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REVEALING HIDDEN ART: AUTHENTICATING AND UNVEILING NEOLITHIC ROCK PAINTINGS THROUGH ADVANCED HYPERSPECTRAL IMAGING TECHNIQUES

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ABSTRACT

Finnish rock paintings from Neolithic Stone Age are located on open-air bedrock panels, being subject to the effects biotic and climatic influences. Consequently, these paintings have predominantly faded and are challenging to discern. Through hyperspectral (HS) imaging and computational unmixing methods, both the delineation of these drawings and the identification of their pigments can be enhanced. In this study, we developed an unmixing method for detecting hematite and compared various techniques for delineating figures from HS images captured from Halsvuori rock painting. The results indicate that HS cameras combined with unmixing methods can successfully identify pigments and render the figures more discernible than before. HS data and source code are open and available in Zenodo [1].

***Index Terms*—** Hyperspectral imaging, spectral unmixing, scandinavian rock paintings

1. INTRODUCTION

Most of the Finnish rock art dates back to the Neolithic Stone Age, being approximately 7000 - 3000 years old pieces of art [2, 3, 4, 5, 6]. The differences and challenges of studying them lie in the fact that rock art is rarely painted in caves in Fennoscandian areas, as it is, for example, in Mediterranean areas [7]. Instead, the sites are typically open-air bedrock panels by inland waters, exposed to various biotic and climatic influences [3, 2]. Typical Fennoscandian rock art has engravings and painted figures [7]. Engravings increase the possibility of visually studying and interpreting rock art, but regional variations exist. In this study, we analyse Finnish rock art, which is interesting since only painted rock art is reported [8, 2], which challenges scientific studies since the painted figures and their pigments are constantly under environmental stress. Without engravings, fine-painted features fade and disappear faster over the years [2]. The Finnish rock art sites have visible figures, stain-looking non-figurative areas, and some noisy figure surroundings, which can be extensions of the artwork or simply natural marks in the rocks [2].

The figures in the Fennoscandian paintings have typically been seen to represent hunted or caught animals (elks, fish, snakes, etc.) and humans. The deeper understanding of the meanings of these iconographic activities has been an ongoing matter of discussion by archaeologists, and the typical interpretation is that the paintings represent ritual activities related to hunting and religion [3]. The pigments of the images are thought to have been made by their artists using an open fire and local soil mixtures. The most common colour in the paintings is reddish; the pigments were made by mixing iron oxide (haematite, red ochre) [3, 9]. The pigments may consist of blood or other binders consisting of lipids or resins [10, 3]. On top of the paintings are silica skins, which derive from the weathering of primary minerals in the bedrock. The silica skin protects the pigments from weathering, but the environmental stress fades it, causing damage to the visibility of the figures [3, 10, 5]. Due to silica skin, the weather conditions affect the visibility of paintings. The pigment may vary from translucent to milky depending on temperature, humidity and exposure to sunlight [5].

So far, traditional studies use RGB imagery captured in the most suitable weather and image-enhancing methods such as saturation corrections (e.g. Adobe Photoshop tools and ImageJ plugin Dstrech [11]) to delineate the figures and general analogy, informed and formal methods to gain iconographic meanings [2, 5, 7, 6]. According to [2], the risk of misinterpretations exists due to the natural colour changes and other marks in the rocks, which may appear as part of the painted figure. There are indicators that to improve the current understanding, qualitative non-invasive analytical methods, such as spectral imaging or near-infrared (NIR) spectroscopy, could be applied [3, 9].

HS imager extends the traditional RGB imaging technology by offering far deeper colour information. Where an RGB sensor captures three channels, an HS imager can capture hundreds or thousands of narrow channels, each representing different wavelengths of light. Therefore, each spatial pixel in an HS image has its spectra, giving a strong basis for analyses since both spatial and spectral resolutions are high. At the core of the HS analysis is the knowledge that each material has its special spectral signature; thus, HS data from visible to near-infrared channels are suitable for chemical analyses since the spectrum of the pigments used in the rock art is known [12, 3, 9].

We can assume that an HS image consists of a combination of pure spectra (ie. endmembers), representing substances in the image. Several approaches exist to modelled combinations, from the simple linear model to the complex non-linear models [13, 14]. In the linear model, detected spectrum $\mathbf{y}$ is combination of several endmember spectra $\mathbf{x_i}$ so that

$$\mathbf{y} = \Sigma_i m_i \mathbf{x_i}, \tag{1}$$

where m_i is abundance of ith endmember $\mathbf{x_i}$. Spectral unmixing is a process where only known things are detected in spectra, and the aim is to find the endmembers and their proportion in each spectrum of the HS image. The problem itself is ill-posed. There is a large variety of methods for how this can be solved. Usually, different methods utilise some optimisation process where we minimise the difference between the model and detected spectra.

Methods have some apriori assumptions about the occurrence and behaviour of endmembers. Usual assumptions are that $m_i > 0$ and $\sum_i m_i = 1$ for each pixel. Another quite meaningful assumption is the existence of pure pixels in the spectral image. This means that for each endmember there should be at least one pixel which only contains endmembers. Spectral unmixing methods such as pixel purity index and vertex component analysis (VCA) rely on this assumption [15, 16]. To be fulfilled, this assumption requires high spatial resolution images.

There is a large variety of approaches to how the endmembers can be found without the existence of pure pixels. One option is to use autoencoders. Traditionally, they are used, for example in dimension reduction or feature extraction. But they can be used also in spectral unmixing. In spectral unmixing, autoencoders can estimate endmembers even if pure pixels are absent. For example, in [17], the encoder part performs abundance estimation, and the linear decoder layer weights are actual endmembers. A network only consists of fully connected layers capable of handling each single spectrum at a time. Computationally more efficient is to use a convolutional approach where it is possible to compute the whole spectral image [18].

We hypothesised that by using spectral umixing, we could identify the pigments used in the rock paintings. Besides, the HS imager provides more spectral and spatial details in the data; this technology can reveal the figures' fine features and delineations more accurately than traditional RGB imagery. We tested our hypothesis by capturing HS images from a Finnish rock painting and performing tests using a novel CNN-autoencoder-based method for spectral endmembers. *As a result, we propose a novel method suitable for authenticity assessments and revealing fine features, being non-invasive and cost-effective since the field imaging technology has recently been developed into more affordable.*

2. MATERIAL AND METHODS

HS images were captured in August 2019 in the town of Jyväskylä, located in the middle of Finland. The name of the rock painting site is Halsvuori. According to literature, the Halsvuori has six figures: Two humans in front poses with raised hands. One human has bent legs; the other one's legs are faded. Both human figures hold small animals in one of their hands; the animal figures represent small game animals [2]. Two stains, probably hand shapes, are one and a half meters away from the humans. All figures are described as small, and the visibility varies; some are recognisable and almost intact, and some are worn, fragmented or scattered areas of paint [4, 2]. The authenticity of the hand stains being as old as the human figures is not clear [19]. Halsvuori paintings are hidden in the woods, near a small pond [19]. We captured HS images from a smaller human figure and hand-representing stains to test the proposed endmember pigment analysis over a known authenticity issue. Besides analysis, we visually compared the results to the digitally enhanced image behind the current figure interpretations of a human and a small game animal. The written ground truth description and related image are from [4].

(a) (b)

Fig. 1. RGB images, captured with a Spectral imager simultaneously capturing the HS image. (a) represents one of the described human figures (red pigments). (b) has been assumed to represent hands or sweep of the hands on the rock's surface. The white object is a white reference calibration target for the HS image. A white rectangle marks the analysed area.

HS images were acquired using Specim IQ, a commercial handheld spectral imager. The camera can record 204 spectral bands from 400 nm to 1000 nm. The recorded spectral image has 512×512 pixels. Specim IQ also has an integrated RGB camera, which records a reference image of the scene. The reference image from Halsvuori is shown in Fig. 1, where we can also see the white reference target. The white reference target is used to calibrate recorded spectra to reflectance.

We tested hematite occurrence in the paintings by developing a variation of the unmixing convolutional autoencoder. Our encoder part follows the idea [18]. The main difference is that the encoder output is split into two parts: R (number of endmembers) channels and one channel. This can be seen in Fig. 2.

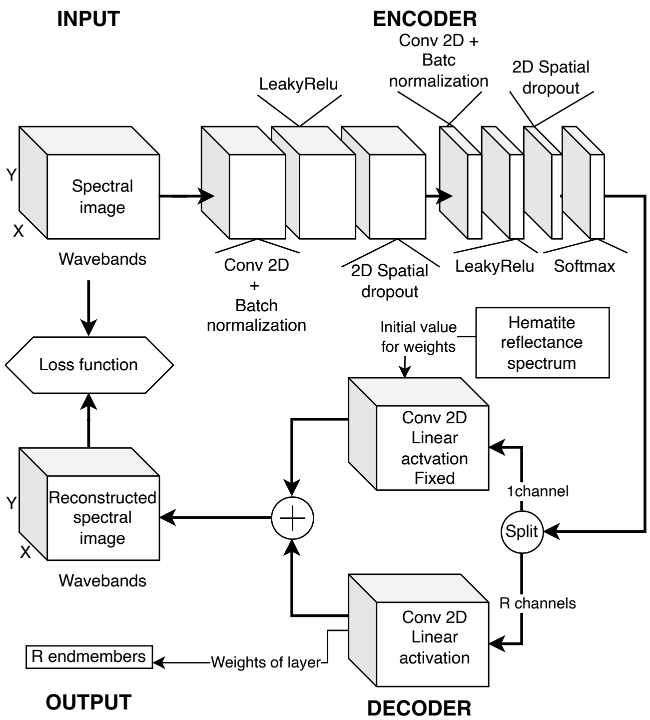

Fig. 2. Proposed autoencoder architecture

The decoder consists of two branches with 2D convolutional layers and linear activation functions. The kernel sizes of the branches are $[3, 3]$ and $[1, 1]$ and the bias is 0. It is shown in [18] that these branches form actually a linear model, shown in Eq. 1. For the results, the outputs of the decoder branches are eventually summed up. The latter branch is fixed so that it has the hematite reflectance spectrum [20] as the initial value for the weights of the kernels, and those are not altered during training. This enables the detection of hematite in the image.

Another branch forms R endmembers during the training to the weights of the layer kernels. Details of this branch and encoder can be found in [18]. Total variation regularisation is applied in weights to reduce changes or variations in the spectral profile of the endmembers. By minimising the total variation along the spectral dimension, the regularisation encourages the model to produce smoother and more continuous spectral profiles for the output. Now, the encoder estimates the abundance of both endmembers and hematite spectra.

Our loss function combines spectral angle similarity L_{sam} and mean squared error L_{mse} so that the total loss

$$L_{tot} = (1 - \alpha)L_{mse} + \alpha L_{sam}, \tag{2}$$

where α is the specified weight between the two terms.

In the comparative analysis of rock painting delineation, three methods were employed. Firstly, Principal Component Analysis (PCA), a prevalent technique in spectral imaging, was utilised. PCA extracts the principal components that account for most variance within the spectral domain, revealing different parts of the image [21]. Additionally, two distinct spectral unmixing methods were incorporated. VCA with least squares minimization were chosen for its rapid and robust capabilities in identifying endmembers and their distribution within the image [15]. Lastly, a neural network-based autoencoder approach (AES) was also used [17]. The approach is limited to handling single spectra at a time. This approach does not assume the presence of pure pixels, as VCA does.

3. RESULTS

Pigment analysis was conducted using the modified autoencoder. As seen in Fig. 3, hematite was detected in the human figure but not in the image of hand-representing stains. The endmembers identified by the autoencoder differ slightly between the images, but on the other hand, the rock seen in Fig. 1 also exhibits different shades.

Delineation comparison in Fig. 4 visualises the results of four analysis methods besides a delineation image of the current ground truth. The human figure is most recognisable using VCA. The autoencoder that focuses solely on the spectrum (AES) performs weakest, whereas PCA (second principal component) brings to the fore the most artefacts. Our model (AEC) emphasises pixels that have more than 30% hematite concentration and confirms the results of best-performing VCA by bringing authenticity information based on pigment analysis. In Fig. 4, the image produced by each method has been thresholded according to the scale to bring out the contrasts best. The VCA results confirm that spectral imaging may bring new information from faded figures, opposite the previous ground truth, the supposed small game animal in the human hand seems to be more of a typical human-like figure with raised hands and a line between legs. Similar human figures are seen in literature, for example, in [4, 5, 2].

4. DISCUSSION AND CONCLUSIONS

The results of the pigment analysis are promising. Based on the results, we can confirm that based on the hematite pigments, the origin of the hand-representing stains may be different than the origin of the human figures. Regarding delineation, the computationally simplest unmixing method, VCA, yielded the clearest result and unveiled new information from

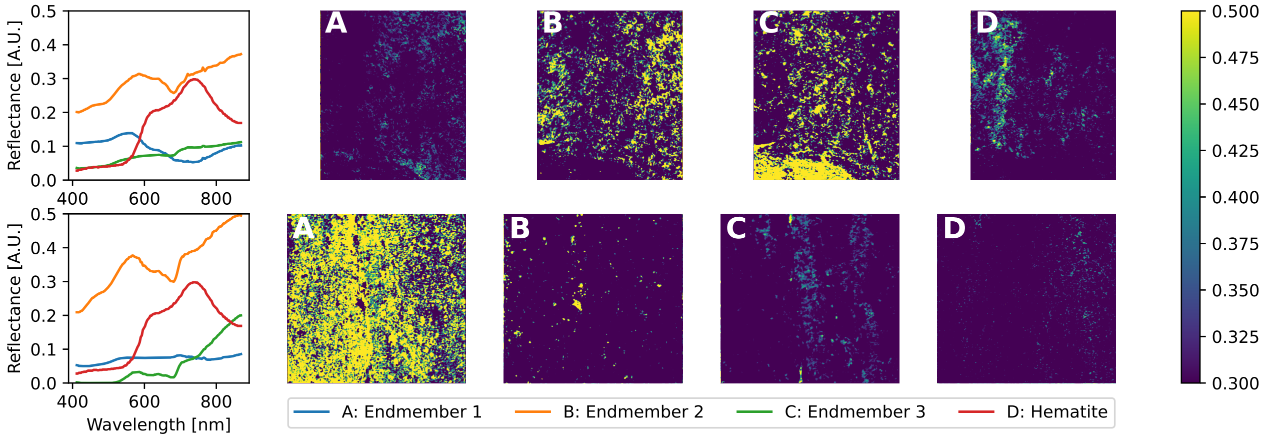

Fig. 3. The first row presents the endmembers identified from the human figure, along with the spectrum of hematite. Following the spectra, the images represent the relative abundances (30-50%) of the endmembers (A-C) and hematite (D) within the image. The second row displays corresponding information for the hand-representing stains. By comparing hematite results, we can see no similar pigment in the hand-representing stains in the human figure.

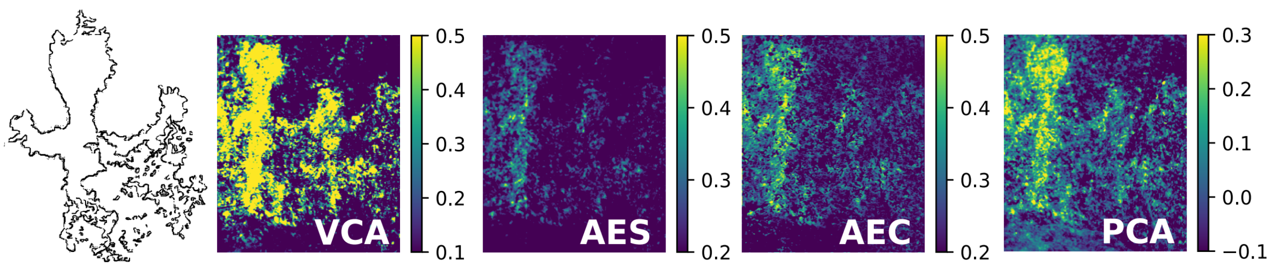

Fig. 4. Delineation of the current ground truth (re-drawn based on digitally enhanced RGB image [4]) and delineation results for four different analysis methods (VCA, AES, AEC and PCA). The human figure and the adjacent figure are most distinctly discernible using VCA, and AEC confirms the pigments are 20-50% hematite-based.

the "small game animal", which may be instead a smaller human figure.

VCAs outperforming suggests that the figure's paint might have been a mixture of pigments, containing not only our reference hematite spectrum, where VCA identified some form of the combined spectrum. As we now understand, the investigation of pigments is not without its challenges. For instance, the spectrum of hematite drastically changes according to particle size, and the particle size varies depending on the heating process. Additionally, paints have utilised various colourants and binding agents depending on the artist, related rituals, available materials, and used techniques [9]. Last, one challenge may lie in the silica skin, which changes the pigment appearance from translucent to milky. Currently, AEC and VCA work nicely together. VCA can reveal features that are not visible in RGB images, and AEC can measure whether there are actual hematite pixels in the pigment. Therefore, these methods can be used for documentation and authenticity assessments. In the future, if the spectra of these other substances are known, an extended spectral library can be integrated into the presented model, thereby enabling a more precise determination of spectral concentrations. More detailed pigment analysis could be used to distinguish between rock paintings created at different times and by various artists. This may lead to one model that can do both: reveal features for delineation and analyse pigments for authenticity.

Convolutional autoencoder makes it possible to use regularisations in the spatial domain. For example, the spatial correlation of the underlying rock texture could be utilised, or 2D total variation could be appropriately applied to enhance the delineation of the drawings. This could improve convergence.

Based on the results, it can be concluded that rock paintings can be detected from spectral images. By using spectral libraries as part of the unmixing process, we can also estimate the pigment concentrations in the paintings and assess their authenticity.

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