# **Multiview Pedestrian Localisation via a Prime** Candidate Chart Based on Occupancy Likelihoods Yuyao Yan<sup>†\*</sup>, Ming Xu<sup>†</sup> and Jeremy S. Smith<sup>\*</sup>



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# INTRODUCTION

A sound way to localize occluded people is to project the foregrounds from multiple camera views to a reference view using homographies and finding the foreground intersections [1].



Fig.1 Phantom occurrence However, this may give rise to phantoms due to foreground intersections between different people. This research aims to identify the phantoms from the real intersections.

## METHODOLOGY

The proposed method has four steps:

- . Extract foregrounds using GMM and segment side-byside pedestrians using convex hull analysis.
- 2. Using waist-plane homography mapping to find the foreground intersections.
- 3. Calculate the joint occupancy likelihood of each intersection.
- 4. Use the Quine-McCluskey method [2], along with the joint occupancy likelihood, to find the optimal solution.

# **COCCUPANCY LIKELIHOODS**

Suppose there are *N* cameras and *F*<sub>i</sub> represents the foreground observation in camera view *i*. Let X be the event that there is a pedestrian at intersection region I in the top view. We are interested in finding the posterior probability of event X occurring.

$$P(X/F_1, F_2, ..., F_N) \propto \prod_{i=1}^N [P(f_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X)P(d_i|X$$

 $P(f_i|X) = \frac{number \ of \ foreground \ pixels \ in \ A_i}{number \ of \ all \ pixels \ in \ A_i}$ 

 $P(h_i|X) = 1 - Q_G(h_i)$  $P(d_i|X) = Q_{\gamma^2}(d_i, 1)$ 

Acknowledgement : This work was supported by the National Natural Science Foundation of China (NSFC) under Grant 60975082 and an XJTLU PhD scholarship under Grant PGRS-12-02-07

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 $(h_i|X)]$ 



Fig.2 Variables related to  $d_i$  and  $h_i$ .

# PRIME CANDIDATE CHARTS

Each foreground region is decomposed into sub-regions according to the overlapping relationship of all the candidate boxes. A prime candidate chart is constructed to select a minimum set of pedestrian candidates to cover all the foreground sub-regions of interest. The prime candidate chart is updated as follows: . Remove the candidates with low occupancy likelihood.

- 2. Find the essential candidates which cover at least a sub-region that is not covered by other candidates and remove the corresponding rows and columns.
- 3. Merge the candidates which are contained by others.
- 4. If there are sub-regions not covered, select a column with two X's. Assume the candidate corresponding to an X is essential and repeat steps 2-3. Then try the other X and select the one with a larger likelihood.

	1		
	2		
3	4	5	
	6		

Sub-region:	1	2	3	4	5	6
Red	+	+	+	Χ	Χ	Χ
Green	Χ	Χ	+	Χ	Χ	+
Blue	+	Χ	Χ	Χ	+	Χ

Fig.3 Decomposition of a foreground region into sub-regions and the corresponding prime candidate chart. If a candidate covers a given sub-region, an X is placed; otherwise a plus sign.

### REFERENCES

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 $I_i$  - Warped foreground intersection  $A_i$  - Candidate box

 $f_i$  - Foreground pixel set in  $A_i$  $t_i$  - The top of the foreground box  $-A_i b_i$  - The bottom of the foreground box  $y_i$  y<sub>i</sub> - The bottom of the candidate box  $d_i$  - Mahalanobis distance from  $y_i$  to  $b_i$  $h_i$  - Distance from  $y_i$  to  $t_i$ 

 $\overline{h}$  - Average height of pedestrians

## EXPERIMENTAL RESULTS



Fig.4 Pedestrians are labelled with circles; phantoms are labelled with crosses.

IO: I1: I2: I3: I4: I5: I6: I7: I8: I9: I9: I10:	LLLLLLLLLLLLLLLLLLLLRRRRRRRRRRRRRRRRRR	LLLLLLLLLLLLLLLLLLLLRRRRRRRRRRRRRRRRRR
I11:	++++++++++++++*XX +++++++++++++++++++++	I11: o ++++++++++++++++++++++++++++++++++
	(a)	(b)
IO:0 I1: I2: I3: I4: I5:0 I6:0 I7:0 I8:0 I9: I10:0 I11:0	LLLLLLLLLLLLLLLLLRRRRRRRRRRRRRRRRRRRRR	LLLLLLLLLLLLLLLLLLLRRRRRRRRRRRRRRRRRRR
	(c)	(d)

Fig.5 The prime candidate charts after step 1, 2, 3 and 4.

#### CONCLUSIONS

The joint occupancy likelihoods and the prime candidate chart used in this paper add robustness to pedestrian localization. Experiment results have shown improved performance.





	Method	Evaluation	RECALL	PRESISION	TER
y	3DMPP	[3]	N/A	N/A	0.31
and	POM	[3]	N/A	N/A	0.27
•	POM	us	0.91	0.82	0.29
-	MvBN	[4]	0.90	0.97	0.13
	Proposed	us	0.96	0.99	0.05

Table 1. Evaluation results.