

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 mobile search system

Performer: student of FAET-323 group Maksym Koval

Supervisor: Olexandr GORDIENKO

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 систем

ДОПУСТИТИ ДО ЗАХИСТУ

Завідувач випускової кафедри

_____ Віктор СИНЕГЛАЗОВ

“ _____ ” _____ 2024 р.

КВАЛІФІКАЦІЙНА РОБОТА
(ПОЯСНЮВАЛЬНА ЗАПИСКА)

ВИПУСКНИКА ОСВІТНЬОГО СТУПЕНЯ
“БАКАЛАВР”

Спеціальність 151 "Автоматизація, та комп'ютерно-інтегровані технології"

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

Тема: Інтелектуальна мобільна пошукова система

Виконавець: студент групи ІК-323Ба Коваль Максим Анатолійович

Керівник: Гордієнко Олександр Миколайович

Нормоконтролер: _____ Філяшкін М.К.

(підпис)

NATIONAL AVIATION UNIVERSITY

Faculty of Aeronautics, Electronics and Telecommunications

Department of aviation computer-integrated systems

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:

Chebanu Oleksii Y

- 1. Topic: "An intelligent mobile search system"**
2. Work Period: March 10, 2024 - June 7, 2024
3. Input Data for the Work: The process of synthetic aperture radar and ground penetrating radar image processing, description of types, features, and applications for data bases integration.
4. Content of the Explanatory Note (List of Issues to be Developed):
5. General analysis of synthetic aperture radar and ground penetrating radar processing systems

6. Analysis of GPS navigation methods
7. Analysis of data bases
8. Analysis of the methodology for designing and architecting intelligent image processing systems
9. Analysis of software for synthetic aperture radar and ground penetrating radar image processing
10. Analysis of methods for classification and interpretation of data bases
11. List of Required Graphic Material: Graphs, images, diagrams.
12. Calendar schedule-plan:

Work stage	Date	Sign
Підготовка та огляд літератури	10.03.2024 – 17.03.2024	
Аналіз програмного забезпечення	18.03.2024 – 24.03.2024	
Аналіз інтелектуальних систем	25.03.2024 – 31.03.2024	
Огляд радару з синтезованою апертурою та підземного проникного радару	01.04.2024 – 07.04.2024	
Інтеграція GPS системи навігації	08.04.2024 – 14.04.2024	
Інтеграція геоінформаційної системи	15.04.2024 – 30.04.2024	
Розробка програми інтеграції баз даних	01.05.2024 – 14.05.2024	
Розробка заходів кібербезпеки	15.05.2024 – 21.05.2024	
Підготовка пояснювальної записки	22.05.2024 – 31.05.2024	
Підготовка презентації	01.06.2024 – 07.06.2024	

Task issue date: 01 “April” 2024.

Supervisor: _____ **Gordienko O.M.**

(sign)

Task is taken for completion by: _____ Koval M.A.

(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 СИНЕГЛАЗОВ

“ _____ ” _____ 2024 р.

ЗАВДАННЯ

на виконання кваліфікаційної роботи студента

Коваль Максим Анатолійович

1. Тема роботи: “Інтелектуальна мобільна пошукова система”
2. Термін виконання роботи: з 10.03.2024 по 7.06.2024
3. Вихідні дані до роботи: Процес обробки зображень з радару з синтезованою апертурою та підземного радару, опис типів, особливостей та застосування баз даних.
4. Зміст пояснювальної записки (перелік питань, що підлягають розробці):
5. Загальний аналіз систем обробки зображень з радару з синтезованою апертурою та підземного радару
6. Аналіз методів GPS навігації
7. Аналіз баз даних

8. Аналіз методології проектування та архітектури інтелектуальних систем обробки зображень

9. Аналіз програмного забезпечення для обробки зображень з радару з синтезованою апертурою та підземного проникного радару

10. Аналіз методів класифікації та інтерпретації баз даних

11. **Перелік обов'язкового графічного матеріалу:** графіки, зображення, діаграми.

12. Календарний план-графік

Етап роботи	Термін виконання	Підпис
Підготовка та огляд літератури	10.03.2024 – 17.03.2024	
Аналіз програмного забезпечення	18.03.2024 – 24.03.2024	
Аналіз інтелектуальних систем	25.03.2024 – 31.03.2024	
Огляд радару з синтезованою апертурою та підземного проникного радару	01.04.2024 – 07.04.2024	
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Підготовка презентації	01.06.2024 – 07.06.2024	

Дата видачі завдання: 25 березня 2024 р.

Керівник дипломної роботи _____ Гордієнко О.М.

Завдання прийняв до виконання _____ Коваль М.А.

ABSTRACT

Qualification work contains 72 pages, 11 figures, 4 Python codes, 59 literature.

Work theme: An intelligent mobile search system

Purpose of Work: The purpose of this work is to provide a comprehensive overview of Synthetic Aperture Radar (SAR) data processing systems and methodologies, focusing on their significance in environmental monitoring and disaster management applications. The study aims to explore the evolution of SAR technology, the challenges associated with SAR data interpretation, and the advancements in machine learning and artificial intelligence algorithms for SAR data analysis. By examining the integration of SAR data with ground penetrating radar and GPS navigation systems, the research seeks to enhance the understanding of complex electromagnetic responses and facilitate informed decision-making in various domains.

Object of Work: The object of this work is to investigate the fundamental principles of SAR data processing, including data collection, storage, processing, and interpretation. By analyzing the methodologies and technologies driving SAR data processing systems, the study aims to uncover the transformative impact of SAR technology on environmental monitoring and disaster response. Through a detailed exploration of anomaly detection techniques and multi-temporal analysis methods, the research seeks to highlight the potential of SAR data for extracting valuable insights and supporting decision-making processes.

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LIST OF ABBREVIATIONS

SAR – synthetic aperture radar

GPR – ground penetrating radar

GPS – global positioning system

GIS – geographic information system

Amazon S3 – amazon simple storage service

DB – data base

INTRODUCTION

The field of Synthetic Aperture Radar (SAR) data processing has experienced significant advancements in recent years, completely transforming the way we collect and interpret information for a wide range of applications. SAR data, obtained through radar sensors, plays a crucial role in environmental monitoring, disaster management, urban planning, and various other domains. The exceptional capabilities of SAR technology, including all-weather imaging and high-resolution data collection, have made it an invaluable tool for extracting valuable insights from remote sensing data.

In this comprehensive introduction, we delve into the fundamental principles of SAR data processing and its importance in modern applications. We explore the intricate process of SAR data collection, storage, processing, and interpretation, shedding light on the complexities and challenges associated with harnessing the full potential of SAR observations. By gaining a deep understanding of the underlying methodologies and technologies that drive SAR data processing systems, we can truly appreciate the transformative impact of SAR technology on diverse fields.

The chapter takes us through the evolution of SAR data processing systems, emphasizing the role of machine learning algorithms, artificial intelligence techniques, and user interfaces in enhancing the efficiency and accuracy of data analysis. We examine the critical role of anomaly detection in environmental monitoring and disaster response, highlighting the significance of early detection and mitigation of potential threats through advanced SAR data processing methods.

Moreover, we discuss the integration of SAR data with ground penetrating radar and GPS navigation systems, exploring the synergies and challenges of combining multiple data sources for comprehensive analysis. The chapter underscores the importance of user-friendly representations of SAR data to facilitate decision-making and improve the accessibility of complex electromagnetic responses for a wider audience.

Throughout our exploration of SAR data processing, our objective is to decipher the complexities of SAR technology, revealing its immense capacity for innovation and influence across diverse industries. Through an analysis of the most recent trends, methodologies, and applications in SAR data processing, we are committed to forging a path towards future advancements in remote sensing technology and data-informed decision-making.

CHAPTER 1

ANOMALY DETECTION AND IT'S FEATURES

1.1. Anomaly Detection as a Means to Improve the Environment

Anomaly detection is a crucial process used in various fields to identify deviations from normal or expected parameters. This process is key to improving environmental quality, particularly in the context of ecological monitoring, pollution detection, and humanitarian demining. With the advancement of technologies such as Synthetic Aperture Radar (SAR) and Ground Penetrating Radar (GPR), anomaly detection has become more efficient and precise.

The Role of Anomaly Detection in Improving the Environment

Anomaly detection plays a significant role in ensuring environmental safety and quality by identifying and mitigating potential threats. Here are several ways in which anomaly detection contributes to environmental improvement:

Pollution Detection: Early detection of chemical or radioactive pollution helps take timely measures for its elimination, minimizing harm to ecosystems and human health.

Protection of Water Resources: Anomaly detection in water systems allows for the identification and prevention of water pollution, ensuring the safety of water supplies.

Land Use Monitoring: Monitoring land for illegal logging or unplanned construction helps preserve natural resources and landscapes.

Humanitarian Demining: Detecting explosive remnants of war (ERW) after conflicts is critical for ensuring population safety and rehabilitating areas.

Technological Aspects of Anomaly Detection

Modern technologies significantly enhance the efficiency and accuracy of anomaly detection. The use of SAR and GPR are examples of such technologies that provide deep penetration and high resolution in anomaly detection.

SAR (Synthetic Aperture Radar):

Principle of Operation: SAR uses radio waves to create high-quality images of the Earth's surface. This is achieved by synthesizing a large aperture from multiple measurements, allowing for detailed images regardless of weather conditions.

Applications: SAR is used for monitoring forests, agriculture, urban areas, and detecting changes in the Earth's surface.

GPR (Ground Penetrating Radar):

Principle of Operation: GPR uses electromagnetic waves to detect objects beneath the Earth's surface. This technology allows for the detection of underground structures and objects at significant depths.

Applications: GPR is used for detecting underground utilities, archaeological finds, and ERW.

Humanitarian Demining as an Example of Anomaly Detection Application

Humanitarian demining is one of the most important examples of anomaly detection application for environmental improvement. After armed conflicts, numerous ERWs remain, posing serious threats to the population and hindering territorial development. The use of SAR and GPR to detect such objects offers key advantages:

High Detection Accuracy: SAR provides high accuracy in detecting anomalies on and beneath the surface, contributing to the effective identification of ERWs.

Deep Penetration: GPR allows for the detection of objects at significant depths, which is critical for identifying buried mines and other explosive devices.

Reduced Risks for Operators: The use of these technologies reduces risks for demining operators, as object detection is carried out at a safe distance.

Anomaly detection is an essential tool for improving the environment and ensuring population safety. The use of modern technologies such as SAR and GPR significantly enhances the efficiency of this process, facilitating timely detection and mitigation of threats. The development and implementation of these technologies are of great importance for ecological monitoring, humanitarian demining, and overall quality of life improvement.

1.2 Structural Diagram of a Mobile Intelligent Search System

History of Search Engines

The history of search engines is crucial for understanding their role and importance in the modern Internet space. From the early stages, when the Internet was just emerging, to contemporary technological achievements, the development history of search engines reflects constant changes and continuous progress.

The Beginning of the Search Engine Era

The beginning of search engine history is associated with the development of the Internet. In the 1960s and 1970s, when the Internet was just emerging, the first tools for searching information were created, such as Archie, which indexed files on FTP servers. However, the real breakthrough occurred in the 1990s with the advent of the World Wide Web.

Early Search Engines

In the 1990s and 2000s, the era of more advanced search engines began. WebCrawler, Lycos, and AltaVista were among the first to offer the ability to search web pages using text queries. These systems, although having their limitations, were an important step towards improving access to information on the Internet.

The Google Revolution

The founding of Google in 1998 is marked as a turning point in the development of search engines. Google used a unique page ranking algorithm called PageRank to determine the relevance of search results. This approach allowed Google to quickly become one of the most popular and efficient search engines in the world.

Technological Innovations

Over the following decades, search engines continued to evolve, employing new technologies such as artificial intelligence, machine learning, and natural language processing. These innovations help search engines provide more accurate and relevant results for users.

Principles of Traditional Search Engine Operations

Understanding the principles of traditional search engines is crucial for grasping their efficiency and impact on the search process. This section reveals the key aspects that underpin the operation and effectiveness of traditional search engines, including web page indexing, result ranking, text and metadata analysis, link detection, partial result storage, continuous index updating, user query processing, and result filtering and sorting.

Web Page Indexing

Web page indexing is a fundamental stage in the operation of any search engine. Search engines use automated bots, known as spiders or crawlers, to scan the Internet and collect information about web pages. These spiders move from page to page via hyperlinks, saving information about each page's content in a database.

The indexing process begins with the crawler visiting a web page, where it downloads and analyzes its content. Every element of the page, from text to images and metadata, is included in the index. In addition to the main text of the page, search engines analyze metadata such as header tags (H1, H2, H3, etc.), meta descriptions, and keywords, which provide additional information about the page's content.

Indexing is not a one-time process. As web page content is constantly updated, search engines regularly repeat the indexing process to ensure that their database reflects the current state of the Internet. This allows users to access new and updated web pages through search results.

Result Ranking

Search result ranking is a key principle that determines which pages will be shown to the user and in what order. Search engines use complex algorithms to assess the relevance of each page in relation to the search query. One of the most well-known algorithms is Google's PageRank, which evaluates the importance of a page based on the quantity and quality of external links.

However, modern search engines use much more complex ranking methods. They take into account hundreds of factors such as:

Keywords: Not only the presence of keywords on the page is considered but also their placement (e.g., in headings or the first paragraph) and frequency of use.

External Links: Pages with a large number of high-quality external links are considered more authoritative.

Internal Links: The structure of internal links also affects ranking, as it helps to understand which pages are important within a single site.

Content: The importance of the page's content, its quality, and originality. Search engines can recognize duplicate content and lower its rank.

User Behavior: Algorithms may consider user behavior, such as how much time they spend on the page or whether they click on other links on the page.

Mobile Optimization: The degree to which a page is optimized for mobile devices is taken into account, as more and more users are conducting searches from smartphones.

These factors together create a complex profile of each page, allowing the search engine to assess its relevance and usefulness to the user.

Text and Metadata Analysis

One of the important aspects of search engines is their ability to analyze the textual content of web pages and their metadata. This allows search engines to understand the topic of the page and its relevance to the search query.

Text Analysis

Text analysis includes several key components:

Keywords: Search engines identify keywords and phrases that frequently appear on the page and correlate them with users' search queries.

Synonyms and Context: The use of semantic analysis allows search engines to recognize synonyms and consider the context, making search results more accurate.

Page Structure: Headers, subheaders, paragraphs, and other structural elements are analyzed to determine the main themes and subtopics of the page.

Metadata Analysis

Metadata, such as meta descriptions and header tags, also hold significant importance. They provide additional information about the page's content and can influence its ranking. For example, a meta description can be used by the search engine to display a brief summary of the page in search results, affecting whether a user will click on the link.

Link Detection

Links are the fundamental building blocks of the Internet, and their role in the operation of search engines is extremely important. Search engines use link analysis to determine the importance and authority of web pages.

External Links

External links (i.e., links from other sites) are important signals of authority. When one page links to another, it is considered a recommendation or endorsement of the quality of that page's content. The more high-quality external links a page has, the higher its authority in the eyes of search engines.

Internal Links

Internal links (links to pages within the same site) also matter. They help search engines understand the site's structure and determine which pages are most important. For example, a site's main page usually has the most internal links, indicating its importance.

Anchor Text

Search engines also consider the anchor text, which often indicates the topic or content of the linked page. This helps search engines better understand the relationship between pages and their relevance.

Partial Result Storage

Due to the vast amount of information added to the internet daily, search engines must be efficient in storing and managing their resources. Therefore, they employ a partial result storage approach, which allows them to store only necessary elements of pages rather than their full copies.

This approach involves storing elements such as headers, keywords, meta descriptions, and URLs. This enables quick retrieval and display of relevant search results while maintaining optimization of server resources usage. Search engines also utilize compression technologies and distributed computing to efficiently manage large volumes of data and ensure fast processing of user queries.

Continuous Index Updating

Considering the constant changes on the internet, search engines must regularly update their indices to reflect the latest content. This means that the process of scanning and indexing web pages is continuous. New web pages are added to the index, and changes to existing pages are reflected according to their updates.

The index updating process can be complex and resource-intensive. Search engines use algorithms to determine the frequency of updating certain pages based on their importance and change dynamics. For example, news sites may be scanned more frequently than pages with static content to ensure timely display of the latest news and events.

User Query Processing

When processing search queries, search engines consider not only the entered keywords but also the context and individual user needs. This includes personalized recommendations, adaptation to location, and other factors that enhance the relevance of search results.

When a user enters a query into a search engine, algorithms analyze this query to understand its intentions. Aspects such as the user's search history, location, language, and other personal parameters are taken into account. This allows search engines to provide more accurate and relevant results.

Additionally, modern search engines use natural language processing (NLP) technologies for better understanding of user queries. This includes grammar, semantics, and context analysis of the query, enabling the search engine to provide results that best match the user's intentions.

Filtering and Sorting of Results

After obtaining search results, search engines filter and sort them according to various criteria to provide the most useful and convenient experience for users. This process involves several stages:

Filtering: Search engines remove duplicates of pages, spam, and irrelevant content from search results. They may also apply filters based on specific criteria, such as safe search, to protect users from unwanted content.

Sorting: Results are sorted based on relevance, publication date, source authority, and other factors. This allows users to quickly find the most important and freshest pages.

Filtering and sorting of search results are critical to ensuring that users receive the most useful and relevant information. Search engines constantly improve their algorithms to enhance the accuracy and efficiency of this process.

Key Components of Traditional Search Engines

Traditional search engines are complex technological platforms composed of many interconnected components. Understanding the main components of these systems allows for a better comprehension of how they work and provide users with quick access to necessary information. In this section, we will discuss the key components of traditional search engines, such as web crawlers, indexes, ranking systems, user interfaces, and query processing mechanisms.

Web Crawlers: The First Line of Data Collection Web crawlers, also known as spiders or bots, are automated programs that scan web pages on the Internet. They play a critical role in collecting and updating data for search engines.

Working Principle of Web Crawlers Web crawlers start their work with a set of initial URLs, known as "seed" pages. They download these pages and analyze their content, extracting links to other pages. This process is repeated recursively, allowing crawlers to cover large portions of the Internet.

Crawlers operate using algorithms that determine scanning priorities, considering factors such as update frequency of pages, page importance, and resources required for scanning. This enables efficient utilization of computational resources and maintains the relevance of collected data.

Challenges in Web Crawler Operation One of the main challenges for web crawlers is scalability. The internet contains billions of pages, with new ones constantly appearing. Crawlers must be able to handle large volumes of data while maintaining high speed and accuracy.

Another challenge is access limitations. Some websites use robots.txt files to control crawler access to their pages, restricting or prohibiting scanning. Crawlers must take these limitations into account and adhere to established rules.

Indexes: Organization and Storage of Information Indexing is the next critical stage after data collection by web crawlers. Indexes are structured databases that store information about the content of web pages, allowing for quick retrieval of relevant search results.

Structure of the Index A search engine's index consists of many components, including:

Vocabulary: This is a list of all unique words found on indexed pages.

Posting Lists: For each word in the vocabulary, there is a list of documents where this word appears, along with information about its position and frequency in each document.

Such indexes enable efficient processing of user queries, providing fast access to information about the presence and location of words on web pages.

Index Updating and Maintenance Since the Internet is constantly changing, indexes must be regularly updated. This requires a continuous process of indexing new and changed pages. Search engines use various methods to optimize this process, including:

Differential Indexing: Giving more attention to frequently updated pages.

Distributed Indexing: Distributing indexes across multiple servers to ensure fast query processing and system reliability.

Ranking Systems: Determining Relevance Ranking systems are responsible for determining the relevance of search results to a user's query. These systems analyze various factors to rank web pages based on their perceived importance and relevance.

Factors Considered in Ranking Ranking algorithms take into account factors such as:

Keyword relevance: How closely the content of a web page matches the user's query keywords.

Authority: The credibility and trustworthiness of the page, often measured by the number and quality of inbound links.

Freshness: The recency of the content, with more recent pages often being considered more relevant.

User signals: Metrics like click-through rates and dwell time, indicating user engagement with search results.

By considering these factors, ranking systems aim to present users with the most useful and relevant search results.

User Interfaces: Providing Accessible Search User interfaces (UIs) are the front end of search engines, through which users interact with the system. UI design plays a crucial role in ensuring a seamless and intuitive search experience.

Components of the User Interface Search engine UIs typically include elements such as:

Search box: Where users enter their queries.

Search results page: Where relevant results are displayed.

Filters and sorting options: Tools for refining and organizing search results.

Additional features: Such as auto-suggestions, search history, and personalization options.

An effective UI enhances usability and helps users find the information they need quickly and efficiently.

Query Processing Mechanisms: Understanding User Intent When processing search queries, search engines consider not only the entered keywords but also the context and individual needs of the user. This involves personalized recommendations, location adaptation, and other factors that enhance the relevance of search results.

Analysis of User Queries Algorithms analyze user queries to understand their intentions. Aspects such as the user's search history, location, language, and other personal parameters are taken into account. This allows search engines to provide more accurate and relevant results.

Natural Language Processing (NLP) Technologies Modern search engines utilize NLP technologies to better understand user queries. This includes analyzing grammar, semantics, and context to provide results that best match the user's intentions.

By incorporating these components, traditional search engines strive to deliver accurate, relevant, and personalized search results, enhancing the overall search experience for users.

Mobile intelligent search systems are key tools for detecting anomalies in various fields, including environmental monitoring and humanitarian demining. These systems integrate various technologies and components to ensure high accuracy and efficiency in anomaly detection. This section will examine the structural diagram of a mobile intelligent search system, its main components, and principles of operation.

Main Components of a Mobile Intelligent Search System

A mobile intelligent search system consists of several key components, each performing a specific function in the anomaly detection process. The main components of such a system include:

Sensor Module:

Synthetic Aperture Radar (SAR): Used to create high-quality radar images of the Earth's surface.

Ground Penetrating Radar (GPR): Applied for detecting underground objects and structures.

Data Collection System:

Data Storage Modules: Responsible for recording and storing collected sensor data.

Data Transmission Modules: Ensure the transmission of collected data to the central computing system for further analysis.

Computing System:

Processors and Computing Units: Perform the processing of large volumes of data obtained from the sensors.

Machine Learning and Artificial Intelligence Algorithms: Used for data analysis and anomaly detection.

User Interface:

Displays and Monitors: For visualizing analysis results and detected anomalies.

Control Systems: Provide an interactive interface for system operators, allowing them to manage the data collection and analysis process.

Navigation and Positioning Systems:

GPS and GSM Modules: Ensure accurate location determination of the system and synchronization of collected data with geographical coordinates.

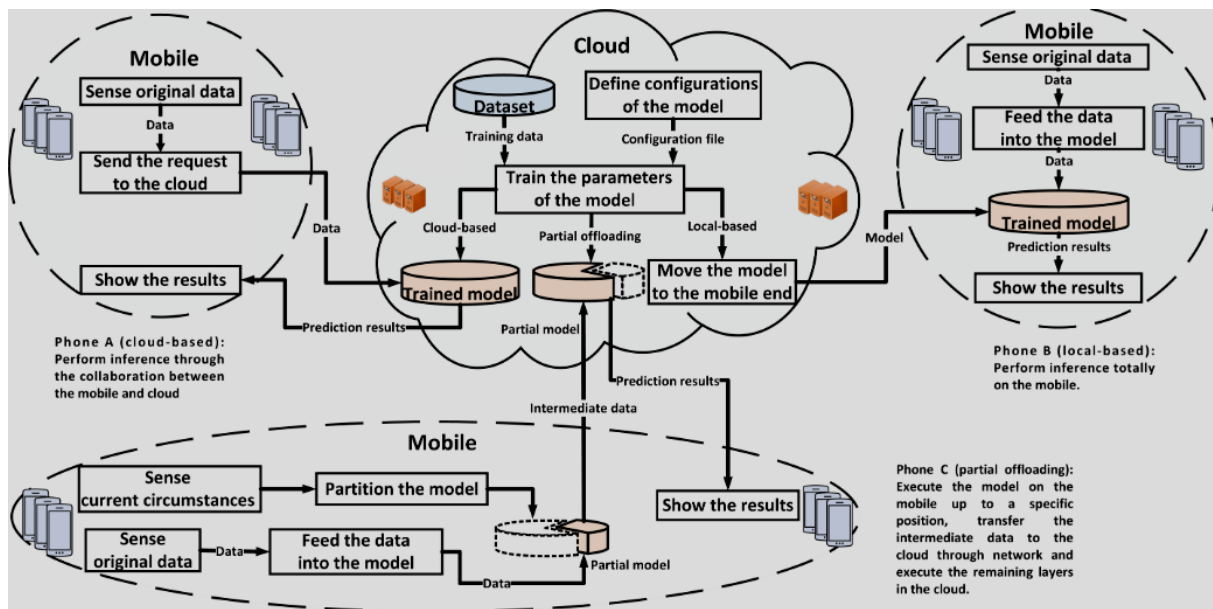


Figure 1.1. Structure scheme of intelligent mobile search system

Principles of Operation of a Mobile Intelligent Search System

The operation of a mobile intelligent search system is based on the integration of its components to ensure effective data collection, processing, and analysis. The main stages of the system's operation include:

Data Collection:

SAR and GPR sensors collect radar and georadar data from the area under investigation. Data is stored in storage modules and transmitted to the computing system for analysis.

Data Processing:

The computing system processes the collected data using machine learning and artificial intelligence algorithms to detect anomalies.

Processed data is visualized on displays for further analysis by operators.

Analysis and Interpretation of Results:

System operators analyze the results obtained from the computing system, identifying potential anomalies.

If dangerous objects, such as explosive remnants of war (ERW), are detected, the information is transmitted to relevant services for further action.

Navigation and Positioning:

GPS and GSM modules provide precise positioning of the system and synchronization of collected data with geographical coordinates, allowing for accurate location determination of detected anomalies.

Interaction of Components

The effective operation of a mobile intelligent search system depends on the coordinated interaction of all its components. Sensors ensure accurate and timely data collection, the computing system quickly and efficiently processes this data, and the user interface allows operators to easily interpret the results and make informed decisions. Navigation and positioning systems ensure the accuracy and reliability of the data, significantly enhancing the effectiveness of anomaly detection.

The structural diagram of a mobile intelligent search system encompasses various components and technologies that work together to ensure effective anomaly detection. The integration of sensors, data collection and processing systems, user interfaces, and navigation modules creates a powerful tool for improving the environment and ensuring safety. The development and refinement of such systems open new possibilities for their application in various fields.

1.3 Overview of Mobile Platforms for Hosting Search Systems

Unmanned Aerial Vehicles (UAVs) are among the most effective platforms for hosting mobile intelligent search systems, especially for tasks such as humanitarian demining and environmental monitoring. This section will review different types of UAVs, their characteristics, advantages, and disadvantages, as well as the technologies used for deploying search systems on these platforms.

1.3.1. Types of UAVs

Rotary UAVs

Description: Rotary UAVs, also known as quadcopters or multicopters, are equipped with multiple rotors to provide lift and maneuverability.

Advantages:

Maneuverability: Capable of vertical take-off and landing, hovering in place, and performing complex maneuvers.

Ease of Use: Easy to control, especially in confined spaces and restricted areas.

High Stability: Provide stable platforms for sensor modules.

Disadvantages:

Limited Range: Typically have shorter flight ranges due to high energy consumption.

Lower Speed: Generally slower compared to fixed-wing UAVs.

Fixed-Wing UAVs

Description: Fixed-wing UAVs, or airplanes with fixed wings, resemble traditional aircraft and use wings to generate lift.

Advantages:

Long-Endurance Flight: Have greater flight range and endurance due to more efficient energy use.

High Speed: Capable of covering large areas quickly.

Disadvantages:

Need for Runways: Require more space for take-off and landing.

Less Maneuverable: Limited ability to hover and perform complex maneuvers in place.

Technologies for Deploying Search Systems

1.3.2. Synthetic Aperture Radar (SAR)

Advantages:

High Resolution: Provides detailed images of the surface and underground structures.

Weather Independence: Operates effectively in any weather conditions and at night.

Disadvantages:

High Cost: Expensive equipment and data processing.

Integration Complexity: Requires specialized platforms for stabilization and data collection.

Essentially, remote sensing is the practice of gathering information about the Earth's land and water surfaces using images captured from an overhead perspective. This involves the use of electromagnetic radiation in various regions of the electromagnetic spectrum, which is either reflected or emitted from the Earth's surface. The key aspects of this definition are the collection of information from a distance and the representation of this information through pictures or series of pictures. Synthetic Aperture Radar (SAR) sensors are particularly valuable in remote sensing due to the unique characteristics of microwaves. These microwaves can penetrate clouds, making SAR sensors unaffected by weather and illumination conditions. However, SAR sensors are not widely utilized in multidisciplinary and operational environments, which are predominantly focused on the exploitation of multispectral (MS) and hyperspectral (HS) data. The availability of MS and HS data has increased with the launch of the Italian spaceborne sensor PRISMA. This preference for MS and HS data is primarily due to their higher information content, wider bandwidth, and intuitive interpretability. As a result, simple and reliable solutions have been developed for extracting geophysical parameters from images. For example, the extent of water surfaces or forests can be determined by applying a ratio of appropriate spectral bands. In the case of SAR, the available bandwidth in a single acquisition is limited, making the information extraction process more challenging. However, temporal information can be leveraged to compensate for this limitation. Despite this, there is a lack of robust algorithms for retrieving even basic information from SAR data, with a few exceptions in the maritime domain and millimeter-scale displacements estimation using Differential SAR Interferometry (DInSAR) methodologies. These exceptions have a significant user base and applications, generating value in the industrial sector.

In most cases, SAR data processing is primarily limited to scientists who possess knowledge in electromagnetics, radar, and signal processing. As a result, the full potential of this imaging system is not fully utilized by end-users, and there is still a lack of identified routes for its exploitation. The objective of this review is to emphasize how SAR observations can support environmental monitoring activities by exploring the latest research that utilizes multi-temporal concepts to enhance the value of data in specific applications. Despite being relatively unknown among end-users, SAR data can enable various applications, particularly in near-real time, and make significant contributions through data assimilation in geophysical, hydrological, and

weather models, as well as integration with multisource information. While this review will primarily focus on applications related to biosphere and hydrosphere monitoring, it will also briefly mention other applications such as urban environment classification and the estimation of small and large displacements. Figure 1 illustrates the lifecycle of SAR data, from acquisition to the generation of value-added products known as Level-2 products, which contain geophysical information about the imaged scene. To successfully extract information, there needs to be a bridging of the information gap between the measurements stored in Level-1 products (provided by data providers) and the parameters relevant to applications and remote sensing data users. Algorithms have played a crucial role in bridging the gap between the ground segment and the user segment in literature. However, some authors have emphasized the importance of analysts and users in the remote sensing information process [5,22,23]. The automation required to process large datasets, such as those used in multi-temporal analysis, can sometimes hinder the involvement of analysts and users. To address this, new classes of products have been developed that combine temporal information and introduce an intermediate processing level [5,15] (refer to Figure 1). These products can either be further developed towards Level-2 or serve as support for visual interpretation [24]. This process model represents an alternative to traditional SAR workflows and aims to cater to the user community. Its goal is to enhance the utilization of SAR information by scientists and professionals who may have access to the data and the capability to integrate it into their processes, but may lack the mathematical background to fully comprehend the underlying phenomena [5]. Reference [25] argues that there are two distinct forms of knowledge: objective knowledge and subjective knowledge. When dealing with images acquired beyond the visible spectrum, such as SAR, the interpretation of the physical principles behind the measurements and pixel arrangements becomes a matter of subjective knowledge. The expertise of the analyst plays a significant role in successfully completing the information process. Classic Level-1 SAR products may not always be suitable for extracting relevant information, leading many multidisciplinary users to explore alternative data sources that are easier to handle.

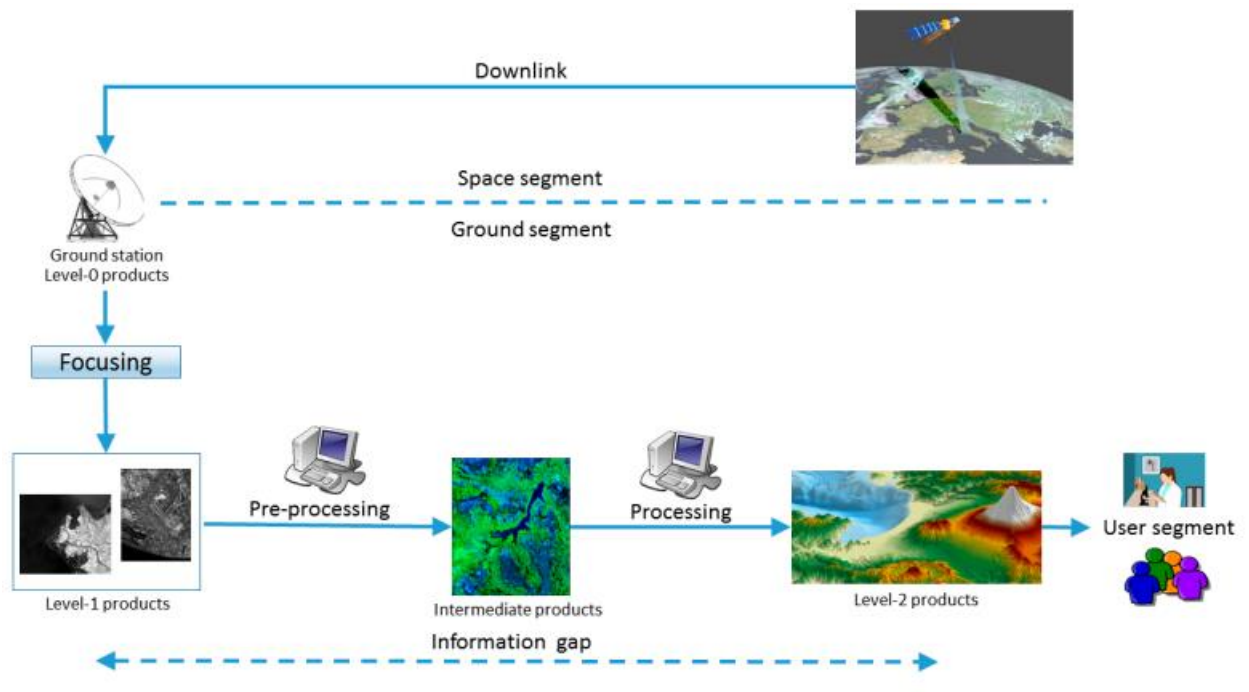


Figure 1.2. Structure scheme of SAR

This concept gives rise to the notion of emergent semantics. According to [26], the information content of an image is not an inherent characteristic but rather a result of the interaction between users and the image. In other words, it is contextual and depends on the specific conditions and the user's perspective. One of the goals of introducing improved representations of SAR images is to create a more consistent context that is less reliant on the operator's background. By having a better understanding of the data, operators can make more informed decisions on extracting relevant information. This process can be illustrated using the Peirce triangle [27], which represents how concepts are formed in our minds. Figure 2 shows the three interconnected elements of the triangle: the sign, the object, and the interpretant.

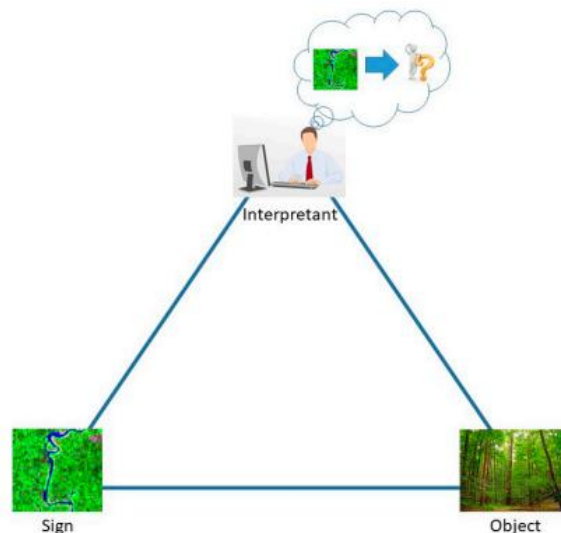


Figure 1.3. Picture getting algorithm

The sign refers to everything that can be perceived, in this case, the real world as captured by the imaging sensor. The object is what the sign is about and exists independently of the sign itself, representing the physical real-world object. Lastly, the interpretant is the understanding that an observer develops regarding the relationship between the sign and the object. When the sign is an image captured beyond the visible spectrum, the formation of the interpretant can be hindered by an unfamiliar representation for many potential users. However, this can be alleviated by introducing a representation that aligns with the expectations of remote sensing data users, who are often accustomed to working with multispectral data and geographical information systems (GISs).

However, as stated in [28], a representation refers to a formal system that explicitly defines certain entities or types of information. For instance, the Arabic, Roman, and binary numeral systems are formal systems used to represent numbers. The Arabic system, being decimal, allows for a clear representation of numbers by breaking them down into powers of 10. Therefore, forty-two can be represented as $4 \times 10^1 + 2 \times 10^0 = 42$ in the Arabic system. In the binary system, it would be represented as 0101010, and in the Roman system, it would be represented as XLII. If the objective is to use the number for calculations using a machine, the binary representation is the most suitable, as long as the output is converted to the base 10 system we are accustomed to. However, if the objective is to determine whether a number is a power of ten or not, the Arabic representation is more effective. The usefulness of a representation depends on how well it serves a specific purpose. For example, when analyzing multi-temporal composites, the focus is on the land cover and its temporal changes, while the phase information is disregarded. Therefore, this representation should not be used if the objective is to estimate land subsidence. Even the speckle, which is often seen as a nuisance in radar imaging, can provide valuable information. It can be tracked to estimate large displacements using cross-correlation similarity measures [19], or it can be utilized to detect urban areas based on its unique statistics [29]. In the following sections, we will discuss how the literature addresses the information gap depicted in Figure 1 by utilizing time series of SAR data. We will explore both traditional and innovative representations of their information.

Section 3 discusses novel change detection methods using advanced data representations. Section 4 focuses on practical applications, with a specific emphasis on biosphere and hydrosphere

applications due to the broad nature of the topic. Market insights and discussions are presented in Section 5, followed by conclusions at the end of the document. Classic SAR Multi-Temporal Pre-Processing and Change Detection Techniques In multi-temporal analysis, it is essential to preprocess data properly to ensure their comparability in terms of geometry and radiometry. This preprocessing phase is well-established in SAR literature, and this section aims to provide a brief overview for the reader's convenience. The general workflow for (amplitude) multi-temporal SAR preprocessing includes data calibration, coregistration, and despeckling. Calibration is crucial for ensuring radiometric comparability of images, ensuring that unchanged objects/surfaces exhibit the same reflectivity function throughout the time series. This process involves calibration coefficients provided in the image metadata, accounting for sensor and orbit effects.

When dealing with stripmap and spotlight data, typically a single calibration constant is applied to the entire image. For example, calibration procedures for COSMO-SkyMed and TerraSAR-X data are detailed in references [31,32]. However, for SCANSAR or TOPSAR acquisitions, a calibration vector/matrix is provided to address signal attenuation in the slant range direction. The use of these calibration coefficients ensures the reliability of data for a wide range of satellite imagery applications. For instance, COSMO-SkyMed single-look complex products boast a radiometric calibration accuracy of less than 1 dB [33], while Sentinel-1A/B images have estimated values smaller than 0.40 dB [34]. Coregistration is crucial for ensuring geometric comparability of images, ensuring that each ground target corresponds to the same pixel across all images in a time series. This step is considered one of the most robust in SAR pre-processing, with standard algorithms capable of achieving alignment at the sub-pixel level [35]. Despeckling plays a vital role in enhancing the information content of SAR images by mitigating speckle, which arises from sub-resolution targets within the resolution cell. The coherent summation of contributions from individual scatterers leads to random returns, even in homogeneous areas, resulting in the characteristic "salt and pepper" appearance of data [35]. However, this can be alleviated using appropriate denoising techniques.

This topic is widely discussed in SAR literature, with numerous papers being published annually. The use of multi-temporal datasets enables achieving high performance by leveraging both spatial and temporal information [37,38], including the application of the non-local

paradigm [39]. Currently, the forefront of research in this field involves the utilization of deep learning concepts [40–43]. Pre-processing operations prepare the data for temporal information extraction or for constructing higher-level representations as outlined in Section 1. The main goal in both cases is to detect changes in the scene captured and potentially assign a higher-level meaning to these changes based on their temporal electromagnetic response. Excluding classification aspects, which may warrant a separate review due to the breadth of the topic and various methodologies, the focus of the following discussion will be on traditional change detection methods that aim to link the sign-object association depicted in Figure 2 without relying on any interpretant.

The graph in Figure 1 visually displays the information gap, which is filled through an algorithm that is often heavily parameterized based on the target being identified. This effectively removes the operator from the information processing, either due to the need for high levels of automation, such as for 24/7 services, or due to the complexities involved in setting up the algorithm, which requires users with a strong technical background. Change detection, as defined in literature, involves identifying differences in the state of an object, target, or pattern by observing it at different points in time. This topic is widely discussed in remote sensing and is the simplest form of multi-temporal analysis, typically involving pairs of images. In the SAR community, change detection is commonly achieved through segmenting a change indicator that is appropriately defined. Various solutions exist in the literature, with the difference operator being the simplest and most commonly used for processing MS data. However, its application can lead to differences in detection accuracy between high and low intensity areas. As a result, the ratio operator is more commonly utilized, as it is more stable in areas with varying reflectivity and provides more robust detection against speckle and calibration inaccuracies. The ratio image is often expressed in a logarithmic scale to make its distribution more symmetrical and enhance the contrast between changed and unchanged pixels. Other change indicators introduced in previous literature include normalized multi-temporal band comparison, information theoretical similarity measures like the Kullback-Leibler divergence and mutual information, as well as likelihood ratios.

The determination of the decision level is commonly achieved through threshold segmentation of the chosen information layer. Nevertheless, this process can be crucial. Basic

algorithms that rely on histogram analysis, such as Otsu thresholding, often do not perform well on SAR images due to the fact that the assumptions they are based on (bi-modal distribution and equal representation of classes in the scene) are usually not met. Empirical trial-and-error thresholding and semi-supervised clustering are not suitable for operational scenarios as they necessitate significant supervision and/or depend on the availability of relevant training samples. Bayes theory and the Kittler–Illingworth minimum-error thresholding have been utilized to enhance automatic thresholding techniques, which are widely used in the literature. Fully multi-temporal change indicators, which operate on the entire time series rather than just two time points, have also been suggested. In such cases, the timing of the change can impact the results since the processing typically reflects the average behavior of the scene. In recent years, the increased access to multisource data has led to the advancement of change detection methods that can integrate diverse data-cubes, with SAR and MS data being the preferred sources of sensory information. Fusion can occur at the pixel-, feature- and decision-level, as stated in the literature.

In the realm of decision-level fusion, various types of data follow an independent workflow to extract information until they are ultimately merged with decision rules tailored to the specific case study. This fusion solution is not widely adopted in change detection problems. An instance of this methodology can be found in [69], where the authors suggested combining deforestation maps derived separately from ALOS-PALSAR and Landsat data. On the other hand, in pixel-based fusion, data are combined at the sensory data level. This approach was exemplified in [70], where the authors introduced a fusion framework for deforestation detection based on an optimized regression model of MS and SAR time series. The feature-based fusion approach necessitates the extraction of features and/or objects from multisensor data. These features are then combined using statistical methods, fuzzy logic, or artificial neural networks. This approach is the most commonly adopted method for data fusion in change detection problems. For instance, Poulain et al. [71] proposed a method to detect new buildings by extracting several features indicative of their presence from both SAR and MS images. These features were then combined using the Dempster-Shafer theory of evidence [72]. The feature-based fusion of SAR and MS data is also utilized in [73] for assessing building damage after an earthquake.

In this study, the intact building's geometric parameters are determined using optical images, and the simulated SAR response is compared to the real image. Any differences between

the simulated and real signatures indicate damage to the building. To detect environmental hazards caused by cattle-breeding facilities in Southern Italy, Reference [74] utilized a feature-based fusion of MS and SAR images within a geographic information system (GIS) environment. Polychronaki et al. [75] proposed an object-based methodology for fusing ALOS-PALSAR with optical images to identify fire scars in Mediterranean forests. This approach, which is more robust and flexible than the pixel-based method, presents challenges in terms of proper image segmentation and retrieving relevant attributes from objects [75,77,78]. Consequently, its implementation in multidisciplinary operative contexts becomes difficult. These principles have been successfully applied to various SAR remote sensing problems and applications, including urbanization [10,79] and its impact on the urban climate [11], flood [80] and deforestation [81] mapping, water resources management [82], estimation of large displacements in terrains [21,83,84] and glaciers [19,20,85] using intensity tracking algorithms, as well as post-disaster recovery [73].

An overview of the literature on forestry, water resources management, and flood mapping will be presented in Section 4. Change Detection Using Higher-Level Multi-Temporal Representations The Introduction highlights the possibility of an alternative SAR processing approach through the utilization of higher-level multi-temporal representations that involve color-coding of microwave data. This method enables the creation of a meaningful interpretation of the relationship between signs and objects, as illustrated in Figure 2, thereby enhancing user interaction with data and comprehension of the electromagnetic response of the scene. This approach has been utilized in various studies. References [86,87] utilized incoherent bi-temporal RGB compositions to improve the detection of flooded areas and evaluate building damages post-typhoon, respectively. The use of interferometric coherence in generating bi-temporal SAR color composites for flood mapping was proposed in [88]. Reference [89] introduced a new category of bi-temporal SAR products, referred to as Level-1 α , which combines intensity and phase information within a more versatile processing framework.

Alves et al. [90] utilized a three-temporal fusion of Cassini images to improve the visualization of Titan drainage networks. A similar approach was taken by [91] to emphasize the occurrence of floods. Schmitt et al. [92] created a technique for colorizing Sentinel-1 images using a variational autoencoder conditioned on Sentinel-2 data. More comprehensive methods for

presenting changes in SAR time series data have been established in [93] with the REACTIV technique (available as free software at <https://w3.onera.fr/medusa/content/reactiv> (accessed on 1 February 2020)) and in [15] with the introduction of Level-1 β products. In Figure 3, the comparison between the standard SLC representation and its corresponding change-detection Level-1 α product [89] is displayed. The scene was captured in a rural area of semi-arid Burkina Faso by the COSMO-SkyMed sensor in stripmap mode with three meters spatial resolution during the wet season, where a land cover rich in water and vegetation is expected [82]. However, this information is not immediately evident from the standard SLC SAR image shown in Figure 3a due to (i) the typical gray-scale representation of data, which is linked to the reflectivity function of the specific land cover type and (ii) the presence of speckle that obscures the emergence of significant textures necessary to differentiate various image features. This representation is inadequate, for instance, in distinguishing vegetation from bare soils.

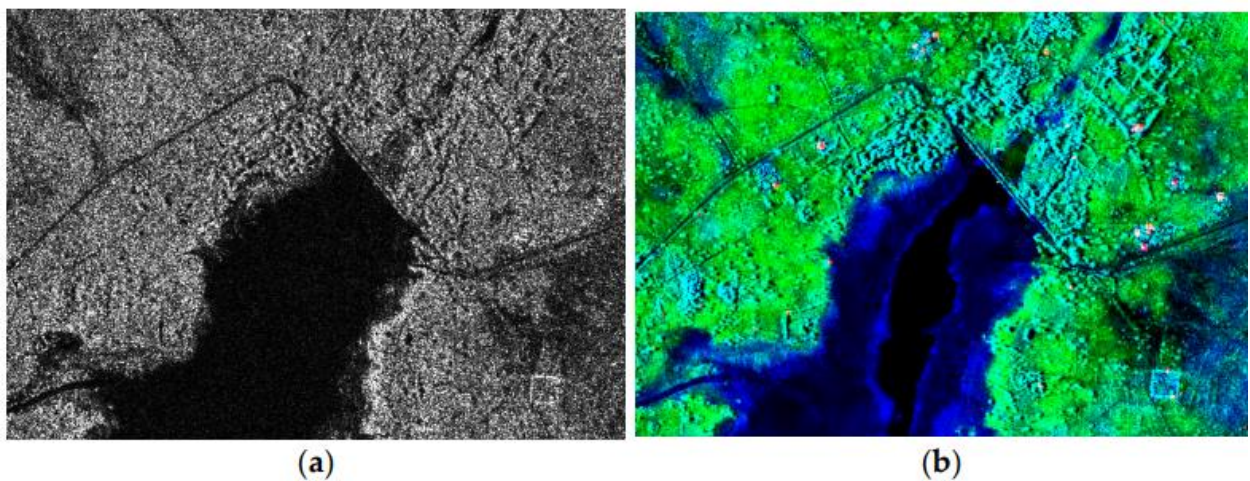


Figure 1.4. Example of SAR images

The observer's understanding and decision-making abilities in information processing can be enhanced by utilizing a higher-level change-detection oriented representation that incorporates multiple temporal perspectives, as outlined in Section 1. The product displayed in Figure 3b is a result of combining an image captured during the dry season, when the landscape is predominantly dry, with the previously introduced wet season acquisition. Specifically, the dry season image is loaded onto the blue channel and serves as the reference for identifying changes. The wet season image is loaded onto the green band, while the red channel is dedicated to interferometric coherence. It is important to note that this representation, referred to as Level-1 α in literature [5], provides significantly more information compared to the standard Level-1. It enables immediate identification of growing vegetation patterns, depicted in green, and the

presence of temporary water, represented in blue. Additionally, the incorporation of comprehensive multi-temporal processing, which utilizes temporal despeckling techniques [37], makes image textures more explicit. This proves beneficial in visually segmenting homogeneous patterns as the edges are better defined.

The extraction of high-quality texture measures, originally defined based on optical/consumer images, is enabled without being affected by speckle. These measures can serve as information layers in automatic change detection and classification methodologies. The introduction of a color representation of microwave backscattering also facilitates information mining for the operator, particularly for features that align with the natural color palette. For instance, temporary water surfaces appear in blue, while vegetation is depicted in green. The color composition is influenced by the dominance of terrain scattering in dry season images over water surface scattering in wet season images. Similarly, the green color of vegetation is attributed to volumetric backscattering enhancement during the wet season due to crop and grass growth. Other features exhibit false colors based on their temporal backscattering behavior. For example, bare soils throughout the year show a balance of blue and green channels. Trees, with consistent high backscattering, are represented in cyan. Permanent water surfaces are depicted in black due to their low and stable backscattering. Interferometric coherence is crucial for distinguishing man-made targets (typically stable in signal phase) from highly reflective natural targets.

The features, such as small human settlements scattered across the study area, are highlighted in white in Figure 3b due to the contribution of the intensity channels. A key challenge in computer vision is enabling the observer to segment the image into meaningful regions, thus avoiding the emergence of bright saturated areas and non-natural colors that can cause distraction and confusion. Essentially, the visualization should support the observer's pre-attentive processing, allowing for the unconscious accumulation of information from the surrounding environment. In Figure 4, a comparison is made between a Level-1 α product (Figure 4a) and a bi-temporal color composite (Figure 4b) depicting two small reservoirs in semi-arid Burkina Faso. The RGB images are created using a dry season image as a reference for change detection, with the wet season image serving as the test data. Specifically, in Figure 4b, the dry season image is loaded on the blue band, the wet season image on the green band, and the red channel represents the difference between the two images.

In order to ensure a fair comparison, a multi-temporal De Grandi despeckling technique was utilized with the same number of images as those used to generate the Level-1 α product shown in Figure 4a. It is evident to the reader that the presentation of information between Figure 4a and 4b is distinctly different. The Level-1 α product displays reservoirs in blue, attributed to the dominance of terrain scattering in the dry reference scenario compared to the water layer during the wet season. Following the methodology outlined in [86], this phenomenon results in a notable presence of the red band (difference image), altering the composition color to magenta. Additionally, Figure 4b lacks the visibility of small settlements surrounding the lakes, which are clearly depicted in Figure 4a.

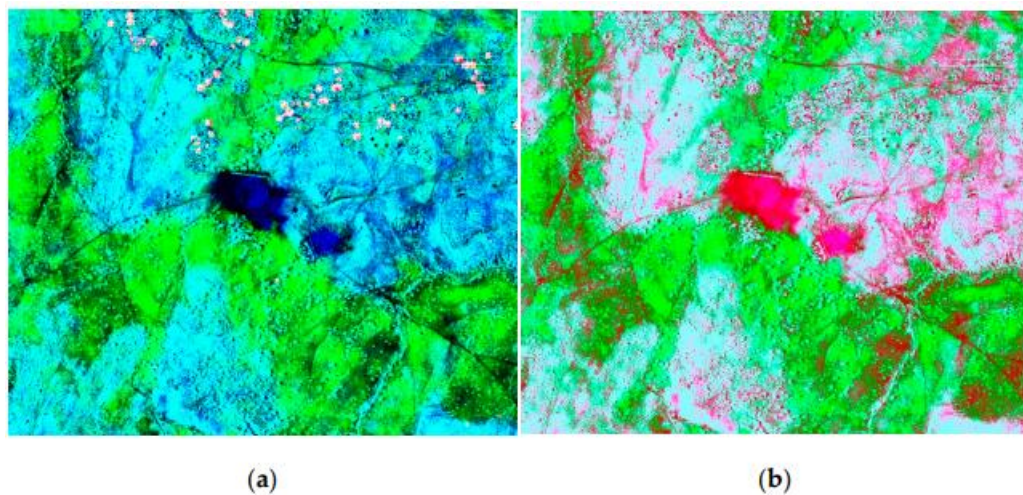


Figure 1.5. Example Level-1 α image

Overall, one could argue that utilizing the composition shown in Figure 4b may hinder the observer's comprehension by providing a distracting and confusing representation of the EM response of the scene. This composition focuses more on highlighting changing patterns, which may not be as effective for labeling activities. Essentially, if the operator does not understand the significance of the changes observed in the data, it can be challenging to assign appropriate labels due to the lack of helpful information in forming the interpretant of the relationship between the sign and the object. On the contrary, the Level-1 α representation enhances changes in a way that assists the operator in giving meaningful semantics to them. This representation is particularly useful for emphasizing temporary water surfaces, which are depicted in blue color, a rendering that non-expert observers would expect for a flooded area, for instance. However, if the goal is to monitor land, this representation may not be ideal as it deviates significantly from the natural color palette for terrains, as shown in Figure 5a.

In this scenario, it may be beneficial to switch the roles of the interferometric coherence and the reference image for change detection [89]. This involves swapping the red and blue channels, resulting in a representation shown in Figure 5b that closely resembles natural color tones, particularly highlighting red components in terrain rendering. Consequently, flooded areas and other changes such as vegetation removal would appear in red hues. Another method to emphasize scene changes is by utilizing temporal statistics from SAR series [15,65,66,93]. Figure 6 displays various fully multi-temporal products. The first (Figure 6a) is a Level-1 β image generated from the method proposed in [15]. The second (Figure 6b) is the output of the REACTIV technique from [93]. The third (Figure 6c) is an absolute change indicator map explained in [65]. Lastly, the fourth is a second order log-cumulants map produced as discussed in [66]. These products are based on a time-series of 6 images captured over Castel Volturno (Italy) between April and October 2010 by the COSMO-SkyMed sensor in stripmap mode with three meters spatial resolution.

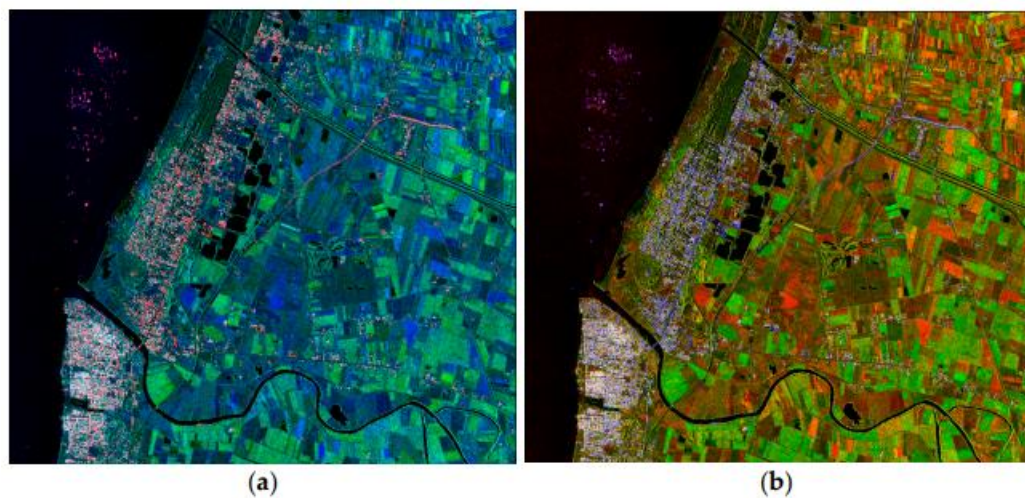


Figure 1.6. Example of Level-1 β image

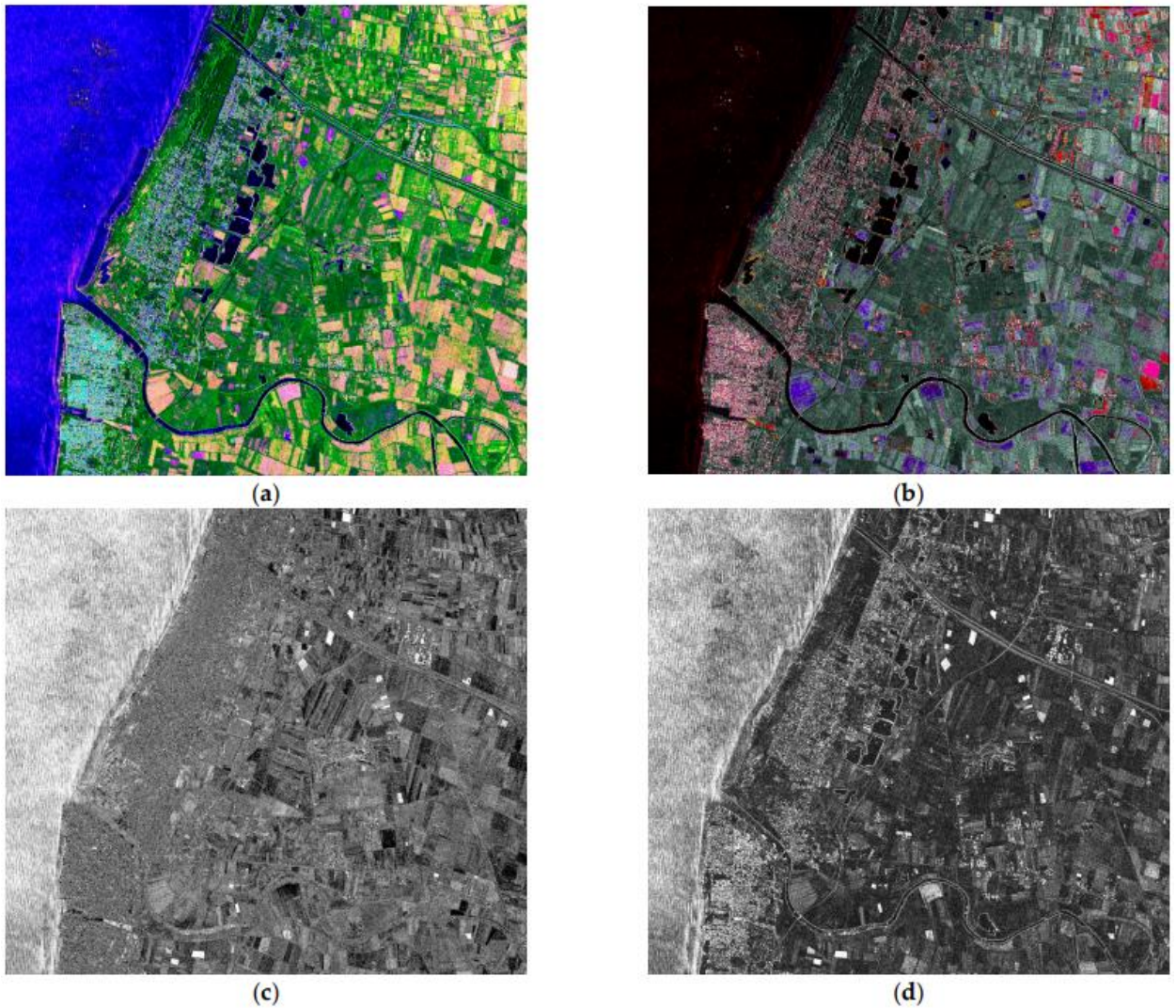


Figure 1.7. Example of Level-1 β image

As detailed in reference [15], the RGB channels in a Level-1 β product are derived from the statistical analysis of the time series data. Specifically, the red channel corresponds to the temporal backscattering variance, the green channel is based on the average backscattering, and the blue channel is a combination of interferometric coherence and the saturation index. The interferometric coherence is utilized only when its average value exceeds a user-defined threshold, indicating the presence of man-made structures. Otherwise, the saturation index is utilized. This approach results in a color scheme that reflects the dynamics of the land cover in the scene. For instance, in Figure 6a, the sea is depicted in shades of blue due to its consistently low backscattering, occasionally interrupted by wave-induced spikes. Areas with stable land cover, such as grasslands, are predominantly green, representing their average backscattering. Urban regions appear cyan, reflecting their stable backscattering and phase signal. Areas

undergoing changes exhibit high variance, leading to a noticeable contribution from the red channel, as seen in crop fields.

The colors of the rendered images vary between yellowish and pinkish, depending on the crop type and/or events such as harvesting that increase the saturation index contribution. The temporal composite shown in Figure 6b is driven by different principles [93], where colors represent the time of change detection rather than the type of change, making it challenging to associate color with specific phenomena. Figure 6b highlights only a portion of the changing patterns visible in Figure 6a, focusing on abrupt changes and is more suitable for long time-series applications. The timing of the change is crucial when considering traditional multitemporal change detection operators like those in [65] (see Figure 6c) and [66] (see Figure 6c). These operators tend to prioritize abrupt changes at the beginning of the time series, resulting in a cumulative layer output map.

This approach may not effectively capture slow changes, such as crop growth, leading to uniformity in most of the agricultural land in the scene. On the other hand, the REACTIV output products are better suited for analyzing long and dense time-series with a higher likelihood of abrupt and long-lasting land cover variations.

As a general comment, Level-1 β images are a more flexible analysis tool with respect to the other considered products. They offer a user-friendly representation of the SAR information with a balanced color displaying, characterized by limited occurrence of saturated and/or distracting patterns. They are able to highlight both slow and abrupt changes and to adequately separate them through the rendering in different colors. The physical-based association between the color of the composition and the change occurred on the scene makes the assignment of a relevant semantics (i.e., label) to the detected changing patterns easier. This is also useful for land cover type classification purposes, while the other analyzed products mainly allow only for the identification of changes. The reviewed change detection literature has been summarized in Table 1, categorized based on the methodology and the application domain.

1.3.3. Ground Penetrating Radar (GPR)

Ground-penetrating radar (GPR) is a geophysical method that uses radar pulses to image the subsurface. It is a non-intrusive method of surveying the sub-surface to investigate underground utilities such as concrete, asphalt, metals, pipes, cables or

masonry. This nondestructive method uses electromagnetic radiation in the microwave band (UHF/VHF frequencies) of the radio spectrum, and detects the reflected signals from subsurface structures. GPR can have applications in a variety of media, including rock, soil, ice, fresh water, pavements and structures. In the right conditions, practitioners can use GPR to detect subsurface objects, changes in material properties, and voids and cracks.

GPR uses high-frequency (usually polarized) radio waves, usually in the range 10 MHz to 2.6 GHz. A GPR transmitter and antenna emits electromagnetic energy into the ground. When the energy encounters a buried object or a boundary between materials having different permittivities, it may be reflected or refracted or scattered back to the surface. A receiving antenna can then record the variations in the return signal. The principles involved are similar to seismology, except GPR methods implement electromagnetic energy rather than acoustic energy, and energy may be reflected at boundaries where subsurface electrical properties change rather than subsurface mechanical properties as is the case with seismic energy.

The electrical conductivity of the ground, the transmitted center frequency, and the radiated power all may limit the effective depth range of GPR investigation. Increases in electrical conductivity attenuate the introduced electromagnetic wave, and thus the penetration depth decreases. Because of frequency-dependent attenuation mechanisms, higher frequencies do not penetrate as far as lower frequencies. However, higher frequencies may provide improved resolution. Thus operating frequency is always a trade-off between resolution and penetration. Optimal depth of subsurface penetration is achieved in ice where the depth of penetration can achieve several thousand metres (to bedrock in Greenland) at low GPR frequencies. Dry sandy soils or massive dry materials such as granite, limestone, and concrete tend to be resistive rather than conductive, and the depth of penetration could be up to 15 metres (49 ft). However, in moist or clay-laden soils and materials with high electrical conductivity, penetration may be as little as a few centimetres.

Ground-penetrating radar antennas are generally in contact with the ground for the strongest signal strength; however, GPR air-launched antennas can be used above the ground.

Cross borehole GPR has developed within the field of hydrogeophysics to be a valuable means of assessing the presence and amount of soil water.

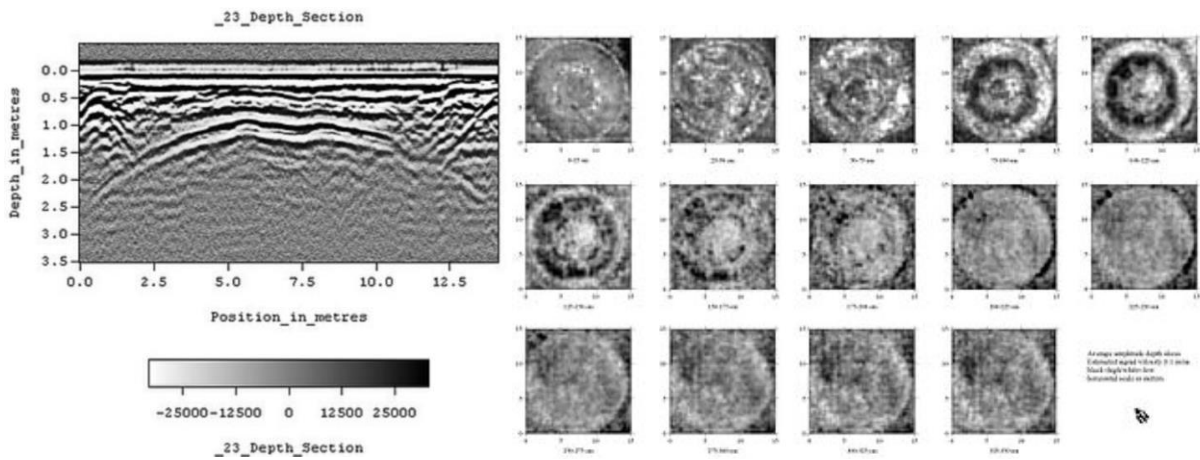


Figure 1.8. Example of GPR result image

Advantages:

Effective in Detecting Underground Objects: Can detect mines and other hazardous objects.

Relative Ease of Use: Easily mounted on various platforms.

Disadvantages:

Limited Penetration Depth: May be less effective at greater depths or in certain soil types.

Sensitivity to Interference: Results can be affected by external sources of radio waves.

Examples of Use

DJI Matrice 300 RTK

Description: A rotary UAV capable of mounting SAR and GPR sensors.

Advantages: High stability, long flight time, supports various sensor types.

Disadvantages: High cost, requires specialized sensors.

SenseFly eBee

Description: A fixed-wing UAV suitable for long-term monitoring of large areas.

Advantages: Large operational range, high flight speed.

Disadvantages: Requires a runway for take-off and landing, limited maneuverability.

Mobile platforms for hosting intelligent search systems, such as rotary and fixed-wing UAVs, offer various advantages and disadvantages that should be considered when choosing means for specific tasks. The development of technologies such as SAR and GPR significantly enhances the efficiency of search systems deployed on these platforms, ensuring more effective anomaly detection and analysis.

1.4 Measurement Result Processing System

The measurement result processing system is a critically important component of the mobile intelligent search system. It is responsible for collecting, processing, and analyzing data obtained from sensors and other sources to detect anomalies. This section will examine the key elements and technologies used in data processing systems, including algorithms, software platforms, and methods for visualizing results.

Data Collection

Sensors and Detectors

The primary sources of data for the search system are sensors and detectors mounted on mobile platforms. These may include:

Synthetic Aperture Radar (SAR): Used for obtaining detailed images of surface and underground structures.

Ground Penetrating Radar (GPR): Used for detecting underground objects.

Optical and Infrared Cameras: Used for visual and thermal monitoring.

LIDAR: Used for high-precision 3D mapping of areas.

Data Processing

Preprocessing

Data preprocessing involves steps to prepare raw data for further analysis. Key stages include:

Noise Filtering: Removing unnecessary data and noise that may distort analysis results.

Normalization: Standardizing data formats to ensure the accuracy of subsequent calculations.

Data Synchronization: Merging data from different sensors into a unified time context.

Analysis Algorithms

Machine Learning and Artificial Intelligence:

Classification and Clustering: Used to identify and group anomalies based on learning from historical data.

Image Analysis: Computer vision algorithms are used to detect and identify objects in images obtained by sensors.

Signal Processing:

Frequency Analysis: Analyzing signals in the frequency domain to detect specific characteristics.

Fourier Transform: Used to convert signals from the time domain to the frequency domain for more detailed analysis.

Cloud Technologies

Cloud computing resources are used for storing large volumes of data and ensuring its availability for analysis and processing.

Amazon Web Services (AWS): Provides a wide range of services for data storage, processing, and analysis.

Google Cloud Platform (GCP): Offers tools for big data processing and machine learning.

Local Servers

For data requiring high levels of security or immediate access, local servers and data storage facilities can be used.

Geographic Information Systems (GIS)

GIS is used to display data processing results on maps, allowing visualization of anomaly locations and other important objects.

ArcGIS: A powerful platform for creating interactive maps and conducting geospatial analysis.

QGIS: An open-source alternative to ArcGIS with a wide range of tools for visualizing and analyzing geospatial data.

Interactive Dashboards and Reports

Interactive dashboards allow users to interact with data in real-time, view different data slices, and generate reports.

Tableau: A tool for creating interactive visualizations and dashboards.

Power BI: A platform by Microsoft for data analysis and creating interactive reports.

The measurement result processing system is the central element of the mobile intelligent search system. It encompasses data collection, preprocessing, analysis, storage, and visualization, ensuring effective anomaly detection and interpretation. The use of modern technologies, such as machine learning, cloud computing, and GIS, significantly enhances the accuracy and speed of analysis, which is crucial for the successful execution of search tasks.

CHAPTER 2

TECHNOLOGICAL BASEMENT OF SYSTEM

2.1. GPS navigation system

The advantage of the traditional Inertial Navigation Systems (INS) is that the data rate is high, but the accuracy of which would be degraded as the times go by [1]. In general, there are two methods to improve the performance. The first one is to increase the accuracy of both the inertial sensors and the computer. The second one is to calibrate the error parameters by using the other navigation information [2], such that the diverging rate can be reduced. The Global Positioning System (GPS) is one of the navigation methods right now. The GPS receiver can decode the navigation messages from the satellites, solve the navigation equations [3-8] and provide positioning data all over the world. Although the data rate is only 1 Hz, the characteristic performance of which is long time stable [9]. Thus it is a good ideal to integrate INS with GPS, the resulting system is not only reliable but also cost-effective, therefore, it is applied in this paper as the central part of the vehicle navigation system.

The purpose of this paper is not only to realize and study the performance of the vehicle navigation system of INS aided with GPS, but also to monitor the vehicle by GSM (Global System for Mobile communication) modem linking. The positioning outputs of GPS receiver are taken as the measurements to calibrate the INS error parameters in the Kalman filter, such as the navigation error covariance matrices of positions, velocities, heading angle and angular speed, as well as the biases, drift rates and scale factors of the rate gyros and accelerometers. The hardware of the system includes one notebook PC, one rate gyro, two accelerometers, three A/D converters and one GPS receiver. On the other hand, the software program is based on TUBRO.C in order to speed up the real time signal processing as well as easier for later-on maintaining. For the practical consideration, not only the normal operating but also the lost tracking conditions of GPS receiver are performed and analyzed. This is scarcely discussed in the other papers [5-8]. The results show that the longer the GPS receiver locks, the better the error parameters of INS are calibrated, thus the integrated system can preserve the advantages and avoid the disadvantages of both systems, i.e., not only the high positioning rate of INS, but the long time stability of GPS receiver are preserved, while the degraded performance as times go by of INS, and the lower positioning rate of GPS receiver are avoided. The other advantage of the proposed system is that

it is modularized, and not sensitive to the environment effect of the vehicle. For example, the heading of the vehicle is obtained by using the integrated velocity results of GPS / INS (which is derived in Eq. (29) later), there is no need of gyrocompass. Thus it is not sensitive to the magnetic field disturbance effects due to the earth or the environments. By the way the wearing and slipping effects of the tire, which are the disadvantages of the vehicle navigation systems by using the odometer [10], can also be avoided. In addition, the vehicle monitoring system is also realized by adding the GSM modems to the vehicle as well as the base station, respectively. Thus the base station can communicate with the vehicle via GSM modem linking, and makes the Differential GPS (DGPS) correction to raise the positioning accuracy of the vehicle [11-12].

The major error sources of INS are rate gyro and accelerometer. Let the sensing axes of the rate gyro and two other accelerometers are respectively along the vehicle's z, x and y axes, respectively, and j is the heading angle as shown in Fig.1., which is defined as the angle between the vehicle's x axis (center line) and the north direction of the navigation system. In general, there are four types of rate gyro errors [1], such as random bias B_g , scale factor SF_g , random drift rate ϵ_g and random noise w_g , i.e.,

$$\varphi = B_g + \epsilon_g + \omega_g + SF_g * \omega$$

where w is the heading angular rate. The models of B_g and SF_g can be defined by the following equations:

$$B_g = 0$$

$$SF_g = 0$$

The random drift ϵ_g is a white noise with zero mean and standard deviation

$$E \{ \epsilon_g(t) \epsilon_g(\tau) \} = \sigma_{\epsilon_g}^2 \delta(t - \tau)$$

and the random noise w_g is modeled as

$$\omega_g = -\omega_g / \tau_g + \omega_{gn}$$

where t_g is the correlation time of the random noise w_g , and w_{gn} is a zero-mean white noise with standard deviation defined as :

$$E\{\omega_{gn}(t)\omega_{gn}(\tau)\} = \sigma_{gn}^2 \delta(t - \tau)$$

The power spectrum of the white noise w_{gn} is [13]

$$Q_{gn} = \sqrt{2\sigma_{gn}^2 \tau_g}$$

Similarly, the outputs of the accelerometers a_i ($i = x, y$) can be expressed in terms of the error parameters such as random drift D_i , random noise B_{a_i} , and scale factor SF_i ($i = x, y$), i.e.,

$$a_i = V_i = \Delta_i + B_{a_i} + SF_i * f_i$$

where f_i is the acceleration along the vehicle's i axis ($i = x, y$), and the errors i SF of scale factor and random noise B_{a_i} can be modeled as follows:

$$SF_i = 0 \quad (i = x, y)$$

$$B_{a_i} = -B_{a_i} / \tau_{a_i} + \omega_{a_i} \quad (i = x, y)$$

where τ_{a_i} is the correlation time of the random noise $a_i B$, and $a_i w$ is a zero-mean white noise with standard deviation as:

$$E\{\omega_{a_i}(t)\omega_{a_i}(\tau)\} = \sigma_{a_i}^2 \delta(t - \tau) \quad (i = x, y)$$

The power spectrum of the white noise w_{a_i} is

$$Q_{a_i} = \sqrt{2\sigma_{a_i}^2 \tau_{a_i}} \quad (i = x, y)$$

The random drift D_i is a zero-mean white noise with standard deviation:

$$E\{\Delta_i(t)\Delta_i(\tau)\} = \sigma_{\Delta_i}^2 \delta(t - \tau) \quad (i = x, y)$$

It should be noted that for the sake of speeding up the Kalman filtering processes, the random biases of the accelerometers are neglected.

Since the positioning results should be expressed in the navigation coordinates, thus the acceleration components of vehicle in the north f_N and the east f_E are respectively obtained as:

$$\begin{bmatrix} f_N \\ f_E \end{bmatrix} = \begin{bmatrix} c\varphi & -s\varphi \\ s\varphi & -c\varphi \end{bmatrix} \begin{bmatrix} a_x \\ a_y \end{bmatrix}$$

where

$$c\varphi = \cos\varphi$$

$$s\varphi = \sin\varphi$$

In general, the positioning outputs of GPS receives are in terms of the latitude L and the longitude λ , one can transform them into the coordinates along the navigation axis, i.e., the positions in the north P_N , and the east P_E are obtained respectively as follows:

$$P_N = (L - L_0)R_e$$

$$P_E = (\lambda - \lambda_0)R_e \cos L_0$$

where R_e is the radius of the earth, L_0 (λ_0) is the initial latitude (longitude) of the vehicle.

By the above derivation, one can formulate the state equation of the vehicle in the navigation system as [14]:

$$\dot{x}(t) = Ax(t) + \omega(t)$$

where

$$x(t) = [P_N \ P_E \ V_N \ V_E \ \varphi \ \omega_g \ B_{ax} \ B_{ag} \ B_g \ SF_n \ SF_e \ SF_g]$$

and the system matrix A is [14]

$$A = \begin{bmatrix} 0 & \dot{\lambda}_I sL & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \dot{\lambda}_I sL & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\frac{g}{R_e} & 0 & 0 & -\dot{\lambda}_I sL & f_E & 0 & c\varphi & -s\varphi & 0 & f_N & 0 & 0 \\ 0 & -\frac{g}{R_e} & \dot{\lambda}_I sL & 0 & -f_N & 0 & s\varphi & c\varphi & 0 & 0 & f_E & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & \omega \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{\tau_g} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{\tau_{ax}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{\tau_{ay}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where

$$\lambda_I = \frac{V_E}{R_e c L}$$

$$g = 9.8 \text{ m/sec}^2$$

and the input noise vector $\omega(t)$ in Eg.(19) is defined as:

$$\omega(t) = [0 \ 0 \ \Delta_N \ \Delta_E \ \varepsilon_g \ \omega_{gn} \ \omega_{ax} \ \omega_{ay} \ 0 \ 0 \ 0 \ 0]^T$$

which is zero mean and with covariance matrix as

$$Q = \text{diag}\{0 \ 0 \ \sigma_{\Delta N}^2 \ \sigma_{\Delta E}^2 \ \sigma_{\varepsilon_g}^2 \ \sigma_{\omega_{gn}}^2 \ \sigma_{\omega_{ax}}^2 \ \sigma_{\omega_{ay}}^2 \ 0 \ 0 \ 0 \ 0\}$$

The measurement equation is

$$z(t) = H(t)x(t) + v(t)$$

where

$$H(t) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

and $v(t)$ is the measurement noise of GPS receiver with zero mean and covariance matrix

$$R(t) = \text{diag} \{ \sigma_{P_N}^2, \sigma_{P_E}^2, \sigma_{V_N}^2, \sigma_{V_E}^2, \sigma_{\varphi}^2 \}$$

Where $\sigma_{P_N}^2$ ($\sigma_{P_E}^2$), $\sigma_{V_N}^2$ ($\sigma_{V_E}^2$) and σ_{φ}^2 are respectively the GPS standard deviation errors of the north (east) position, north (east) velocity and heading angle, and

$$\varphi = \tan^{-1} \left(\frac{V_E}{V_N} \right)$$

The GPS/INS integrating method uses the loosely-coupled closed-loop structure [5,6], as shown in Fig.2 by the trade-offs of implementation, accuracy performance, and system reliability.

Let the discrete state and measurement equations are as [6]

$$x_k = \Phi_{k-1} x_{k-1} + \Gamma_{k-1} \omega_{k-1}$$

and

$$z_k = H_k x_k + v_k$$

$$\hat{x}_k(-) = \Phi_{k-1} \hat{x}_{k-1}(t)$$

$$P_k(-) = \Phi_{k-1} P_{k-1}(t) \Phi_{k-1}^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T$$

$$K_k = P_k(-) H_k^T [H_k P_k(-) H_k^T + R_k]^{-1}$$

$$\hat{x}_k(t) = \hat{x}_k(-) + K_k \left[z_k - H_k \hat{x}_k(-) \right]$$

$$P_k(t) = [I - K_k H_k] P_k(-)$$

where $\hat{x}_k(-)$ ($P_k(-)$) and $\hat{x}_k(+)$ ($P_k(+)$)

are the estimated state (covariance matrix) before and after taking the measurements into consideration, and K_k is the Kalman filter gain matrix. By the way, the sampling period of the INS is 40 ms in this study.

The block diagram of the vehicle navigation and monitoring system is shown in Fig 3(a), in which the GSM modems are added to the vehicle as well as the base station, respectively, such that the positioning information of the vehicle, e.g., the navigation results, obtained by using GPS/INS as well as DGPS correction, can be received by the base station via GSM communication. The signal flow graph of the GPS/INS signal processing algorithm is shown in Fig.3(b).

The test site for evaluating the performance of the integrated system is in a trapezoidal region in Hsin-Chu, Taiwan as shown in Fig.4. The sequence of the path is along the points s_1 , s_2 , s_3 , s_4 , and s_5 , then back to s_1 finally. The average speed of the vehicle is 40km/hr. The total distance is about 3.4 km, and the testing period is 320 sec. The part numbers and the error parameters of the accelerometers, rate gyros as well as the GPS receiver are listed in Table 1. Fig.5 shows the positioning result obtained by the system with only INS, as it was anticipated that the accuracy of which is degraded with time. Fig.6 shows the positioning output of GPS receiver in which the differential GPS correction is accomplished by GSM linking from the base station, thus the standard deviation of the positioning result is reduced to 5 m. Although the results are not degraded with time, but there is only one output per second. On the other hand, the result obtained by the integration method, with GPS receiver locked all the way, is shown in Fig.7. It

can be seen that the characteristic performances of both GPS long-time stability and INS high speed data rate are preserved. In addition, the standard deviations of the position, velocity and heading errors are converged as long as the GPS locks which are shown in Figs.8-10.

2.2. Geographic information system

The coupled system has two main operational modes: decision support for prevention or reaction to hazardous events, which requires fast results, and a learning system for better understanding and prognosis of landslide movements. Decision makers use the decision support system to identify at-risk areas, while experts utilize the learning system for assessment and GIS-based analysis of simulation results. Input data is selected and prepared, with the GIS controlling the transfer of data. The simulation system then executes finite element modeling of the slope and simulates slope failure formation.

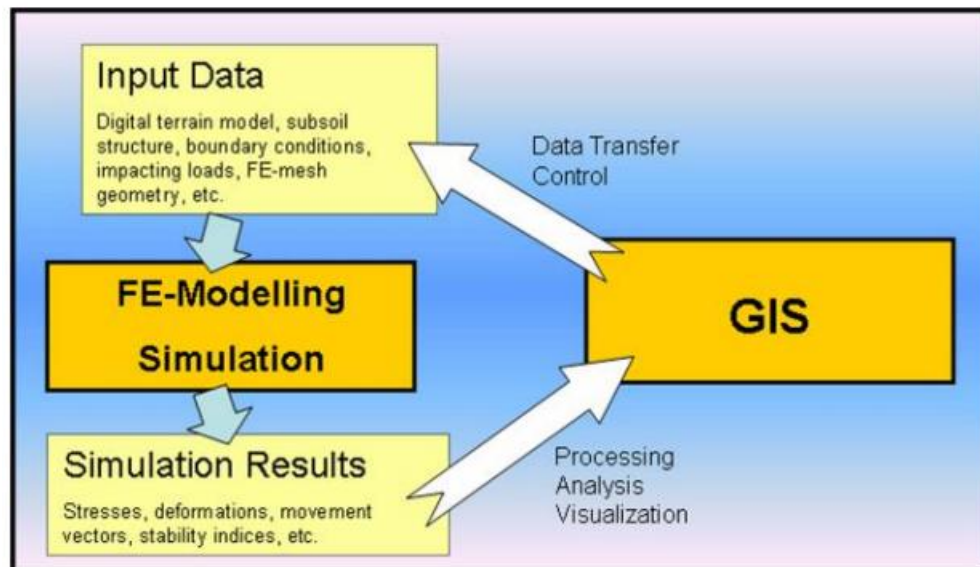


Figure 2.1. GIS structure scheme

The diagram in Figure 9 illustrates the structure of the interconnected system. After conducting the simulation, a large set of vectors (such as deformation vectors in our specific case) is obtained. These vectors are then transmitted to the GIS for further processing, analysis, and visualization. Figure 10 showcases the outcomes of a 3D simulation. However, the challenge lies in the fact that the simulation results are intricate and perplexing, making them unsuitable as a foundation for decision-making. To address this issue, it is imperative to employ methodologies that facilitate user-friendly preparation and visualization. These methodologies

aim to assist users in both decision-making and the learning process.



Figure 2.2. Example of 3D simulation result

Figure 2.2.2 showcases the visualized 3D simulation results. To effectively handle this extensive data, the slope needs to be divided into two areas: one where deformations occurred during the simulation, and another where little to no deformations took place. In Figure 11 (above), a section through the sliding body is displayed. Here, one can observe deformation vectors of varying sizes, but it is not possible to determine whether the slope should be classified as landslide susceptible or not. Hence, a methodology is required to cluster the intricate simulation results. Initially, the deformation vectors can be categorized based on their length and deformation direction. Subsequently, clusters can be identified, which consist of deformation vectors belonging to the same deformation class, direction class, and are spatially adjacent. Once the deformation vectors are aggregated within the clusters, the area of validity is determined. To enhance visualization, the detected deformation areas are classified as small (green), moderate (yellow), and large deformation (red). The outcome of this method can be presented to the decision-maker in charge to provide decision support.

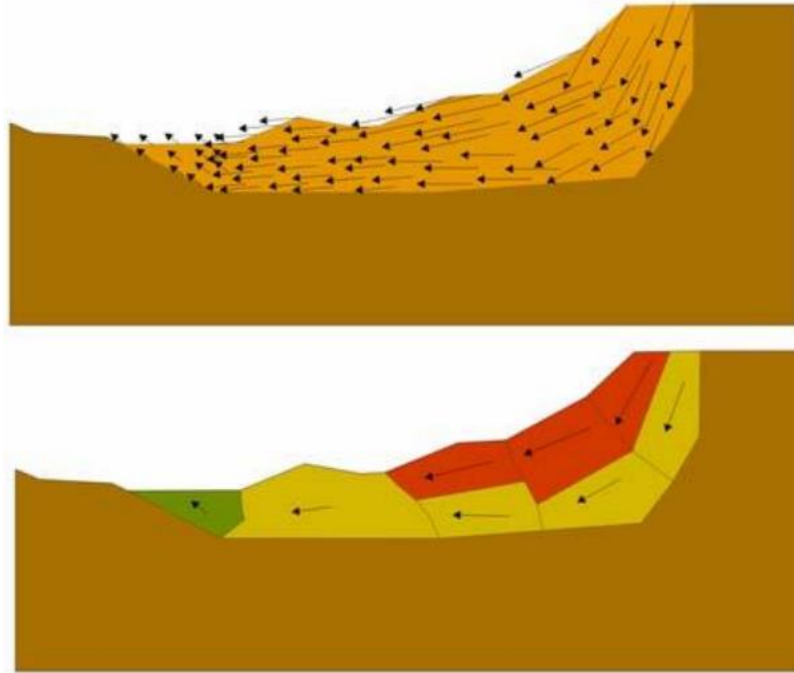


Figure 2.3. GIS working algorithm

In addition to enhancing data processing for creating user-friendly diagrams, various GIS techniques can be applied to aid in decision-making. For instance, simulation outcomes can be overlapped with existing digital topographic data to identify at-risk infrastructure (e.g. buildings and roads). By integrating simulation findings with this supplementary data, a foundation for proactive measures, emergency response, and risk mitigation is established. This valuable information can assist users in making informed decisions, such as issuing timely warnings.

CHAPTER 3

SYSTEM DATA BASES DEVELOPMENT

3.1. MongoDB connection

To connect to a MongoDB database and interact with a drone equipped with a ground penetrating radar (GPR), you can use the PyMongo libraries for working with MongoDB and DroneKit for controlling the drone. Here is an example code that performs the following tasks:

- a) Connecting to MongoDB.
- b) Obtaining data from GPR.
- c) Saving or updating data in MongoDB.
- d) Execution of basic commands for the drone.

Installation of necessary libraries

Before starting work, you need to install the necessary libraries:

```
pip install pymongo dronekit
```

Code:

```
from pymongo import MongoClient
```

```
from dronekit import connect, VehicleMode, LocationGlobalRelative
```

```
import time
```

```
# Function to connect to MongoDB
```

```
def connect_to_mongodb(uri, db_name):
```

```
    client = MongoClient(uri)
```

```
    db = client[db_name]
```

```
    return db
```

```
# Function to connect to the drone
```

```
def connect_to_drone(connection_string):
```

```
    vehicle = connect(connection_string, wait_ready=True)
```

```
    return vehicle
```

```
# Function to save data to MongoDB
```

```
def save_data_to_mongodb(db, collection_name, data):
```

```
    collection = db[collection_name]
```

```
    collection.insert_one(data)
```

```
# Main code
```

```
if __name__ == "__main__":
```

```
    # Connection parameters
```

```
    mongodb_uri = "mongodb://localhost:27017/"
```

```
    db_name = "drone_data"
```

```
    collection_name = "gpr_readings"
```

```

drone_connection_string = '127.0.0.1:14550' # Change to the actual connection string to your
drone

# Connect to MongoDB
db = connect_to_mongodb(mongodb_uri, db_name)
print("Connected to MongoDB")

# Connect to the drone
vehicle = connect_to_drone(drone_connection_string)
print("Connected to the drone")

# Example GPR data (replace with actual GPR data)
gpr_data = {
    "timestamp": time.time(),
    "location": {"lat": vehicle.location.global_relative_frame.lat, "lon":
vehicle.location.global_relative_frame.lon},
    "anomaly_detected": True, # or False, depending on your data
    "gpr_values": [100, 150, 200] # Sample GPR data
}

# Save data to MongoDB
save_data_to_mongodb(db, collection_name, gpr_data)
print("Data saved to MongoDB")

# Close the drone connection
vehicle.close()
print("Drone connection closed")

```

Explanation of the code:

Connecting to MongoDB: The pymongo library is used to connect to the MongoDB database and store data.

Connecting to the drone: The dronekit library is used to connect to the drone and retrieve its location data.

Saving data to MongoDB: GPR data is stored in the gpr_readings collection in the MongoDB database.

Example GPR data: Replace the example with actual GPR data.

This code serves as a basic example and can be extended to handle specific GPR data and drone control according to your requirements.

3.2. MySQL connection

To connect to a MySQL database and interact with a drone equipped with a ground penetrating radar (GPR), you can use the mysql-connector-python libraries to work with MySQL and DroneKit to control the drone. Here is an example code that performs the following tasks:

- e) Connecting to MySQL.
- f) Obtaining data from GPR.
- g) Saving or updating data in MySQL.
- h) Execution of basic commands for the drone.

Installation of necessary libraries

Before starting work, you need to install the necessary libraries:

```
pip install mysql-connector-python dronekit
```

Code:

```
import mysql.connector
```

```
from mysql.connector import errorcode
```

```
# Function to connect to MySQL
```

```
def connect_to_mysql(host, user, password, database):
```

```
    try:
```

```
        connection = mysql.connector.connect(
```

```
            host=host,
```

```

    user=user,
    password=password,
    database=database
)
return connection
except mysql.connector.Error as err:
    if err.errno == errorcode.ER_ACCESS_DENIED_ERROR:
        print("Something is wrong with your user name or password")
    elif err.errno == errorcode.ER_BAD_DB_ERROR:
        print("Database does not exist")
    else:
        print(err)
    return None

```

Function to save data to MySQL

```

def save_data_to_mysql(connection, table_name, data):
    cursor = connection.cursor()
    query = "INSERT INTO {} (timestamp, location, anomaly_detected, gpr_values) VALUES
(%s, %s, %s, %s)".format(table_name)
    cursor.execute(query, (data["timestamp"], data["location"], data["anomaly_detected"],
data["gpr_values"]))
    connection.commit()
    cursor.close()

```

Main code

```

if __name__ == "__main__":
    # Connection parameters
    mysql_host = "localhost"
    mysql_user = "your_username"
    mysql_password = "your_password"

```

```

mysql_database = "drone_data"
table_name = "gpr_readings"

# Connect to MySQL
connection = connect_to_mysql(mysql_host, mysql_user, mysql_password, mysql_database)
if connection:
    print("Connected to MySQL")

# Example GPR data (replace with actual GPR data)
gpr_data = {
    "timestamp": time.time(),
    "location": "latitude: {}, longitude: {}".format(latitude, longitude),
    "anomaly_detected": True, # or False, depending on your data
    "gpr_values": "100, 150, 200" # Sample GPR data
}

# Save data to MySQL
save_data_to_mysql(connection, table_name, gpr_data)
print("Data saved to MySQL")

# Close the MySQL connection
connection.close()
print("MySQL connection closed")

```

Explanation:

Connecting to MySQL: The `mysql.connector` library is used to establish a connection to the MySQL database.

Saving data to MySQL: GPR data is inserted into a specified table in the MySQL database.

Example GPR data: Replace the example data with your actual GPR data.

This code provides a basic framework for interacting with a MySQL database in Python, allowing you to store and retrieve GPR data.

3.3. Amazon S3 connection

To connect to Amazon S3 and interact with a drone equipped with ground penetrating radar (GPR), you can use the boto3 libraries for working with Amazon S3 and DroneKit for controlling the drone. Here is an example code that performs the following tasks:

Connecting to Amazon S3.

Obtaining data from GPR.

Data storage in Amazon S3.

Execution of basic commands for the drone.

Installation of necessary libraries

Before starting work, you need to install the necessary libraries:

```
pip install boto3 dronekit
```

Code:

```
import boto3
```

```
import json
```

```
# Function to connect to Amazon S3
```

```
def connect_to_s3(aws_access_key_id, aws_secret_access_key, region_name):
```

```
    try:
```

```
        s3_client = boto3.client(
            's3',
            aws_access_key_id=aws_access_key_id,
            aws_secret_access_key=aws_secret_access_key,
            region_name=region_name
        )
```

```
        return s3_client
```

```
    except (NoCredentialsError, PartialCredentialsError):
```

```
        print("Credentials not available")
```

```
        return None
```

```
# Function to save data to Amazon S3
```

```

def save_data_to_s3(s3_client, bucket_name, file_name, data):
    s3_client.put_object(Bucket=bucket_name, Key=file_name, Body=json.dumps(data),
ServerSideEncryption='AES256')

# Main code
if __name__ == "__main__":
    aws_access_key_id = "your_access_key_id"
    aws_secret_access_key = "your_secret_access_key"
    region_name = "your_region"
    bucket_name = "your_bucket_name"
    data = {
        "timestamp": time.time(),
        "location": "latitude: {}, longitude: {}".format(latitude, longitude),
        "anomaly_detected": True, # or False, depending on your data
        "gpr_values": [100, 150, 200] # Sample GPR data
    }
    file_name = 'example_data.json'

# Connect to Amazon S3
s3_client = connect_to_s3(aws_access_key_id, aws_secret_access_key, region_name)
if s3_client:
    print("Connected to Amazon S3")

# Save data to Amazon S3
save_data_to_s3(s3_client, bucket_name, file_name, data)
print("Data saved to Amazon S3")

```

Explanation:

Connecting to Amazon S3: The boto3 library is used to create a client object for interacting with Amazon S3.

Saving data to Amazon S3: GPR data is saved as a JSON object to a specified bucket in Amazon S3.

Example GPR data: Replace the example data with your actual GPR data.

This code provides a basic framework for interacting with Amazon S3 in Python, allowing you to store GPR data in the cloud.

3.4. Cybersecurity

MongoDB Data Encryption

Data-at-Rest Encryption: Use server-side encryption in MongoDB to protect data while it's stored.

Data-in-Transit Encryption: Employ TLS/SSL to secure data while it's being transmitted between the client and the server.

Authentication and Authorization

Authentication: Require authentication for all users and services connecting to the database.

Authorization: Implement role-based access control (RBAC) to restrict data access based on user roles.

Monitoring and Audit

Audit Logs: Enable audit logs to track access and changes to the database.

Monitoring: Utilize monitoring tools to detect suspicious activities.

Protection Against Attacks

Defense Against DoS Attacks: Configure resource limitations and monitoring to prevent DoS attacks.

Network Security: Place MongoDB servers behind a firewall and restrict access only from trusted IP addresses.

Code:

```
from pymongo import MongoClient, encryption
```

```
from pymongo.encryption_options import AutoEncryptionOpts
```

```
# Функція для підключення до MongoDB з використанням шифрування і автентифікації
```

```
def connect_to_mongodb(uri, db_name, key_vault_namespace, kms_providers):
```

```
    client = MongoClient(uri, auto_encryption_opts=AutoEncryptionOpts(
```

```
kms_providers=kms_providers,  
key_vault_namespace=key_vault_namespace  
)  
db = client[db_name]  
return db
```

ОСНОВНИЙ КОД

```
if __name__ == "__main__":  
    mongodb_uri = "mongodb+srv://username:password@cluster.mongodb.net"  
    db_name = "drone_data"  
    key_vault_namespace = "encryption.__keyVault"  
    kms_providers = {  
        'aws': {  
            'accessKeyId': 'your_aws_access_key_id',  
            'secretAccessKey': 'your_aws_secret_access_key'  
        }  
    }
```

Підключення до MongoDB

```
db = connect_to_mongodb(mongodb_uri, db_name, key_vault_namespace,  
kms_providers)  
print("Connected to MongoDB with encryption and authentication")
```

MySQL Data Encryption

Data-at-Rest Encryption: Utilize Transparent Data Encryption (TDE) to encrypt data in MySQL.

Data-in-Transit Encryption: Enable TLS/SSL to protect data during transmission between the client and server.

Authentication and Authorization

Authentication: Use strong passwords and authentication for all users.

Authorization: Implement granular access control to restrict user access only to necessary data.

Monitoring and Audit

Audit Logs: Enable audit logs to track access and changes to the database.

Monitoring: Utilize monitoring tools to detect suspicious activities.

Protection Against Attacks

Defense Against DoS Attacks: Configure resource limitations and monitoring to prevent DoS attacks.

Network Security: Place MySQL servers behind a firewall and restrict access only from trusted IP addresses.

Code:

```
import mysql.connector
```

```
from mysql.connector import errorcode
```

```
# Функція для підключення до MySQL з використанням шифрування і  
автентифікації
```

```
def connect_to_mysql(host, user, password, database, ssl_ca):
```

```
    connection = mysql.connector.connect(
```

```
        host=host,
```

```
        user=user,
```

```
        password=password,
```

```
        database=database,
```

```
        ssl_ca=ssl_ca
```

```
    )
```

```
    return connection
```

```
# Основний код
```

```
if __name__ == "__main__":
```

```
    mysql_host = "localhost"
```

```
    mysql_user = "your_username"
```

```
    mysql_password = "your_password"
```

```
    mysql_database = "drone_data"
```

```
    ssl_ca = "/path/to/ca-cert.pem" # Шлях до сертифіката CA
```

```
# Підключення до MySQL
try:
    db_connection = connect_to_mysql(mysql_host, mysql_user, mysql_password,
mysql_database, ssl_ca)
    print("Connected to MySQL with encryption and authentication")
except mysql.connector.Error as err:
    if err.errno == errorcode.ER_ACCESS_DENIED_ERROR:
        print("Something is wrong with your user name or password")
    elif err.errno == errorcode.ER_BAD_DB_ERROR:
        print("Database does not exist")
    else:
        print(err)
else:
    db_connection.close()
```

Amazon S3 Data Encryption

Data-at-Rest Encryption: Use server-side encryption (SSE) or client-side encryption to protect data in S3.

Data-in-Transit Encryption: Enable TLS/SSL to protect data during transmission to and from S3.

Authentication and Authorization

Authentication: Utilize AWS Identity and Access Management (IAM) to manage access to S3.

Authorization: Configure IAM policies and S3 bucket policies to control access to data.

Monitoring and Audit

Access Logs: Use AWS CloudTrail to log access to S3 resources.

Monitoring: Utilize AWS CloudWatch to monitor activity and detect suspicious behavior.

Protection Against Attacks

Defense Against DoS Attacks: Use AWS Shield to protect against DoS attacks.

Network Security: Utilize Virtual Private Cloud (VPC) and configure access policies to protect S3 resources.

General Cybersecurity Measures for Drones Authentication and Encryption

Authentication: Use strong authentication methods to connect to drones.

Data-in-Transit Encryption: Employ TLS/SSL to secure commands and data transmitted between the drone and ground station.

Code:

```
import boto3
```

```
from botocore.exceptions import NoCredentialsError, PartialCredentialsError
```

```
# Функція для підключення до Amazon S3 з використанням шифрування і автентифікації
```

```
def connect_to_s3(aws_access_key_id, aws_secret_access_key, region_name):
```

```
    try:
```

```
        s3_client = boto3.client(
            's3',
            aws_access_key_id=aws_access_key_id,
            aws_secret_access_key=aws_secret_access_key,
            region_name=region_name
        )
```

```
        return s3_client
```

```
    except (NoCredentialsError, PartialCredentialsError):
```

```
        print("Credentials not available")
```

```
        return None
```

```
# Функція для збереження даних у Amazon S3 з використанням шифрування
```

```
def save_data_to_s3(s3_client, bucket_name, file_name, data):
```

```
    s3_client.put_object(Bucket=bucket_name, Key=file_name, Body=json.dumps(data),
ServerSideEncryption='AES256')
```

```
# Основний код
```

```
if __name__ == "__main__":
```

```
    aws_access_key_id = "your_access_key_id"
```

```
aws_secret_access_key = "your_secret_access_key"
region_name = "your_region"
bucket_name = "your_bucket_name"
data = {
    "example_key": "example_value"
}
file_name = 'example_data.json'

# Підключення до Amazon S3
s3_client = connect_to_s3(aws_access_key_id, aws_secret_access_key, region_name)
if s3_client:
    print("Connected to Amazon S3 with encryption and authentication")

# Збереження даних у Amazon S3
save_data_to_s3(s3_client, bucket_name, file_name, data)
print("Data saved to Amazon S3 with encryption")
```

Intrusion Prevention

Protection Against Unauthorized Access: Utilize firewalls and VPNs to restrict access to the drone.

Intrusion Detection: Implement intrusion detection systems (IDS) to monitor network activity and detect suspicious behavior.

Recovery After Failures

Disaster Recovery Plan: Develop and test a disaster recovery plan for quickly restoring drone operation in case of incidents.

Software Updates

Firmware Updates: Regularly update drone firmware to address vulnerabilities.

Software Updates: Ensure timely updates of ground station software and other system components.

Implementing these cybersecurity measures will help protect data and ensure the safe operation of drones and databases.

Code:

```
from dronekit import connect, VehicleMode
import ssl

# Функція для підключення до безпілота з використанням TLS/SSL
def connect_to_drone(connection_string, ssl_context):
    vehicle = connect(connection_string, wait_ready=True, ssl=ssl_context)
    return vehicle

# Основний код
if __name__ == "__main__":
    drone_connection_string = '127.0.0.1:14550'
    ssl_context = ssl.create_default_context(purpose=ssl.Purpose.CLIENT_AUTH)
    ssl_context.load_cert_chain(certfile='path/to/certfile', keyfile='path/to/keyfile')

    # Підключення до безпілота
    vehicle = connect_to_drone(drone_connection_string, ssl_context)
    print("Connected to drone with TLS/SSL")
    vehicle.close()
```

This Python code snippet establishes a connection to a drone using TLS/SSL protocol. Here's a breakdown of the code:

The code imports the necessary modules:

- `from dronekit import connect, VehicleMode`: Imports the `connect` function and `VehicleMode` class from the DroneKit library.
- `import ssl`: Imports the SSL module for handling secure connections.

Defines a function `connect_to_drone(connection_string, ssl_context)`:

- This function takes a connection string and an SSL context as input parameters.
- It uses the `connect` function from DroneKit to connect to the drone with the specified connection string and SSL context.
- Returns the connected vehicle object.

In the main block (if `__name__ == "__main__":`), the following steps are performed:

- Sets the drone connection string to '127.0.0.1:14550'.
- Creates an SSL context using `ssl.create_default_context()` with the purpose set to `ssl.Purpose.CLIENT_AUTH`.
- Loads the certificate chain and keyfile for SSL/TLS communication.

Connects to the drone using the `connect_to_drone()` function with the drone connection string and SSL context as arguments.

- Prints a message confirming the successful connection.
- Closes the connection to the drone.

Overall, the code establishes a secure connection to a drone using TLS/SSL protocol by creating an SSL context, loading the necessary certificates, and connecting to the drone using the provided connection string.

CONCLUSIONS

In conclusion, the analysis of SAR data processing systems and methodologies reveals the significant potential of SAR observations in various applications, particularly in environmental monitoring. The integration of SAR data with other sources of information, such as ground penetrating radar and GPS navigation, opens up new possibilities for enhanced data interpretation and decision-making.

The development of advanced data representations, change detection methods, and multi-temporal analysis techniques has shown promising results in extracting valuable information from SAR data. By bridging the gap between raw measurements and user-relevant parameters, SAR data processing systems can provide actionable insights for a wide range of applications, from urbanization mapping to disaster recovery.

Moving forward, continued research and innovation in SAR data processing will be crucial to unlocking the full capabilities of this technology and maximizing its impact on environmental monitoring and other domains. Collaborative efforts between researchers, scientists, and industry professionals will be essential in driving the evolution of SAR data processing systems towards more efficient, user-friendly, and impactful solutions.

LITERATURE

1. Campbell, J.B.; Wynne, R.H. *Introduction to Remote Sensing*; The Guilford Press: New York, NY, USA, 2011.
2. Moreira, A.; Prats-Iraola, P.; Younis, M.; Krieger, G.; Hajnsek, I.; Papathanassiou, K.P. A tutorial on synthetic aperture radar. *IEEE Geosci. Remote Sens. Mag.* 2013, 1, 6–43.
3. Srivastava, P.K.; Malhi, R.K.M.; Pandey, P.C.; Akash Anand, P.; Singh, M.K.; Pandey, A.G. Revisiting hyperspectral remote sensing: Origin, processing, applications and way forward. In *Hyperspectral Remote Sensing*; Pandey, P.C., Srivastava, P.K., Balzter, H., Bhattacharya, B., Petropoulos, G.P., Eds.; Elsevier: Amsterdam, The Netherlands, 2020; pp. 3–21.
4. Giardino, C.; Bresciani, M.; Braga, F.; Fabbretto, A.; Ghirardi, N.; Pepe, M.; Gianinetto, M.; Colombo, R.; Cogliati, S.; Ghebrehiwot, S.; et al. First Evaluation of PRISMA Level 1 Data for Water Applications. *Sensors* 2020, 20, 4553.
5. Amitrano, D.; Di Martino, G.; Iodice, A.; Riccio, D.; Ruello, G. A New Framework for SAR Multitemporal Data RGB Representation: Rationale and Products. *IEEE Trans. Geosci. Remote Sens.* 2015, 53, 117–133.
6. McFeeters, S.K. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *Int. J. Remote Sens.* 1996, 17, 1425–1432.
7. Carlson, T.C.; Ripley, D.A. On the relationship between NDVI, fractional vegetation cover, and leaf area index. *Remote Sens. Environ.* 1997, 62, 241–252.
8. Di Martino, G.; Iodice, A. *Maritime Surveillance with Synthetic Aperture Radar*; IET Digital Library: London, UK, 2020; Available online: <https://shop.theiet.org/maritime-surveillance-with-synthetic-aperture-radar> (accessed on 1 February 2020).
9. Lanari, R.; Mora, O.; Manunta, M.; Mallorqui, J.; Berardino, P.; Sansosti, E. A small-baseline approach for investigating deformations on full-resolution differential SAR interferograms. *IEEE Trans. Geosci. Remote Sens.* 2004, 42, 1377–1386.
10. Taubenböck, H.; Esch, T.; Felbier, A.; Wiesner, M.; Roth, A.; Dech, S. Monitoring urbanization in mega cities from space. *Remote Sens. Environ.* 2012, 117, 162–176.
11. Cecinati, F.; Amitrano, D.; Leoncio, L.B.; Walugendo, E.; Guida, R.; Iervolino, P.; Natarajan, S. Exploitation of ESA and NASA Heritage Remote Sensing Data for Monitoring the Heat Island Evolution in Chennai with the Google Earth Engine. In *Proceedings of the IEEE*

Geoscience and Remote Sensing Symposium, Yokohama, Japan, 28 July–2 August 2019; pp. 6328–6331.

12. Ban, Y.; Jacob, A. Fusion of Multitemporal Spaceborne SAR and Optical Data for Urban Mapping and Urbanization Monitoring. In *Multitemporal Remote Sensing. Remote Sensing and Digital Image Processing*; Ban, Y., Ed.; Springer: Berlin/Heidelberg, Germany, 2016; Volume 20, ISBN 978-3-319-47035-1.

13. Bargiel, D.; Herrmann, S. Multi-temporal land-cover classification of agricultural areas in two European regions with high resolution spotlight TerraSAR-X data. *Remote Sens.* 2011, 3, 859–877.

14. Kayabol, K.; Zerubia, J. Unsupervised amplitude and texture classification of SAR images with multinomial latent model. *IEEE Trans. Image Process.* 2013, 22, 561–572.

15. Amitrano, D.; Cecinati, F.; Di Martino, G.; Iodice, A.; Mathieu, P.-P.P.-P.; Riccio, D.; Ruello, G. Multitemporal Level-1 β Products: Definitions, Interpretation, and Applications. *IEEE Trans. Geosci. Remote Sens.* 2016, 54, 6545–6562.

16. Di Martire, D.; Paci, M.; Confuorto, P.; Costabile, S.; Guastaferro, F.; Verta, A.; Calcaterra, D. A nation-wide system for landslide mapping and risk management in Italy: The second Not-ordinary Plan of Environmental Remote Sensing. *Int. J. Appl. Earth Obs. Geoinf.* 2017, 63, 143–157.

17. Di Martire, D.; Iglesias, R.; Monells, D.; Centolanza, G.; Sica, S.; Ramondini, M.; Pagano, L.; Mallorqui, J.; Calcaterra, D. Comparison between Differential SAR interferometry and ground measurements data in the displacement monitoring of the earth-dam of Conza della Campania (Italy). *Remote Sens. Environ.* 2014, 148, 58–69.

18. Tapete, D.; Cigna, F. InSAR data for geohazard assessment in UNESCO World Heritage sites: State-of-the-art and perspectives in the Copernicus era. *Int. J. Appl. Earth Obs. Geoinf.* 2017, 63, 24–32.

19. Strozzi, T.; Luckman, A.; Murray, T.; Wegmüller, U.; Werner, C.L. Glacier motion estimation using SAR offset-tracking procedures. *IEEE Trans. Geosci. Remote Sens.* 2002, 40, 2384–2391.

20. Amitrano, D.; Guida, R.; Di Martino, G.; Iodice, A. Glacier monitoring using frequency domain offset tracking applied to sentinel-1 images: A product performance comparison. *Remote Sens.* 2019, 11, 1322.
21. Amitrano, D.; Guida, R.; Dell'Aglio, D.; Di Martino, G.; Di Martire, D.; Iodice, A.; Costantini, M.; Malvarosa, F.; Minati, F. Long-Term Satellite Monitoring of the Slumgullion Landslide Using Space-Borne Synthetic Aperture Radar Sub-Pixel Offset Tracking. *Remote Sens.* 2019, 11, 369.
22. Datcu, M.; Seidel, K. Human-Centered Concepts for Exploration and Understanding of Earth Observation Images. *IEEE Trans. Geosci. Remote Sens.* 2005, 43, 601–609. [CrossRef]
23. Madhok, V.; Landgrebe, D.A. A Process Model for Remote Sensing Data Analysis. *IEEE Trans. Geosci. Remote Sens.* 2002, 40, 680–686.
24. Amitrano, D.; Guida, R.; Ruello, G. Multitemporal SAR RGB Processing for Sentinel-1 GRD Products: Methodology and Applications. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 2019, 12, 1497–1507.
25. Mendel, J.M. Fuzzy Logic Systems for Engineering: A Tutorial. *Proc. IEEE* 1995, 83, 345–377.
26. Santini, S.; Gupta, A.; Jain, R. Emergent semantics through interaction in image databases. *IEEE Trans. Knowl. Data Eng.* 2001, 13, 337–351.
27. Atkin, A. Peirce's Theory of Signs; Zalta, E.N., Ed.; *The Stanford Encyclopedia of Philosophy*: Stanford, CA, USA, 2013; Available online: <https://plato.stanford.edu/> (accessed on 2 March 2020).
28. Marr, D. *Vision*; W. H. Freeman: San Francisco, CA, USA, 1982.
29. Esch, T.; Thiel, M.; Schenk, A.; Roth, A.; Muller, A. Delineation of Urban Footprints From TerraSAR-X Data by Analyzing Speckle Characteristics and Intensity Information. *IEEE Trans. Geosci. Remote Sens.* 2003, 48, 905–916.
30. Freeman, A. SAR Calibration: An Overview. *IEEE Trans. Geosci. Remote Sens.* 1992, 30, 1107–1121.
31. Italian Space Agency. COSMO-SkyMed Mission and Products Description; IEEE: New York, NY, USA, 2019.

32. Infoterra Radiometric Calibration of TerraSAR-X Data. 2008. Available online: https://www.asi.it/wp-content/uploads/2019/08/COSMO-SkyMed-Mission-and-Products-Description_rev3-2.pdf (accessed on 1 June 2020).
33. Torre, A.; Calabrese, D.; Porfilio, M. COSMO-SkyMed: Image quality achievements. In Proceedings of the 5th International Conference on Recent Advances in Space Technologies—RAST2011, Istanbul, Turkey, 9–11 June 2011; pp. 861–864.
34. Schwerdt, M.; Schmidt, K.; Ramon, N.T.; Klenk, P.; Yague-Martinez, N.; Prats-Iraola, P.; Zink, M.; Geudtner, D. Independent system calibration of Sentinel-1B. *Remote Sens.* 2017, 9, 511.
35. Franceschetti, G.; Lanari, R. *Synthetic Aperture Radar Processing*; CRC Press: Boca Raton, FL, USA, 1999.
36. Di Martino, G.; Poderico, M.; Poggi, G.; Riccio, D.; Verdoliva, L. Benchmarking Framework for SAR Despeckling. *IEEE Trans. Geosci. Remote Sens.* 2014, 52, 1596–1615.
37. De Grandi, G.F.; Leysen, M.; Lee, J.S.; Schuler, D. Radar reflectivity estimation using multiple SAR scenes of the same target: Technique and applications. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, San Diego, CA, USA, 27 July–1 August 1997; pp. 1047–1050.
38. Yu, Y.; Acton, S.T. Speckle Reducing Anisotropic Diffusion. *IEEE Trans. Image Process.* 2002, 11, 1260–1270.
39. Su, X.; Deledalle, C.; Tupin, F.; Sun, H. Two-Step Multitemporal Nonlocal Means for Synthetic Aperture Radar Images. *IEEE Trans. Geosci. Remote Sens.* 2014, 52, 6181–6196.
40. Cozzolino, D.; Verdoliva, L.; Scarpa, G.; Poggi, G. Nonlocal SAR Image Despeckling by Convolutional Neural Networks. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 28 July–2 August 2019; pp. 5117–5120.
41. Wang, P.; Zhang, H.; Patel, V.M. SAR Image Despeckling Using a Convolutional Neural Network. *IEEE Signal Process. Lett.* 2017, 24, 1763–1767.
42. Cao, X.; Ji, Y.; Wang, L.; Ji, B.; Jiao, L.; Han, J. SAR image change detection based on deep denoising and CNN. *IET Image Process.* 2019, 13, 1509–1515.

43. Ferraioli, G.; Pascazio, V.; Vitale, S. A Novel Cost Function for Despeckling using Convolutional Neural Networks. In Proceedings of the 2019 Joint Urban Remote Sensing Event (JURSE), Vannes, France, 22–24 May 2019.
44. Singh, A. Digital change detection techniques using remotely-sensed data. *Int. J. Remote Sens.* 1989, 10, 989–1003.
45. Lu, D.; Mausel, P.; Brondízio, E.; Moran, E. Change detection techniques. *Int. J. Remote Sens.* 2004, 25, 2365–2407.
46. Lee, J.S.; Jurkevich, I. Segmentation of SAR images. *IEEE Trans. Geosci. Remote Sens.* 1989, 27, 674–680.
47. Bruzzone, L.; Prieto, D.F. Automatic analysis of the difference image for unsupervised change detection. *IEEE Trans. Geosci. Remote Sens.* 2000, 38, 1171–1182.
48. Bovolo, F.; Bruzzone, L. The Time Variable in Data Fusion: A Change Detection Perspective. *IEEE Geosci. Remote Sens. Mag.* 2015, 3, 8–26.
49. Rignot, E.J.M.; Zyl, J.J. Change Detection Techniques for ERS-1 SAR Data. *IEEE Trans. Geosci. Remote Sens.* 1993, 31, 896–906.
50. Bazi, Y.; Bruzzone, L.; Melgani, F. An Unsupervised Approach Based on the Generalized Gaussian Model to Automatic Change Detection in Multitemporal SAR Images. *IEEE Trans. Geosci. Remote Sens.* 2005, 43, 874–887.
51. Grover, K.; Quegan, S.; Da Costa Freitas, C. Quantitative estimation of tropical forest cover by SAR. *IEEE Trans. Geosci. Remote Sens.* 1999, 37, 479–490.
52. Bovolo, F.; Bruzzone, L. A Detail-Preserving Scale-Driven Approach to Change Detection in Multitemporal SAR Images. *IEEE Trans. Geosci. Remote Sens.* 2005, 43, 2963–2972.
53. Amitrano, D.; Di Martino, G.; Iodice, A.; Riccio, D.; Ruello, G. Small Reservoirs Extraction in Semiarid Regions Using Multitemporal Synthetic Aperture Radar Images. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 2017, 10, 3482–3492.
54. Cian, F.; Marconcini, M.; Ceccato, P. Normalized Difference Flood Index for rapid flood mapping: Taking advantage of EO big data. *Remote Sens. Environ.* 2018, 209, 712–730.

55. Inglada, J.; Mercier, G. A New Statistical Similarity Measure for Change Detection in Multitemporal SAR Images and Its Extension to Multiscale Change Analysis. *IEEE Trans. Geosci. Remote Sens.* 2007, 45, 1432–1445.
56. Aiazzi, B.; Alparone, L.; Baronti, S.; Garzelli, A.; Zoppetti, C. Nonparametric Change Detection in Multitemporal SAR Images Based on Mean-Shift Clustering. *IEEE Trans. Geosci. Remote Sens.* 2013, 51, 2022–2031.
57. Lombardo, P.; Oliver, C.J. Maximum likelihood approach to the detection of changes between multitemporal SAR images. *IEE Proc. Radar Sonar Navig.* 2001, 148, 200–210.
58. Xiong, B.; Chen, J.M.; Kuang, G. A change detection measure based on a likelihood ratio and statistical properties of SAR intensity images. *Remote Sens. Lett.* 2012, 3, 267–275.
59. Su, X.; Deledalle, C.; Tupin, F.; Sun, H. NORCAMA: Change Analysis in SAR Time Series by Likelihood Ratio Change Matrix Clustering. *ISPRS J. Photogramm. Remote Sens.* 2015, 101, 247–261.