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A survey of landmine detection using hyperspectral imaging

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Abstract

Hyperspectral imaging is a trending technique in remote sensing that finds its application in many different areas, such as agriculture, mapping, target detection, food quality monitoring, etc. This technique gives the ability to remotely identify the composition of each pixel of the image. Therefore, it is a natural candidate for the purpose of landmine detection, thanks to its inherent safety and fast response time. In this paper, we will present the results of several studies that employed hyperspectral imaging for the purpose of landmine detection, discussing the different signal processing techniques used in this framework for hyperspectral image processing and target detection. Our purpose is to highlight the progresses attained in the detection of landmines using hyperspectral imaging and to identify possible perspectives for future work, in order to achieve a better detection in real-time operation mode.

Keywords: Hyperspectral imaging, remote sensing, landmine detection, target detection, image processing.

1. Introduction

Due to the increasing number of war zones and conflicts worldwide, the menace of landmines and unexploded ordnances is becoming a very serious problem that is going to affect the interested countries for years to come. According to Landmine and Cluster Munition Monitor [1], 61 states and areas are classified as mine-affected as of November 2015. Often, landmines are triggered by children and innocent civilians after the end of the war. Moreover, besides killing and maiming innocent people, the menace of landmines also affects the socio-economic situation in some region and prevents their development. After the end of a war, landmines remain active for a very long time. The cost and time per mine needed for demining are much more than those needed for mine manufacturing and deployment. This motivates both the governments and the scientific

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1 community to find out demining solutions that are safer, faster and more accurate. However, this
2 is becoming very challenging, since in the past decade funding for landmine detection has dropped
3 significantly.

4 Our goal in this review is to describe past projects that used infrared hyperspectral imaging for
5 landmine detection and that have been presented in conferences proceedings and journal articles.
6 Note that additional military research may exist in this field. Such projects, however, are not
7 described herein due to lack of information.

8 In the literature, several reviews deal with the problem of landmines, regarding both detection
9 techniques and data processing algorithms. A comprehensive review about landmine detection
10 problems, with an evaluation of the strengths and limitations of each detection technique, could be
11 found in [2]. In [3] the authors first discuss the history of landmines, highlighting the number of
12 victims, the ease of deployment compared to the slow demining process, the development of new
13 landmines, and how they are more sophisticated making their detection more difficult. After that,
14 they present various target detection algorithms used in the demining process. A study of the
15 applicability of different landmine detection techniques in Antioquia, Colombia, is presented in
16 [4]. In [5], a presentation of the different types of mines is given. A detailed explanation of the
17 detection techniques is highlighted in [6]. Similarly, the authors of [7] present various landmine
18 detection techniques, with a particular emphasis on Ground Penetrating Radar (GPR), photons and
19 neutrons reflectance, and thermal detectors. A review of the technologies that were used as of 1998
20 can be found in [8].

21 In addition, there are several reviews in the literature specialized in a particular detection
22 technique. For example, ground penetrating radar techniques are discussed in [9] and [10], whereas
23 a good review on biological techniques for landmine detection can be found in [11]. The latter
24 shows that the use of animals such as dogs, African giant rats, pigs, honeybees, bacteria, or of
25 genetically engineered plants, antibodies and biometric sensors for landmine detection could be
26 effective. All these techniques detect the leakage of low amounts of chemical constituents in the
27 surrounding area. Due to their high sensitivity, even low concentrations of explosives in the soil
28 could be detected [11]. A review of the methods that use chemical vapor sensing in order to detect
29 landmines is given in [12]. Such methods focus on electronic sensors in order to construct devices
30 that work more efficiently than dogs, which usually get tired after 30-120 minutes. These sensors
31 are usually made of an array of receptors, where each receptor is sensitive to a specific chemical
32 compound. Researchers have also developed single sensors that are able to react to specific
33 explosives such as trinitrotoluene (TNT), the explosive component commonly used in landmines
34 [12]. Such sensors can detect very low levels of explosive vapor. The main advantages of sensor
35 arrays over single sensors are the sensitivity to a wide range of analytes, better selectivity,
36 multicomponent analysis, and analyte recognition [12]. A review of different airborne and satellite
37 sensors able to detect landmines is presented in [13].

38 Finally, a good review on nuclear quadrupole resonance techniques providing several technical
39 explanations is presented in [14].

1 To the best of our knowledge, a survey of landmine detection techniques based on hyperspectral
2 imaging does not exist presently, so this is the first review paper related to this subject. Our paper
3 highlights several significant studies addressing landmine detection using hyperspectral imaging,
4 that have appeared in conferences, in recent articles, in technical reports, and shows promising
5 directions for future research. The paper is organized as follows. In Section 2, we will present the
6 main projects that used hyperspectral imaging for the purpose of landmine detection. Section 3
7 describes the most relevant mathematical methods used in hyperspectral imaging for this task.
8 Finally, in Section 4 we discuss the main strengths and weaknesses of the different approaches,
9 while conclusions are drawn in Section 5.

10

11 2. Projects using hyperspectral imaging in landmine detection

12 2.1. Defence Research and Development Canada projects

13 One of the earlier projects doing research on landmine detection using infrared wavelengths took
14 place at Defence Research & Development Canada (DRDC). DRDC started their research, in
15 support of the Canadian army on landmine and unexploded ordnance detection in 1978 and, in
16 collaboration with Itres Research, on hyperspectral imaging for landmine detection in 1989.
17 Detection of sparse targets using optical imaging was previously studied. Algorithms developed
18 during this project could be applied to preprocessed images of hyperspectral imagers. An early
19 project proposed a hierarchical image-processing algorithm to detect sparsely distributed bright
20 region of several pixels wide in a monochromatic image [15]. A preprocessing operation is
21 performed in order to remove distortions, dropouts, overlapping areas, misregistration, and any
22 other artifacts and imperfections. Non suspected areas are discarded to reduce the data size. Then,
23 suspected regions are segmented into homogeneous sub-regions and the morphological features of
24 the sub-regions are extracted. Based on the extracted features, sub regions are classified. Finally,
25 the spatial relationships between mine-like objects are determined. A supervised method analyzes
26 these relationships and classifies the areas as a minefield providing a specific likelihood ratio. This
27 hierarchical method can potentially achieve real-time detection of surface-laid mines. With the
28 aim of improving the detection system, scientific research was focused on two topics: the first one
29 dealt with the enhancement of the detection algorithms in order to achieve real-time detection,
30 while the second one was related to the improvement of proper imaging technologies in order to
31 obtain a higher image quality.

32 After the development of Visible and Near Infrared (VNIR) hyperspectral imagers (400-1000 nm),
33 several experiments showed their compatibility with the detection of surface-laid and buried
34 landmines. While testing the possibility to detect surface-laid mines, it was found that their spectral
35 reflectance has similar behavior under different illumination conditions with different scaling
36 factors and offsets. More precisely, a linear correlation exists between the mine spectra under
37 different incident illuminations if the spectral vector is confined between 500nm and 680nm [16].
38 For classification purposes, the authors tested two methods: Linear Cross Correlation (LCC) and
39 linear spectral unmixing. LCC is better in the case of high spatial resolution images. The linear
40 unmixing method has a higher Probability of detection in the case of subpixel sized mines; but has
41 also a higher false alarm rate.

1 Other tests led to study the possibility of detecting buried landmines using a VNIR imager. It was
2 noticed that buried mines could not be detected by calculating the shift of the red edge of vegetative
3 spectra. However, by using linear correlation, some mines with low vegetative cover were detected
4 [17]. It was also noticed that Anti-Tank surrogates were more detectable than Antipersonnel
5 surrogates, presumably due to the increased area of disturbance required to bury the former [18].
6 The probability of detection (PD), intended as the number of mines detected over all existing mines
7 in the image, obtained during the experiment varies between 33% and 100% and the False Alarm
8 Rate (FAR), measured as the number of falsely detected mines per unit area, varies between 0.1
9 and 0.52/m². According to the authors of [18], improving the classification algorithms and
10 optimizing the spectral vectors, involving a systematic pattern classification study and
11 emphasizing discriminant analysis and feature analysis, are possible steps to achieve better PD and
12 lower FAR.

13 The spatial resolution of the image affects the performance of the detection algorithm [19]. As the
14 pixel size gets closer to the size of the mine, the possibility to isolate landmines increases. This
15 has been proven by the research team of DRDC in [20]. The authors acquired two types of images
16 using a VNIR imager: Medium resolution images at the altitude of 300m and high-resolution
17 images at the altitude of 6m in a different place. In the medium resolution experiment, they
18 obtained a 100% PD and 0.00034/m² FAR. In the high-resolution experiment, all mines were
19 detected with a false alarm rate of 0.0043/m². Linear Cross Correlation (LCC) and Orthogonal
20 subspace projection (OSP) were used in classification. The best detection is achieved when taking
21 the result of the combination of the two techniques.

22 In order to have quasi real-time detection of surface-laid mines using a VNIR imager, the authors
23 in [21] proposed a system consisting of two modes: in the first mode, the system learns the target
24 spectra. In the second mode, the system looks for the targets by acquiring spectral data for each
25 pixel and then applying comparative algorithms to the candidate pixels, using the stored reference
26 spectra. The processing platform involves a system that generates the results of data acquisition
27 and target analysis to an operator by displaying probability information alongside the base
28 imagery. The entire process (data acquisition - radiometric correction - data fusion from different
29 systems) finishes within few time frames of acquisition (a time frame is approximately 15-35 ms).
30 The radiometric and target identification processes can be applied independently to each frame, so
31 the processing of a frame will not affect the results related to the processing of other frames [21].

32 In [25], which is a continuation of the research in [21], we find the first experiment that aims at
33 detecting landmines from an airborne hyperspectral imaging system in real time. The above paper
34 describes how software and hardware improvements can achieve real time detection from an
35 airborne platform. First, radiometric correction is applied on raw data, then custom classification
36 algorithms are applied to the corrected data. A spectral signature library provides reference spectral
37 vectors. The classification results are stored and displayed in real time. The first real time landmine
38 detection system was mounted on a slow vehicle (1-2 km/h) [21]. A display system shows selected
39 bands including corrected spectral bands, partial data results or final target bands. The second real-
40 time detection system was an improvement of the first system to be compatible with airborne
41 imaging data rates. A hardware/software system was implemented measuring the change in slit

1 contamination (filings, dust, paint flecks) relative to the slit performance during calibration and
2 modifying the correction matrix accordingly during radiometric conversion. Detection rates were
3 not the prime concern of the test. The authors wanted to test the ability to detect landmines from
4 an airborne platform in real time. There are no indications regarding the algorithms used for data
5 correction, band selection, and classification.

6 Short wave infrared (SWIR) bands (1000-2500nm) have also been considered to detect landmines.
7 As the spectrum is wider with the inclusion of SWIR bands, the possibility to distinguish
8 landmines is higher. A simple classification boundary should be able to distinguish surface-laid
9 mines from many human-made artifacts and natural materials. However, old buried landmines are
10 hard to be detected using SWIR. [22]

11 A project studying Long Wavelength Infrared (LWIR) hyperspectral imaging of landmines led to
12 the development of a commercially available LWIR hyperspectral imager suitable for airborne
13 landmine detection [23]. The instrument was used to collect imagery of surface and buried mines
14 and improvised explosive devices over full diurnal cycles in arid, desert-like conditions and was
15 found to provide some advantages over broad-band imaging in the detection of buried threat
16 objects [24].

17 The team of DRDC started in 1997 a project testing the combination of various detection
18 technologies called Improved Landmine Detector Project ILDP. Since a single detection technique
19 will not be able to detect all types of landmines in all conditions, the fusion of various techniques
20 can be more effective [27,29]. The authors tested a small teleoperated vehicle carrying four types
21 of detectors: Forward Looking Infrared imager, down looking electromagnetic induction detector,
22 down-looking Ground Penetrating Radar (GPR) and finally a thermal neutron activation detector
23 used as confirmatory detector of suspected targets. In order to apply sensor data fusion, several
24 methodologies were used, including spatial correspondence and custom designed navigation. The
25 above system was intended for anti-vehicle landmines, but not for anti-personnel mines. In order
26 to address the latter, a smaller system with different sensors was proposed. Therefore, using a high
27 mobility robotic platform, the authors proposed a system that contains five separate technologies:
28 2 hyperspectral cameras (thermal infrared (TIR) and VNIR), a scanning sensor imaging system
29 which is mounted on a custom built articulated robotic scanner, and a nuclear confirmation sensor
30 [28]. The role of each technique is as follows:

- 31 ➤ Forward looking SWIR or TIR cameras should detect thermal contrast between a landmine
32 and its surroundings.
- 33 ➤ VNIR camera should detect spectral reflectance differences between disturbed and
34 undisturbed soil and the presence of a trip wire.
- 35 ➤ Articulated Robotic Scanner affords the mechanical precision to provide images from scans
36 of a lightweight non imaging sensor.
- 37 ➤ Nuclear imaging is used for confirmation.
- 38 ➤ High mobility platform helps in moving the sensor payload.

39 In order to handle the enormous volume of data generated by hyperspectral imaging, the authors
40 proposed to use real-time techniques and algorithms described in [21,25] to compress the

1 hyperspectral images into single band images, which could then be processed by the minefield
2 detection algorithms described in [15]. The results of these projects were encouraging and show
3 that a teleoperated replacement of a human operator may be possible in the future.

4 A discussion of the results obtained after landmine detection tests using VNIR, SWIR, and TIR
5 imagers by DRDC and Itres was presented in [30]. Reliable surface-laid mine detection in various
6 weather conditions was achieved using VNIR and SWIR spectra, even if not in real time. Reliable
7 buried landmine detection was not achieved. There is no huge difference in the VNIR range
8 between the signatures of buried landmines and background materials, however they could be
9 indirectly detected by observing differences in reflectance between compact soil over mines and
10 background.

11 DRDC and Itres presented a review of the research on infrared and hyperspectral technologies for
12 landmine detection in [31]. Besides providing the theoretical background for the detection of
13 surface-laid and buried mines and the results of their experiments, the authors also described
14 examples of Hyperspectral Imagery (HSI) images of trace amounts trinitrotoluene (TNT) and
15 Cyclotrimethylenetrinitramine (RDX) distributed on the ground surface. The mechanism of the
16 distribution of the trace explosives by ants is further discussed in [32], [33].

17 The Canadian research and development conducted a project between 2004 and 2008 called Shield
18 ARP 12rl in order to develop and exploit optical imaging sensors for mine detection. Airborne
19 tests of real time hyperspectral imaging and a SWIR HSI imaging phenomenology study were
20 completed in October 2006. Tests on vehicle mounted optical tripwire imager and development of
21 Thermal infrared hyperspectral imager were completed on March 2008 [34]. After the realization
22 of simultaneous imaging in VNIR and SWIR bands, the ability of classifiers to separate
23 camouflage coatings from background improves when the VNIR and SWIR spectra are combined.
24 Simultaneous collection of SWIR and TIR images from an airborne platform in an environment
25 with minimal infrastructure has also been done. In vehicle-mounted trip wire detector tests, the
26 SWIR provided better wire/background contrast than the VNIR band. The above report describes
27 the tests and the results obtained during the project without mentioning the algorithms used or the
28 way the real time airborne detection is performed.

29 DRDC and Itres proposed in [35] a new design of hyperspectral camera with a range-gated
30 intensifier and combined the camera with selected pulsed lasers. The authors showed that it is
31 possible to relate the reflected signal to specific light matter interactions, like induced fluorescence.
32 This approach is independent of the ambient light conditions and can be customized to specific
33 wavelengths. In addition, it could help in surveying a specific area in order to increase the SNR.
34 The preliminary results indicate that the false alarm rate associated with this scenario might be too
35 high for ground area scanning speeds of practical interest.

36 DRDC also began a project in 2005 to demonstrate the military utility of space-based reflective
37 hyperspectral imagery (0.4-2.5 microns), especially in the domain of target detection and
38 identification for land and marine mapping applications. The results achieved are encouraging and
39 show that target abundance can be retrieved with high accuracy at the subpixel level using the
40 Constrained Energy Minimization (CEM) algorithm. The fact that the estimated abundances are

1 generally lower than the true abundances is consistent with an error introduced during the manual
2 delineation of targets area, by assigning to targets larger areas than their true area [26].

3 2.2. Equinox Corporation fusion test

4 The fusion of visible and SWIR bands could give better detection results. A basic fusion of two
5 spectrum bands produces acceptable segmentation of objects against background, irrespective of
6 illumination conditions. In other words, selecting a set of two or three spectral image bands has
7 been found to be just as effective in differentiating man-made objects from background as using
8 all spectral bands at once [36]. Such fusion has the potential to detect mine-like objects in an image
9 using an integrated camera with visible and SWIR sensors and more sophisticated and specialized
10 detection algorithms.

12 2.3. Hyperspectral mine detection program HMD

13 In [37], a Defense Advanced Research Project Agency (DARPA) sponsored experiment testing
14 the potential to detect buried landmines using hyperspectral Mid-wave Infrared (MWIR) (3 to 5
15 μm) and Long-wave Infrared (LWIR) (8 - 12 μm) bands is described. The project emphasizes the
16 detection of surface disturbances due to landmine burying. Previous experiments showed the
17 capability of VNIR and SWIR imagers to detect surface disturbances [17, 18, 22]. However, the
18 problem was the high false alarm rate induced by surrounding vegetation and rocks. According to
19 the authors, the main rationale behind the detection of buried landmines using the spectral
20 properties is that the surface properties are in some way different from the properties of subsurface
21 soil. The soil exposure at the surface changes some of its physical and chemical properties. These
22 experiments showed that spectral information are necessary for landmine detection.

23 In addition, the researchers of the Hyperspectral mine detection program HMD tried to detect
24 buried landmines by evaluating the contrast in thermal reflectivity between the mine and the soil
25 in just two bands of the thermal IR region [38]. They noticed that recently buried landmines could
26 be seen in thermal infrared imaging as bright spots because the disturbed soil has an apparent
27 temperature different from that of the surrounding undisturbed soil. In addition, they claimed that
28 even mines buried for a very long time could be detected in some types of soil as the subsurface
29 mine will have different thermal properties.

30 2.4. Hyperspectral mine detection phenomenology program

31 The American army also started the project “Hyperspectral mine detection phenomenology
32 program” (HMDP). Their main objective was to determine the existence of spectral characteristics
33 that are useful for landmine detection [39]. Therefore, they collected high quality hyperspectral
34 signatures of background materials and mines, measured temporal effects on buried landmines and
35 measured a statistically significant set of hyperspectral signatures of surface and buried mines in
36 natural soils, under variations of controlled variables. The spectral analysis results obtained during
37 the HMDP project recordings are presented in [40]. The authors concluded that uncontrolled
38 variables, mainly wind and rainfall, usually affect the results. The mines affected by more rainfall
39 continue to produce a signature distribution that is different from the background. Also, it is
40 remarkable that the temporal evolution of vegetation around landmines is too complex and makes

1 the characterization of temporal signature evolution extremely difficult. The following general
2 observations were made: 1) A light shower won't significantly reduce the signature; 2) The
3 signature is reduced by one-half inch of rain, 3) One-inch of rain further reduces the signature, but
4 does not eliminate it, and 4) For some conditions, several inches of rain may not eliminate the
5 signature. Overall, the VNIR and LWIR spectral regions show the most consistent and highest
6 performance. SWIR and LWIR show good performance for some conditions. MWIR showed the
7 least consistent and lowest performance.

8 2.5. Joint Multispectral Sensor Program (JMSP)

9 The goal of the research presented in [41] is to test the design of multispectral and hyperspectral
10 imagers that are able to obtain better detection performance by respecting the requirements and
11 conditions of target detection. For target detection, it is necessary to detect targets both in daylight
12 and nighttime conditions. Panchromatic or multispectral images in VNIR and SWIR ranges give
13 this capability during daylight. However, for military use, the MWIR and LWIR ranges are
14 necessary for nighttime operation. Due to high correlation of spectral bands of background
15 materials in all background conditions, the possibility to detect targets is high using MWIR and
16 LWIR ranges. After testing dual bands in MWIR and LWIR ranges, the authors concluded that
17 thermal multispectral images would give a better target detection and false alarm rate than a single
18 band infrared sensor. Tests showed that appropriately chosen small bands could provide good
19 detection, the optimal bands range being between 8 and 10.5 micrometers. There is a significant
20 increased utility of using LWIR with MWIR compared to the use of MWIR alone. Thanks to the
21 obtained results, the authors manufactured a new hyperspectral imager called SEBASS that works
22 in the ranges 2.9 to 5.2 micron and 7.8 to 13.4 micron. The Aerospace Corporation is still using
23 this sensor to take remote hyperspectral images in MWIR and LWIR ranges.

24 2.6. Night Vision and Electronics Systems Directorate (NVESD)

25 Night Vision and Electronics Systems Directorate (NVESD) has conducted during the fall of 2002
26 and spring of 2003 a wide variety of tests to examine airborne sensors for landmine detection [42].
27 The examined hyperspectral sensors were the Airborne Hyperspectral Imager (AHI) of the
28 University of Hawaii, which is a Long-wave Infrared (LWIR) imager, and the Compact airborne
29 hyperspectral sensor (COMPASS) which is an NVESD VNIR/SWIR sensor. In addition, a high
30 frequency Synthetic Aperture Radar (SAR) and GPR have been used. The authors tested two
31 methods for classification: Signature based and anomaly detection. Further, for anomaly detection
32 two approaches were considered: Local like Reed-Xioli method and Global like NFINDR. The
33 latter is an unmixing model method and alone is not sufficient for classification since it produces
34 only abundance fractions as output. For that purpose, the authors proposed to use it with a
35 Stochastic Target Detector (STD). The output of STD is a detection stochastic map that can be
36 thresholded. The tests showed the capability of LWIR and reflection bands to detect landmines
37 with the use of proper algorithms. The detection of landmines at subpixel level is challenging, but
38 indeed possible with the use of high quality hyperspectral instruments and algorithms.

39 Using the LWIR hyperspectral images acquired by AHI, another test has been conducted by
40 researchers at the Georgia Institute of Technology to detect a grid pattern of landmines and to use
41 this information to improve the detection performance. First, an anomaly detector is applied to the

1 hyperspectral data; in this case, the authors used the Dual Window-based Eigen Separation
2 Transform (DWEST). Then, pattern parameters are extracted and used to form a pattern projection
3 image. Finally, a pattern-based false alarm reduction is performed [43]. Using this process, higher
4 probability of detection at lower false alarm rate is obtained. Therefore, the results prove that the
5 inclusion of spatial pattern information in anomaly detection improves the detection of landmines
6 in minefields [43].

7 2.7. Defense Science and Technology Laboratory DSTL countermine project

8 A project similar to those of DRDC and DARPA was started in Britain with the goal to detect
9 landmines using a VNIR imager [44]. The program was called DSTL countermine project. Using
10 the VNIR hyperspectral camera SOC 700 mounted on a tripod, the team took high spatial
11 resolution images of landmines. However, the data is mainly used to investigate different
12 processing methods and not to evaluate the PD and the FAR of the sensor. For data processing,
13 the authors used Principal Component Analysis (PCA) for dimensionality reduction and anomaly
14 detection method for classification. The authors avoid the use of spectral comparisons between the
15 target and each pixel of the image, as it will be very time consuming due to the low
16 target/background ratio. The results were still preliminary, however the authors concluded that
17 VNIR has the potential to distinguish surface-laid landmines from background.

18 2.8. Indian Test to detect landmines using infrared images

19 In India, researchers proposed a hierarchical algorithm to detect landmines from infrared images
20 that consist of preprocessing (contrast enhancement- filtering- smoothing), segmentation, feature
21 extraction, and ANN based classification [45]. The authors tested the algorithm on surface-laid
22 mines in two types of soil: black cotton and sand. During the preprocessing, the image is converted
23 to gray level. The two most important preprocessing stages are the contrast enhancement and noise
24 removal. Segmentation is the process of grouping homogenous pixels sharing some common
25 attributes such as color, intensity or texture in an image. The aim is to separate the image into
26 regions of interest and background, in order to make further analysis easier. Clustering, edge
27 detection, and threshold based region growing are the main three categories encompassing the
28 various existing image segmentation techniques [45]. Therefore, feature extraction and further
29 processes are applied on the clusters that are deemed mine like. A Neural Network (NN) based
30 algorithm is used to classify the mine from the surrounding. During the tests, the authors used a
31 small NN of 1 hidden layer and 4 neurons. The results provided on a simple dataset are good,
32 however the algorithm is not expected to work well on another field or type of soil as the data used
33 during the phase of learning are not rich enough.

34 2.9. NATO project

35 In the Netherlands, a project took place in cooperation with NATO to make a remote detector of
36 landmines. The main objective was to obtain near real time minefield detection during a conflict
37 using an Unmanned Aerial Vehicle (UAV) at a typical altitude of 100 m. First, the authors
38 presented the imaging technologies available at that time: Radar, Microwave radiometers, visible
39 wavelengths, near, middle and far infrared. After that, the authors showed the principal signal
40 processing techniques used for mine detection at that time. The main steps involved can be
41 categorized as:

- 1
- 2 * image enhancement
- 3 * edge detection
- 4 * segmentation
- 5 * feature extraction and classification
- 6 * morphology

7 At the end of the report, the authors gave the following main recommendations based on various
8 experimental results [46]

- 9 1. Conventional medium-resolution imaging radars are less suitable for remote mine
10 detection.
- 11 2. Microwave radiometry detection principle is promising for remote mine detection.
- 12 3. The characteristics of visible and near infrared imaging are often requested. This is because
13 imaging systems in these bands are often low cost, compact, have a high spatial resolution
14 and can be used in real time detection.
- 15 4. The mid- or long-wave infrared wavelength band is a promising band for remote mine
16 detection.
- 17 5. As Meteorological conditions (such as rain showers) can make mine and minefield
18 detection in mid- and longwave infrared wavelength bands difficult, it is better to combine
19 several wavelength bands.
- 20 6. A study on the best processing techniques and a reliable and accurate interpretation of the
21 images of a remote mine detection system has to run in parallel with the development of a
22 mine (field) detection system.

23 2.10. Humanitarian DEMining (HUDEM) and Belgian Mine Action Technology (BEMAT)

24 In Belgium, a research project focused on using the fusion of data from multiple sensors (Ground
25 penetrating radar, metal detector and infrared sensor) [47]. In the above paper, the authors
26 presented their views regarding multi-sensor data fusion potentials in improving the close-in
27 detection of landmines and reduction of mined area. Modelling and fusion of the extracted features
28 are based on belief function theory and possibility theory. After modelling, the fusion part is
29 performed in two steps: the first step consists in analyzing all data measured by one sensor. The
30 second step combines the results of the three sensors. The final part of the fusion approach is the
31 decision. According to the authors, the final decision about the identity of the object should be left
32 to a human observer with field experience. Therefore, the fusion output is an informative decision.
33 The experience showed that the fusion gives better detection than any input sensor used alone.

34 2.11. FOI Multiple-Optical Mine detection System (MOMS) project

35 FOI, A Swedish defense research agency, worked on a project for the Swedish armed forces called
36 Multi-Optical Mine detection System (MOMS). The objective of the project was to provide
37 knowledge and competence for fast detection of surface-laid mines using multiple optical sensors
38 [48]. The authors conducted research to test the feasibility of detecting landmines using optical
39 sensors and the possibility to combine multiple sensors. According to the authors, hyperspectral
40 imaging is an encouraging candidate for automatic detection and recognition of exposed and semi-
41 hidden mines, when a priori knowledge of the target spectral signature is available. However, the

1 detection performance is limited when the targets are camouflaged by natural vegetation or hidden
2 under other objects. In addition, the authors claim that no single detection architecture is able to
3 meet the performance needed under all operating conditions; the choice of the particular sensors
4 and algorithms will depend on environmental and operations conditions [48].

5 2.12. TELOPS test to detect buried object using airborne thermal hyperspectral images

6 In 2015, a Canadian research company specialized in infrared and hyperspectral imaging named
7 TELOPS proved the possibility to detect buried objects using an airborne LWIR hyperspectral
8 imager [49]. From an aircraft platform, they acquired thermal hyperspectral images of areas that
9 contain man-made objects previously buried. They found that the disturbed soil right above a
10 buried target is warmer than the undisturbed soil area next to it [49]. By comparing the emissivity
11 data obtained through the Temperature-Emissivity separation, the buried target sites show up as
12 part of the hottest ground area within the scene but further classification or additional information
13 are needed to discriminate the buried objects from other naturally hot areas.

14 A summary of the above projects and of the results obtained is given in Table 1.

15 3. Mathematical methods used in hyperspectral data treatment

16 In this section, we present the main processing algorithms that can be used when dealing with
17 hyperspectral images. Most of these methods were developed during research on general problems
18 regarding the processing of hyperspectral images and are not specific for the landmine detection
19 problem. However, advances in that research will directly impact the success of landmine detection
20 using hyperspectral imaging. A review of different processing techniques used for data fusion,
21 spectral unmixing, classification and target detection could be found in [50].

22 After the acquisition of a hyperspectral image, the data pass through several steps. First, the image
23 is preprocessed to remove impurities, noise, and to reduce the image size. The main pre-processing
24 steps are contrast enhancement, filtering and smoothing. Then, segmentation is done to separate
25 useful data from background. After that, feature extraction is applied to extract the most
26 appropriate features for classification. Finally, classification or clustering methods are applied to
27 locate a target. In the following, we present the main algorithms used for target detection using
28 hyperspectral images. There are many other methods that may be used in each phase. However, in
29 this paper we detail the most commonly used ones.

30 3.1. Contrast enhancement

31 The image enhancement process consists of a collection of techniques that try to improve the visual
32 appearance of an image or to convert the image into a better form suited for analysis by a human
33 or a machine [51]. Image enhancement methods are divided into two main categories: spatial
34 domain methods and frequency domain methods. Spatial domain methods are applied directly on
35 the pixels of the image. In frequency domain methods, the image is processed in the frequency
36 domain after applying the Fourier transform on the original data. Contrast enhancement is one of
37 the most commonly used image enhancement methods. For the mine detection case, the role of
38 contrast enhancement is to enhance the difference between the landmine and the background
39 materials [52]. The main contrast enhancement methods used are:

3.1.1. Histogram equalization

Histogram Equalization (HE) is the most widely used contrast enhancement technique due to its simplicity and effectiveness. The aim of HE is to make the probability distribution of gray levels approximately uniform in the output image. It is a global method that flattens the histogram and stretches the dynamic range using the cumulative density function of the image [52].

The probability of the k th gray level in an image f can be described as $p_f(f_k) = \frac{n_k}{n}$

where $k \in [0, L-1]$, L is the number of gray levels in an image, n_k is the number of times the k th level appears in the image, and n is the total number of pixels in the image. The histogram is the plot of $p_f(f_k)$ versus k , and the goal of the histogram equalization is to obtain an image with a uniform histogram. The uniform histogram can be achieved by

$$g_k = T(f_k) = \sum_{j=0}^k \frac{n_j}{n} = \sum_{j=0}^k p_f(f_j)$$

Keeping two conditions,

(a) $T(f_k)$ is single valued and monotonically increasing in the range $k \in [0, L-1]$.

(b) $T(f_k)$ should be $T(f_k) \in [0, L-1]$ for $k \in [0, L-1]$.

The drawback of HE is that the brightness of the image is changed. To overcome this drawback and improve the performance, many derivations of this method were proposed. Among them, we list the following:

Brightness Bi-Histogram Equalization (BBHE)[53], Dualistic Sub Image Histogram Equalization (DSIHE) [54], Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)[55], Recursive Mean Separate Histogram Equalization (RMSHE)[56], Multi Histogram Equalization (MHE)[57], Brightness Preserving Dynamic Histogram Equalization (BPDHE)[58], Recursive Separated and Weighted Histogram Equalization (RSWHE)[59], Global Transformation Histogram Equalization (GHE)[60] and Local Transformation Histogram Equalization (LHE)[60].

3.1.2. Morphological Contrast Enhancement

Morphological theory has been introduced in image processing to overcome a number of problems like image distortion due to noise. The first step in morphological contrast enhancement is to find peaks and valleys in the original image. Peaks are light shades of gray tone image, while valleys are dark ones. Peaks are obtained by subtracting the opening from the original image, and valleys are obtained by subtracting the original image from the closing as

$$p(f) = f - \gamma(f),$$

$$v(f) = \phi(f) - f,$$

where $p(f)$ denotes the peaks, $v(f)$ denotes the valleys, $\gamma(f)$ denotes the opening, and $\phi(f)$ denotes

1 the closing of an image function f . Basic definitions of morphological methods and operators
 2 (erosion, dilation, opening and closing) could be found in [61]. To improve the contrast, the
 3 peaks and valleys are multiplied by constants as follows:

$$4 \quad p'(f) = p(f) \times c_1, \quad v'(f) = v(f) \times c_2 \quad \text{where: } c_1 = \left| \frac{\max(f) - \max(I)}{\max[p(f)]} \right| \quad \text{and } c_2 = \left| \frac{\min(f) - \min(I)}{\max[v(f)]} \right|$$

5 where I indicates the gray level. In the case of 8 bit gray levels, $\max(I)=255$ and $\min(I)=0$.

6 The contrast-enhanced image is obtained as the summation of the original image, the peaks, and
 7 the negative valleys $f' = f + p'(f) - v'(f)$ [52].

8

9 3.2. Filtering

10 Filtering is an operation that allows to reduce the noise or to sharpen blurred areas in an image in
 11 order to make it clearer and more suitable for further processes. In the filtering of hyperspectral
 12 images, several techniques usually used in image processing have been upgraded to obtain
 13 multichannel restoration. For example, the well-known Wiener filter used in image processing has
 14 been extended to be used in hyperspectral images. There are two groups of filters: One is based on
 15 the assumption that the within-channel information is separable from between-channel
 16 information, i.e., spectral and spatial information are separable. These filters are called Hybrid
 17 filters. In this case, the first step is to decorrelate channels using Fourier Transform or PCA and
 18 then apply a classic 2D restoration method such as Wiener filter or Static Wavelet Transform. The
 19 other group consists of a few proposed filters that do not rely on the assumption of spectral and
 20 spatial separability. [62]

21

22 3.2.1. Wiener filter

23 The Wiener filter is a widely used filter based on minimum mean square estimation. The original
 24 image is obtained from the received image by minimizing the mean square error. It assumes that
 25 the acquired image is composed of the original image and a white noise component that has a zero-
 26 mean Gaussian distribution [63].

27 $g(t) = f(t) + n(t)$ Where $f(t)$ is the original image, $g(t)$ the acquired image and $n(t)$ the noise.

28 The estimation of $f(t)$ is $\hat{f}(t) = \sum_{k=0}^{L-1} h(k)g(t-k)$. It is estimated using L samples taken from
 29 the received signal. $h(k)$ is a variable independent of time to be found. It is calculated by
 30 minimizing the approximation error $J = E(e^2(t)) = E\left[\left(f(t) - \hat{f}(t)\right)^2\right] = E\left[\left(f(t) - \sum_{k=0}^{L-1} h(k)g(t-k)\right)^2\right]$

32 The minimum is achieved by $\frac{\partial J}{\partial h(i)} = E\left[2\left\{f(t) - \sum_{k=0}^{L-1} h(k)g(t-k)\right\} \frac{de(t)}{dh(i)}\right] = 0$

33 and $\frac{de(t)}{dh(i)} = -g(t-i)$

1 We can reformulate it in a matrix form. $H=[h_0, h_1, h_2, \dots, h_{L-1}]^T$ and $G(k)=[g(k) \ g(k-1) \ \dots \ g(k-$
2 $L+1)]^T$

3 Thus $\frac{\partial J(H)}{\partial H} = 2RH - 2P \Rightarrow H^* = R^{-1}P$. This is called Wiener-Hopf equation.

4 Note that R is the autocorrelation of G . It is a symmetric Toeplitz matrix and therefore it is positive
5 definite and non singular so R^{-1} has a solution. P is the cross-correlation between H and the input
6 image.

7 3.2.2. Adaptive 3D Wiener filter

8 As most of the filters used while preprocessing hyperspectral images are based on the assumption
9 of spectral and spatial separability, Gaucel et al [62] proposed a new filter for hyperspectral images
10 relying on spectral and spatial information simultaneously.

11 First the authors assume that the channel vector $v(n_1, n_2)$ represents the zero-mean white Gaussian
12 noise, uncorrelated with the original image $f(n_1, n_2)$. The received image is
13 $g(n_1, n_2) = f(n_1, n_2) + v(n_1, n_2)$. Then, they apply the filter in local regions in which the signal-pixel
14 vector $f(n_1, n_2)$ is assumed homogeneous. So f could be modelled as $f(n_1, n_2) = m_f + w(n_1, n_2)$, where
15 m_f is the local mean of $f(n_1, n_2)$ and $w(n_1, n_2)$ a zero mean white noise.

16 The linear solution of Wiener filter is $\hat{f} = m_f + \Gamma_{fg} \Gamma_{gg}^{-1} (g - m_g)$ where Γ_{fg} is the covariance of
17 f and g , and Γ_{gg} is the variance-covariance matrix of g . From the received image we could estimate
18 Γ_{gg} . But as the noise and the signal are uncorrelated, $\Gamma_{gg} = \Gamma_{ff} + \Gamma_{vv}$ and $\Gamma_{fg} = \Gamma_{ff}$

19 Since the noise is zero-mean, $m_f = m_g$ and the equation becomes

$$20 \hat{f} = m_g + H(g - m_g) \text{ and } H = (\Gamma_{gg} - \Gamma_{vv}) \Gamma_{gg}^{-1}$$

21 Using the local region model, Γ_{gg} is estimated and m_g is updated at each pixel.

22

23 3.2.3. Multiway filtering

24 Multiway filtering is another reformulation of the Wiener filter based on modelling the
25 hyperspectral image by a third order Tensor.

26 The collected hyperspectral image R is modeled as the sum of the desired original image X and the
27 additive white and Gaussian noise N

$$28 R = X + N$$

29 The goal is to estimate the original image by applying multidimensional filtering on the received
30 data

$$31 \hat{X} = R \times_1 H_1 \times_2 H_2 \times_3 H_3$$

32 Where \times_n represents the n -mode product. The n -mode product between a data tensor R and matrix
33 H_n represents the consecutive matrix product between matrix H_n and the I_n -dimensional vectors
34 obtained from R by varying index i_n and keeping the other indexes fixed [64].

1 In order to determine the optimal n-mode filters H_1 , H_2 and H_3 , the criterion used is the
 2 minimization of the mean squared error between the estimated signal \hat{X} and the original one X .

3 $e(H_1, H_2, H_3) = E[\|X - R \times_1 H_1 \times_2 H_2 \times_3 H_3\|^2]$

4 To estimate H_n , an Alternative Least Square algorithm is used, consisting of the following steps
 5 [64]:

6 1. Initialization $k = 0$: $R^0 = R \Leftrightarrow H_n^0 = I_n$ for all $n = 1$ to N ($=3$ in this case).

7 2. ALS loop: while $\|X - R^k\|^2 > \text{thr}$, with $\text{thr} > 0$ fixed *a priori*.

8 (a) for $n = 1$ to N :

9 i. $R_n^k = R \times_1 H_1^k \cdots \times_{n-1} H_{n-1}^k \times_{n+1} H_{n+1}^k \cdots \times_N H_N^k$.

10 ii. $H_n^{k+1} = \text{argmin}_{Q_n \in \mathbb{R}^{I_n \times I_n}} \|X - R_n^k \times_n Q_n\|^2$ subject to $Q_n = H_1^T H_1 \otimes \dots \otimes H_{n-1}^T H_{n-1} \otimes H_{n+1}^T H_{n+1} \otimes \dots \otimes H_N^T H_N$
 11 $Q_n \in \mathbb{R}^{I_n \times I_n}$.

12

13 (b) $R^{k+1} = R \times_1 H_1^{k+1} \cdots \times_N H_N^{k+1}$, $k \leftarrow k + 1$.

14 3. Output: $\hat{X} = R \times_1 H_1 \times_2 H_2 \times_3 H_3$

15

16 Step (2)(a)(ii) of the ALS algorithm can be decomposed into the following sub-steps:

17 1. n-mode unfold R_n^k into $R_n^k = R_n(H_1^k \otimes \dots \otimes H_n^{k-1} \otimes H_n^{k+1} \dots \otimes H_N^k)$, and R
 18 into R_n ;

19 2. Compute $\gamma_{RR}^n = E(R_n^k R_n^{kT})$, perform its eigenvector decomposition (EVD) and place the
 20 eigenvalues in λ_{γ}^k , for $k = 1$ to I_n ;

21 3. Estimate K_n using Akaike Information Criterion or Minimum Description Length criterion.

22 4. Estimate $\sigma_{\gamma}^{(n)2}$ by computing $\frac{1}{I_n - K_n} \sum_{k=K_n+1}^{I_n} \lambda_{\gamma}^k$ and estimate β_i by computing $\lambda_{\gamma}^i - \sigma_{\gamma}^{(n)2}$ for $i =$
 23 1 to K_n ;

24 5. compute $\Gamma_{RR}^{(n)} = E(R_n^k R_n^{kT})$, perform its EVD, keep in matrix V_s^n the K_n eigenvectors
 25 associated with the K_n largest eigenvalues of $\Gamma_{RR}^{(n)}$, and keep the R_n largest eigenvalues λ_{Γ}^k for

26 $k = 1$ to K_n ;

27 6. Compute the $(k + 1)^{\text{th}}$ iteration of n-mode Wiener filter H_n^{k+1} using the expression of n-mode
 28 Wiener filter.

29 This method has been tested in [64] on different images and proved its efficiency by increasing
 30 the SNR by about 3dB. However, one of the main drawbacks is an increased complexity and
 31 computational time.

32

3.3. Segmentation

In the remote sensing community, segmentation is defined as the process of searching for homogenous regions in an image, that is later followed by the classification of these regions [65]. In image processing, there are many methods used for segmentation, however not all of them are applicable to multispectral and hyperspectral images. Some methods like watershed algorithms have been upgraded in order to segment hyperspectral images. Globally, segmentation algorithms are divided into two categories: Boundary-based and Region-based. Boundary based methods detect the boundary using the discontinuity property. In region-based algorithm, pixels in a region are grouped using the similarity property. In the following, we present the main methods used in hyperspectral image segmentation.

3.3.1. Watershed Algorithm

The watershed algorithm is a powerful tool usually used for mathematical morphology segmentation. In [66] the authors proposed to use spatial gradients and spectral markers for segmentation. The algorithm works as follows:

First, to avoid obtaining a large number of minima while flooding the watershed using the gradient function (over-segmentation), they determine markers for each region of interest using Clara Clustering algorithm [67]. Then, the Factor Correspondence Analysis FCA [68] data reduction method is applied to remove the redundancy of channels and filter the image. Next, a chi-squared distance based gradient is performed on the filtered image, then watershed segmentation is computed. This approach works well and proves that an adapted data reduction is necessary for multivariate gradient segmentation.

3.3.2. Hierarchical segmentation

In 1989, Beaulieu and Goldberg [69] proposed a hierarchical process to segment images based on hierarchical step-wise optimization. Hierarchical segmentation is defined as a set of segmentations of the same image at different levels of detail in which the segmentations at coarser levels can be produced from a simple merging of regions at finer levels [69]. First, each pixel is assigned to a region label. Then, spatially adjacent regions with small dissimilarity value are merged. The dissimilarity between new spatially adjacent regions are calculated and the pairs with smallest value are merged. The process is repeated until the number of regions needed is obtained or all values of dissimilarity are below a predefined threshold. The drawback of this method is the long computational time while dealing with large data.

Tilton in 1998 [70] proposed a new hierarchical segmentation method called HSEG. The main improvement of this method is that non-adjacent regions could be merged together and the dissimilarity function is selectable. Another recursive version of this algorithm called RHEG was proposed in [71] to overcome the problem of long computational time of HSEG. These algorithms are registered patents for US government.

3.4. Feature extraction

Feature extraction consists in transforming the data from a high dimensional space to a lower dimensional space chosen in such a way as to conserve as much as possible the information of interest in the data. Feature extraction is used in hyperspectral image analysis to overcome the

1 problem of a low number of data training samples in comparison to the high spectral resolution of
2 the image and to reduce the computational time. There are many feature extraction algorithms that
3 are introduced; some are linear while others are nonlinear. While working on landmine or target
4 detection, not all feature extraction algorithms are useful, because the targets of interest are
5 generally sparse and the feature extraction may remove the key features of the target. In the
6 following, we are going to list some of these algorithms, their implementation and their
7 advantages.

8 3.4.1. Principal Component Transformation (PCT)

9 Principal Component Transformation, also called principal component analysis, Hotelling
10 transformation or Karhunen-Loeve transformation is a dimensionality reduction method based on
11 the minimization of the representation error. The idea is to choose the most representing bands
12 with the help of the eigenvalue decomposition of the covariance matrix of the hyperspectral image
13 [72]. The first step of PCT is the calculation of the covariance matrix of the image matrix. Then,
14 the eigenvalues of the covariance matrix are calculated and the eigenvectors are extracted. Finally,
15 the image matrix is projected onto the new subspace formed by the k orthogonal eigenvectors
16 corresponding to the highest eigenvalues. $Y=W^T x$ where x is a $d \times 1$ -dimensional vector
17 representing one image pixel, y is the transformed $k \times 1$ -dimensional sample in the new subspace
18 and W is the transformation matrix of k orthogonal eigenvectors.

19 Note that while computing the PCT algorithm, the variance of the projections along the principal
20 components is equal to the eigenvalues of the principal components. In theory, PCT transformation
21 affects the classification of hyperspectral images. However, the overall effect on classification
22 does not change the general class patterns and, therefore, the dominating classification result
23 remains correct.

24 3.4.2. Linear Discriminant Analysis (LDA)

25 Linear discriminant analysis is a statistical based method often used for feature extraction and
26 dimensionality reduction. It is also named Discriminant Analysis Feature Extraction (DAFE). It is
27 an extension of the well-known Fisher discriminant analysis, which is limited to binary class
28 decomposition. LDA computes an optimal transformation by minimizing the within-class distance
29 and maximizing the between-class distance simultaneously, thus achieving maximum class
30 discrimination [73]. Therefore, the first step is to calculate the within-class, between-class and total
31 scatter matrices. A transformation matrix is then defined and computed by applying the
32 eigenvector decomposition on the scatter matrix [74]. The main disadvantage of this method is
33 that it requires that the scatter matrix of the data be nonsingular. This method has also other
34 drawbacks: the maximum number of features extracted is equal to the number of classes minus
35 one. The number of training samples should be large enough to estimate the between-class and
36 within-class scatter matrix reliably. The between-class will be biased toward the class that has very
37 different mean value. Also, it is very time consuming compared to other methods. In addition, it
38 requires more training samples for hyperspectral images to calculate the class statistical parameters
39 at full dimension. [75]. Many LDA extensions have been proposed to deal with the singularity
40 problem like PCA+LDA, regularized LDA (RLDA) , null space LDA (NLDA) , orthogonal

1 centroid method (OCM) , uncorrelated LDA (ULDA) , orthogonal LDA (OLDA), LDA/GSVD,
2 etc. [76].

3

4 In addition to the main methods we described above for feature extraction of hyperspectral
5 images, many other techniques exist like matched pursuit [75], neighborhood embedding [77],
6 Sammon's mapping [78] and nonparametric weighted feature extraction [79].

7 3.5. Classification

8 It is the most important step in landmine and target detection. The performance of the algorithms
9 used in each of the previous steps and in the classification phase are evaluated by the study of the
10 classification results. The classification phase in an image based target detection process could be
11 defined as the step in which the pixels are discerned between target and non-target. Globally, the
12 classification algorithms are divided into two main classes: Supervised and unsupervised.
13 Supervised classification methods are based on the knowledge of the target and the use of training
14 samples. Unsupervised classification methods consist of grouping pixels that have similar
15 properties without the knowledge of target properties. Considering the way the classifier computes
16 the information in the pixels, classification algorithms are divided into per pixel classifiers,
17 subpixel classifiers, per-field classifiers, knowledge based classifiers, contextual and multiple
18 classifiers [80]. In landmine detection, unsupervised classification techniques are used when there
19 is no information on the type of mine present in the field or when there is the possibility that a
20 particular type of mine is deployed but its reflectance spectrum is not in the library of known
21 spectra. However, unsupervised classification methods do not work well in every possible
22 condition and suffer from high false alarm rate due to the generally low number of target pixels
23 compared to background pixels. While the use of unsupervised methods could help in detecting
24 unknown types of landmines, the use of supervised classification methods is necessary for the
25 identification of mines. In the following, we are going to mention the major classification methods
26 used in landmine detection:

27 3.5.1. Support vector machine (SVM)

28 Support vector machine is a powerful non-parametrical supervised classification method. Firstly,
29 it was proposed for binary classification and regression [81]. Then, it has been used in the
30 classification of hyperspectral images [82]. SVM consists in finding the best separation between
31 two classes based on the separation of representative training samples called support vectors. In
32 addition, SVM does not suffer from Hughes effect and may perform separation of classes having
33 very close means even with a very small number of training samples [83]. First, we start with a
34 couple of training samples (x_i, y_i) where y_i is a class label equal to ± 1 which indicates the class of
35 the pixel and x_i is a d -dimensional vector which represents the spectrum of the pixel in d
36 wavelengths in the case of hyperspectral images. If the classes are linearly separable by a
37 hyperplane, the SVM classifier is represented by the function $f(x)=w \cdot x+b$ where w is a vector \in
38 R^d and b is a real bias $\in R$ that could separate the classes without errors. The decision is made
39 according to the sign of f . The SVM approach consists in finding the separating hyperplane that
40 has the largest distance from the closest training samples. This distance is expressed as $1/\|w\|$. The
41 margin is defined as $2/\|w\|$. So to calculate W and b , the following optimization must be calculated:

1 $\min\{1/2 \|w\|^2\}$ with $y_i(w \cdot x + b) \geq 1$, for all samples. By introducing the Lagrangian formalism, the
2 problem is transformed to the dual problem:

3 Max of: $\sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$ with the condition $\sum_{i=1}^N \alpha_i y_i = 0$ and $\alpha_i \geq 0$.
4 Where α_i are Lagrange multiplier that can be estimated using quadratic programming.

5 If the samples are not linearly separable, suitable kernel functions are used to project the data into
6 a higher dimensional feature space in which the data could be linearly classified. Profiting from
7 this transformation, the inner product in the maximization $(x_i \cdot x_j)$ is replaced with the function
8 $k(x_i, x_j)$.

9 There are many types of kernel functions, including: polynomial: $K(x_i, x_j) = (1 + x_i \cdot x_j)^q$; Gaussian
10 radial basis $K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / (2\sigma^2))$; Laplacian radial basis $K(x_i, x_j) = \exp(-\|x_i - x_j\| / (2\sigma^2))$
11 ; Sigmoidal $K(x_i, x_j) = \tanh(\alpha_0(x_i \cdot x_j) + \sigma^2)$. In the case of multiclass classification, two approaches
12 could be used: One against all, where each class is discriminated using the samples of all classes.
13 One against one, where a larger number of classifiers are computed using each time the training
14 samples of two different classes.

15 3.5.2. K means clustering

16 K means clustering is one of the most used clustering methods for hyperspectral images. In k
17 means clustering, the pixels of the image are grouped into classes based on spectral similarity.
18 First, k random centroids are assigned. Then each pixel is assigned to the closest centroid. The
19 norm used to calculate the distance between the pixel and the centroid could be the Euclidian
20 distance, Manhattan distance, max distance, or linear combination of the above distances. After
21 that, new centroids are found by calculating the mean value of each cluster. Then, the clusters are
22 reformulated. This process is repeated until the total number of iterations is achieved or the total
23 distance between classes is minimized [84].

24 3.5.3. Orthogonal subspace projection (OSP)

25 Orthogonal subspace projection is a supervised classification method used to detect targets in
26 hyperspectral images at subpixel level. This method is based on the theory of spectral unmixing
27 which consists in subdividing the reflectance spectra of each pixel into endmembers spectra. This
28 method was proposed by Harsanyi and Chang in 1994 [85] in order to exploit a priori knowledge
29 of the target and facilitate the target detection. Suppose the image pixel is modeled by the equation:
30 $\mathbf{x} = \mathbf{t}\mathbf{a} + \mathbf{B}\boldsymbol{\alpha} + \boldsymbol{\xi}$ where:

31 \mathbf{x} = spectral vector characterizing the pixel

32 \mathbf{t} = spectral vector associated with the target

33 \mathbf{a} = unknown fractional abundance of the target within the pixel

34 \mathbf{B} = matrix of vectors of the scene endmembers (materials found in the scene background)

35 $\boldsymbol{\alpha}$ = unknown fractional abundance of each basis vector

36 $\boldsymbol{\xi}$ = residual error associated with this model.

1 After the background suppression, OSP uses the matched filter to determine if the target spectrum
2 is a part of the pixel spectra by calculating its abundance. This is done using the OSP operator
3 $\delta_{OSP}(x) = t^T P_B^\perp x$ where $P_B^\perp = I - BB^\#$ is the orthogonal background operator, and I is the identity
4 matrix. The fractional abundance of the target within the pixel can be computed as follows:
5 $\hat{a} = T_{osp}(x) = (t^T P_B^\perp t)^{-1} \delta_{OSP}(x)$. [85]

6 3.5.4. Linear Cross-Correlation

7 Cross-correlation is a mathematical tool used in signal processing to evaluate the similarity
8 between two functions or vectors [86]. In case of target detection using hyperspectral imaging,
9 Cross-correlation is used to compare an a priori known reflectance spectrum of the target with the
10 reflectance spectrum of the pixel under test. As much as the reflectances are similar, the probability
11 of target existence at the pixel location is higher. Therefore, this method treats the pixel value and
12 target spectra as vectors and computes the spectral angle between them. The first step is to
13 normalize the image pixels to remove brightness differences by subtracting the mean and dividing
14 by the standard deviation. Then, the cosine of the angle between the pixel \vec{P} and target \vec{T} is
15 computed to evaluate the similarity between the target and the pixel, where $\cos(\phi) = \frac{\vec{P} \cdot \vec{T}}{\|\vec{P}\| \|\vec{T}\|}$.

16 3.6. Recent developments in target detection using hyperspectral images.

17 In recent years, researchers proposed various new algorithms to detect targets in a hyperspectral
18 image. Although the different approaches are devoted to generic target detection, they represent
19 promising candidates for improving the performance of current landmine detection techniques. As
20 a matter of fact, landmines constitute a special type of targets, since they are usually rare and sparse
21 in the scene, and they have different shapes, colors and reflectance spectra. For example, various
22 approaches to model a hyperspectral image, in addition to a comparison between supervised
23 Matched filter and unsupervised Reed-Xioli target detection algorithms, are presented in [87]. A
24 nonlinear version of the algorithm *Target Constrained Interference Minimized Filter* based on
25 kernels is recently proposed in [88]. In [89], the authors propose a new endmember extraction
26 process to detect anomalies in a hyperspectral image. Some researchers proposed new models to
27 interpret the hyperspectral data in order to simplify the target detection process. Here we mention:
28 Forward modelling working in radiance space [90], Sparse Representation Based Binary
29 Hypothesis Model (SRBBH) [91], Sparsity and Compressed sensing based models [92] and spatio-
30 spectral Gaussian random field modeling [93].

31

32 4. Discussion

33 Since the introduction of hyperspectral imaging in 1985, applications of this technique have
34 increased in several fields. As this technique gives the ability to distinguish different materials
35 remotely, it has been applied to landmine detection research. Every material has its special spectral
36 signature. Therefore, knowing the mine spectral curve, by a simple comparison between the mine
37 spectrum and the pixel spectrum, we can decide on the presence or the absence of the mine at that
38 specific position. It was found that spectral reflectance of each type of surface-laid mines has a
39 constant shape between 500-680 nm but varies in offset and scale according to the illuminance of

1 the scene [16]. So, the detection of this particular shape in the pixel spectrum proves the presence
2 of the landmine.

3 Using VNIR band, recently buried landmines could be detected. Also, the fusion of VNIR and
4 SWIR could give better results. Landmine burying changes the thermal properties of the upper
5 level of some type of soils. It also changes its surface reflectivity and stresses vegetation. Hence,
6 buried landmines can be detected by measuring the change of reflectivity both between
7 manipulated soil and background and between stressed and unstressed vegetation. Consequently,
8 as anti-tank mine deployment is done by digging up a larger area of surface (soil and/or vegetation)
9 and a larger volume of soil is disturbed, the possibility of detecting them is higher than with anti-
10 personnel mines. MWIR and LWIR bands are also used to detect buried landmines. Even if SWIR
11 and VNIR alone could detect soil disturbances due to buried mines, MWIR and LWIR can reduce
12 the false alarm rate. However, the use of SWIR bands is more common since the majority of
13 manufactured imagers operates in the VNIR and SWIR bands. After testing several hyperspectral
14 imagers of different bands, it was found that imagers in LWIR bands have the potential to detect
15 buried landmines with the use of proper algorithms. The algorithms could be supervised or
16 unsupervised based on the data availability. Note that this does not eliminate the possibility to
17 detect landmines with the use of other bands. However, proper algorithms and thresholds should
18 be used for each case.

19 If we consider high spatial resolution images, which means the image has ground sample distance
20 close to the size of landmine, the possibility to detect a landmine is higher as the reflectance
21 spectrum of the pixel will result only from the reflectance of the mine, or at least the reflectance
22 of the landmine will be present with a high abundance. In addition, military target detection could
23 be achieved at subpixel level using hyperspectral images. This means that by acquiring images
24 from high altitude, using UAV or aircrafts, fast target detection is possible even if the target
25 constitutes a small part of the pixel.

26 In order to attain quasi real-time detection, all the processes involved, starting from geocorrection
27 until classification, must be studied and organized so as to reduce the computational time. Since
28 the detection performance will be possibly affected by some optimizations, a tradeoff between
29 computational time and detection performance has to be achieved.

30 Several factors affect the reflectance signature obtained by the imager. Wind and rain are the main
31 factors, but the effect of rain is the dominant one. In the case of buried landmines, rainfall decreases
32 the reflected portion of the thermal energy and therefore the reflectance signal received. However,
33 the shape of the signature remains the same. More rainfall will result in more reduction and
34 therefore the reflected signal will be more and more similar to the background.

35 The design of active hyperspectral imagers by joining a laser illuminator with the light detector is
36 beneficial to obtain images independently of light and weather conditions. However, it was found
37 that this method has a higher false alarm rate. This may be caused by the emission of excess light
38 that is reflected by the target and background in a similar way. Therefore, the contrast between
39 target and background has decreased. The distance between the laser emitter and the ground must
40 be made as small as possible, to improve the system performance.

1 Many projects proposed the fusion of multiple sensors in order to detect landmines like the project
 2 in Belgium and in DRDC [27,29,47]. Even if the Belgian project considers the system output as
 3 an aid to a human operator who is in charge of the final decision, both projects proved that a well-
 4 organized hierarchical fusion gives better results than the use of a single detection technique.

5 5. Conclusions

6 According to the previous results, in order to achieve a reliable detection, a comparative study
 7 between different classification algorithms in different conditions must be considered. To do this,
 8 one should take into consideration the effect of imager elevation, which affects the spatial
 9 resolution, the number of pixels in each frame, the imager holder velocity, in order to optimize the
 10 capturing time and to minimize the computational time. Various images captured in different time
 11 and weather conditions and from different angles should be compared to model the effect of
 12 sunlight and weather on the detection performance and to come out with the best conditions for a
 13 better detection.

14 Previous tests used an airborne hyperspectral imaging system for landmine detection, mounted on
 15 a fixed wing manned aircraft or a helicopter. However, for the landmine detection purpose, a high
 16 spatial resolution is necessary for a good detection. Therefore, it is necessary to test the ability of
 17 a multicopter drone to carry the hyperspectral imager. Landmine detection with a multicopter drone
 18 could be very promising, since it allows to detect high quality images with few artifacts caused by
 19 undesired motions.

20 In parallel with the use of new image acquisition techniques, the development of new target
 21 detection algorithms and the introduction of different approaches of hyperspectral image
 22 modeling, like the use of sparse signal models, are expected to have a great impact on landmine
 23 detection in future works. The development of such techniques helps in making new fully
 24 automated landmine detection systems that have higher probability of detection and lower false
 25 alarm rate.

26 The fusion of multiple landmine detection techniques may improve the detection performance. For
 27 example, the fusion of lightweight techniques that can be embedded in small UAVs, has to be
 28 investigated. This may lead to test the fusion between hyperspectral imaging and the Ground
 29 penetrating Radar detector as these techniques are lightweight and can be handled with quadrotors.
 30 We neglected the fusion with metal detectors as they necessitate the proximity between the sensor
 31 and the ground. Also, the acoustic and seismic detectors are discarded because they use very heavy
 32 equipment.

33 *Table 1: summary of projects studied landmine detection using infrared and hyperspectral imaging.*

Research Project	Type of data	Techniques Used	Comments
Detection of surface-laid minefields using a hierarchical image processing	Infrared monochromatic Image	Hierarchical image processing	Method would be useful as follow-on stage to process airborne hyperspectral imagery after preprocessing in order to reduce the hyperspectral image to a single band.

algorithm (DRDC)			
Surface laid Landmine detection using VNIR (DRDC)	VNIR	LCC & Linear Unmixing	Surface-laid mines have consistent shape in VNIR bands; LCC performs well in case of high spatial resolution images; Unmixing techniques have higher PD in the case of subpixel target at the price of higher FAR
Buried Landmines detection using VNIR (DRDC)	VNIR	LCC	Using VNIR, buried mines are not directly detected, however the change of soil characteristics and vegetative stress due to mine burying is detectable.
Effect of Spatial resolution on mines detection (DRDC)	VNIR	LCC & OSP	LCC performs better when the pixel size is smaller than mine size. OSP is better when mine size is smaller than pixel size. Best detection is achieved when the result of two methods are combined.
Surface-laid Landmine detection using VNIR in real time (DRDC)	VNIR	Pipeline image processing	the proposed suite of algorithms proves the possibility to detect landmines in quasi real time using an airborne platform
Landmines detection using SWIR bands (DRDC)	SWIR	LCC	Similarly to VNIR bands, the use of SWIR is beneficial to detect surface-laid mines and recently buried landmines.
Landmines detection using LWIR bands (DRDC)	LWIR (TIR)	Spectral comparison	LWIR hyperspectral imaging provides advantages over broadband LWIR
Multiple sensors mounted on a robot (DRDC)	Fusion of VNIR, SWIR, LWIR HSI and other sensors	Dynamic range detector and contrast enhancement	A proposed system employing hyperspectral imagers for close-in anti-personnel mine detection.
Active hyperspectral imaging (DRDC/Itres)	VNIR	Casi imager with intensifier	With the addition of external illumination, the FAR increases as reflectivity of background increases.
Equinox Project	Fusion of visible and SWIR	Thresholded Ratio vegetation index	Here a ratio between two or three bands is used. More bands using other approaches may improve the results.

DARPA project to detect buried landmines	MWIR and LWIR	spectral comparison	LWIR and MWIR are more suitable to detect buried landmines.
Hyperspectral mine detection phenomenology program	VNIR,SWIR,MWIR,LWIR	Data collection using spectrometers	Weather conditions affect the intensity of the reflected spectra. The effect of rain is more important than other effects.
Joint Multispectral Sensor Program	VNIR,SWIR,MWIR,LWIR	Fourier Transform	Thermal sensors are beneficial for target detection at nighttime. LWIR bands are more effective than MWIR
airborne sensors tests (NVESD)	VNIR,SWIR,MWIR,LWIR	RX and NFINDR with STD anomaly detection. Grid pattern detection of landmines	LWIR gives a good detection with the use of proper algorithms. The inclusion of spatial pattern information in anomaly detection improves the detection performance.
DSTL countermine project	VNIR	PCA	more tests and other algorithms shall be tested to evaluate the effectiveness of VNIR bands in landmine detection
Indian Test to detect landmines using infrared image	Infrared Image	Hierarchical image processing	More images are needed to train the Neural network based classifier. A more complex one may be used in complex situations.
NATO project	VNIR,SWIR,MWIR,LWIR	Hierarchical image processing	Radars are less suitable for airborne mine detection. Combination of bands is necessary to overcome the meteorological effects. Improvement of algorithms and techniques in parallel is necessary.
Humanitarian demining (HUDEM & BEMAT)	GPR, metal detector, infrared sensor	belief and possibility theory	Fusion of sensors may give better results than single sensor.
FOI (MOMS)	VNIR,SWIR,MWIR,LWIR, 3D LADAR.	Anomaly detection, Support Vector Machines	Hyperspectral imaging is useful for automatic detection of open and semi-hidden mines. The choice of sensor suite and algorithms depends on environmental and operational conditions.
TELOPS	LWIR	Temperature-Emissivity separation, Linear Unmixing to study the mineral distribution	Soil above landmines is warmer than surrounding undisturbed soil. Complementary information are needed to reduce the FAR.

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4

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