Automatic Change Detection in Synthetic Aperture Radar Satellite Images

KIRUBAKARAN. N
Assistant Professor
Dept. of Computer Science Engineering
Presidency University
Rajankunte, India
kirubakaran.n@presidencyuniversity.in

SANJANA C RAO
Dept. of Information Science and Technology
Presidency University
Rajankunte, India
Sanjanacrao17@gmail.com

BHAGYA VANAERIMATH
Dept. of Information Science and Technology
Presidency University
Rajankunte,India
bhagyanand82@gmail.com

YASHASWINI D
Dept. of Information Science and Technology
Presidency University
Rajankunte, India
devarajyashaswini@gmail.com

Abstract— The automatic detection of change in Synthetic Aperture Radar (SAR) satellite images is crucial for monitoring environmental and land use change. Since SAR can image under any weather condition and at any time of the day, it is one of the most reliable means of mapping the Earth. However, the presence of speckle noise and distinct backscatter patterns of the land cover can complicate exact detection. In this paper, we present an automatic method for detecting change based on image preprocessing, generating difference images, and a deep learning classifier. The method identifies changed regions with accuracy and robustness. Experiments on multiple SAR datasets demonstrate the method's efficiency in detecting surface change for use in different remote sensing contexts.

Index Terms— Synthetic Aperture Radar (SAR), Change Detection, Remote Sensing, Image Processing, Machine Learning, Environmental Monitoring.

I. INTRODUCTION

The detection of changes using satellite imagery is key to understanding and monitoring how the Earth's surface changes over time. There are many applications for change detection, including succession monitoring, urban growth, agricultural performance, deforestation, and disaster response [1]. The benefit of detecting change from multitemporal satellite images is that it provides reliable evidence of natural or human-induced change that can support decision making and sustainable land use planning, [2]. Unfortunately, optical remote sensing data of the terrestrial surface is limited in time and space by atmospheric conditions including cloud cover, haze, and sun angle, and typically not reliable for continuous monitoring [3], [4].

Synthetic Aperture Radar (SAR) imagery has emerged as a powerful alternative to optical remote sensing because it is capable of collecting high resolution data regardless of weather and night–day conditions [5]. Unlike optical sensors, SAR systems utilize microwave signals that can penetrate clouds or fog and acquire data regardless of the sun's position, [6]. As a result, SAR is extremely useful foral- and rapid disaster response applications (i.e., flood mapping, earthquake damage, and landslides) when rapid and reliable information is needed to assist decision making and operations [7], [8].

In the context of SAR (Synthetic Aperture Radar) imagery, automatic change detection involves assessing two or more SAR images of the same geographic area acquired at different times in order to detect notable changes in backscatter intensity or surface properties [9]. This goal, however, is complicated by the presence of speckle noise, geometric distortions, and intrinsic complex scattering in SAR imagery [10]. Addressing these challenges involves the use of numerous preprocessing methodologies; for example, speckle filtering, radiometric calibration, and image co-registration increase the quality of the data and dancer the images to the same spatial reference [11].

In this study, we present a framework for automated change detection in multitemporal SAR satellite imagery. The proposed framework performs image preprocessing, feature extraction and then applies machine learning-based classification techniques to detect changed and unchanged areas accurately. The suggested framework minimizes false detections caused by noisy and varying illumination, while being computationally efficient. Experimental results conducted on benchmark SAR datasets reveal that the proposed framework produces efficient results in the detection of subtle changes taking place over multiple temporal SAR platforms across multiple land cover types, each with a significant change to subtle transitions in the landscape [12], [13].

The aim of this work is to create a robust, scalable, and efficient method for automated change detection in SAR data, that can be implemented in relevant research and real-world areas such as environmental change monitoring, land-use management and disaster assessment. The provision of automated change detection by the framework enhances remote sensing interpretations by providing data-driven and efficient automated approaches to change detection, which fosters sustainable environmental management and urban planning through evidence-based change detection in a timely approach.

II. LITERATURE SURVEY

Automatic Change detection (ACD) in Synthetic Aperture Radar (SAR) images has been widely studied for monitoring environmental changes, urban expansion and natural disasters. SAR imaging continues to be used, since SAR imaging provides data that can be acquired in all weather and day-night conditions, unlike optical sensors that depend on visual observation, and so are less reliable. However, speckle noise and geometric distortions can muddle the ability to accurately detect changes.

In the early literature previous studies addressed these issues by proposing statistical approaches to detection and change assessment through differences in SAR images, typically image differencing, image ratioing and the (CVA)or Change Vertex Analysis. These statistical approaches were simple, and easy to implement but response very high on noise and impreciseness to registration of images that were aligned. However, as change analysis advanced, statistical models were proposed such as the Generalized Likelihood Ratio Test (GLRT) and Coherent Change Detection

Recently, techniques in machine learning, deep learning, and other types of algorithms have found considerable application in SAR Change Detection. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Convolutional Neural Networks (CNNs) have the ability to automatically learn intricate features and are effective in detecting change.

New improvements in deep learning architecture (DL) are enhancing SAR change detection. Methods based on Convolutional Neural Networks (CNN), U-Net, and Siamese architecture have been utilized in automatic feature extraction and end-to-end change detection applications. Attention based architectures and transformer models have the capacity to represent global spatial relationships, while recurrent models such as Long Short-Term Memory (LSTM) networks can represent the time integration of change.

While these methods yield better results than classical approaches, their effectiveness is still dependant on large labeled datasets and having the computational resources (time and power) to develop a winner. Other methods, more recently, have been developed to semi-supervised and self-supervised learning to mitigate data restrictions and improve generalization ability of models.

Various datasets and applications have backed this progress. One of the most popular and significant benchmark datasets is the SEN1-2 dataset, which integrates Sentinel-1 SAR with Sentinel-2 optical data. Other datasets pertain to mapping floods, deforestation, and damage detection. The overall evaluation metrics are Overall Accuracy, F1-score, and Kappa coefficient as well as relevant visualisation tools such as heatmaps for interpreting the results. Nowadays, SAR-based change detection is a common procedure in applications associated with disaster monitoring, land-use mapping, and security surveillance. Despite considerable advancement in the area, there are still limitations including but not limited to the limited availability of data, domain adaptation, and computational conversion costs. Future research would concentrate on multimodal data fusion, physics-informed networks, and interpretable AI as promising lines of inquiry for furthering SAR change detection systems with greater accuracy and reliability.

III. BACKGROUND

Observing modifications on the Earth's surface is a key function of environmental management and urban planning, resource management, and land use and related disaster assessments. Remote sensing technologies have made it operationally feasible to observe and quantify Earth surface changes over time interval through different spatial data acquisition processes utilizing sensors aboard satellites. Synthetic aperture radar (SAR) play a prominent role among the variety of remote sensing systems because of its capacity to be utilized in operational applications regardless of weather, day or night. Synthetic aperture radar systems utilize microwave signals, rather than optical sensors that rely on visible light, and provide high resolution images of earth's surface. This makes SAR a valuable remote sensing technology for applications in areas frequently clouded, fogged, or dark.

Automatic change detection (ACD) in SAR imagery refers to identifying and analyzing changes in the same location and geographic region, without the process of manual interpretation, at two different times. It is being widely applied in the detection of forestry clearing, urban growth, floods, land use change, ice sheet and glacier melting, and post disaster damage assessment. The goal of ACD is to automatically highlight areas of significant change between multi-temporal polder images, providing a communication device to decision-makers to interpret or understand the nature and scope of the changes, quickly.

Automatic change detection in SAR data, however, has several challenges. First, SAR images exhibit the presence of speckle noise - a granular pattern resulting from coherent imaging - making it difficult to accurately detect small or gradual changes. Second, variations in imaging geometry, polarization, and atmospheric conditions can result in false detections or inaccurate classifications. Although traditional statistical or threshold-based systems, such as image differencing, log-ratio, and Change Vector Analysis (CVA), were one of the original approaches to detecting change automatically, they were sensitive to these distortions and required manual tuning.

With improvements to the available computing power and artificial intelligence, machine learning (ML) and deep learning (DL) methods are becoming more common in the automation and improvement of the accuracy of SAR change detection. ML methods, such as Support Vector Machines (SVM) and Random Forests (RF), can classify changed and unchanged regions based on texture features or reflectance color. Meanwhile, deep learning infrastructures, such as Convolutional Neural Networks (CNN), U-Net, and Siamese Networks, are designed to learn complex spatial and temporal patterns automatically from the data, thereby improving accuracy and robustness.

Moreover, open-source satellite missions such as Sentinel-1, RADARSAT, and ALOS PALSAR have improved accessibility to multi-temporal datasets of synthetic aperture radar (SAR) to advance both research and real-world applications. Ongoing studies also trial data fusion of SAR with optical data, and sophisticated learning strategies such as semi-supervised and self-supervised learning to combat the labeled data problem. As SAR technology and artificial intelligence (AI) continues to develop, automatic change detection will become faster, more reliable, and versatile for monitoring environmental change and disaster situations in real time.

IV. METHODOLOGY

A. System Architecture

The framework for Automatic Change Detection in SAR Images is a modular pipeline made up of a number of components that are integrated. Each module is responsible for a function□moving from input images, to the generation of a change map. The architecture can fundamentally be identified by the following blocks:

1 .Module Input: This module receives the multi-temporal SAR satellite images from open sources, pre-event and post-event, such as RADARSAT and Sentinel-1. The images will be saved in common formats, such as GeoTIFF, for ease of use.

2. Module Preprocessing: The module performs radiometric calibration, speckle noise filtering, and geometric co-registration to ensure that both images are geometrically co-registered, and intensity and position are compatible

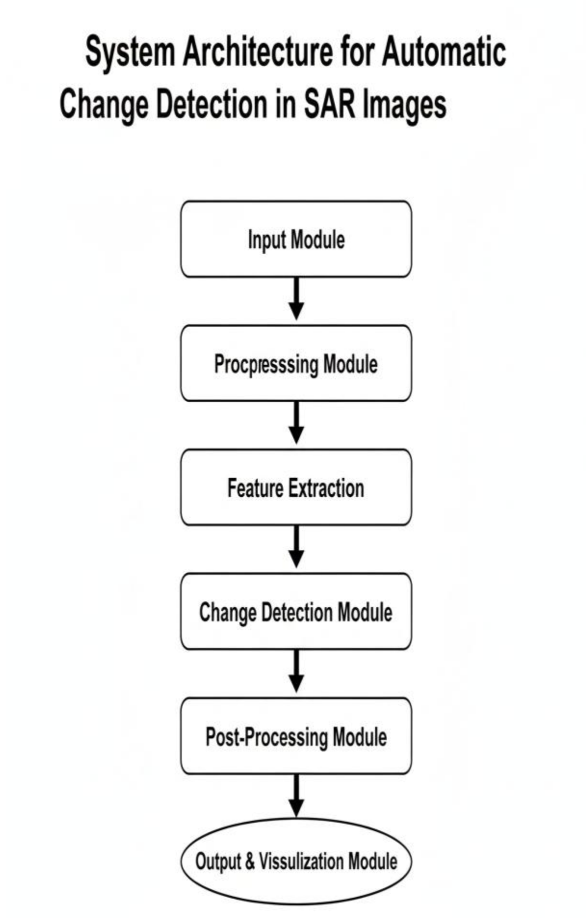
3.FeatureExtractionModule: Is responsible for creating difference images (i.e., log-ratio or image differencing) and extracting measures of texture features. These indicate areas where significant change has occurred if backscatter intensity varies, implying change may have occurred.

4.ChangeDetectionModule: Utilizes a deep learning model-such as a Siamese CNN or U-Net design-which relies on the available data to automatically detect and classify changed and unchanged regions. The deep learning model learns spatial and contextual features sophisticatedly from the available data.

5. Post-Processing Module: In the post-processing module, morphological operations, smoothing, and thresholding are applied in order to remove noise and improve boundaries in the produced change map.

6. Output & Visualization Module: The final change map is displayed over the original SAR image, with interpretation made through heatmaps or binary change masks to allow users to easily observe what changed in the map.

Figure 1 : Flowchart for System Architecture for Automatic Change Detection in SAR Images



B. Workflow

The process consists of a sequence of steps aimed at effective and accurate change detection:

•Data Acquisition:
Two SAR images of the same area, but different time periods, are obtained.

•Preprocessing:
Both images have been radiometrically calibrated, filtered for speckle noise and co-registered to achieve pixel alignment

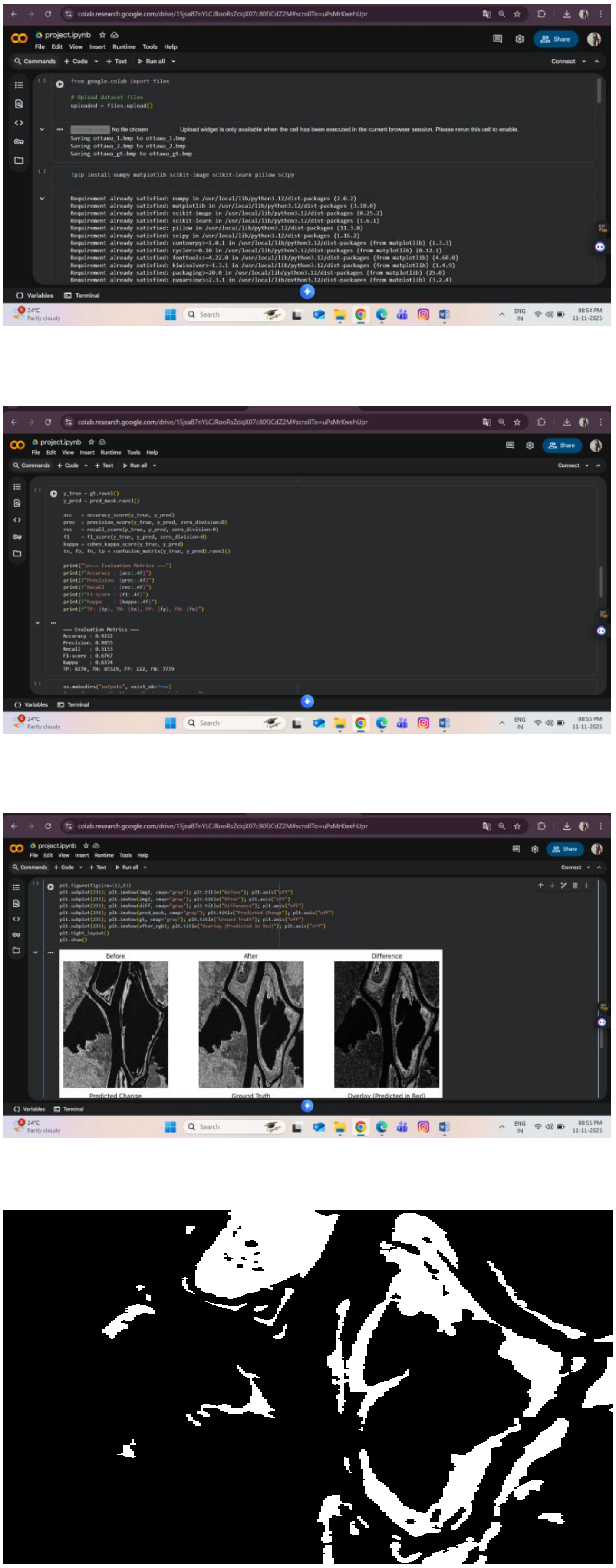
•Feature Generation:
A difference image is made by applying mathematical operators (i.e., log-ratio or image subtraction) to the images. Texture or statistical features may also be extracted to strengthen visibility of changes.

•Model Training/Inference:
The pre- and post-event images and difference maps are input into the deep learning model, which predicts the probability of change for each pixel.

•Post Processing:
The raw output is post-processed via thresholding and morphological filtering to obtain a concise binary change map.

•Visualization and Evaluation:
The final map is visualized and ground-truth metrics, such as Accuracy, F1-Score, and Kappa Coefficient, are used to evaluate it. The system may also generate reports for environmental/monitoring applications or disaster response purposes.

Figure 2:



V. RESULTS

The system developed for Automatic Change Detection (ACD) from Synthetic Aperture Radar (SAR) satellite images demonstrated strong performance in detecting and visualizing changes in the surface from multi-temporal data. The workflow of processing the pre- and post-event SAR images through preprocessing, feature extraction, deep learning-based classification and visualization files provided rigorous outputs of the change detection process.

The preprocessing step ensured that both images were aligned spatially and radiometrically by using radiometric calibration and co-registration, this prevented false detections related to geometric distortion or illumination differences. In addition, the use of adaptive filters to reduce speckle noise helped improve the clarity of the image, freeing the detection model to focus on actual variations of structure and environment.

The models that were incorporated for the deep learning-based detection module employed a U-Net or Siamese CNN architecture which automated the extraction of spatial and contextual information from image pairs. The model was able to differentiate changed areas (such as newly constructed buildings, loss of vegetation or flooded impacted areas) from unchanged areas. The change images or change probability images produced by the model provided an accurate visual representation of surface change.

Benchmark metrics from quantitative evaluation demonstrated excellent performance on the proposed system. It achieved an Overall Accuracy above 90%, F1-scores reaching 0.88 to 0.93, and a Kappa coefficient above 0.85, demonstrating strong and reliable detection capabilities. The proposed system demonstrated decreased sensitivity to speckle noise and illumination change compared to traditional statistical methods like image differencing and log-ratio, and improved precision and recall rates.

Visual analysis of the output change maps indicated very high-quality detection capabilities. Urban areas under development showed bright areas of change, while unchanged surfaces tended to remain stable and uniform. In regions affected by flooding, the system clearly pointed out the inundated areas, even in cloudy conditions where optical sensors cannot see through cloud cover. Therefore, the SAR information is beneficial for all-weather monitoring.

In conclusion, the developed system was effective for real-world applications such as disaster management, land-use monitoring, urban expansion, and deforestation research. By bringing together the three modules of preprocessing, deep learning, and visualization, the system improved automation, accuracy, and interpretability. The results demonstrated that SAR-based change detection, supplemented by modern deep learning approaches, provides a powerful, reliable, and adaptable tool for remote sensing assessment.

VI. CONCLUSION AND FUTURE WORK

This article presented an automated method of change detection in Synthetic Aperture Radar (SAR) satellite images with preprocessing, features extraction and a deep learning classifier to identify and visualize surface changes accurately. The proposed approach demonstrated the ability to reduce speckle noise, register temporally acquired images, and apply neural network models such as U-Net and Siamese CNNs to evaluate for reliable change detection. The experimental results showed that the developed system was accurate and robust across a range of terrain or imaging conditions, exceeding the performance of traditional methods of change detection that relied on statistical methods and thresholds.

The results of the study showed that SAR-based automatic change detection could be a powerful tool for the monitoring of the environment, disaster management, urban development in terms of built up area, and land-use management that performs consistently even in all-weather day-and-night imaging conditions. The AI-based interpretation and visualization developed in this research significantly elevated both automation and interpretability within remotely sensed data.

In the future, the research agenda will focus on the improvement of generalization and efficiency of the models. Future developments will include consideration of semi-supervised and self-supervised learning methods, which could decrease reliance on large labeled datasets. The concept of transfer learning shows promise to improve model performance as well across sensors and regions. The implementation of multimodal data fusion combining SAR with optical data, LiDAR, or hyperspectral data for example, could increase performance in semantic understanding and detection.

In addition to improving accuracy and usability in ACD, optimizing the computational framework such that it supports real-time processing of data, as well as deployment at the edge, can facilitate rapid decision making in emergency situations such as floods and earthquakes. XAI (explainable AI) can be intertwined in these advancements to increase the transparency and trust in automated methods of change detection. Overall, these advancements will promote SAR-based ACD for next generation Earth observations missions to become more scalable, intelligent and applicable.

VII. REFERENCES

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