Consiglio Nazionale delle Ricerche
Istituto di Calcolo e Reti ad Alte Prestazioni

Petroglyph Segmentation: an overview

Version v1

Lucia Maddalena, Francesco Gregoretti, Laura Antonelli

Istituto di Calcolo e Reti ad Alte Prestazioni del Consiglio Nazionale delle Ricerche (ICAR-CNR)

lucia.maddalena@icar.cnr.it, francesco.gregoretti@icar.cnr.it, laura.antonelli@icar.cnr.it

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Consiglio Nazionale delle Ricerche, Istituto di Calcolo e Reti ad Alte Prestazioni (ICAR) – Sede di Cosenza, Via P. Bucci Cubo 8/9C, 87036 Rende, Italy, URL: www.icar.cnr.it – Sede di Napoli, Via P. Castellino 111, 80131 Napoli, URL: www.na.icar.cnr.it – Sede di Palermo, Via Ugo La Malfa 153, 90146 Palermo, URL: www.pa.icar.cnr.it

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Petroglyph Segmentation: An Overview

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Lucia Maddalena[1], Francesco Gregoretti[1], and Laura Antonelli[1]

[1]Institute for High-Performance Computing and Networking, National Research Council of Italy

Abstract

This report provides an overview of current methods, datasets, metrics, and available software for petroglyph segmentation. Petroglyphs are indeed valuable artifacts that provide insights into ancient civilizations. Still, their preservation and analysis can be challenging due to factors like degradation, location, and the sheer volume of data to process. Automatic segmentation tools offer promising solutions by reducing manual effort and increasing the efficiency of the whole analysis process. The report focuses on techniques that exploit depth information or curvature analysis of the 3D data and methods that perform the semantic partition directly on 2D images. The study serves as a starting point for designing a new automatic tool for image segmentation and analysis that will enable archaeologists to analyze petroglyphs on site efficiently.

1 Introduction

A glyph is an elemental symbol or picture representing an understandable character. Petroglyphs act as ancient human rock art to leave messages through glyphs. They involve removing part of a rock surface by incising, picking, carving, or abrading. Petroglyphs can be found all over the world, in protected areas such as caves or overhangs, and represent a valuable source of information for archaeologists and historians. However, analyzing these carvings can be challenging due to weathering, erosion, and overlapping imagery. Automatic segmentation, separating the petroglyphs from the background rock surface, is crucial in analyzing and interpreting these images.

This report reviews existing methods for petroglyph segmentation, focusing on techniques that exploit depth information (3D data) or curvature analysis and methods that perform semantic segmentation directly on 2D images. We discuss the details of each approach, including representative works and the datasets used for evaluation. The report is organized as follows: it first introduces publicly available datasets designed explicitly for petroglyph segmentation, also mentioning other datasets that could be of interest. We then discuss the evaluation metrics commonly used for petroglyph segmentation tasks, and finally, the report dives into different segmentation methods categorized based on the data they utilize. This comparative analysis aims to understand current methods for automatic petroglyph segmentation comprehensively and lays the groundwork for future advancements in this field.

2 Annotated Datasets

This section introduces publicly available datasets containing 3D scans and imagery of petroglyphs. These resources can be valuable for researchers developing automated methods for analyzing and understanding petroglyphs.

2.1 3D-Pitoti Dataset

The 3D-Pitoti dataset[1] [15] contains 26 high-resolution surface reconstructions of natural rock surfaces with several petroglyphs. Data were acquired in Valcamonica[2], Italy, using structured light scanning (SLS) and structure from motion (SfM) scanning techniques. The dataset provides 3D point clouds, mesh triangulations, ortophotos, and depth maps for each surface. The ground truths (GTs) are given as 2D masks of the orthoimages. An example is given in Fig 1.

(a) (b)

Figure 1: 3D-Pitoti dataset: (a) example orthoimage and (b) corresponding GT.

The related paper [15] also presents results using two baseline segmentation methods based on Random Forests and CNNs, using the color (2D) information and the depth (3D) information, showing that depth leads to much better results. The dataset has been adopted by the same authors in [18], but also by other authors [1].

[1]The 3D-Pitoti dataset is available at http://www.tugraz.at/institute/icg/research/team-bischof/learning-recognition-surveillance/downloads/3dpitotidataset.

[2]whc.unesco.org/en/list/94

2.2 Petroglyphs Dataset

The Petroglyphs Dataset[3] [13] includes 34 rock art images of size 512 $\times$ 512 and corresponding GTs. Examples are given in Fig. 2. The dataset has been adopted for experiments in [14].

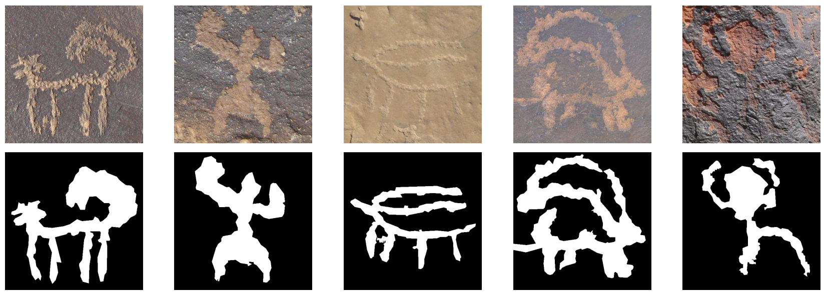

Figure 2: Petroglyphs Dataset: example images (first row) and corresponding ground truths (second row).

2.3 Other Datasets

Other datasets that could be of interest include

- the RockArt Database `https://rockartdatabase.com` (see also [6]);
- the Swedish Rock Art Research Archives (SHFA) is a national archive for rock art documentation and research at the University of Gothenburg `https://sketchfab.com/SHFA-3D`;
- the Hodjikent Petroglyphs `https://cs.pollub.pl/zasoby/?lang=en`, dataset 1 and 2 (see also [16]).

3 Metrics

This section explores various metrics used in the literature to evaluate the performance of algorithms designed to segment petroglyphs in images. These metrics quantify how well the automatically identified petroglyphs (the computed segmentation) align with the actual petroglyphs (the GT). These metrics are crucially helpful in comparing the performance of different segmentation methods.

Three performance metrics frequently adopted in the literature (e.g., [18, 15]) include the Dice Similarity Coefficient (DSC), the Hit Rate (HR), and the False Acceptance Rate (FAR).

[3]The Petroglyphs Dataset is available at `https://universe.roboflow.com/lums-z1nde/petroglyphs/dataset`.

The DSC measures the mutual overlap between the computed segmentation X and the ground truth Y, given by

$$DSC(X, Y) = \frac{2|X \cap Y|}{|X| + |Y|}.$$

The HR measures the rate of correctly classified foreground (engraving) pixels, given as

$$HR(X, Y) = \frac{|X \cap Y|}{|X \cap Y| + |Y/X|}.$$

The FAR measures the rate of pixels incorrectly classified as foreground, given as

$$FAR(X, Y) = \frac{|X/Y|}{|X \cap Y| + |X/Y|}.$$

The three metrics above range between 0 and 1, while for DSC and HR, the higher, the better; for FAR, lower values indicate better performance.

The performance metrics adopted in [1, 14, 15] also include the mean Intersection over Union (IoU) and the pixel accuracy (PA).

The mIoU measures the ratio between the number of pixels correctly labeled as positive to the number of positive pixels:

$$mIoU = \frac{|TP|}{|TP + FN|},$$

where the mean is taken over all the images of the considered dataset.

The Pixel Accuracy (PA), also used in [1] and named ~~as~~ Binary Accuracy in [14], is the ratio between correctly classified pixels and the overall number of pixels.

$$PA = \frac{|TP + TN|}{|TP + FP + TN + FN|}.$$

Matlab scripts for computing the above metrics are provided[4] for the 3D-Pitoti dataset.

In [3], performance has been evaluated using the F_1 score, measured based on the vertex labels, and the Segmented Inscription Recognition Index (SIRI), which (according to a paper unfortunately available only in Korean) gives a performance measure closer to the subjective evaluation. For its computation, the GT is divided into four areas: inside of strokes, boundaries of strokes, background adjacent to strokes, and remaining background. Since each area has different relevance for recognizing inscriptions, each contributes differently to TP, FN, and FP calculations. Then, SIRI is obtained using the weighted TP, FN, and FP as follows:

$$SIRI = \frac{TP_w}{TP_w + \frac{FN_w + FP_w}{2}}.$$

[4] https://github.com/poier/3d-pitoti-dataset-evaluation-scripts

Finally, Melnik et al. [14] consider the Earth's Mover's Distance (EMD), also known as Wasserstein distance, which measures the distance between image intensity distributions.

4 Methods

This section explores various techniques for automatically segmenting petroglyphs from 3D scans of rock surfaces. These methods typically involve analyzing the depth information of the surface to distinguish between petroglyphs (raised or lowered areas) and the background. Some approaches rely on setting a depth threshold to separate foreground and background, while others leverage more sophisticated techniques like curvature analysis or machine learning.

4.1 Methods Exploiting Depth

Some methods for extracting reliefs and details from 3D information of relief surfaces estimate the depth at each position and identify reliefs or background based on a depth threshold [10, 11, 12, 17].

Some methods focus on specific families of reliefs, including isolated reliefs on a smooth background [10], reliefs lying on a textured background [11], and periodic reliefs [12]. These methods are specifically designed for reverse engineering of reliefs, where a model of an existing relief superimposed on an underlying surface needs to be automatically extracted to be applied on a different base surface. Applications include decorating porcelain or applying brands to packaging.

In detail, Liu et al. [10] consider the specific case of simple reliefs delimited by a single outer contour and lying on a smooth background surface. For their segmentation, they rely on user input for delimiting the area of interest and adopt an active contour model [8] suitably adapted to cope with contour concavities and noisy background. The method could be extended to *negative reliefs* or *embossing* with minor changes. However, the limitations concerning the single outer contour (and thus no internal holes) and smooth background (and thus hardly applicable to stones) prevent its use for segmenting petroglyphs. In [11], the same authors consider geometric reliefs lying on a textured background~~,~~ and propose two approaches for their segmentation. One is based on classifying parts of a surface mesh as relief or background; then, it uses a snake that moves inwards towards the desired relief boundary, which is coarsely located using energy based on the classification. The second approach starts by smoothing the surface to eliminate the background texture; then it applies the previous segmentation method [10].

Zatzarinni et al. [17] present an approach (named DRE in [3]~~,~~ for Depth estimation-based Relief Extraction) for extracting reliefs and details from relief surfaces. The surface is considered to be composed of two components: a base (unknown) surface and a height function defined over this base. The relief is found by estimating the base surface normals and determining the depth values by globally optimizing the local relative depths of each point with respect to its adjacent points. By modeling the depths for relief and background regions as a mixture of Gaussians, the segmentation is obtained by an EM algorithm. Applications include relief segmentation and shape editing by detail exaggeration and dampening, cut and paste of reliefs and details (e.g., to decorate models or embedding logos), or curve drawing (e.g., to aid archaeologists in visualizing the reliefs). Their method aims at reliefs with enough height (or depth). Moreover, for a severely rough surface, the normals of the base surface cannot be obtained accurately, and the Gaussian assumption of the depth distribution does not hold.

Zeppelzauer et al. [18] present an automatic 3D segmentation approach that is able to extract rock engravings from reconstructed 3D surfaces. They transfer the task of segmentation from 3D input data (point cloud) to the image space (depth map) and extract the surface topography by enhancing the geometric micro-structure captured by the depth map. A classifier estimates the probability that a given pixel of the enhanced depth map belongs to a relief. The contour of the segmented shapes is optimized by a gradient, preserving energy minimization to improve the smoothness and reduce noise. The segmentation is finally refined interactively based on scribbles input by the user. The evaluation is performed on the 3D-Pitoti dataset using the DSC, HR, and FAR metrics.

4.2 Methods Exploiting Curvature

Other methods exploit the curvatures of the 3D data [3, 9].

Lawonn et al. [9] propose a framework for interactive exploration of carving structures from 3D data, using different techniques for detecting, selecting, visualizing, and generating them. For detection, they propose a relief extraction method (named CRE in [3], for Curvature-based Relief Extraction), adapting the Frangi filter to define the *vesselness* measure of the data mesh. Detection results are visually compared with those by DRE [17].

Choi et al. [3] propose a method where relief candidate segments are initially obtained exploiting curvature (using MCRE - Modified CRE [paper unavailable]), then refined based on an SVM classifier trained various features based on appearance, cross-section, and local extrema of candidate relief segments. The method is evaluated on a dataset of the stele Musul-ojakbi, registered as a national treasure of Korea, but unfortunately not publicly available. Results are compared to DRE [17], CRE [9], and MCRE using the F_1 and SIRI metrics. The same authors in [2], present another method evaluated on the same dataset and compared to DRE, CRE, MCRE, DCRE, and SRE.

4.3 Semantic Segmentation in 2D Images

Bai et al. [1] present a framework for the segmentation of petroglyphs from 2D high-resolution images, based on the UNet architecture with a loss function (boundary enhancement with Gaussian - BEGL) aiming at refining and smoothing the segmentation boundaries. The method is evaluated using data from the 3D-Pitoti dataset to produce high-resolution non-overlapping and rotation corrected images of size 512×512 from the available orthoimages. The adopted metrics include PA, mean precision, recall, and F-measure, mean IoU, and DSC. Comparisons are provided against the UNet architecture using different loss functions.

In [14], Melnik et al. introduce a deep neural network that, given 2D images of characters in palimpsests or symbols in petroglyphs, computes their segmentation while overcoming occlusions, missing parts, and degradation. The network interleaves pixel-level classification with global prediction of the object structure; it incorporates a generative component for the global segmentation mask and an adversarial component for its refinement. Due to its inference abilities, the network infers and completes missing and corrupted parts beyond segmenting the symbol's foreground pixels. To train and test the network for petroglyphs, they developed the Petroglyph annotated dataset [13], manually labeled by expert archaeologists, based on the Negev Rock-Art dataset [4]. For the evaluation, they adopted binary accuracy, MSE, mIoU, F1, and the Earth's Mover's Distance (EMD), also known as Wasserstein distance.

4.4 Other Methods

Horn et al. [5] train a model that locates and classifies image objects using a faster region-based convolutional neural network (Faster-RCNN) based on data produced by a novel method to improve visualizing the content of 3D documentation. The 3D models are publicly available[5]. They developed a publicly available tool[6] named ratopoviz for rock art topographic visualization to automate the creation of 2D visualizations for 3D rock art data. It generates depth maps, normal maps, topographic maps, enhanced topographic maps, and blended maps in colour and greyscale. The code for the rock art detection model is also publicly available[7]. 2D images extracted from the 3D models are annotated with bounding boxes and assigned one of 11 class labels.

Jalandoni and Shuler [7] propose a method for the automated tracing of petroglyphs using open-source spatial algorithms on enhanced 3D derivatives of an engraved rock art site. This step highlights lines engraved in the rock, providing only an initial aid for detecting the engraved figures. The results are evaluated by comparing the automated tracing with on-screen digitization, based on a 3D model they created.

Wojcicki et al. [16] describe the process of digitally recording a historic object using the Artec Eva scanner. The process of data acquisition from points in space and the processes of highlighting petroglyphs are described. The created Hojikent Petroglyphs dataset is publicly available.

[5] `https://sketchfab.com/SHFA-3D`: Swedish Rock Art Research Archives.

[6] `https://github.com/Swedish-Rock-Art-Research-Archives/rock-art-ratopoviz`: Rock Art Topographical Visualization.

[7] `https://github.com/Swedish-Rock-Art-Research-Archives/rock-art-radnet`: Rock Art Detection Network.

5 Conclusions and Future Works

Image segmentation helps preserve cultural heritage by facilitating the identification, documentation, and preservation of petroglyphs, which are valuable artifacts of ancient civilizations. Automatic segmentation tools reduce the manual effort required for analyzing petroglyphs, making the process more efficient and scalable. This report presented an overview of existing petroglyph segmentation methods to collect features of different segmentation approaches and information on the availability of private and public datasets. On one side, some segmentation methods, particularly those involving deep learning or complex algorithms, may require significant computational resources, making them less accessible for archaeologists with limited computing infrastructure. On the other side, despite the existence of some publicly available datasets, there is still a scarcity of annotated data specifically tailored for training and evaluating petroglyph segmentation algorithms, hindering the development of robust methods. In the future, the aim will be to contribute new automatic tools for image segmentation and analysis that permit archaeologists to analyze findings on site.

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