Surveillance (PETS 2006), New York, IEEE, (2006).
- [2] Rota, M. and M. Thonnat. "Video sequence interpretation for visual surveillance" 3rd IEEE Int. Workshop on Visual Surveillance. (2000).
- [3] Valera, M. and S. Velastin (2005). "Intelligent distributed surveillance systems: a review" in Proc. Of IEE Vision, Image and Signal Processing. (2005)
- [4] Wang, Y., et. al. "A video analysis framework for soft biometry security surveillance". Int. Workshop on Video Surveillance and Sensor Networks. (2005).
- [5] http://www.tiscali.co.uk/money/features/insurance_bicycl e.html
- [6] http://www.tfl.gov.uk/cycles/safety-security/avoidingtheft.shtml