A Survey on Change Detection in Synthetic Aperture Radar Satellite Images

Saili Sable[1], Omkar Unde*[2], Deepak Singh[3], Aditya Jadhav[4]

[1,2,3,4] Nutan College of Engineering and Research, Talegaon-Dabhade, Pune, Maharashtra, India
sailisable@ncer.com
*omkarunde1418@gmail.com
deepakawsingh@gmail.com
adityajadhav14143@gmail.com

Abstract. Change detecting in Synthetic Aperture Radar (SAR) satellite images has garnered significant attention for its applications in urban planning, disaster management, and environmental monitoring. SAR's ability to operate under all weather and lighting conditions makes it indispensable for monitoring dynamic changes on Earth's surface. However, distinguishing man-made changes from natural variations, such as vegetation growth or seasonal water fluctuations, remains a critical challenge. This survey explores recent advancements and methodologies in change detection for multi-temporal SAR images, focusing on hybrid approaches that integrate traditional techniques and deep learning. Key methods, including Change Vector Analysis (CVA), Principal Component Analysis (PCA), and Fuzzy C-Means (FCM), are discussed alongside emerging techniques like self-supervised learning and contrastive loss functions designed to minimize false positives. We review experimental results from the Sentinel-1 dataset, highlighting trends, strengths, and limitations of existing approaches. Outputs in standard formats such as GeoJSON or shapefiles demonstrate their utility for GIS-based real-time monitoring systems. By providing a comprehensive overview, this paper aims to inform future research and development of scalable, accurate solutions for change detection in SAR remote sensing applications.

Keywords: SAR, change detection, Sentinel-1, PCA, FCM clustering, GIS applications, CVA, CACo.

1 Introduction

Different changes noticed in remote sensing looks at alteration in multi-temporal satellite imagery so as to monitor changes on the surface of the earth vital in planning and developing cities, during disasters, checking deforestation as well as management of infrastructural developments. SAR or Synthetic Aperture Radar is very useful for this purpose because SAR is useful for all weather and any lighting conditions, however SAR data sets a number of problems such as speckle noise and low signal-to-noise ratios as well as the problem associated with detecting differences between images. At

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the pixel level, the commonly applied generic methods such as Changes Vector Analysis (CVA) and Principal Components Analysis (PCA) work well but suffer from high false alarm rates because of the influence of environment.

Two recent approaches of machine learning are self-supervised learning and contrastive learning, which provide solutions by learning from the raw data from the web which are not labeled. To enhance the sensitivity to permanent man-made changes and filter out short-term natural fluctuations, Contrastive Loss is extended with Change-Aware Contrastive Loss (CACo). The current work presents a conceptual model developed through exploring the use of both conventional and deep learning techniques. For initial change mapping it incorporates CVA, while PCA is used to reduce the data dimensionality and Fuzzy C-Means (FCM) clustering to classify the data. Despite such development, false alarms remain a headache, which is why a self-supervised learning framework with CACo Loss is integrated. The method identifies anthropogenic changes and can be applied for large areas using satellite Sentinel-1 (SAR) data by Google Earth Engine, providing reasonable approaches to urban planning, disasters, and environmental monitoring.

2 Literature Review

[1] Ramesh and Kryzsztof (2018) : It focused on describing the difficulties of satellite image understanding through the DeepGlobe 2018 competitions. Their work organized for the IEEE CVPR Workshops presented these challenges in satellite imagery; these include noise, resolution, and environmental complexity. They focused on the use of deep learning to acquire relevant data and also noted patterns in the competition's results, which would provide insights for further development of approaches for analyzing satellite images.

[2] Singh (1989): In his review, Singh has also described differencing of images and Change Vector Analysis (CVA). The study focused on how the mentioned techniques are useful in measuring variations in pixels especially in environmental context while noting high rates of false alarms in situations where the environment is complex.

[3] Nielsen et al. (1998): The authors presented a technique called Multivariate Alteration Detection for change detection. In this method, multivariate statistics and thresholding were used to successfully extract meaningful details in the multi-temporal image that demonstrated effectiveness in environmental and urban monitoring.

[4] Bruzzone and Prieto (2000): In this paper, an adaptive multispectral image change detection method that belongs to the domain of semiparametric models was proposed. By including the spatial context, the method minimized noises and enhanced the detection of ACCURATE particularly in the heterogeneous land cover. However, RTA suffered from shortcomings mostly arising from image registration required for processing SAR data.

[5] Celik's (2009): Change detection in the satellite imagery was achieved with the help of unsupervised method known as Principal Component Analysis (PCA) combined with k-Means clustering. Despite the effectiveness of the method shown in the paper in identifying changes in urban areas, there was a challenge in identifying the natural oscillations such as seasonality. This drew an even more significant focus to the issue of noise that exists in SAR images, hence the need for better methods for its elimination.

[6] Huang and Zhang (2014): This study compared pixel-based and object-oriented methods for change detection in remote sensing imagery. The object-oriented approach proved more effective in minimizing noise and improving detection accuracy, especially for high-resolution datasets. However, it was observed to require higher computational resources.

[7] Gong and Yang (2013): The work employed a deep learning model based on autoencoders for learning changes in SAR imagery forms. With high classification accuracy, this approach highlighted that deep learning remains vital in SAR imagery classification given features such as noise defeated by the algorithm.

[8] Peng and Zhang (2017): An Object-Based Change Detection (OBCD) method including segmentation optimization and multi-feature fusion for high-resolution remote sensing images was presented in the study. Further, watershed segmentation implementation together with the Dempster-Shafer theory and with the Expectation-Maximization (EM) algorithm improved the detection rates. This was achieved and after the improvement refined the object boundary delineation and effected the reduction of false alarms which made it even suitable for more complex environments such as cities.

[9] Volpi and Tuia (2017): The topic of this research focused on the use of convolutional neural networks in change detection from very high-resolution satellite imagery. The findings showed that deep learning models accurately captured fine details and reduced the number of false negatives for densely-built-up areas. However, their implementation required considerable labeled data and significant amounts of computation.

[10] Bekkouche and Fizazi (2022): This research proposed a hybrid change detection approach that combines Principal Component Analysis (PCA), ISODATA, and Fuzzy C-Means (FCM). By integrating these techniques, the method enabled automatic thresholding and clustering, leading to precise change detection in multi-temporal satellite images. The approach demonstrated strong performance in differentiating synthetic changes from natural ones, achieving high accuracy in experimental assessments.

3 Data Research

3.1 Dataset Selection

Sentinel-1 SAR dataset was chosen because of its availability, high revisit cycle, and effectiveness in change detection purposes. Sentinel-1 occupies a place in the framework of the Copernicus pro-gram and ESA and offers free C-band SAR imagery that is available in any weather conditions or at any time of the day. Among the data products of the product list is the Ground Range Detected (GRD) images which are pre-processed and registered by default, minimizing the levels of pre-processing needed on the acquired image. Coherent with revisit time of 6-12 days, Sentinel-1 can only provide the large area frequent change detection. Google Earth Engine integration is useful when it comes to scaling analysis; the product also fits in the study of changes in the urban structures and structure while excluding the natural variability.

Key Features of Sentinel-1 SAR Dataset.

Imagery Type . C-band Synthetic Aperture Radar has been used because the imagery is robust for applications such as urban dynamics, disaster response, and environmental research.

Data Products. Ground Range Detected (GRD): Raw input images that have been pre-processed for change detection and analysis purpose.
Single Look Complex (SLC): For applications in which phase information is needed.
Temporal Resolution. The revisit time takes between 6 to 12 days which allows for revisit times to capture changes after intervals.
Spatial Resolution. It is, however, likely to take anything between 5m and 40m depending on the kind of acquisition mode.
Processing Platform. Scientists prefer Google Earth Engine (GEE) for processing Sentinel-1 data because of the system's flexibility and compatibility with geographical information systems.
Links to Access Sentinel-1 SAR Data:
Copernicus Open Access Hub:
https://scihub.copernicus.eu/
This is the official place for downloading Sentinel-1 data.
Google Earth Engine. https://earthengine.google.com/
An online solution for largescale analysis of Sentinel-1 datasets.
ASF Data Search Tool (Vertex). https://search.asf.alaska.edu/
Aimed entirely at SAR data, it provides extended search capabilities and more preparation features.
ESA Sentinel Online. https:///www.sentinel.esa.int/web/sentinel/home
Offers information about the Sentinel-1 mission including documentation and tutorials.
Radiometric Terrain Correction Tool (RTC). https://asf.alaska.edu/how-to/data-tools/rtc/

SAR Image Terrain Correction: Guides and Tools

The data employed for this study are the Sentinel-1 Synthetic Aperture Radar (SAR) images, which belong to the Copernicus program run by European Space Agency (ESA). Sentinel-1 offers a high spatial resolution radar image data that are accurate and can be obtained irrespective of cloud cover or lighting conditions which make it suitable for applications that require regular time series data acquisition. The dataset includes two primary products: Preprocessed images called Ground Range Detected (GRD) images are ready for use for the change detection while other images that retain the phase information are Single Look Complex (SLC) images. The outcomes of these products permit a vast number of uses such as urban designing, disaster management and development, and environmental management.

Sentinel-1 is available at spatial resolution of from 5m to 40m according to acquisition mode and with temporal resolution with revisit time of from 6 to 12 days. This capability of frequent monitoring makes it possible to detect changes in large areas always. It is also a global coverage system that gives us wide swather imagery for coverage of large areas in one run. Further, the data is properly geo-referenced, the temporal data sets are easily aligned which are pre co-registered and have some radiometric and geometric corrections for better results.

The dataset (Fig.1) is also free to download and combined with the Copernicus Open Access Hub and Google Earth Engine, user-interface with a GIS tool is easily facilitated..

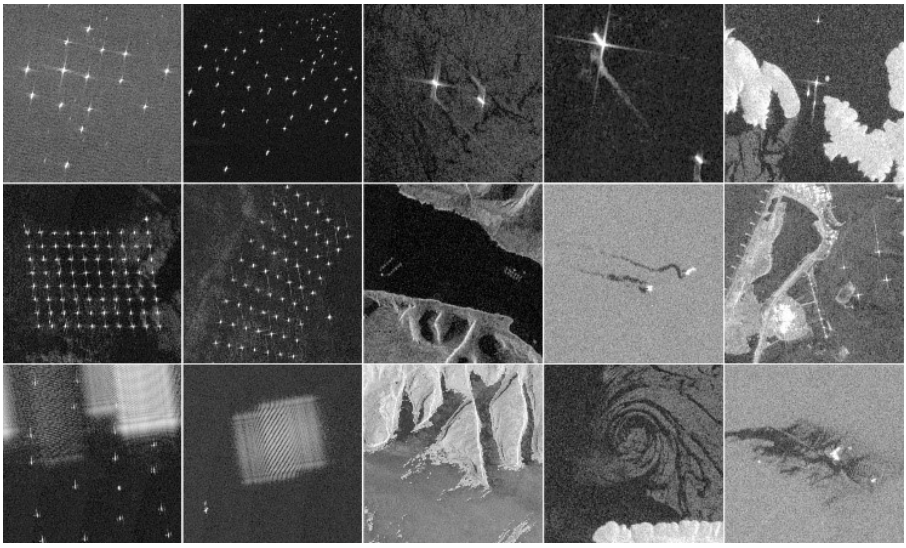

Fig. 1. A selected dataset

3.2 Data Preprocessing

When using Sentinel-1 SAR data it is crucial to perform some form of data normalization to improve the quality and accuracy of the image change detection data. The first pre-processing step includes radiometric calibration that corrects SAR intensity data by factorizing raw intensity data to sigma nought, \(\sigma^0\)to better represent surface characteristics. This calibration eliminates effects due to the sensor so that pixel values can be related to radar reflectivity's of the sky or the ground. Subsequently, speckle noise reduction is performed in this step by using filters similar to the Lee or Frost filter to remove granular noise in SAR imagery that is inherent to this sort of image while improving the image clarity thereof without obviating important details of this imagery.

Following noise reduction, terrain flattening (radiometric terrain correction) is performed to normalize the backscatter values across varying terrain slopes, using a Digital Elevation Model (DEM) for correction. This step is crucial to account for the influence of uneven terrain, ensuring consistent reflectivity measurements. Geometric correction (orthorectification) is then conducted to align the SAR images to a true geographic coordinate system, correcting distortions caused by the side-looking nature of SAR sensors.

Further, there is the co-registration process to ensure that the changes observed on the temporal images are genuine, any area of shift comes from actual ground change rather than the images being misaligned. Additional enhancement to machine and human interpretability can be achieved through the applying logarithmic scale transformation i.e., changing backscatter values from a linear scale to dB scale. Lastly, the image is also restricted to the area of interest (AOI as a way to show the particular region of interest when analyzed reduces the data volume and increases the computing rate. Here are these preprocessing steps that collectively enhance the quality of the data by reducing distorting effects of natural changes and highlight dreadful man-made changes:

3.3 Methodology

Data Acquisition and Preprocessing. In this form of analysis, the first procedure is to obtain Sentinel-1 SAR GRD images from Google Earth Engine (GEE). These two are registered images; in other words, both images' pixels will match up on the corresponding coordinates. Because changes detected by VHR stereo-imagery may comprise of other unrelated factors such as cloud cover, vegetation growth and changes in features types, the identified change is filtered for time of interest, with the change resulting from either urban expansion or infrastructure development. Preprocessing steps are essential to improve image quality, including speckle noise reduction using filters like the Lee filter or Median Filtering:

$$I_{filtered} = \frac{1}{N}\sum_{i=-N/2}^{N/2} \sum_{j=-N/2}^{N/2} I(i,j) \quad (1)$$

Where,
$I_{filtered}$: The intensity value of the filters that achieved after filtering the current pixel that being processed.
I(i,j): The actual intensity values of the pixel within the neighborhood.

First Level to identify change by identifying Change Vectors: Change Vector Analysis (CVA) is carried out in order to detect first alterations between the first and the second image. CVA superimposes two SAR images so that the pixel values are aligned and then subtracts or divides them. The change vector CV is defined as:

$$CV=\sqrt{(I_1-I_2)^2} \tag{2}$$

Where,

I_1 and I_2 are two consecutive frames of the temporal SAR images where the pixel intensities are different.

Principal Component Analysis (PCA) for dimensionality reduction: In an attempt to improve the change detection, Principal Component Analysis is used for reducing the dimensionality of the change map and extracting only the distinctive features of the change. The principal components are derived by solving the eigenvalue problem.

$$Cv=\lambda v \tag{3}$$

Where,
C is the covariance matrix of the change map of the WMSs frequencies.
The last part of the analysis is the eigenvalue (which shows the proportion of the variance that each component contributes to the total).
They should be noted that v is the eigenvector associated with each eigenvalue the principal axes of the data.

Input Layer: The model takes two co-registered SAR images: They are recommended to select one case from the pre-change period and another from the post-change period. These images are in the same spatial reference and are then fed into the network. The patterns of each image appear in two dimensions' height and width with respective values in terms of SAR image pixel intensity.

Convolutional Layers. The convolutional layers are really the heart of the CNN; in this case small filters (or kernels) scan the input images to learn the spatial features. When used for change detection in SAR images the filters may well be learning such features as edges, gradients or patterns that are symptomatic of change in the surface

structure. These convolutional layers are then usually followed by activation functions (most often ReLU) in order to bring non-linearity to the network as well as to enable it to consider other patterns of data.
The convolution operation can be mathematically expressed as:

$$I_{out}(x,y) = \sum_{i=0}^{k-1} \sum_{j=0}^{k-1} \mathrm{w(i,j)} I_{in}(x+i, y+j) + b \quad (4)$$

Where:
I_{out} is the output feature map,
I_{in} is the input image,
w(i,j) are the weights (filter kernels),
b is the bias term,
K is the kernel size.

Pooling Layers. After convolution, there are going to be numerous features maps hence there is a thing called pooling so as to minimize the features maps to make the computation faster and also to eliminate overfitting. One of them is max pooling which only takes the maximum of an expected patch of the image and therefore lessens the density of the image.
The max pooling operation is defined as:

$$P(x,y) = \max_{i,j} (I_{in}(x+i, y+j)) \quad (5)$$

Where P(x,y) represents the pooled feature map:
Stands for the output value of the pooling operation at the certain position
In the output feature map, the location is identified as vector $|n|\{i\}<|ai|>(x,y)$(x,y).
Max
(i, j):
Refers to a max operation that is performed in some coverage area of the input.
and correspond to the window of values being pooled.
I_{in}(x+i,y+j): Stands for the input pixel intensity or value at position of a two dimensional matrix $(x+i,y+j)$(x+i,y+j).

Fully Connected Layers. The Fully connected layers work to compile learned features by other layers and provide the final result of classification. These layers are used to differentiate between the change types by using the extracted features mentioned above, including man made changes and natural changes.

Output Layer. The last layer of the CNN model often provides a binary decision (man-made or natural) or multicategorial decision (urban region, deforestation, flood and etc.). This classification is typically performed using a SoftMax activation function for multi-class problems or sigmoid activation for binary problems:

$$\text{Sigmoid}(z) = \frac{1}{1+e^{-z}} \tag{6}$$

$(1 + e^{-z})$: Converts the output to the range in order to normalize it (0,1)(0,1).

4 Result and Discussion outcomes

The proposed change detection methodology effectively identified man-made changes in Sentinel-1 SAR images while minimizing false positives from natural changes. Labeling the techniques as Change Vector Analysis (CVA), Fuzzy C-Means clustering, and self-supervised Change-Aware Contrastive Loss (CACo), the approach committing between permanent structural changes and environmental fluctuations. That is why the feature set usage was facilitated by Principal Component Analysis (PCA) which increased certain measures of accuracy and speed, as well as decreased computational cost.

These change detection results (Fig. 2) in form of change maps were an accurate representation of ur-ban development and infrastructure change and affirmed to known growth patterns. The outputs in formats such as shapefiles or GeoJSON could be easily integrated with GIS applications for real time monitoring as well as for making decisions. The above study employed methodology that was generic and therefore fot well because it could be applied cross region and therefore cross the many cases required for large scale change detection.

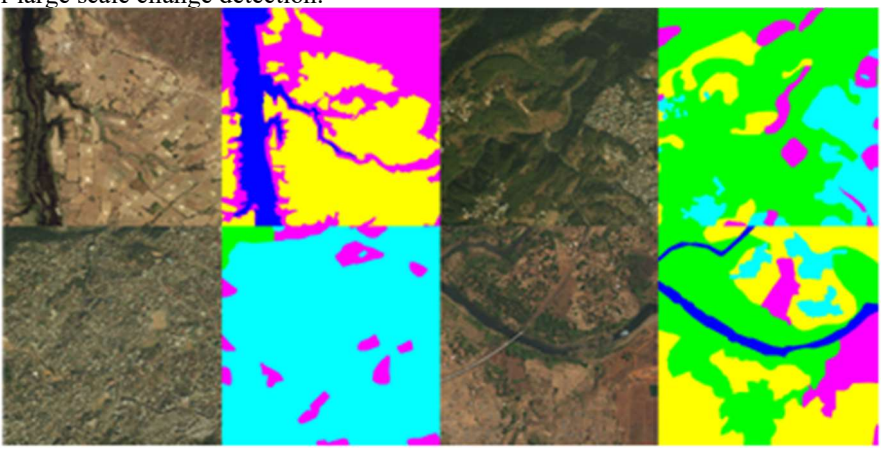

Fig. 2. Result from a dataset

4.1 Latest work done.

- **PCA with Two-Level Clustering.** Acquires and integrates Principal Component Analysis (PCA) with innovative clustering algorithms to extend flexibility and improve dimensionality reduction measure that contributes to the resolution increase in change detection technique.
- **Spatial Pyramid Pooling with Attention Mechanisms.** Introduces spatial pyramid pooling to extract features of multiple scales within SAR images. To this end, attention mechanisms are used to guide the feature maps to improve the OD model's detection accuracy across different scales and regions.
- **Saliency Detection with Attention Capsule Networks.** Detects and locates prominent features in SAR images. Uses attention mechanisms for the identification of focus and important features, thus minimizing cases of false positive in its model.
- **Noise-Tolerant Networks with Layer Attention Modules**. Scalable combines feature of different convolutional layers with an ability to dynamically adjust the weights being used. Proposes signal-to-noise ratio robust loss functions to reduce the noise interference from the labels and enhance the detection accuracy.
- **Dual-Path Denoising Networks**. Uses random label propagation to tackle noise issue of labels. This work employs unique patch convolution, which helps in reducing feature representation costs.
- **Wavelet-Based Self-Attention Networks**. Uses wavelet analysis in order to achieve down sampling while preserving an important part of data. Strengthen the awareness of the environment without inserting assumptions of more structure in local space, which, improves the chances of accurate detection where environment is fairly cluttered.

5 Conclusion

The proposed method for change detection in SAR images is as follows: It gives higher efficiency in detecting man-made changes while also reducing as much as possible false alarms from natural changes. It also balances employing already developed methods, for example, Change Vector Analysis (CVA) with employing new and modern methodologies, which include Fuzzy C-Means clustering and also self-supervised learning using a change-aware contrastive loss (CACo), but all while utilizing Sentinel-1 SAR data and the Google Earth Engine. The solution provides specific threshold controls and outputs in formats of GIS, for example, shapefiles or GeoJSON. This scalable approach works best in large and Arcuo changes within the urban and rural areas and therefore may be suited for use in urban planning, in disaster management, and monitoring of environ-mental changes.

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