Hyperspectral imaging through partially transparent media

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ABSTRACT

The operation of hyperspectral imaging systems in industrial environments can be a challenge. In the nuclear industry, partially transparent elements such as gloveboxes or panels are often used to cover samples for protection against the risk of contamination. In practical terms, this means that the hyperspectral sensors can only capture data through partially transparent media, which interferes the vision between sensor and sample. Representative examples of these media are Polymethyl Methacrylate (PMMA) or acrylic and Polycarbonate (PC). In this work, we evaluate the effect that the transparent media can have on the data when captured under these conditions, where transparent materials are placed between sensor and sample. Experiments include hyperspectral images of the same samples captured with and without panel obstruction for a direct comparison of spectral responses, suggesting potential artificial intelligence techniques and methods to identify these effects and mitigate them.

Keywords: Hyperspectral imaging, industrial environment, vision obstruction, transparent media, acrylic

1. INTRODUCTION

Hyperspectral imaging (HSI) captures high-resolution spectral responses at each pixel of a 2D image, resulting in a 3D data cube of spatial and spectral information. Hyperspectral cameras typically capture at least a few hundred spectral bands and can have ranging that include not only the visible light but also extend into either the ultraviolet or infrared spectrum [1]. The technology has a wide range of applications for identifying the presence of materials [2] or tracking changes in surface chemistry [3]. The non-destructive nature of this technology makes it particularly useful in hazardous industrially scenarios where it is critical not to disturb the subject being imaged. In such cases it is common for the subject to be secured behind clear panels so as to protect human operators from harm, or indeed to protect the subjected itself. The materials from which these clear panels are made, such as acrylics, are often only partially transparent. The clear appearance only guarantees approximate transparency in the visible range, while it may be the case the an apparently clear panel is in-fact blocking some light in the infrared range. They also normally absorb at least some of the light at all wavelengths so at least darken the signal captured by a camera the other side of the panel.

In this study, we perform HSI on several samples, with and without panels of different types and thickness to study the effects of imaging through partially transparent media. We also propose how such effects could be corrected, and when the panel used might limit the performance of an HSI camera.

2. MATERIALS AND METHODS

The effect of partially transparent media on HSI data was investigated by imaging samples of known spectral response through two materials; Polymethyl Methacrylate (PMMA) and Polycarbonate (PC). Two different thickness of each material were used, 3mm and 10mm, to establish the effect of panel thickness on the measured spectra. Hyperspectral images were captured in the wavelength range of 400-2500nm. Different samples were imaged through the panels, to provide features across this range. These samples included a Spectralon reference bar, which should reflect evenly across the full range after calibration procedures, coloured chalks that will have features below 700nm depending on the colour stainless steel (316L mesh type), provided by Sellafield Ltd, as a representative of the types of materials that may be included in samples imaged in challenging environments in the nuclear industry. Two layouts of these materials were used in imaging and are shown in Figure 1.

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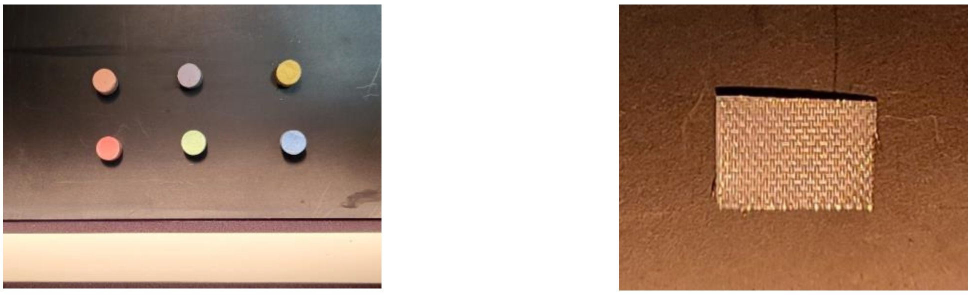


a) b)

Figure 1. Materials imaged through the partially transparent panels where a) colour chalk (and Spectralon bar) for viewing effects in the visible range, and b) 316L for viewing the effect in the shortwave infrared range.

Data was captured using two separate cameras (see Figure 2) from Headwall Photonics Inc. [4], each operating in different regions of the electromagnetic spectrum. Data in the visible and near infrared range was captured using the VNIR-E series camera, which has 1600 spatial pixels and 373 spectral channels in the range 400-1000nm, thus giving a resolution of ~1.63nm. Data in the shortwave infrared range was captured using the SWIR-640 camera, which has 640 spatial pixels and 272 spectral channels in the range 900-2500nm, giving a resolution of ~6nm.

a) b)

Figure 2. Hyperspectral cameras used to capture data: a) VNIR-E series (400-1000m), and b) SWIR-640 series (900-2500nm). A resolution test chart the size of a credit card is included for scale.

Both systems are line-scanners and require translation of either camera or subject in order to image a 2D area, such as shown in Figure 1. This is common for this type of sensors and is referred to as a "push-broom" mechanism [1]. To achieve this, the setup shown in Figure 3 was used, which included a translation stage to move the sample at a fixed speed and a halogen lamp to illuminate the sample across all relevant wavelengths.

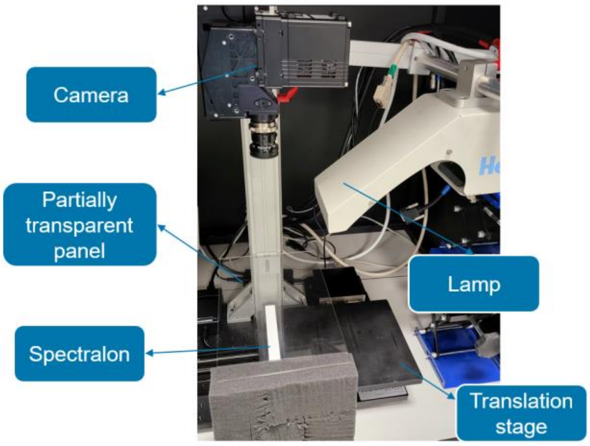
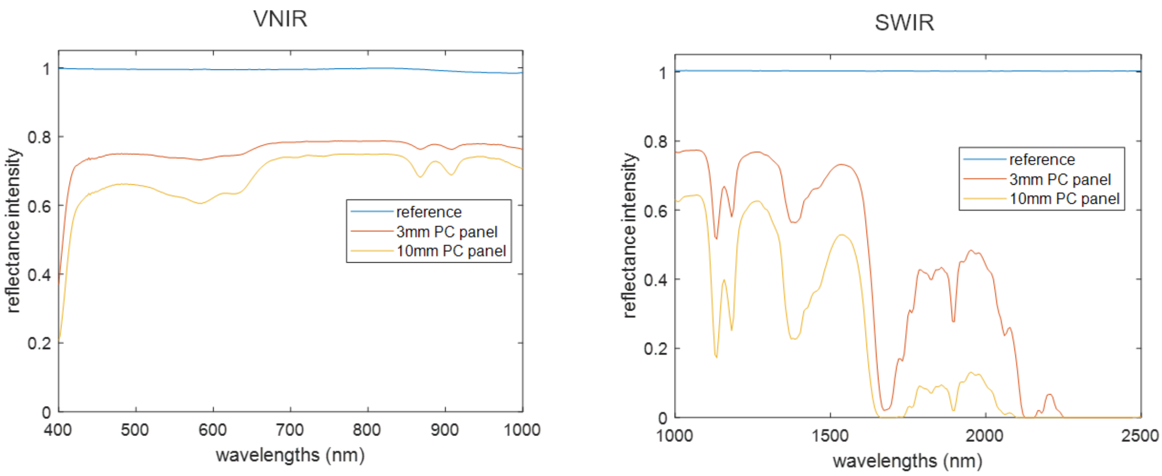


Figure 3. HSI imaging setup showing each element used.

Calibration of this system is critical to ensure good performance and properly capture the intended data. The halogen bulb provides illumination across the 400-2500nm range, but camera sensors are often not equally sensitive to light at all wavelengths. Thus, the Spectralon bar, which is known to have the highest diffuse reflectance across this range is used to correct for this effect and normalise the reflectance to the range [0-1] (zero for 0% reflectance and one for 100% reflectance). The height at which the camera is fixed should be set depending on the field of view and resolution required. The speed of the translation stage should then be set based on this height to ensure each pixel covers a square area and is not stretched or distorted. In this experiment the panel was placed 10cm above the translation stage and the camera 25cm above the panel. To observe the true effect of the panel, data was captured based on a prior calibration without the panel in place. Data was also recaptured later on with calibration based on Spectralon imaged through the panels, to determine if any negative effects could be removed in this way.

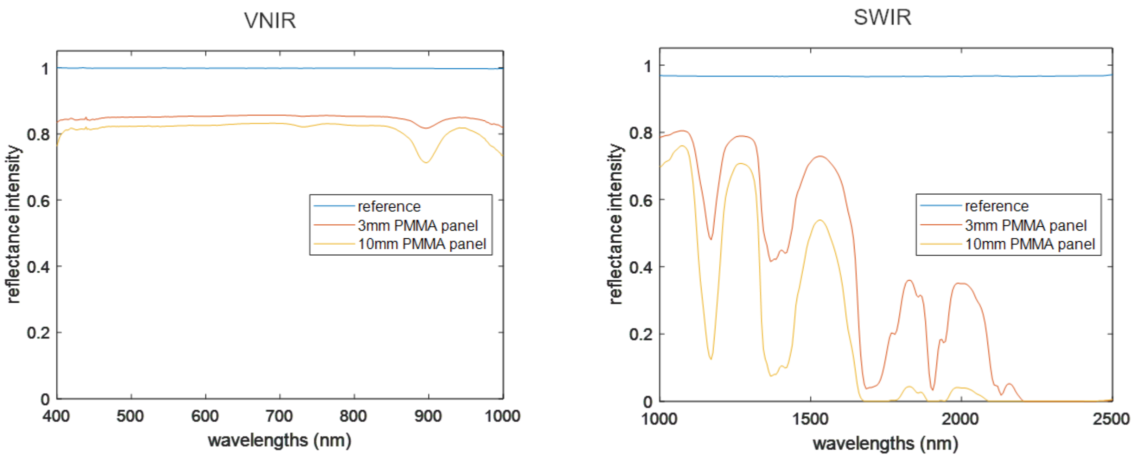
3. EFFECT OF THE PANELS ON THE DATA

The effect of the panels can be easiest observed by evaluating the spectra captured for the Spectralon bar through each panel and comparing it to the original expected response for Spectralon in normal conditions after calibration (reference). The effect of the PC panel is shown in Figure 4 and the effect of the PMMA panel is shown in Figure 5.



a) b)

Figure 4. Effect of PC panel on captured spectra for Spectralon bar where a) VNIR, and b) SWIR.

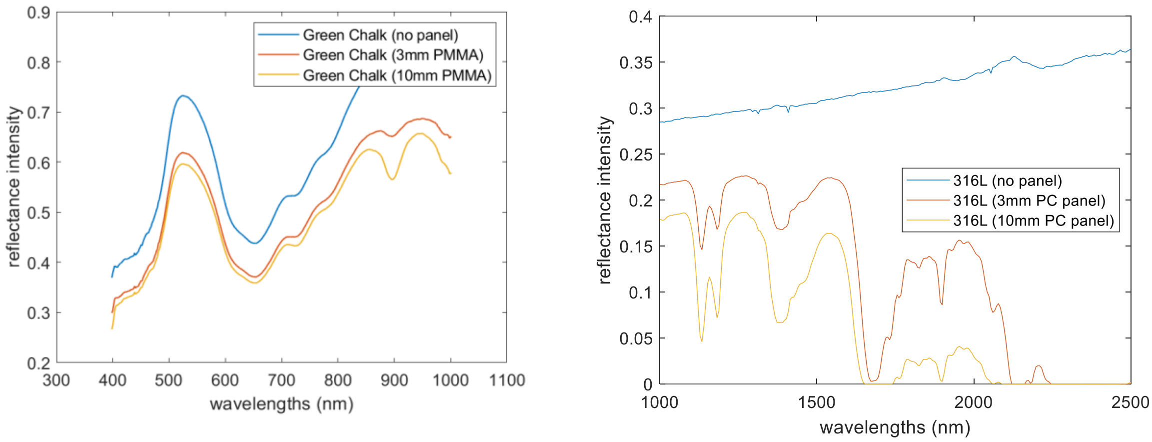


a) b)

Figure 5. Effect of PMMA panel on captured spectra for Spectralon bar where a) VNIR, and b) SWIR.

In all cases it can be observed that the captured signal is affected by the media it was imaged through, with the level of light reflected back always reduced compared to the reference due to the absorption of the panel. The 10mm panel absorbs more light than the 3mm panel, increasing the distortion on the captured data in each case. However, some effects of the panel are more severe than others. The PMMA panel, Figure 5 a), absorbs light quite consistently between 400-800nm, so while the magnitude of captured spectra would be reduced, the features of this spectra would experience very little distortion. Conversely, at 900nm there is a band of increased absorption that creates a feature in the spectra where one should not exist. This characteristic is likely to be more problematic when processing this data for classification tasks [5]. The most significant problems occur in the SWIR range, where for the thickest 10mm panel the absorption is such that no light is reflected back above ~2100nm. Thus, in addition to the requirement to process out the false features induced in Figure 4 b) and Figure 5 b) the range of the camera is reduced by around 400nm.

The problems caused by the absorption of light for measuring real samples can be observed in Figure 6. In Figure 6 a) the even absorption of light up to 800nm means that the shape of the green feature is largely unaffected, with this feature just a little dimmer due to the absorbed light. There is, however, a feature at 900nm, most prominent for the 10mm panel, that is not representative of the colour chalk. In Figure 6 b) the effect of the panel is so severe that, as a result, the captured spectra is dominated by panel absorption and information about the 316L material is lost.



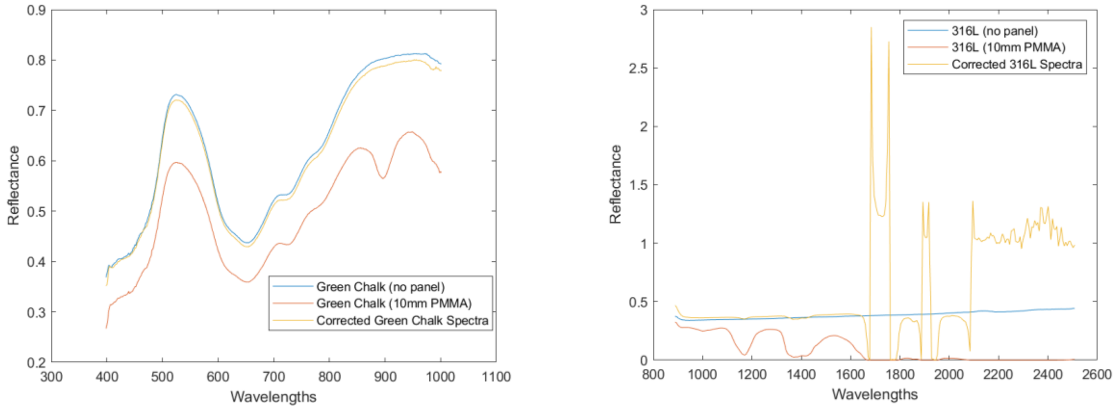
a) b)

Figure 6. Effect of panels on captured spectra where a) green colour chalk in VNIR range through PMMA, and b) 316L in SWIR range through PC.

4. POTENTIAL AI TECHNIQUES TO SOLVE THE CHALLENGE

Removing the effect of the panels on the captured spectra is a slightly different challenge depending on the severity of the effect that it has. In the best case, there are only small features added to the data due to additional absorption at certain wavelengths, which may be removed by amplifying the received signal at these wavelengths, similar to the calibration procedure used to adjust the effect of the sensors sensitivity to different wavelengths of light. However, for more severe cases, such as seen in the SWIR range, this may not be sufficient and more advanced methods may be required.

The limitations of amplifying the signal in the absorbed regions via a calibration procedure (calibration based on Spectralon imaged through the panels) are shown in Figure 7. For minor effects and false features this can be quite effective, as shown in Figure 7 a). However, in the case shown in Figure 7 b), where the panel had greater absorption, this technique adds significant artefacts and does not work well.



a) b)

Figure 7. Correction of panel effects using calibration procedures where a) shows adequate correction of minor panel absorption issues in VNIR range, and b) shows artefacts induced by attempts to correct more significant panel effects in SWIR range.

Machine learning technologies may offer more effective solutions for post-processing these signals and removing panel effects when calibration through panels is not possible. In particular, deep learning methods could be used [6]. For example, Generative Adversarial Networks (GANs) [7] could be trained to generate the original/reference spectra based on the distorted captured spectra. Stacked-Autoencoder [8] or Support Vector Machines (SVMs) [9] could also be used for similar purposes. Further work is required to establish the optimal approach for these more challenging cases, however, some early promise has been shown using a combination of a feed forward neural network and Singular Spectrum Analysis (SSA) [10]. Figure 8 shows an attempt to recover a 316L spectra using this method. It is clear that the recovered spectra better approximate the original spectra, however, key features above ~2100nm may not be fully restored.

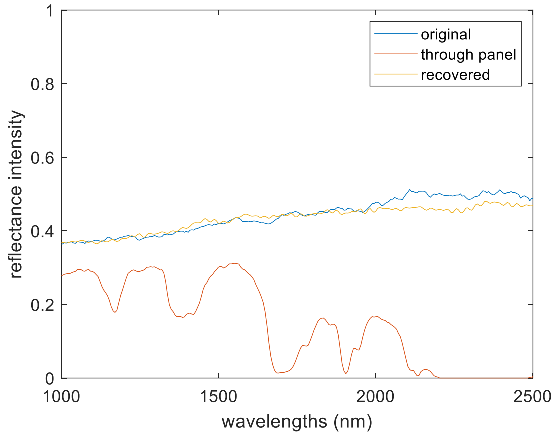


Figure 8. Attempt at recover of 316L spectra using a feedforward neural network and SSA.

5. CONCLUSIONS

Partially transparent media, such as PMMA and PC panels, can have a significant effect on the captured spectra when samples are imaged through these panels in the industries such as nuclear. In the VNIR range (400-1000nm), this results in false features and distortion of the spectra that can be largely corrected using standard calibration procedures, provided a calibration tile can be placed the other side of the panel. In the SWIR range (1000-2500nm), these panels have a more significant effect, completely absorbing light in some wavelengths, including all wavelengths above ~2100nm. In this range, it is significantly harder to correct the spectra for panel effects and it may not be possible to fully recover all features. In all circumstances the thicker panel lead to an increased distortion of the underlying spectra. A few methods are suggested that may be used to correct for panel features in future work, with a feedforward neural network showing some promise. However, it is expected that the complete absorption of light at the upper end of the range may lead to unrecoverable spectra information unless complementary approaches, e.g., prior knowledge based, are introduced to support the data recovery process.

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