Visualization of hyper spectral imagery

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ABSTRACT

We developed four new techniques to visualize hyper spectral image data for man-in-the-loop target detection. The methods respectively: (1) display the subsequent bands as a movie ("movie"), (2) map the data onto three channels and display these as a colour image ("colour"), (3) display the correlation between the pixel signatures and a known target signature ("match") and (4) display the output of a standard anomaly detector ("anomaly"). The movie technique requires no assumptions about the target signature and involves no information loss. The colour technique produces a single image that can be displayed in real-time. A disadvantage of this technique is loss of information. A display of the match between a target signature and pixels and can be interpreted easily and fast, but this technique relies on precise knowledge of the target signature. The anomaly detector signifies pixels with signatures that deviate from the (local) background. We performed a target detection experiment with human observers to determine their relative performance with the four techniques,. The results show that the "match" presentation yields the best performance, followed by "movie" and "anomaly", while performance with the "colour" presentation was the poorest. Each scheme has its advantages and disadvantages and is more or less suited for real-time and post-hoc processing. The rationale is that the final interpretation is best done by a human observer. In contrast to automatic target recognition systems, the interpretation of hyper spectral imagery by the human visual system is robust to noise and image transformations and requires a minimal number of assumptions (about signature of target and background, target shape etc.) When more knowledge about target and background is available this may be used to help the observer interpreting the data (aided target detection).

Keywords: Target Acquisition, detection, , colour, noise, multi-band, human observer

1 INTRODUCTION

Electro-Optical (EO) imaging sensors are widely used in military tasks, e.g. Target Acquisition (TA: detection, recognition and identification of military relevant objects) or visual search. These tasks can be performed by a human observer, by an algorithm (Automatic Target Recognition) or by both (Aided Target Recognition). In the past decades, the development of night vision devices in the thermal infrared and image intensifying systems has greatly extended the applicability of EO systems. Despite of these rapid developments, the current generation of sensors has important limitations. Until now, operational thermal imagers are sensitive to IR (infrared) radiation from a single spectral band in the Long Wave (8-14 μm, LWIR) or Mid Wave (3-5 μm, MWIR) region. These so-called broad band sensors basically produce a monochrome (i.e. black-and-white) image that deviates considerably from a normal daylight view. With these systems, the distinction between real targets and decoys, or between military and civilian targets is often difficult to make. Also, camouflaged targets or targets that are hidden deep in the woods are difficult to detect. Examples of misinterpretations when using an Image Intensifier system are grass that looks like snow, or trees that look like bushes, when seen from a helicopter. These misinterpretations may lead to disorientation (loss of Situational Awareness) or to a (fatal) wrong distance estimation.

Currently, multi-band and hyper spectral imaging sensors in the thermal infrared are under development. These systems promise significant improvements in military task performance. With these new systems, targets may be distinguished not only on the basis of differences in radiation magnitude, but also on differences in spectral properties. Multi-band sensors are sensitive to several (2 to 10) sub-bands in a spectral region. Hyper spectral sensors are sensitive to many (in

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the order of 100) sub bands. Hyper spectral sensors have existed for a while, and have mainly been used for remote sensing from a platform or a satellite. Only recently these sensors entered the infrared spectral regions; They provide a large amount of information (a 3-D hyper cube with the 3rd dimension coding the spectral information) at the cost of a reduced speed. A recent overview on hyper spectral image technology is provided by Vagni[1]. The additional spectral information from multi-band or hyper spectral sensors may be used, for instance, for automatic detection, recognition or identification. Alternatively, the information is visualised for human inspection. In addition, alternative presentation methods to human observers are possible. Ergonomic presentation techniques may simplify the interpretation of the images and enhance TA performance, Situational Awareness and/or viewing comfort. Until now, the potential of the new systems is largely unknown and it is not clear how the data should be presented to the observers. In this study, we developed and evaluated several new visualisation techniques.

Human and automatic target acquisition both have their advantages and disadvantages. In this study we focus on human performance, although this may be supported by automatically derived information. A major advantage of the human visual system is its superiority in pattern recognition. It is able to analyze an image at different (spatial and temporal) scales simultaneously and the interpretation is robust to spatial and temporal noise and to many types of image distortions. The system is very flexible and able to tell which part of an image differs from the background without having to specify what characterizes these differences. In contrast to automatic target recognition systems the number of assumptions (signature of target and background, target shape etc.) can be small. Therefore, often the final interpretation is best left to a human observer. Of course, when more knowledge about target and background (signature, shape etc.) is available this can be used to help the observer interpreting the data. A combination of automatic target recognition and presentation techniques (i.e. aided target recognition) can elevate the drawbacks of the use of human interpreters, such as limited processing capacity, memory and attention.

A problem with presenting hyper spectral imagery to a human observer is the huge amount of information. The question is how the data should be made available to the human visual system, i.e. which presentation offers the best information transfer. This also depends on the task at hand (e.g. detection, situational awareness, identification) and the prior information available.

In automatic target detection a distinction can be made between anomaly detectors and spectral signature-based detectors. The former assume no a priori information about the target spectral signature and simply detect those pixels that have a spectral behaviour anomalous with respect to the surrounding background. The latter rely on the fact that the spectral reflectance of the target is known (e.g. by ground measurements) and assume that the atmosphere can be accurately modelled in order to predict the spectral radiance expected at the sensor level. Of course, the step of atmospheric modelling is critical and poses serious limitations to the application of this kind of algorithms in operating conditions. Nonetheless, spectral signature based detectors allow target recognition while anomaly detectors simply detect the positions where candidate targets are located (target cueing). In this latter case a further step is needed to mark those regions that possibly contain a true target. Also when a human observer (instead of an automatic system) interprets the data, which presentation type suits the application best depends on prior knowledge. Our main focus is on potential) target detection without prior knowledge. We explored various image transformations and presentation types in order to optimize the information transfer to the human observer, who interprets the (transformed visual) information. The presentation techniques are evaluated in a human observer experiment in which the task is to indicate (potential) targets. The observers perform the task without a priori knowledge about the targets. The targets are defined by the fact that they are limited in size and have a spectrum that deviates from the background. The task resembles anomaly detection. Several newly developed presentation techniques will be evaluated along with a presentation showing the level of anomaly (using a standard RX-detector[2]).

2 IMAGERY

For evaluation purposes two hyper spectral images (hyper cubes) are used obtained by an airborne hyper spectral sensor operating in the visible and NIR (near infrared) domain. It has a high spatial resolution resulting in a pixel size of approximately 0.3 meters and 160 spectral bands in the range from 0.4 µm to 1.0 µm. The targets consist of commercially available camouflage nets. The data sets were recorded in a rural environment containing mainly forest, grass and bare soil. The two hyper cubes used in this study are referred to as set A and set B. The two data sets were acquired from the same altitude (1000 m) and along the same (nominal) route. Set A was recorded in clear weather conditions around noon and set B was recorded in overcast conditions at about 6:00 pm.

3 PRESENTATION TECHNIQUES

We will discuss various presentation methods some of which rely on more prior information than others.
The focus is on unsupervised target detection. The hyper spectral image is a 3-D data set M_{ijk}, in which *i* represents the (spatial) y-dimension, *j* the spatial x-dimension and *k* the index of the band (representing the wavelength dimension).

3.1. BROADBAND SIGNAL

The average over all bands can be regarded as the baseline signal. In formula (with N_k the number of bands)

$$A_{ij} = \sum_k M_{ijk} / N_k \quad (1)$$

An advantage of viewing the average signal is that the noise is low relative to the noise in the separate bands. It is therefore advisable to inspect the average signal, especially when the amount of noise in the image is relatively large. The resulting image is similar to that of a broad band sensor. Figure 1a shows an example of a broadband signal (set A). The designated targets are depicted in Figure 1b. In the broadband signal some targets may be visible while others may remain invisible because much of the potential target information in the data set is unavailable.

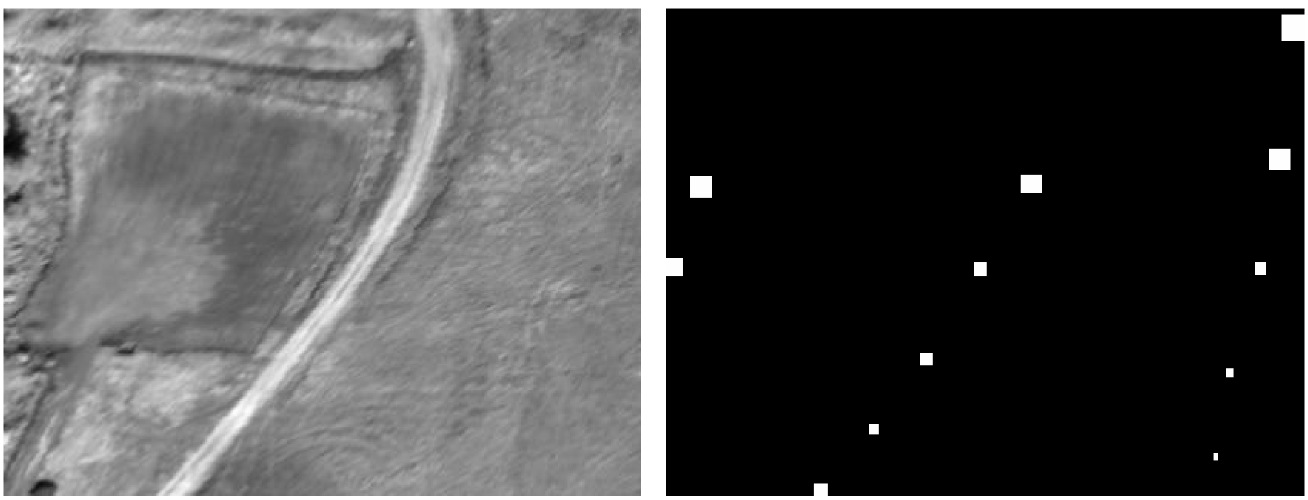

Figure 1. Average signal of sample set A (a) and designated target locations (b).

3.2. MOVIE PRESENTATIONS

When the hyper spectral data cube is displayed as a movie sequence all bands can be displayed. In principle there is no loss of information. In practice there are limitations to the temporal and spatial processing capabilities of the visual system which have to be taken into account when designing a good presentation form. A useful property of the data is that the (meaningful) signal varies slowly from band to band (in most cases). This means that rapid variations can be regarded as noise. When the raw data is displayed as a movie sequence the movie is almost indistinguishable from the static image of the average output. This is due to the fact that (in our case) the spatial variation between pixels is much larger than the band-to-band (wavelength dependent) variations in the output. We expect that this is a common property of hyper spectral data sets.

A solution to this problem is to subtract the average output value (of each pixel; Av_{ij}) from the output of each band and display this difference ($D_{ijk} = M_{ijk} - Av_{ij}$) as a movie sequence. In a previous study[3] using different hyper spectral data this method was successful in revealing many of the designated targets visible. However, with the data sets used here this method did not work. We therefore developed yet another method. We found that the difference-from-average signal D_{ijk} of each pixel is well modelled by a factor (f_{ij}) times the average profile (F_k):

$$D_{ijk} = f_{ij} \cdot F_k + \varepsilon_{ijk} \qquad (2)$$

Figure 2a shows the difference-from-average (D_{ijk}, $i = 1$, $j = 1$) of the top-left pixel as a function of band index along with a scaled version of the average profile ($f_{ij}\, F_k$). The signal of the individual pixel (solid line) closely follows the scaled average profile (dashed line). Figure 2b shows the deviation (ε_{ijk}) from this model (solid line). Also shown is a version in which the band-to-band noise is reduced (dashed line). Reduction of band-to-band noise is not strictly necessary since the human visual system is highly robust to noise, but is more comfortable for the user. Standard noise reduction techniques can be applied to reduce the noise. We filtered the spectral signal with a Difference-of-Gaussians kernel (DOG) given by 2*Gauss(σ) - Gauss($\sigma\sqrt{2}$) (see inset Figure 2b), with $\sigma = 2$. We used no spatial filtering to reduce the noise, since this would obscure small targets. The underlying assumption is that the fast fluctuations in the signal are due to noise. In cases in which this assumption is not appropriate information is lost by using noise reduction methods. This is the case when peaks in the signal are meaningful. In practice the width of the filter should be based on a prior analysis of the noise (preferably by inspection of a constant reference sample).

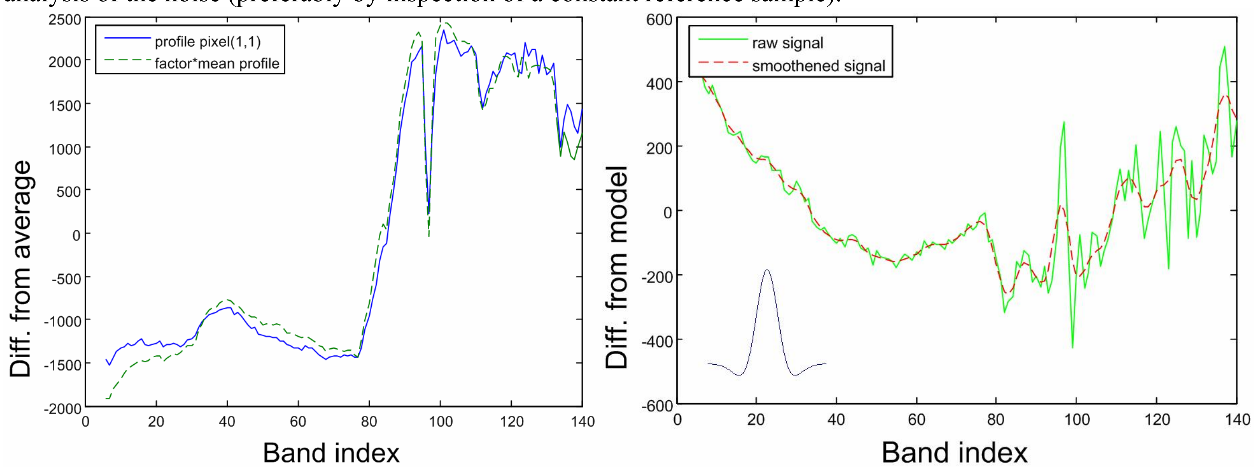

Figure 2. a) difference-from-average output for pixel (1, 1) (top-left pixel; solid line) along with a scaled version of the mean profile (factor * mean profile; dashed line) of the difference-from-average signal. b) the deviation from the scaled average profile (solid line). This is the difference between the signals shown in Figure 2a. Also shown is a version in which the band-to-band noise is reduced (dashed line). This signal is obtained by filtering the raw signal with a Differences-of-Gaussians-kernel (see text); the filter shape is shown as an inset in Figure 2b.

Figure 3 shows three frames of a movie sequence containing the deviations from the scaled profile (see Figure 2b). In the first and last of the three example frames no targets are visible. In the middle frame most of the targets are visible. This shows the advantage of using a movie sequence as a presentation technique. Ideally, when the differences are apparent in (at least) some of the frames, this information will be picked up by the observer. Differences in spectrum between the targets and the background become apparent as a difference in the temporal profile. Furthermore, human observers take into account the fact that targets differ in shape and size from elements in the background.

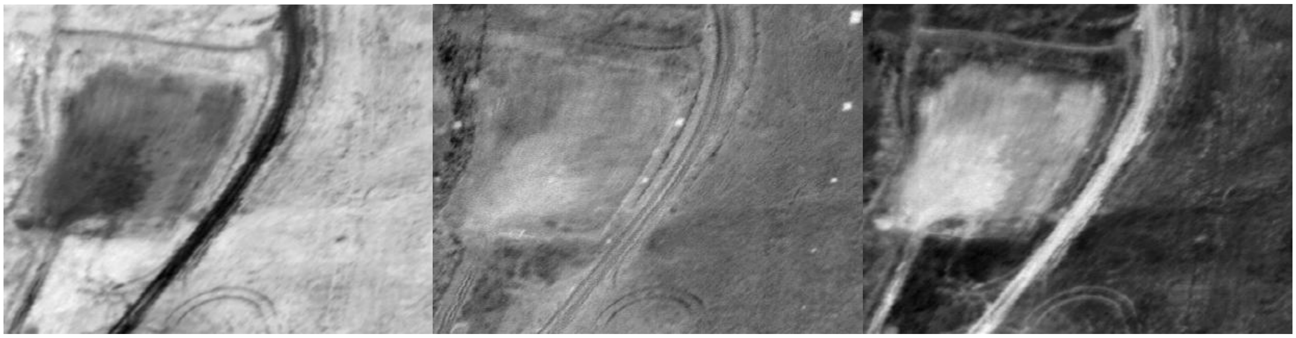

Figure 3. Three frames of a movie sequence showing the differences from average for band indices 6, 34 and 52. The targets are invisible in bands 6 and 52 but visible in band 34. In this case we also applied dynamic noise reduction in which the temporal noise is reduced (see text). This latter transformation is not strictly necessary since the human visual system is highly robust to noise.

3.3. COLOUR SCHEMES

The colour presentation technique produces a single image. In this case all bands of the hyper spectral signal are mapped to three independent channels. We tested several different colour schemes. In the first scheme the hyper spectral data set is divided into three broadband signals. First, the three broadband images are deduced and mapped onto the range (0, 1). Then, the average over the three images is calculated and subtracted from the broadband images. The reason for this is that (in our case) the average signal does not contain much information about the targets (see e.g. Figure 1). The difference images are then mapped onto the range (0, 1). Finally, the three (difference) images are fed into the Red, Green and Blue channels of a colour image. In a previous study[3] using other hyper spectral data sets this method worked quite well. However, in the current study this method did not reveal the targets. This is not surprising since a movie sequence showing the differences from the average output described in the previous section did not show the targets either. Therefore, a second data transformation was developed in which differences from the scaled average profile (see section 3.2 and Figure 2) are used. First we tried to apply the method described above for transforming the data into a colour image. This also did not result in an image revealing the targets. The reason for this is that this signal fluctuates rapidly from band to band from positive to negative values. So, the signal averages out in the broadband channels.

To map the signals onto a colour image we therefore resorted to a different method. We apply a principle component analysis to the (differences-from-scaled average profile) data set. The main three components are mapped into HSV-space (hue, saturation, and value components). Finally, the HSV data is transformed into an RGB-image and displayed. Figure 4a shows the result of this transformation.

The result of the principle component analysis is interesting in its own right. Figure 5 shows the first 16 principle components. Figure 5 shows that the useful information in the hyper spectral data set (containing 160 bands) is limited to a small number of independent components (smaller than 16 in our case). With increasing component index the amount of noise increases. The targets appear in some of the components. Also visible in some of the components is fixed pattern noise with the shape of a sinusoidal corrugation (e.g. in components 5 and 6).

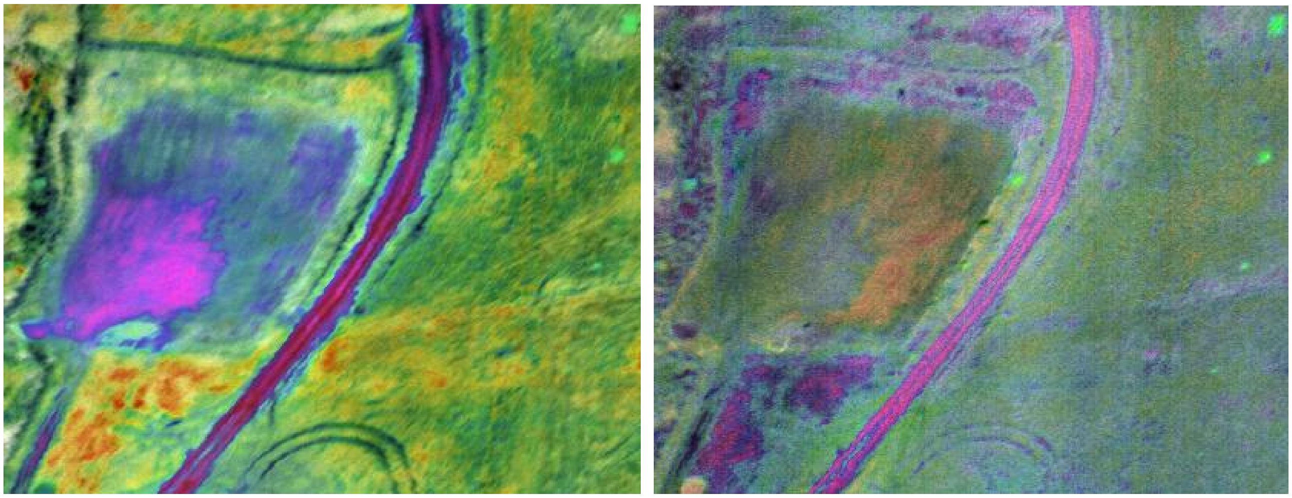

Figure 4. a) a colour representation using the first three principal components of the differences-from-scaled average profile. The components are used as HSV-signals and converted into RGB. b) similar presentation using principal components 4, 7 and 8 (see Figure 5).

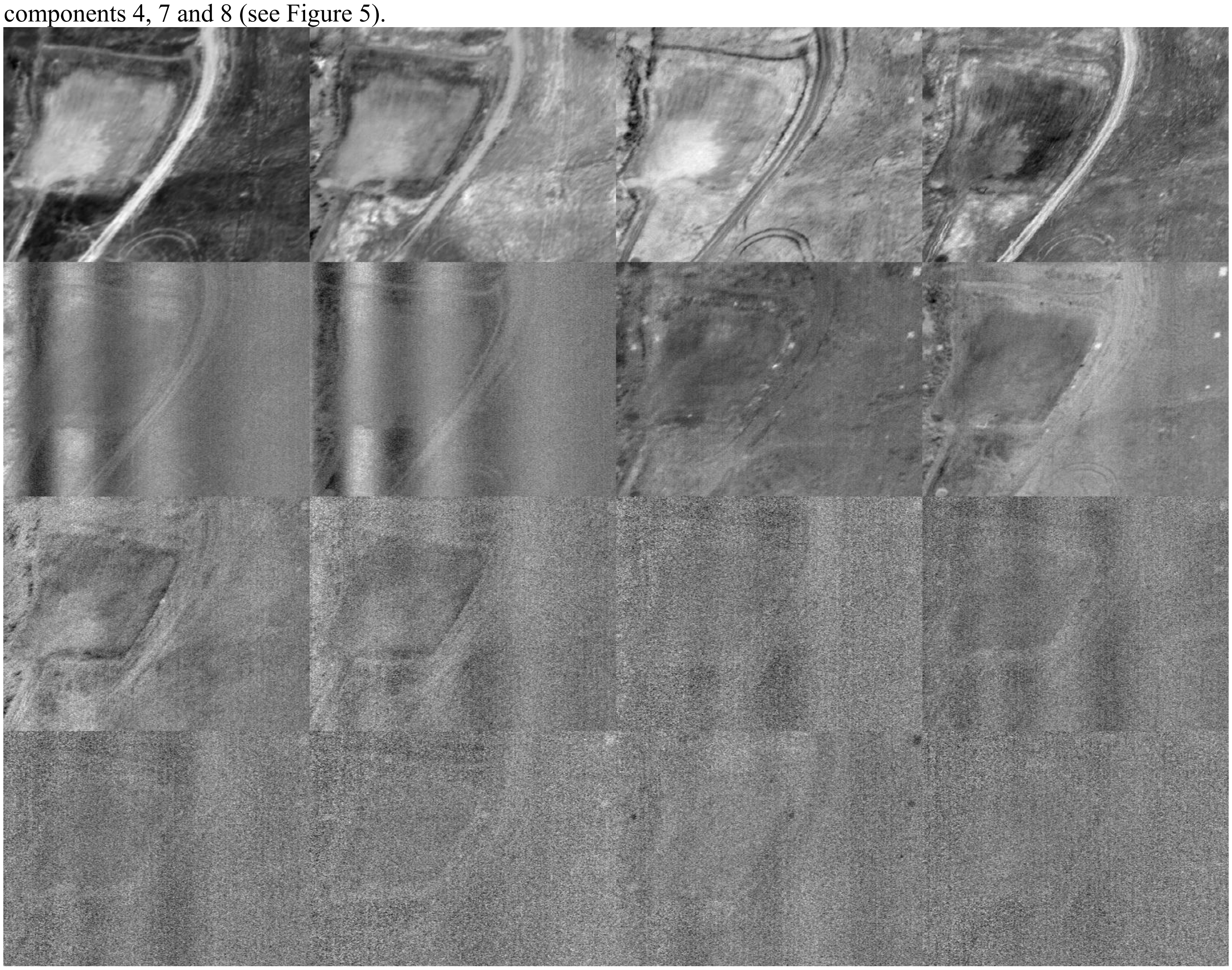

Figure 5. First 16 principle components of difference from model (scaled average profile) data. The information content is limited to several bands: the amount of noise increases with the component index.

Which three components to combine into a colour image is difficult to decide beforehand. By default we use the first three components (Figure 4a). A more optimal combination may be found for these targets (Figure 4b). Since it is not clear from the start what the targets look like it seems reasonable to inspect all useful principle components for (potential) targets. In the evaluation experiment the default colour scheme (using the three main components) was used (assuming no prior knowledge about the targets). An alternative would be to present all informative principle components as a movie sequence, such that the loss of information is reduced.

The disadvantage of the colour scheme is that some information is lost. The advantage of this presentation type is that it can be displayed as a single image and is therefore suitable for real time presentation.

3.4. SIGNATURE MATCH

When the spectral signature of the target is (reasonably) well known it can be used to highlight the target in the image. For each pixel the resemblance between its signature and that of the target can be calculated. As in previous sections we used the difference-from-scaled average profile as the basic data set. We calculated the correlation between the signal of each pixel and that of the target signal. We took the average signal of the top-right target (see Figure 1b) as the target signal. The result is displayed in Figure 6a. Since (in this case) all (designated) targets have similar profiles many of the targets show up in the image. This method is well suited for finding targets with profiles similar to the one that has been identified (by inspection or prior knowledge). Of course, one also can look for multiple targets with different profiles simultaneously.

3.5. ANOMALY DETECTION

The task of the observer is to indicate (potential) targets without prior knowledge of the target or background signatures. This is similar to the task faced by an anomaly detector. We used a standard RX-detector as developed by Reed and Yu[2] to calculate the degree of anomaly. This detector is commonly used to detect targets whose signatures are distinct from their surroundings. Instead of resorting to automatic detection, the interpretation of the data is left to a human observer. In our implementation of the RX detector a dual window was used to estimate the background mean vector and covariance matrix. It consists of a guard window that should match the size of the maximum expected target and an outer window where the training samples are collected. The following parameters were used. For data set A we used an inner window size of 71 pixels and an outer window size of 75 pixels. For data set B we used an inner window size of 80 pixels and the outer window size of 84 pixels. Figure 6b shows the output of the RX-detector for data set A.

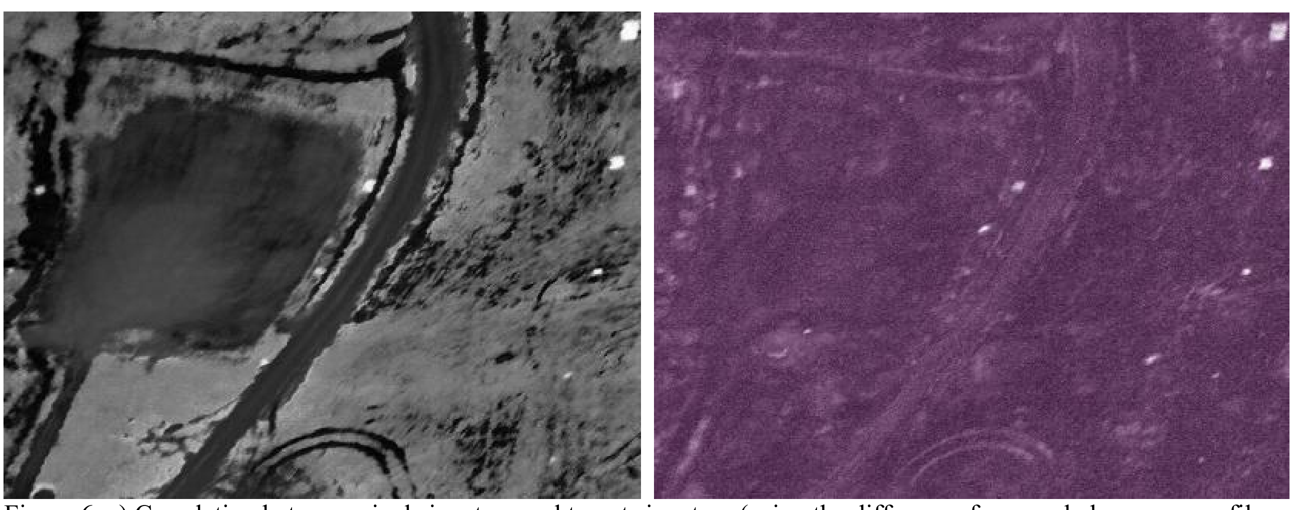

Figure 6. a) Correlation between pixel signature and target signature (using the difference-from-scaled average profile data). b) Output of the RX-detector.

EVALUATION EXPERIMENT

3.1 METHOD

Two data sets were used, referred to as set A and set B which were registered by the hyper spectral sensor described in section 2.4. We compared performance for detecting targets for 4 different presentation techniques:

- Movie
- Anomaly
- Match
- Colour

The experiments were carried out in a dimmed room. Subjects were seated in front of a 22 inch CRT-monitor (40x30 cm, 1280x1024 pixels) with a refresh rate of 75 Hz and a monitor-gamma of 2.2. Twenty four subjects participated in the experiment. Each subject was shown data sets A and B using two distinct presentation types. All combinations of presentation types and presentation order were used. The data was balanced with respect to presentation order and combination of presentation types. Each session started with an instruction showing all presentation types. In this instruction a data set was used that differed from the ones used in the experiment. The subject was told that the images represented airborne images of a natural environment containing targets. We also told the subjects that potential targets were characterized by the fact that their spectrum differs from that of the background, and that the targets differ in shape (are restricted in size) and form from background elements. They were also told that the number of targets could be anywhere between 1 and 20. The task of the subjects was to indicate potential targets by clicking the mouse in the chosen locations.

In some cases the subjects picked the same location more than once. In our analysis we treated locations less than 8 pixels apart as the same target, and the average location was used as the perceived target location.

3.2 RESULTS

Figure 7 gives an overview of the performance for the different presentation types. Shown are the hit-rate and one minus the false alarm (FA) rate, in which the hit rate corresponds to the number of indicated targets divided by the total number of targets, and the false alarm rate corresponds to the number of false alarms divided by the total number of indications. Two-sided student-t tests on each of the separate data sets (A and B) were carried out (using the individual hit- and FA-rates) to determine which pairs of conditions differed significantly from each other (at a significance level of $p = 0.05$).

The best performance was found in the condition showing the match between pixel and target signature (of the top-left target), with the highest hit-rates and lowest FA-rates. Pair wise comparisons show that the hit-rate in this condition is significantly higher than the hit-rate in the “anomaly detection” and “colour” conditions in set A, while in set B the hit-rate significantly deviates from the “colour” condition. The FA-rate in this condition is significantly lower than the FA-rates of all other conditions in set A. In set B we did not find any significant differences in the FA-rates of the conditions. The “match” condition relies on prior knowledge of the target signature. This may be obtained through analysis of the data using a different presentation type. Alternatively, the target spectrum may be known from other sources of information. The results show that this information (whenever available) can be used to increase performance.

Performance in the “colour” conditions was the poorest. Pair wise comparisons reveal that the hit-rate in this condition is significantly lower than the hit-rate in all other conditions in set A, and significantly lower than the hit-rates in the “movie” and “match” conditions in set B. Also, the FA-rate is significantly higher than the FA-rate in the “match” condition in set A.

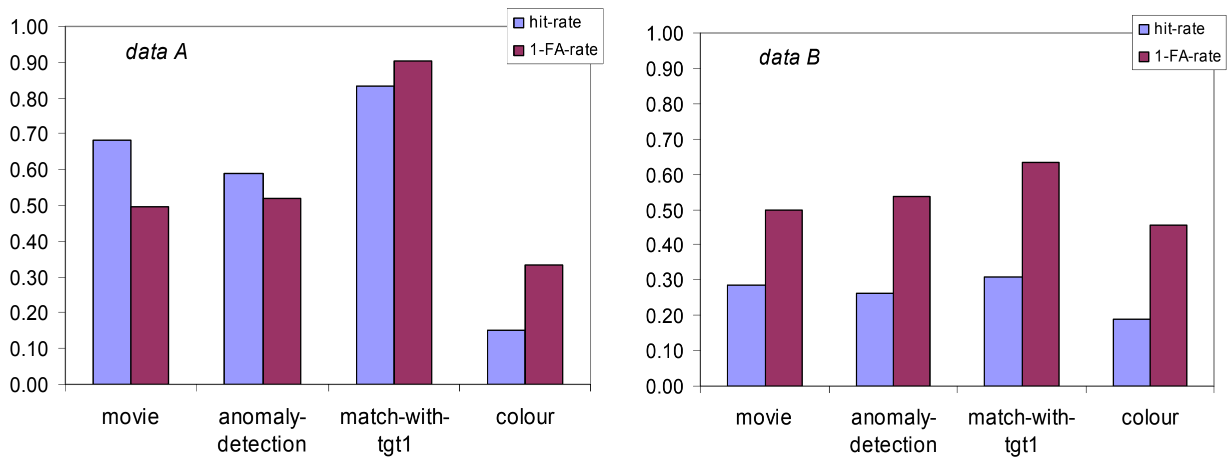

Figure 7. Overall performance measures HIT-rate and 1 – FA-rate (one minus false alarm rate) for the different presentation types for data sets A and B.

Intermediate performance was found in the “movie” and “anomaly” conditions. The hit-rate for the “movie” type is somewhat higher than that for “anomaly”, but the FA-rate is also somewhat higher, although these differences are not significant. The combination of a higher hit-rate and higher FA-rate is consistent with the fact that in the “movie” condition the number of indications is higher (on average about 19%) than in the “anomaly” condition. The number of indications was found to be the largest in the “movie” condition, followed by “anomaly”, “match” and “colour” conditions.

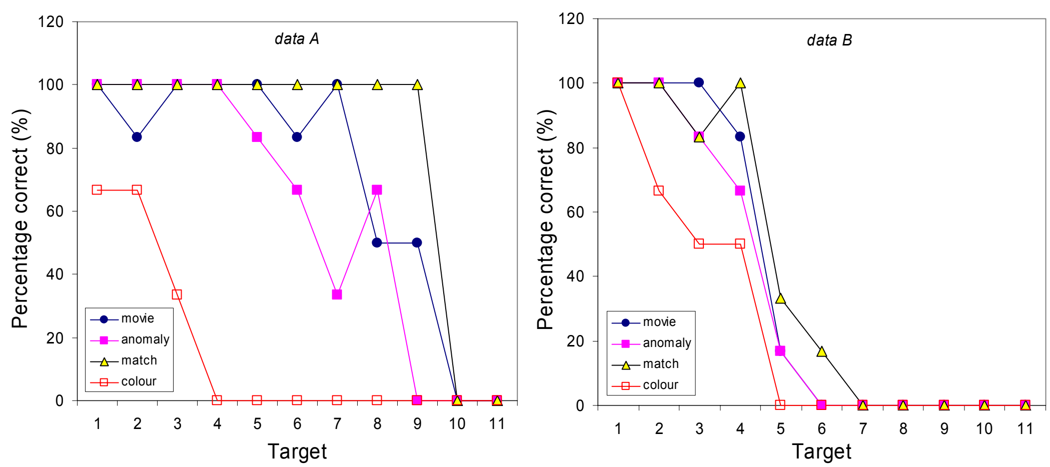

Figure 8. Hit-rate per target for the different presentation types for data sets A and B. The targets are ordered according to difficulty of detection.

Figure 8 shows the hit-rate per target. The targets are ordered such that the average hit-rate decreases with increasing target number (set A contains 14 targets and set B contains 11 targets). Some targets are detected with (almost) all presentation types, other targets are never detected, while some targets are only detected with certain presentation types. As noticed before, hit-rate increases from “colour” to “anomaly” to “movie” to “match”.

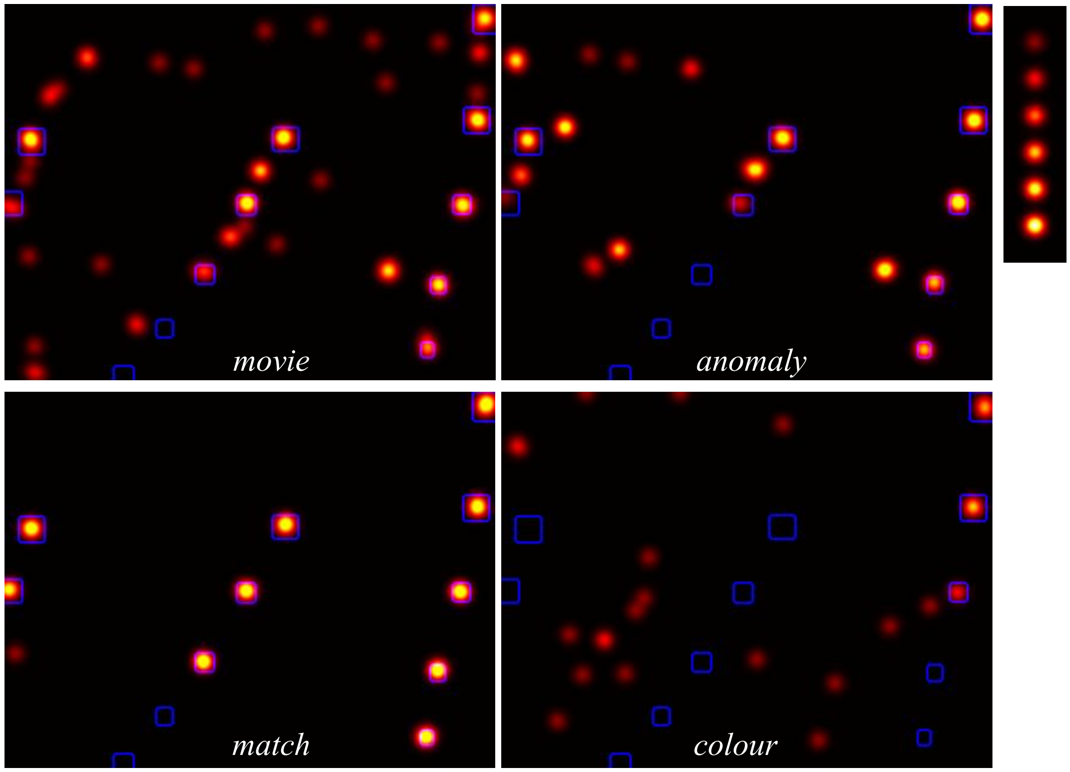

Figure 9. Density graphs showing the density of target indications for the 4 different presentation types for data set A (for set B: see Appendix). The (blue) borders indicate the designated target positions.

Figure 9 shows the densities of target indications for the various presentation types, along with the designated target positions for data set A. This figure shows that some areas consistently act as false targets. Also, some of the targets are missed by all of the subjects (see also Figure 8).

4 CONCLUSION AND DISCUSSION

We have presented four new methods to visualise hyper spectral data for human target detection. The human visual pattern recognition system is exploited to find potential targets and to decide whether a certain image detail is a potential target. The advantage of relying on human interpretation is that the human visual system is highly robust to noise and image transformations such as drift, translation and distortion. For instance, when the sensor (or parts of the environment) moves while the hyper spectral data is recorded, the pixels in the various bands will not be in correspondence. Automatic target recognition algorithms will have a difficult job in finding the targets in this case, while this does not represent much of a problem to the human visual system.

The first presentation type we developed is referred to as the “movie” type. In this presentation (transformed versions of) the different bands are shown in sequence. In principle no information is lost in the transformation process. The method does not rely on specific assumptions about the target signature. Its effectiveness heavily relies on the way the data is transformed before display. This determines whether the information in the data can be picked up by the human observer. For instance, a movie displaying the raw data looks very similar to the average broadband signal. This is due to the fact that the spatial variations are often much larger than the differences in the band-to-band variations between pixels, effectively overriding the spectral information. To overcome this problem we displayed differences from the average output per pixel. With the current data sets this still did not reveal the targets, although in a previous study with different hyper spectral data[3] this did work. Instead, we used deviations from the scaled average profile.

Dynamic noise reduction can help to create a clearer movie sequence, although this is not strictly necessary since the visual system is well capable of discarding the noise. Even so, noise reduction can make it easier and faster to interpret the data and lead to better visual comfort and less fatigue. The downside is that noise reduction removes small details from the image. In cases in which these contain meaningful information this transformation is not appropriate. For the same reason we do not recommend spatial averaging, since this makes it harder to detect small targets.

The second presentation type we investigated was the “colour” type. The advantage of such a presentation is that it results in a single image, and can therefore be used to present the data in real-time (on-the-fly). However, because a colour image contains only three independent channels, some information is lost and a suitable choice of channels has to be made. Again, the pre-processing steps in creating the colour image crucially determine whether the targets become visible. One option is to use three broadband channels which are used as input to the RGB-channels of an image. With the current data sets this did not result in a good presentation. Instead, we used the difference-from-scaled average profile as the basic data set. We applied principle component analysis to this data and used the three main components to create a colour image. The result was an image that revealed only some of the targets. In general, the three (broadband) channels used for creating the colour image should be tailored to the signature of the targets and the background. In that case a better result can be expected. Inspection of the principle components can lead to a choice of the most informative components (for a particular target), and is a useful analyzing tool in its own right. The choice of the particular colours also affects performance. Different colour schemes may be optimal for different applications. Detection and identification performance depends on the distribution of noise among the different colour channels[4]. Situational Awareness benefits from naturally looking colour schemes[5].

The third presentation type we investigated was “anomaly detection”. This method relies on a few assumptions. The size of the targets has to be known reasonably well, although the output is not too critically dependent on this. We used the standard RX-detector[2]. A difference with the way it is commonly used is that here the interpretation is left to a human observer (aided target detection), who can take into account the shape and size of the (potential) target. In contrast to most automatic detection algorithms the human observer does not merely analyze the output of individual pixels, but takes the context into account.

The fourth presentation type we analysed was a presentation showing the “match” between the signature of each pixel and the target signature (using the difference-from-scaled average profile data). The method relies on the fact that the target signature is known a priori. It can also be used to find targets with similar signature once one target has been identified (e.g. from using a different presentation technique). Targets with similar signature become clearly visible. The disadvantage of this method is that targets with a different signature are not revealed by this method. When one tries to simultaneously find targets with different signatures the match with these different signatures can be calculated and (possibly) presented in a single (colour) image (or as a movie sequence).

The four presentation types were evaluated in a human observer experiment. This showed that the “match” presentation led to the best performance, with the highest hit-rate and lowest false-alarm-rate. This result was expected since all targets had similar signatures (this does not hold in general). Performance with the “colour” presentation was found to be quite poor (poorer than with previous data sets[3]). One reason for this is that the default colour scheme was used (with the three main principle components) to prevent the use of prior knowledge. We expect that a more optimal colour scheme can be determined (see e.g. Figure 4b). In search for this more optimal colour scheme a look into the separate principle components might be helpful. With the “movie” presentation the hit-rate was higher than in the “anomaly” presentation, but the false-alarm-rate was also somewhat higher. Which presentation type is better to use in general is difficult to decide at this stage. This will also depend on the cost associated with a hit and a false alarm. In principle, the movie sequence contains more information. However, it seems to be harder to interpret (and may be improved by training). On the other hand, the result of the anomaly detection can be displayed in a single image and is therefore more suited for real-time display.

Noise can sometimes override the signal in the separate bands of a hyper spectral sensor. In hyper spectral systems there is a trade-off between the number of bands and the noise in each band. The noise in a hyper spectral system effectively limits the useful number of bands. We have found that an indication for the number of useful independent bands can be obtained from principal component analysis (in our case only about 10 useful independent components remain). An advantage of a hyper spectral system over a fixed broadband system is that the user can decide how to combine the information across bands. Several methods[6,7] have been developed to find the optimal set of broadband channels.

In order to improve search performance by prior knowledge, one may start a search by recording the signature of targets similar to the ones that one tries to find (although this may lead to a loss of targets with signatures that differ from the recorded ones). In this way, one can tune the system to the targets of interest while taking the circumstances (weather conditions etc) into account. Similarly, it is advantageous to record the signatures of various types of background. Such information can help in tailoring the system to the interesting targets.

Some presentation types are more suitable for real-time processing (e.g. the colour scheme) and some schemes are more suitable for post-hoc analysis (e.g. the movie type). Still, schemes of the second type can be applied immediately after recording. Some of the presentation types rely more heavily on knowledge about the target than others. It is advisable to use more than one presentation type to be sure that certain information is not overlooked (e.g. in the average image) and all available information is used (and unexpected targets are not missed).

Summarizing, we have presented and evaluated a number of ways to present hyper spectral data. The various presentation types differ in the way the information is displayed and in the way information will be picked up by the observer. The general idea is that the final interpretation is best left to a (trained) human observer. Thus, the number of assumptions (signature of target and background, target shape etc.) can be restricted. Human interpretation is robust to noise and many image transformations, and can take the target background into account. Whenever knowledge about target and background (signature, shape etc.) is available this can be used to help improve the interpretation of the data by the observer (aided target detection).

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APPENDIX: DATA SET B

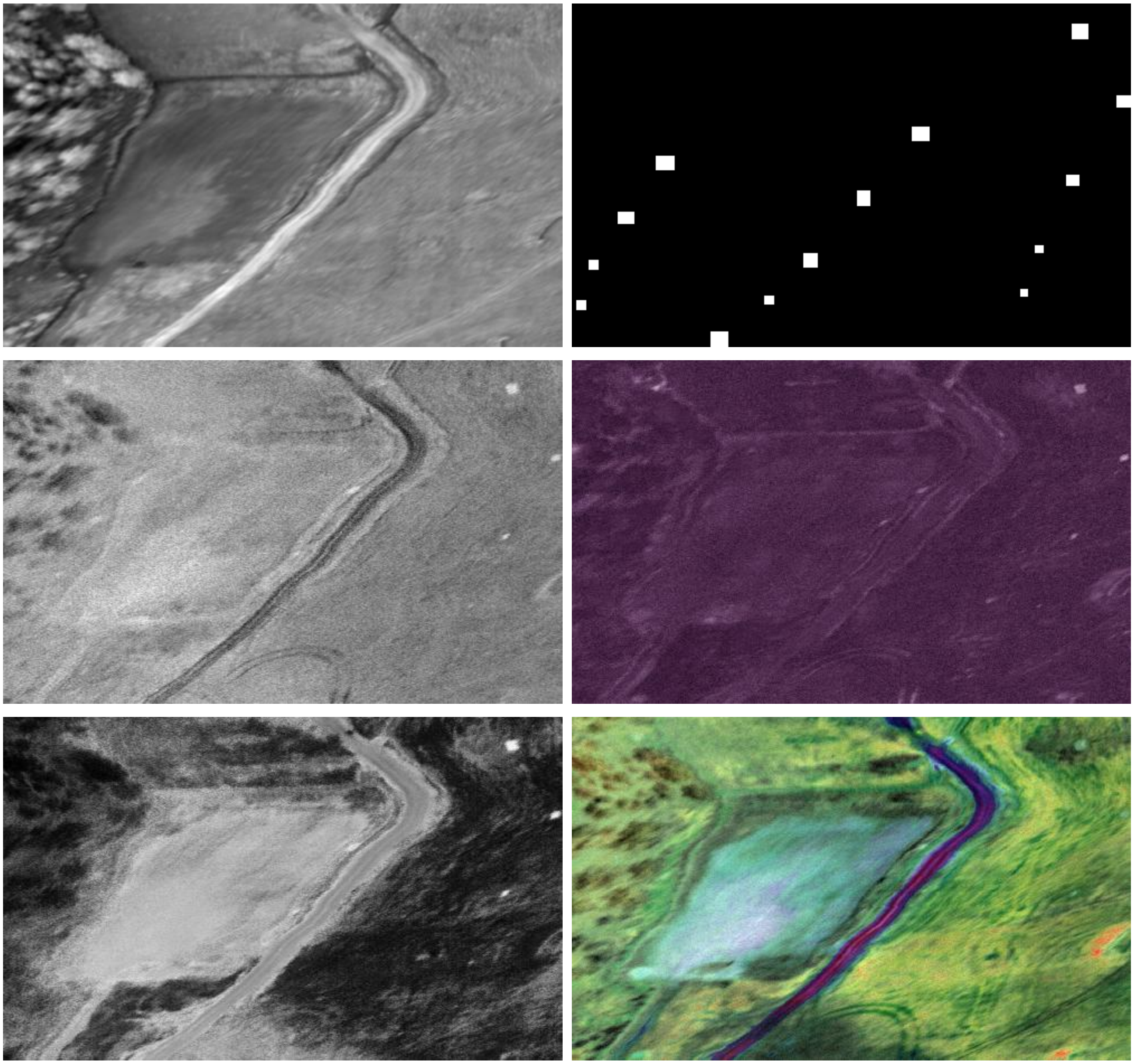

Figure A1. Various presentation types of data set B, with a) the average, b) the designated target locations, c) band 37 of the movie sequence (the frame that reveals the targets best), d) anomaly, e) match with target 1 (highest target), and f) colour representation.

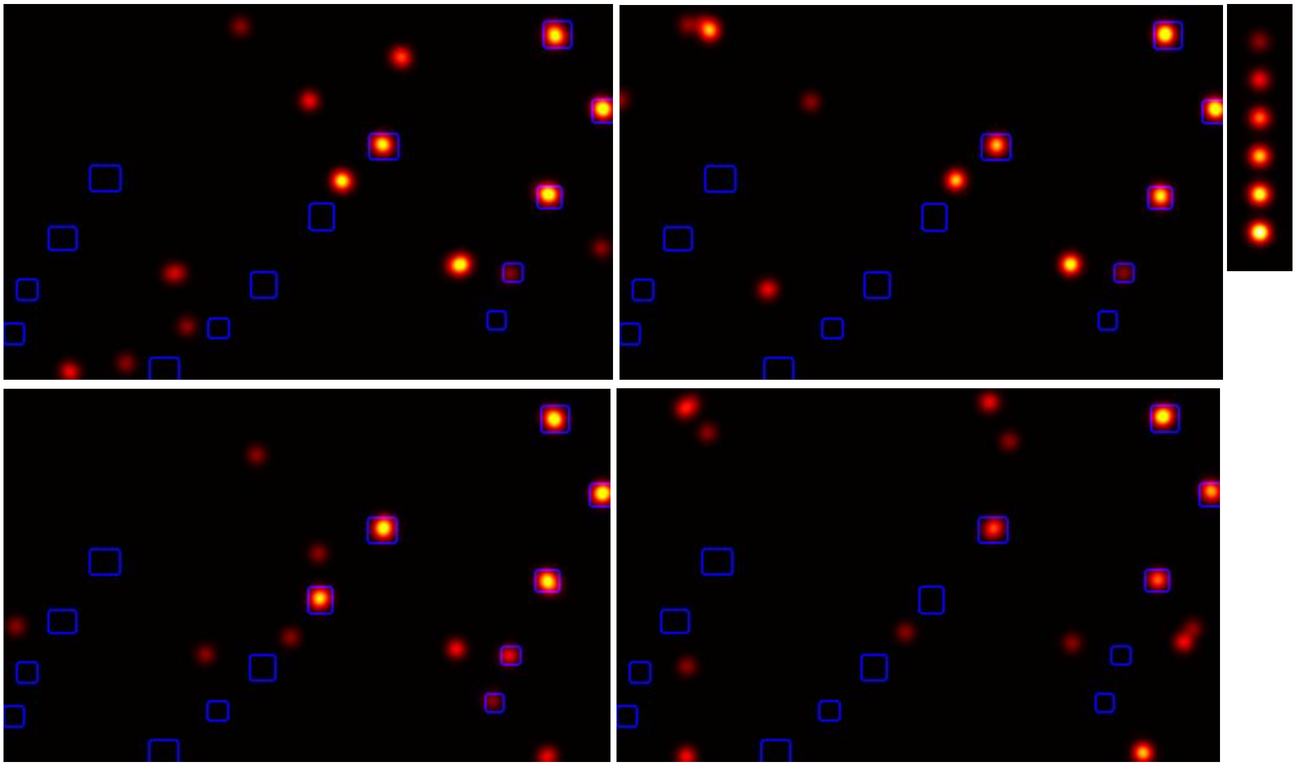

Figure A2. Density graphs showing the density of target indications for the 4 different presentation types for data set B. The blue borders indicate the designated target positions.