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AN INTELLIGENT MOBILE SEARCH SYSTEM

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Abstract**—***This article is devoted to the development of an intelligent mobile system used for humanitarian demining. At the same time, the problems of detection, localization and storage of the obtained data are solved. The system operation is based on the use of a synthetic aperture ground penetrating radar, which makes it possible to detect mines both on the earth's surface and underground. A quadcopter is used as a carrier. A set of technical means has been developed. The central and graphic processors are used as a processing unit. Intelligent elements for processing the obtained data are convolutional neural networks, for machine learning of which a synthetic dataset was used. The data is organized into S3 segments based on various parameters, such as date, location and sensor type. This organization facilitates data retrieval and management. Data is encrypted both during transmission and at rest using AWS Key Management Service to ensure confidentiality.*

Index Terms—Synthetic aperture ground penetrating radar; humanitarian demining; quadcopter; convolutional neural networks; data detection; localization and storage tasks.

I. 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 toward future advancements in remote sensing technology and data-informed decision-making.

II. SUBSYSTEMS FOR DETERMINING AND SAVING G-INFORMATION DATA

This subsystem is a critical component of the intelligent mobile search system, designed to accurately determine and save geolocation data (G-information) related to the detection of explosive devices [1]. The subsystem integrates multiple technologies and processes to ensure precise data collection, processing, and storage.

A. Data Collection

Synthetic Aperture Radar (SAR) (Fig. 1).

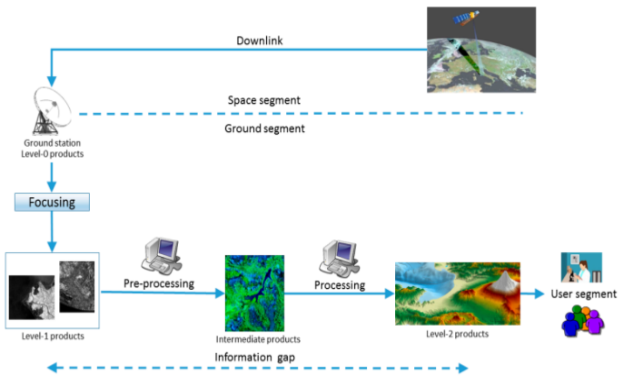

Fig. 1. Structure scheme of SAR

High-Resolution Imaging: SAR uses radio waves to create detailed images of the Earth's surface. It synthesizes a large aperture from multiple measurements, allowing for high-resolution imaging regardless of weather conditions.

Surface and Near-Surface Detection: Ideal for detecting anomalies on the surface and just below the surface. SAR can penetrate through vegetation, soil, and other non-metallic objects, making it effective in diverse environments.

Frequency Bands: Different frequency bands (e.g., X-band, C-band, L-band) are used to optimize detection capabilities based on the target and environmental conditions.

Ground Penetrating Radar (GPR)

Subsurface Exploration: GPR employs electromagnetic waves to detect objects buried beneath the ground. It can identify underground structures and objects at various depths.

Material Differentiation: Capable of distinguishing between different materials based on their dielectric properties, which is crucial for identifying explosive devices hidden underground.

Depth Penetration: The depth of penetration varies with frequency; lower frequencies penetrate deeper but offer lower resolution, while higher frequencies provide better resolution but shallower penetration.

GPS Integration

Precise Location Tagging: GPS data is used to geotag detected anomalies, providing accurate location information. This is essential for mapping and revisiting detected objects [2].

Real-Time Tracking: Ensures continuous tracking of both the mobile platform and the detected explosive devices, aiding in the coordination of response efforts.

B. Data Processing

Anomaly Detection Algorithms

Machine Learning Models: Utilizes supervised and unsupervised learning algorithms to identify patterns and anomalies in the radar data. Training datasets include various known explosive device signatures and environmental backgrounds.

Real-Time Analysis: Processes data in real-time to detect potential threats immediately, allowing for prompt action.

Multi-Sensor Fusion: Combines data from SAR and GPR sensors to improve detection accuracy and reduce false positives. The fusion process considers the strengths of each sensor type to provide a comprehensive analysis.

Signal Processing Techniques

Filtering and Noise Reduction: Employs advanced filtering techniques to eliminate noise and enhance signal quality. This includes adaptive filtering, wavelet transforms, and other methods to extract relevant features [3].

Image Reconstruction: SAR and GPR data are processed to reconstruct high-quality images, highlighting potential explosive devices. Techniques like back-projection and Fourier transforms are used to achieve this (Fig. 2).

Fig. 2. Example of 3D simulation result

Feature Extraction: Key features such as shape, size, and material properties are extracted from the radar images to aid in identifying explosive devices.

C. Data Storage and Management

Amazon S3 Integration

Scalability: Amazon Simple Storage Service (S3) offers scalable storage solutions to handle the large volumes of data generated by SAR and GPR sensors. S3's scalability ensures that data storage can grow as needed without compromising performance.

High Availability: S3's robust infrastructure guarantees high data availability, ensuring that stored information is always accessible for analysis and retrieval.

Data Redundancy: Amazon S3 replicates data across multiple locations to prevent data loss and ensure durability. This redundancy is crucial for maintaining the integrity of critical detection data [4].

D. Data Security

Encryption: All data stored in Amazon S3 is encrypted both in transit and at rest using AWS Key Management Service (KMS). This ensures that sensitive data related to explosive device detection is protected from unauthorized access.

Access Control: Implements stringent access control policies using AWS Identity and Access Management (IAM). Access to the stored data is restricted to authorized personnel only, ensuring data security and compliance with regulatory standards.

Audit Logs: Maintains detailed logs of all data access and modifications, enabling traceability and accountability.

E. Data Management Practices

Automated Data Upload: The system automatically uploads collected radar and GPS data to Amazon S3 in real-time or at scheduled intervals. This ensures that the data is promptly available for analysis.

Bucket Organization: Data is organized into S3 buckets based on parameters such as collection date, location, and sensor type. This organization facilitates easy retrieval and management of the data [5].

Lifecycle Policies: Implements lifecycle policies to manage data storage costs and ensure compliance with data retention requirements. These policies automatically transition data between different storage classes and delete data that is no longer needed.

By integrating advanced radar technologies, GPS, and secure data storage solutions, the subsystem for determining and saving G-information data significantly enhances the capabilities of the intelligent mobile search system. This comprehensive approach ensures accurate detection, precise location tagging, and secure management of data related to explosive devices.

III. STRUCTURE OF SYSTEM FOR DETERMINING THE POSITION OF EXPLOSIVE DEVICES

The structure of the intelligent mobile search system for determining the position of explosive devices is designed to integrate various hardware and software components seamlessly. This integration ensures accurate detection, precise localization, and effective response to potential threats.

A. Hardware Components

Radar Sensors

Synthetic Aperture Radar (SAR): SAR sensors are mounted on mobile platforms such as unmanned aerial vehicles (UAVs), ground vehicles, or handheld devices. These sensors collect high-resolution images of the surface and near-surface areas to detect anomalies that may indicate the presence of explosive devices [6].

Ground Penetrating Radar (GPR): GPR sensors are also mounted on mobile platforms, providing subsurface exploration capabilities. These sensors emit electromagnetic waves and analyze the reflected signals to identify buried objects.

GPS Receivers

High-Precision GPS: The system uses high-precision GPS receivers to provide accurate geolocation data. This ensures that the position of detected anomalies can be precisely mapped and recorded [7].

Real-Time Tracking: GPS receivers enable real-time tracking of the mobile platform and the detected objects, facilitating efficient coordination during search and detection operations.

Mobile Platforms

Unmanned Aerial Vehicles (UAVs): UAVs equipped with SAR and GPR sensors provide aerial surveillance and detection capabilities. They can cover large areas quickly and access difficult-to-reach locations.

Ground Vehicles: Ground vehicles equipped with radar sensors and GPS receivers are used for detailed exploration of specific areas. They offer stability and can carry heavier sensor payloads.

Handheld Devices: Portable handheld devices with integrated radar sensors and GPS are used for on-the-ground inspection and confirmation of detected anomalies.

B. Software Components

Data Processing Unit

Central Processing Unit (CPU): The CPU is the core component that handles all data processing tasks. It integrates sensor data, processes geolocation information, and runs machine learning algorithms to analyze the collected data in real-time.

Graphics Processing Unit (GPU): For intensive computational tasks such as image processing and machine learning, GPUs are used to accelerate data processing and improve system performance.

Machine Learning Algorithms

Anomaly Detection: Machine learning models are trained to identify patterns and anomalies in the radar data. These models use historical data and known signatures of explosive devices to improve detection accuracy.

Data Fusion: Algorithms are employed to fuse data from multiple sensors (SAR, GPR, GPS) to provide a comprehensive analysis. Data fusion enhances detection reliability by combining the strengths of each sensor type.

User Interface (UI)

Real-Time Visualization: The UI provides real-time visualization of the collected data, displaying high-resolution images and geolocation information. Detected anomalies are highlighted on a map, allowing operators to quickly assess the situation.

Interactive Controls: The UI includes interactive controls for operators to initiate searches, adjust sensor parameters, and review detected anomalies. This user-friendly interface ensures that operators can efficiently manage the detection process.

C. Communication and Data Transfer

Wireless Communication Modules

Secure Data Transmission: Wireless communication modules ensure real-time data transfer between the mobile platform and the ground control station. Secure communication protocols (e.g., SSL/TLS) are used to protect data integrity and confidentiality [8].

Low-Latency Networks: The system utilizes low-latency communication networks to minimize delays in data transmission, ensuring timely processing and response.

Ground Control Station

Data Aggregation: The ground control station aggregates data from multiple mobile platforms, providing a centralized view of the detection operations. This centralized approach facilitates coordinated responses and comprehensive analysis.

Command and Control: Operators at the ground control station can remotely control the mobile platforms, adjust sensor settings, and manage data collection processes. This remote control capability enhances operational flexibility and safety.

D. System Workflow

Initiation of Search Operation

Deployment of Mobile Platforms: Mobile platforms (UAVs, ground vehicles, handheld devices) are deployed to the target area. Operators initiate the search operation through the user interface.

Sensor Activation: Radar sensors (SAR, GPR) and GPS receivers are activated to start collecting data. The system continuously monitors the environment and collects geolocation data.

Data Collection and Processing

Real-Time Data Analysis: Collected data is transmitted to the data processing unit, where it is analyzed in real-time using machine learning algorithms and signal processing techniques. Anomalies indicating potential explosive devices are identified and geotagged [9].

Data Fusion and Validation: Data from different sensors is fused to validate detected anomalies. This multi-sensor approach reduces false positives and increases detection reliability.

Alert Generation and Response

Automatic Alerts: When an anomaly is detected, the system generates automatic alerts, providing detailed information about the location, size, and type of the detected object. Alerts are displayed on the user interface.

Operator Review and Action: Operators review the detected anomalies and decide on the appropriate response. This may include deploying additional resources for further inspection or immediate action to neutralize the threat [10].

Data Storage and Management

Data Upload to Amazon S3: Processed data, including radar images and geolocation information, is automatically uploaded to Amazon S3 for secure storage. The data is organized and indexed for easy retrieval.

Long-Term Data Management: Lifecycle policies and access controls are applied to manage data retention and ensure compliance with regulatory requirements. Stored data can be accessed for post-operation analysis and reporting.

By integrating advanced radar technologies, precise GPS tracking, and robust data processing and storage solutions, the system for determining the position of explosive devices offers a comprehensive and reliable approach to explosive detection and response. This structured integration of hardware and software components ensures that the system operates efficiently, providing accurate and timely information to enhance safety and decision-making processes.

IV. STRUCTURE OF DATA SAVING SUBSYSTEM

This subsystem focuses on the secure and efficient storage of collected data using Amazon S3 (Fig. 3).

Data Ingestion

Automated Data Upload: The system automatically uploads collected radar and GPS data to Amazon S3. This process is initiated once the data is collected and processed, ensuring minimal delay in data availability [11].

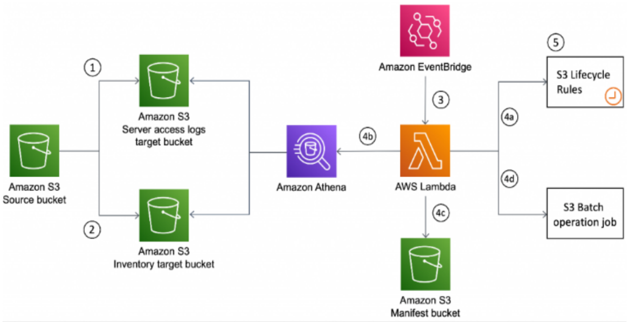

Fig. 3. Structure scheme of AWS

Data Storage

Bucket Organization: Data is organized into S3 buckets based on various parameters such as date, location, and sensor type. This organization facilitates easy retrieval and management of the data.

Data Redundancy and Backup: Amazon S3's built-in redundancy ensures that data is replicated across multiple locations, providing high availability and protection against data loss [12].

Data Security

Access Control: Implements strict access control policies using AWS Identity and Access Management (IAM). Only authorized users can access the stored data (Fig. 4).

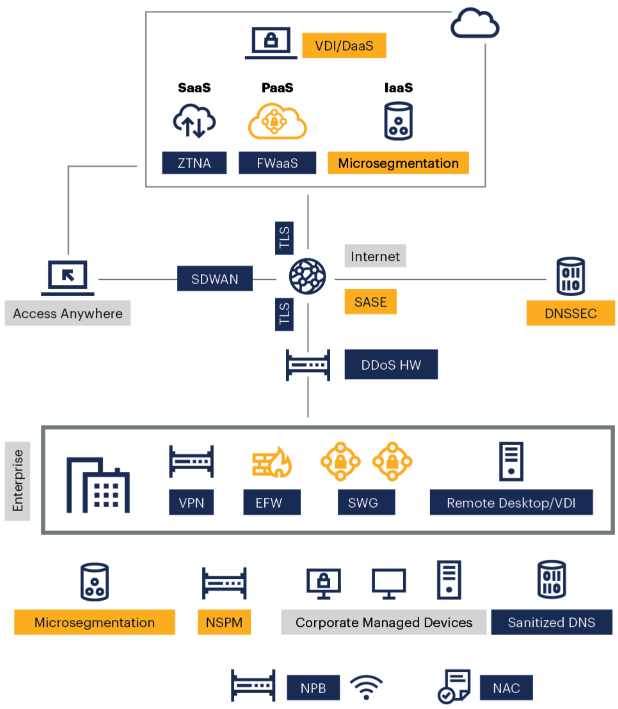

Fig. 4. Security structure

Encryption: Data is encrypted both in transit and at rest using AWS Key Management Service (KMS) to ensure data confidentiality. [13]

V. Database Development

The development of the database involves setting up a robust structure on Amazon S3 to manage the collected data efficiently.

Schema Design

Metadata Storage: Includes storing metadata for each dataset, such as collection time, sensor details, and location coordinates. This metadata helps in quick identification and retrieval of relevant data.

Data Indexing: Implements indexing strategies to optimize data search and retrieval operations. Indexes are created based on key parameters such as location and anomaly type [14].

Integration with Data Processing Tools

ETL Processes: Extract, Transform, Load (ETL) processes are used to integrate data from various sources into the Amazon S3 database. These processes ensure that the data is cleaned, transformed, and loaded into the database in a structured format [15].

Machine Learning Integration: The stored data is integrated with machine learning framework.

VI. Conclusions

Thus, the use of deep reinforcement learning provides new opportunities for effective automated control, especially in the face of changing operating conditions. The introduction of a reinforcement learning correction component in stabilisation systems opens up new horizons for the development of automated control systems, providing optimal parameters in the face of uncertainty and dynamic changes.

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В. М. Синєглазов, М. А. Коваль. Інтелектуальна мобільна пошукова система

Статтю присвячено розробленню інтелектуальної мобільної системи, яка використовується для гуманітарного розмінування. При цьому вирішуються завдання виявлення, локалізації та зберігання отриманих даних. Робота системи базується на використанні георадару із синтезованою апертурою, що дає можливість виявляти міни як на поверхні землі, так і під землею. Як носій використовується квадрокоптер. Розроблено комплекс технічних засобів. Як блок обробки використовується центральний і графічний процесори. Інтелектуальними елементами обробки даних є згорткові нейронні мережі, для машинного навчання яких використовувався синтетичний набір даних. Дані організовані в сегменти S3 на основі різних параметрів, таких як дата, місцезнаходження та тип датчика. Така організація полегшує пошук даних і керування ними. Дані шифруються як під час передачі, так і в стані спокою за допомогою AWS Key Management Service для забезпечення конфіденційності.

Ключові слова: георадар із синтезованою апертурою; гуманітарне розмінування; квадрокоптер; згорткові нейронні мережі; завдання виявлення; локалізації та зберігання даних.

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