Deep-Learning Based Super-Resolution of Aeolianite Images on the Purpose of Edge Detection and Pattern Extraction

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Abstract: In the current work processing of Aeolianite images, from a quarry in the island of Naxos in Greece, is presented. The deep-learning based technique called Densely Residual Laplacian Super-Resolution (DRLN) is applied on the original images of size 3000×4000 pixels to increase their spatial resolution per the factor of 4. Edge detection is applied on the initial images as well as on the super-resolved images of 12000×16000 pixels. Visual and numerical comparisons on several Aeolianite scenes prove that the super-resolved images are advantageous in relation to the initial images of lower spatial resolution, as far as edge detection and pattern delineation are concerned. The improvement in edge detected components reaches 83%. Classification or pattern extraction could significantly benefit from encompassing the proposed methodology for Aeolianite images as a preprocessing step.

1 INTRODUCTION

Geology and in particular geomorphology could greatly benefit from techniques of pattern recognition and pattern extraction (Erginal et al., 2022; Helm et al., 2021; Liu et al., 2019; Toulia et al., 2018). Facies analysis and the optical age of coastal carbonate Aeolianites serve for the investigation of the imprints of multiple Mediterranean transgressions during Middle Pleistocene in the Black Sea in (Erginal et al., 2022). In opposition to the contemporary hydro-climate of the Black Sea, the Aeolianites demonstrate the transformation of the Black Sea into a warm inland sea during successive Mediterranean invasions. Before the inception of aeolian deposition, paleosols were formed on the Eocene-aged hardened sandy silts, which indicates strongly washed soil. The particular study suggests that the carbonate-rich and ooid-containing Aeolianites were time and time again formed in the many Mediterranean transgression stages. In fact, there was a start with an increasingly severe dry phase coming after the Brunhes-Matuyama magnetic reversal.

With regard to geological and geomorphology monitoring, due to the requirement for automatic processing of the numerous remotely sensed imagery, numerous techniques of pattern extraction have been developed. Segmentation, mapping, recognition and monitoring of rocks, terrain morphology, ebipenthic/benthic sea communities, salt marsh and corals have been presented in the literature (Fan et al., 2020; Goode et al., 2021; Janowski et al., 2021; Juniani, 2021; Lou et al., 2022; Song et al., 2021; Untiedt et al., 2021). Deep seafloor exploration is presented in (Juliani, 2021). The interpretation of the nature of the geological phenomena as well as of their complicated interactivities requires the investigation of seafloor processes and spatial patterns or motives. Indeed, huge zones of undersea eruptions represent crucial territory candidates for new mineral findings. In specific, seafloor mounds can be greatly informative about surface changes that are occasionally caused by seafloor mineral accumulations. The study in (Juliani, 2021) investigates seafloor mounds by a 2-folded methodology namely a) semantic segmentation b) morphological similarity analysis and clustering of segmented features. Overall, the

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model developed in the particular study segmented 1,659 features and achieved accuracy up to 84% pixel-wise, and 80% object-wise, using data combination of bathymetry and terrain attributes as input. Morphological patterns that are immediate after-effects of diversified eruption mechanisms have been discovered.

Additionally, machine-learning based classification of rocks, marine coralline algae and geological structure are met in (Chen et al., 2021; De Lima et al., 2019; Dos Anjos et al., 2021; Janke et al., 2015; Piazza et al., 2021; Zhang et al., 2018). Geological structures being exposed on the Earth surface namely Anticline, Ripple marks, Xenolith, Scratch, Ptygmatic folds, Fault, Concretion, Mudcracks, Gneissose structure, Boodin, Basalt columns and Dike are under study in (Zhang et al., 2018). In the particular study there were utilized 2,206 images with 12 labels to identify geological structures relying on the Inception-v3 model. Classification of the geological structures was performed by applying K-nearest neighbors, artificial neural network and extreme gradient boosting, relying on features extracted by the Open Source Computer Vision Library. Experimentation indicates that model overfitting often leads to poor performance while accuracy may be smaller than 40%. However, deep-learning based transfer learning proves robust in the classification of images with geological structures, where model accuracy equal to 83.3% and 90% was achieved. Image texture turns out a crucial feature throughout the specific study.

In the present work deep-learning based SR is applied on Aeolianite images having been captured in a qaurry in the island Naxos, Greece. The increased image spatial resolution offers the advantage of more accurate and successfull pattern delineation on the Aeolianites after edge detection has been performed. Visual and numerical comparison are carried out. Section 2 presents the area of deep-learning based SR and in particular the Densely Residual Laplacian Super-Resolution (DRLN) (Anwar and Barnes, 2022). The experimental procedure along with the results are given in Section 3. The conclusions are drawn in Section 4.

2 DEEP-LEARNING BASED SUPER-RESOLUTION: DENSELY RESIDUAL LAPLACIAN

The spatial resolution of images can be increased beyond the resolution of the image acquisition sensor through the application of Super-Resolution techniques (Bratsolis et al., 2018; Stefouli et al., 2019). SR methodologies stemming from the area of machine learning and in particular deep learning have gained tremendous usage increase in the last years up to now (Anwar and Barnes, 2022; Niu et al., 2020; Panagiotopoulou et al., 2021; Panagiotopoulpou et al., 2022; Wenlong et al., 2021). In the current study the deep-learning based SR technique called DRLN (Anwar and Barnes, 2022) serves for super-resolution by a factor 4. The particular technique presents as basis a modular convolutional neural network that consists of various components for performance boosting. There is a cascading residual on the residual network architecture facilitating the circulation of low-frequency information.. Additionally, the densely linked residual blocks end up in “deep supervision” and learning from high-level complex features. Furthermore, the DRLN super-resolution technique presents the Laplacian attention characteristic. Due to Laplacian attention, the modelling of crucial features is done per multiple scales whilst the network catches the inter- and intra-level dependencies among the maps of features.

3 EXPERIMENTAL PROCEDURE AND RESULTS

Images of Aeolianites that are situated in a quarry in Naxos island, Greece are used for the demonstration of the proposed methodology. The utilized images can be found in Figure 1.

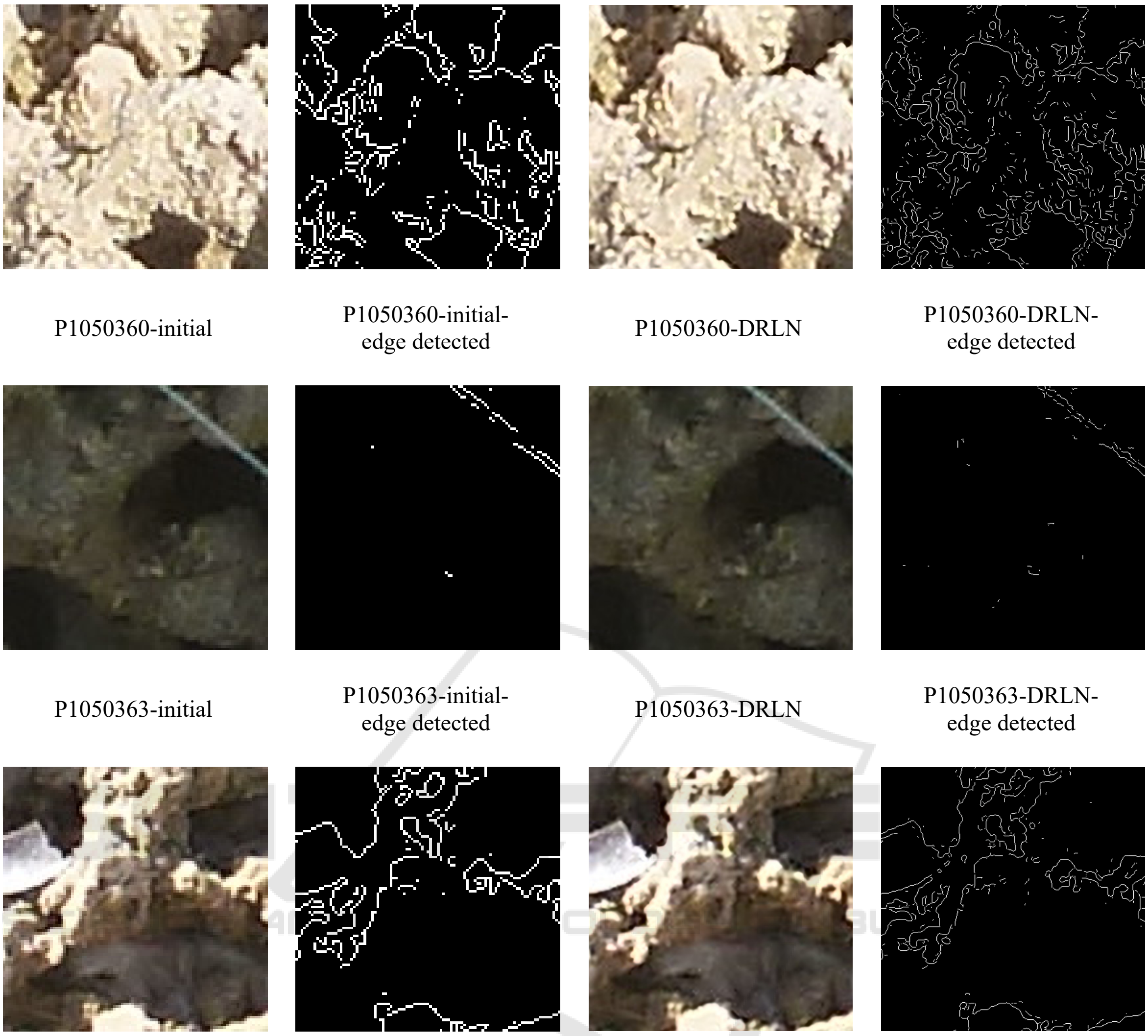
The initial images have resolution in pixels equal to 3000 × 4000 pixels. Their spatial resolution gets increased per the factor of 4 by means of the DRLN super-resolution technique. The resulting SR images have the resolution in pixels of 12000 × 16000. Selected Aeolianite parts from the initial images as well as from the SR images are depicted in Figures 2-5. Sobel edge detection (Jiang and Scott, 2020) is applied on the images for the delineation of any inherent patterns. The corresponding selected edge detected parts are also shown in Figures 2-5. The number of connected components in the edge detected Aeolianites can be found in Table 1.

Figure 1: The Aeolianite images under consideration, from quarry in Naxos island, Greece.

The kernel size of the Sobel algorithm is equal to 3 × 3. Automatic count by means of Matlab has given the number of connected components in Table 1. The enhanced image resolution allows to detect patterns in the Aeolianites much more successfully than the lower spatial resolution of the initial images. Apart from visually, the proposed methodology is also numerically validated. The percentage differences of the connected components or objects in the initial and in the DRLN super-resolved images in Table 1 prove that super-resolution contributes to the disclosure of patterns in Aeolianites. In all 10 Aeolianite image scenes under consideration, the SR enables the detection of connected components per 63.30% to 83%.

Table 1: The number of connected components or objects in the initial images and the corresponding super-resolved images.

Image ID	Initial	DRLN Super-Resolved	% Difference
P1050360	126	642	80.37
P1050363	11	65	83.08
P1050372	43	240	82.08
P1050377	217	938	76.87
P1050388	75	228	67.10
P1050396	76	342	77.78
P1050404	126	463	80.40
P1050411	143	699	79.54
P1050422	40	109	63.30
P1050426	144	570	74.74



P1050360-initial | P1050360-initial-edge detected | P1050360-DRLN | P1050360-DRLN-edge detected

P1050363-initial | P1050363-initial-edge detected | P1050363-DRLN | P1050363-DRLN-edge detected

P1050372-initial | P1050372-initial-edge detected | P1050372-DRLN | P1050372-DRLN-edge detected

Figure 2: Selected small parts from the initial images and the super-resolved images of Aeolianite. The corresponding edge detected images are also depicted.

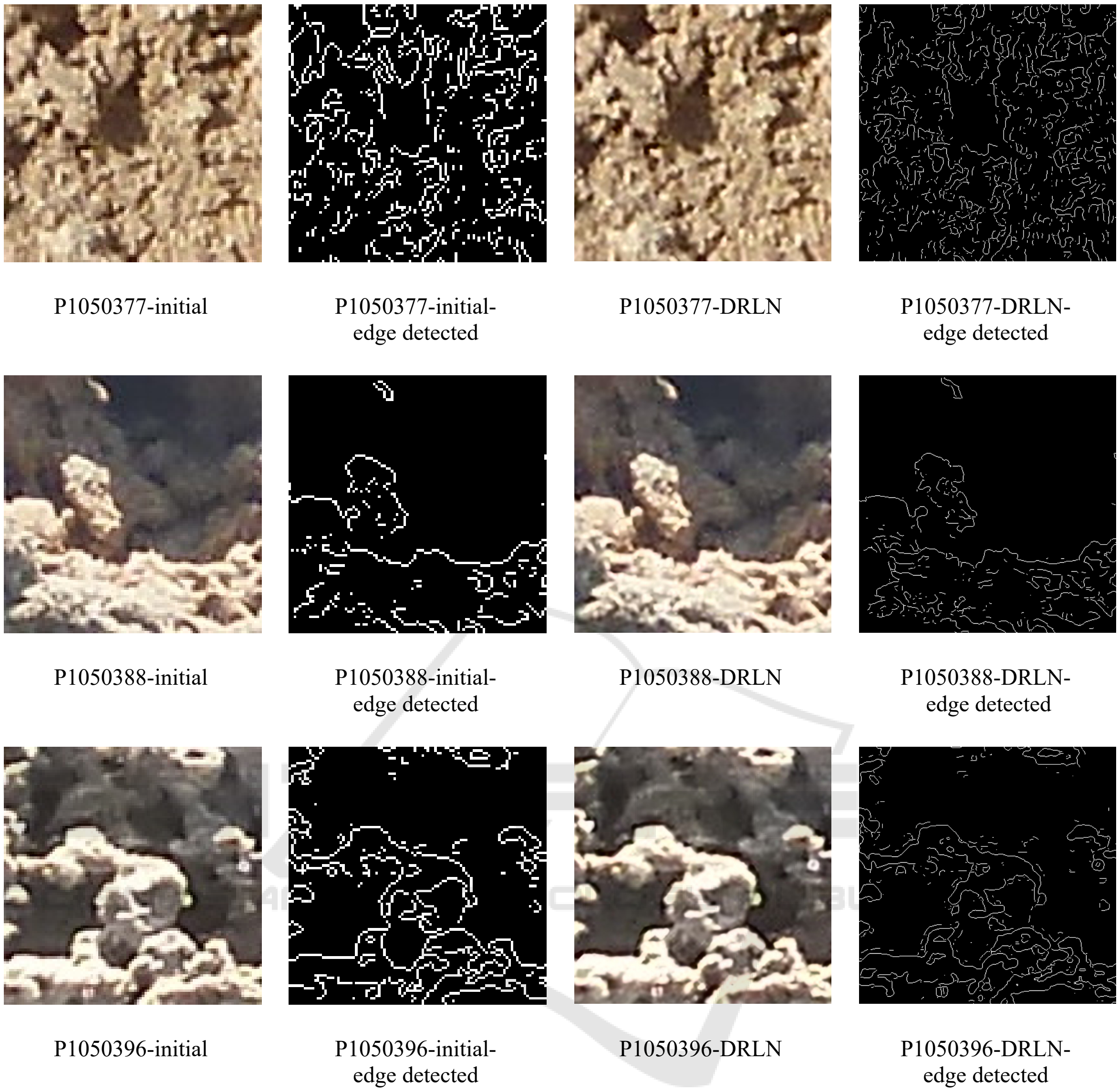


Figure 3: Selected small parts from the initial images and the super-resolved images of Aeolianite. The corresponding edge detected images are also depicted.

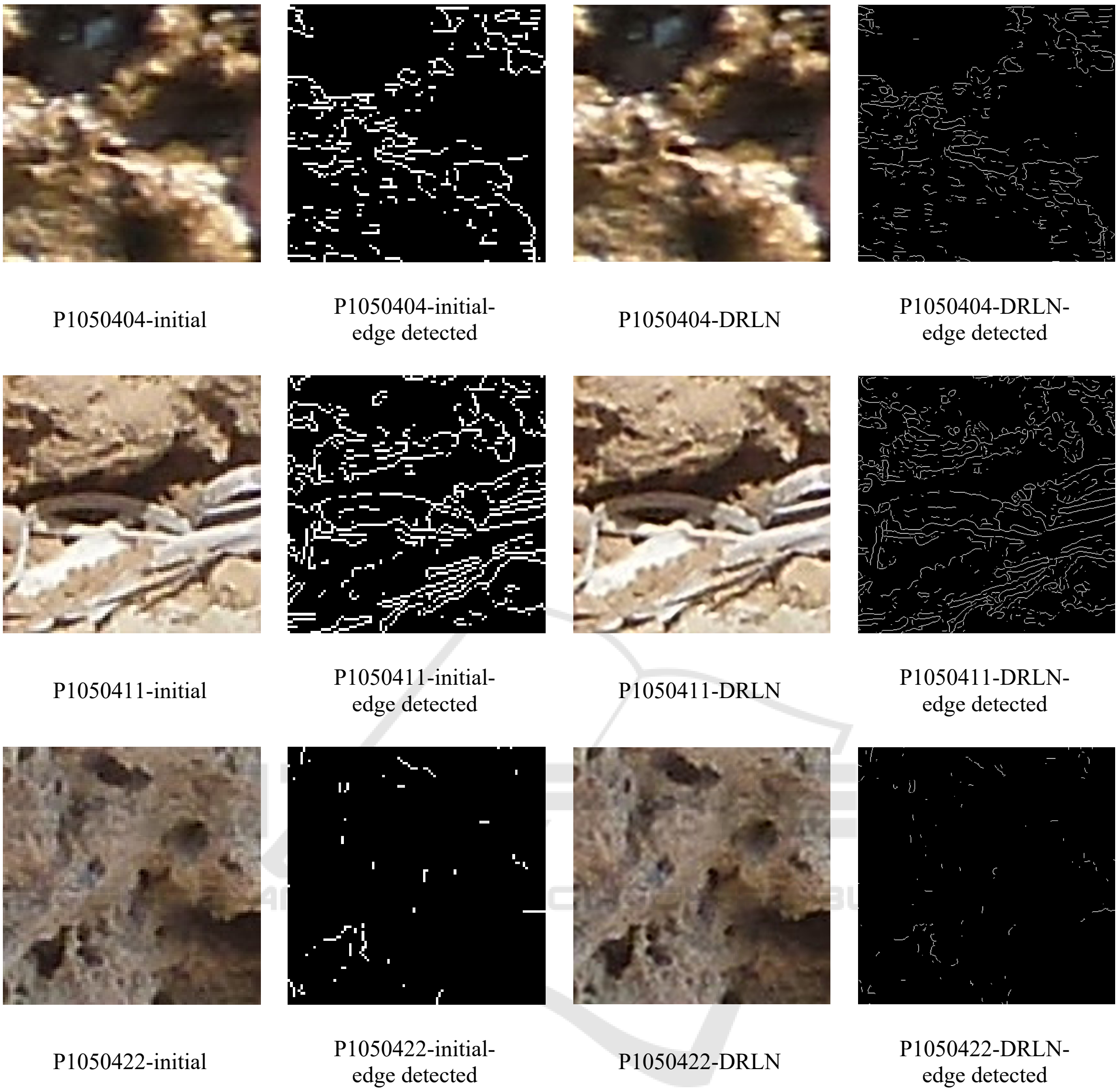


Figure 4: Selected small parts from the initial images and the super-resolved images of Aeolianite. The corresponding edge detected images are also depicted.

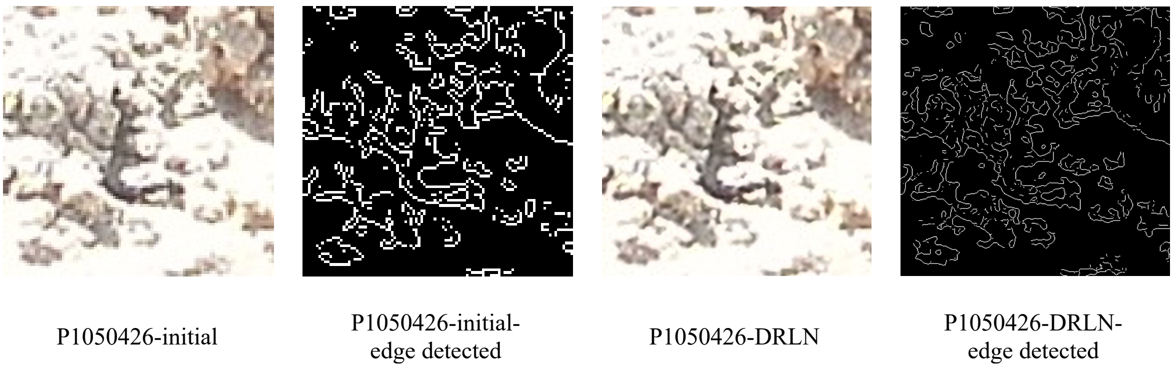


Figure 5: Selected small parts from the initial images and the super-resolved images of Aeolianite. The corresponding edge detected images are also depicted.

4 CONCLUSIONS

In this work the deep-learning based super-resolution technique called DRLN is applied on images of Aeolianites from a quarry in Naxos, Greece. Edge detection for the delineation of patterns on the images is performed on both the initial images and the super-resolved images per factor 4. The SR Aeolianite images reveal the inherent patterns better than the initial images up to the percentage of 83%. The methodology that is presented in this work could serve as an excellent tool for Aeolianite image preprocessing before a classification or pattern extraction task.

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