MINISTRY OF EDUCATION AND SCIENCE OF UKRAINE
NATIONAL AVIATION UNIVERSITY
Faculty of Aeronavigation, Electronics and Telecommunications
Department of computer integrated complexes

ADMIT TO DEFENSE
Head of the graduating department
__________ Viktor M. Sineglazov
“_____”_________________2024y.

QUALIFICATION WORK

(EXPLANATORY NOTE)

OF THE GRADUATE OF THE EDUCATIONAL DEGREE
“BACHELOR”

Specialty 151 "Automation and computer-integrated technologies"

Educational and professional program "Computer-integrated technological processes and production"

Theme: An intelligent system for detection and classification of anomalous objects

Performer: student of FAET-421 group Kulakevych Illia Vitaliyovych
Supervisor: Hordienko Oleksandr Mykolayovych

Norm controller: ___________ Filyashkin M.K.
(sign)

Kyiv – 2024

МІНІСТЕРСТВО ОСВІТИ І НАУКИ УКРАЇНИ

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ

Факультет аеронавігації, електроніки та телекомунікацій

Кафедра авіаційних комп'ютерно-інтегрованих комплексів

ДОПУСТИТИ ДО ЗАХИСТУ

Завідувач випускової кафедри

______ Віктор СИНЄГЛАЗОВ

“____” ______________2024 р.

КВАЛІФІКАЦІЙНА РОБОТА

(ПОЯСНЮВАЛЬНА ЗАПИСКА)

ВИПУСКНИКА ОСВІТНЬОГО СТУПЕНЯ

“БАКАЛАВР”

Спеціалність 151 "Автоматизація, та комп’ютерно-інтегровані технології"

Освітньо-професійна програма "Комп’ютерно-інтегровані технологічні процеси і виробництва"

Тема: Інтелектуальна система виявлення та класифікації аномальних об’єктів

Виконавець: студент групи КП-421Ба Кулакевич Ілля Віталійович

Керівник: Гордієнко Олександр Миколайович

Нормоконтроллер: ___________ Філяшкін М.К.

(підпис)

Київ – 2024

NATIONAL AVIATION UNIVERSITY

Faculty of Aeronautics, Electronics and Telecommunications

Department of aviation computer-integrated complexes

Educational degree: Bachelor

Specialty 151 "Automation, computer-integrated technologies and robotics"

Educational and professional program "Computer-integrated technological processes and production"

APPROVED

Head of department

__________ Sineglazov V.M

“____” ____________2024.

TASK

For the student’s thesis

by: Kulakevych Illia Vitaliyovych

1. **Thesis topic** (project topic) “ An intelligent system for detection and classification of anomalous objects”
2. **Deadline for an execution of a project**: from May 10 of 2024 to June 7 of 2024
3. **Initial data for the project**: Development of an intelligent system for detecting and classifying anomalous objects.
4. **Contents for explanatory note:** Anomaly detection process and its features, hyperspectral cameras and images, hyperspectral image processing, practical implementation of an intelligent system.
5. **List of required graphic material**: figures, tables and diagrams.

6. **Calendar schedule-plan:**

№	Task	Execution term	Execution mark
1.	Getting the task	01.04.2023 – 02.04.2023	Done
2.	Formation of the purpose and main objectives of the study	02.04.2023 – 14.04.2023	Done
3.	Analysis of existing methods	15.04.2023 – 30.04.2023	Done
4.	Theoretical consideration of problem solving	01.05.2023 – 05.05.2023	Done
5.	Practical implementation of the task	06.05.2023 – 25.05.2023	Done
6.	Preparation of an explanatory note	26.05.2023 – 03.06.2023	Done
7.	Preparation of presentation and handouts	04.06.2023 – 06.06.2023	Done

7. **Task issue date:** 01 “April” 2023.

Supervisor: ___________________________ Hordienko O.M

(sign)

Task is taken for completion by: _________________ Kulakevych I.V

(sign)

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ

Факультет аеронавігації, електроніки та телекомунікацій

Кафедра авіаційних комп’ютерно-інтегрованих комплексів

Освітній ступінь: Бакалавр

Спеціальність 151 "Автоматизація та комп’ютерно-інтегровані технології"

Освітньо-професійна програма "Комп’ютерно-інтегровані технологічні процеси і виробництва"

ЗАТВЕРДЖУЮ

Завідувач кафедри

_____ Віктор СИНЄГЛАЗОВ

“____” __________2024 р.

ЗАВДАННЯ

на виконання кваліфікаційної роботи студента

Кулакевич Ілля Віталійович

1. **Тема роботи** “Інтелектуальна система виявлення та класифікації аномальних об’єктів”
2. **Термін виконання роботи**: з 10.03.2024 по 7.06.2024
3. **Вихідні дані до роботи**: Розробка інтелектуальної системи виявлення та класифікації аномальних об'єктів.

4 **Зміст пояснювальної записки (перелік питань, що підлягають розробці):** Процес пошуку аномалій та його особливості , гіперспектральні камери та зображення , обробка гіперспектральних зображень , практична реалізація інтелектуальної системи.

5 **Перелік обов’язкового графічного матеріалу**: графіки, таблиці, зображення. діаграми.

6 **Календарний план-графік:**

№	Завдання	Термін виконання	Відмітка про виконання
1.	Отримання завдання	01.04.2023 - 02.04.2023	Виконано
2.	Формування мети та основних завдань дослідження	02.04.2023 – 14.04.2023	Виконано
3.	Аналіз існуючих методів	15.04.2023 – 30.04.2023	Виконано
4.	Теоретичний розгляд вирішення поставлених завдань	01.05.2023 – 30.04.2023	Виконано
5.	Практична реалізація завдання	01.05.2023 – 05.05.2023	Виконано
6.	Оформлення пояснювальної записки	26.05.2023 – 03.06. 2023	Виконано
7.	Підготовка презентації та роздаткового матеріалу	04.06.2023 – 06.06.2023	Виконано

7 **Дата видачі завдання** ___ «01» березня 2024р.

Керівник: ______________________ Гордієнко О.М

(підпис)

Завдання прийняв до виконання: ______________ Кулакевич І.В

(підпис)

ABSTRACT

Explanatory note to the qualification work “Intelligent system for detection and classification of anomalous objects”

Keywords - hyperspectral imaging, classification of anomalous objects, artificial intelligence, image processing, drones.

Object of research - hyperspectral images and their processing for detection and classification of anomalous objects.

The subject of research is methods and algorithms for processing and analyzing hyperspectral data.

The purpose of the qualification work is to develop an intelligent system for detecting and classifying anomalous objects based on hyperspectral images.

The research methods are comparative analysis, processing of literature sources, digital modeling, and machine learning.

The theoretical research consists of an in-depth analysis of hyperspectral imaging methods, data processing and classification algorithms, as well as integration with other sources of information.

The research results showed that the use of hyperspectral data in combination with machine learning methods can significantly improve the accuracy of detecting and classifying anomalous objects. Integration with other sensors (radar, LiDAR) further increases the reliability of the system.

The practical significance of the qualification work results can be used to create effective monitoring and analysis systems that provide accurate detection and classification of anomalous objects in various fields, such as environmental monitoring, agriculture, security, etc. This qualification work may be useful for specialists in the field of image processing, machine learning and data analysis, as well as for those involved in the development of monitoring and anomaly detection systems.

РЕФЕРАТ

Пояснювальна записка до кваліфікаційної роботи "Інтелектуальна система виявлення та класифікації аномальних об’єктів"

Гіперспектральна зйомка, класифікація аномальних об’єктів, штучний інтелект, обробка зображень, дрони.

Об'єкт дослідження - гіперспектральні зображення та їх обробка для виявлення та класифікації аномальних об’єктів.

Предмет дослідження - методи та алгоритми обробки та аналізу гіперспектральних даних.

Мета кваліфікаційної роботи - розробити інтелектуальну систему для виявлення та класифікації аномальних об’єктів на основі гіперспектральних зображень.

Метод дослідження - порівняльний аналіз, обробка літературних джерел, цифрове моделювання, машинне навчання.

Теоретичні дослідження полягають у глибокому аналізі методів гіперспектральної зйомки, алгоритмів обробки та класифікації даних, а також інтеграції з іншими джерелами інформації.

Результати досліджень показали, що використання гіперспектральних даних у поєднанні з методами машинного навчання дозволяє значно підвищити точність виявлення та класифікації аномальних об’єктів.

Практичне значення результатів кваліфікаційної роботи можуть бути використані для створення ефективних систем моніторингу та аналізу, що забезпечують точне виявлення та класифікацію аномальних об’єктів у різних сферах, таких як екологічний моніторинг, сільське господарство, безпека та інше.

Content

LIST OF ABBREVIATIONS

ANN - Artificial Neural Network

API - Application Programming Interface

CNN - Convolutional Neural Network

DL - Deep Learning

DNN - Deep Neural Network

FFT - Fast Fourier Transform

FPGA - Field-Programmable Gate Array

GIS - Geographic Information System

GPS - Global Positioning System

HSI - Hyperspectral Imaging

IoT - Internet of Things

LiDAR - Light Detection and Ranging

MAE - Mean Absolute Error

ML - Machine Learning

PCA - Principal Component Analysis

RGB - Red, Green, Blue

RMSE - Root Mean Square Error

RNN - Recurrent Neural Network

ROI - Region of Interest

SAR - Synthetic Aperture Radar

SNR - Signal-to-Noise Ratio

SVD - Singular Value Decomposition

SVM - Support Vector Machine

UAV - Unmanned Aerial Vehicle

INTRODUCTION

The current state of the art in security and environmental protection technologies requires continuous improvement of methods for detecting and classifying anomalous objects. Anomalies, such as environmental pollution, oil spills, illegal logging, or potential explosive devices, can have serious consequences for the environment and public safety.

Traditional methods, such as metal detectors and X-ray scanners, have limited effectiveness in difficult environments. For example, they are often unable to detect sophisticated explosive devices that can be made of non-metallic materials or disguised as ordinary objects. Also, these methods are often ineffective in detecting environmental anomalies, such as oil spills or water pollution.

One of the most promising areas in this field is the use of hyperspectral cameras, which allow analyzing objects in a wide range of electromagnetic radiation. Hyperspectral images contain much more information than traditional color or monochrome images, which opens up new opportunities for identifying and classifying materials based on their spectral characteristics. This is especially important for tasks requiring high identification accuracy, such as detecting environmental contamination or security threats.

The relevance of this topic is due to the need to improve the efficiency of methods for detecting anomalies that are critical to environmental safety and public security. To date, research in this area has shown that the use of hyperspectral imagery can significantly improve the accuracy of anomaly identification. However, existing methods of hyperspectral image processing require further improvement, in particular in the direction of automating data analysis and using modern machine learning algorithms.

The innovation of this work is the development of an intelligent system for detecting and classifying anomalous objects based on hyperspectral images, which will use advanced neural network methods for data processing and analysis. This will increase the speed and accuracy of detecting potentially hazardous objects, which is extremely important for preventing environmental disasters, terrorist attacks, and ensuring public safety.

The aim of this work is to develop an intelligent system for detecting and classifying anomalous objects based on hyperspectral images.

CHAPTER 1
ANOMALY DETECTION PROCESS AND ITS FEATURES

1.1. Finding anomalies as a method of improving the environment

An anomaly is a deviation from the normal state or functioning of a system that may indicate the presence of a problem that requires attention. In the context of the environment, anomaly detection can identify negative changes in ecosystems, pollution, illegal activities, and other issues that have a significant impact on the environmental situation[6].

Anomaly detection has become an important tool for environmental improvement due to its ability to quickly and accurately identify problem areas. This process involves collecting data, analyzing and interpreting the results to identify deviations from normal conditions. For example, a hyperspectral camera can be used to detect vegetation anomalies that may be caused by pollution, disease, or other stressors[1].

A hyperspectral camera can capture light in a wide spectral range and obtain detailed information about the spectral characteristics of an object. This allows you to detect anomalies that cannot be seen by conventional observation methods. For example, the NDVI vegetation index (Normalized Difference Vegetation Index) is used to assess the condition of vegetation. The NDVI formula looks like this:

$$NDVI = \frac{NIR-RED}{NIR+RED}$$

where NIR (near-infrared) and RED are the values of reflectivity in the near-infrared and red ranges, respectively. Using this formula, it is possible to detect anomalies in vegetation that may indicate the presence of pollution or other environmental problems (Fig. 1.1).

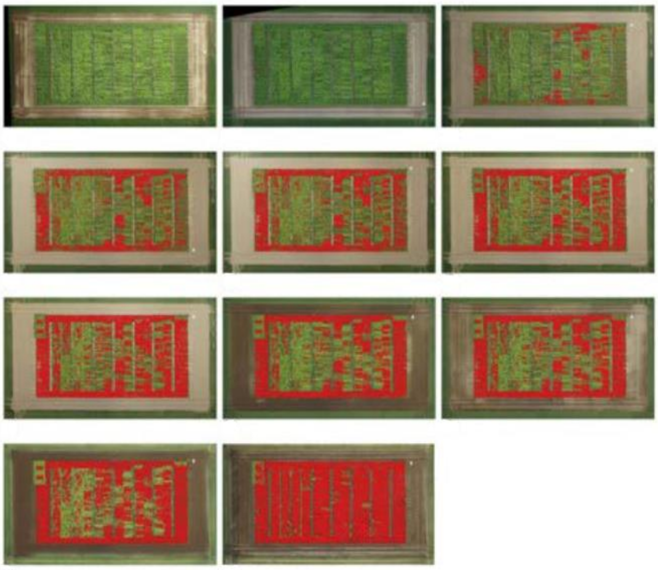


Fig. 1.1 Progression of potato blight over time. the red overlay shows the damaged parts detected during image processing

The NDVI index helps to understand how plants grow and develop. If the index value is between medium and high (0.5-0.85), there are most likely no serious problems in this area of the field. If the index is low, there are probably some problems, such as a lack of moisture or nutrients. It is better to check this part of the field yourself.

Another example of using a hyperspectral camera is water monitoring. Hyperspectral images allow you to determine the concentration of algae and other biological components in water, which is an important indicator of the ecological state of aquatic ecosystems. For example, areas of oil contamination in water can be detected due to their unique spectral characteristics (Fig. 1.2)[6].

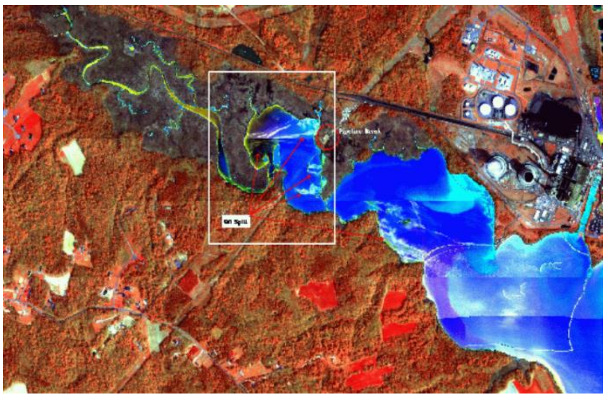


Fig. 1.2 Hyperspectral image of the AISA oil spill in the Patuxent River due to a ruptured oil pipeline

Machine learning algorithms are used to improve the effectiveness of anomaly detection, which can analyze large amounts of data and find patterns that indicate anomalies. These algorithms can adapt to new data and improve predictions over time. Neural networks can be used to classify spectral data and detect anomalies.

The use of hyperspectral cameras and advanced data processing algorithms can significantly improve the accuracy and speed of environmental monitoring. This ensures the timely detection of environmental problems, facilitates their rapid resolution and, as a result, has a positive impact on the environment. For example, hyperspectral imaging can help identify illegal waste dumps, eliminate them, and take measures to mitigate the negative impact on ecosystems.

Thus, studying anomalies is an important way to improve the environment. By integrating hyperspectral cameras with the latest spectroscopic analysis techniques, environmental problems can be detected at an early stage and contribute to effective natural resource management and environmental protection[1].

1.2. Block diagram of an intelligent search system

This section describes the general block diagram of an intelligent search system for anomaly detection, using the DJI Matrice 600 drone equipped with a hyperspectral camera and other sensors as an example. The block diagram (fig 1.3) demonstrates the interaction between the various components of the system, which together provide an efficient process of data collection, processing, and analysis[15].

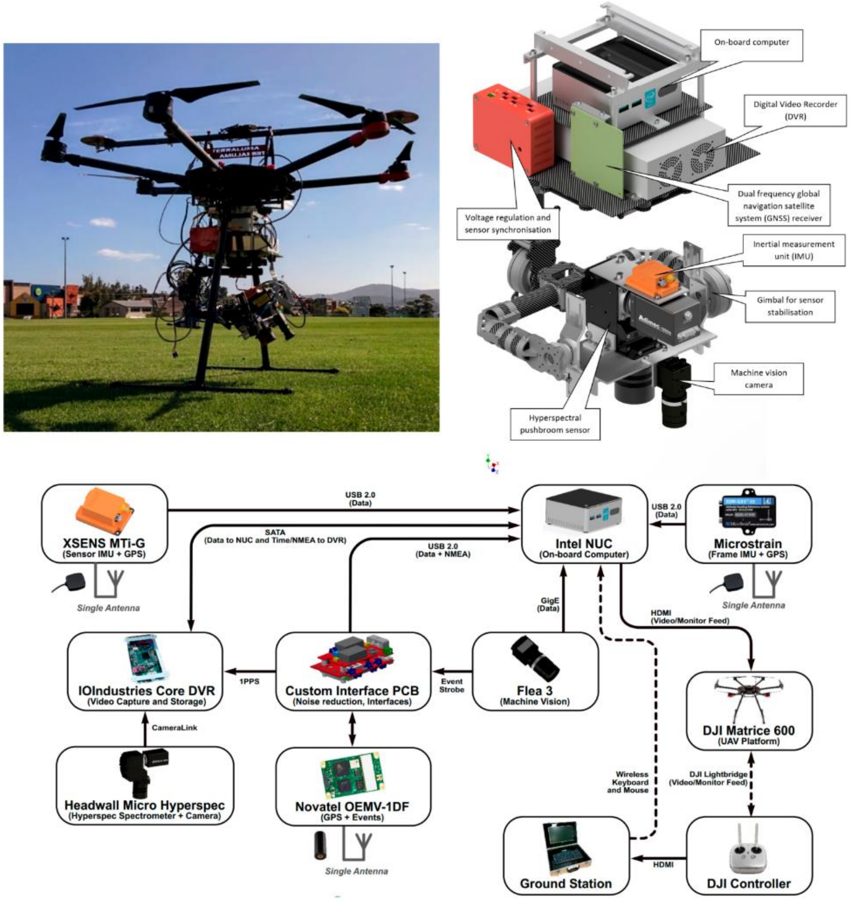


Fig. 1.3 Block diagram of the DJI Matrice 600

The main components of an intelligent search engine are:

- Drone platform: The DJI Matrice 600 is a high-performance platform that provides stable operation in various conditions. The drone has a high payload capacity and long flight time, which allows for long missions with a large amount of equipment on board, and is the basis for the integration of other system components.
- Sensor modules: The Headwall Micro Hyperspectral Sensor provides image acquisition in a wide spectral range, capturing data with high spectral resolution, which allows you to get detailed information about objects on the ground. The hyperspectral sensor is connected to the data processing system via the CameraLink interface, as shown in the diagram.
- Inertial measurement unit (IMU) and GPS: The XSENS MTi-G sensor, which includes IMU and GPS, is used to determine the spatial position and orientation

of the drone. This module ensures accurate positioning and image stabilization, which is critical for further data analysis. The information from the IMU and GPS is transmitted via USB 2.0 and SATA interfaces to the computing unit.

- Data pre-processing system. To reduce noise and improve image quality, a special Custom Interface PCB is used to perform data pre-processing functions, including noise reduction and interface of various sensors. This helps to ensure the high quality of the collected data before it is transferred to the computing unit.
- The computing unit is represented by an Intel NUC, which processes data in real time. It is connected to various sensors via USB 2.0 and GigE interfaces, providing high-speed data exchange. The computing unit performs sophisticated data analysis algorithms, including machine learning algorithms to detect anomalies.
- Video recording and data storage system: provided by the IOIndustries Core DVR unit, which stores video information and other collected data for long periods of time. This allows for detailed analysis of the collected data after the mission is completed.
- Ground Station and Controller: provides real-time drone control and mission monitoring. The DJI controller allows the operator to control the drone and receive a video stream and other data in real time. This is important for quick decision making during the mission.

The block diagram of the DJI Matrice 600-based intelligent search engine demonstrates a complex but efficient process of data collection, processing, and analysis. The integration of various sensors and computing units provides highly accurate anomaly detection, which contributes to timely response to environmental problems and improvement of the environment.

1.3. Measurement and result processing system

Effective anomaly detection requires the use of highly accurate and reliable measurement and processing systems. This is a key step in ensuring the quality of the data used for analysis and decision-making. Modern measurement systems include a variety of sensors that allow for high accuracy data collection, as well as sophisticated algorithms for pre-processing this data[5].

1.3.1. Classification of sensors

Remote sensing systems widely use different types of sensors. Optical sensors, such as hyperspectral and multispectral cameras, operate in the visible and infrared spectral ranges. Hyperspectral cameras, such as the Headwall Micro Hyperspec (Fig. 1.4), are capable of capturing high-resolution spectral images, which allows for detailed spectral analysis of objects on the ground. Multispectral cameras, in turn, capture data in several separate spectral bands, which allows you to identify the main characteristics of objects.

Fig. 1.4 Micro-Hyperspec VNIR (400-1000nm) E-Series Imager

Inertial sensors, which include accelerometers, gyroscopes, and inertial measurement units (IMUs), are used to determine the position and motion of the drone. For example, the XSENS MTi-G (Fig. 1.5) is a combination sensor that includes IMU and GPS and provides accurate positioning and stabilization.

Fig. 1.5 XSENS MTi-G -710

Thermographic sensors (Fig. 1.6) detect infrared radiation from objects, which allows them to detect temperature anomalies. They are widely used to detect underground objects or heat loss in buildings. Lidar systems, which use laser pulses to measure distances to objects, create three-dimensional surface models and provide highly accurate mapping of territories.

Fig. 1.6 A Velodyne HDL-64E, an HDL-32E, a Puck, and an Ultra Puck

1.3.2. Measurement results pre-processing system

After collecting data using various sensors, it is necessary to pre-process it to improve the quality and accuracy of the final results. This process involves several steps, each of which is aimed at eliminating noise, correcting geometric distortions, and calibrating the data[13].

First, noise filtering and reduction are necessary. The data collected by sensors often contains noise that needs to be eliminated to improve the quality of the analysis.

Various filtering methods are used for this purpose, such as RMS smoothing, Gaussian filtering, and other digital signal processing algorithms.

The formula for RMS smoothing is as follows:

$$y(n) = \frac{1}{N} \sum_{k=0}^{N-1} x(n-k)$$

Where y(n) is the smoothed value, x(n-k) is the original signal, N is the number of smoothing points

To ensure accurate correlation of data with real coordinates, geometric distortions must be corrected. This stage includes coordinate transformation, perspective distortion correction, and orthorectification. Geometric distortions can significantly affect the accuracy of measurements, so their correction is critical.

Data calibration is necessary to eliminate systematic errors that can occur due to the peculiarities of sensor operation. This includes temperature correction, radiometric calibration, and other methods. The radiometric calibration formula helps to normalize the signal and ensures comparability of data from different sensors. It looks like this:

$$L_{\mathrm{cal}} = \frac{L_{\mathrm{meas}} - L_{\mathrm{dark}}}{L_{\mathrm{white}} - L_{\mathrm{dark}}}$$

Lcal – calibrated signal, Lmeas – measured signal, Ldark – dark current signal, Lwhite – signal from white calibrated object.

Spectral normalization is used to bring spectral data to a common standard, allowing for comparisons between different data sets. This includes reflectance normalization, spectral smoothing, and other processing techniques. These methods allow for more accurate and comparable spectral analysis results.

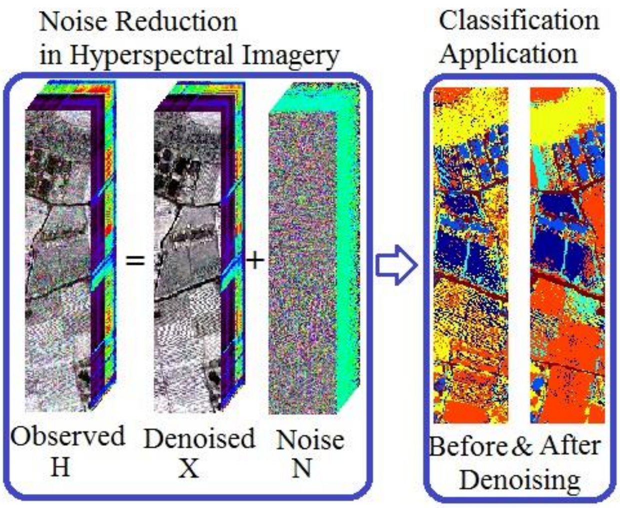


Fig. 1.7

In the fig. 1.7 you can see a schematic representation of the data pre-processing process, namely noise filtering.

Thus, an effective measurement and processing system includes the use of a variety of sensors and comprehensive data pre-processing. This ensures high accuracy and reliability of the results obtained, creating the basis for further analysis and informed decision-making in the context of anomaly detection and environmental management.

CHAPTER 2
HYPERSPECTRAL CAMERAS AND IMAGING

2.1.Physical basis of the work

Hyperspectral imaging (HSI) is a technology that allows for high spectral resolution imaging by dividing light into numerous narrow contiguous spectral bands in the electromagnetic (EM) spectrum, primarily between the visible and infrared wavelengths. This is achieved because different materials on the Earth's surface reflect, absorb, scatter, and emit light at specific wavelengths, creating unique spectral fingerprints that can be identified using hyperspectral imagery (Figure 2.1). Thanks to this technology, our perception of the Earth's surface, its features, other planets and outer space has improved significantly compared to the use of multispectral images[21].

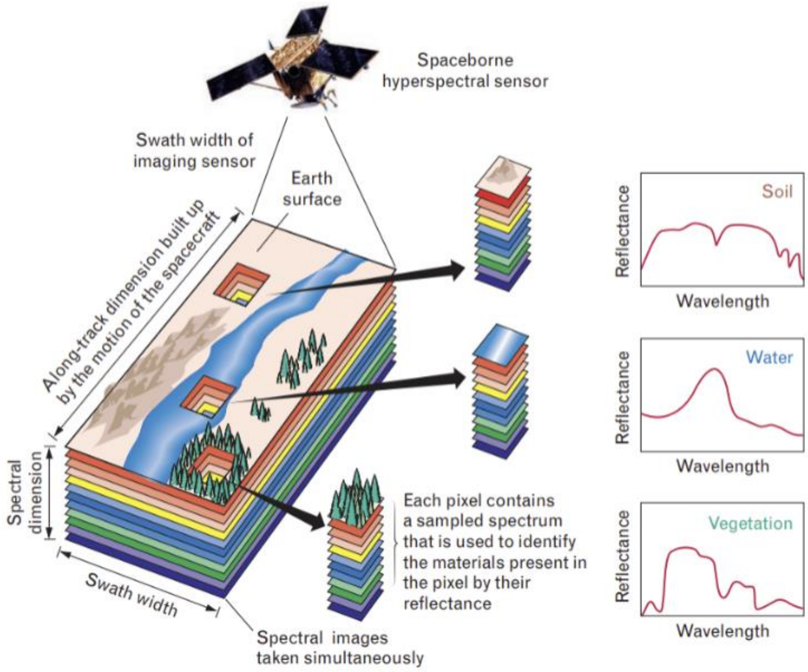


Fig. 2.1 Diagram of the principles

Compared to multispectral cameras, which capture electromagnetic radiation in a relatively small number (typically 4 to 36) of broad spectral bands, hyperspectral cameras collect data from a much larger number of spectral bands (up to hundreds) that are contiguous and cover narrow wavelength ranges (typically less than 10 nm). This makes it possible to obtain spectral signatures without wavelength gaps, providing high spectral resolution.

The basis of hyperspectral imaging is spectroscopy, where light is decomposed into spectral components. Diffraction gratings and prisms play an important role in this process. Diffraction gratings are used to decompose light, and this process is described by the equation:

$$d \sin \theta = n\lambda$$

Prisms, in their turn, use the dispersion of light to decompose it, as described by the formula:

$$n(\lambda) = \frac{c}{v(\lambda)}$$

Interference filters are used to select narrow spectral bands due to the phenomenon of interference. The formula for interference is as follows:

$$2d \cos \theta = m\lambda$$

The main components of hyperspectral cameras include an optical system, a detector array, and a data acquisition system. The optical system consists of lenses, prisms, or diffraction gratings that are responsible for focusing and decomposing light. An example is the Headwall Photonics Micro-Hyperspec camera, which uses a high-quality optical system to achieve high spectral resolution.

The detector matrix records light intensity in different spectral bands. Different types of detectors are used, such as CCD (Charge-Coupled Device) or CMOS (Complementary Metal-Oxide-Semiconductor), which have high sensitivity and resolution.

The data acquisition system includes hardware and software for processing and storing the obtained spectral data. An important component is a detector cooling system that reduces noise and improves data quality.

A hyperspectral image consists of a stack of images, each of which corresponds to one spectral band, represented as a three-dimensional “spectral cube” (Fig. 2.2). These images have two spatial dimensions and one spectral dimension, shown as stacked image layers. The dimensions of the cubes are based on the satellite bandwidth across the track, along the track, and the wavelength range[21].

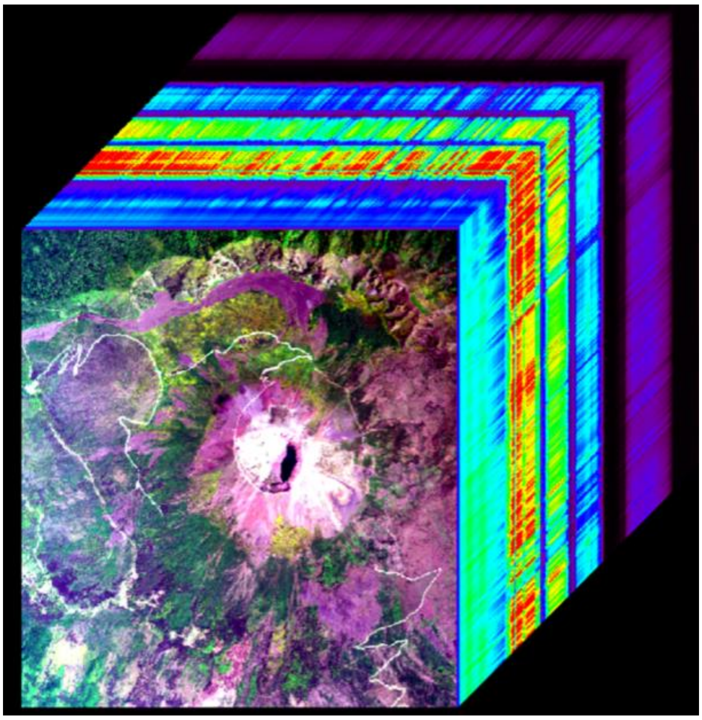


Fig. 2.2 Hyperspectral image cube

For each wavelength band measured in a hyperspectral image, a spectral reflectance image is created (Fig. 2.3). This means that an entire reflectance curve can be built for each pixel of the image. Reflectance curves allow for in-depth pixel-by-pixel analysis of a scene and are often combined with a spectral cube to analyze areas of interest. Reflectance curves can be thought of as a slice of the spectral cube along the (spectral) z-axis, isolating the reflectance information for a specific pixel or region of a 2D image[21].

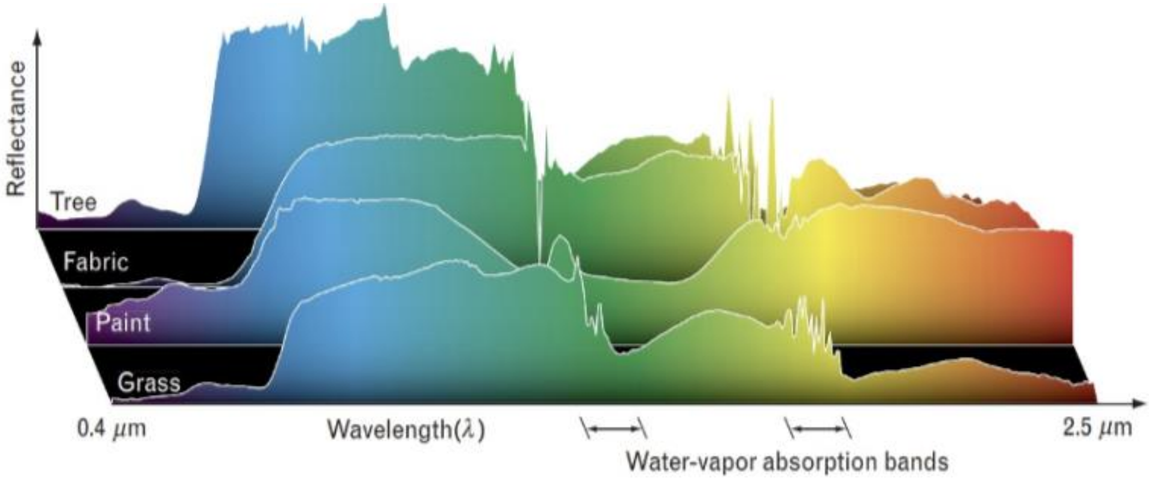


Fig. 2.3 Reflection curves

Thus, the physical basis of hyperspectral cameras involves a complex process of decomposing light into spectral components and registering them, which allows obtaining detailed information about the objects of study. This opens up wide opportunities for the application of hyperspectral technology in various fields, including environmental monitoring, agriculture, medicine, and industry.

2.2. Classification

Hyperspectral cameras, due to their unique capabilities, are divided into several main types depending on their design, operating principle and purpose. The classification of hyperspectral cameras is an important step in understanding their capabilities and limitations, which allows to choose the optimal camera for specific tasks.

2.2.1.Types of hyperspectral cameras by the principle of operation

Let's consider the main types of hyperspectral cameras (Fig. 2.4), which differ in their operation and have their unique advantages and disadvantages.

First, let's pay attention to point scanning cameras, also known as whiskbroom cameras. They capture one pixel at a time, including all the spectral information for that pixel. Such cameras provide high spectral resolution, which allows for a detailed analysis of the spectral signatures of various objects. However, the time required to acquire a full image is long, which can be a disadvantage when shooting large areas or fast-moving scenes. An example of such cameras is the Hyperion on the EO1 satellite, which performs point scanning to obtain detailed spectral data.

The next in line are line scan cameras, or pushbroom cameras. They capture one row of pixels of the scene at a time, which provides higher spectral resolution and shorter acquisition time compared to whiskbroom cameras. Due to their efficiency, these cameras are widely used in remote sensing. For example, the AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) camera is a typical representative of pushbroom cameras, providing high resolution for environmental research and monitoring.

Spectral scanning cameras capture all the spatial information of the scene for each wavelength separately. They have high spatial resolution and fast acquisition times, but their spectral resolution is usually lower than that of whiskbroom and pushbroom cameras. These cameras are less suitable for capturing moving objects because of the time required for spectral scanning. An example of such a camera is the Cubert UHD-185, which is used for a variety of scientific research due to its ability to capture high-quality images quickly.

The last are the “snapshot” cameras, which capture the entire scene in a single image, including both spectral and spatial information. They allow you to create hyperspectral video with the shortest shooting time, which is important for capturing moving objects without spatial or spectral scanning. The main disadvantage of such cameras is their relatively low spectral and spatial resolution compared to other types. An example of such cameras is the IMEC Snapscan, which is used for rapid data collection in time-sensitive environments.

For a detailed comparison, the order of cameras in terms of spectral resolution from highest to lowest is as follows: line scanning (pushbroom), point scanning (whiskbroom), spectral scanning, and snapshot. In terms of spatial resolution, the order is as follows: spectral scanning, pushbroom, whiskbroom, and snapshot. In terms of shooting speed, the order is as follows: snapshot, spectral scan, pushbroom, whiskbroom of the camera[2].

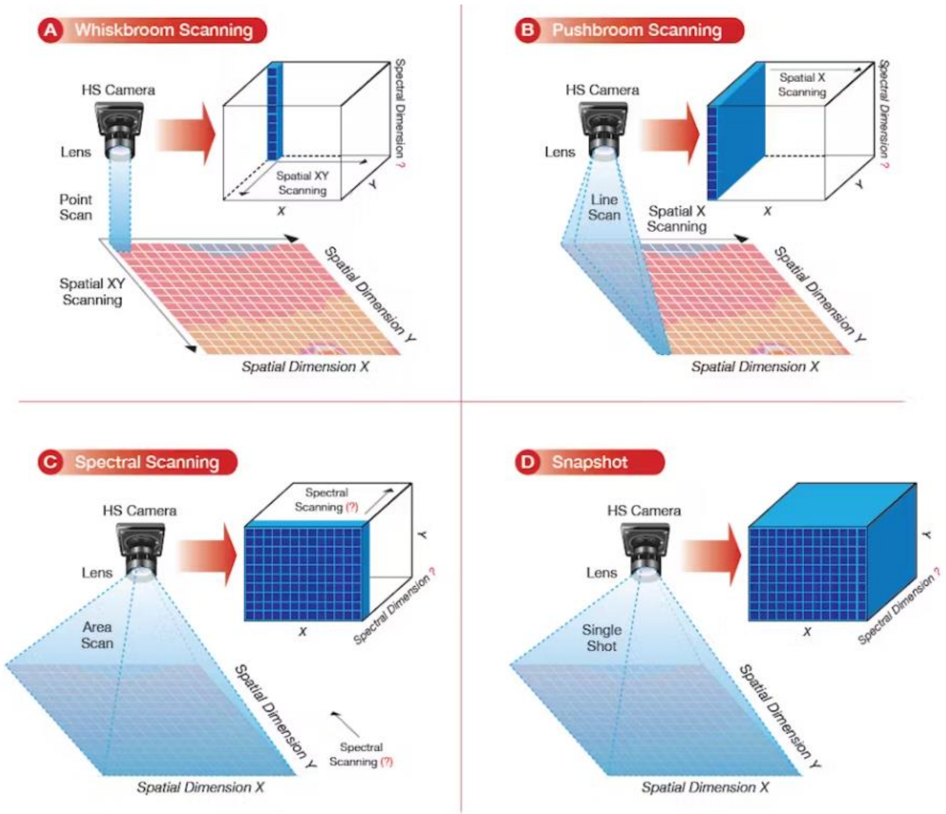


Fig. 2.4 Types of hyperspectral cameras

2.2.2 Types of hyperspectral cameras by wavelength range

Hyperspectral cameras are distinguished by the wavelength ranges they are capable of capturing (Fig. 2.5). This allows you to solve various tasks depending on the spectral region in which the camera operates. In view of this, there are four main types of hyperspectral cameras, each of which has its own characteristics and applications[3].

The first type is NUV (Near Ultraviolet) hyperspectral cameras, which operate in the 350-800 nm wavelength range. These cameras have a high spatial resolution and are used for tasks where the detail of the ultraviolet spectrum is important. An example of such cameras is the Specim FX17, which provides detailed UV images thanks to high-performance lenses optimized for this range. Their characteristics include enhanced response in the blue region of the spectrum and excellent temperature stability, making them indispensable in scientific and industrial research.

The second type is short-wavelength infrared (SWIR) hyperspectral cameras, which cover the wavelength range of 450-950 nm. They are divided into three subtypes. The first sub-type is based on the latest optical technologies, such as Headwall Photonics Nano-Hyperspec, which has a high spectral resolution of up to 3600 spectra/cube and interchangeable prisms for selecting the imaging ranges. The second sub-type includes frame-based, non-scanning spectrometers, such as Ocean Insight's NIRQuest512, which can operate in both laboratory and field environments, providing easy hyperspectral image acquisition and real-time processing. The third sub-type is the simplest and combines the accuracy and ease of use of conventional cameras. For example, Specim's SisuCHEMA allows for rapid data analysis during aerial photography by transmitting data to ground stations during the flight.

The third type is hyperspectral mid-infrared (MWIR) cameras operating in the 600-1000 nm wavelength range. They are based on the technology of a single-chip filtering system. The Telops Hyper-Cam is a typical representative of this type, shooting in sixteen or twenty-five spectral channels. The data is saved to a memory card, and the built-in processor allows for automatic image processing. Such cameras can be installed on unmanned aerial vehicles for aerial photography.

The last type is a hyperspectral long-wavelength infrared (LWIR) camera, which operates in the 900-1700 nm wavelength range. These cameras are used to take pictures in the far infrared region of the spectrum and often have a high frame rate. For example, ITRES CASI-1500 provides high-quality infrared images, which is important for environmental and security monitoring. Their applications range from environmental protection to military tasks.

Thus, the type of hyperspectral camera that is chosen for a particular task depends on the spectral range in which it is necessary to operate, as well as on the requirements for spatial and spectral resolution, acquisition speed, and operating conditions. Each camera type has its own unique characteristics and capabilities that make them effective for different applications.

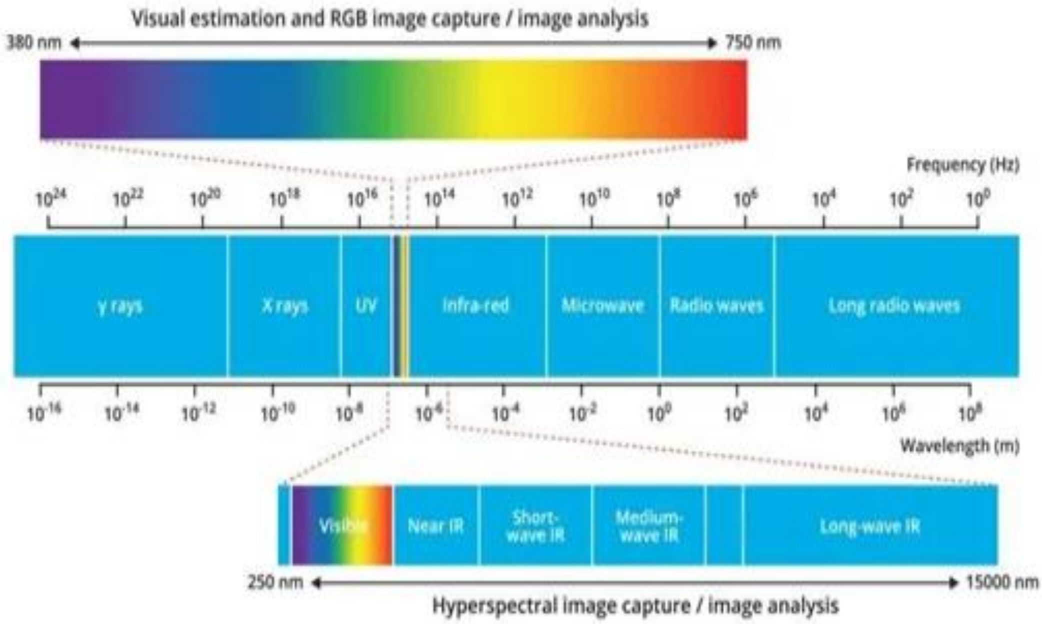


Fig. 2.5 Wavelength ranges

2.2.3 Types of hyperspectral cameras by their application

Hyperspectral cameras are classified not only by the principle of operation and wavelength range, but also by their application. This classification helps to determine the most optimal models for performing specific tasks in various industries[3].

Satellite hyperspectral cameras are used for remote sensing of the Earth from space. They provide a large territorial coverage and allow obtaining data on the state of the environment, agriculture, forests and other environmentally important objects. For example, the Sentinel-2 satellite (Fig. 2.6) from the European Space Agency (ESA) is equipped with a hyperspectral camera that can provide detailed images of the Earth's surface with a resolution of up to 10 meters. Another example is NASA's Hyperion satellite, which provides high-quality spectral data with a resolution of 30 meters per pixel, covering 220 spectral bands in the range from 400 to 2500 nm. These satellites are used to monitor environmental changes, identify natural resources, and control pollution.

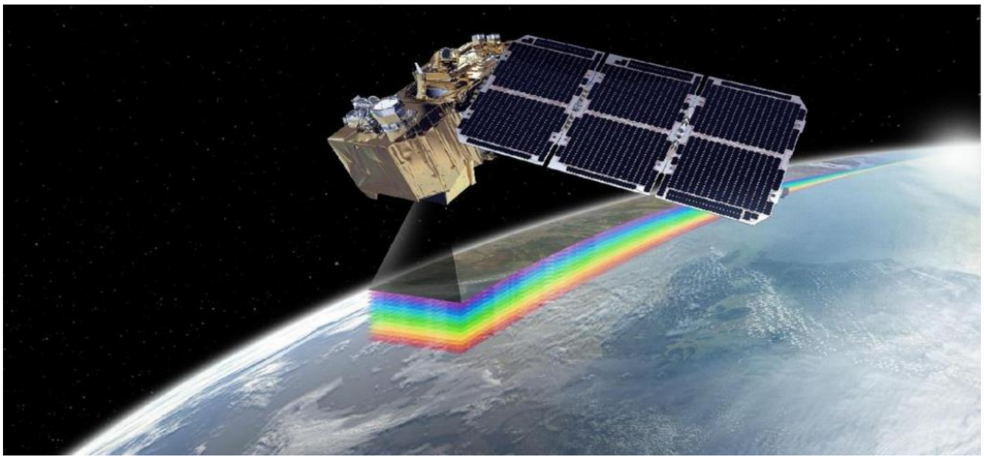


Fig. 2.6 Sentinel-2 satellites equipped with a hyperspectral camera

Airborne hyperspectral cameras are mounted on airplanes or drones for detailed aerial surveys of specific areas. They are used to monitor crops, forests, water bodies, and industrial areas. For example, the Headwall Photonics Nano-Hyperspec camera(fig 2.7), which can be mounted on unmanned aerial vehicles, provides highly accurate spectral data with a resolution of up to 2 nm in the range from 400 to 1000 nm. It is widely used in agriculture for plant disease detection and yield estimation, as well as in environmental monitoring to detect

Fig. 2.7 Headwall Photonics Nano-Hyperspec

Ground-based hyperspectral cameras are used for scientific research, industrial control, medical diagnostics, and other applications. They provide high accuracy and allow obtaining spectral data from objects at close range. An example of such a camera is the Specim IQ (Fig. 2.8), a portable hyperspectral device that can capture spectral data in the range of 400 to 1000 nm with a resolution of 7 nm. This camera is used for material analysis in industry, product quality control, and medical research, such as diagnosing skin diseases.

Fig. 2.8 Specim IQ hyper-spectral camera

Therefore, the classification of hyperspectral cameras by application helps to better understand their capabilities and choose the best solutions for specific tasks. This ensures the effective use of hyperspectral technology in various fields of science and industry, allowing to achieve high accuracy and detail in solving a wide variety of problems.

2.3. How hyperspectral cameras work

Hyperspectral cameras are sophisticated optical devices that provide high-precision spectral images and are used in various fields such as environmental monitoring, agriculture, geology, medicine, and many others. This section describes in detail the principles of hyperspectral cameras, their main components, and real-life examples of their use.

2.3.1. Image acquisition process

The process of image acquisition by hyperspectral cameras is based on the decomposition of light into narrow spectral bands using a dispersive element such as a prism or diffraction grating. Each spectral band is detected by a separate detector, which allows obtaining spectral data for each pixel of the image. This ensures high spectral resolution and accuracy of the data obtained[4].

The process begins when light from an object enters the camera lens. The light then passes through a dispersive element, which breaks it down into its individual spectral components. This can be achieved by using a prism, which refracts light at different angles depending on the wavelength, or by using a diffraction grating, which decomposes light into spectral bands through interference.

Each spectral band is then registered by a separate detector, which provides spectral data for each pixel of the image. As a result, a three-dimensional data array is formed, where two dimensions correspond to the spatial coordinates of the image, and the third to the spectral bands.

Detectors used in hyperspectral cameras can be built on the basis of various technologies, including CCD (Charge-Coupled Device) and CMOS (Complementary Metal-Oxide-Semiconductor) sensors. These sensors provide high sensitivity and readout speed, which is critical for obtaining high-quality hyperspectral images.

2.3.2. Data storage

Images captured by a hyperspectral camera are stored in the form of spectral cubes. Each spectral cube contains a three-dimensional array of data, where two dimensions correspond to the spatial coordinates of the image, and the third one corresponds to the spectral bands (Fig. 2.9). The spectral cube can be represented in the ENVI format, which is widely used for storing and processing hyperspectral data. The ENVI format consists of two files: .hdr (header) and .dat (data). The .hdr file contains metadata about the image, such as cube size, number of spectral bands, resolution, and other parameters. The .dat file contains the actual spectral data in binary format[14].

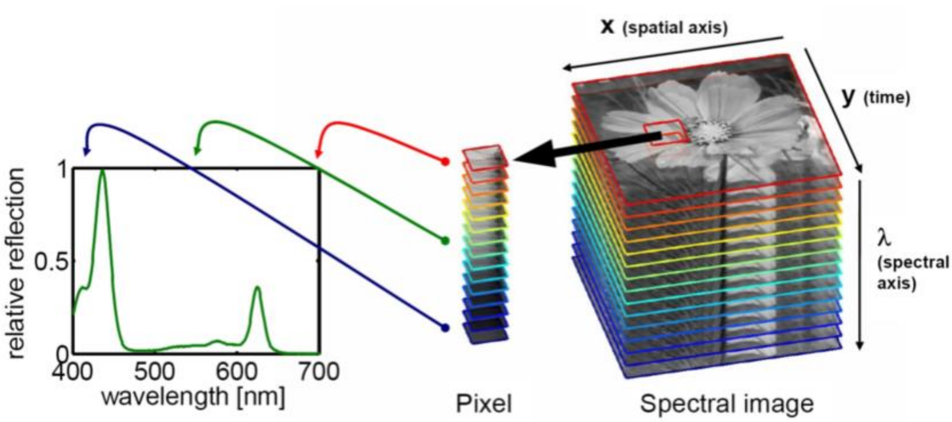


Fig. 2.9 Hyperspectral image data cube

2.3.3 Transition between frequencies

The transition between spectral bands in hyperspectral cameras is a key aspect of their functioning, as it allows obtaining detailed information about the spectral composition of the scene. This process is carried out with the help of optical elements that decompose light into its spectral components. The main methods of achieving this are the use of rotating filters, dispersive elements such as prisms or diffraction gratings, and interference filters. Each of these methods has its advantages and disadvantages, which are determined by the requirements of a particular application[17].

Let's look at the methodologies Rotary filters, also known as Fabry-Perot filters, are used to selectively transmit certain spectral bands of light. They consist of a set of interchangeable filters that can be rotated to adjust to the desired wavelength (Figure 2.10). This method allows you to quickly change spectral bands and provides high accuracy of data collection. The principle of rotating filters is that the light from the object passes through the camera lens and hits the rotating filter. Depending on the angle of rotation, the filter transmits only a certain spectral band, which is then registered by the detector. By rotating the filters sequentially, a complete spectral image of the scene can be obtained.

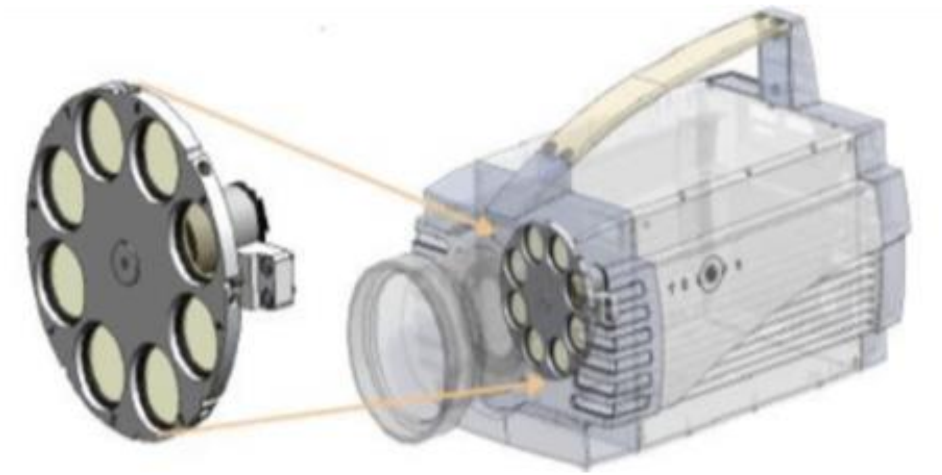


Fig. 2.10 Filter wheel system

Prisms and diffraction gratings are other common elements for decomposing light into spectral components. They use the phenomena of dispersion and diffraction to separate light into individual wavelengths. Prisms refract light at different angles depending on the wavelength, breaking it down into its spectral components. Prisms are commonly used in high-precision laboratory hyperspectral systems where high spectral resolution is important. Diffraction gratings decompose light through interference, creating spectral bands. They provide high spectral resolution and can be used in a variety of applications, including satellite and aviation systems. The equation for the diffraction angle θ in a diffraction grating is defined as:

$$d\sin(\theta) = n\lambda$$

Another approach is interference filters (Fig. 2.11), which use the phenomenon of interference to selectively transmit certain wavelengths. They consist of multilayer coatings that create interference bands. These filters provide high accuracy and are often used in portable hyperspectral cameras. For example, the Headwall Photonics Nano-Hyperspec aviation hyperspectral camera uses interference filters to capture images in the visible and near-infrared. The camera is installed on drones and airplanes for monitoring crops, forest resources, and other objects.

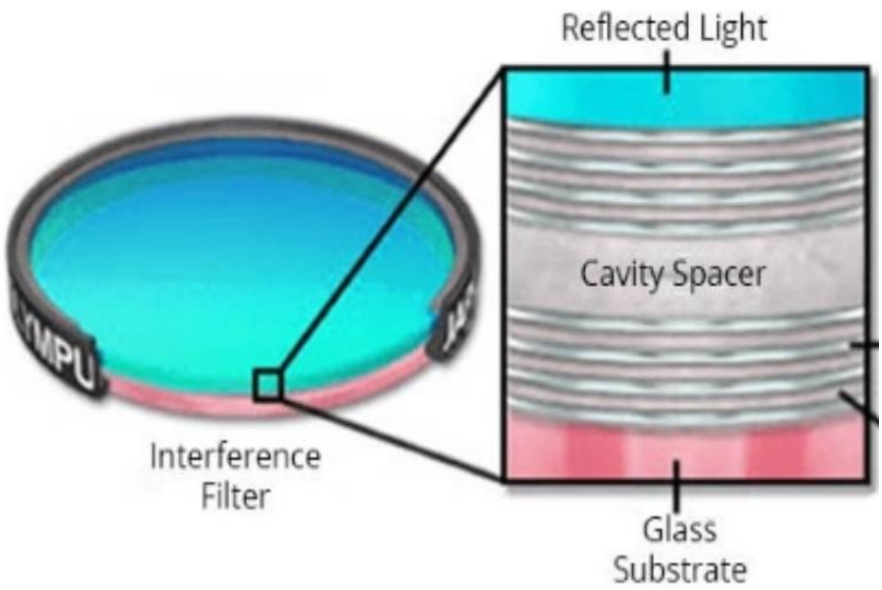


Fig. 2.11 Interference Optical Filters

2.3.4. Camera configuration

Hyperspectral cameras have a complex configuration that includes optical elements, detectors, signal processing electronics, and other components. The camera configuration determines its characteristics, such as spectral and spatial resolution, sensitivity, wavelength range, and other parameters. The main components of a hyperspectral camera - the lens, dispersive element, detector, and data processing and storage electronics - work together to provide an accurate and detailed image of a scene[14].

The first step in configuring a hyperspectral camera is to select a lens. The lens focuses the light onto the detector and can be of different types, from simple lenses to complex multiple lens systems (Figure 2.12) or mirror-lens systems. The type of lens is selected depending on the spatial resolution requirements and the field of view of the camera.

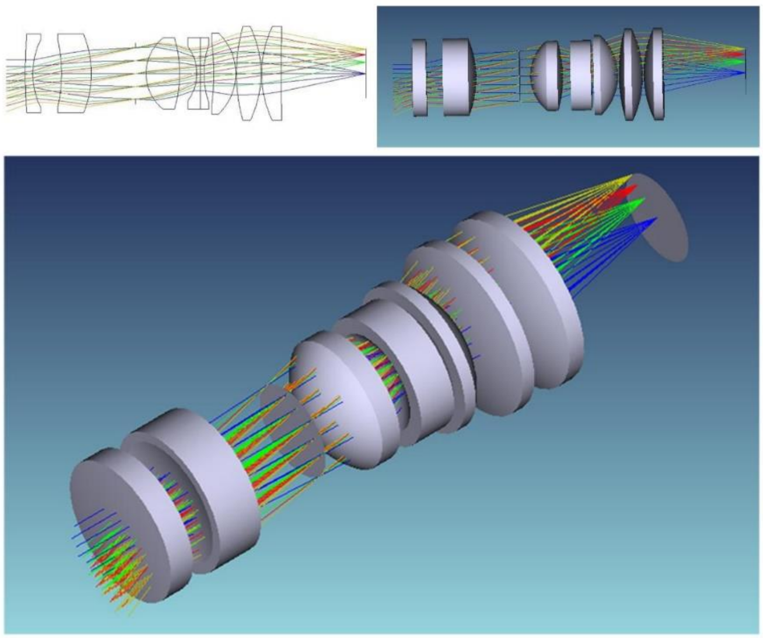


Fig. 2.12 Hyperspectral lens 1.0 μm-2.5 μm SWIR

After the light has passed through the lens, it hits the dispersive element, which decomposes it into spectral components. The most commonly used are prisms or diffraction gratings. A prism uses the principle of light refraction, and a diffraction grating works by diffraction (Figure 2.13). This element allows you to decompose light into narrow spectral bands, which is critical for obtaining high-quality hyperspectral data.

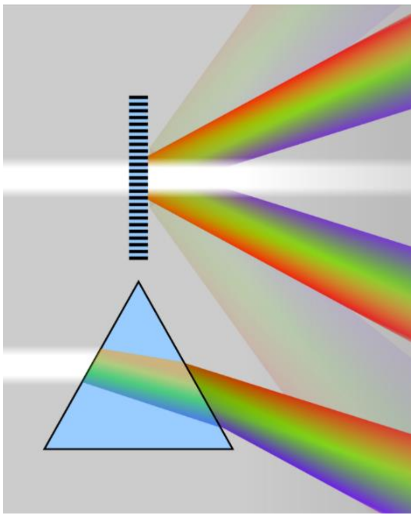


Fig. 2.13 Comparison of the spectra obtained from a diffraction grating by diffraction , and a prism by refraction.

The decomposed light is transmitted to a detector that records the spectral data. Detectors can be of different types, but the most commonly used are CCD or CMOS detectors (Figure 2.14). They provide high sensitivity and resolution, which allows you to record the intensity of light in each spectral band.

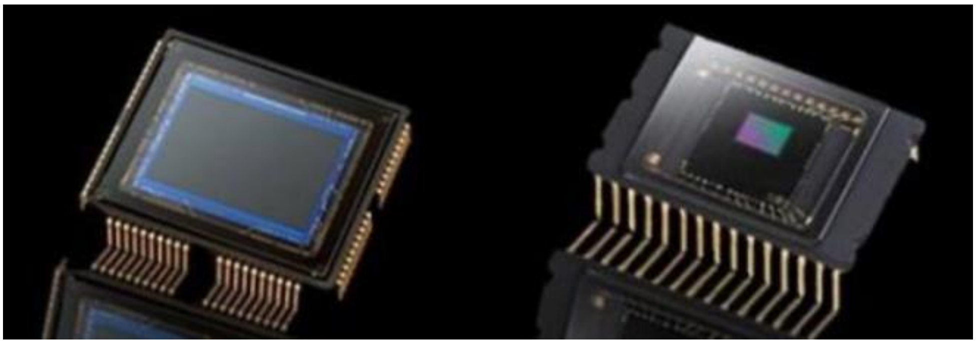


Fig. 2.14 CCD and CMOS detectors

Signal processing electronics play a key role in the configuration of hyperspectral cameras. It provides digitization of analog signals from the detector, noise filtering, signal amplification, and data transmission to an external device for storage and analysis. The main electronics components include analog-to-digital converters (ADCs), amplifiers, filters, and microprocessors.

Some hyperspectral cameras are equipped with cooling systems to reduce noise and increase detector sensitivity. This is especially important for cameras operating in the infrared range, where thermal noise can significantly affect image quality. Cooling can be provided by thermoelectric coolers or liquid cooling.

Software also plays an important role in the configuration of hyperspectral cameras. It provides control over the imaging process, setting of imaging parameters, such as exposure, number of spectral bands, resolution, etc., as well as processing of the data obtained. The software allows you to perform initial data processing, including calibration, geometric distortion and noise correction.

A stable power supply and communication interfaces are also an integral part of the hyperspectral camera configuration. These can be USB, Ethernet or specialized high-speed interfaces such as Camera Link. Reliable power supply and high-speed data transfer are critical for the smooth operation of cameras in the field or when installed on unmanned aerial vehicles.

Finally, to ensure measurement accuracy, hyperspectral cameras are equipped with calibration mechanisms. They include systems for radiometric, geometric and spectral calibration. Calibration mechanisms allow taking into account various factors that can affect the accuracy of measurements, such as temperature changes, changes in the characteristics of the detector or optical elements.

Thus, the configuration of hyperspectral cameras is a complex process involving the selection and adjustment of various components to achieve high measurement accuracy and sensitivity. These components work together to provide detailed and accurate information about a scene, which is critical for many scientific and industrial applications.

2.4. Carriers

Carriers for hyperspectral cameras are key elements that provide mobility and the ability to cover large areas for spectral analysis. The most common carriers are satellites, airplanes, and unmanned aerial vehicles (drones). This section will discuss the use of unmanned aerial vehicles, in particular drones, as carriers for hyperspectral cameras, which allows for high-precision aerial surveys.

Drones are the most flexible and cost-effective carriers for hyperspectral imaging. They allow to obtain high-quality data from low altitudes, providing high spatial and spectral resolution. Drones can be quickly deployed to survey localized areas, making them indispensable for operational research and monitoring tasks. Modern drones, such as the DJI Matrice 600, have a large payload and long flight time, which allows them to mount heavy scientific instruments and conduct long-term research. The main limitations of drones are their limited flight time and dependence on weather conditions, including wind and precipitation.

2.4.1 Classification of drones

Quadcopters can be classified according to various criteria such as size, payload, flight time, purpose, and design features. Here are some of the main types of quadcopters[6]:

- Micro quadcopters are the smallest quadcopters, usually measuring less than 20 cm. They are lightweight, maneuverable, and cheap, making them popular for beginners and for indoor use. They are equipped with small batteries that provide a short flight time of 5 to 10 minutes. An example of a micro-quadcopter is the Cheerson CX-10 (Figure 2.15), which has a flight time of up to 8 minutes and weighs only 12 grams. Although their payload capacity is very limited, these drones are great for training and entertainment.

Fig. 2.15 Cheerson CX-10

- Compact quadcopters are slightly larger devices, up to 40 cm in size. They can carry a small load, for example, a camera for amateur filming. The flight time of these quadcopters can be from 10 to 20 minutes, depending on the battery capacity. The DJI Spark (Figure 2.16) is an example of a compact quadcopter that has a flight time of up to 16 minutes and can carry a small camera for HD filming. These quadcopters offer better stability and longer flight times than micro quadcopters.

Fig. 2.16 DJI Spark

- Medium-sized quadcopters are 40 to 70 cm in size and are capable of carrying heavier loads, including professional cameras. They are commonly used for commercial and industrial applications. The flight time of medium-sized quadcopters can reach 30 minutes or more. For example, the DJI Phantom 4 Pro (Fig. 2.17) has a payload of up to 500 grams and a flight time of up to 30 minutes. It is equipped with a 20-megapixel camera with the ability to shoot 4K video. This quadcopter is a great choice for professional photography and videography.

Fig. 2.17 DJI Phantom 4 Pro

- Large quadcopters are the largest and most powerful devices, measuring more than 70 cm. They can carry heavy loads, such as hyperspectral cameras, and are used in professional and industrial applications. Flight time can reach 60 minutes or more, depending on battery capacity and design features. The DJI Matrice 600 (Figure 2.18) is an example of a large quadcopter that can carry up to 6 kg of cargo and has a flight time of up to 35 minutes with a maximum payload. Its modular design allows for the use of a variety of equipment, making it ideal for complex industrial applications.

2.4.2 Characteristics of the DJI Matrice 600 drone

The DJI Matrice 600 is one of the most popular drones used for professional aerial photography and hyperspectral imaging. This drone has high technical characteristics that ensure flight stability and high quality data.

Fig. 2.18 DJI Matrice 600

Main features of DJI Matrice 600:

- Maximum takeoff weight: 15.5 kg
- Payload capacity: up to 6 kg
- Flight duration: up to 35 minutes (with a load of 6 kg)
- Maximum speed: 18 m/s
- Control system: A3 Pro
- GPS: support for dual GPS/GLONASS
- Video transmission system: Lightbridge 2
- Operating temperature range: -10°C to +40°C

These features make the DJI Matrice 600 an ideal choice for heavy hyperspectral camera installations that require stable and long flight times.

2.4.3. Installing the hyperspectral camera on the DJI Matrice 600

Mounting the hyperspectral camera on the drone is an important step that affects the quality of the image and flight stability. The DJI Matrice 600 uses special gimbals to stabilize and minimize vibrations during flight[19].

The process of installing a hyperspectral camera:

1. Selecting a gimbal: To install a hyperspectral camera, choose a gimbal that is compatible with the drone model and camera weight. For example, the Gremsy T3 gimbal (Fig. 2.19), which supports a load of up to 3.5 kg and provides three-axis stabilization.

Fig. 2.19 Gremsy T3

2. Mounting the gimbal: The gimbal is attached to the bottom of the drone using special mounting kits. It is important to ensure a secure mount to avoid shifting or losing the camera during flight.

3. Calibration: Once the gimbal and camera are installed, the stabilization system is calibrated. This is necessary for optimal performance of the gimbal and to obtain clear, blur-free images.

4. Connecting the camera: The hyperspectral camera is connected to the drone's power system and control system to ensure that the camera is synchronized with the drone. This may include power and data transmission through dedicated cables.

5. Test flight: Before performing the main tasks, a test flight is conducted to verify the operation of the gimbal and camera. It is important to check flight stability and image quality.

Installing a hyperspectral camera on the DJI Matrice 600 allows you to obtain high-quality spectral data necessary for a variety of research and monitoring tasks.

2.4.4. Flight and route specifications for hyperspectral imagery

Effective flight and route planning are key factors in obtaining accurate and detailed hyperspectral imagery. Below are the technical aspects of flight and route planning for hyperspectral imaging with the DJI Matrice 600[6].

Flight planning:

1. Flight altitude: The choice of flight altitude depends on the required spatial resolution and coverage area. For hyperspectral imaging, an altitude of 100-150 meters is usually used, which provides an optimal ratio between image detail and coverage area.

2. Overlapping images: To ensure full coverage of the territory, the overlap of images is set at 60-80% in the transverse and longitudinal directions. This avoids gaps in the data and provides the ability to create mosaic images.

3. Flight route: The flight route is planned in such a way that the drone moves along parallel lanes, covering the entire area of the surveyed territory. Special software tools for automatic route planning are used, such as DJI Ground Station Pro or Pix4Dcapture.

An example of route calculation:

Let's take an example of surveying an agricultural field of 50 hectares. For this purpose, a DJI Matrice 600 drone with a hyperspectral camera will be used.

- Flight altitude: 120 meters
- Width of the shooting band: 30 meters
- Overlap of images: 70%
- Strip length: 500 meters

To cover 50 hectares (500,000 m^2), 34 swaths (500,000 m^2 / (30 m * 500 m)) are required.

Flight trajectory:

1. The drone starts from a starting point at the edge of the field.

2. It flies along the first lane at an altitude of 120 meters, capturing images with 70% overlap.

3. After reaching the end of the lane, it turns and moves to the next lane, moving in the opposite direction.

4. The procedure is repeated for all 34 lanes until the field is completely covered.

Time to complete the task:

With a flight duration of 35 minutes and an average flight speed of 5 m/s, the time required to complete the task is calculated as:

$$\text{Час польоту на одну смугу} = \frac{500\ \text{метрів}}{5\ \text{м/с}} = 100\ \text{секунд}$$

$$\text{Загальний час зйомки} = 100\ \text{секунд} \times 34\ \text{смуги} = 3400\ \text{секунд} = 56.7\ \text{хвилин}$$

Thus, the drone will be able to survey the entire field in two flights, which ensures efficiency and high quality of the data obtained.

In summary, proper flight planning and installation of a hyperspectral camera on the DJI Matrice 600 drone allows you to efficiently perform hyperspectral imaging of large areas with high accuracy and quality of the data obtained.

CHAPTER 3
PROCESSING OF HYPERSPECTRAL IMAGES

3.1. Preliminary processing of hyperspectral images

Pre-processing of hyperspectral images is an important stage that ensures high-quality further data analysis and interpretation. It includes several main steps: calibration correction, atmospheric correction and geometric distortion correction.

3.1.1. Calibration correction

Calibration correction is the primary step required to bring hyperspectral data to a standardized form. This process involves the correction of systematic errors that may occur due to the peculiarities of the sensor or the camera optical system[1].

One of the main tasks of calibration is to convert the raw data into a reflectance. This is done by normalizing the measured signal to the corresponding radiometric response of the camera. The formula for this is as follows:

$$R(\lambda) = \frac{L(\lambda) - L_{dark}(\lambda)}{L_{white}(\lambda) - L_{dark}(\lambda)}$$

3.1.2. Atmospheric correction

Atmospheric correction is necessary to take into account the influence of the atmosphere on hyperspectral data, as light passing through the atmosphere undergoes scattering and absorption. This process can significantly distort the data obtained, so it is important to correct it to accurately reflect the properties of objects on the Earth's surface (Fig. 3.1).

For atmospheric correction, models such as MODTRAN (MODerate resolution atmospheric TRANsmission) are often used, which allow to simulate atmospheric conditions and take into account their effect on spectral data[13].

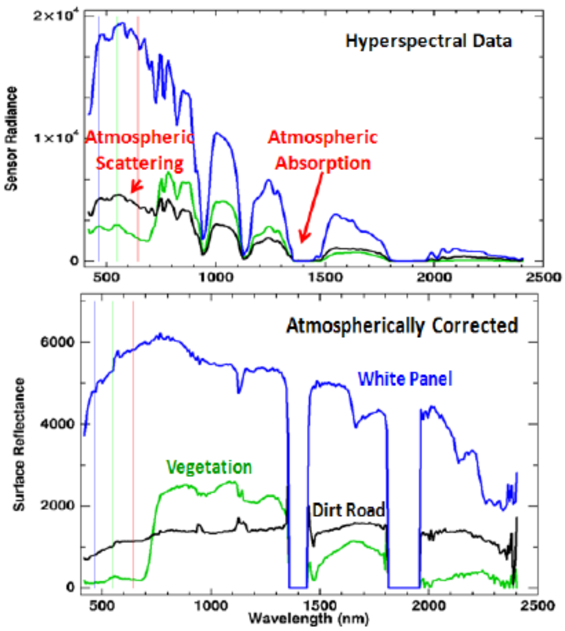


Fig. 3.1 An example of atmospheric correction processing for hyperspectral imaging sensors, showing several pixel spectra of the sensor (top) and their corresponding atmospherically corrected surface reflectance spectra (bottom).

3.2. Reducing the dimensionality of hyperspectral data

Hyperspectral images contain a huge amount of spectral and spatial data, which can make them difficult to process and analyze. Reducing the dimensionality of hyperspectral data allows for easier processing while retaining important information. The main methods of dimensionality reduction include principal component analysis (PCA), linear discriminant analysis (LDA), and negative matrix factorization (NMF).

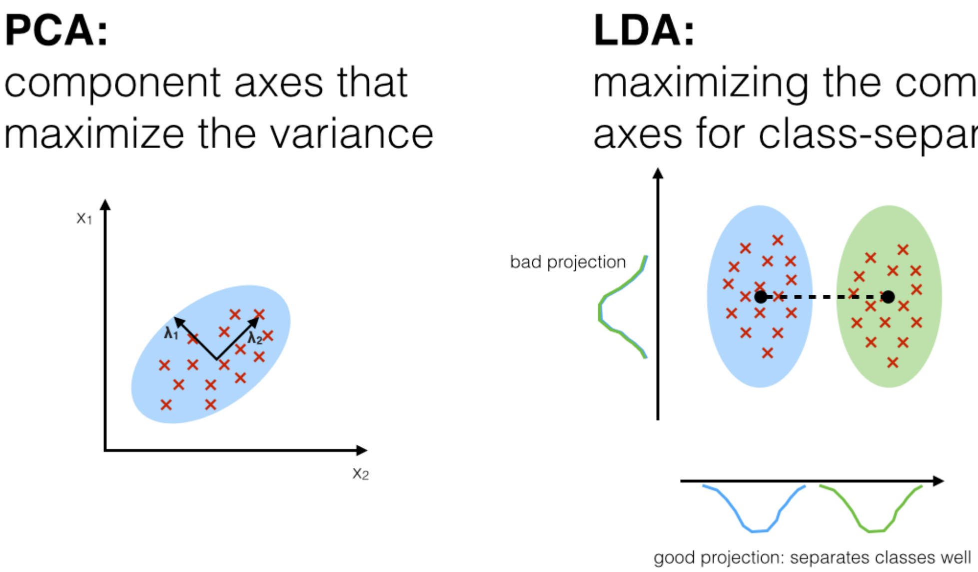


Fig. 3.2 Comparison of PCA and LDA methods

3.2.1. Principal component analysis (PCA) methods

Principal component analysis (PCA) is one of the most common dimensionality reduction methods used to analyze hyperspectral data. PCA transforms the original variables into a new set of variables called principal components that are orthogonal and contain the largest part of the variance in the data[17].

The formula for finding the principal components:

$$\mathbf{Z} = \mathbf{X}\mathbf{W}$$

3.2.2. Linear discriminant analysis (LDA)

Linear discriminant analysis (LDA) is used to reduce the dimensionality of a classification problem. LDA projects the data into a lower dimensional space, maximizing the difference between classes and minimizing the scatter within classes.

The main goal of LDA is to find linear combinations of variables that maximize the ratio of between-class variance to within-class variance:

$$\mathbf{W}_{opt} = \arg\max_{\mathbf{W}} \frac{|\mathbf{W}^T \mathbf{S}_B \mathbf{W}|}{|\mathbf{W}^T \mathbf{S}_W \mathbf{W}|}$$

3.3 Classification and segmentation of hyperspectral images

Classification and segmentation of hyperspectral images are important steps in data analysis, as they allow to identify different materials and objects in the images. There are two main approaches to classification: supervised and unsupervised methods.

3.3.1. Supervised classification methods

Supervised classification methods use pre-labeled data to train a model. These methods include support vector machines (SVMs), decision trees, random forests, neural networks, and deep learning.

3.3.1.2. Decision trees and random forests

Decision trees use a hierarchical structure to make decisions by dividing data into subsets based on the values of their attributes. Random forests (Figure 3.2) consist of a large number of decision trees and use the ensemble method to improve classification accuracy[15].

Formula for entropy in a decision tree:

$$H(D) = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

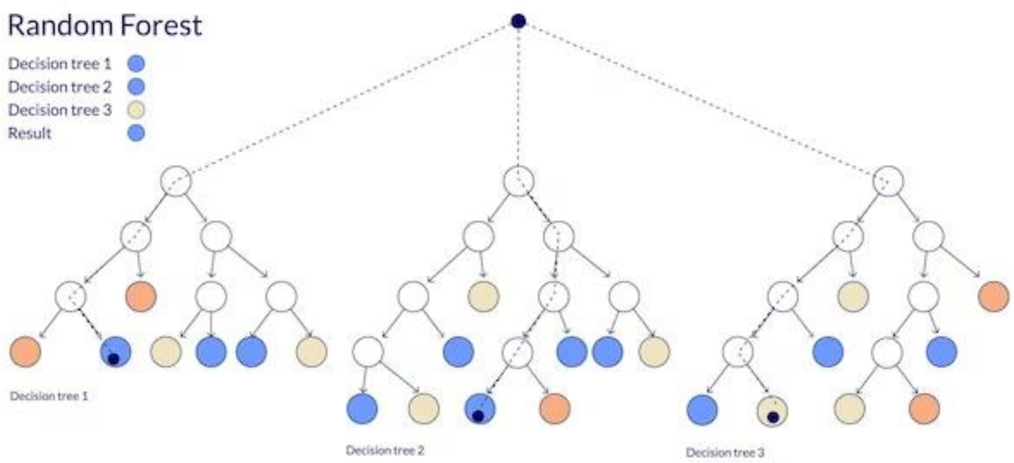


Fig. 3.3 Schematic of a random forest

3.3.1.3. Neural networks and deep learning

Neural networks and deep learning use multi-layer models to learn complex patterns in data. Deep neural networks, such as convolutional neural networks (CNNs), are particularly effective for hyperspectral image classification due to their ability to automatically extract features from the data (Figure 3.4)[19].

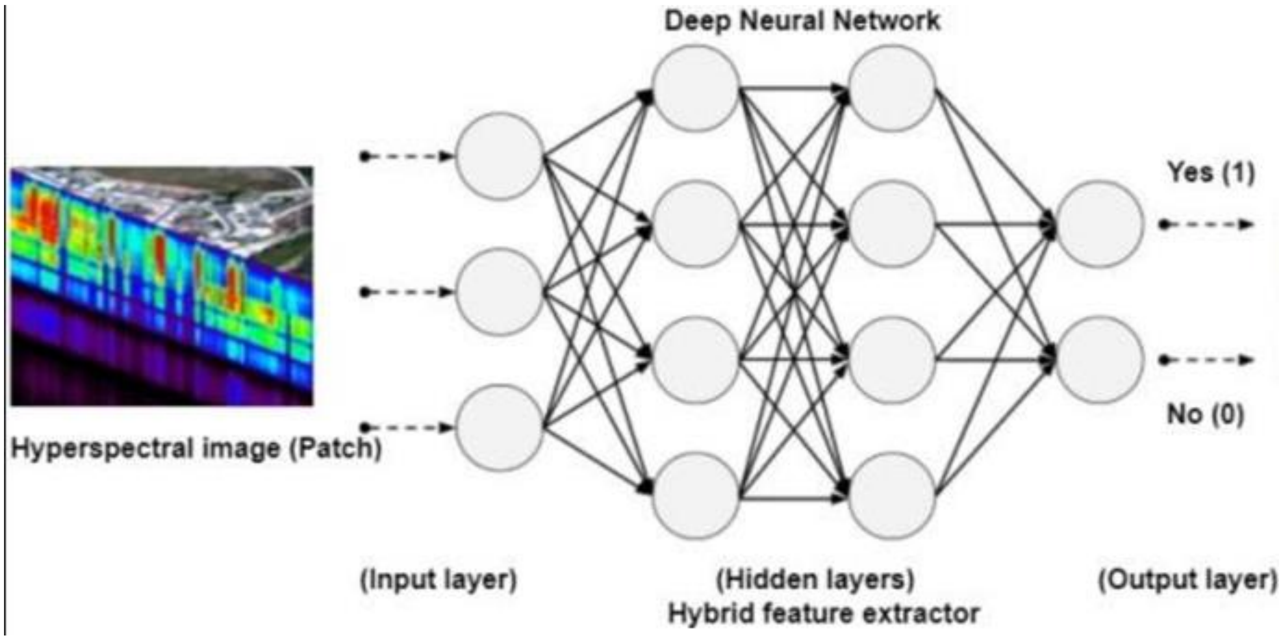


Fig. 3.4 Hyperspectral image processing using a deep neural network

3.4 Detecting and extracting objects in hyperspectral images

Detecting and extracting objects in hyperspectral images is an important processing step that allows you to identify specific materials and changes in the environment. This process involves the use of spectral indices, detection of anomalies, changes, and extraction of information using templates.

3.4.1 Spectral indices and indicators

Spectral indices are used to enhance certain characteristics in hyperspectral images. They allow you to highlight specific objects or phenomena, such as vegetation, water, or minerals, based on their spectral signatures. For example, the Normalized Difference Vegetation Index (NDVI) is widely used for vegetation detection and monitoring[7].

3.4.2 Anomaly and change detection

Anomaly detection is the identification of pixels or areas that are significantly different from the surrounding data. This can be useful for identifying changes in the environment, such as water pollution, plant disease detection, or man-made changes. Anomaly detection methods can include thresholding methods, statistical models, and machine learning[11].

The formula for statistical anomaly detection methods can be represented as follows:

$$D(x) = \frac{|x-\mu|}{\sigma}$$

3.4.3. Information extraction using templates

Template-based information extraction from hyperspectral images involves the use of predefined spectral signatures to identify specific materials or objects. This can be done using correlation analysis techniques, where spectral signatures are compared to a database of templates[10].

Formula for correlation analysis:

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2 \sum(y_i-\bar{y})^2}}$$

These object detection and extraction techniques greatly facilitate the analysis of hyperspectral data, allowing the identification of important environmental, agricultural, and industrial features in images.

3.5. Visualization and interpretation of hyperspectral data

Visualization and interpretation of hyperspectral data are important steps for understanding and analyzing the information contained in hyperspectral images. They allow for a more convenient representation of multidimensional data and qualitative and quantitative analysis of spectral signatures.

3.5.1. Pseudo-color mapping methods

Pseudo-color display methods are used to present hyperspectral data in a human-readable format. Since hyperspectral data contain information from numerous spectral channels, it is impossible to display them directly on the monitor screen. Therefore, various visualization techniques are used to display multichannel data in the form of color images[14].

One popular method is to stack RGB channels from three selected spectral bands (Figure 3.6), which allows you to create a color image. The choice of spectral bands depends on the task under study.

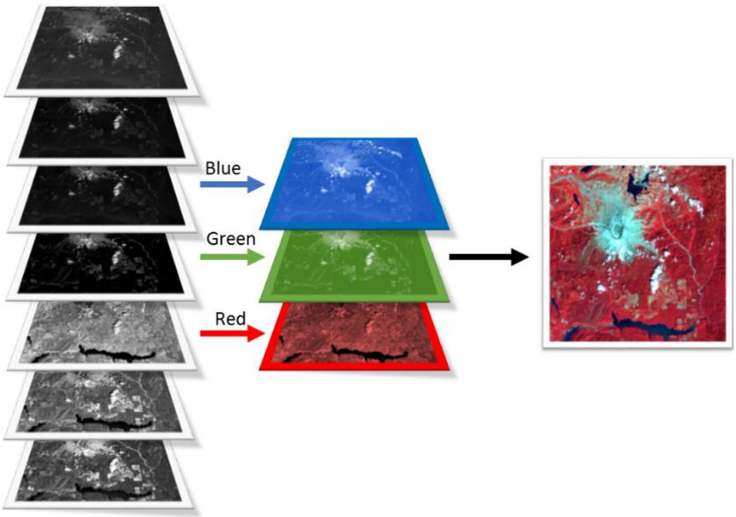


Fig. 3.6 Schematic of the process of selecting spectral bands for RGB channel compilation

3.5.2. Visualization in three-dimensional space

Visualization in three-dimensional space allows you to display spectral data in the form of three-dimensional models, where two dimensions represent spatial coordinates, and the third is the intensity of light reflection at different wavelengths (Fig. 3.7). This helps to better understand the structure and distribution of spectral characteristics in the image.

Three-dimensional visualization methods include the use of volume renderings and isosurfaces. Iso-surfaces allow you to display levels of reflectance intensity for different spectral bands[16].

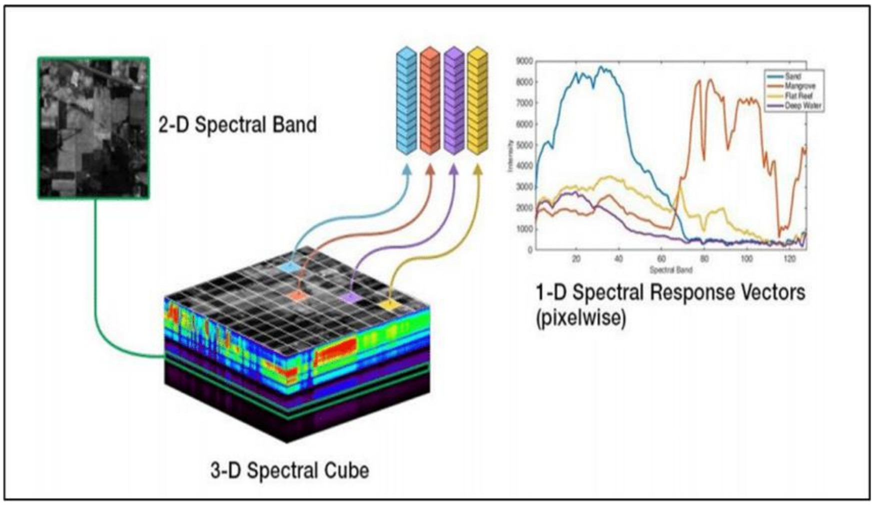


Fig. 3.7 Three-dimensional model of hyperspectral data

3.5.3. Interpretation of spectral signatures

Spectral signature interpretation is the detection and analysis of unique spectral characteristics that allow the identification of materials and objects in hyperspectral images. Spectral signatures reflect the reflectivity of materials at different wavelengths and can be used to recognize types of vegetation, minerals, water resources, and other objects[16].

To interpret spectral signatures, we use correlation analysis and spectral signature libraries. Correlation analysis allows comparing the obtained spectral signatures with known reference values contained in libraries.

Methods of visualization and interpretation of hyperspectral data allow to effectively use hyperspectral information for solving a wide range of problems in science and industry.

3.6. Integration of hyperspectral data with other sources of information

Integration of hyperspectral data with other sources of information allows to expand the possibilities of analysis and improve the accuracy and reliability of the results obtained. Interaction of hyperspectral images with multispectral data, geographic information systems (GIS), as well as data from other sensors, such as radar and LiDAR, opens up new horizons for research in various fields of science and industry.

3.6.1. Combining hyperspectral and multispectral data

Hyperspectral and multispectral data are complementary, as each type of data has its own advantages. Multispectral data provides wider spectral bands and can cover larger areas at a time, while hyperspectral data provides high spectral resolution. Combining these data allows the strengths of both technologies to be used for more accurate and detailed analysis (Figure 3.8).

Fusion techniques include the use of image fusion algorithms such as PCA (Principal Component Analysis) and other approaches that preserve the spatial resolution of multispectral data while adding spectral information from hyperspectral imagery[11].

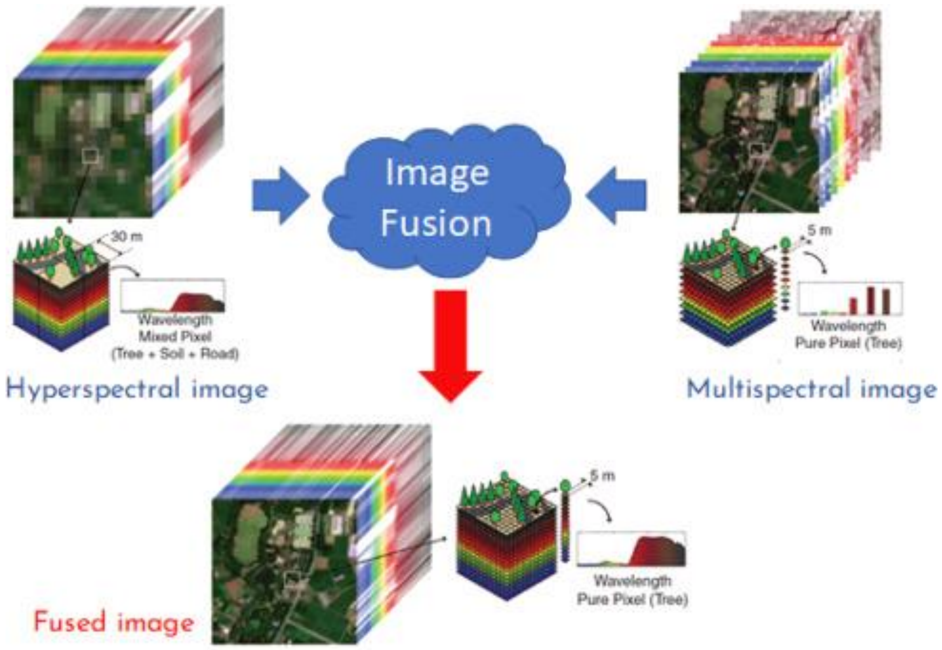


Fig. 3.8 Scheme of combining hyperspectral and multispectral images

3.6.2. Integration with GIS (geographic information systems)

Integration of hyperspectral data with GIS allows to effectively combine spectral information with spatial information about objects and territories. This greatly expands the possibilities for analyzing, monitoring and managing resources.

GIS is used to store, analyze and visualize geospatial data. By integrating hyperspectral imagery with GIS, it is possible to conduct more accurate spatial analysis, create maps of the distribution of various materials or vegetation conditions, and monitor environmental changes[10].

3.6.3. Using data from other sensors (radar, LiDAR)

Data from other sensors, such as radar and LiDAR, can be integrated with hyperspectral data to achieve a more comprehensive analysis. LiDAR (Light Detection and Ranging) provides three-dimensional information about the surface structure and height of objects, while radar data provides information about surface properties and moisture (Figure 3.9).

Combining these data with hyperspectral imagery allows for a more complete picture of the area under study. For example, LiDAR can help determine the structure of vegetation, while hyperspectral data reveals its chemical and physiological properties[9].

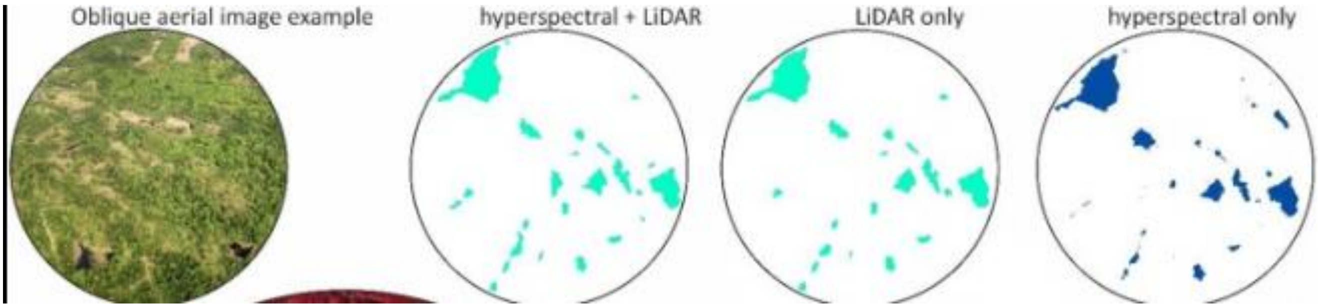


Fig. 3.9 Examples of integrated images of hyperspectral data with LiDAR and radar data

The integration of hyperspectral data with other sources of information greatly expands the possibilities for analyzing and applying this technology in various fields, from environmental monitoring to precision agriculture and natural resource management.

3.7. Practical cases of hyperspectral image processing

Hyperspectral images open up wide opportunities for detailed analysis and monitoring in various fields. They provide highly accurate data about objects and processes, which is important for making informed decisions. This section discusses several practical cases of using hyperspectral images.

3.7.1. Crop analysis

Hyperspectral cameras are widely used to analyze the condition of agricultural crops (Fig. 3.10). They help to determine the content of chlorophyll, nitrogen and other elements in plants, which allows agronomists to effectively manage fertilizers, plan irrigation and detect diseases or pests in time[8].

The main stages of crop analysis using hyperspectral images include:

- Data collection: A hyperspectral camera mounted on a drone or airplane takes pictures of the field.

- Pre-processing: Noise correction, signal normalization, and other methods to improve image quality.
- Analysis: Using machine learning algorithms and spectral indices to assess the condition of plants.

Fig. 3.10 An example of a field image taken by a hyperspectral camera

3.7.2. Environmental monitoring

Hyperspectral imagery is effective for monitoring various aspects of the environment, such as water quality, air pollution, forest health, etc. Due to its high spectral resolution, it is possible to identify and classify different types of vegetation, detect harmful impurities in water, and study ecosystems[11].

The process of environmental monitoring includes:

- Data collection: The use of satellite or airborne platforms to survey areas.
- Data processing: Applying spectral analysis and classification techniques to extract the necessary features.
- Interpretation of results: Analyzing the data to make decisions about environmental protection.

3.7.3. Medical and biological research

Hyperspectral images are used in medical and biological research to study tissues, diagnose diseases, and investigate biological processes (Figure 3.11). They allow detecting changes in tissues that may not be visible with conventional visual diagnostics[1].

Key steps in the use of hyperspectral images in medicine and biology:

- Image acquisition: A hyperspectral camera takes pictures of biological samples or organs.
- Image analysis: Using spectral methods to detect abnormalities and pathological changes.
- Interpretation of results: Using the data for diagnosis, treatment planning, and research.

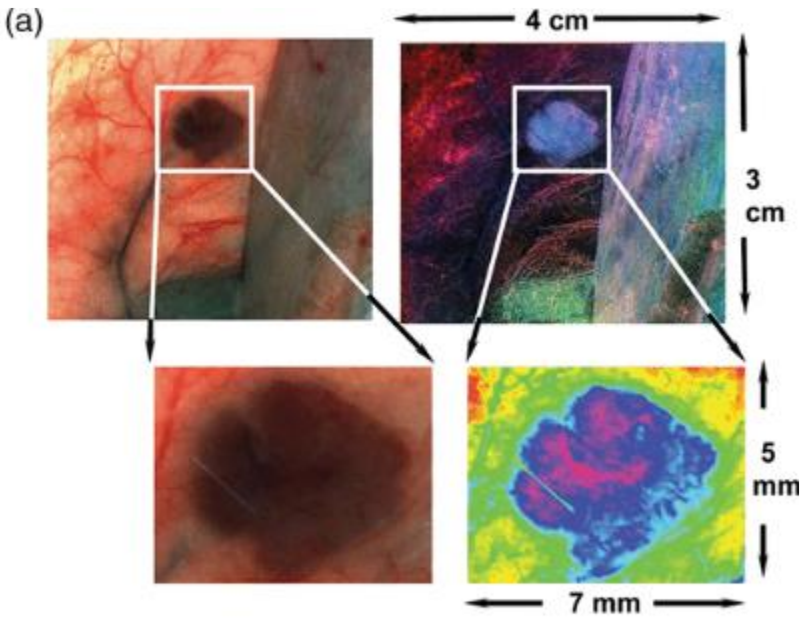


Fig. 3.11 Tissue images taken with a hyperspectral camera

Hyperspectral images provide unique opportunities for detailed analysis and monitoring in various industries. They provide highly accurate information that can be used to make informed decisions in agriculture, environmental protection, medicine and many other areas.

CHAPTER 4
PRACTICAL IMPLEMENTATION OF A NEURAL NETWORK FOR ANOMALY CLASSIFICATION

4.1 Architecture of a neural network

This subsection discusses the details of the neural network architecture that was developed for the detection and classification of offshore oil spills. The use of convolutional neural networks (CNNs) allows to effectively analyze the spatial and spectral characteristics of hyperspectral images, which ensures high accuracy of anomaly detection.

4.1.1. Model structure

Our model consists of two main branches: spatial and spectral. This architecture allows for deep data analysis and integration of different types of features, which improves classification accuracy.

The spatial branch consists of several convolutional layers that process the spatial features of images. The spectral branch uses 1x1 convolution to process spectral features.

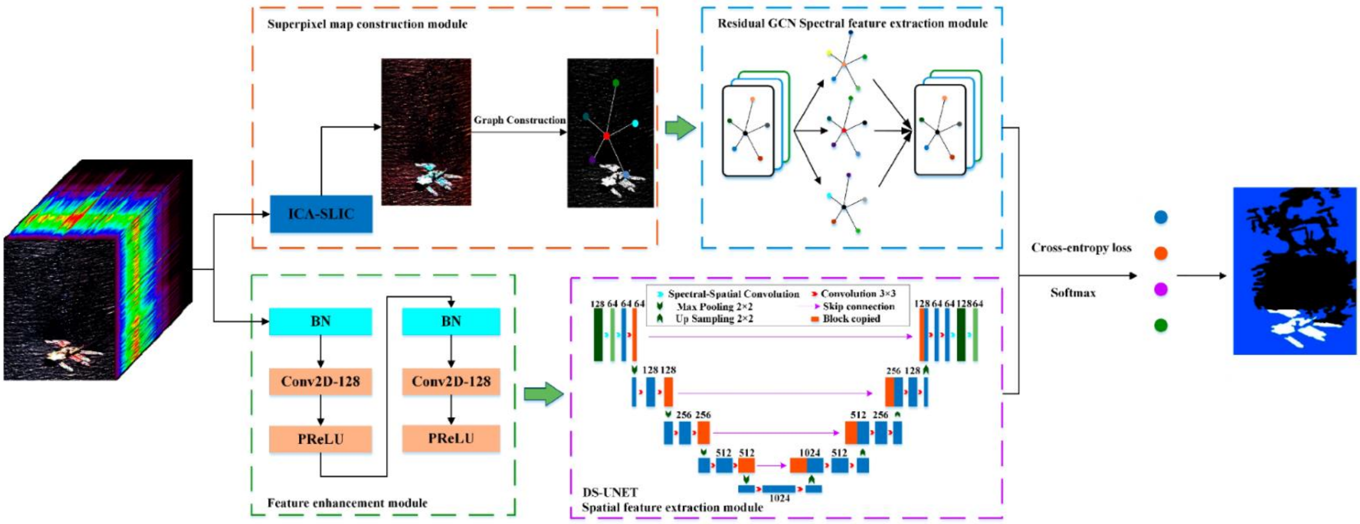


Fig. 4.1 Architecture of the Model

4.1.2. Building the model

Below is the code for building a model in Python using the TensorFlow library:

```
import tensorflow as tf
from tensorflow.keras import layers, models


def build_model(input_shape):
```

```
inputs = layers.Input(shape=input_shape)

# Spatial branch
x = layers.Conv2D(32, (3, 3), activation='relu', padding='same')(inputs)
x = layers.MaxPooling2D((2, 2))(x)
x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = layers.MaxPooling2D((2, 2))(x)
x = layers.Conv2D(128, (3, 3), activation='relu', padding='same')(x)
spatial_features = layers.Flatten()(x)

# Spectral branch
y = layers.Conv2D(32, (1, 1), activation='relu', padding='same')(inputs)
y = layers.MaxPooling2D((2, 2))(y)
y = layers.Conv2D(64, (1, 1), activation='relu', padding='same')(y)
y = layers.MaxPooling2D((2, 2))(y)
y = layers.Conv2D(128, (1, 1), activation='relu', padding='same')(y)
spectral_features = layers.Flatten()(y)

# Integration of spatial and spectral features
combined_features = layers.concatenate([spatial_features, spectral_features])

# Classification layer
z = layers.Dense(256, activation='relu')(combined_features)
```

```
    z = layers.Dropout(0.5)(z)
    outputs = layers.Dense(1, activation='sigmoid')(z)

    model = models.Model(inputs, outputs)
    return model

input_shape = (128, 128, 30)  # приклад розміру гіперспектральних даних
model = build_model(input_shape)
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

This code creates a CNN model with two branches: the spatial branch processes spatial features and the spectral branch processes spectral features. The combined features are used to classify anomalies.

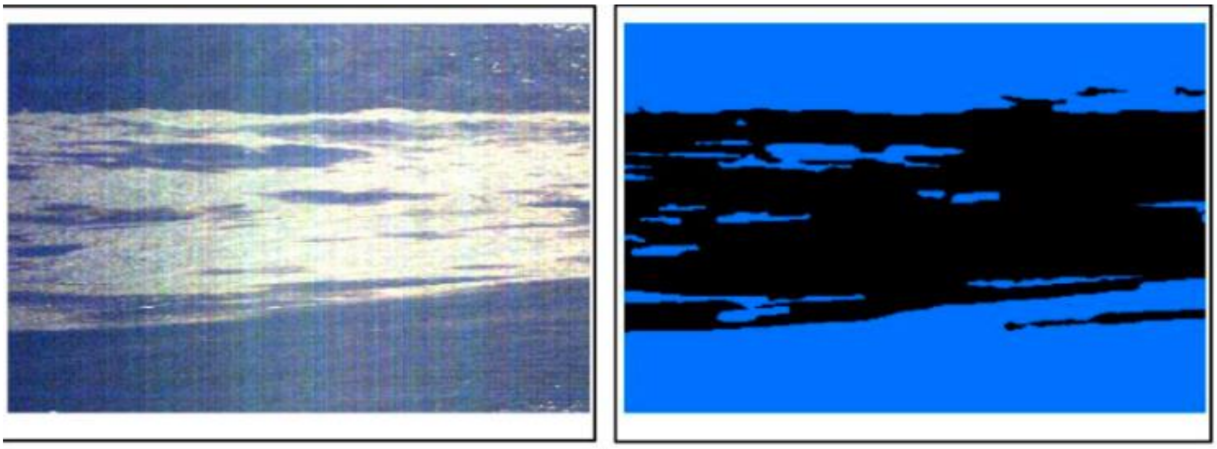
4.2. Data preparation

Data preparation is a critical step in creating an effective neural network. In this subsection, we discuss the processes of data collection, preprocessing, and augmentation for model training. We used hyperspectral imagery to detect offshore oil spills, providing the model with a sufficient amount of high-quality data.

4.2.1. Description of the datasets

Hyperspectral images with labeled anomalies were used to train and test our model. Hyperspectral data provides the ability to analyze objects in many spectral bands, which greatly improves the ability to distinguish between different materials.

Fig. 4.2 shows a hyperspectral image with labeled oil spills. It illustrates how the data was collected and what anomalies we are trying to detect.



(a) (b)

Fig. 4.2 Hyperspectral oil spill image and corresponding ground truth image

4.2.3 Pre-processing

Data preprocessing includes several steps such as normalization, noise removal, and augmentation. This helps to improve the quality of the data used to train the model.

Data normalization:

- The hyperspectral data was normalized to reduce the differences in pixel values and facilitate the model training process.

Noise removal:

- Filtering was applied to reduce noise in the hyperspectral images.

Data augmentation:

- To increase the amount of training data, augmentation techniques such as rotation, displacement, and zooming of the images were used.

```
import numpy as np

from sklearn.model_selection import train_test_split


# Downloading data (example)
```

```
data = np.load('hyperspectral_data.npy')  # Гіперспектральні зображення
labels = np.load('labels.npy')  # Мітки розливів нафти

# Data normalization
data = data / np.max(data)

# Remove noise (example of using a filter)
from scipy.ndimage import gaussian_filter
data = gaussian_filter(data, sigma=1)

# Separation into training and validation sets
train_data, val_data, train_labels, val_labels = train_test_split(data, labels, test_size=0.2, random_state=42)

# Data augmentation (example)
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(rotation_range=20, width_shift_range=0.2, height_shift_range=0.2, zoom_range=0.2)
datagen.fit(train_data)
```

4.2.4. Preparation of hyperspectral images

To prepare hyperspectral images, several important steps were performed, such as artifact removal, geometric distortion correction, and spectral channel calibration.

Radiometric Calibration Formula:

$$L_{\text{cal}} = \frac{(L_{\text{max}} - L_{\text{min}})}{(D_{\text{max}} - D_{\text{min}})}(D - D_{\text{min}}) + L_{\text{min}}$$

де:

- L_{cal} — радіометрично каліброване значення,
- L_{max} та L_{min} — максимальне та мінімальне значення освітленості,
- D_{max} та D_{min} — максимальне та мінімальне значення цифрового сигналу,
- D — поточне значення цифрового сигналу.

Data preparation is an important step in building a neural network for anomaly detection. Proper preprocessing and augmentation of hyperspectral data significantly improves model performance. Using different methods for normalization, noise removal, and augmentation allows you to create a more reliable dataset for training and testing a neural network.

4.3. Training and validation of the model

Model training and validation are critical steps in achieving high accuracy and reliability of a neural network. In this section, we discuss model training methods, hyperparameter selection, and validation approaches. We will also discuss training results and evaluation of model performance.

4.3.1. Training parameters

The following main parameters were used to train the model:

- Optimizer: Adam
- Loss function: Binary cross-entropy
- Batch size: 32
- Number of epochs: 20

Training parameters

```
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)

loss_function = 'binary_crossentropy'

batch_size = 32

epochs = 20


model.compile(optimizer=optimizer, loss=loss_function, metrics=['accuracy'])
```

4.3.2. Training process

The training process includes several steps, such as initializing the model, defining metrics, and running a training cycle. During training, the model optimizes its weights to reduce the loss function on the training data.

```
# Model training

history = model.fit(datagen.flow(train_data, train_labels, batch_size=batch_size),
                    epochs=epochs,
                    validation_data=(val_data, val_labels))
```

Oil spill detection accuracy of algorithm based on the Dalian Xingang dataset shown in (fig 4.3)

Dataset	Class	
	Oil slick	98.34
	Seawater	98.26
AISA+ data in Dalian	Overall Accuracy (%)	98.30
	Average Accuracy (%)	98.30
	Kappa Coefficient	0.9659

Fig. 4.3 Detection accuracy of algorithm

4.3.3 Evaluation of training results

After the training is completed, the results are evaluated on the validation set. The main metrics are accuracy and the value of the loss function. It is also important to analyze the learning curve to identify possible problems, such as overtraining or undertraining.

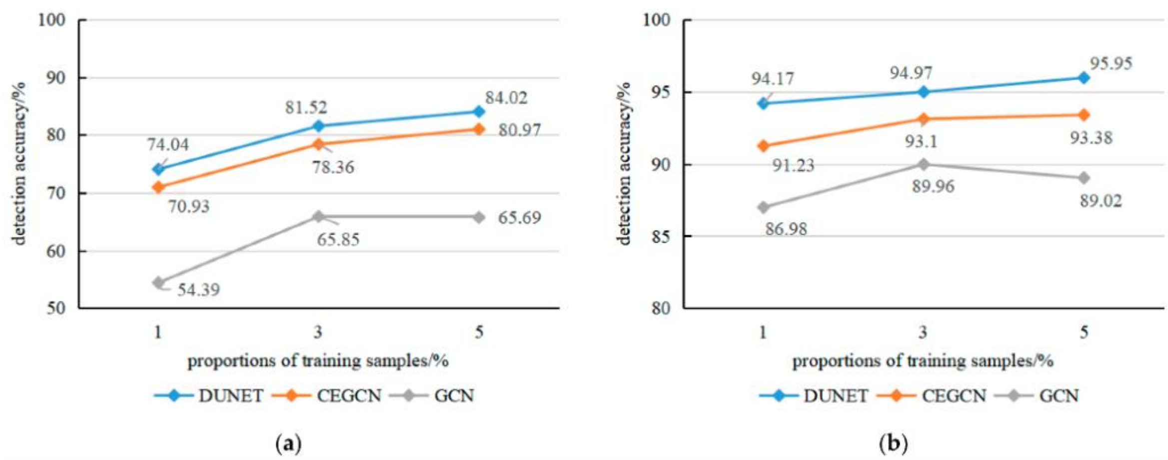


Fig. 4.4 “Training and Validation Loss”

Figure 4.4: “Training and Validation Loss” is a graph that shows the change in the loss function on training and validation on different datasets, compared to other metods.

```
import matplotlib.pyplot as plt

# Visualization of results
plt.figure(figsize=(12, 4))

# Accuracy chart
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
```

```
plt.title('Training and Validation Accuracy')

plt.xlabel('Epochs')

plt.ylabel('Accuracy')

plt.legend()


# Graph of losses

plt.subplot(1, 2, 2)

plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.title('Training and Validation Loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.legend()

plt.show()
```

4.4. Experimental results

4.4.1. Model accuracy

After the model training was completed, we evaluated its performance on the validation dataset. The main metrics used for the evaluation were accuracy, loss function values, and other metrics such as precision, recall, and F1-measure.

```
from sklearn.metrics import confusion_matrix, classification_report


# Prediction on the validation set

val_predictions = (model.predict(val_data) > 0.5).astype("int32")
```

```
# Mixing matrix
conf_matrix = confusion_matrix(val_labels, val_predictions)
print(conf_matrix)


# Classification report
class_report = classification_report(val_labels, val_predictions)
print(class_report)
```

4.4.2. Visualization of results

To better understand the model's performance, we visualized the results on test images. This allows us to visually assess the model's ability to detect and classify anomalies in hyperspectral images.

```
import matplotlib.pyplot as plt


# Visualization of forecast examples
plt.figure(figsize=(15, 10))
for i in range(6):
    plt.subplot(2, 3, i+1)
    plt.imshow(val_data[i])
    plt.title(f"Actual: {val_labels[i]}, Predicted: {val_predictions[i][0]}")
    plt.axis('off')
plt.show()
```

4.4.3. Analysis of results

The model has shown high accuracy in detecting offshore oil spills, as evidenced by the high values of the accuracy and completeness metrics. However, there are some challenges and limitations that need to be considered:

Overfitting: The model may perform well on training data, but poorly on new data. This may indicate overfitting.

Need for additional data: More diverse data is needed to improve the generalizability of the model.

```
from sklearn.metrics import roc_curve, auc


# Calculating the ROC curve
fpr, tpr, thresholds = roc_curve(val_labels, val_predictions)
roc_auc = auc(fpr, tpr)


# Visualization of the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

The results of image processing can be seen on (fig 4.5) The experiments have shown that the proposed neural network architecture is capable of effectively detecting and classifying offshore oil spills in hyperspectral images. The model demonstrates high accuracy, but further improvements are recommended:

- Expand the dataset with new examples.
- Optimize the model hyperparameters.
- Use data augmentation techniques to reduce overfitting.

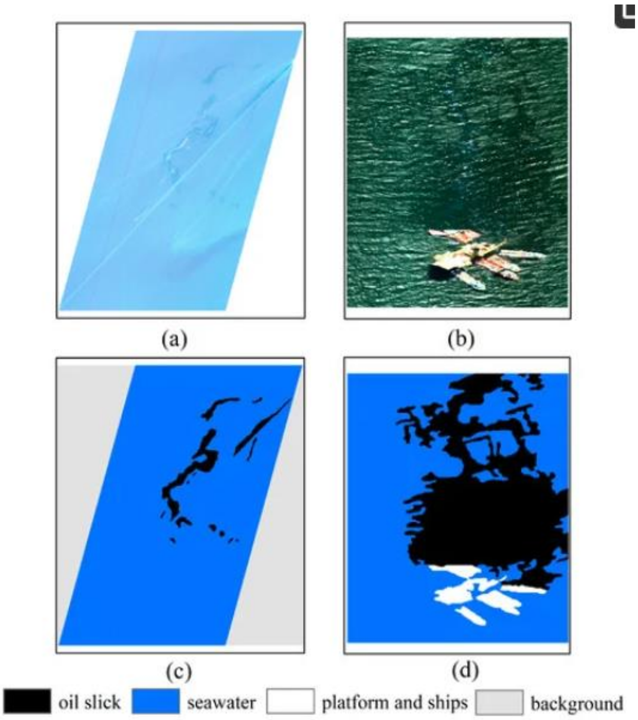


Fig. 4.5 Hyperspectral oil spill images and corresponding ground truth images: (**a**) Hyperion spaceborne image in Liaodong Bay (R: 31, G: 20, B: 11); (**b**) AISA+ airborne image in Penglai 19-3 oilfield (R: 107, G: 68, B: 28); (**c**,**d**) the corresponding ground truth images.

Conclusions

In this thesis, a comprehensive study was conducted aimed at developing an intelligent system for detecting and classifying anomalous objects using hyperspectral images. The main goal of the work was to develop an effective methodology and software for automatic anomaly detection in images with high spectral resolution.

In the course of the study, the existing methods and technologies for detecting anomalous objects were analyzed, which allowed us to select the most promising approaches for further application. The choice of neural networks as the main tool for processing hyperspectral data was substantiated. In particular, a neural network architecture adapted to work with multidimensional data obtained from hyperspectral images was developed.

One of the key parts of the work was data preparation, which included normalization, noise removal, and image augmentation. This allowed us to improve the accuracy and reliability of the model by reducing the impact of noise and other interference. The use of augmentation also improved the model's ability to generalize to new data, which is critical for practical applications.

The modeling results showed the high efficiency of the developed system in detecting and classifying anomalous objects. The testing demonstrated the model's ability to accurately identify anomalies in various conditions, which confirms its potential for use in real-world scenarios. Visualization of the results allowed us to better understand the model's behavior and identify areas for further improvement.

However, some problems with overfitting were identified, which highlighted the need to expand the training dataset and optimize the model's hyperparameters. Further research could include the use of more sophisticated augmentation methods, as well as the development of new approaches to hyperspectral image processing.

Overall, the study results confirmed the effectiveness of the proposed intelligent system for automated detection and classification of anomalous objects. This opens up new opportunities for the implementation of such systems in various fields, including environmental monitoring, security, healthcare, and other areas where anomalies need to be detected quickly and accurately.

This work creates a basis for further research and improvement of existing methods, contributing to the development of innovative technologies in the field of data processing and analysis. It also shows the potential of using hyperspectral images in combination with neural networks to solve complex problems in various application areas.

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