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Short and Project Papers

Detection and Classification of Petroglyphs in Gigapixel Images –Preliminary Results

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Abstract

With the advances of digital photography, the number of high quality images of rock panels containing petroglyphs grows steadily. Different time-consuming manual methods to determine and document the exact shapes and spatial locations of petroglyphs on a panel have been carried out over decades. We aim at automated methods to a) segment rock images with petroglyphs, b) classify the petroglyphs and c) retrieve similar petroglyphs from different archives. In this short paper, we present an approach for the unsolved problem of rock art image segmentation. A first evaluation demonstrates promising results.

Categories and Subject Descriptors (according to ACM CCS): I.4.6 [Image Processing and Computer Vision]: Segmentation—Pixel Classification

1. Introduction

Many known sites of pre-historic rock peckings or engravings (petroglyphs) exist. These sites are frequently visited by archaeologists and the interested public. With the advances of digital photography and automatic stitching technique, the number of digital images of complete panels (a rock with several petroglyphs) will grow steadily. These images allow scholars and the interested public to examine and investigate the panels without potential abrasion of the rock and without traveling. The spatial locations and the shapes of the petroglyphs on such a panel are relevant for archaeologists and the interested public, e.g. to highlight the petroglyphs in the image, or to perform analysis on the locations, sizes and orientations of the petroglyphs. Different time-consuming manual methods to determine and document the exact shapes and spatial locations of petroglyphs on one panel have been carried out over decades [AC94]. In the long run, we aim at robust automated methods to a) determine the exact shapes and spatial positions of petroglyphs in images of full panels (i.e. segmentation of the image in pecked and non-pecked regions), b) classify the petroglyphs regarding their shapes and pecking styles and c) retrieve similar petroglyphs from different archives of petroglyph images (see Figure 1). There is no related work that deals with petroglyphs containing all these goals. In this short paper, we present promising preliminary results for the unsolved problem of rock art image segmentation in foreground pixels and background pixels. We define any pixel, that is inside a petroglyph, as foreground pixel, and subsequently any other pixel as background pixel.

Figure 1: *Rock art image analysis workflow.*

In Section 2 we present related work. Section 3 contains our approach. In Section 4, we describe a first evaluation of our approach and show preliminary results with rock art images and reference material.

2. Related Work

Only a few works dealing with petroglyphs exist. Zhu et al. [ZWKL10] propose a semi-automatic approach that utilizes CAPTCHAs for rock art image segmentation. Furthermore, they propose a distance measure for petroglyphs based on the generalized hough transform and demonstrate the performance of the distance measure on different petroglyph datasets. Landon and Seales [LS06] propose a system for 3D scanning and presentation of Puerto Rican petroglyhps. Our current task, image segmentation, is a fundamental and therefore well researched problem in computer

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Figure 2: *Petroglyph segmentation evaluation material.*

vision [YJS06] [DJLW08]. We summarize related work in fields with segmentation approaches comparable to our task, and in texture classification. Yin et al. [YLH*09] use color and edge features in a k-NN classifier for rock structure classification in FMI images. Partio et al. [PCGV02] use gray level co-occurence matrices (GLCM, see [HSD73]) and Gabor filters to model textures of rock images. They perform classification with k-NN. The results of the evaluation on a limited test database are reasonable. GLCM performs better than Gabor filters.

Khoo et al. [KOW08] model textures as GLCM and use a support vector machine (SVM) to classify textures. They evaluate their segmentation approach on few synthetic texture mosaics and two satellite images with good results. Kim et al. [KJPK02] use a support vector machine (SVM) for texture classification. They use the pixel intensities as input for the SVM, i.e. no prior feature extraction is performed. The evaluation of their approach against synthetic texture mosaics delivers good results. Varma and Zisserman [VZ05] [VZ03] use textons (see [LM99]) as texture models. They evaluate their approach on the Columbia-Utrecht reflectance and texture database (CURet [DvGNK99]) and achieve very good classification results with and without the usage of filter banks.

3. Our Approach

We approach rock art segmentation as *pixel-wise classification*. First, for each pixel to classify we obtain a block of the input image with this pixel in the center. Second, we extract visual features of each of these blocks. Third, we train a SVM. Fourth, we classify new data with the model obtained in step three.

According to Yilmaz et al. [YJS06], features for object detection include color, edge and texture based features. Datta et al. [DJLW08] state, that the major types of features in image retrieval are color, texture, shape and salient points. Shape features are not suitable for our task, as shape is an attribute of an image segment, i.e. shape features are extracted post segmentation. Furthermore, we assume, that our material contains too many salient points (i.e. interest points or corner points) due to its structured surface (see Section 4.1). Hence, we rule out shape features and salient points. The three feature categories we consider for our task are color, edge and texture.

4. Evaluation

4.1. Rock art material

Figure 3: *Exemplary problematic regions in the evaluation material. Grass (top left), shadow (top right), Horizontal scratches due to glacial polish (bottom left) and a deep crack (bottom right).*

We acquired a 2D image of a complete rock panel (Rock 12 on site Seradina I in Capo di Ponte, Valcamonica (a UNESCO world heritage site), Italy). The image contains a large number of Petroglyphs and is stitched of more than two hundred single images. It has a size of around three gigapixels.

The context of the image acquisition is described in more detail in [SJB*11]. We use two single source images as preliminary data (see Figure 2). We selected the two images carefully. They are differently lit, and the typical rock structure appears visually different in the two images. Furthermore, they contain petroglyphs with different pecking styles. The test image composed of these two images has a size of more than 40 million pixels. We obtain 128px*128px blocks with a horizontal and vertical stepsize of 16px, i.e. we do not classify each pixel, but each 256th. This resolution is sufficient for our task. It results in more than 150.000 blocks.

From each block, we extract color histograms with different numbers of bins (RGBHist32, RGBHist16, RGBHist8), luminance histograms (LumHist16, LumHist8), MPEG-7 edge histograms (EdgeHist), gray level co-occurence matrices with different numbers of gray levels (GLCM32, GLCM16, GLCM8) and statistical features of these (GLCMStat32, GLCMStat16, GLCMStat8 [HSD73]). Finally, we extract dense SIFT features with and without prior Gaussian blurring (DSIFT_gauss, DSIFT_nogauss [VF08]). For our experiments, we randomly split the data in training data and test data.

Our material is difficult. Petroglyphs are pecked out of the rock panel. They consist of the same material and have the same color as the background. The alteration of the rocks causes a highly structured surface with cracks, holes, scratches and pecks. Additionally, grass and visible fungus or lichen can grow on the stones, and leaves or other organic remainders can be found on the surface (see Figure 3).

Figure 4 contains the classification results. We observe, that the RGB histograms and the GLCM statistics are the best performing feature categories. The edge histogram performs comparably well. This is remarkable, as it consists of 5 bins only. The dense SIFT descriptor and the luminance histograms are far behind.

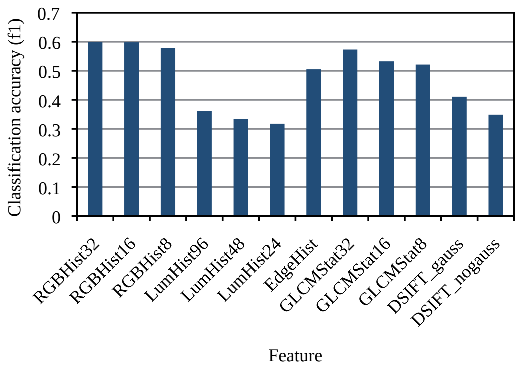

Figure 4: *Preliminary classification results. Please note, that this is the raw output of the classifier without any post processing.*

The good performance of the color histograms in comparison with the poor performance of the luminance histograms is interesting. The petroglyphs consist of the same material as the rest of the surface. The pecks cause shadows, and therefore the petroglyphs appear darker. Hence, we expected the luminance features to perform better than the color features, as there is no visible color difference, only a visible luminance difference.

Independently of the peckings, different regions of the rock images appear in different colors (due to alteration, sunlight, etc.) and luminances (e.g. due to shadows of trees). Therefore, we expected the texture features to perform superior to color and luminance features. This is the case in comparison with the luminance histograms only. Again, the good performance of the color features raises questions. We assume, that the employment of more images as test data will decrease the performance of the color features. However, the color features need further investigation.

Figure 5 contains a part of the evaluation image. We observe, that the results are promising, as many of the false positives and false negatives are in regions at the borders of the petroglyphs.

Figure 5: *Segmentation results with the feature GLCMStat32 overlayed with the ground truth. Light gray pixels denote true positives, dark gray pixels true negatives, black pixels false positives and white pixels false negatives. Please note that the results are without any post processing.*

4.2. Reference material

To validate our approach, we will evaluate it against different reference data. In this stage of the project, we evaluate it against the Columbia-Utrecht reflectance and texture database (CURet [DvGNK99]). This database is widely used for the evaluation of texture classification approaches. It contains images of 61 different materials. Each of the materials is depicted under various angles and lighting conditions.

The rock image segmentation results and their discussion in Section 4.1 indicate, that texture features are very relevant for our problem. Therefore, we aim at reference feedback for the question, how many different materials our approach can separate. We use the cropped texture images provided by Varma and Zisserman [VZ05] which contain 92 images per material. We employ our best performing texture feature from the previous step. Starting with 2 classes, we repeatedly select random subsets of the reference data. We randomly split this data in training and test data.

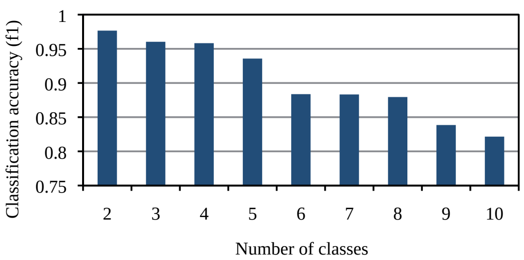

Figure 6: *Classification results for the CURet database with the feature GLCMStat32. For each number of classes 20 experiments with randomly selected data have been carried out. Results per class are the arithmetic mean of these 20 experiments.*

Figure 6 shows the experimental results of our approach carried out with reference material. We observe, that the features we employ are distinctive enough to separate up to five material classes satisfactory.

5. Conclusion and Future Work

In this paper, we present promising preliminary results for the detection of petroglyphs in gigapixel images. Future work will include a) a detailed analysis of false positives and false negatives to answer the question raised in Section 4.1, b) the employment of other features, feature variants as well as feature combinations with different fusion strategies, c) post processing for the verification of results and d) evaluation of our approach with other reference data sets.

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