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

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

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

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

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

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

2. Projects using hyperspectral imaging in landmine detection

2.1. Defence Research and Development Canada projects

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

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

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

The spatial resolution of the image affects the performance of the detection algorithm [19]. As the pixel size gets closer to the size of the mine, the possibility to isolate landmines increases. This has been proven by the research team of DRDC in [20]. The authors acquired two types of images using a VNIR imager: Medium resolution images at the altitude of 300m and high-resolution images at the altitude of 6m in a different place. In the medium resolution experiment, they obtained a 100% PD and $0.00034/m^2$ FAR. In the high-resolution experiment, all mines were detected with a false alarm rate of $0.0043/m^2$. Linear Cross Correlation (LCC) and Orthogonal subspace projection (OSP) were used in classification. The best detection is achieved when taking the result of the combination of the two techniques.

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

In [25], which is a continuation of the research in [21], we find the first experiment that aims at detecting landmines from an airborne hyperspectral imaging system in real time. The above paper describes how software and hardware improvements can achieve real time detection from an airborne platform. First, radiometric correction is applied on raw data, then custom classification algorithms are applied to the corrected data. A spectral signature library provides reference spectral vectors. The classification results are stored and displayed in real time. The first real time landmine detection system was mounted on a slow vehicle (1-2 km/h) [21]. A display system shows selected bands including corrected spectral bands, partial data results or final target bands. The second real-time detection system was an improvement of the first system to be compatible with airborne imaging data rates. A hardware/software system was implemented measuring the change in slit contamination (filings, dust, paint flecks) relative to the slit performance during calibration and modifying the correction matrix accordingly during radiometric conversion. Detection rates were not the prime concern of the test. The authors wanted to test the ability to detect landmines from an airborne platform in real time. There are no indications regarding the algorithms used for data correction, band selection, and classification.

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

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

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

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

In order to handle the enormous volume of data generated by hyperspectral imaging, the authors proposed to use real-time techniques and algorithms described in [21,25] to compress the hyperspectral images into single band images, which could then be processed by the minefield detection algorithms described in [15]. The results of these projects were encouraging and show that a teleoperated replacement of a human operator may be possible in the future.

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

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

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

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

DRDC also began a project in 2005 to demonstrate the military utility of space-based reflective hyperspectral imagery (0.4-2.5 microns), especially in the domain of target detection and identification for land and marine mapping applications. The results achieved are encouraging and show that target abundance can be retrieved with high accuracy at the subpixel level using the Constrained Energy Minimization (CEM) algorithm. The fact that the estimated abundances are generally lower than the true abundances is consistent with an error introduced during the manual delineation of targets area, by assigning to targets larger areas than their true area [26].

2.2. Equinox Corporation fusion test

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

2.3. Hyperspectral mine detection program HMD

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

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

2.4. Hyperspectral mine detection phenomenology program

The American army also started the project “Hyperspectral mine detection phenomenology program” (HMDP). Their main objective was to determine the existence of spectral characteristics that are useful for landmine detection [39]. Therefore, they collected high quality hyperspectral signatures of background materials and mines, measured temporal effects on buried landmines and measured a statistically significant set of hyperspectral signatures of surface and buried mines in natural soils, under variations of controlled variables. The spectral analysis results obtained during the HMDP project recordings are presented in [40]. The authors concluded that uncontrolled variables, mainly wind and rainfall, usually affect the results. The mines affected by more rainfall continue to produce a signature distribution that is different from the background. Also, it is remarkable that the temporal evolution of vegetation around landmines is too complex and makes the characterization of temporal signature evolution extremely difficult. The following general observations were made: 1) A light shower won't significantly reduce the signature; 2) The signature is reduced by one-half inch of rain, 3) One-inch of rain further reduces the signature, but does not eliminate it, and 4) For some conditions, several inches of rain may not eliminate the signature. Overall, the VNIR and LWIR spectral regions show the most consistent and highest performance. SWIR and LWIR show good performance for some conditions. MWIR showed the least consistent and lowest performance.

2.5. Joint Multispectral Sensor Program (JMSP)

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

2.6. Night Vision and Electronics Systems Directorate (NVESD)

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

Using the LWIR hyperspectral images acquired by AHI, another test has been conducted by researchers at the Georgia Institute of Technology to detect a grid pattern of landmines and to use this information to improve the detection performance. First, an anomaly detector is applied to the hyperspectral data; in this case, the authors used the Dual Window-based Eigen Separation Transform (DWEST). Then, pattern parameters are extracted and used to form a pattern projection image. Finally, a pattern-based false alarm reduction is performed [43]. Using this process, higher probability of detection at lower false alarm rate is obtained. Therefore, the results prove that the inclusion of spatial pattern information in anomaly detection improves the detection of landmines in minefields [43].

2.7. Defense Science and Technology Laboratory DSTL countermine project

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

2.8. Indian Test to detect landmines using infrared images

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

2.9. NATO project

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

* image enhancement
* edge detection
* segmentation
* feature extraction and classification
* morphology

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

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

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

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

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

FOI, A Swedish defense research agency, worked on a project for the Swedish armed forces called Multi-Optical Mine detection System (MOMS). The objective of the project was to provide knowledge and competence for fast detection of surface-laid mines using multiple optical sensors [48]. The authors conducted research to test the feasibility of detecting landmines using optical sensors and the possibility to combine multiple sensors. According to the authors, hyperspectral imaging is an encouraging candidate for automatic detection and recognition of exposed and semi-hidden mines, when a priori knowledge of the target spectral signature is available. However, the detection performance is limited when the targets are camouflaged by natural vegetation or hidden under other objects. In addition, the authors claim that no single detection architecture is able to meet the performance needed under all operating conditions; the choice of the particular sensors and algorithms will depend on environmental and operations conditions [48].

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

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

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

3. Mathematical methods used in hyperspectral data treatment

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

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

3.1. Contrast enhancement

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

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

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

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

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

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

3.2. Filtering

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

3.2.1. Wiener filter

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

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

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

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

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

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

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

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

3.2.2. Adaptive 3D Wiener filter

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

First the authors assume that the channel vector $v(n_1,n_2)$ represents the zero-mean white Gaussian noise, uncorrelated with the original image $f(n_1,n_2)$. The received image is $g(n_1,n_2)=f(n_1,n_2)+v(n_1,n_2)$. Then, they apply the filter in local regions in which the signal-pixel 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 m_f is the local mean of $f(n_1,n_2)$ and $w(n_1,n_2)$ a zero mean white noise.

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 f and g, and Γ_{gg} is the variance-covariance matrix of g. From the received image we could estimate Γ_{gg}. But as the noise and the signal are uncorrelated, $\Gamma_{gg} = \Gamma_{ff} + \Gamma_{vv}$ and $\Gamma_{fg} = \Gamma_{ff}$

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

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

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

3.2.3. Multiway filtering

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

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

$$R = X + N$$

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

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

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

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

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

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

1. Initialization $k = 0$: $R^0 = R \Leftrightarrow H^0_n = I_{In}$ for all $n = 1$ to N (=3 in this case).

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

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

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

ii. H_n^{k+1}=argmin $\|X - R^k_n \times_n Q_n\|^2$ subject to $Q_n = H_1^T H_1 \otimes \ldots H_{n-1}^T H_{n-1} \otimes H_{n+1}^T H_{n+1} \otimes \ldots H_N^T H_N$ $Q_n \in R^{In\times In}$.

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

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

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

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

2. Compute $\gamma_{RR}^n = E(R_n^k R_n^T)$, perform its eigenvector decomposition (EVD) and place the eigenvalues in λ_γ^k, for $k = 1$ to In;

3. Estimate K_n using Akaike Information Criterion or Minimum Description Length criterion.
4. Estimate $\sigma_\gamma^{(n)2}$ by computing $\frac{1}{I_n - K_n}\sum_{k=K_n+1}^{I_n} \lambda_k^\gamma$ and estimate β_i by computing λ^γ_i- $\sigma_\gamma^{(n)2}$ for i= 1 to K_n;

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 associated with the K_n largest eigenvalues of $\Gamma_{RR}^{(n)}$, and keep the R_n largest eigenvalues $\lambda^n_{\Gamma k}$ for

$k = 1$ to K_n;

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

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

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

3.4.1. Principal Component Transformation (PCT)

Principal Component Transformation, also called principal component analysis, Hotelling transformation or Karhunen-Loeve transformation is a dimensionality reduction method based on the minimization of the representation error. The idea is to choose the most representing bands with the help of the eigenvalue decomposition of the covariance matrix of the hyperspectral image [72]. The first step of PCT is the calculation of the covariance matrix of the image matrix. Then, the eigenvalues of the covariance matrix are calculated and the eigenvectors are extracted. Finally, the image matrix is projected onto the new subspace formed by the k orthogonal eigenvectors corresponding to the highest eigenvalues. $Y=W^T x$ where $\mathbf{x}$ is a d x1 -dimensional vector representing one image pixel, y is the transformed $\mathbf{k}$ x1-dimensional sample in the new subspace and W is the transformation matrix of k orthogonal eigenvectors.

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

3.4.2. Linear Discriminant Analysis (LDA)

Linear discriminant analysis is a statistical based method often used for feature extraction and dimensionality reduction. It is also named Discriminant Analysis Feature Extraction (DAFE). It is an extension of the well-known Fisher discriminant analysis, which is limited to binary class decomposition. LDA computes an optimal transformation by minimizing the within-class distance and maximizing the between-class distance simultaneously, thus achieving maximum class discrimination [73]. Therefore, the first step is to calculate the within-class, between-class and total scatter matrices. A transformation matrix is then defined and computed by applying the eigenvector decomposition on the scatter matrix [74]. The main disadvantage of this method is that it requires that the scatter matrix of the data be nonsingular. This method has also other drawbacks: the maximum number of features extracted is equal to the number of classes minus one. The number of training samples should be large enough to estimate the between-class and within-class scatter matrix reliably. The between-class will be biased toward the class that has very different mean value. Also, it is very time consuming compared to other methods. In addition, it requires more training samples for hyperspectral images to calculate the class statistical parameters at full dimension. [75]. Many LDA extensions have been proposed to deal with the singularity problem like PCA+LDA, regularized LDA (RLDA) , null space LDA (NLDA) , orthogonal centroid method (OCM) , uncorrelated LDA (ULDA) , orthogonal LDA (OLDA), LDA/GSVD, etc. [76].

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

3.5. Classification

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

3.5.1. Support vector machine (SVM)

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

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

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

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

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

3.5.2. K means clustering

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

3.5.3. Orthogonal subspace projection (OSP)

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

x = spectral vector characterizing the pixel

t = spectral vector associated with the target

a = unknown fractional abundance of the target within the pixel

B = matrix of vectors of the scene endmembers (materials found in the scene background)

α = unknown fractional abundance of each basis vector

ξ = residual error associated with this model.

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

3.5.4. Linear Cross-Correlation

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

3.6. Recent developments in target detection using hyperspectral images.

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

4. Discussion

Since the introduction of hyperspectral imaging in 1985, applications of this technique have increased in several fields. As this technique gives the ability to distinguish different materials remotely, it has been applied to landmine detection research. Every material has its special spectral signature. Therefore, knowing the mine spectral curve, by a simple comparison between the mine spectrum and the pixel spectrum, we can decide on the presence or the absence of the mine at that specific position. It was found that spectral reflectance of each type of surface-laid mines has a constant shape between 500-680 nm but varies in offset and scale according to the illuminance of the scene [16]. So, the detection of this particular shape in the pixel spectrum proves the presence of the landmine.

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

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

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

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

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

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

5. Conclusions

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

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

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

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

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 sensor 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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