

Conference on Spatial Information Theory

COSIT 2009

Spatial Cognition of Geometric Figures in the Context of Proportional Analogies.

A. Schwering, K-U. Kuhnberger, U. Krumnack and H. Gust

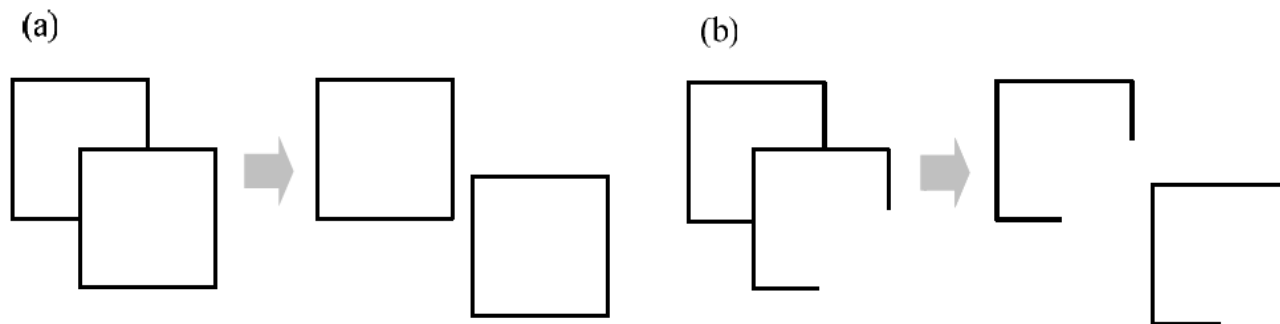


Fig. 2. The perception of a figure is influenced by its context: figure (a) is usually perceived as two complete squares one covering the other, although the covered square is only incompletely visible. In figure (b), the “covered” square is usually perceived as incomplete, because the other square (the context) is incomplete as well.

- Description of human-subject test
- Develop a computational model to solve analogies.

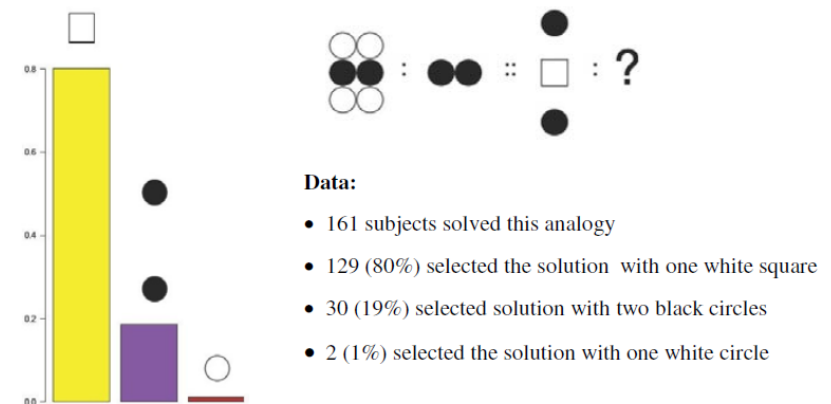


Fig. 4. The first analogy can be solved by focusing on the position of the elements or on the color. The results show that the majority of subjects preferred to keep the middle object, while several subjects chose to keep the black objects. Only two subjects selected the white circle as solution.

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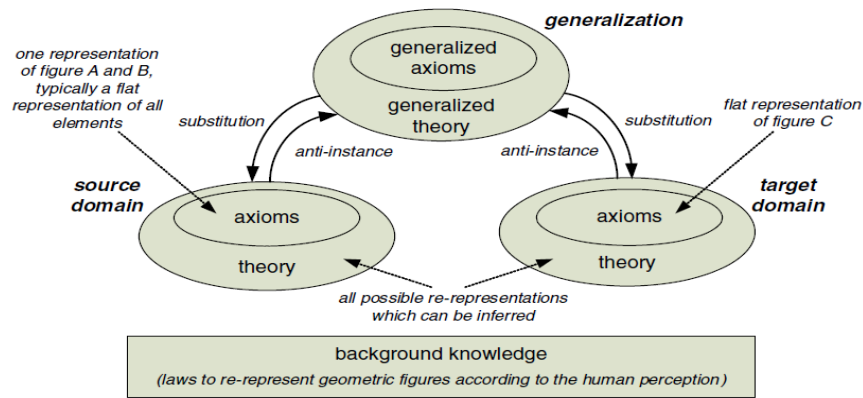


Fig. 9. Overview of the HDTTP architecture

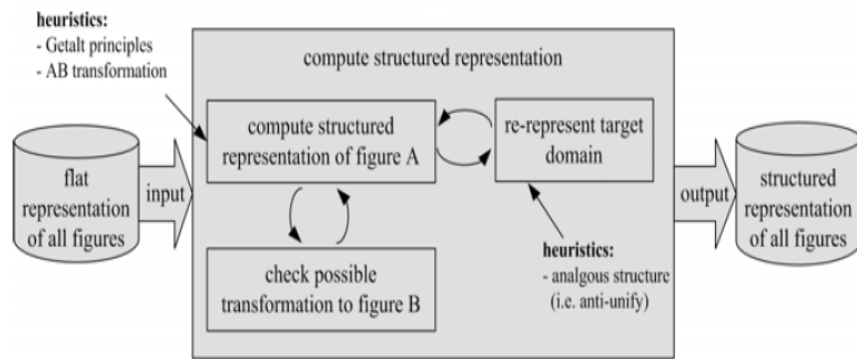


Fig. 12. Iterative process of computing the correct structured representation of the analogy

- Heuristic Driven Theory Projection HDTTP
 - Construct a general theory that subsumes many common structures of target and source domains.

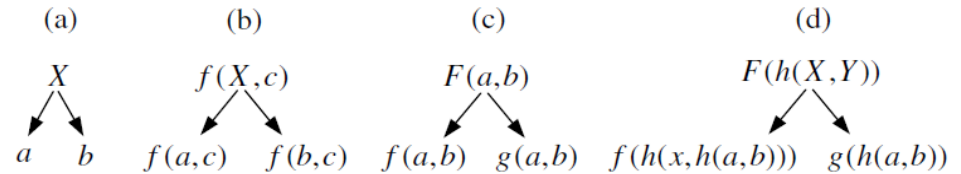


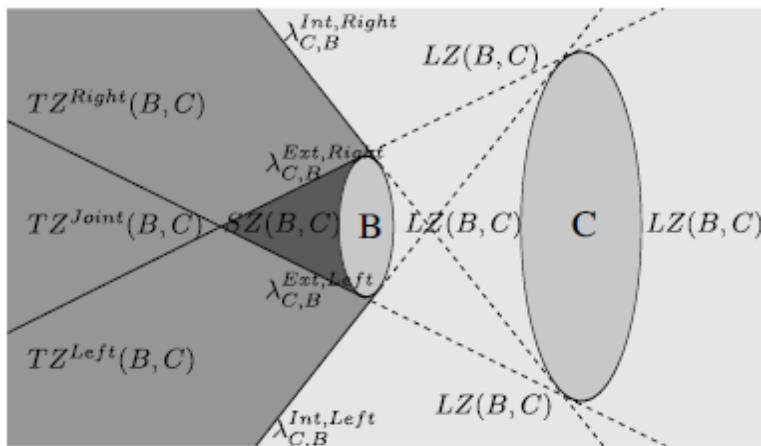
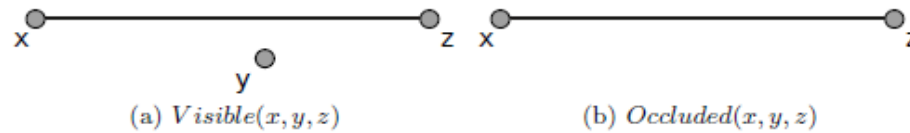
Fig. 8. Anti-unification compares two formulae and creates the least general generalization. While (a) and (b) are first-order anti-unification, (c) and (d) require second-order anti-unification to capture the common structure of the formulae.

- Results (not in the paper)
 - Applying the model to the experiments results showed ~ 80% of accuracy in obtaining the most common selected analogy.

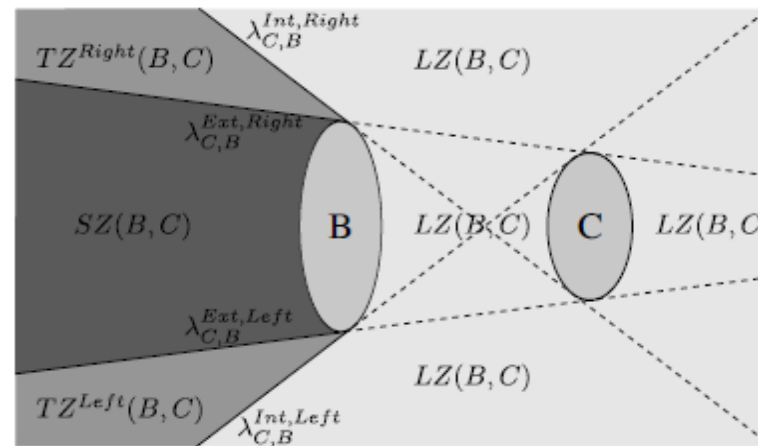
A Qualitative Approach to localization and Navigation based on Visibility Information

P. Fogliaroni, J. Wallgrun, E. Clementi, F. Tarquini and D. Wolter

- Method for creating a topological map based on the sensor's input, in a qualitative manner without exact coordinates.



(a) Limited *ShadowZone*



(b) Unlimited *ShadowZone*

$$Visible(A, B, C) \iff A \subseteq LZ(B, C)$$

$$PartiallyVisible^{Left}(A, B, C) \iff A \subseteq TZ^{Left}(B, C)$$

$$PartiallyVisible^{Right}(A, B, C) \iff A \subseteq TZ^{Right}(B, C)$$

$$PartiallyVisible^{Joint}(A, B, C) \iff A \subseteq TZ^{Joint}(B, C)$$

$$Occluded(A, B, C) \iff A \subseteq SZ(B, C)$$

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- Creation of topological map:
 - Division of space based on visibility model.

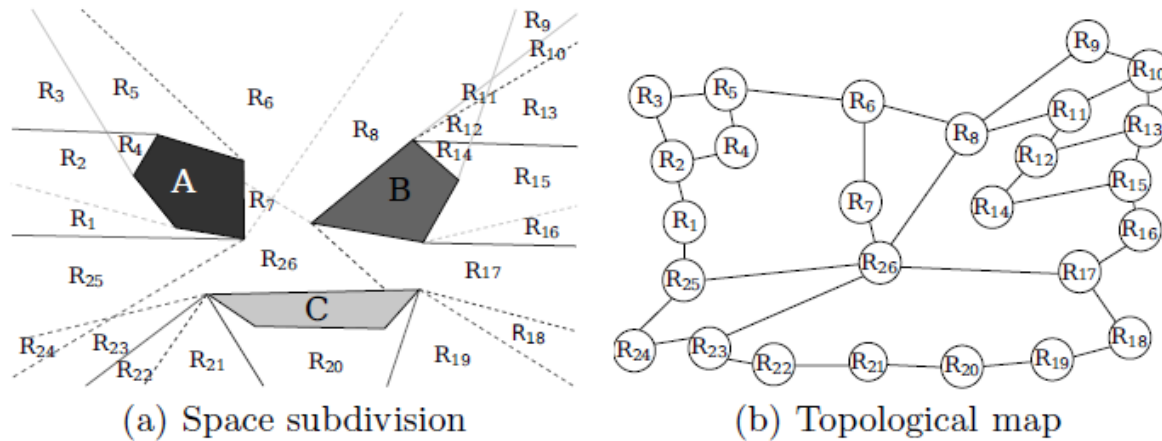
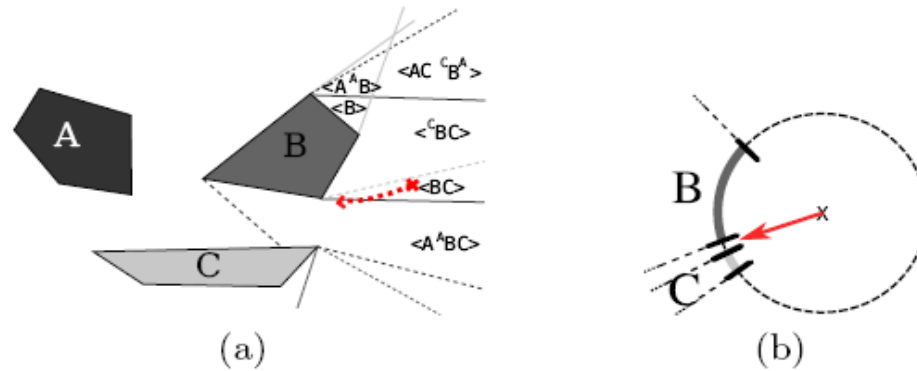


Fig. 3. The subdivision and topological map based on the visibility model

A Qualitative Approach to localization and Navigation based on Visibility Information

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- Topological map can be created automatically, while the agent explores the territory:



$$PartiallyVisible^{Right}(a, B, C) \Rightarrow C \cap LZ(B, a) \neq \emptyset \wedge C \cap SZ(B, a) \neq \emptyset$$

$$Visible(a, B, A) \Rightarrow Visible(A, B, a)$$

$$Visible(a, C, A) \Rightarrow Visible(A, C, a)$$

$$Visible(a, A, B) \Rightarrow Visible(B, A, a)$$

$$Visible(a, C, B) \Rightarrow Visible(B, C, a)$$

$$Visible(a, A, C) \Rightarrow Visible(C, A, a)$$

$$Occluded(a, B, C) \Rightarrow Occluded(C, B, a)$$

Case Based Reasoning for Eliciting the evolution of Geospatial Objects.

J.S. Motta, G. Camara, M.I. Sobral, O. Bittencourt, L.M. Garcia and L.Vinas

- Automated approach for describing how geospatial objects evolve.

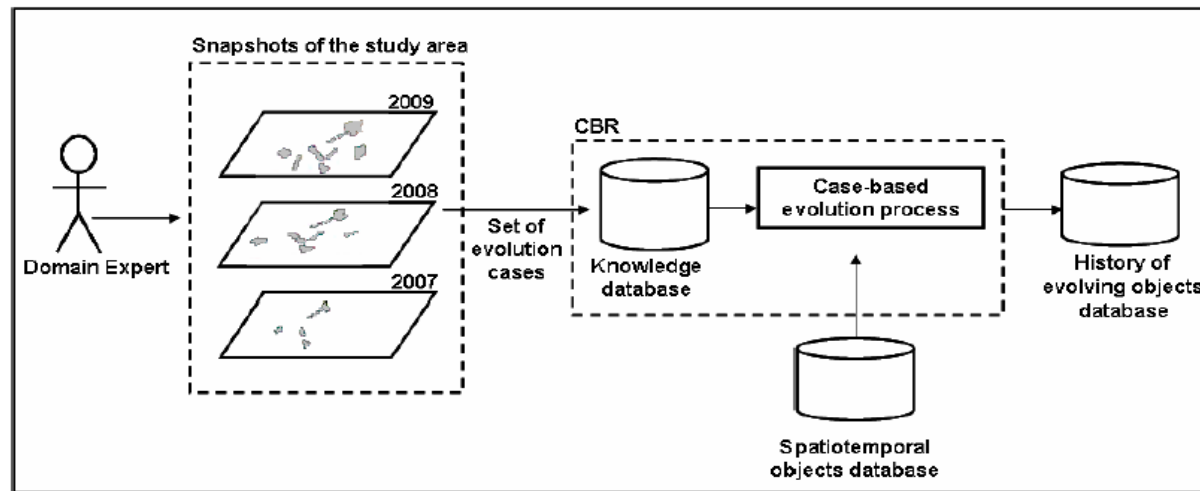


Fig. 3. General view of CBR method for eliciting geospatial objects evolution

Challenges:

- Objects history can be describe using creation, merging and splitting **BUT** these operations should take into account the type of geospatial object.
 - Ex:
 - Merging two parcels -> parcel
 - Merging a street and a parcel -> Expanding the street

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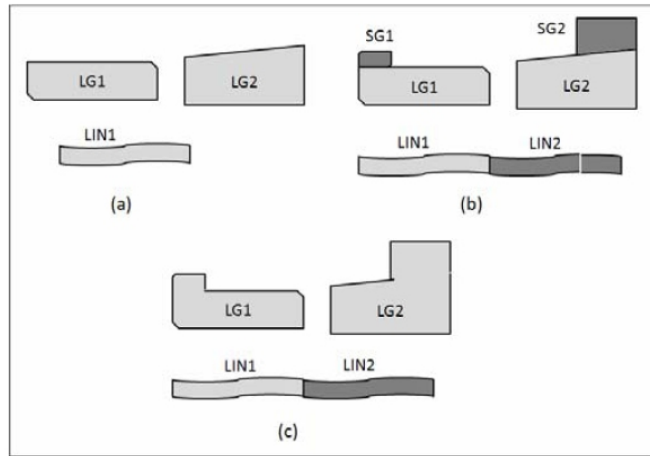
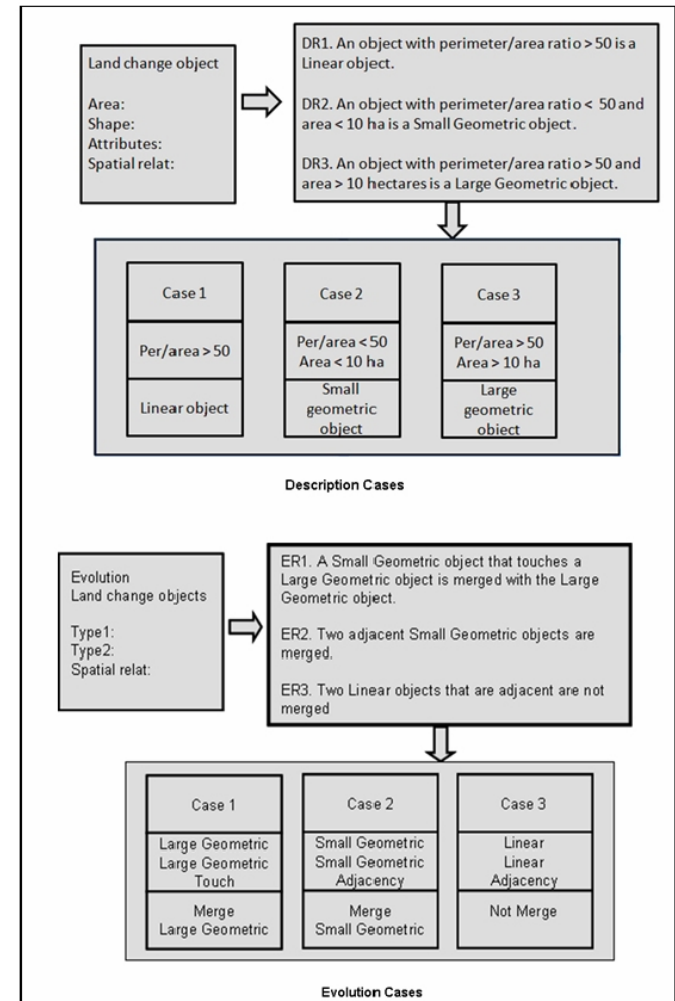


Fig. 4. Evolution of prototypical land change objects: (a) Time T1; (b) Time T2 before application of description rules; (c) Time T2 after application of evolution rules

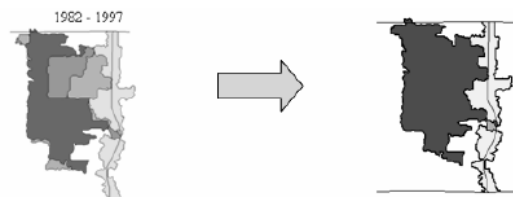
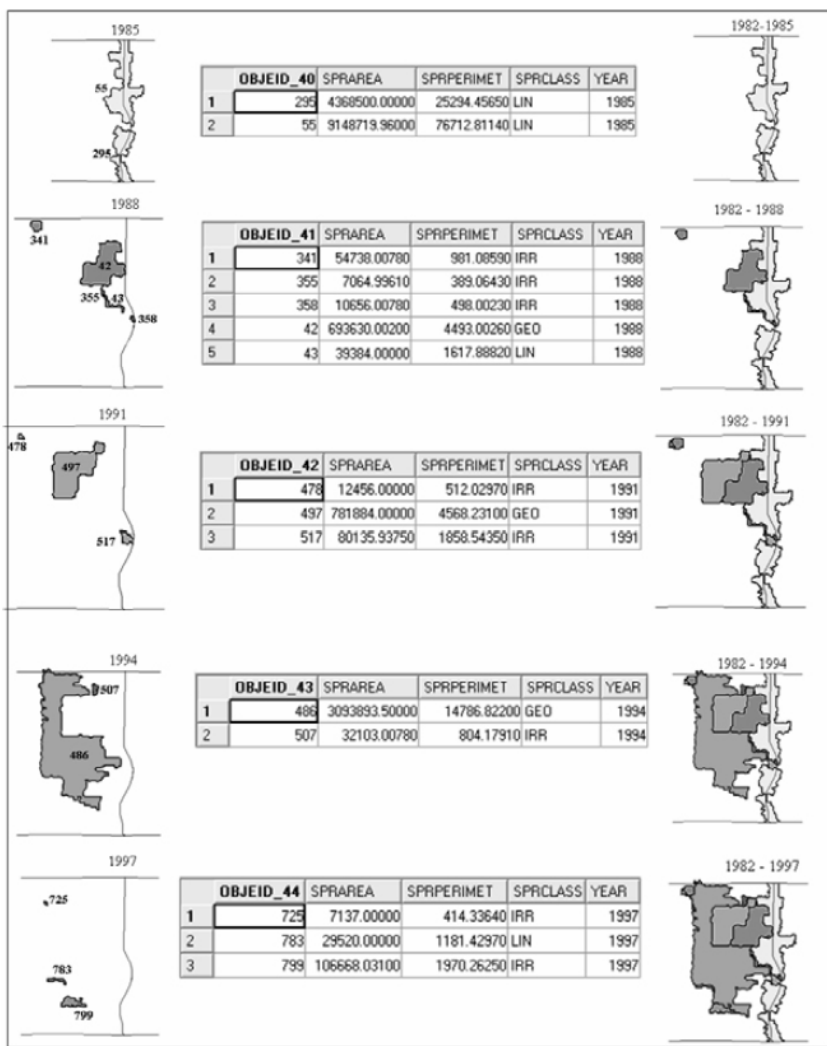
1. Let $T = 1$.
2. Take the objects from time T from the Geospatial Objects Database. Describe these objects according to the Description Cases Database. Store the results in the Typed Geospatial Objects Database.
3. Take the objects from time $T+1$ from the Geospatial Objects Database. Describe these objects according to the Description Cases Database. Store the results in the Typed Geospatial Objects Database.
4. Compare the objects of times T and $T+1$ using the Evolution Cases Database. Evolve the objects if possible. Store the results in a History Objects Database.
5. If there are further snapshots in the Geospatial Objects Database, make $T = T+1$ and go to step 2 above. Otherwise, exit the program.



Case Based Reasoning for Eliciting the Evolution of Geospatial Objects.

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- Case study: Deforestation in Brazilian Amazonia



Report Object's History									
New Object	Father's Object 1	Type	Year	Father's Object 2	Type	Year	Result	New Area	Year
10	9	Concentration	1997	799	Small Lot	1997	Concentration	4858470,5447	1997
9	8	Concentration	1997	783	Small Lot	1997	Concentration	4751810,5137	1997
8	7	Concentration	1994	725	Small Lot	1997	Concentration	4722290,5137	1997
7	6	Concentration	1994	1	Small Lot	1991	Concentration	4715153,5137	1994
6	5	Concentration	1994	4	Concentration	1994	Concentration	4647959,5059	1994
5	2	Concentration	1991	507	Small Lot	1994	Concentration	1507617,0086	1994
4	3	Concentration	1994	43	Small Lot	1988	Concentration	3140342,4961	1994
3	486	Concentration	1994	355	Small Lot	1988	Concentration	3100958,4961	1994
2	42	Concentration	1988	497	Concentration	1991	Concentration	1475514,002	1991
1	478	Small Lot	1991	341	Small Lot	1988	Small Lot	67194,0078	1991

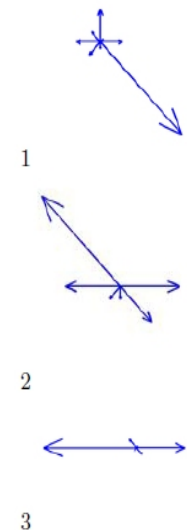
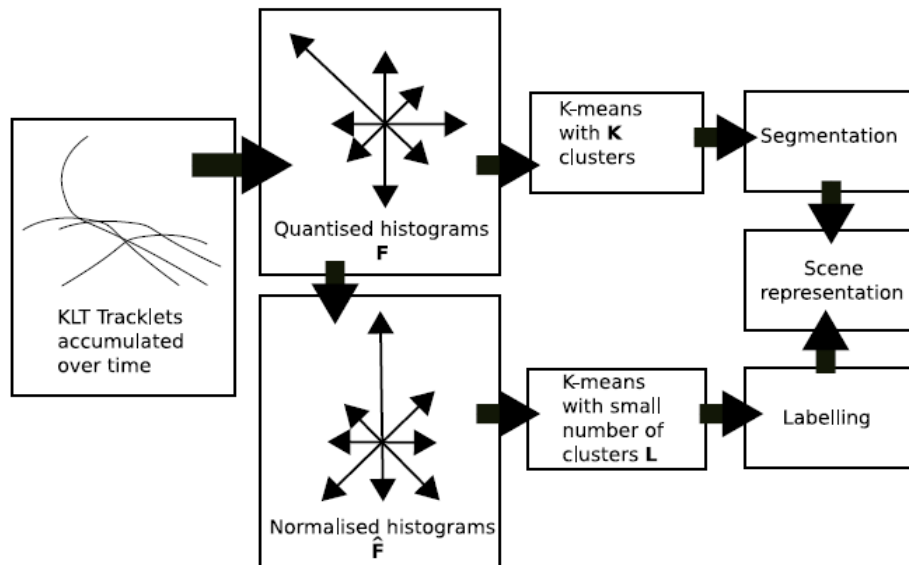


object 478 (1991) merge with object 341(1988) – Rule ER3
 object 497 (1991) merge with object 42 (1988) – Rule ER1
 object 517 don't merge – Rule ER2

Scene Modelling and Classification Using Learned Spatial Relations.

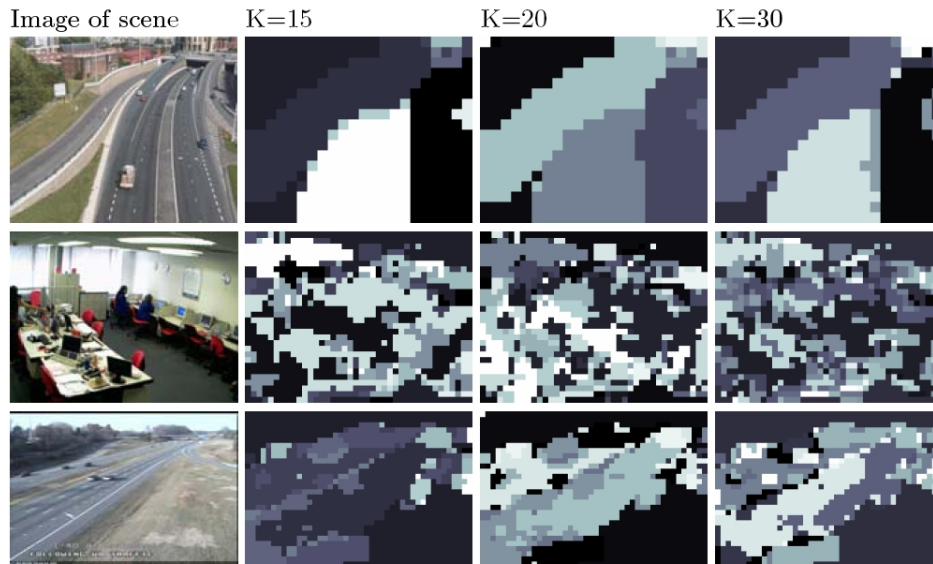
H.M. Dee, D.C. Hogg and A. Cohn

- Model the variation motion pattern on videos to determine similar behaviors.
- Tracking done using KLT.



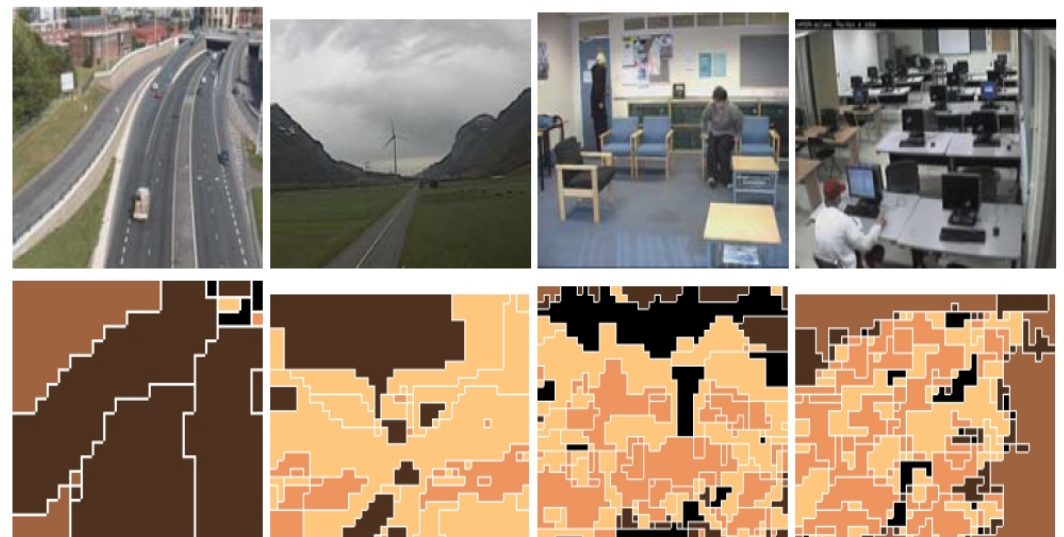
Scene Modelling and Classification Using Learned Spatial Relations.

H.M. Dee, D.C. Hogg and A. Cohn



- Give a model of the scene in terms of types of motions.
- Capture similar movements in different directions

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Direction invariant prototypes $\{p_i\}$ ($L = 5$)					
Directional prototypes $\{p_k\}$ ($K = 20$)					



Scene Modelling and Classification Using Learned Spatial Relations.

H.M. Dee, D.C. Hogg and A. Cohn

- See how regions of different classes are found together -> learn spatial relations from the set of learned regions.
- Evaluation:

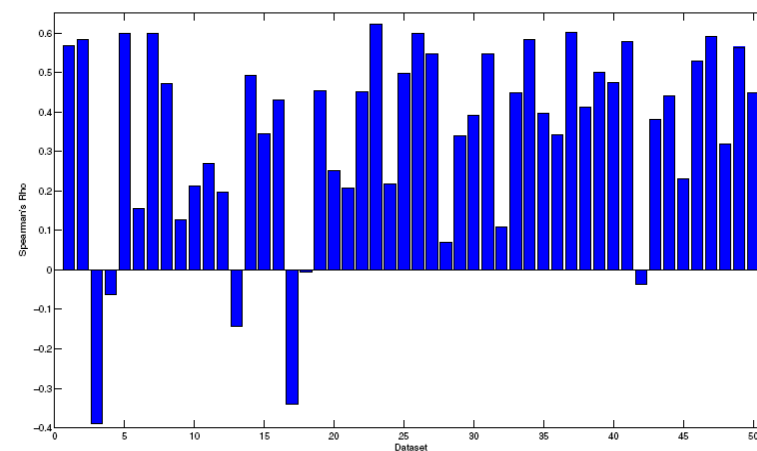
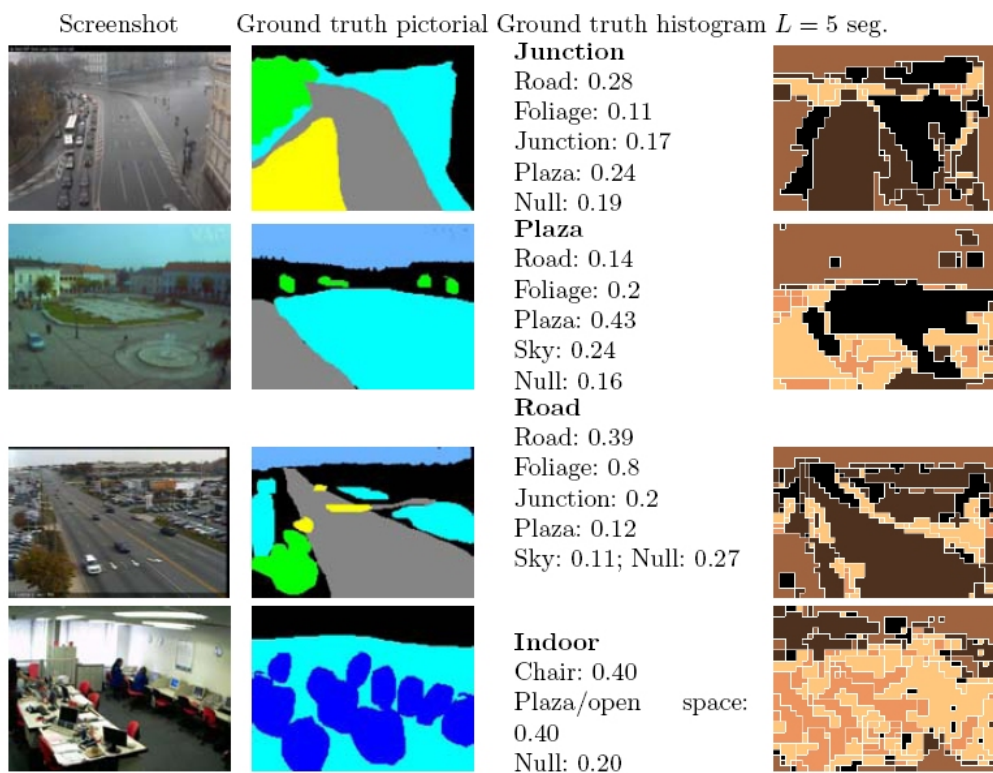


Fig. 12. Correlation results between rankings derived from histogram ground truth and rankings derived from spatial relationships using $L = 10$

Fig. 9. Pictorial (column 2) and histogram (column 3) ground truth shown alongside segmentations and screen shots for sample scenes. The histogram ground truth is represented as text with empty categories omitted for space reasons. The top row shows a scene classed “junction”, but the junction part of the scene comprises 17%, and the video also includes elements of road and plaza. This shows that single-class ground truth must be an approximation.