AUTOMATED REMOTE BIOSIGNATURE DETECTION USING MODIFIED SPACESeg MODEL

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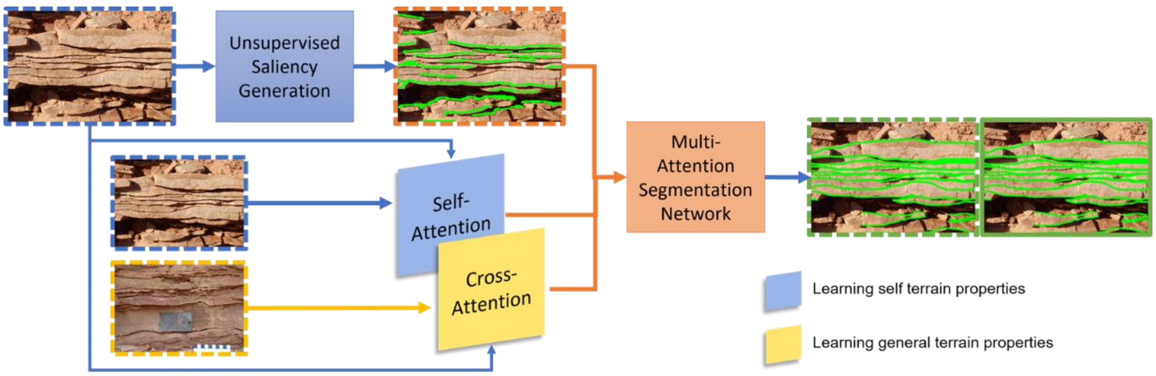

Figure 1: Overview of proposed MCA-aided SPACESeg for automated ripple detection

Introduction: The Precambrian geologic record is one of the most valuable sources of information for developing our understanding of the history and distribution of life in our Universe as it archives the origins and diversification of life on Earth and, in turn, is an image that captures life and its sedimentological signatures in the geologic records of other planets [1], [2]. Of particular astrobiological interest is the terminal Ediacaran Period (574-539 Ma), which, along with its preservation of the first macroscopic, multicellular animals on Earth, preserves a remarkable abundance of organic mats that were ubiquitous in Ediacaran seas and played a pivotal role in shaping the sedimentological record of the time [3], [4], [5]. One key way in which the organic mats of the Ediacaran impacted sedimentation was through the stabilization of storm-generated ripples on the seafloor which prevented the erosion of ripples and led depositional events to fill in ripples instead of eroding them as is typical in non-stabilized sediments. The result of this is a sedimentological record unique to Ediacaran-aged rocks that is characterized by stacks of successive, discrete bedforms that have ripples on the top-most and bottom-most surfaces [5]. This type of bedform, here referred to as “Double-Rippled” Bedforms (DRBs or “ripples”), therefore, represents a discrete and definitive biosignature. To harness the astrobiological and paleobiological potential of DRBs, an objective method of remote and automated detection and characterization of cross-sectional bed junction morphologies of mat-dominated bedforms is of significant value. To that end, we recently developed “Scene-aware Perception Automation using Composite Embedding for Segmentation” (SPACESeg) for the recognition of DRBs in images of rock cross-sections [8]. To develop this methodology, we utilized images from the Ediacara Member of the Rawnsley Quartzite in the Flinders Ranges of South Australia, because the Ediacara Member is characterized by meters of stacked DRBs and outcrops extensively throughout the Flinders Ranges region [6]. This technique can be leveraged to identify fossiliferous rocks in the deeper Precambrian and can additionally be translated to remotely recognize biologically-mediated sedimentary structures on other planets, thereby allowing for the rapid and remote detection as well as quantitative classification of astrobiologically significant outcrops on other planets. This utility aligns with the central goal of the Mars 2020 Perseverance rover, which is to “seek signs of ancient life and collect samples of rock and regolith for possible return to Earth” [7], and the SPACESeg system can be trained to analyze the images taken by Perseverance to recognize the presence or absence of the definitively biologically-mediated DRBs.

Contribution: Improving upon the SPACESeg segmentation model for detecting DRBs by adding a multi-channel attention module for incorporating local and global landscape features for improved overall image and scene understanding.

Technical Approach: The standard SPACESeg algorithm [8] follows a two-step process. The first step is unsupervised and generates a saliency map by activating relevant regions of importance. This input is subsequently given to the next step – a supervised deep learning network. The network is guided by the saliency at every level of abstraction. This method provides excellent results in segmentation [8] against variations in many practical imaging conditions and the landscape itself. One of the variations here is the field of view versus ripple thickness ratio. For our dataset, this is a very dynamic value – and thereby sometimes causes the method to detect some ripples incorrectly. We improve upon this issue of SPACESeg by adding a Multi-Channel Attention block (MCA). The MCA is designed to provide information to the deep segmentation network (Figure 1) that the unsupervised saliency generation module is unable to provide. This information is aimed to aid in scene parsing. While the network is fairly robust to the overall landscape and practical imaging conditions, it is noted in [8] that in extreme conditions where we have a skewed ratio of field of view versus ripple diameter, some details are lost. Thus, the MCA generates attention via two channels to provide the network with a sense of the scene. This is done by calculating first the self-attention of the scene being learnt and then computing cross-attention against different scenes. We select random patches of the training data – one for the image being trained and one for a randomly chosen sample. By selecting random patches at different zoom and orientation levels, we are essentially providing the model with new samples of various landscape conditions. Mathematically speaking, we compute self-attention between different transformations of the sample set and cross-attention for different transformations of the population. We note that this helps us distinguish the very thin ripples. The combined SPACESeg + MCA performs segmentation against a robust set of dynamic scene variations, imaging conditions and complex artifacts. Notably, this model is able to distinguish between the shadows and ripples – which are otherwise indiscernible due to their very similar feature sets.

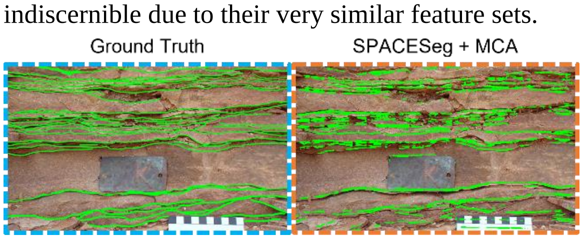

Figure 2: Output of proposed (right) and ground truth (left)

Experiments and Results: We demonstrate the importance of this modified algorithm in the case of a particularly difficult landscape (Figure 2). Here, the field of view captured versus the ripple diameter ratio is very high. In that case, we note that a few ripples get lost in segmentation due to insufficient learning. Using the SPACESeg + MCA, we see that the granularity of ripple detection has improved. Comparing with SPACESeg, we note that the accuracy increased by 2%. It is noteworthy is that SPACESeg has high performance but lower recall – and adding an MCA block improves overall performance over SPACESeg with improvement in recall as well. Visually, this means we are able to detect ripples more precisely while simultaneously rejecting artifacts more efficiently. We also show our results compared against other models [8] in Table 1.

Conclusions: It can be seen qualitatively and quantitatively that the MCA module improves upon the segmentation of SPACESeg. We note that in extreme landscape condition, we are able to detect the ripples slightly better with MCA. From an astrobiological perspective, the SPACESeg + MCA system takes us one step closer in automating the process of remote image analysis. It also does so by tackling various practical imaging issues. From a computational perspective, SPACESeg and MCA both can be applied to any model and trained. All of these allow for its deployment in remote and translational research – thereby creating an opportunity for automated analysis of various periods of evolution as well as extraterrestrial landscape analysis.

	ACC	**PRE**	**REC**	**SSIM**
U-Net	80 (08)	58 (10)	82 (06)	70 (14)
PSPNet	72 (13)	50 (13)	85 (04)	67 (16)
SPACESeg	89 (03)	71 (05)	82 (08)	85 (03)
SPACESeg + MCA	**91 (03)**	**75 (07)**	**83 (07)**	**88 (04)**

Table 1: Quantitative results with the inclusion of the MCA module in SPACESeg. Results are reported as mean (std). ACC is Accuracy, PRE is Precision, REC is Recall, SSIM is Structural SImilarity Metric

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References:

[1] Eriksson, P. G., Altermann, W., Nelson, D. R., Mueller, W. U., Catuneanu, O., & Catuneanu, O. (2004). The Precambrian Earth: Tempos and Events, Developments in Precambrian Geology, 12, *Elsevier Science.* [2] Antcliffe, J.B. & McLoughlin, N. (2009). Records of Life on Earth and the Search for Extraterrestrial Biosignatures, ed. Seckbach, J. & Walsh, M., pp. 211–232. *Springer, Dordrecht*. [3] Xiao, S., Laflamme, M. (2009) *Trends in Ecology & Evolution 24*. [4] Gehling, J.G., Droser, M.L. (2009) *Earth-Science Reviews* 96. [5] Tarhan, L.G., Droser, M.L., Gehling, J.G., Dzaugis, M.P. (2017) *PALAIOS 32*. [6] Gehling, J.G. (2000) *Precambrian Research 100*. [7] Kenneth A.F., et al. (2020) *Space Science Reviews 216*. [8] Jonnalagedda P, Surprenant R, Droser M, Bhanu B (2021). *IEEE/CVF Conference on Computer Vision and Pattern Recognition*.