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A multi-temporal hyperspectral target detection experiment: evaluation of military setups

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A MULTI-TEMPORAL HYPERSPECTRAL TARGET DETECTION EXPERIMENT - EVALUATION OF MILITARY SETUPS

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ABSTRACT

This paper shows three experiments from our HyperGreding'19 campaign that combine multi-temporal hyperspectral data to address several essential questions in target detection. The experiments were conducted over Greding, Germany, using a Headwall VNIR/SWIR co-aligned sensor mounted on a drone with a flight altitude of 80 m. Additionally, high-resolution aerial RGB data, GPS measurements, and reference data from a field spectrometer were recorded to support the hyperspectral data pre-processing and the evaluation process for the individual experiments. The focus of the experiments is the detectability of camouflage materials and camouflaged objects. When the goal is to transfer hyperspectral analysis to a practical setting, the analysis must be robust regarding realistic and changing conditions. The first experiment investigates the SAM and the SAMZID approaches for change detection to demonstrate their usefulness for target detection of moving objects within the recorded scene. The goal is to eliminate unwanted changes like shadow areas. The second experiment evaluates the detection of different camouflage net types over two days. This includes camouflage nets in shadows during one flight and brightly illuminated in another due to varying solar elevation angles during the day. We demonstrate the performance of typical hyperspectral target detection and classification approaches for robust detection under these conditions. Finally, the third experiment aims to detect objects and materials behind the cover of camouflage nets by using a camouflage garage. We show that some materials can be detected using an unmixing approach.

Keywords: hyperspectral, multi-temporal, target detection, change detection, classification, camouflage, unmixing

1. INTRODUCTION

Hyperspectral sensors measure the electromagnetic spectrum in hundreds of narrow and contiguous spectral bands. The recorded data can resolve characteristic features of materials and objects without direct interaction. Consequently, it is possible to use hyperspectral data to discriminate between very similar materials and objects in a remote sensing setting.¹⁻³ This is especially important for military applications to increase the robustness of detecting and classifying objects and areas where errors can potentially have severe consequences.

The availability of hyperspectral remote sensing data with a security and defense background is very limited.

Due to the sensitivity of the recorded information, there are no data sets openly available to our knowledge. With the support from the *WTD 81 (Bundeswehr Technical Center)* and *armasuisse W + T*, we conducted our measurement campaign with a diverse set of German and Swiss camouflage nets. For this publication, we are not allowed to share specific information about the used materials. However, the results can still be essential to judge the capability of hyperspectral sensors for this sector. The experiments of previous measurement campaigns can be found in Ref. 1,2.

Our most recent experiments from the HyperGreding'19 campaign combine multi-temporal hyperspectral data to address several essential questions in target detection. The experiments were conducted at the training area of the WTD 81 in Greding, Germany. Additionally, high-resolution RGB data, GPS measurements, and reference data from a field spectrometer were recorded to support the hyperspectral data pre-processing and the evaluation process for the individual experiments.

Multiple experiments were prepared on the ground, mainly focused on the detectability of camouflage materials and camouflaged objects. We designed the individual experiments with an emphasis on the campaign's multi-temporal component since hyperspectral data recording is usually synchronized with ideal environmental conditions. When the goal is to transfer hyperspectral algorithms to a practical setting, analyses have to be robust for realistic and changing conditions.

Following, we give a short description of the measurement campaign from 2019 before going into more detail about the three main experiments. The first experiment evaluated different approaches for change detection of multi-temporal hyperspectral data, focusing on eliminating natural variations of illumination, vegetation, etc. The second experiment analyzes the detection capability of different types of camouflage nets over two days. This includes camouflage nets in shadows during one flight and brightly illuminated in another. Additionally, some camouflage nets are further concealed by freshly cut vegetation to reduce detectability. We discuss approaches to mitigate spectral variability and robust detection under these conditions. The third experiment aims to detect objects and materials behind the cover of camouflage nets inside a camouflage garage. We show that some materials can be detected using an approach based on spectral unmixing.

2. MEASUREMENT CAMPAIGN

The data used for the experiments in this publication are part of the HyperGreding'19 campaign, which was conducted as a joint German-Swiss measurement campaign at facilities of the WTD 81, Greding, Germany. The focus of our experiments was on exploiting the high spectral and spatial resolution of our Headwall VNIR/SWIR co-aligned sensor mounted on a DJI Matrice M600 Pro drone. With an average altitude of 80 m, the data have a ground sampling distance of approximately 0.05 m. Additionally, the APEX (Airborne Prism EXperiment^{4,5}) sensor mounted on a plane was used to acquire airborne hyperspectral imagery over the area at 2400 m above ground, and a Sensefly eBee drone with an integrated high-resolution RGB camera was flown. The APEX data will be used in the future to determine potential scale-invariant approaches to hyperspectral data processing. During pre-processing, the eBee data were used to improve the georeferencing and co-registration accuracy of the Headwall mosaics used for the individual experiments. In general, we recorded four different scenarios at different times with individual target and object placements during a single day and repeated the setup over two days. Table 1 gives an overview of flight times and corresponding solar elevation. Due to the size of the experiment area, we had to perform three separate drone flights for each scenario, as the drone's batteries only allowed for an approximate measurement time of 17 minutes. Most targets and camouflage objects were located in the western part of the experiment area, and we mostly used the corresponding data that best fit each experiment.

Table 1: Overview of the four Headwall scenarios acquired on 5 June 2019.

	Scenario S1	Scenario S2	Scenario S3	Scenario S4
Acquisition Time (UTC)	0624 - 0701	0919 - 1004	1112 - 1201	1335 - 1415
Acquisition Time (LT)	0824 - 0901	1119 - 1204	1312 - 1401	1535 - 1615
Solar Elevation	28° - 34°	55° - 60°	63° - 61°	51° - 45°

Figure 1: RGB representation of the Headwall hyperspectral mosaic used for the experiments.

Figure 1 shows the RGB color composite of the Headwall sensor for this test site. It contains two camouflage garages on the meadow east of the road, three 7×7 m square molton fabric targets below the camouflage garages, several other fabric targets on the south-western meadow next to the road, and several camouflage nets in and around the shrubbery on the north-western and western side of the scene, as well as in the quarry located in the south-western part of the scene. The quarry lies approximately 8 m lower compared to the rest of the scene and has difficult lighting conditions during the morning flights due to shadows.

More information about the measurement campaign, sensors, and data pre-processing can be found in Ref. 6.

3. EXPERIMENTS

This section describes the individual experiments from the HyperGreding'19 campaign. First, different approaches for general change detection tasks are discussed. The second part deals with detecting and classifying camouflage nets from different manufacturers under varying conditions, such as vegetation cover or illumination changes. Finally, we evaluate the transparency of two camouflage setups covering a set of molton fabric targets.

3.1 Change Detection

Detecting changes in a time series of images is an essential topic in the security and defense context. Those changes can be either natural or man-made, where the latter can pose potential threats to operations, e.g., improvised explosive devices (IEDs) along the route of a convoy.⁷

Hyperspectral sensors can register small spectral deviations compared to RGB cameras. This can be used to derive accurate change maps between a given reference and subsequent test data sets of the same area. There are several prerequisites to computing these change maps. Ideally, the data sets have to be co-registered with pixel accuracy. Additionally, the results can be improved if the two data sets to be compared were recorded at the same time during a day to mitigate the influence of different illumination angles. However, this is not always possible, which is why we investigate the performance of two change detection approaches that promise

(a) Change map calculated with the SAM difference image approach. Yellow areas correspond to high spectral differences.

(b) ROC curve for the detection of moving targets with the SAM image difference approach.

(c) Change map calculated with the SAMZID approach. Yellow areas correspond to high spectral differences.

(d) ROC curve for the detection of moving targets with the SAMZID approach.

Figure 2: Change detection maps and corresponding ROC curves for the target detection with SAM difference image and the SAMZID approaches.

a suppression of natural changes such as shadows. The first approach is based on the Spectral Angle Mapper (SAM).⁸ We calculate the SAM between the spectra in the reference data set $X \in \mathbb{R}^{b \times n}$ and the corresponding pixels in the test data sets $X' \in \mathbb{R}^{b \times n'}$ according to

$$SAM(x, x') = \text{acos} \left(\frac{x^T x'}{\|x\|_2 \|x'\|_2} \right), \quad (1)$$

where $x \in X$ and $x' \in X'$ are the pairs of spectral signatures of each data set given by the co-registration. b is the number of spectral bands in both data sets and n, n' are the number of samples in X and X' , respectively. The output has small values when the spectral similarity is high and high values, where the spectral similarity has changed between the scenes. Since the SAM is calculated from the normalized spectral signatures, it is often considered to be invariant towards illumination changes. This is only partially true, as the absence of direct illumination results in non-linear signal variations.⁹ However, computing a physical model of these effects is very complicated and, in most cases, not possible due to the lack of auxiliary information, such as slope angles, atmospheric conditions, etc. Fortunately, it is possible to compute a change map without a complete description of these effects.

The second method is called SAMZID, which is a concatenation of SAM, the modified Z-score metric MZ and

the image difference (ID).¹⁰ Here, the authors claim a better suppression of natural changes compared to the aforementioned SAM difference calculation. The SAMZID algorithm is calculated by first computing the ID between a reference and the test data set. From the output, the modified Z-score is calculated for each difference spectrum x as

$$MZ(x) = \text{normalized}_{\text{w.r.t. } \|\cdot\|_2} \left(\sum_{i=1}^b \left(\frac{x_i - \mu}{\delta} \right)^2 \right), \quad (2)$$

where b is the number of spectral bands, μ is the mean value, and δ is the standard deviation of the ID data set. Finally, the resulting SAMZID change images are calculated by

$$\text{SAMZID}_{tan} = \text{normalized}_{\text{w.r.t. } \|\cdot\|_2} (\tan(\text{SAM})) * MZ(\text{ID}), \quad (3)$$

where $*$ indicates a pixel-wise multiplication.

We selected one mosaic from our measurement campaign as the reference and calculated the change maps based on the two previously mentioned approaches for the evaluation. Examples for the change detection results with the same reference and test data sets are compared in Figure 2 for both methods. The upper row of images shows the change map and the receiver operating characteristic (ROC) curve of the SAM difference calculation. The lower images correspond to the SAMZID_{tan} results. The ROC curve was calculated by comparing the manually generated ground truth maps of each scene. Due to inaccuracies of the georeferencing process, a safety distance of ± 3 pixels was established. The x-axis of the ROC curves was cut off at a false positive rate of 0.2 to better focus on the correct detections. Especially the SAMZID_{tan} results show almost no false positives until a true positive rate of 70 % is reached. A visual interpretation of the two change maps shows that the SAM result has a higher false positive rate (FPR), especially in the lower-left corner, which contains a quarry with almost vertical walls and many shadows. Also, areas with tall vegetation have a higher probability of being detected as changes. One possible reason for these false positives is the small shadows and natural changes in the foliage that the SAM difference calculation can not properly account for. The SAMZID_{tan} change map below shows a higher contrast between the actual changes and the natural variations of the background. It even allows the detection of the two small camouflage nets on the bottom of the quarry in the lower-left corner. The corresponding ROC curve is also better, which supports the claim of Ref. 10 that their approach is better suited to suppress natural changes and variations of the illumination and shadows. It appears that the ROC curve of the SAM image difference is able to discover some changes before the SAMZID_{tan} method, starting around a FPR of 0.04. The better results at smaller FPR values together with the higher contrast make SAMZID_{tan} superior for detecting the relevant changes.

3.2 Camouflage Detection

To assess the impact of varying illumination conditions on the camouflage detection performance, the SAM from equation (1) and the Adaptive Coherence Estimator (ACE) target detection from Ref. 11 were applied to detect two distinct types of camouflage net (CN1 and CN2) in four temporally different Headwall mosaics (see Table 1).

Instead of the pixel-wise comparison of spectral signatures from Section 3.1, here, the SAM calculates the spectral angle between each measured image pixel spectrum $x \in \mathbb{R}^b$ and a single fixed reference spectrum $t \in \mathbb{R}^b$. The ACE is a threshold detection test that jointly exploits spectral signatures' detection statistics while searching for a common threshold that optimizes the separation between the target t and the background. The ACE for

Table 2: Target detection rates for Headwall scenario S1 to scenario S4 for camouflage nets CN1 and CN2, assessed with SAM and ACE, and expressed in DRFPR0.1. The results of S3 are given in parentheses due to the smaller evaluation area.

Target	Algorithm	DRFPR0.1 in %			
		S1	S2	S3	S4
CN1	SAM	70.05	80.96	(93.56)	85.06
CN1	ACE	81.08	81.88	(94.39)	88.22
CN2	SAM	63.84	81.58	(99.84)	74.12
CN2	ACE	80.04	76.82	(99.84)	83.51

a single spectral signature x can be calculated as follows

$$ACE(x) = \frac{(x - \mu)^T \Sigma^{-1} (t - \mu)}{(x - \mu)^T \Sigma^{-1} (x - \mu) (t - \mu)^T \Sigma^{-1} (t - \mu)}, \quad (4)$$

where $\mu \in \mathbb{R}^b$ is the band-wise mean of the data set X and $\Sigma^{-1} \in \mathbb{R}^{b \times b}$ is the inverse covariance matrix of X . To optimize the contrast between target and background, it is best to exclude any potential target areas in the data set for the calculation of μ and Σ^{-1} .¹ This appears counterintuitive, but when the same landscape is monitored on a regular basis, it can be beneficial to use the image statistics from a data set that contains no targets. In our experiments, the amount of pixels covered by camouflage nets in the scene was high enough to affect the image statistic and reduce detectability.

The detection performances were measured using the *detection rate at a false positive rate of 0.1%* (DRFPR0.1). The reference for the assessment of the detection rates was a ground truth mask based on the differential GPS measurements of the targets' positions, which was adapted to the Headwall data employing visual inspection.

The target detection results of the two camouflage net types CN1 and CN2 in the four Headwall mosaics S1-S4 are summarized in Table 2. Exemplary SAM outputs for scenarios S1 and S4 are shown in Figure 3. The SAM results were selected for this publication for their better visibility compared to the ACE results.

In general, the target detection performance improved from morning toward noon and afternoon, shown by the steadily increasing DRFPR0.1 percentages. The improvement is related to a better illumination of the targets due to an increasing solar elevation angle, leading to improved separation of target and background areas. This can be seen in the left part of Figure 3. During the recording of scenario S1, the two camouflage nets inside the quarry area were shadowed due to a low solar elevation angle, which resulted in a low detection result. With a higher sun elevation in scenario S4, they could be detected well. Scenario 3 has the highest detection rates of all evaluated scenarios. This is mainly affected by the smaller mosaic size, which lacks some of the more difficult targets. Based on the solar elevation angle, a slightly better detection rate compared to scenario S2 can be expected.

With both algorithms and throughout all scenarios, CN1 was slightly easier to detect than CN2. This finding corresponds to the observations from previous years.^{1,2} Although the specific performance of the algorithms was not a significant focus of the analyses, it was found that with few exceptions, the ACE led to higher detection rates than the SAM. Still, the SAM benefited to a more considerable degree from good illumination conditions. This can be observed comparing the detection percentages for S1 and S2, where the SAM showed a more significant increase in DRFPR0.1 than the ACE.

(a) S1: CN1

(b) S1: CN2

(c) S4: CN1

(d) S4: CN2

Figure 3: SAM results for the camouflage nets CN1 and CN2 in scenarios S1 and S4. Dark areas correspond to a smaller spectral angle between the measured image pixel spectrum and the reference spectrum, which means a higher similarity. Red outlines indicate the CN1 locations, whereas blue outlines denote the CN2 areas.

3.3 Camouflage Transparency

The experimental results for the detection of camouflage nets with hyperspectral sensors are outstanding (see Section 3.2) and even work reliably on a sub-pixel level.^{1,2} Camouflage nets are generally used to conceal other objects, which might pose a much more significant threat to an operation compared to an empty net. We devised a specific experimental setup where various fabric targets are placed on the ground and concealed by a camouflage garage with a height of approximately 2.5 m. Additionally, a vehicle with specific camouflage paint was parked in the camouflage garage.

The recorded hyperspectral signal of a given spectrum is a combination of the observed materials. This means that we try to determine the object's fractional signal in the combined spectrum to detect an object concealed by a camouflage net. This approach is referred to as spectral unmixing. It is often used to mitigate insufficient spatial resolution in hyperspectral data, where multiple materials are mixed in a single image pixel.¹²

(a) OSP results with empty camouflage garage.

(b) OSP results with *molton green* target on the ground of the camouflage garage.

(c) OSP results with the *molton white* target on the ground of the camouflage garage.

Figure 4: RGB representation and OSP results of the camouflage garage for different target materials. The columns show the RGB representation and the calculated fraction of the target spectrum for *molton green* (middle) and *molton white* (right).

For our experiment, we assume a linear mixing model and use the Orthogonal Subspace Projection (OSP) method.¹³ The algorithm requires a single target spectrum and several background spectra to determine the remaining components after the individual spectra are projected onto the subspace given by the background spectra. Our experiment uses the spectra of the differently colored patches of the camouflage nets (green, brown, and black) as background material. They were measured with an ASD field spectrometer during the experiment and resampled to fit the spectral bands of the hyperspectral sensor.

In this case, we only visually evaluate the results since the exact locations of the concealed materials were not recorded during the measurement campaign. Figure 4 shows an RGB color representation and the OSP results for the camouflage garage without a target material and the *molton white* and *molton green* fabric target, respectively.

The RGB color images of the camouflage garage in Figure 4 show minor differences due to the time of day the corresponding scenario was recorded and the off-nadir angle. The middle and the right column of the graphic show the amount of detected *molton green* (middle) and *molton white* (right) in the OSP results. Consequently, the images in Figure 4a, which correspond to the scenario without any target in the camouflage garage, emit only a minor abundance for each of the fabric targets. Figure 4b shows a clear target outline in the camouflage garage for *molton green* in the middle image. The right image also shows a small abundance for *molton white*, which is likely due to the similarity in spectral signatures of the fabric targets beyond the visible spectrum. The abundance for *molton white* in the right image of Figure 4c clearly shows the location of the target inside the camouflage garage. There is no confusion with the abundance of *molton green*. Our experiments with the vehicle with camouflage paint inside the camouflage garage did not indicate the target's presence. Possible explanations are the spectral similarity between the camouflage paint and the camouflage net or the generally low signal of the dark camouflage paint further reduced by shadowing caused by the camouflage garage.

Overall, this experiment shows that it is possible to detect and classify targets concealed by camouflage nets. It also indicates that brighter targets can be detected more easily. It is important to note that only a single layer of a specific camouflage material was used for the experiments. The results may vary with different camouflage materials and additional forms of concealment.

4. OUTLOOK

This publication presents the results of individual experiments from our HyperGreding'19 measurement campaign, specifically evaluating the change detection, camouflage detection, and camouflage transparency experiments.

In conclusion, we can say that the results match our expectations from previous experiments. The detection and classification capabilities of hyperspectral sensors for camouflage materials are outstanding. Even additional precautions such as tree branches and leaves on top of the camouflage nets could not completely prevent their detection. However, spectral variations due to changes in illumination, shadows, and off-nadir angles of the recorded data can negatively impact the change detection. Additionally, further methods need to be tested to calculate better discrimination between natural variations and the desired changes between the different data sets. The camouflage transparency experiment was the first practical approach to detect and classify camouflaged objects. The results indicate that the OSP approach works for strong contrasts between the camouflage cover and the target object. Additionally, the OSP assumes a linear mixing model of target and background material. However, the shadowing of the camouflage net on top of our target might be better modeled with a non-linear mixing model. Additional experiments are planned to determine detection limits for various height differences

between the camouflage topping and the object to be detected. The next measurement campaign to evaluate the camouflage transparency detection limits will take place during summer 2021.

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