Teaching Spatial Thinking, Computer Vision, and Qualitative Reasoning Methods

Zoe Falomir

Bremen Spatial Cognition Centre, Universität Bremen, Germany
Erasmus Teaching Professor at Universitat Jaume I, Castellón, Spain
zfalomir@informatik.uni-bremen.de

Abstract. Computer vision discretizes space in pixels and then proposes approaches (i.e. segmentation, edge detectors, feature detectors, etc.) to arrange those pixels together again in order to detect objects and to describe them inside space by naming its location, topology, distance, etc. in a scene. As the basics in computation are the discretization of continuous signals (i.e. Boolean calculus, light waves represented in colour coordinates, etc.), properties of the space must be reminded to students when teaching computer vision from a spatial cognition perspective. Psychological spatial thinking tests help students to remind which abilities they use to solve spatial problems such as inferring cross sections or canonical views of a 3D object, which are common problems in industrial design engineering or computer-aided design (CAD) tasks. According to our experience, Qualitative Spatial and Temporal Reasoning methods provide students with tools to represent space and its continuous transformations, which enable them to define approaches closer to spatial cognitive reasoning.

1 How Computer Vision discretizes Space

In computer vision, images of scenes are digitalized, that is, divided into pixels or points corresponding to 3 colour coordinates (i.e. RGB). In order to recognize objects inside digital images, these pixels can be: (i) split by a boundary (i.e. transforming the image into grey scale and analysing intensity transitions between the pixels [1]); (ii) brought together using a similarity measure (i.e. based on colour closeness or other features); (iii) matched to predefined pixels corresponding to objects know *a priori* (i.e. feature detectors SURF [2]), etc. (see Fig. 3 for overview). Those methods try to recompose the continuity of the space lost in the digitalization, since this continuity is important in order to detect/recognize objects, give them a name/meaning and describe its spatial features in space (i.e. location, topology, shape, colour) [4]. In 3D object recognition the problem is similar: a scene is represented as a set of points floating in the air, called point clouds (Fig. 2). To recognize objects there, these points must be put together again by learning different views of the object using machine learning methods [5].

Some of the problems intelligent systems must solve, are spatial problems which require spatial thinking such as inferring cross sections or canonical views of a 3D object, in order to recognize it. In real space, objects preserve continuity, that is, if a change happens to an object side (dimension), it also affects the other dimensions automatically. For example, when a cup handle breaks, we humans do not need to check from all perspectives to perceive the change in shape and depth, since continuity in space (i.e.

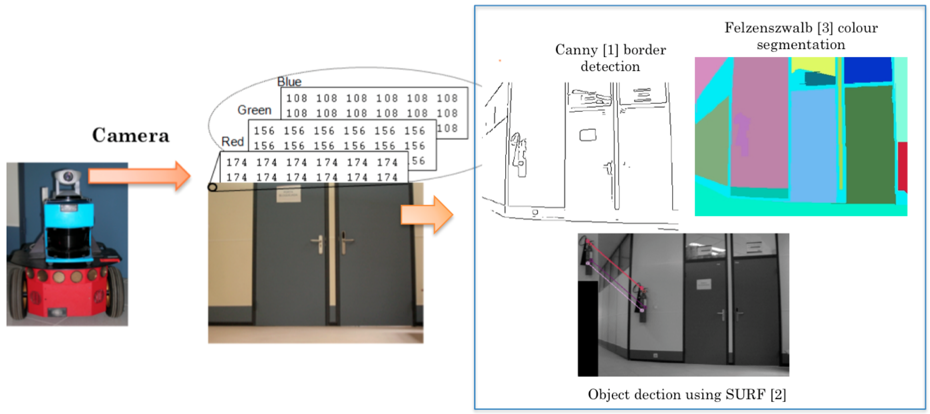
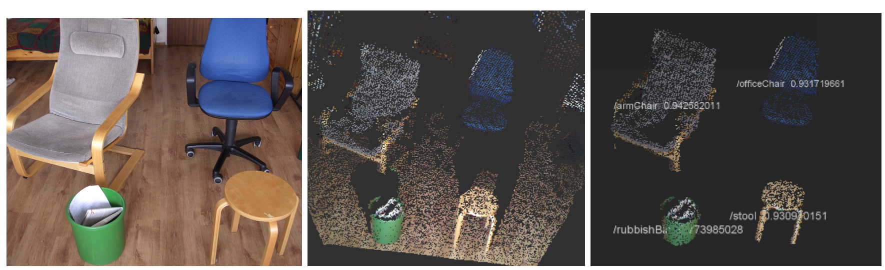


Fig. 1. Image of a scene represented as a matrix of pixels Red Green and Blue (RGB), then segmented by the boundary extraction method by Canny [1]; colour segmentation by Felzenszwalb [3]; and an example of object detection by SURF [2] feature matching.



(a) Original image (b) Point clouds (c) Object recognition

Fig. 2. Scene captured by a RGB-depth sensor (b) resulting point clouds and (c) classifying point-clouds by machine learning (see [5] for methods and details).

edge parallelism [6]) is in our common sense from our childhood. In computer vision, pixels or cloud points do not automatically preserve this continuity. Therefore, discretizing space and then finding its continuity again is computationally very expensive and a challenge in AI and computer vision nowadays, as far as we are concerned.

2 The Spatial Thinking Perspective

What can we learn from spatial cognition research that we can apply to computer vision and computer systems in general, so that the process of interacting with space is more 'intelligent or intuitive'?

In my teaching classes, spatial cognition is introduced from the point of view of spatial problem solving. Students in computer science get surprised when I ask them to answer some psychological tests on: (i) diagrammatic representations, translation from 3D to 2D and viceversa [7], (ii) two dimensional mental transformations [8], (iii) object perspectives in spatial orientation [9, 10], (iv) topographic map assessment [11],

(v) inferring cross sections of 3D objects [12], (vi) visualization of 3D views test [13, 14], (vii) visualization of 3D rotations [15], etc.

After carrying out these tests, students realize some of the skills required in spatial problem solving. Then they are required to define logical approaches to solve these spatial problems. In their bachelor degree, they acquire knowledge about the digitalized information that computer systems get. So, they must think out of the box to identify ways to solve 'spatial-analog' problems in a digitalized world. Some of the properties students get aware of after solving the spatial problems are:

– **Abstraction:** people abstract dimensions in space (i.e. by assuming one dimension as constant) and re-represent data in a way that helps visualizing a problem to solve. For example, a map of the Earth represents 3D space in a 2D paper, sometimes assuming relief or altitude as constant.
– **Continuity:** dimensions in space are continuous. Although they can be abstracted or considered as constant in a representation, this representation must be coherent with the space and transmit changes in the dimension abstracted, if produced. If a change in relief is produced (i.e. a road is cut), this change should be transmitted to all dimensions and the map should represent this discontinuity.
– **Relativity:** most dimensions in space are relative or inter-related to each other. For example, when comparing roads in a map, if the roads are represented by abstracting the same dimension, then they can be compared directly. If one road considers relief while the other does not, then they are not comparable.

Qualitative Reasoning methods is also introduced to students by Allen's model of temporal relations which is very useful to introduce continuity and reasoning constraints in time which then we can extrapolate to space by explaining the notion of conceptual neighbourhood in common space [16] and in other spaces, such as colour spaces [17].

3 Result Example: Qualitative Description of Objects using Depth

The result of teaching spatial thinking related to computer vision and to qualitative modelling leaded to the definition of a model for 3D object description which takes into account depth in the 3 canonical perspectives of the object at the same time [18] (see Fig. 3). Thus, it propagates changes in object volume, and it can also identify inconsistent descriptions. Further evaluation is needed to study how cognitive is the proposed model.

Acknowledgments

The COGNITIVE-AMI[1] project (GA 328763) funded by EU-FP7 Marie Curie IEF actions and the *Cognitive Qualitative Descriptions and Applications*[2] (CogQDA) project funded by Universität Bremen are acknowledged. Also the support by the Bremen Spatial Cognition Center[3] (BSCC) and the EU Erasmus+ *Staff Mobility for Teaching* program are acknowledged.

[1] `https://sites.google.com/site/cognitiveami/`
[2] `https://sites.google.com/site/cogqda/`
[3] `http://bscc.spatial-cognition.de/`

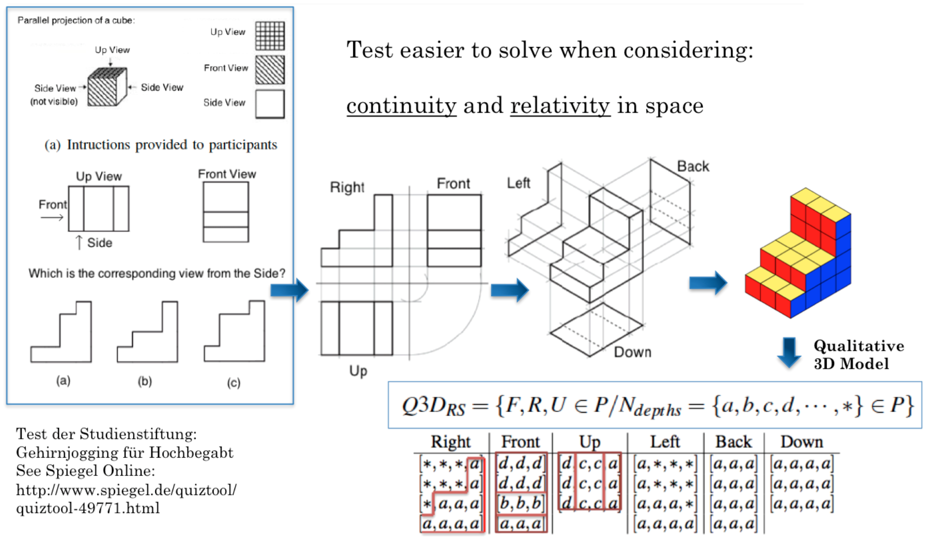


Fig. 3. Tests that motivated the Q3D model and example of its utility.

References

1. Canny, J.F.: A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) **8** (1986) 679–697
2. Bay, H., Ess, A., Tuytelaars, T., Van Gool, L.: Speeded-up robust features (SURF). Comput. Vis. Image Underst. **110**(3) (June 2008) 346–359
3. Felzenszwalb, P.F., Huttenlocher, D.P.: Efficient graph-based image segmentation. International Journal of Computer Vision **59**(2) (September 2004) 167–181
4. Falomir, Z., Olteţeanu, A.M.: Logics based on qualitative descriptors for scene understanding. Neurocomputing **161** (2015) 3–16
5. Kluth, T., Falomir, Z.: Studying the role of location in 3D scene description using natural language. In: XV Workshop on Qualitative Reasoning and its Applications: Qualitative Systems and their applications to Diagnosis, Robotics and Ambient Intelligence. (2013) 33–36
6. Sinclair, N., de Freitas, E., Ferrara, F.: Virtual encounters: the murky and furtive world of mathematical inventiveness. ZDM. The International Journal on Mathematics Education **45**(2) (2013) 239–252
7. Frick, A., Newcombe, N.S.: Young children's perception of diagrammatic representations. Spatial Cognition and Computation: An Interdisciplinary Journal (in press)
8. Ehrlich, S., Levine, S.C., Goldin-Meadow, S.: Young children's perception of diagrammatic representations. The importance of gesture in childrens spatial reasoning. Developmental Psychology **42** (2006) 1259–1268
9. Kozhevnikov, M., Hegarty, M.: A dissociation between object-manipulation and perspective-taking spatial abilities. Memory & Cognition **29** (2001) 745–756
10. Hegarty, M., Waller, D.: A dissociation between mental rotation and perspective-taking spatial abilities. Intelligence **32** (2004) 175–191
11. Matt Jacovina, Carol Ormand, T.S., Weisberg, S.: The topographic map assessment document. SILC Tests and Instruments
12. Cohen, C.A., Hegarty, M.: Inferring cross sections of 3D objects: A new spatial thinking test. Learning and Individual Differences **22**(6) (2012) 868–874

13. Hegarty, M., Keehner, M., Khooshabeh, P., Montello, D.R.: How spatial abilities enhance, and are enhanced by, dental education. Learning and Individual Differences **19**(1) (2009) 61–70
14. Keehner, M., Hegarty, M., Cohen, C.A., Khooshabeh, P., Montello, D.R.: Spatial reasoning with external visualizations: What matters is what you see, not whether you interact. Cognitive Science **32**(7) (2008) 1099–1132
15. Maeda, Y., Yoon, S.Y., Kim-Kang, K., Imbrie, P.K.: Psychometric properties of the revised psvt:r for measuring first year engineering students spatial ability. International Journal of Engineering Education **29** (2013) 763–776
16. Freksa, C.: Temporal reasoning based on semi-intervals. Artificial Intelligence **54**(1–2) (1992) 199 – 227
17. Falomir, Z., Museros, L., Gonzalez-Abril, L.: A model for colour naming and comparing based on conceptual neighbourhood. an application for comparing art compositions. Knowledge-Based Systems **81** (2015) 1–21
18. Falomir, Z.: A qualitative model for reasoning about 3d objects using depth and different perspectives. In T. Lechowski, P. Waga, M.Z., ed.: LQMR 2015 Workshop. Volume 7 of Annals of Computer Science and Information Systems., PTI (2015) 3–11