Leveraging Robotics and AI for Geosciences: Rock Search, Mapping, and Dynamic Analysis

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Abstract

Despite the rapid adoption of robotics and artificial intelligence (AI) in the industry, their applications to scientific studies remain under-explored. Combining industry-driven advances with scientific exploration can provide new perspectives and a greater understanding of the planet and its environmental processes. We present technical methodologies and scientific results for leveraging robots and AI in the geosciences, with a focus on rock mapping, detection, and dynamics simulations. We demonstrate an interdisciplinary research direction to push the frontiers of both robotics and geosciences, with potential for translational contributions to commercial technologies for hazard monitoring and prospecting.

Driven by the need for automation of data collection and data processing, this research investigates robotics and AI technologies to enable statistical modeling in geomorphology, seismology, and hazards analysis. Specifically, to segment and identify rocks in 2D, we develop a generalized data processing template for instance segmentation in remote sensing. This template integrates unpiloted aerial vehicle (UAV) surveys, structure from motion (SfM), and deep learning to solve unique technical challenges of instance segmentation in large-scale, high-resolution maps. By applying this template for geomorphological study in Bishop Volcanic Tablelands California, we quantify and analyze rock trait distributions to better understand rocky fault scarp formation processes. Besides 2D rock detection, we also present methods to search and segment 3D rocks such as precariously balanced rocks (PBRs). Mapping PBRs facilitates earthquake studies via providing fragility constraints to uncertainties in probabilistic seismic hazard analysis. To obtain 3D geometries of PBRs, an offboard pipeline combines deep learning techniques of 2D rock detection and 3D point cloud segmentation. This offboard pipeline segments PBRs in point clouds restructured from a UAV survey, and its applications can be extended to any existing dense point cloud datasets for 3D rock segmentation. Different from the offboard pipeline, an onboard UAV-based mapping system searches, detects, and maps PBRs in real time. The onboard mapping system offers immediate availability of PBR locations and geometries during a UAV survey. The onboard system also emphasizes the mapping of complete visible surface features on PBRs including their visible contact points with pedestals, which are critical factors of fragility. Additionally, we investigate PBR dynamics by building a virtual shake robot that can repeatedly simulate ground motions and monitor PBR dynamic responses. The virtual shake robot enables studies of PBR large displacements by tracking a toppling PBR trajectory, presenting novel methods of hazard analysis.

2D Rock Detection: An Instance Segmentation Template

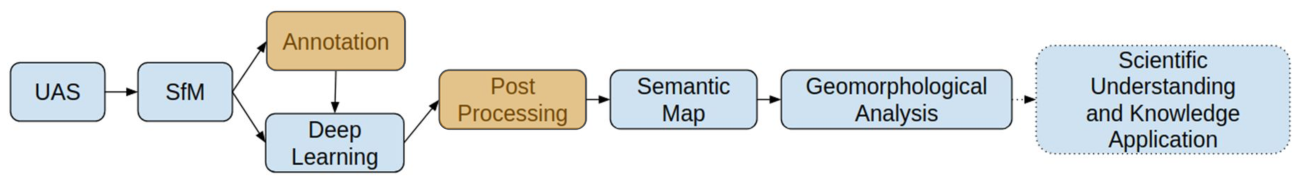

Figure 1: A data processing pipeline integrating Unpiloted Aircraft System, Structure from Motion, and Deep Learning (UAS-SfM-DL). (Chen et al., 2020, 2021)

Annotation Challenge: split shapefile polygon annotations to tiles

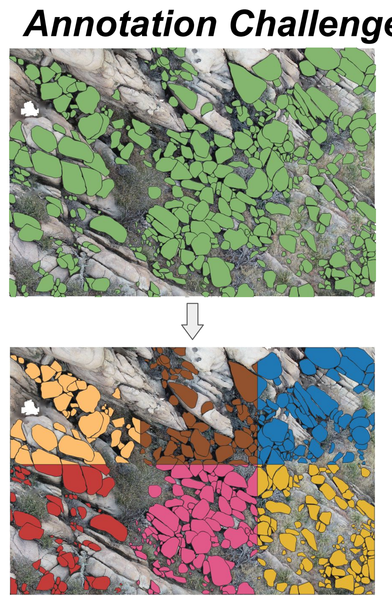

Figure 2: Annotation challenge

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Algorithm I. Generating annotation tiles from a large annotation map

Input:
  1) annotation map; 2) annotation tile metric size; 3) map coordinates
Output:
  1) annotation tiles

for each polygon in annotation map:
    get bounding box of polygon
    calculate tile indices (i, j) of all four concerns of bounding box
    get unique tile indices/ purge redundant tile indices
    get intersections of polygon and indexed tiles
    assign intersections to indexed tiles
```

Time complexity is linear O(N), where N is the number of polygons in the large annotation map.

Post-processing Challenge: merge prediction polygons from tiles

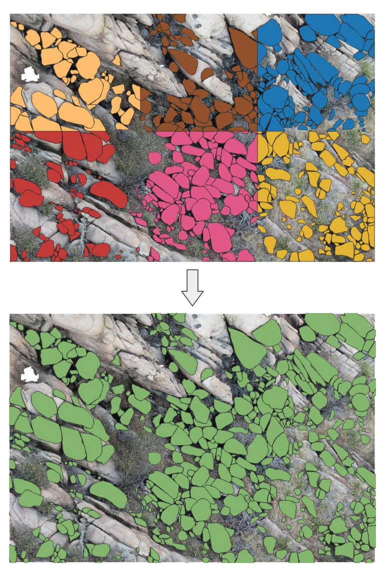

Figure 3: Post-processing challenge

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Algorithm II. Instance registration

Data structure:
  1) registered instances are stored in an array
  2) each instance has a lookup table
  3) tiles are stored in a lookup table
  4) each tile has a linked list data type. Each tile is first linked to
local regions. Each region is linked to the indices of registered
instances in that region.

for tile in tiles:
  for instance in tile:
    if instance is in middle region:
      register(instance)
    else:
      for adjacent_location in adjacent_locations:
        for adjacent_instance in adjacent_location:
          if bounding_box_overlap(instance, adjacent_instance) > 0:
            if mask_overlap(insance, adjacent_instance) >
mask_overlap_threshold:
              merge_instance(instance, adjacent_instance)
              next instance
      register(instance)
```

Time complexity is linear O(N), where N is the number of tiles. Given the maximum instance count in a tile M, time complexity of instance registration is O(NM[2]/4). Efficient computing algorithms are critical for instance application in large-scale maps. (Chen et al., 2022a in prep)

2D Rock Detection: An Application to Study Rocky Scarps Formation Processes

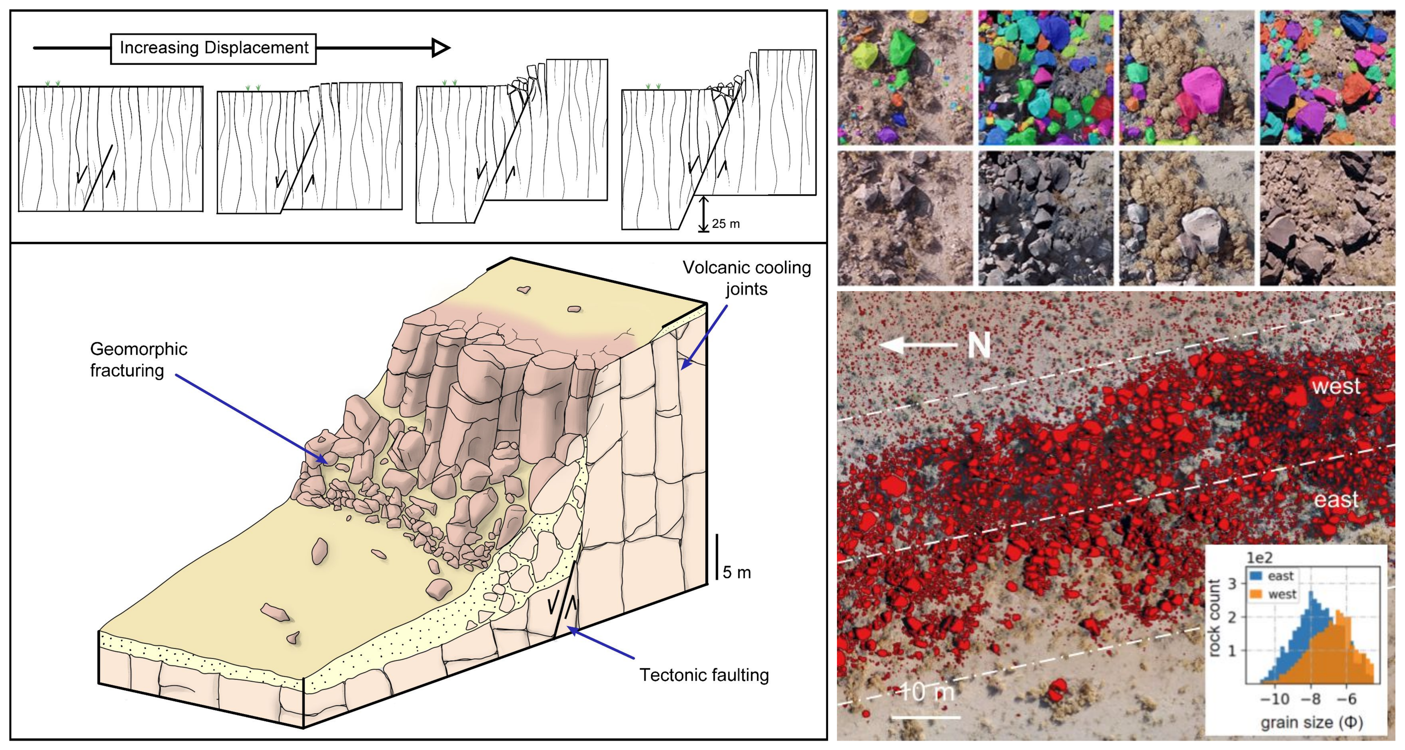

Figure 4: (Left) Formation of rocky fault scarps in the Volcanic Tablelands, Eastern California and (right) machine learning results. (Chen et al., 2022b under review)

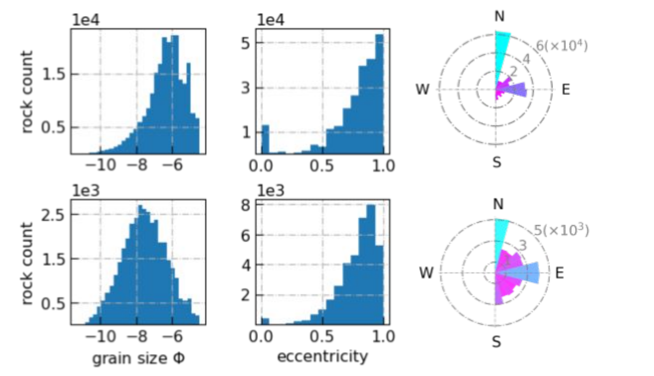

Figure 4: Rock trait histograms of (top) the fault scarp and surrounding topographic flats and (bottom row) the fault scarp alone.

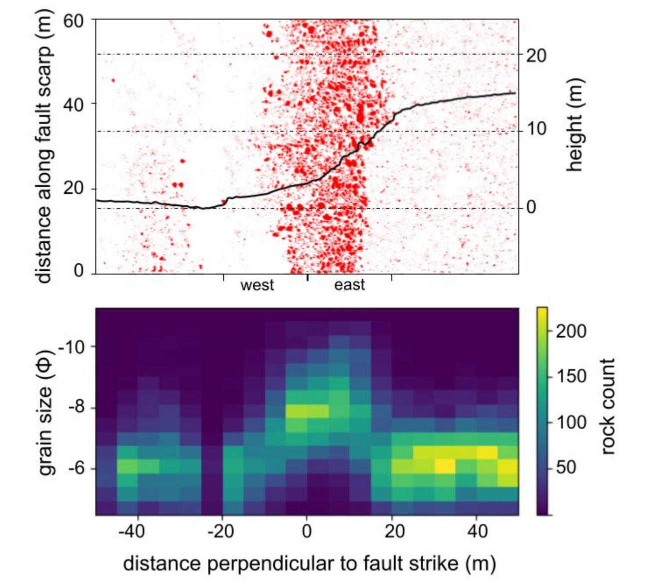

Figure 5: Spatial distributions of median grain size perpendicular to fault strike.

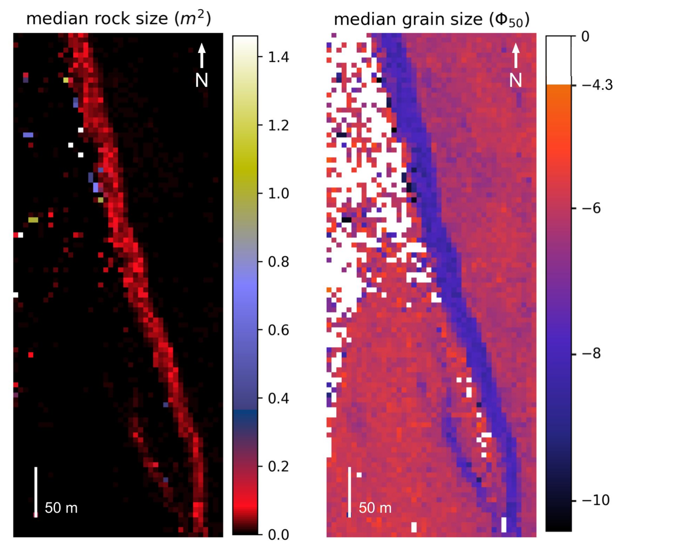

Figure 6: Spatial distributions of (left) median rock size (area in plan view, m^2) and (right) median grain size (Phi 50)

Table 1: Rock traits and fault scarp height correlation statistics

	R^2	p-value
Median grain size 50	0.60	4.0e-04
Largest grain size M	0.76	1.0e-05
Sorting	0.81	2.3e-06
Small to large rock count ratio (=-8)	0.40	8.5e-03
Tangent to normal rock count ratio (whole scarp)	0.24	5.3e-02
Tangent to normal rock count ratio (western half)	0.46	4.0e-03

3D Rock Detection: Offboard Method

Precariously balanced rocks (PBRs) are naturally negative indicators of earthquakes. Distributions of geometric characteristics of PBRs inform less biased ground motions than individual models. However, an engineering challenge is search and map a large number of PBRs.

Figure 7: Precariously balanced rocks (PBRs) and the minimum contact angles to indicate earthquakes.

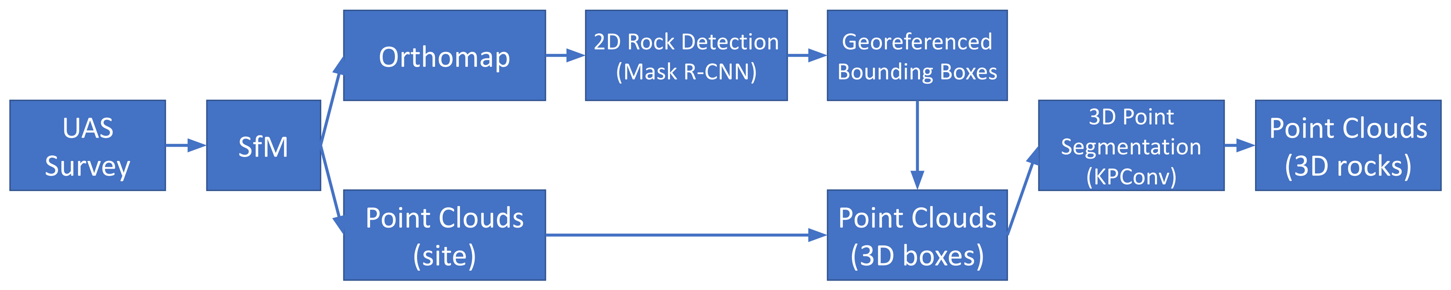

Figure 8: Workflow diagram of the offboard method of 3D rock detection and segmentation. (Chen et al., 2023 in prep)

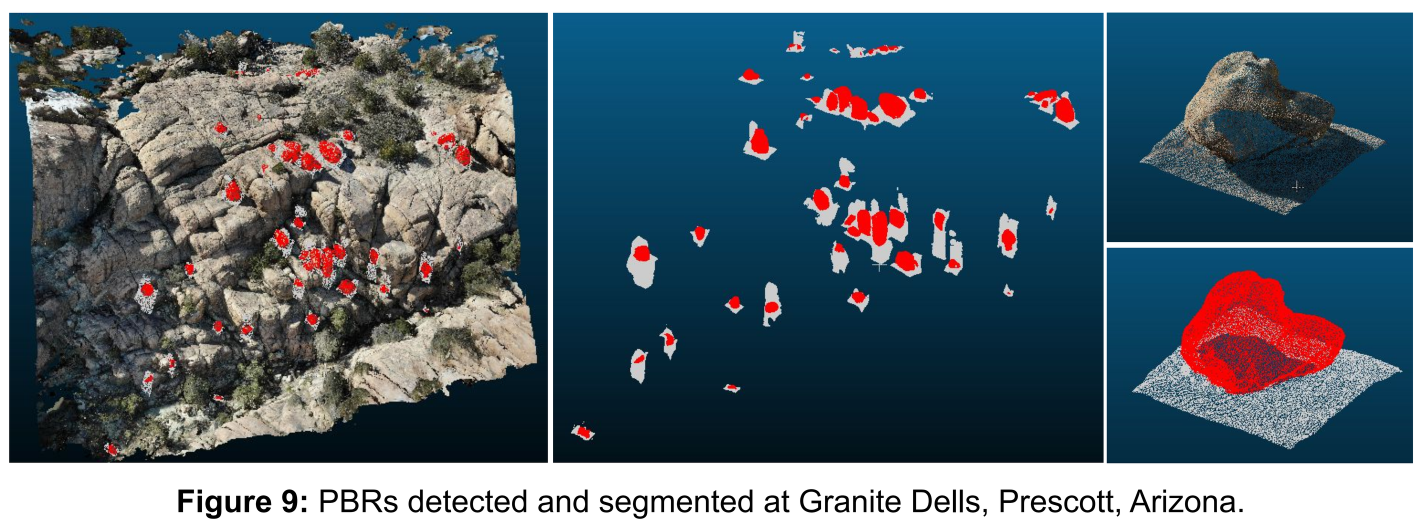

Figure 9: PBRs detected and segmented at Granite Dells, Prescott, Arizona.

3D Rock Detection: Onboard Method

Offboard method limitations:

a) Waste of computing and memory: e.g., dense point cloud for sparse rock fields
b) Basal contact information loss since imaging flight not adaptive to rock geometry

Onboard method advantages:

a) Basal contact information as a result of precise and adaptive flight
b) Immediate availability of PBR mapping results
c) PBR-targeted mapping (semantic path planning)

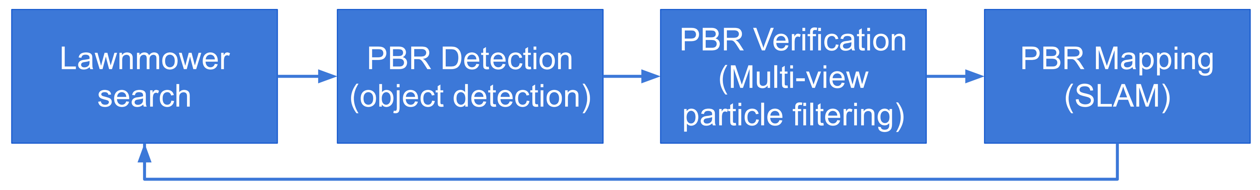

Figure 10: Workflow diagram of the onboard method for PBR search and mapping. The system integrates online object detection, multi-view particle filtering, and simultaneous localization and mapping (SLAM). (Chen et al., 2022c in prep)

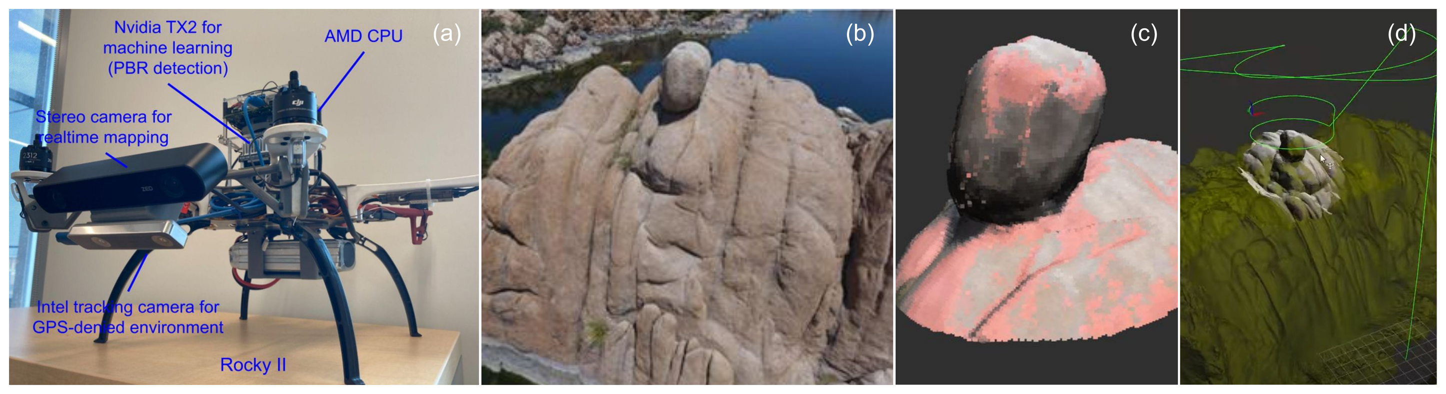

Figure 11: (a) Hexrotor with companion computers and stereo cameras found and mapped a (c) PBR at (b) Granite Dells, Prescott, Arizona. The search and mapping path is shown in Figure 11(d).

Rock Dynamics Analysis: Virtual Shake Robot

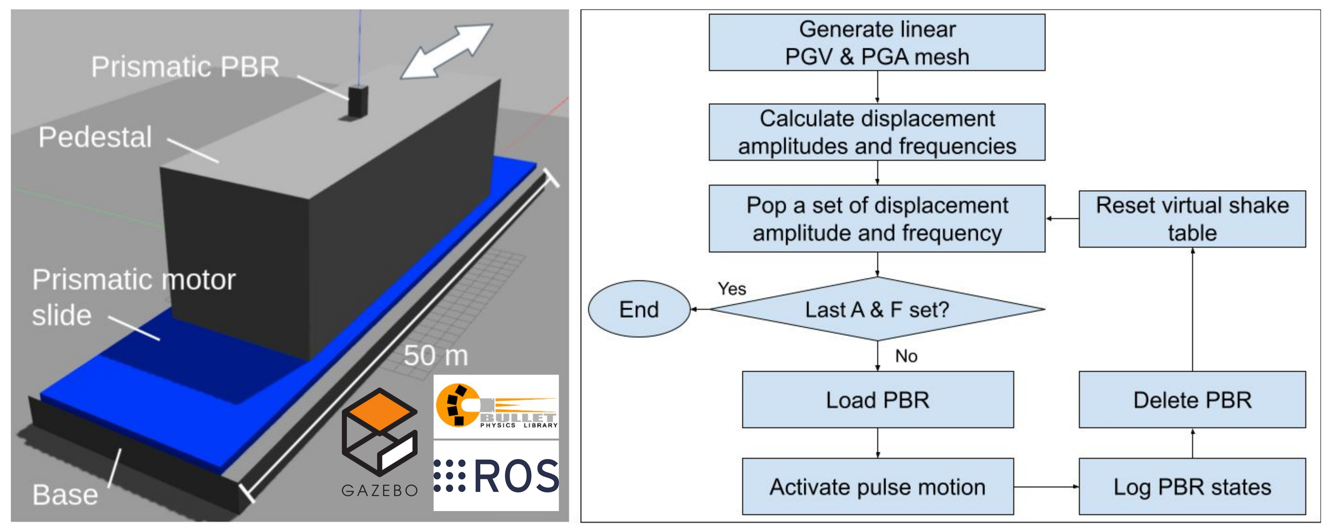

Figure 12: (Left) Virtual shake robot and (right) automation diagram. The virtual shake robot integrates Robot Operating System (control and status monitoring), Bullet Physics engine (dynamics simulation), and Gazebo (modeling). (Chen et al., 2022d in prep)

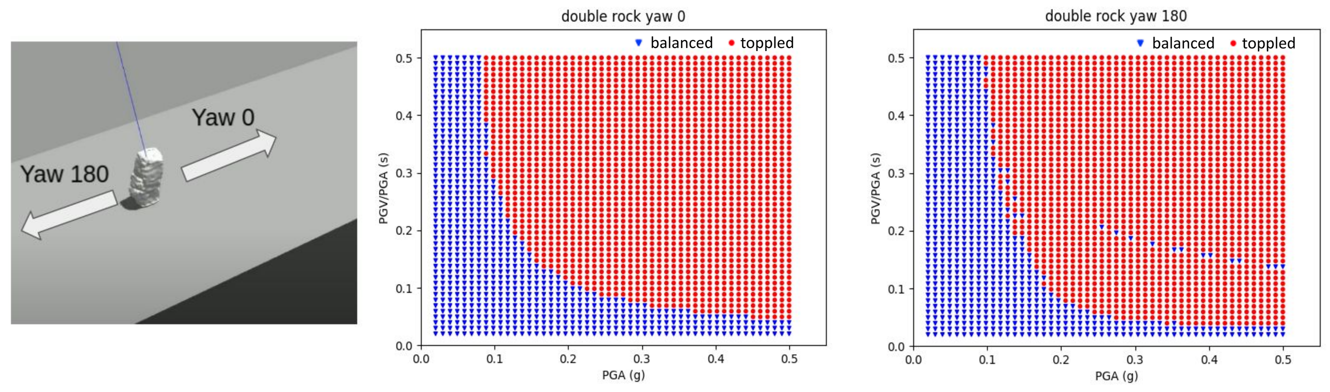

Figure 13: Arrows indicate motion directions in terms of initial orientation yaws (left). Yaw 0 (middle) is more fragile than Yaw 180 (right). Balanced points within unstable zone (right) represent overturning moment perfectly balanced by restoring moment.

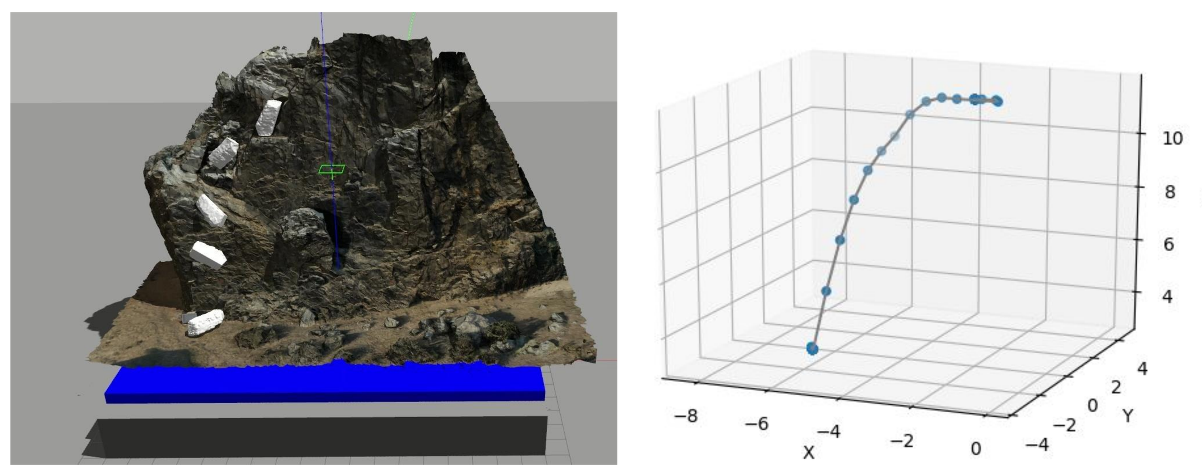

Figure 14: Simulation of the large displacement dynamics of a boulder after simple impulsive motion on SfM mapped terrain of PBR sites in Double Rock, CA. Left panel shows the sequential positions of the Double Rock PBR toppled by a sinusoid ground motion. Right shows the trajectory of the particle centroids during the tumbling motions through initial and final states.

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