University of Tehran

*Earth Observation and Geomatics Engineering*

Online ISSN: 2588-4360

Homepage: https://eoge.ut.ac.ir/

# Anomaly Detection in SAR Images Using a Hybrid Self-Supervised Approach

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## Article Info

**Article type:**
Research Article

**Article history:**
Received 2025-10-20
Received in revised form 2026-01-04
Accepted 2026-01-17
Available online 2026-05-12

***Keywords***:
Synthetic Aperture Radar,
Anomaly Detection,
Speckle Noise Reduction,
Statistical Thresholding,
Remote Sensing,
Image Processing.

## ABSTRACT

Anomaly detection in Synthetic Aperture Radar (SAR) imagery plays a critical role in identifying rare and abnormal targets in complex environments such as maritime and urban scenes. However, the presence of speckle noise and heterogeneous background backscatter significantly degrades detection reliability and increases false alarm rates. In this study, a simple and computationally efficient framework is proposed for anomaly detection in SAR images based on statistical thresholding of preprocessed intensity values.

The proposed approach first applies median filtering to suppress speckle noise while preserving structural details. Subsequently, statistical indices including the mean and standard deviation of pixel intensities are used to define an adaptive threshold for separating anomalous regions from the background. An anomaly map is then generated by normalizing pixel deviations from the background statistics.

The method was evaluated using Sentinel-1 SAR images from the TenGeoP-SARwv dataset, which contains more than 37,000 samples representing diverse geophysical conditions. Experimental results on representative SAR scenes demonstrate that the proposed framework effectively highlights anomalous regions while maintaining low false alarm rates across varying backscatter intensities. Histogram analysis and anomaly maps confirm the consistency between statistical outliers and detected anomalies.

Due to its simplicity, robustness, and low computational cost, the proposed method is suitable for large-scale SAR anomaly detection and can serve as a baseline for more advanced learning-based approaches.

**Cite this article:** Shojaei, M.J., Sharifi, A.R., Sadeghian, S. & Shirazian, M. (2025). Anomaly Detection in SAR Images Using a Hybrid Self-Supervised Approach, *Earth Observation and Geomatics Engineering*, Volume 9, Issue 1, Pages 75-84. http//doi.org/10.22059/eoge.2026.404683.1192



Publisher: University of Tehran.
DOI: http//doi.org/10.22059/eoge.2026.404683.1192

## 1. Introduction

Overview one of the most significant data sources in the field of remote sensing in recent decades has been Synthetic Aperture Radar (SAR) imagery (Henderson & Lewis, 1998; Bamler & Hartl, 1998). Based on microwave signals, these systems offer imaging capabilities that are not affected by weather or illumination, allowing for the collection of high-precision data even in the presence of clouds and rain. Due to its special ability, SAR imagery is now essential for a variety of purposes, such as environmental monitoring, disaster relief, maritime and military target detection, border security, and land change monitoring (Touzi, 2007). Anomaly detection is important in many of these situations. Any pattern, object, or phenomenon in SAR imagery that substantially differs from the background's dominant statistical distribution is referred to as an anomaly (Kwon & Nasrabadi, 2005). Unauthorized ships in waterways, oil spills on the ocean floor, man-made structures in natural areas, and abrupt changes in land cover are a few examples (Li et al., 2021; Wei et al., 2020). Finding these anomalies is important from a scientific standpoint, but it is also very useful in security, defense, and environmental monitoring. Anomaly detection in SAR data is still a difficult task, despite its importance. Speckle noise, a multiplicative and coherent phenomenon that makes SAR images appear grainy and uneven, is one of the main challenges (Lee, 1981). In addition to impairing visual clarity, this noise interferes with the functionality of numerous learning and statistical algorithms. The intrinsic heterogeneity of the background and the non-Gaussian character of SAR data present additional difficulties for statistical modeling and analysis (Bamler & Hartl, 1998). SAR backscatter shows highly variable characteristics across urban, forest, and marine environments and rarely follows simple probabilistic distributions. Furthermore, a recurring challenge is the lack of labeled data. Building trustworthy and sizable training datasets is costly and time-consuming due to anomalies' inherent rarity and unpredictability (Pang et al., 2021). These challenges are exacerbated by the constantly increasing amount of high-resolution SAR imagery, which makes it urgently necessary to develop computationally effective techniques that can maintain high detection accuracy (Marino et al., 2016; Mateos et al., 2015).

Numerous approaches have been studied to deal with these issues. Early efforts relied heavily on classical statistical detectors such as the RX [1]algorithm and its local and nonlinear extensions (Reed & Yu, 1990; Kelly, 1986; Kelly & Forsythe, 1989) Because of their ease of use and computational effectiveness, these methods which calculate the Mahalanobis distance between each pixel and the estimated background distribution remain common benchmarks. However, when applied to complex, real-world SAR data, their efficacy is frequently limited by their dependence on accurate covariance estimation and simplified distributional assumptions (Scharf, 1991; Kraut et al., 2001).

Model-based and low-rank representation techniques have been created to lessen these restrictions. RPCA[2] is a popular example of such techniques, which usually assume a low-rank background with sparse anomalous components (Candès et al., 2011; Bouwmans et al., 2016; Mateos et al., 2015; Zhou et al., 2010). It is successful in separating small targets within complex scenes. Nevertheless, RPCA still requires a lot of computing power and is susceptible to significant background heterogeneity and speckle noise (Marino et al., 2016).

Recent progress in deep learning has broadened the anomaly detection toolkit (Pang et al., 2021). For example, GANs[3] model the distribution of normal samples to find outliers. Auto encoder-based setups rebuild nominal backscatter and then use the error in reconstruction as a score for anomalies (Zhai et al., 2016). Self-supervised learning methods are becoming popular because they don't need labeled anomalies. SAR2SAR uses self-supervision to reduce speckle, showing that preprocessing based on learning can improve data quality and detection results (Dalsasso et al., 2021). Some hybrid approaches combine learned models with standard statistical assumptions, such as ViT[4] based setups and methods that add RX detector outputs as assumptions inside neural networks (Pang et al., 2021). Vision Transformer architectures are also worth mentioning. For instance, TRANSAR has shown good results in detecting small objects in SAR images.

Standard datasets are important for progress in this area. Collections like SSDD, HRSID, and MSTAR are still used for evaluations (Li et al., 2021; Wei et al., 2020). The newer SARIAD dataset allows for extensive comparisons of different techniques. Current research shows that no single type of method completely solves the problem of finding anomalies in SAR data. Traditional statistical methods are simple but not very strong. RPCA offers good decomposition but takes a lot of computing power. Deep learning methods are creative but can be affected by speckle noise. Because of this, we need a combined system that uses the best parts of all three approaches: self-supervised speckle reduction, low-rank background modeling, and deep nonlinear representation. This gap in research is why we propose the method in this paper.

Natural habitats are vital for healthy ecosystems. They maintain biodiversity, regulate ecological functions, and

[1] Reed–Xiaoli

[2] Robust Principal Component Analysis

[3] Generative Adversarial Networks

[4] Vision Transformer

support key environmental services. Different habitats, such as forests, grasslands, wetlands, and mountains, are distinctive in their ecological, botanical, and geographical characteristics (Henderson & Lewis, 1998). Population growth and economic expansion increase environmental pressures. These pressures habitat fragmentation, pollution, plant damage, and altered water availability increase ecosystem vulnerability (Touzi, 2007). Assessing and mapping habitat sensitivity to human disturbance becomes important. This is critical for sustainable resource management and practical conservation planning (Bouwmans et al., 2016). Conventional methods of assessing a habitat's health typically involve direct inspection and the use of local data. This works well in small spaces but is time-consuming, expensive, difficult to implement in larger areas, and inefficient. We have new tools to monitor ecosystems across vast regions, such as remote sensing, GIS[5], and drone photography (Henderson & Lewis, 1998; Li et al., 2021). These tools assist us in identifying key indicators of environmental health, including height, slope, direction, and the amount of plant cover. This allows us to examine in detail how habitats change over time and in various locations, as well as the threats they face (Wei et al., 2020).

Vegetation indices, such as the NDVI[6], are often used to assess ecosystem health (Pang et al., 2021). By examining how plants reflect light, these indices can detect seasonal changes, shifts in plant communities, and the impact of human activities (Henderson & Lewis, 1998). Land shape and nearness to human structures like towns and roads can also influence how easily habitats are damaged, as areas near dense populations or roads often experience greater ecological problems (Bouwmans et al., 2016). The environment is complex and unpredictable, making it difficult to make accurate habitat judgments even with a wealth of data. Due to their ability to handle uncertainty and work with a variety of data types, fuzzy logic models are gaining popularity (Bouwmans et al., 2016; Wei et al., 2020). In contrast to straightforward approaches, fuzzy logic assigns varying degrees of importance to various objects to illustrate the relationship between human behavior and nature. According to recent research, mapping habitat risks can be significantly enhanced by incorporating plant data, land features, and building information into fuzzy models (Pang et al., 2021).

Recent pairings of tech like Wireless Sensor Networks and the Internet of Things with remote sensing offer chances for watching the environment and predicting dangers as they happen. Because of this, my work gives a way to see how many natural places are at risk from people. I use fuzzy logic to find spots that are sensitive and at high risk, using things like digital elevation models, pictures from space, and vegetation measurements. The results I get can guide planners and leaders in making specific plans to save nature and keep ecosystems healthy.

## 2. Literature Review

Research into spotting unusual things in SAR images has grown steadily over the last few decades, shifting from standard statistical methods to more modern deep learning approaches. The RX detector was often a starting point in earlier studies using statistical methods. Because of its simple idea and ability to find strange pixels in noisy SAR images, the RX detector, which relies on the Mahalanobis distance, became well known (Kelly, 1986; Reed & Yu, 1990; Kraut et al., 2001; Pang et al., 2021). Later studies presented better versions of the RX algorithm, like Kernel RX and Local RX. To address background changes, these modifications relied on local neighbourhood analysis and nonlinear kernels (Kelly, 1986; Reed & Yu, 1990). Despite these advancements, complex, real-world SAR scenarios continue to present challenges for RX-based approaches. This is primarily since their effectiveness is heavily reliant on precise covariance estimates and the assumption that background data has a Gaussian distribution (Kwon & Nasrabadi, 2005; Kraut et al., 2001).

Researchers have looked into model-based decomposition methods and low-rank representation as ways to overcome these constraints. The main idea behind this family of techniques is to distinguish sparse, unstructured anomalies from the background, which is usually defined by a low-rank structure. RPCA has proven to be particularly effective in identifying weak or small targets that are embedded in cluttered backscatter (Scharf, 1991; Kraut et al., 2001). To better account for noise and uncertainty, additional extensions were added, such as Bayesian and probabilistic formulations of RPCA (Candès et al., 2011; Bouwmans et al., 2016; Marino et al., 2016; Mateos et al., 2015). However, these methods are still computationally demanding and susceptible to background and speckle variability, which restricts their scalability for the analysis of large-scale SAR data (Mateos et al., 2015; Zhou et al., 2010).

A new method for identifying anomalies in SAR images has been made possible by recent advancements in deep

[5] Geographic Information System

[6] Normalized Difference Vegetation Index

learning. AEs[7] have emerged as a popular unsupervised technique among the various approaches. By learning to rebuild normal data and then identifying errors in the rebuilt images that suggest potential anomalies, AEs are able to identify anomalies. Latent distribution modelling is incorporated into more sophisticated variants, like VAEs[8], to improve and expand detection capabilities. (Lee, 1981; Marino et al., 2016). Due to the limited availability of labelled SAR data, SSL[9] methods have gained traction. Generative Adversarial Networks GANs are good at learning complex data patterns (Zhai et al., 2016; Pang et al., 2021). Combining GANs with good feature representation methods has improved the detection of anomalies in difficult areas like cities and seas (Pang et al., 2021).

SAR2SAR is a key advance, using self-supervision to lower speckle noise without needing perfect reference images (Zhai et al., 2016; Pang et al., 2021). Self-supervision has been used in anomaly detection, where deep neural networks use the outputs of common detectors, such as RX, as starting clues (Dalsasso et al., 2021). Attention mechanisms have been used in more recent models based on ViTs, like TRANSAR, to achieve exceptional accuracy in detecting small or subtle targets within SAR imagery (Pang et al., 2021).

Additionally, benchmark datasets have been essential in advancing this field. Among the most frequently used references are collections like SSDD and HRSID, which were created mainly for ship detection in SAR imagery (Li et al., 2021; Wei et al., 2020). Similarly, the traditional MSTAR dataset has offered a trustworthy platform for testing target detection techniques in a variety of imaging scenarios. The first extensive, large-scale reference created especially for SAR anomaly detection is the SARIAD benchmark, which was developed more recently and allows for the methodical and uniform assessment of rival algorithms (Pang et al., 2021).

Prior work indicates that deep learning, low-rank approaches, and statistical methods each have different strengths and weaknesses. Statistical methods are simple and computationally quick, but rely on strong distributional assumptions. Deep learning techniques represent data well but can be sensitive to noise and require a lot of data. Low-rank models are quite accurate but need a good bit of computing power. Because of this, recent work has focused on hybrid methods that bring together the strengths of these approaches, such as combining low-rank representations and statistical priors in deep neural networks (Bouwmans et al., 2016; Marino et al., 2016).

Self-supervised learning has gained traction because labelling SAR data by hand is both hard and costly. Studies suggest that combining self-supervision with RX-based methods can boost anomaly detection and cut down the need for labelled data *(Dalsasso et al., 2021; Pang et al., 2021)*. Transformer models and masked pertaining now allow for the extraction of global context from sizable SAR image collections. For instance, TRANSAR models propose that self-supervised pertaining on bigger SAR datasets might outperform standard convolutional networks in spotting small and rare anomalies when labelled data is limited (Pang et al., 2021).

Speckle noise continues to be a key problem in SAR analysis. It acts as a distortion that multiplies errors, which can lead to incorrect alarms and hide small details. Current progress has focused on self-supervised despeckling networks. These networks can reduce noise without needing clear reference data and maintain important target structures. This step is important for finding anomalies in real-world SAR uses with accuracy (Dalsasso et al., 2021).The creation of benchmarks and tools to assess SAR data, for example, SARIAD, has sped up research. These resources provide shared datasets, standardized evaluation metrics, and reproducible experimental setups, enabling fair comparisons among different methods. They have significantly facilitated progress in SAR anomaly detection by making it easier to replicate experiments and consistently evaluate performance (Pang et al., 2021).

In hybrid systems, low-rank plus sparse decomposition techniques, such as RPCA, remain crucial. The goal of recent modifications like adaptive weighting and non-convex factorization is to increase their speed and strength. Research from various disciplines demonstrates that incorporating local links and spatial context into reconstruction models can significantly increase detection accuracy (Candès et al., 2011; Mateos et al., 2015). Spatial association learning, for instance, is used by techniques such as SARAD to model spatial correlations, which are crucial for identifying anomalies in SAR data over time. This goes beyond merely examining reconstruction error (Bouwmans et al., 2016).

Datasets like TenGeoP-SARwv, SSDD, and HRSID remain very important for training and checking models. These, along with current standards like SARIAD, help ensure that performance is measured accurately and consistently. Recent work suggests that the best SAR anomaly detection systems usually combine transformer-based feature extraction, self-supervised despeckling, and standard ways of checking results to get the best accuracy and to be as widely applicable as possible (Pang et al., 2021; Dalsasso et al., 2021).

To summarize, studies suggest that future SAR anomaly detection systems will likely use multi-stage hybrid designs. These designs might use self-supervised pre-processing to

[7] Autoencoders

[8] Variational Auto encoders

[9] self-supervised learning

improve signal-to-noise ratio and lessen speckle, Vision Transformer-based feature extraction to improve global representation learning, and statistical or low-rank prior-guided thresholding for more accurate anomaly localization.

## 3. Materials and Methods

### 3.1. Dataset Description

In this work, we evaluated the performance of our anomaly detection system on SAR images using the TenGeoP-SARwv dataset. In geophysics and anomaly detection, this dataset is frequently used as a benchmark. It has a variety of scenes and precise labels, allowing us to consistently evaluate the performance of our algorithm.

Key characteristics of the TenGeoP-SARwv dataset are as follows:

1. **Image Type:** The TenGeoP-SARwv dataset consists of SAR images. These images were taken in Wave Mode by the Sentinel-1A satellite. They offer medium spatial resolution and good radiometric quality. Like all SAR data, these images show speckle noise.
2. **Polarization:** VV polarization, where both transmission and reception are vertical, is frequently employed to study land and sea surfaces.
3. **Geophysical Phenomena:** The dataset contains images of ten different geophysical phenomena, including clouds, atmospheric storms, vegetation cover, urban areas, oil spills, and ocean waves. This variety makes it possible to test algorithms thoroughly in a variety of real-world situations.
4. **Accurate Labeling:** The images are labeled by hand with their geophysical category. This allows us to measure how well detection works and how dependable the algorithms are.
5. **Number of Images:** The dataset has more than 37,000 SAR images, which is enough to train, validate, and test self-supervised and statistical learning models.
6. **Source and Accessibility:** The images come from the Sentinel-1A mission in 2016 and are available to the public through the SEANOE data repository.

To prepare the SAR images for the algorithm, I first standardized and normalized them. This made sure that the pixel intensity and scale were consistent across all images. This step helped reduce the ways radiometric properties and geophysical features might change how the model performs. Next, I split the dataset into training and testing groups. This allowed for self-supervised training, after which I checked how well the system could detect anomalies.

**Table 1. Statistical summary of SAR images used in this study**

| Attribute | Description |
|---|---|
| **Data type** | SAR images (Sentinel-1A, Wave Mode) |
| **Polarization** | VV (Vertical transmit, Vertical receive) |
| **Resolution** | Medium resolution |
| **Number of images** | More than 37,000 |
| **Acquisition year** | 2016 |
| **Geophysical phenomena** | Ocean waves, oil spills, vegetation, urban areas, clouds, atmospheric storms, etc. |

### 3.2. Methodology

In this study, an integrated multi-stage framework was developed for anomaly detection in SAR imagery. The proposed approach is designed to accurately detect abnormal regions within heterogeneous backgrounds and in the presence of speckle noise. The overall workflow comprises three main stages: SAR image pre-processing, anomaly separation, and abnormal region detection. All components of the framework were implemented and evaluated using the TenGeoP-SARwv dataset.

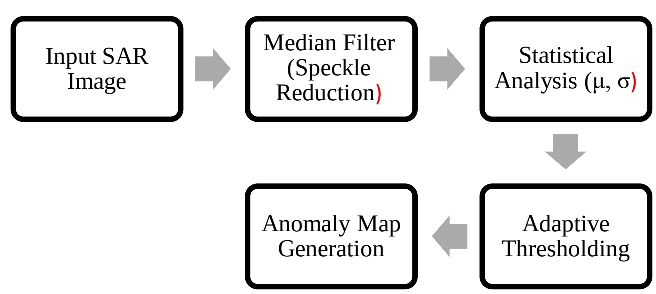


Figure 1. Flowchart of the proposed SAR anomaly detection framework.

#### 3.2.1. SAR Image Preprocessing

SAR images, such as those in the TenGeoP-SARwv dataset, frequently contain speckle noise. Because of the random variations in pixel brightness caused by this noise, it is more difficult to identify true anomalies because they are obscured by the overall background changes. Analysis can be challenging because these noisy pixels can be confused for anomalies (Lee, 1981; Bamler & Hartl, 1998). A median filter was applied to the pictures in order to address this. While reducing speckle noise, this type of filter preserves significant textures and structures. Unlike some other filters, the median filter eliminates noise spikes without causing excessive blurring. Since blurring can reduce the accuracy of the results, it is crucial to maintain sharp details in order to identify anomalies later.

Mathematically, the pre-processed image $X^{\wedge}$ is defined as:

$$X^{\wedge}_{i,j} = median X_{k,l} \mid (k,l) \in N_{i,j} \quad (1)$$

In this method, a neighbourhood window $N_{i,j}$ structures and possible unusual areas. The size of N was chosen through testing, based on image resolution and the amount of noise present.

3.2.2. Anomaly Separation

Following preprocessing, the anomaly separation stage is initiated. It is assumed that the majority of pixels correspond to the background, while anomalies are sparse and exhibit unusual intensity values (Candès et al., 2011; Bouwmans et al., 2016; Marino et al., 2016). To separate anomalies from the background, a statistical thresholding method was employed. First, the mean $\mu$ and standard deviation $\sigma$ of the preprocessed image are computed as:

$$\sigma = \sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{1}{MN}(X^{\wedge}_{i,j}-\mu)^2} \quad (2)$$

$$\mu = \sum_{i=1}^{M}\sum_{j=1}^{N}\frac{1}{MN}X^{\wedge}_{i,j} \quad (3)$$

Where M and N are the image dimensions [37]. An adaptive threshold $\tau$ is then defined based on these statistics:

$$\tau = \mu + \kappa.\sigma \quad (4)$$

The parameter k controls the sensitivity of anomaly detection. A value of k = 2 was empirically selected, as it provides a balance between suppressing false alarms and preserving true anomalous pixels. Preliminary tests with different k values showed that k = 2 produces stable anomaly detection results across diverse SAR scenes. This choice is consistent with commonly used statistical thresholding practices. [25, 27]. Pixels with intensities above the threshold are classified as anomalies:

$$S_{i,j} = \begin{cases} 1, if X^{\wedge}_{i,j} > \tau \\ 0, otherwise \end{cases} \quad (5)$$

where $S_{i,j}$ denotes the binary anomaly mask. This step is similar to low rank and sparse methods like Principal Component Analysis, but it doesn't need difficult solving. Because of this, it's faster and works better with big datasets like TenGeoP-SARwv. The main benefit is that it keeps the background looking good while picking out unusual things.

This capability is particularly effective in SAR images, where small targets such as ships or oil spills can easily be obscured by sea or natural land backgrounds. Furthermore, the method offers high flexibility, allowing the threshold $\tau$ to be adjusted according to the imaging environment to tune the sensitivity for detecting noise or anomalies.

3.2.3 Anomaly Detection

In the final stage, the regions identified by the matrix S are used to generate an Anomaly Map. The intensity of each pixel in this map is computed as its deviation from the background mean:

$$A_{i,j} = \frac{X_{i,j} - \mu}{\sigma} \quad (6)$$

This normalization makes the anomaly score independent of the image scale and allows comparison across different SAR scenes. Using the regions identified by matrix S, an anomaly map is created in the final step. Each point's brightness on this map serves as an anomaly score, indicating how different it is from the background average (Pang et al., 2021; Dalsasso et al., 2021). We employ local filtering and brightness level adjustments to make the map easier to read, which highlights the points that are probably anomalies. With this enhancement, the anomaly map is easier to see and more useful for gauging outcomes and contrasting with alternative methods of anomaly detection.

## 4. Implementation and Results

Although the TenGeoP-SARwv dataset contains more than 37,000 images, five representative samples were selected for detailed visualization. These images illustrate the behavior of the proposed method under different backscatter and noise conditions. To check how well the method worked, five SAR images were taken from the Sentinel-1 collections in the TenGeoP-SARwv repository. The images were picked to have different backscatter intensities, environmental situations, and amounts of speckle noise, which made sure the evaluation was varied. The process had three main steps:

1. Preprocessing to reduce speckle noise.
2. Calculation of statistical indices and application of thresholding.
3. Extraction of anomalous regions.

In the initial stage, a median filter was applied to the original images to suppress speckle noise while retaining essential structural details. The improvement achieved through this preprocessing step is evident, as the filtered images exhibit enhanced clarity and a noticeable reduction in visual artifacts.

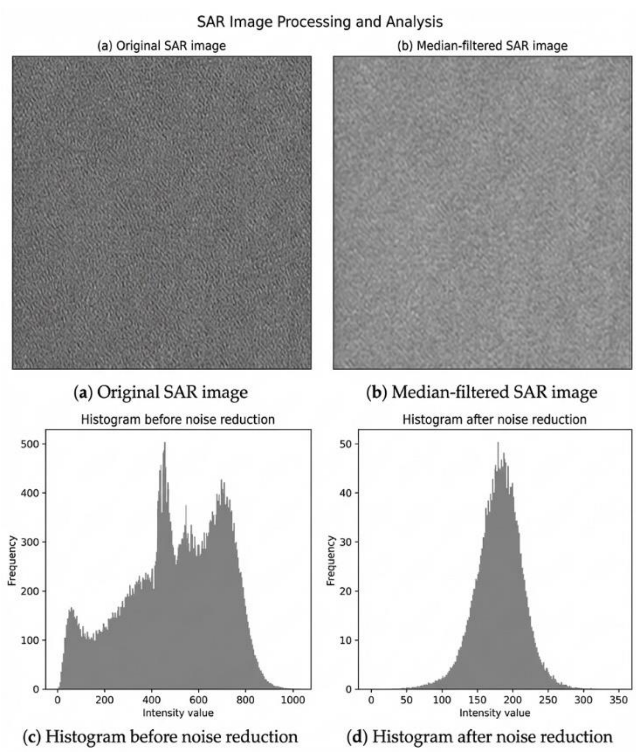


Figure 2. Effect of speckle noise reduction using median filtering: (a) original SAR image, (b) median-filtered SAR image, (c) histogram of pixel intensities before noise reduction, (d) histogram after noise reduction.

The results show a reduction in intensity dispersion while preserving structural information. To visually assess the impact of speckle noise reduction, Figure X compares the original SAR image with its median-filtered counterpart. The histogram analysis indicates that median filtering significantly reduces intensity dispersion caused by speckle noise, while preserving dominant structural patterns. This preprocessing step improves the reliability of subsequent statistical thresholding and reduces the likelihood of false anomaly detections. Without noise reduction, high-intensity speckle pixels may be incorrectly classified as anomalies, whereas median filtering suppresses such artifacts. Subsequently, statistical thresholding was applied using the mean (μ) and standard deviation (σ) of the pixel intensities to determine the adaptive threshold (τ). Pixels with intensity values exceeding τ were classified as anomalous regions. The outcomes of this stage were visualized in the form of anomaly maps, illustrating the spatial distribution of the detected irregularities.

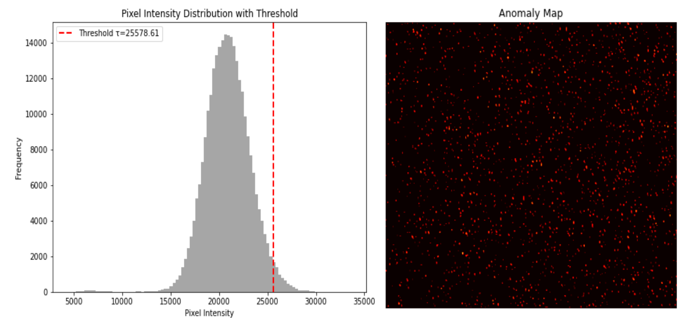


Figure 3 – Histogram and anomaly map of Image 1

To assess the robustness of the proposed method under varying conditions, the same procedure was applied to the fourth image. Among the analyzed samples, this image contained the highest proportion of anomalous regions. A comparison with the first image clearly demonstrates the algorithm's capability to maintain reliable performance across contrasting scenarios.

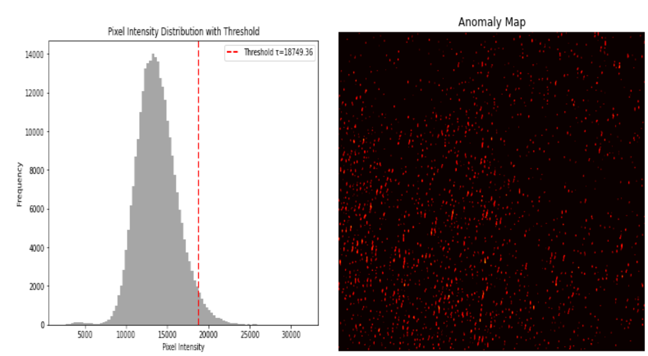


Figure 4 – Histogram and anomaly map of Image 4

The quantitative results are also presented in Table 2. This table shows the mean intensity (μ), standard deviation (σ), threshold (τ), and the percentage of anomaly regions for each of the five images.

**Table 2 – Statistical results of the images**

| Image | Mean intensity (μ) | Standard deviation (σ) | Threshold (τ) | Anomaly percentage (%) |
|---|---|---|---|---|
| **Image 1** | 20920.30 | 2329.15 | 25578.61 | 2.44 |
| **Image 2** | 21531.86 | 3030.07 | 27592.00 | 2.72 |
| **Image 3** | 25487.56 | 3621.61 | 32730.78 | 2.52 |
| **Image 4** | 13763.85 | 2492.76 | 18749.36 | 3.25 |
| **Image 5** | 20306.20 | 2686.83 | 25679.87 | 2.51 |

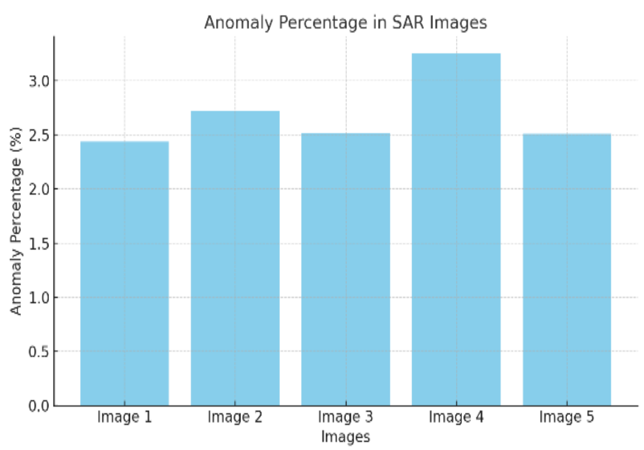


Figure 5 – Anomaly percentage chart for the SAR images


Figure 6 – Statistical comparison chart of the SAR images

The data shows that our method finds anomalies in test images with a rate consistently under 4%. This suggests the method is good at spotting real issues while keeping false alarms low. For example, comparing Images 1 and 4, Image 4 has a lower mean intensity but a higher rate of anomalies. This suggests the method works well even when backscatter intensities change. It can still find unusual things in SAR images with low intensity. The anomaly maps show a clear visual match with the histogram tails, where outlier pixels gather. This link between statistical measures and visual patterns supports the algorithm's accuracy and consistency. Also, the difference between low- and high-anomaly samples shows the method can adjust to different imaging situations.

In summary, despite its computational simplicity, the proposed approach achieves a strong balance between efficiency, statistical reliability, and visual interpretability. These attributes make it a practical and scalable solution for real-world applications, including environmental monitoring, detection of floating or drifting objects at sea, and identification of critical or anomalous regions in large-scale radar datasets.

## 5. Conclusion and Recommendations

In this study, a simple yet effective method was proposed for anomaly detection in SAR images. The approach is based on statistical analysis of pixel intensities and thresholding using the mean and standard deviation. Experiments conducted on Sentinel-1 images from the TenGeoP-SARwv dataset demonstrated that this method, despite its simplicity, can accurately identify anomalous regions. Quantitative results from five sample images showed anomaly percentages ranging from 2.44% to 3.25%. This low rate indicates the algorithm's ability to pinpoint specific regions without generating extensive noise or false positives. Qualitative assessments using anomaly maps and histograms confirmed that highlighted areas matched the statistical distribution of pixel intensities, demonstrating both visually and statistically reliable performance.

One of the method's key strengths is its robustness across diverse data and conditions. Comparing the results from Image 1 (lowest anomaly percentage) and Image 4 (highest anomaly percentage) shows that the algorithm is resilient to variations in overall image intensity and can extract abnormal patterns even when backscatter levels are low. This characteristic is particularly valuable in real-world scenarios where radar data may be influenced by environmental, geometric, or noise-related factors. From a computational standpoint, the method relies on simple statistical indices (mean and standard deviation), making it fast and lightweight. This allows implementation in operational systems with time or hardware constraints. For example, in applications such as real-time monitoring of ocean changes, ship detection, or oil spill tracking, processing speed is critical, and the proposed method meets this requirement effectively.

Despite its strengths, the method has limitations. First, it depends on the threshold parameter $\kappa$, which influences sensitivity and detection accuracy. Second, the algorithm only considers pixel intensity information and ignores other textural or spectral features. In cases where anomalous patterns do not significantly differ in intensity, this may reduce effectiveness. To overcome these limitations and improve results, the following future research directions are suggested:

1. **Combining statistical and machine learning methods**: Integrating algorithms such as SVM[1] or CNN[1] can enhance accuracy and [1]capture more complex patterns.
2. **Incorporating textural and frequency features:** Adding spatial correlation indices, GLCM[1], or wavelet transforms can provide complementary information to improve anomaly detection.
3. **Comparative evaluation on diverse datasets:** Although this study used Sentinel-1, extending the method to datasets such as RADARSAT or TerraSAR-X would better assess algorithm stability and reliability.
4. **Development of operational systems:** Given its computational simplicity, the method could be implemented in real-time systems for environmental monitoring, facilitating practical applications.
5. **Multi-source data integration:** Combining SAR data with optical or hyperspectral imagery could provide a more comprehensive view of anomalous regions and improve final system accuracy.

In conclusion, the proposed method represents a simple yet efficient approach for SAR anomaly detection, achieving a favorable balance between computational simplicity and detection accuracy. With further development and integration with advanced techniques, it has the potential to become a powerful tool for large-scale radar data analysis in sensitive environmental and security applications.

## References


Henderson, F. M., & Lewis, A. J. (1998). Principles & Applications of Imaging Radar. Wiley.

Bamler, R., & Hartl, P. (1998). Synthetic aperture radar interferometry. Inverse Problems, 14(4), R1–R54. https://doi.org/10.1088/0266-5611/14/4/001

Touzi, R. (2007). Target scattering decomposition in terms of roll-invariant target parameters. IEEE Transactions on Geoscience and Remote Sensing, 45(1), 73–84. https://doi.org/10.1109/TGRS.2006.886176

Zhou, J., Kwan, C., Ayhan, B., & Eismann, M. T. (2016). A Novel Cluster Kernel RX Algorithm for Anomaly and Change Detection Using Hyperspectral Images. IEEE Transactions on Geoscience and Remote Sensing, 54(11), 6497–6504. https://doi.org/10.1109/TGRS.2016.2585495

Choi, H., & Jeong, J. (2019). Speckle Noise Reduction Technique for SAR Images Using Statistical Characteristics of Speckle Noise and Discrete Wavelet Transform. Remote Sensing, 11(10), 1184. https://doi.org/10.3390/rs11101184

Kelly, E. J. (1986). An adaptive detection algorithm. IEEE Transactions on Aerospace and Electronic Systems, AES-22(2), 115–127. https://doi.org/10.1109/TAES.1986.310745

Xiao, D., Liu, W., Chen, H., Li, H., & Li, B. (2024). An Adaptive Radar Target Detection Method Based on Alternate Estimation in Power Heterogeneous Clutter. *Remote Sensing*, 16(13), 2508. https://doi.org/10.3390/rs16132508

Reed, I. S., & Yu, X. (1990). Adaptive multiple-band CFAR detection of an optical pattern with unknown spectral distribution. IEEE Transactions on Acoustics, Speech, and Signal Processing, 38(10), 1760–1770. https://doi.org/10.1109/29.60107

Wang, Z., Liu, J., Li, Y., Chen, H., & Peng, M. (2022). Adaptive subspace signal detection in structured interference plus compound Gaussian sea clutter. *Remote Sensing*, 14(9), 2274. https://doi.org/10.3390/rs14092274

Candès, E. J., Li, X., Ma, Y., & Wright, J. (2011). Robust principal component analysis? Journal of the ACM, 58(3), Article 11. https://doi.org/10.1145/1970392.1970395

Sun, Y., Lei, L., Guan, D., Li, X., & Kuang, G. (2020). SAR Image Change Detection Based on Nonlocal Low-Rank Model and Two-Level Clustering. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13(1), 293–306. https://doi.org/10.1109/JSTARS.2019.2960518

Ong, F., & Lustig, M. (2016). Beyond low-rank + sparse: Multi-scale low rank matrix decomposition. IEEE Journal of Selected Topics in Signal Processing, 10(4), 672–687. https://doi.org/10.1109/jstsp.2016.2545518

Zhou, T., Tao, D., & Others. (2010). Stable principal component pursuit. IEEE International Symposium on Information Theory (ISIT) Proceedings. https://doi.org/10.1109/ISIT.2010.5513502

Pang, G., Shen, C., Cao, L., & van den Hengel, A. (2021). Deep learning for anomaly detection: A review. ACM Computing Surveys, 54(2), Article 35. https://doi.org/10.1145/3439950

Bo, F., Ma, X., Hu, S., An, G., Li, Y., & Cen, Y. (2025). Speckle-Driven Unsupervised Despeckling for SAR Images. IEEE Journal of Selected Topics in Applied


[1] Support Vector Machines [0]
[1] Convolutional Neural Networks [1]
[1] Gray-Level Co-occurrence Matrix [2]

Earth Observations and Remote Sensing, 18, 13023–13034. https://doi.org/10.1109/JSTARS.2025.3568854

Li, J., et al. (2021). SSDD: SAR Ship Detection Dataset. Remote Sensing, 13(11), 2201. https://doi.org/10.3390/rs13112201

Wei, S., et al. (2020). HRSID: High-Resolution SAR Images Dataset for ship detection. IEEE Access, 8, 120234–120254. https://doi.org/10.1109/ACCESS.2020.3005861