

Persona de seguimiento y reconocimiento de eventos en una

red de sensores



Queen's University Belfast

CENTRE FOR SECURE INFORMATION TECHNOLOGIES









Secure Corridors

 "CCTV was originally seen as a preventative measure. Billions of pounds has been spent on kit, but no thought has gone into how the police are going to use the images and how they will be used in court. It's been an utter fiasco: only 3% of crimes were solved by CCTV. There's no fear of CCTV. Why don't people fear it? [They think] the cameras are not working."

Detective Chief Inspector Mick Neville, officer in charge of the Metropolitan police unit, talking at the Security Document World Conference in London.





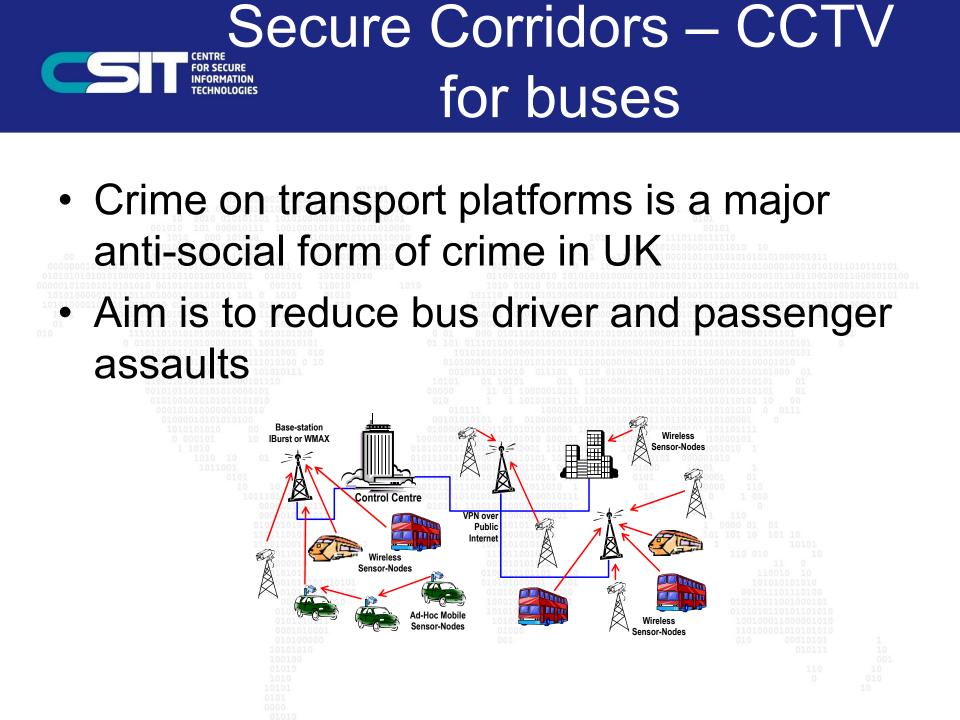
"I want public transport to become world renowned for its safety and to banish the sad minority of hoodlums and troublemakers that have blighted our buses." *Boris Johnson, Mayor of London*

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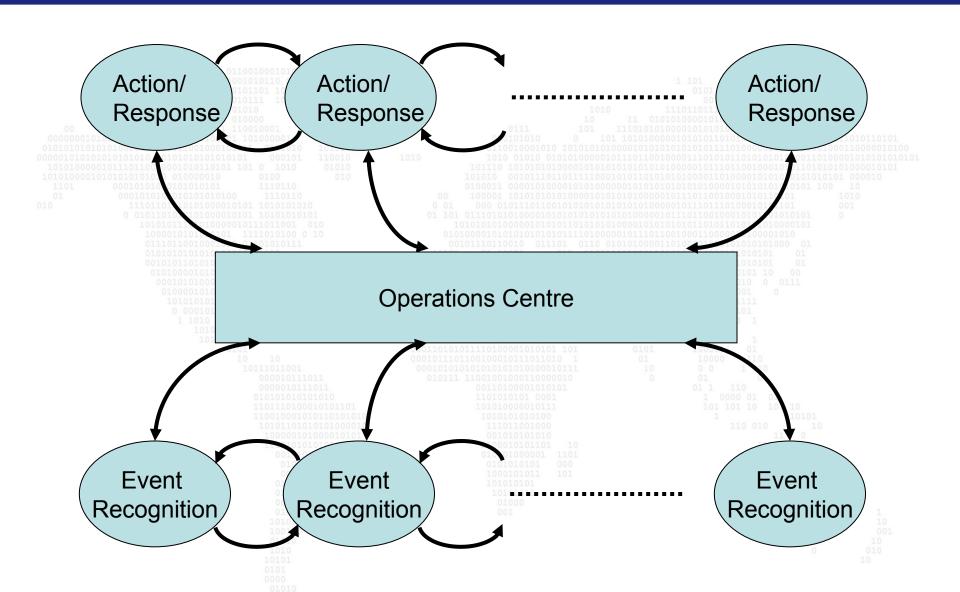
Introduction

- Massive investment in CCTV in the UK
- Impact on anti-social and criminal behaviour has been minimal
 - e.g. assaults on public transport
- CCTV operates in a passive mode
- "Active" CCTV has to alert security analysts to prevent undesirable behaviour
- Greatly increase the likelihood of being caught a major factor in crime prevention
- Persistent analysis of CCTV video footage in real-time



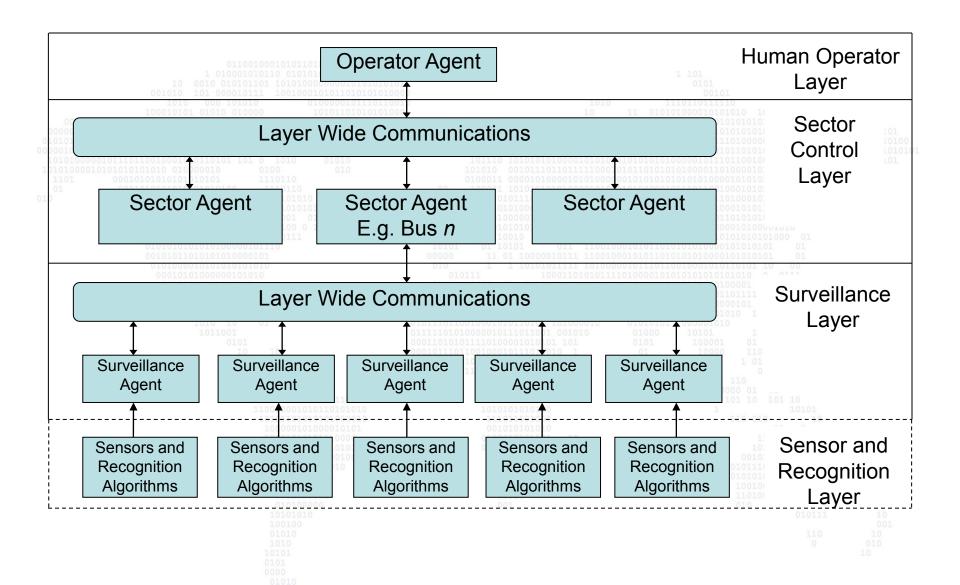


Event Management & Response



Architecture for Multi-Agent Surveillance







Event Recogniton

- Key requirement for active CCTV is to automatically determine the threat posed by each individual
- Focus of the computer vision community has been on behavior/action recognition
- Experienced security analysts profile individuals in the scene to determine their

threat



Event Recognition

- They identify individuals who look as though they may cause trouble
 Most majority of offenders are young
- Vast majority of offenders are young adolescent males
- Key to automatic threat assessment is:
 - to automatically measure the relative locations and motions of subjects in the scene
 - to automatically profile people in the scene based on their gender and age





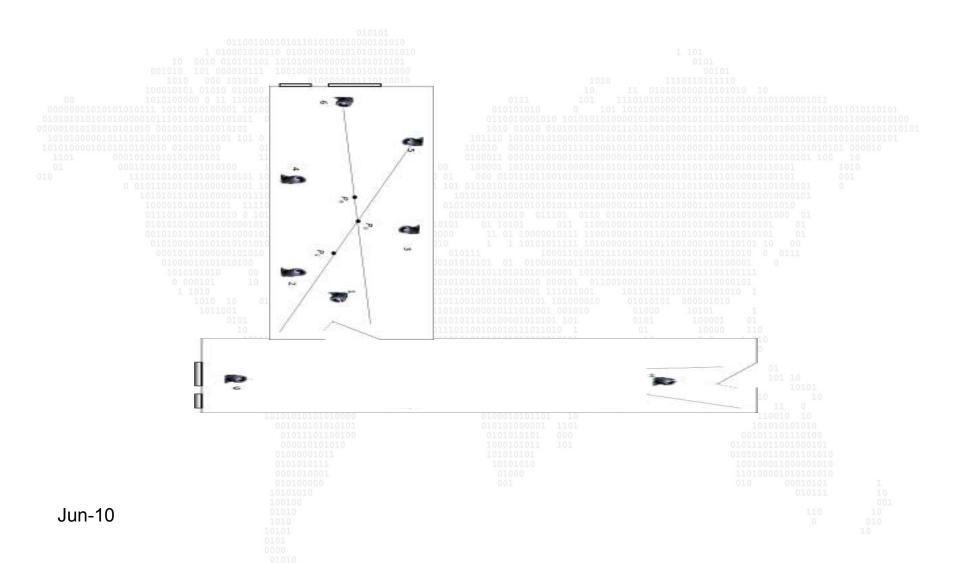
- Introduction & Motivation
- Tracking over a sensor network
- Gender Profiling
 - Multi agent surveillance architecture
 - Conclusion & Summary

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CSIT Sensor Network

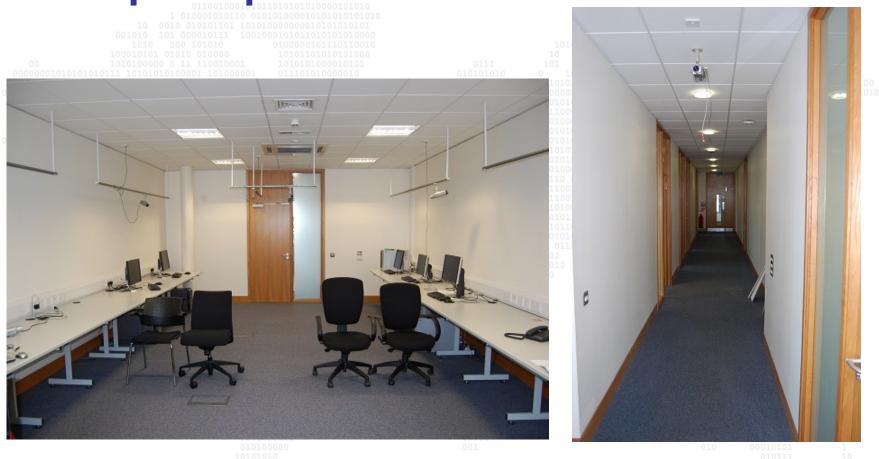






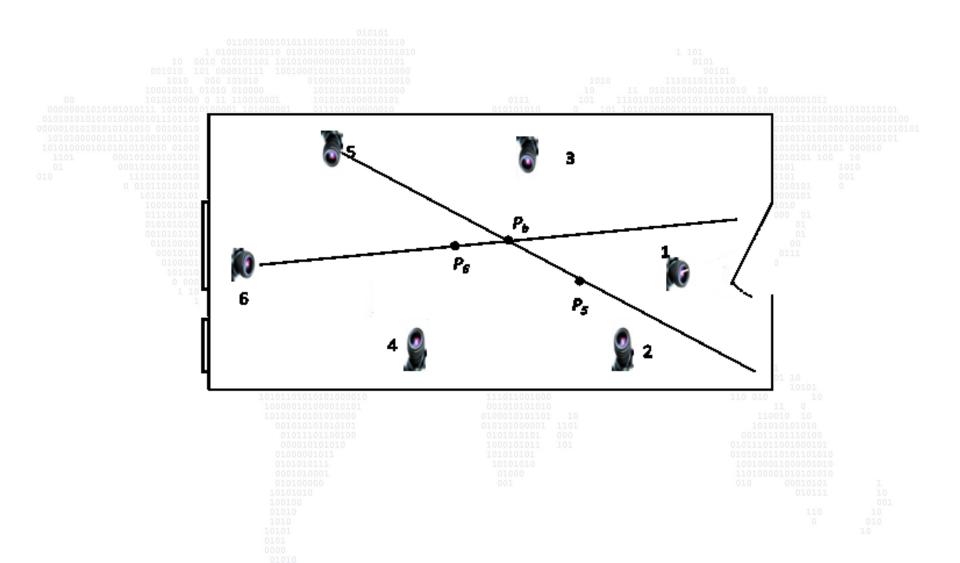
CSIT Sensor Network

Open Spaces / Narrow Corridors



Laboratory







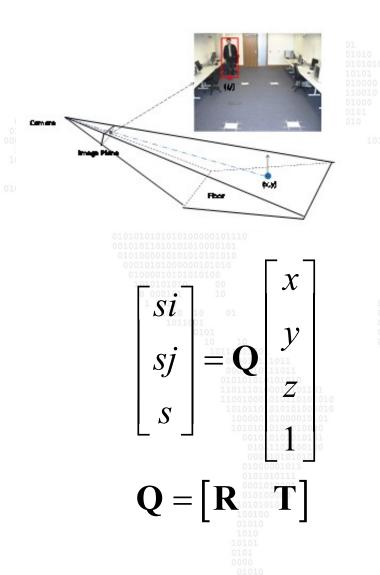
Motivation

- Moving object detection on buses likely to be poor
- Passenger obscuration by seats
- Cannot assume bottom of bounding box is coincident with floor





Single Camera



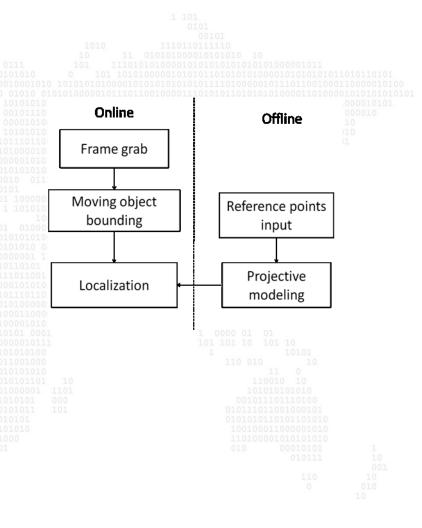
 Assumption: centre of detected object's bottom boundary is coincident with feet z value is zero, only need to find (x, y) coordinates Measure positions of four key points Solve for the eight unknowns in Q



Single Camera

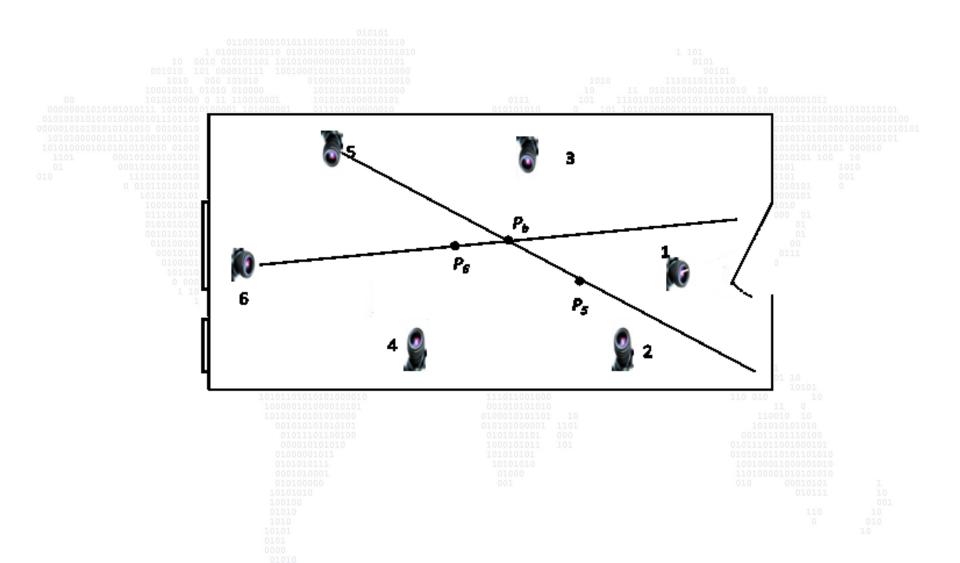
- Foreground extracted by background subtraction
- Bounding box placed around foreground
- Corner coordinates passed to localization module

Solves for x and y



Two camera







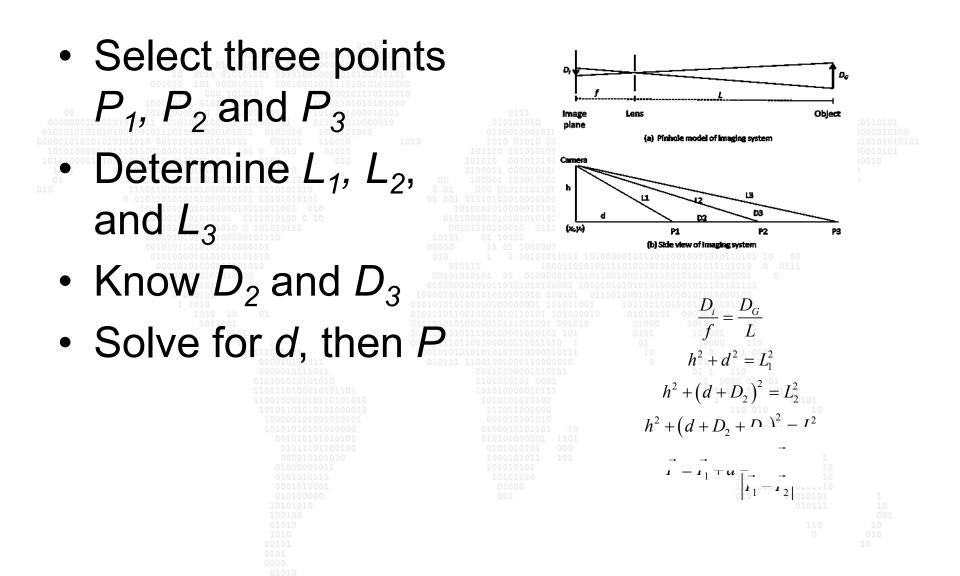
Two-camera Localisation

- For each camera determine its position in the room coordinates
- Determine the object position in the room coordinates for each camera
- Draw a line from the camera to object
- Object position is the intersection of lines

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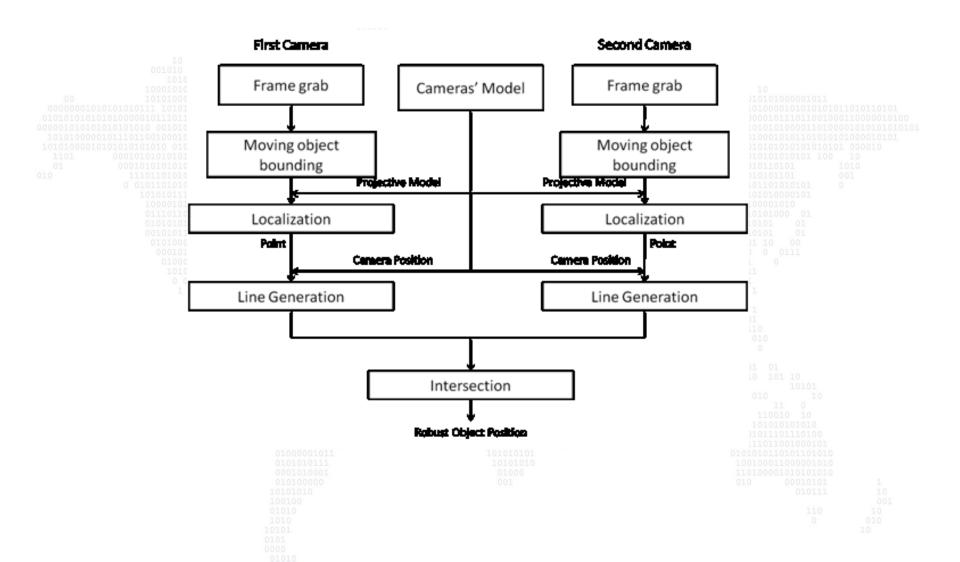


Two camera





Two camera

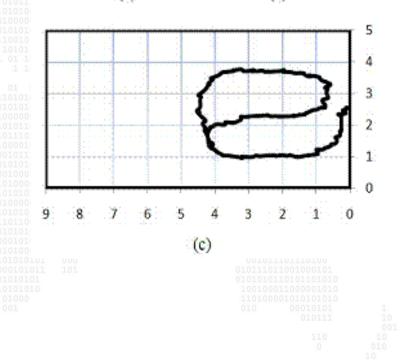




Experiments

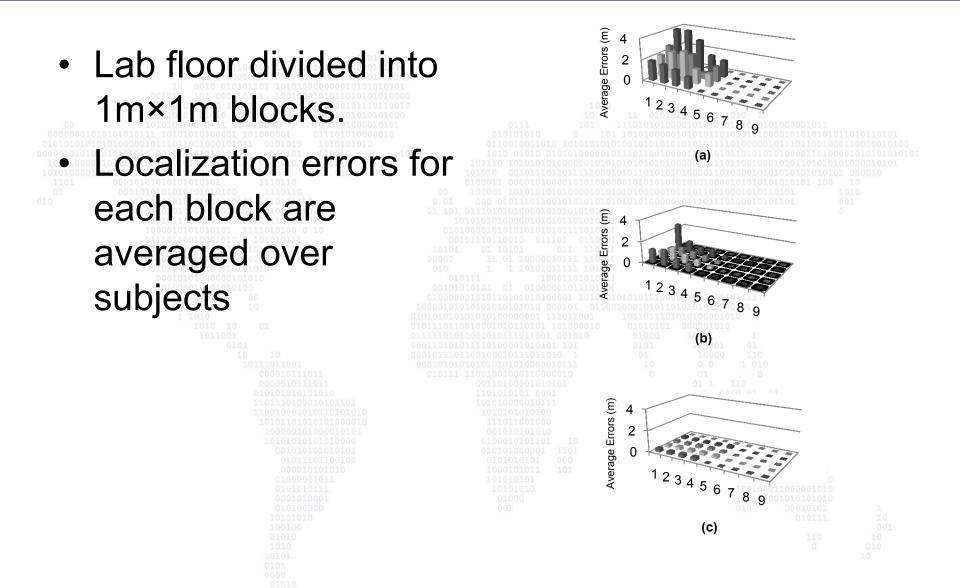
- Selected cameras 5 and 6 because they had largest coverage of any camera-pair
- 11 individuals were asked to roughly follow a route in the lab
- Chairs placed in the route
- 12400 video frames were collected
- Sequences manually analysed to give ground truth of real world position in each frame





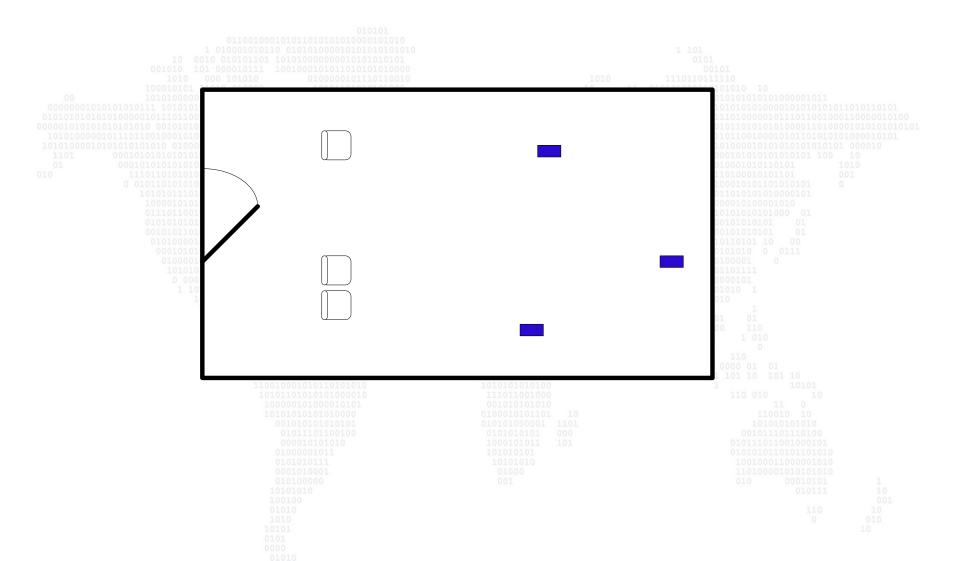


Position based error analysis



Three Camera

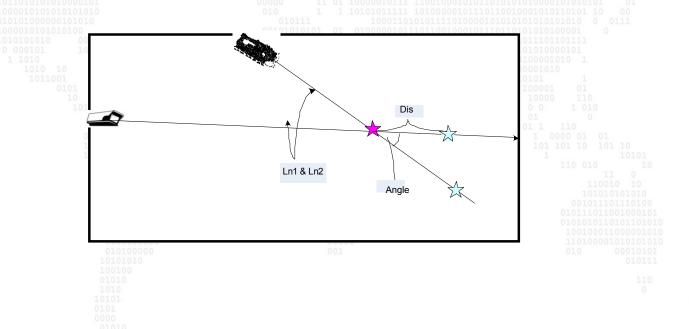








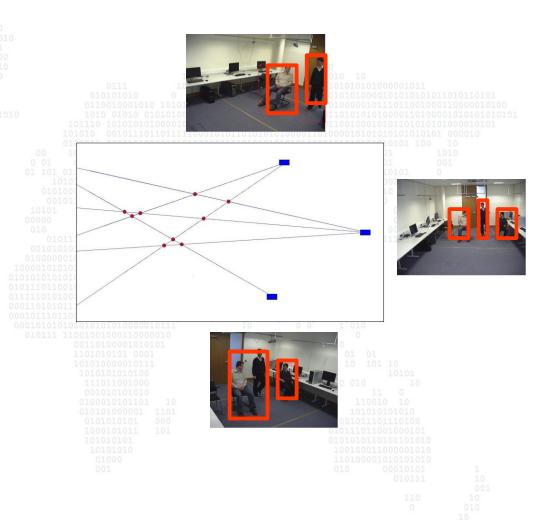
- Position: Ground floor co-ordinates, denoted by (*x*,*y*).
- Dis: The distance to the nearest localisation point inferred by a single camera observation.
- Ln1, Ln2: The two intersecting lines generated by the two single-camera observations.
 - Angle: The angle between Ln1 and Ln2.





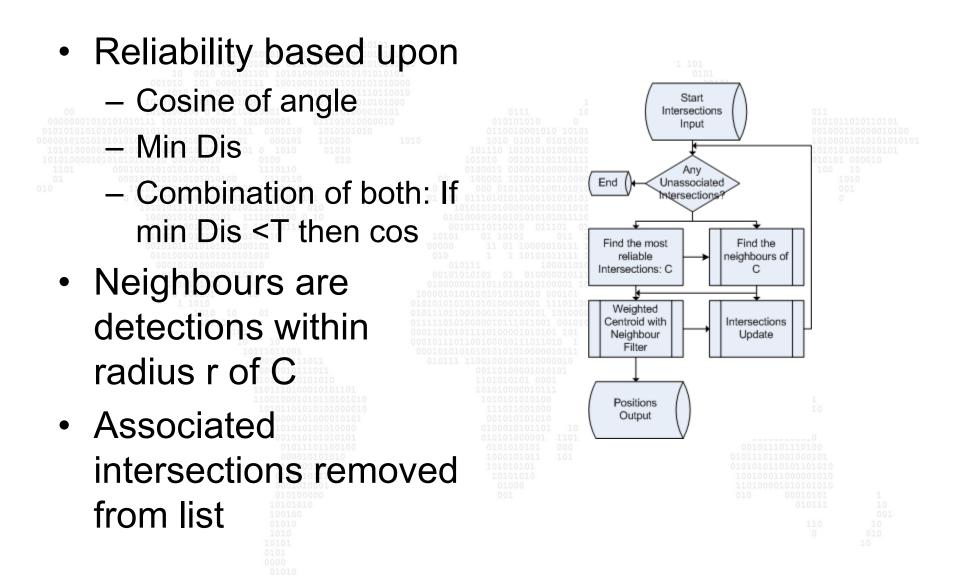
Detection Association

- Multiple cameras mean multiple detections
- Some erroneous detections due to false alarms and occlusion
- Need to associate detections within subjects





Detection Association





"Bus Journey"

- 10 min sequence of 4 subjects entering, sitting, standing and exiting
- Corresponding to 2210 frames captured by each camera
- No. of subjects in each frame, summed over whole sequence, was 3870





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Evaluation

subjects

• *T_i* is true positive rate

S_i is the actual no. of

 A_i is no. of subjects

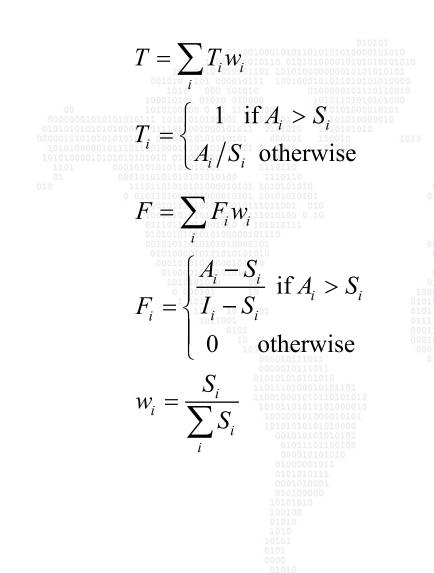
 I_i is input no. of

intersections

output from detection

association algorithm

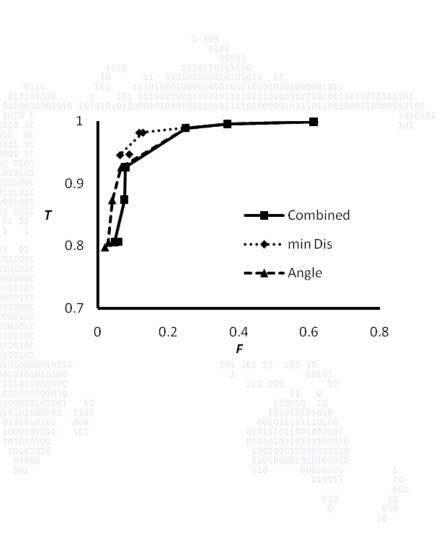
F_i is false positive rate





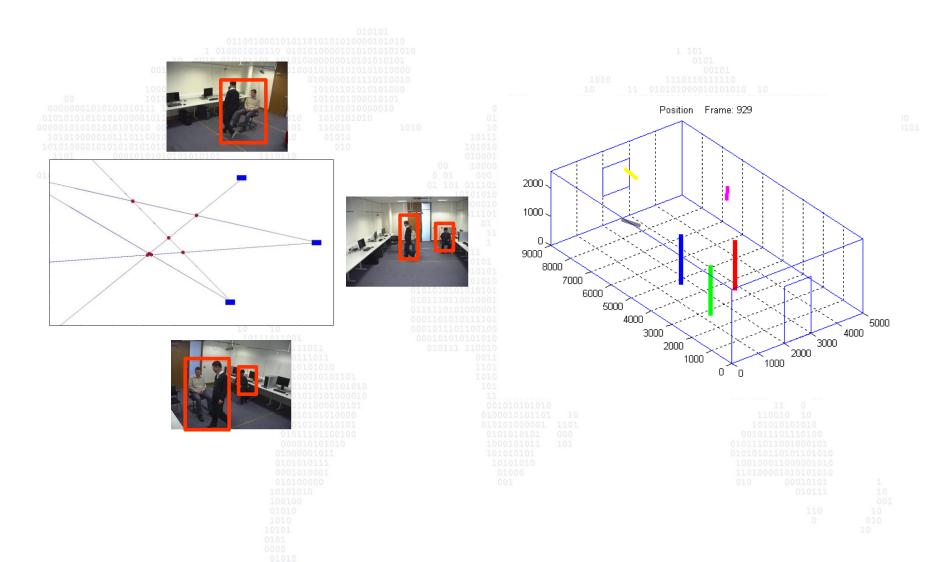
Evaluation

- Tis a measure of subject underestimation
- F is a measure of overestimation
- Vary radius *r* to obtain ROC curves
- r varies from 10cm to 2m left to right



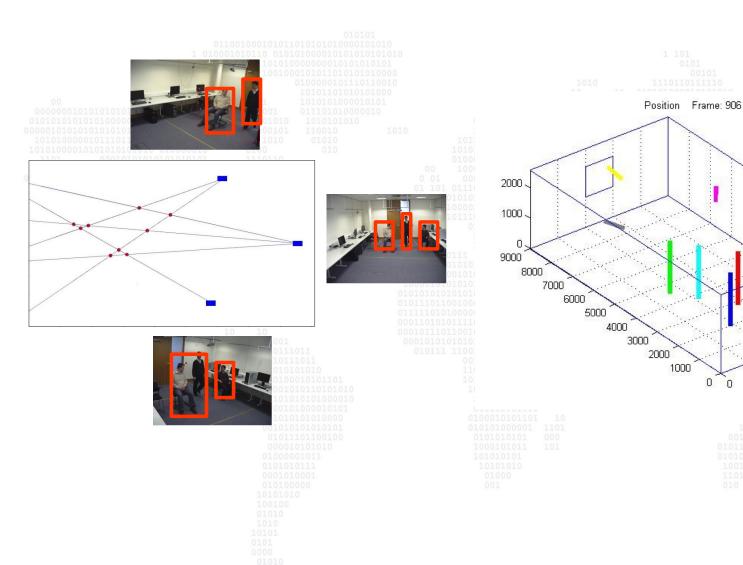
Correct Estimation





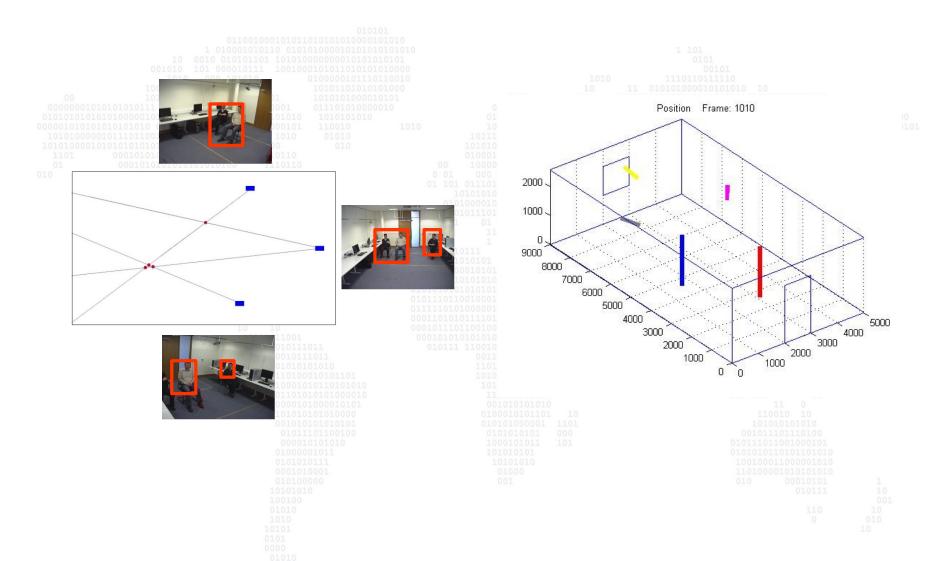
Over Estimation





Under Estimation







Tracking

 Bayesian framework 	$p(x_t z_{1:t-1}) = \int p(x_t x_{t-1}) p(x_{t-1} z_{1:t-1}) dx_{t-1}$
- Prediction - Filter	$p(x_t z_{1:t}) = \frac{p(z_t x_t) p(x_t z_{1:t-1})}{\int p(z_t x_t) p(x_t z_{1:t-1}) dx_t}$
 Cannot be evaluated for most 	$\hat{x}_{t} = \underset{x_{t}}{\arg\max} p(x_{t} z_{1:t})$
state-space models	



Particle filter

 $p(x_t) \approx \frac{1}{N_n} \sum_{i=1}^{N_p} \delta(x_t - x_t^i)$

 $p(x_t | z_{1:t}) \approx \sum_{i=1}^{N_p} w_t^i \delta(x_t - x_t^i)$

 $w_t^i \propto w_{t-1}^i rac{p\left(z_t \left| x_t^i
ight) p\left(z_t \left| x_t^i
ight)
ight)}{q\left(x_t^i \left| x_{t-1}^i, z_t
ight)}$

- Represent posterior by set of random samples and weights
- Weights are updated according to observation likelihood
- Sequential importance sampling



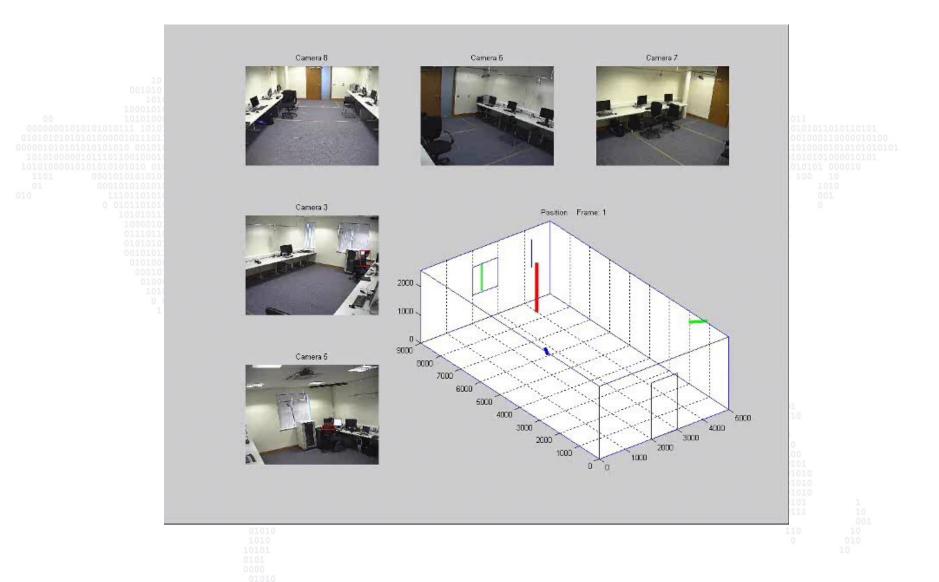
Kalman particle filter

- Kalman filter used to propagate each particle
- Steers particles towards regions with high likelihoods
- Fewer particles, less computation

 $\overline{x}_{t} = Ax_{t-1} + K(y_{t} - H.$

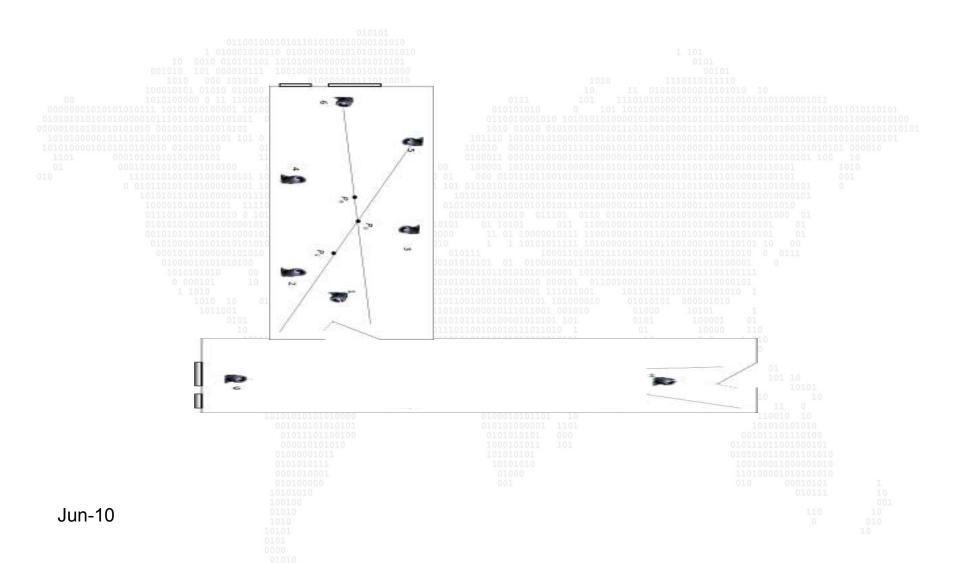
Tracking





CSIT Sensor Network







Subject Reacquisition

- Camera field of views are non-overlapping requires subject reacquisition for tracking
- Subject reacquisition is identification through applied detection, tracking and learning.
- Association of a current observed object with a previously observed object.
- Time gap could be seconds, hours, days etc.



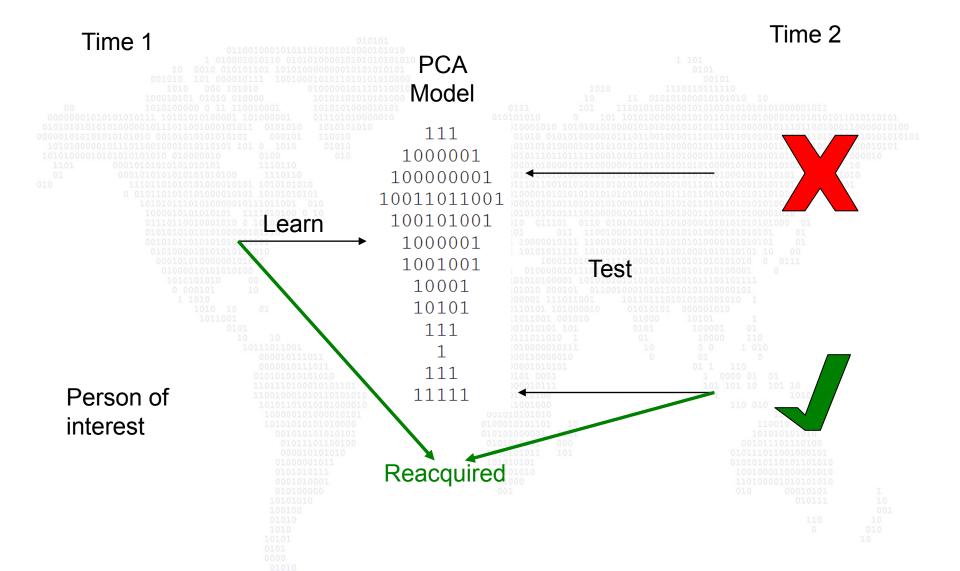
Subject Reacquisition

- Online principal component analysis
- Ten components are learnt
- Temporal voting used for reacquisition

 $\mathbf{v}(0) = \mathbf{x}(1)$ $\mathbf{v}(t) = \frac{n-1}{n} \mathbf{v}(t-1) + \frac{1}{n} \mathbf{x}(t) \mathbf{x}^{T}(t) \frac{\mathbf{v}(t-1)}{\|\mathbf{v}(t-1)\|}$ $\mathbf{x}_{2}(t) = \mathbf{x}(t)_{1} - \mathbf{x}_{1}^{T}(t) \frac{\mathbf{v}_{1}(t)}{\|\mathbf{v}_{1}(t)\|}$ $S(\mathbf{x}_t) = \|\tilde{\mathbf{x}}_t\|$ i=1

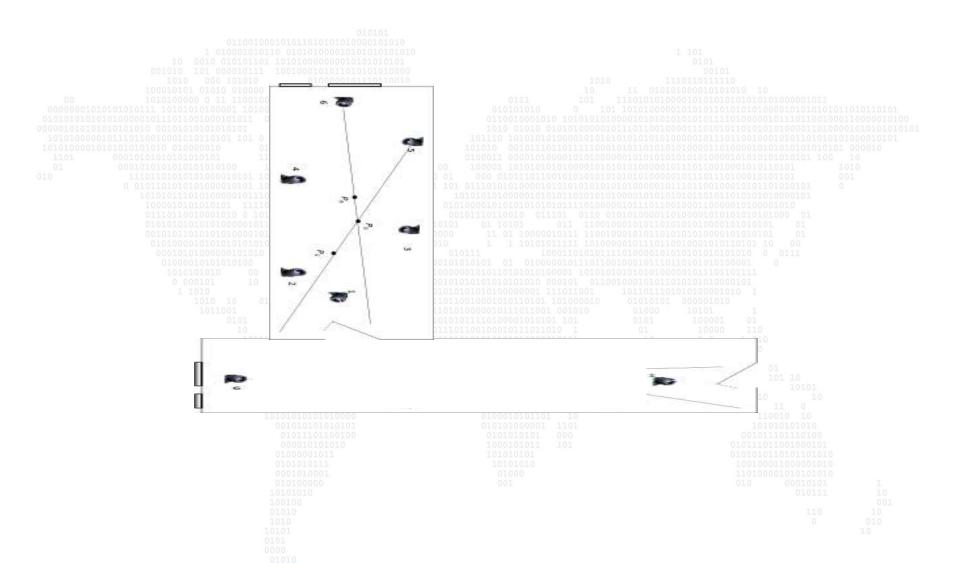
Subject Reacquisition





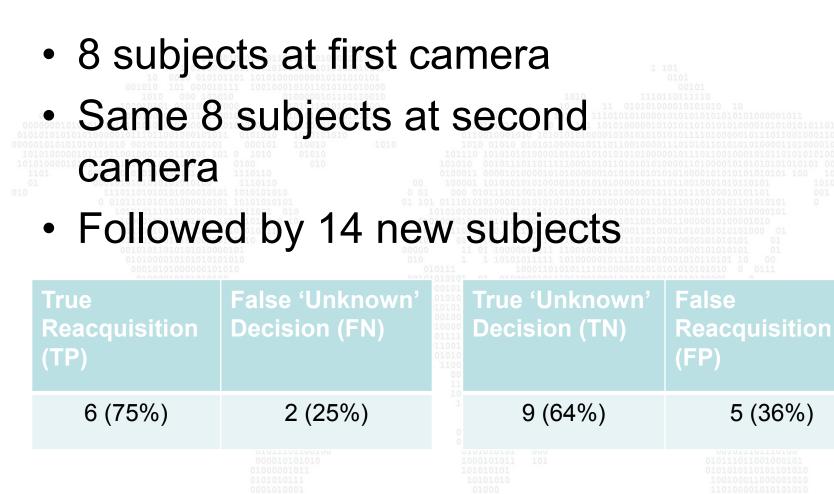
CSIT Sensor Network







Reacquisition Video



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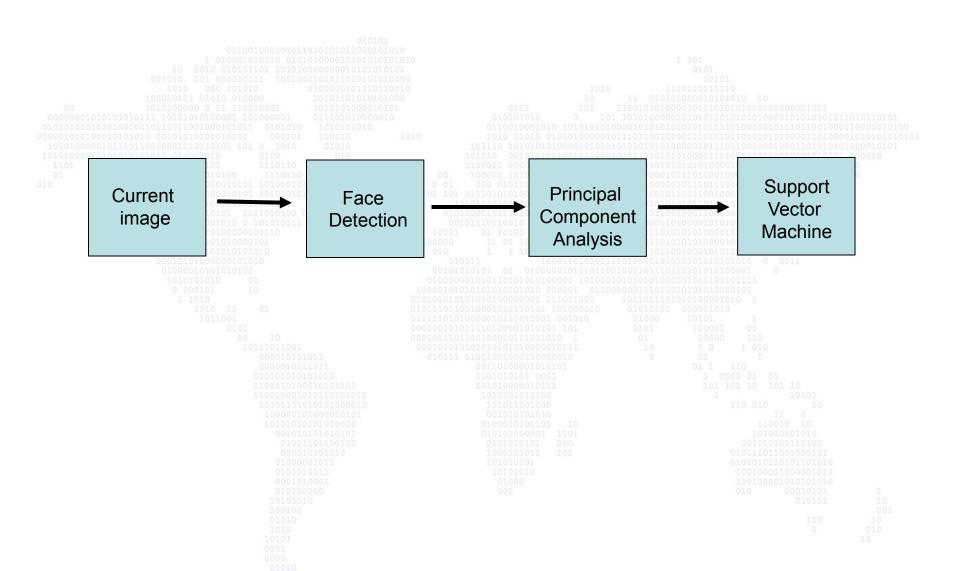




Introduction & Motivation Tracking over a sensor network Gender Profiling Multi agent surveillance architecture Conclusion & Summary

Face-based Gender Profiling





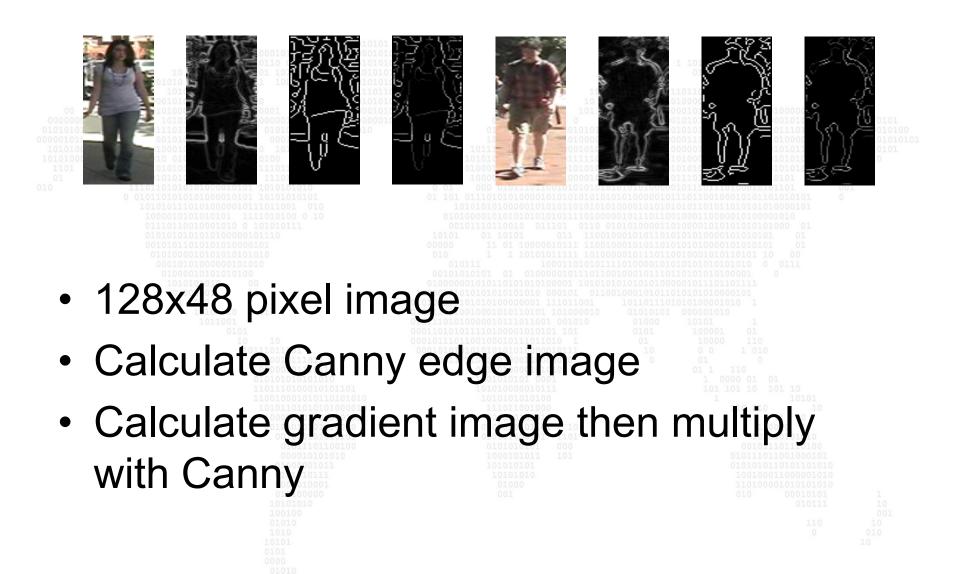


Body-based Gender Profiling





Body-based Gender Profiling



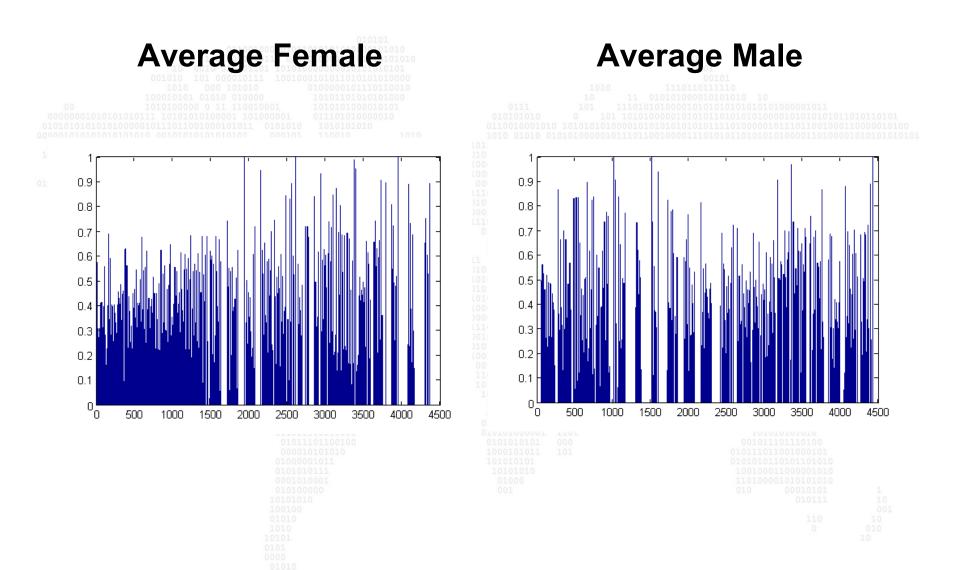


Canny Histogram of Gradients (CHoG)

 21x8 grid of cells of 6x6 pixels
 Histogram of cell edge orientations with 8 bins
 Bin value is sum of intensity gradients
 Cells grouped into overlapping blocks of 2x2
 Blocks overlap to give140 (20x7) blocks.
 Concatenated HoGs from each block gives 4480 element feature vector



CHoG







• Dataset of 413 images for each gender

– MIT pedestrian recognition set

- Viewpoint invariant pedestrian recognition set
- Entropy Boost classifier

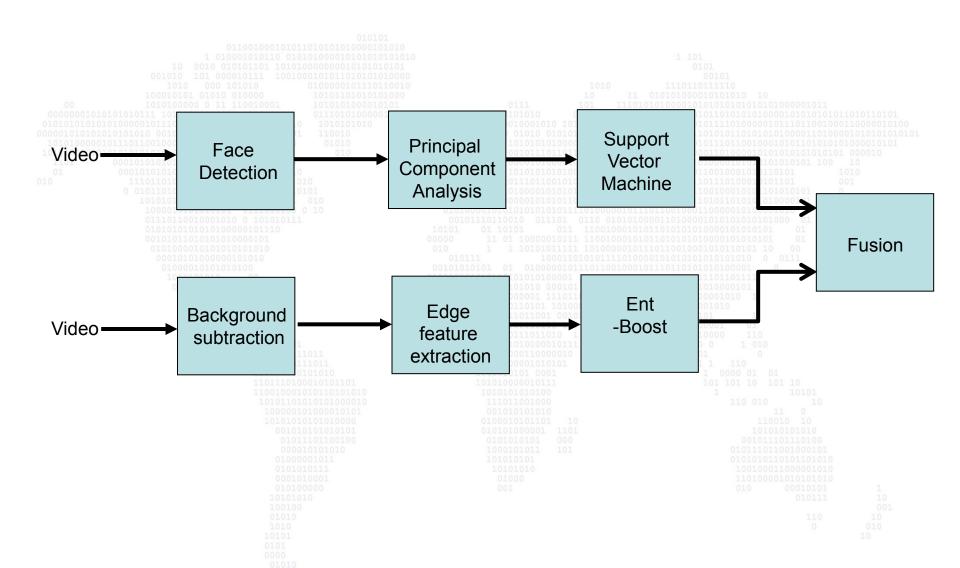
(VIPeR)

testing)

- Five-fold validation (80% training, 20%)
- 81% correct recognition

Gender Profiling







subjects.

Experimental Results

• Five sequences consisting of one or more

Video resolution is 640×480 and frame rate is 10 fps (Panasonic WV-LZ62 camera).

ypes	Total images	Pedestri	ians Genders	Positive dete	ctions
Single-1	763	1	Female	672	
Single-2	854	0001010101	10101010101 Male 111	807	
Single-3	1013	1	Male	755	
Single-4	1015	1	Female	870	
Multiple-1	805	2	Female/male	730	10101
Multiple-2	623	2	Male/male	571	11 0 110010 10





- EB-Fusion approach is compared against:
 - Face based gender classification using PCA coefficients with SVM (FACE-PCA)
 - Full body based gender classification using HOG features with SVM (BODY-HOG)
 - Concatenated HOG features of face and full body components with SVM (CP-FB).

Types E	B-FUSION	CP-FB	FACE-PCA	BODY-HOG	000001010	
Single-1	8.2%	16.4%	67.6%	17.8%	01	
Single-2	9.1%	14.4%	43.2%	16.3%		
Single-3	9.5%	13.2%	95.6%	14.0%	.10	
Single-4	10.1%	14.1%	94.4%	15.5%	101 101 10	
Multiple-1	11.6%	15.4%	95.2%	16.3%	.10 0	
Multiple-2	9.0%	13.3%	95.9%	14.2%		

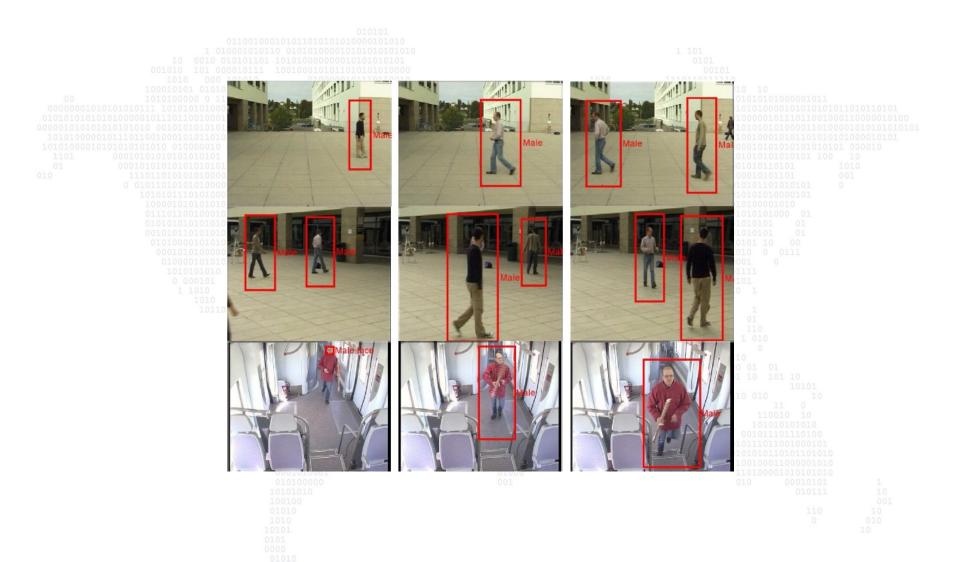


Experimental Results

Campus-1 2000 > 3 Male/female 1613 Campus-2 2000 > 3 Male/female 1554 Train-1 1626 > 3 Male/female 1019 Table 2 Error statistics of gender classification in Experiment 3. Types EB-FUSION CP-FB FACE-PCA BODY-HOG Campus-1 16.4% 18.2% 99.6% 19.8% Campus-2 15.1% 17.4% 99.2% 19.1% Train-1 14.7% 19.8% 76.3% 19.6%	Types	Total images	Pedestrians	Gender	Positive detect	ions
Train-1 1626 > 3 Male/female 1019 Table 2 Error statistics of gender classification in Experiment 3. Types EB-FUSION CP-FB FACE-PCA BODY-HOG Campus-1 16.4% 18.2% 99.6% 19.8% Campus-2 15.1% 17.4% 99.2% 19.1% Train-1 14.7% 19.8% 76.3% 19.6%	Campus-1	2000	> 3	Male/female	1613	0111011
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Types EB-FUSION CP-FB FACE-PCA BODY-HOG Campus-1 16.4% 18.2% 99.6% 19.8% Campus-2 15.1% 17.4% 99.2% 19.1% Train-1 14.7% 19.8% 76.3% 19.6% 1 1 14.7% 19.8% 76.3% 19.6% 1 1 14.7% 19.8% 76.3% 19.6% 1 1 14.7% 19.8% 76.3% 19.6% 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1		Table 2 Error sta	-		iment 3.01000011010	
Campus-1 16.4% 18.2% 99.6% 19.8% Campus-2 15.1% 17.4% 99.2% 19.1% Train-1 14.7% 19.8% 76.3% 19.6% Image: Compus-2 15.1% 17.4% 99.2% 19.1% Image: Compus-2 15.1% 19.8% 76.3% 19.6% Image: Compus-2 16.4% 19.8% 76.3% 19.6% Image: Compus-2	Types	EB-FUSION	CP-FB	FACE-PCA	BODY-HOO	
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		14.7%	19.8%	76.3%		

Results





Gender Profiling





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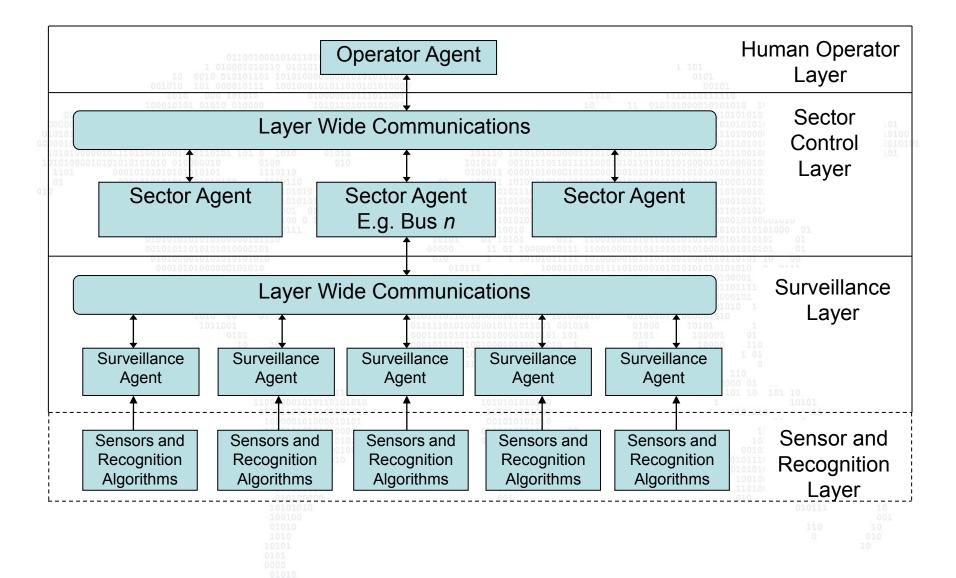








Architecture for Multi-Agent Surveillance





Event Composition

 Third step in threat assessment is to combine the who's in the scene with the

where in the scene

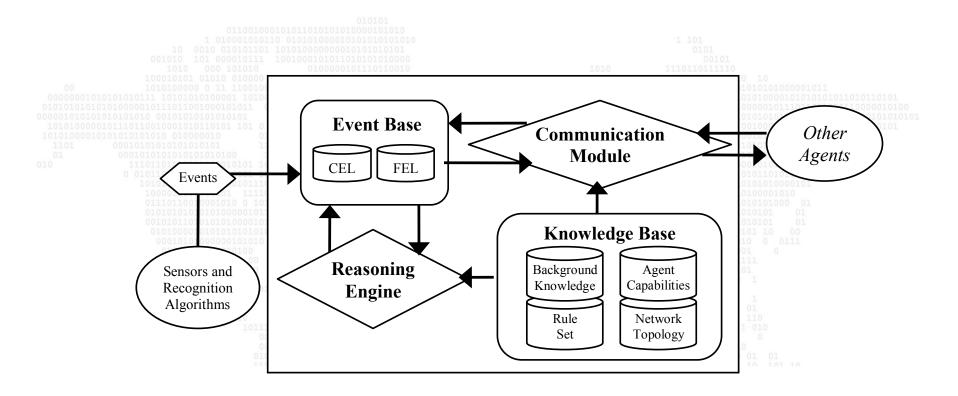
- Event management framework
- Implemented using multi-agent
 architecture

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Surveillance Agent







Event Representation

- Passenger boarding
- e₁=(PBV,21:05:31,1,0.85,0.7,{male})
- PBV is for event type Person Boarding Vehicle
 - 21:05:31 is the time of occurrence occurT
 - 1 denotes the source, in this case a video analytics algorithm
 - 0.85 is the source reliability
 - 0.7 denotes the significance
 - male is the value for the gender attribute



Knowledge Base

- Rule 1: Infers the event abusive behaviour
 - towards driver

• $R_1 = (LS_1, EType_1, Condition_1, m_1)$

- LS1=(TPL, TPL+120)
- EType1=DA abbreviated for driver abuse
- Condition is :

ei.Etype =PL ^ ej.Etype = PS ^ ei.location=Drivers Cabin



Communication Protocol

- Centralised reasoning has scalability limitations.
 Subscription-only presents a huge overhead for events that are produced frequently but are rarely needed.
- Communication protocol works on a "need to know" basis.
 - onetime event queries
 - event subscriptions

L LO LO L 1 L 10 L 10 00



Onetime queries

- Used where an agent only needs to know about that type of event for one individual event pattern.
- Sets other events in that pattern as a trigger for a onetime request of that event
- Reduces the communication whilst still ensuring the agent has complete knowledge for reasoning.



Experiments

• 55 sequences in total

 40 of normal passenger behaviour; person boards bus, sits and then exits the bus

- 15 of suspicious behaviour
 - 5 of people loitering in the saloon area
 - 5 of loitering in the driver's cabin
 - 5 of people obscuring face from cameras

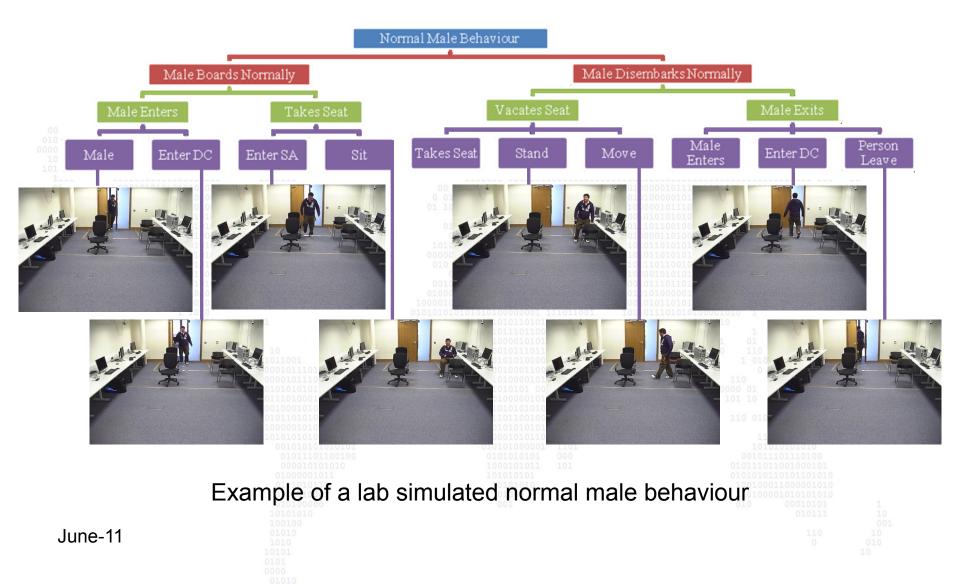


Experiments

- Lab was partitioned out into 2 sections to represent the driver's cabin and the saloon area.
 Area surrounding the door up to the first set of
- seats is regarded as driver's cabin
- Rest of the floor space and chairs are saloon area.
- Multi Agent System is developed using the agent middle ware JADE.
- Reasoning module for the agents and centralized reasoner developed using PROLOG.



Normal Male Behaviour





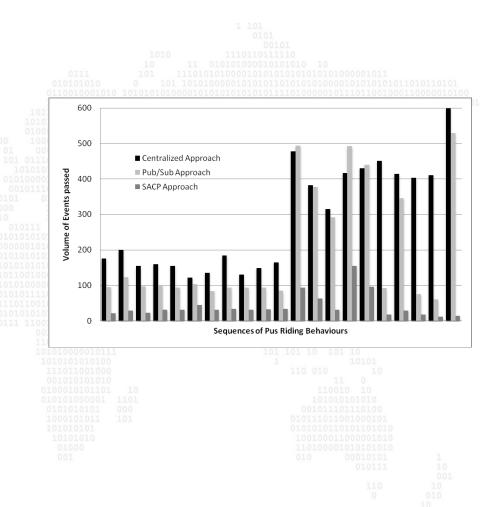
Event Composition Results

- Ground Truth (GT)
 True Positives (TP)
 False Positives (FP)
 - False Negatives (FN)
 - Sensitivity (S = TP/(TP+FN))
 - Precision (P = TP/(TP+FP)).

			0101					
	Compound	GT	ТР	FP	F	S (%)	P (%)	
11	Event				Ν			
000	Male Normal	20	18	2	2	90%	90%	
101	Behaviour							
100	Female	20	16	2	4	80%	89%	
.110	Normal							
001	Behaviour							
.0	Loitering	5	4	1	1	80%	80%	
100	Saloon Area							
01	Loitering	5	4	1	1	83%	80%	
101	Drivers Cabin							
000	Person	5	4	0	1	80%	80%	
.011	Obscuring							
110	Face							
011	0110000010 0 01 0 001010101 01 110							

CENTRE FOR SECURE Communication Results

- Measured events
 sent for reasoning
 - centralized
 agent using publish/subscribe
 - agent using SACP





Conclusion & Summary

- Video analytics for tracking and gender profiling have been demonstrated
- Event recognition and composition for a sensor network demonstrated in laboratory conditions
- Preliminary evaluation of architecture for multi-agent surveillance
- Bus trial for further evaluation