

2010

Detection and Filtering of Landmark Occlusions using Terrain Spatiograms

Damian M. Lyons

Fordham University, dlyons@fordham.edu

Follow this and additional works at: https://fordham.bepress.com/frcv_posters

Part of the [Robotics Commons](#)

Recommended Citation

Lyons, Damian M., "Detection and Filtering of Landmark Occlusions using Terrain Spatiograms" (2010). *Posters*. 2.
https://fordham.bepress.com/frcv_posters/2

This Article is brought to you for free and open access by the Robotics and Computer Vision Laboratory at DigitalResearch@Fordham. It has been accepted for inclusion in Posters by an authorized administrator of DigitalResearch@Fordham. For more information, please contact considine@fordham.edu.

Detection and Filtering of Landmark Occlusions using Terrain Spatiograms

Damian M. Lyons

Robotics & Computer Vision Lab

Department of Computer & Information Science

Fordham University, New York

Overview

A team of robots cooperating to quickly produce a map needs to share landmark information between team members so that the local maps can be accurately merged. However, a landmark visible to one robot may be partially occluded to another!

Terrain Spatiograms are a landmark representation in which the image spatial information relates to the scene rather than the image. This makes it possible to identify and filter potential landmark occlusions.

We present an approach to identifying and filtering occlusions using Terrain Spatiograms, and we report experimental results on 20 landmark datasets for varying states of occlusion. We show that occlusion can be detected and filtered, resulting in improved landmark matching scores.

Terrain Spatiograms

- A Histogram of image I captures the number of times each pixel value occurs in the image.
- A *Spatiogram* adds information on *where in the image* the values occur.
- A *Terrain Spatiogram* h_I represents 'where' as a 3D point in the field of view.

$$h_I(b) = \langle n_b, \mu_b, \Sigma_b \rangle \quad n_b = \eta \sum_{i=1}^{|P|} \delta_{ib}$$

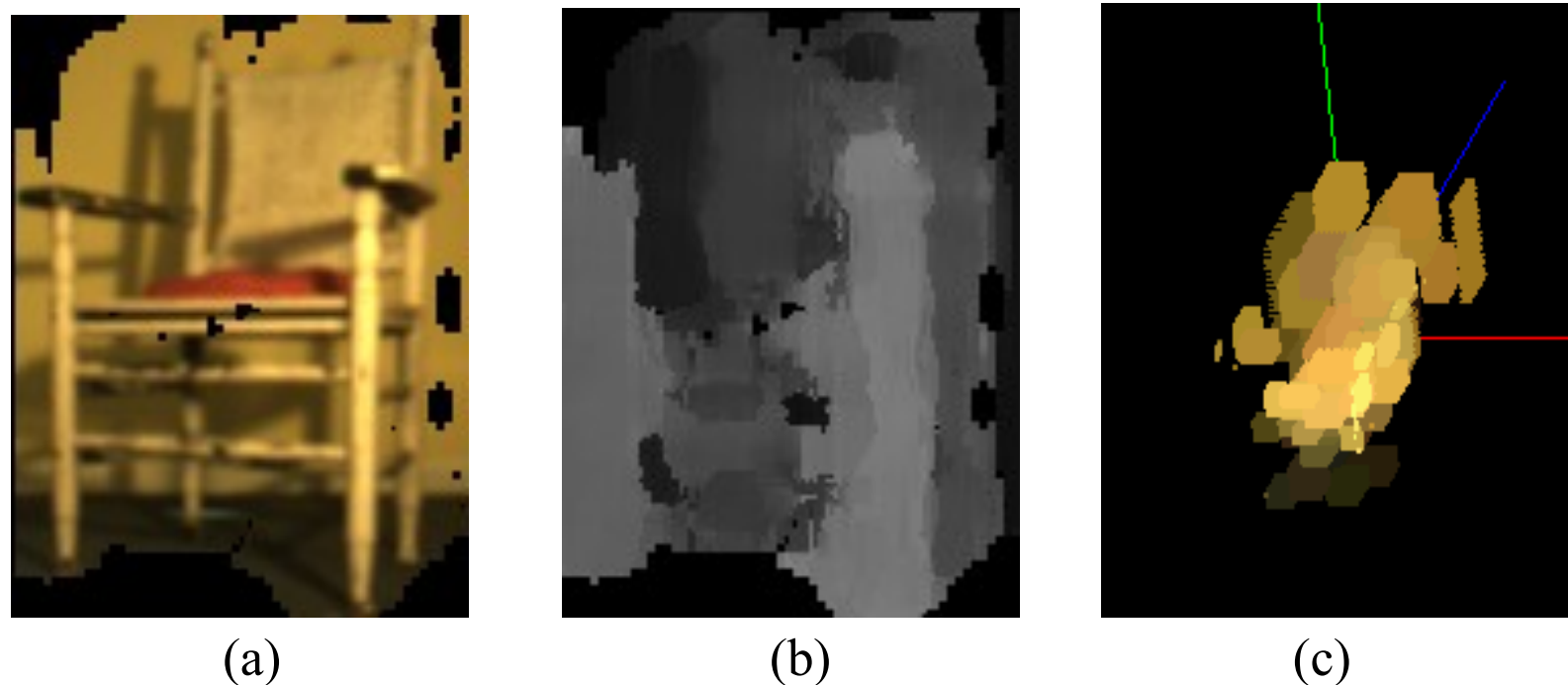


Image of chair landmark (a); monochrome stereo disparity for landmark (b); perspective view of color terrain spatiogram for landmark (c).

Recognizing a Landmark

- Compute the terrain spatiogram of the landmark
- Compare with the terrain spatiograms of a list of stored landmarks.

To compare h and h' :

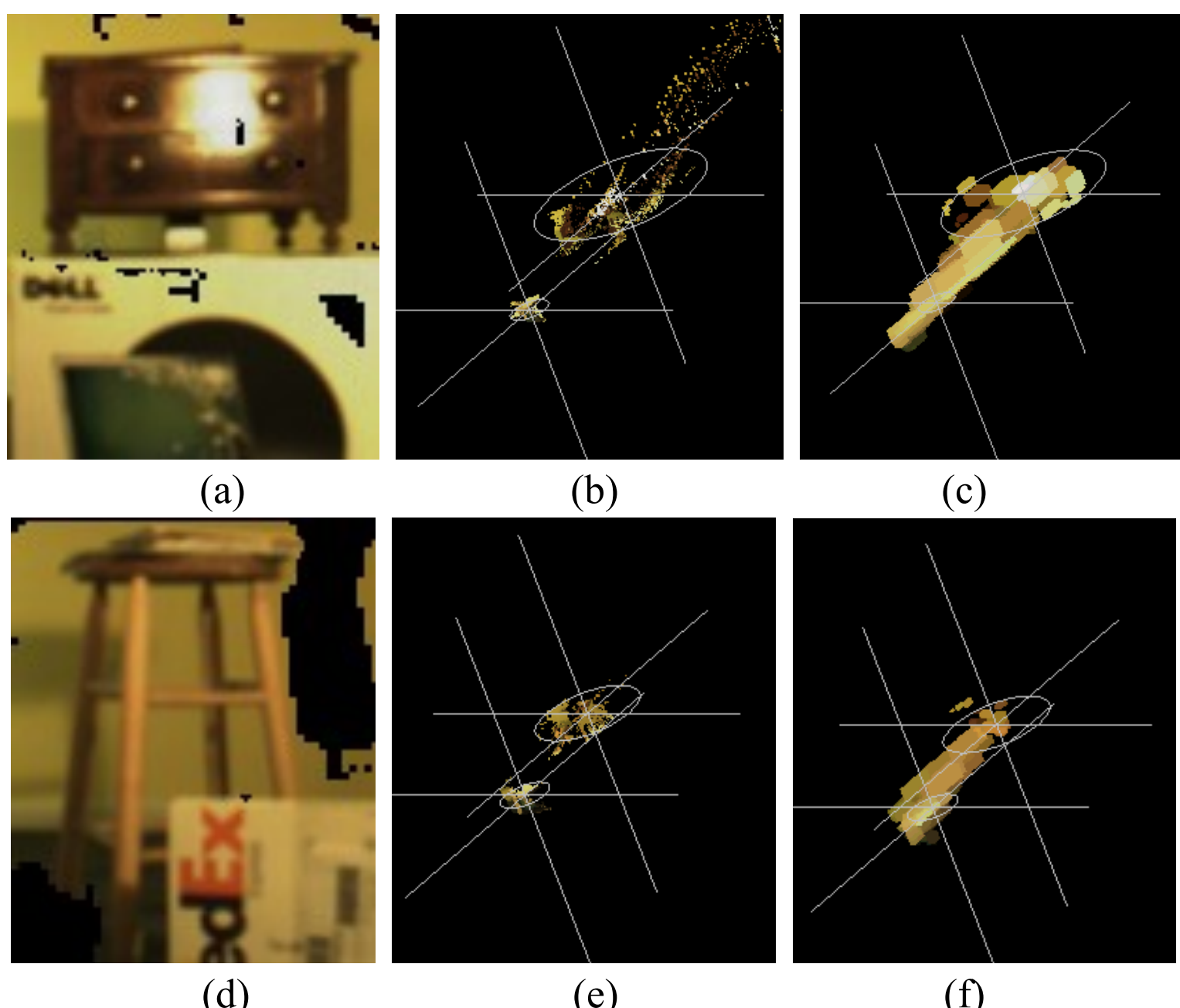
$$\rho(h, h') = \sum_{b=1}^{|B|} \psi_b \sqrt{n_b n'_b}$$

where

$$\psi_b = 2(2p)^{0.5} |S_b S'_b|^{0.25} N(m_b; m'_b, 2(S_b + S'_b))$$

Identifying Landmark Occlusions

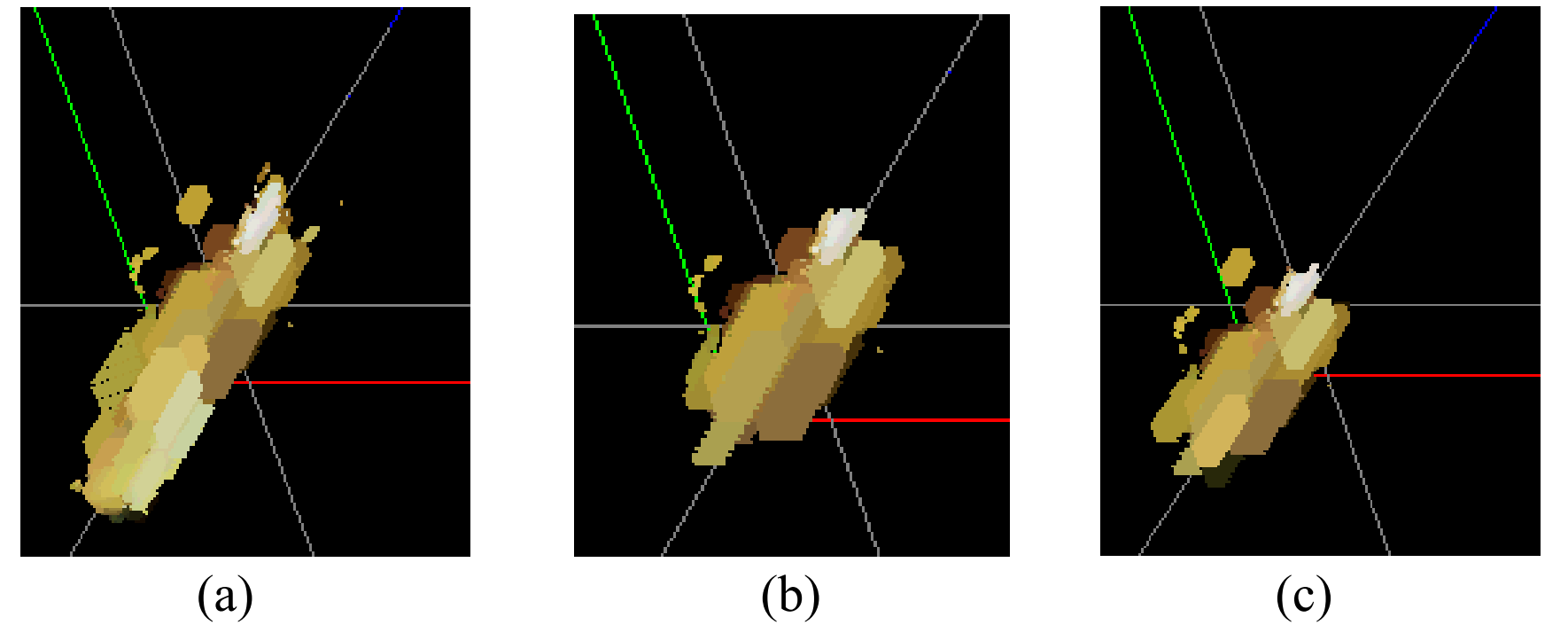
- For any occluded landmark h_o *K-means clustering* performed in the XZ plane \rightarrow cluster centers C_i , weights W_i
- Largest, rear-most cluster is identified as the candidate landmark cluster $C_o = \text{argmax}(W_i) \ \& \ \text{argmax}_Z(C_i)$
- and *any other clusters* are considered occlusions.



Occluded Landmark left image of stereo pair (a, d); perspective view of image pixels mapped to absolute depth (b, e); perspective view of terrain spatiogram with XZ cluster center and 1SD circle (c, f). We will assume: occlusions fall outside this circle.

Matching Occluded Landmarks

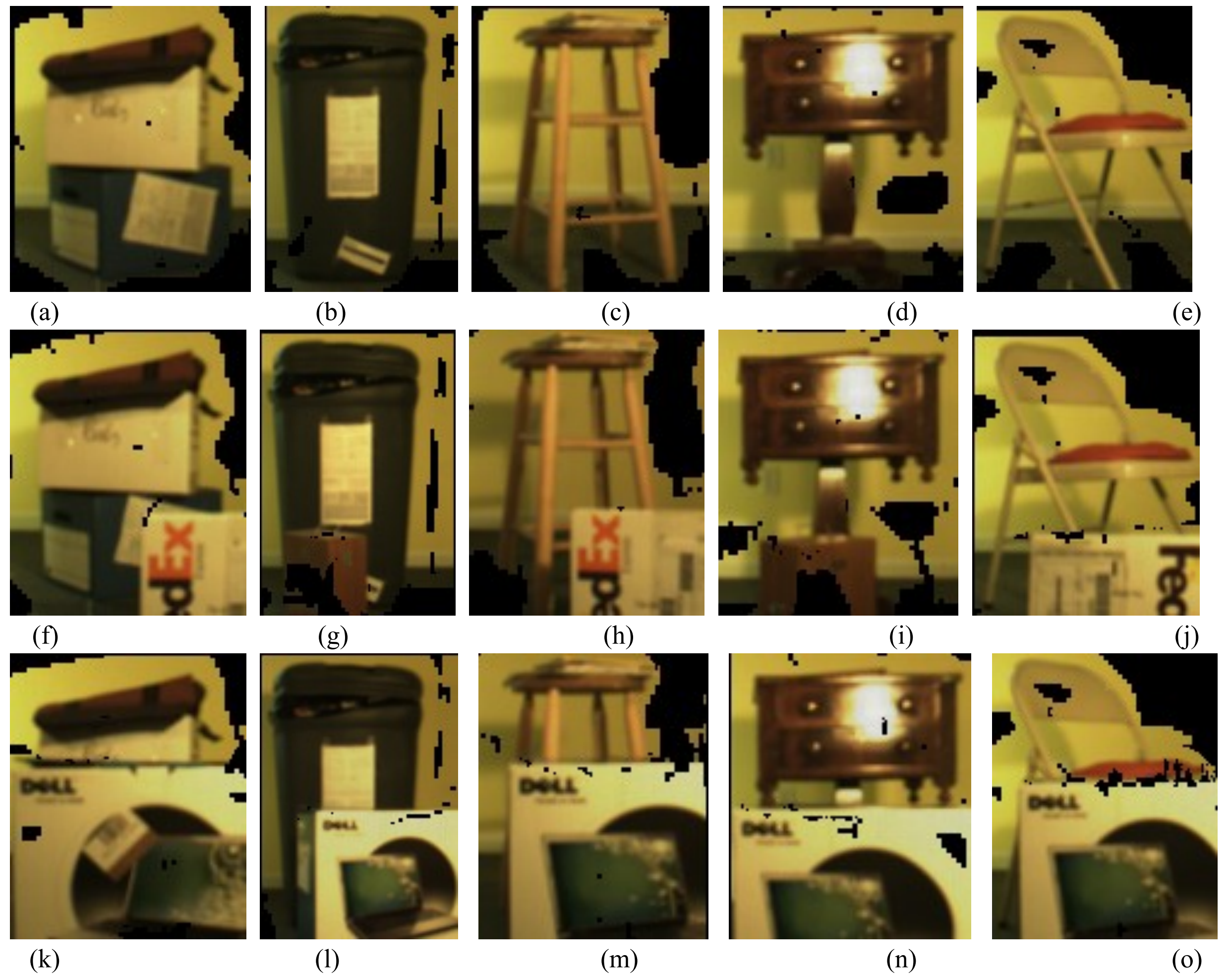
- A visibility vector V_o is calculated to trim away the occlusions
- Both landmark spatiograms h_l and candidate landmark spatiogram h_o are translated to the origin for comparison, h'_l and h'_o respectively.
- Only the depth (z) information is used to translate the candidate landmark:
- Each is renormalized about the location of intersection of their visibility vectors.
- The filtered candidate and landmark are compared using the normalized comparison.



Candidate landmark spatiogram showing landmark cluster center (a); trimmed to landmark moments (b); and translated (c).

Results

This landmark occlusion detection and filtering method was evaluated on a collection of occluded and unoccluded landmarks (shown in the image table below). Terrain spatiograms of corresponding unoccluded and occluded landmarks were compared before and after occlusion filtering.



Five landmarks used in occlusion experiments: top row (a-e), unoccluded objects; middle row (f-j), small occlusions; bottom row (k-o), larger occlusions.

	ρ_{11}	ρ_{22}	ρ_{33}	ρ_{12}	ρ_{13}			$\rho_{1'2'}$	$\rho_{1'3'}$	$\rho_{1'2'}$ % change	$\rho_{1'3'}$ % change
a	1	1	1	0.815	0.485	a	0.905	0.694	11.113	42.86	
b	1	1	1	0.828	0.697	b	0.893	0.885	7.871	26.92	
c	1	1	1	0.571	0.405	c	0.632	0.549	10.721	35.628	
d	1	1	1	0.868	0.632	d	0.917	0.812	5.687	28.574	
e	1	1	1	0.835	0.483	e	0.914	0.611	9.536	26.455	

Comparison *before* occlusion filtering.
(ρ_{12} compares landmark in row 1 with same occluded landmark in row 2, etc.)

Comparison *after* occlusion filtering..

Conclusions

- Introduced an approach to identifying landmark occlusions using Terrain Spatiograms.
- Presented a procedure to match occluded landmarks against candidate landmarks.
- Demonstrated results showing the method is effective for a set of indoor landmarks with a range of occlusions.