

# Qualitative Relational Mapping for Rover Surface Operations

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When available, absolute position systems such as GPS or orbital imaging can provide near-ideal estimates of the position and attitude estimates necessary for long-term autonomous robotic operation. Unfortunately, such systems are unavailable for a number of interesting mission locations, including explorations of Venus, Titan, or small bodies.

In the absence of absolute position sensors, existing robot localization systems tend to either rely solely on local sensors of ego-motion (such as IMUs and wheel encoders) as in the current GESTALT system for the Mars Exploration Rovers (MER) discussed in [1], or incorporate measurements of the rover's relative position and orientation with respect to certain landmarks in the environment using vision or ranging sensors. This may consist of triangulation from known reference positions as in [2], or the construction of adaptive feature maps as in the Simultaneous Localization and Mapping (SLAM) framework [3]. These methods have definite strengths, including the ability to provide both global position and orientation estimates as well as accurate estimates of the uncertainty in the parameters. They can also provide global localization of environmental features and thus allow the accumulation of information for the assembly of stable maps necessary for long-distance planning. However, these approaches often face a number of limitations, including computational expense, a reliance on point estimates of landmarks, and the need for high quality sensing to determine the exact distance to visible landmarks.

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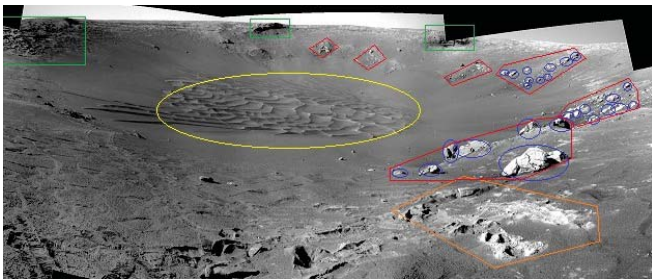


Fig. 1. Example of objects and groups of objects comprising a crater region on Mars, including distinctive rocks (Blue), groups of rocks (Red), exposed crater wall (Green), and the crater basin (Yellow). The orange outline highlights an area of exposed outcrop.

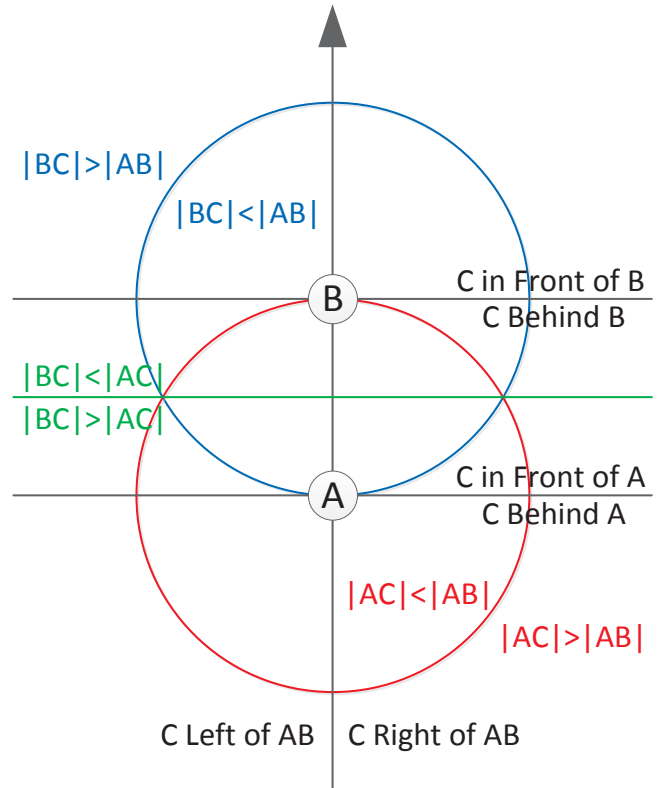


Fig. 2. Schematic of the Extended Double Cross (EDC) for 2 landmarks  $A$  and  $B$ . The qualitative location of a third point  $C$  can be described using the dichotomies which split up the space around the vector  $AB$ .

This work focuses on mapping unstructured spaces with sparse landmarks, such as the crater region shown in figure 1, using an extension to the qualitative geometry discussed previously in [4]. The aim is to decouple the robot position estimation problem from that of map building as much as possible. This is inspired by the insight that many robot tasks, such as navigation, do not require a fully defined metrical map. Use of qualitative relations between objects allows maps to remain useful in the presence of many types of distortion common in traditional metrical mapping approaches. For example, global position uncertainty can grow rapidly due to odometry errors resulting from wheel slippage. Unlike the graphical models used in many algorithms from the SLAM community, this framework considers the relationships between observed features, rather than considering them primarily in relationship to the robot [5].

In this approach, landmark positions are specified in terms of qualitative relationships with other landmarks, rather than

by metrical positions. The underlying representation used is the Extended Double cross, shown in figure 2. The position of a point  $C$  can be specified in terms of the six boundaries around the line between points  $A$  and  $B$ , resulting in 20 discrete regions for each landmark pair. Constraints on which region a given landmark lies in can be extracted from single camera images by solving a series of nonlinear feasibility problems. As the rover moves, these constraints are stored in a graph called the ‘Qualitative Relational Map’ (QRM), with an edge between each observed landmark triple. Given a traversal of sufficient coverage, the graph is guaranteed to converge on the single true relationship between each landmark triple. The test case used to evaluate system performance is the exploration and mapping of a Mars-like environment, evaluated using as ground truth the 3D reconstruction of the JPL Mars Yard shown in figure 3.

The QRM algorithms bears some resemblance to topological approaches, however the underlying representations of map elements are fundamentally different. While topological and topometric algorithms, such as those presented in [6] and [7], have achieved great success in mapping indoor and highly structured urban environments, they often perform poorly in open environments with sparse features. In such areas, the regions represented as nodes in a topological graph become poorly defined, as do the edges representing transitions between such regions. In contrast, the graph structure used in this work represents geometrical constraints on the relative positions of landmarks in an open environment.

The underlying motivation is to explore how much information about objects of interest can be extracted from a minimal set of low-cost sensors. The qualitative mapping approach relies on a single camera with minimal quality requirements. Like all monocular mapping strategies, the map is unable to specify a global scale. While most recent work on monocular navigation, in particular mono-SLAM algorithms such as those discussed in [8], attempts to infer a scale from estimates of ego-motion, this can be impractical in high-slip environments or with low-cost platforms. In contrast, the qualitative geometries used in this work operate in a naturally scale-free environment and do not require any information as to the location of imaging locations.

Preliminary work on using the qualitative map for navigation purposes shows that it is possible to navigate close to an arbitrary point in the interior of the map without relying on a metrical localization. One possible strategy relies on the ability to extract the landmark relative neighbor graph (RNG) from the qualitative map. The RNG is a sub-graph of the Delaunay triangulation which links points  $A$  and  $B$  if there is no third point lying within the lune formed by circles of radius  $|AB|$  centered at  $A$  and  $B$  [9]. The RNG and associated Voronoi regions for landmarks found in the JPL Mars Yard are shown in figure 4. Long distance navigation to a goal Voronoi region can be achieved by successively homing on landmarks found by a graph search on the RNG, at which point a local strategy can be employed to achieve a desired set of qualitative relationships with nearby landmarks.

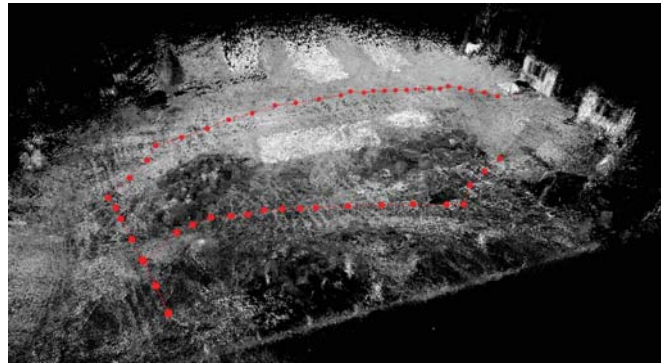


Fig. 3. 3D reconstruction of the JPL Mars Yard. The pointcloud was generated from stereo panoramas taken at the imaging points denoted by red circles. Landmarks include medium sized rocks such as those in the image center as well as similarly sized objects such as the generators in the upper left and right corners.

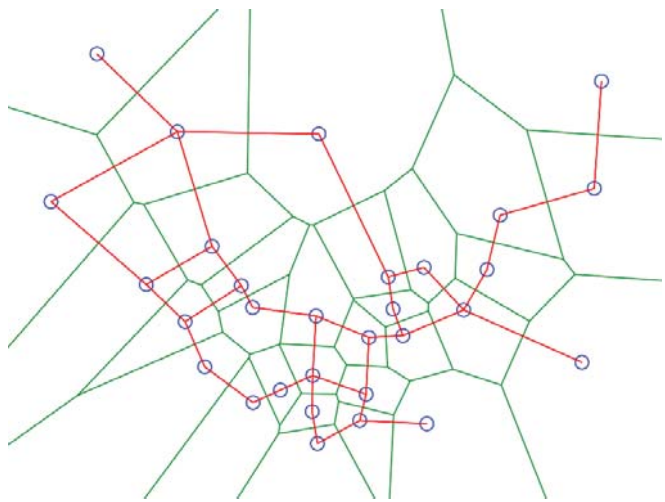


Fig. 4. Relative Neighbor Graph (RNG) in red and Voronoi regions in green for landmarks found in the JPL Mars Yard.

## REFERENCES

- [1] K. Ali, C. Vanelli, J. Biesiadecki, M. Maimone, Y. Cheng, A. S. Martin, and J. Alexander, “Attitude and position estimation on the mars exploration rovers,” in *Proceedings of the IEEE Conference on Systems, Man, and Cybernetics*, 2005.
- [2] B. J. Kuipers and T. S. Levitt, “Navigation and mapping in large scale space,” *AI Magazine*, vol. 9, no. 2, pp. 25–43, 1988.
- [3] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. MIT Press, 2006.
- [4] M. McClelland, M. Campbell, and T. Estlin, “Qualitative relational mapping for robotic navigation,” in *AIAA Infotech@Aerospace*, 2012.
- [5] S. Thrun and M. Montemerlo, “The graphslam algorithm with applications to large-scale mapping of urban structures,” *International Journal on Robotics Research*, vol. 25, no. 5/6, pp. 403–430, 2005.
- [6] D. Hoiem, A. A. Efros, and M. Hebert, “Recovering surface layout from an image,” *International Journal of Computer Vision*, vol. 75, no. 1, pp. 151–172, October 2007.
- [7] G. Sibley, C. Mei, I. Reid, and P. Newman, “Vast-scale outdoor navigation using adaptive relative bundle adjustment,” *The International Journal of Robotics Research*, vol. 29, no. 8, pp. 958–980, July 2010.
- [8] A. J. Davison, I. D. Reid, N. D. Molton, and O. Stasse, “Monoslam: Real-time single camera slam,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, pp. 1052–1067, 2007.
- [9] J. Jaromczyk and G. Toussaint, “Relative neighborhood graphs and their relatives,” *Proceedings of the IEEE*, vol. 80, pp. 1502–1517, 1992.