

Original Article

# Privacy-Preserving Remote Sensing Image Crypto-Watermarking using Discrete Wavelet Transform and Improved Performer Optimization Algorithm based on Slow Learner Enhancement Scheme for Band Selection

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**Abstract** - Rapid growth in multimedia, communication, and deep learning technologies increases privacy, integrity, authenticity, and security issues for Remote Sensing Hyperspectral Images (RSHIs). This paper presents a crypto-watermarking framework based on the Block-based Discrete Wavelet Transform (BBDWT) to ensure the privacy, integrity, authenticity, and security of RSHIs. It uses an improved Slow Learner Improvement Scheme-based Performer Optimization Algorithm (SLIS-POA) for spectral band selection, leveraging higher entropy and higher variance across bands. Furthermore, it uses the Arnold Tent Map (ATM) to encrypt the message image, providing privacy and security for the authentication message. The effectiveness of the system is evaluated on the public Indian Pines (IP) and Salinas datasets based on Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Metrics (SSIM) and Normalized Correlation (CC). The SLIS-POA-DWT provides improved PSNR in the range of 52.26 dB to 62.20 dB, SSIM in the range of 0.9947 to 0.9999 and NC in the range of 0.9835 to 0.9999 for Salinas and IndianPines dataset for recovered images and message.

**Keywords** - Crypto-watermarking, Remote sensing images, Hyperspectral images, Discrete wavelet transform, Performer optimization algorithm, Watermarking, Image encryption.

## 1. Introduction

Remote Sensing Hyperspectral Images (RSHI) contain rich spatial and spectral information about materials and objects across hundreds of bands. RSHIs are widely used in diverse applications, including mineral exploration, agricultural monitoring, water treatment, healthcare, environmental monitoring, and defense [1-4].

The RSHIs are capable of distinguishing the material type, spectral, and spatial properties of the objects, which makes it popular for various remote sensing applications compared with conventional color images [5]. RSHIs are often subject to unauthorized access, privacy violations, and content tampering due to their higher cost, importance, and information richness [6].

Huge growth in communication technology, social media networks, and digital technology increases the production, sharing, and accessibility of multimedia data. High-speed

mobile devices, internet services, and cloud computing frameworks enable seamless data transmission over the globe [7]. Social media platforms handle the sharing of large volumes of multimedia data, such as videos, images, instant messages, and remote sensing data [8]. However, this digital transformation leads to misuse, forgery, deepfake creation, data tampering, copyright violations, object and skin disease detection, cyber threats, unauthorized access, and illegal sharing, which undermine the privacy, authenticity, and integrity of data [9].

To ensure the privacy, integrity, and authenticity of the RSHIs, crypto-watermarking is essential. Crypto-watermarking combines watermarking with encryption to ensure authenticity: it embeds an authentic message in the original image and encrypts the image to protect its security. The primary aim of the system is to ensure that the RSHIs are not altered or corrupted by various cyberattacks during transmission [10].



In existing privacy-preservation techniques, limited attention has been given to preserving privacy in high-complexity multispectral and HSIs due to their intricate band structures and complex image patterns. Ensuring the security and integrity of images is challenging due to limited authenticity and information security, without degrading the context and content of the HSIs [11]. Thus, there is a need to present a privacy-preserving crypto-watermarking scheme that helps claim the authenticity of HSIs and protect the data from various attacks and manipulations on the images. There is a need to develop a framework that minimizes the system's computational complexity by selecting specific bands for watermarking [12].

This paper presents a crypto-watermarking framework for ensuring the integrity, privacy, security, and authenticity of images. The major contributions of the paper are summarized as follows:

- Development of a band selection scheme based on SLIS-POA, which uses a Logarithmic Chaotic Map (LCM) to improve the population diversity, Levy's flight during exploration to enhance the search space, and a slow learner improvement scheme to boost the exploitation capability, and improve the convergence of the band selection algorithm.
- Image watermarking using BBDWT to ensure the authenticity of the RSHIs while preserving the structural, perceptual, and visual quality of the images.
- Message image encryption using the Arnold tent map to ensure the privacy and security of the authentication message.
- Performance evaluation of proposed crypto-watermarking on the public Indian Pines and Salinas dataset based on various performance metrics.

The rest of the paper is structured as follows: Section 2 details the crypto-watermarking framework. Section 3 presents discussions of the dataset, experimental results, and analytical findings. Section 4 delivers the conclusions, highlighting the major achievements, limitations, and future direction for the work.

## 2. Literature Survey

Various privacy-preserving techniques have been presented for remote sensing images in recent years. Yang et al. [13] suggested Zero Watermarking (ZW) to retain the spectral and spatial information of the HSI. The ZW watermarking technique used zigzag scanning and Zernike moments for HSI watermarking, resulting in superior normalized correlation. Bodke et al. [14] showed that band selection is crucial in HSI watermarking to improve the watermark's robustness against different attacks. It uses the Forensic Beauro-Archimedes Optimization Algorithm (FBIAO) to select bands with minimum variance and DWT-based watermarking for HSI watermarking. The watermarked

image is encrypted using an Arnold tent map to enhance watermark security. The FBIAO-DWT-based crypto-watermarking scheme provided better visual, perceptual, and structural image quality. The FBIAO-DWT offers invisible watermarking with higher embedding capacity while preserving the system's edge, texture, spectral, and spatial information. Though the crypto-watermarking scheme has shown better resilience against the different geometrical and non-geometrical watermarking attacks, the computational complexity of the band selection is higher, and solution diversity and exploration-exploitation balance are limited for FBIAO. De Li et al. [15] suggested a deep encoder-decoder framework for image watermarking that uses an attention module, which provides greater robustness to various noise and compression attacks. It provided the overall PSNR of 48.05 dB for the extracted watermark. However, the system's effectiveness is limited by its higher computational complexity. Panthakkan et al. [16] developed reversible watermarking techniques to preserve the privacy and ownership of HSIs. The system focused on resisting various attacks and reducing the computational complexity of the watermarking system.

Khosravi and Rostami [17] developed an improved binary watermarking scheme based on XOR for information hiding in satellite images. The blind extraction scheme helps achieve high visual and perceptual quality in the watermarked image. Though the method is simple and has lower computational complexity, its effectiveness is limited for color and multispectral images. It fails to resist various crypto attacks, compromising its security and privacy. Zhang et al. [18] suggested a dual watermarking scheme based on DWT, based on Singular Value Decomposition (DWT-SVD) and Chebyshev Chaotic Map (CCM) for RSIs watermarking. The DWT-SVD has shown strong robustness against the filtering, rotation, scaling, noise and compression attack. The CCM increases the unpredictability of the watermark image retrieval. Combining SVD with DWT increases the robustness and imperceptibility of the watermarking scheme. However, the system suffers from a poor tradeoff between invisibility and robustness.

Hua et al. [19] designed an adaptive watermarking method based on DWT and maximum entropy. It increases the robustness and invisibility of the watermark by converting RGB color images to the YCbCr color space. The system demonstrated resilience under various attack conditions for single-band HSIs, but its application is limited to HSIs due to the high complexity of spectral bands. Zope-Chaudhari et al. [20] proposed a DWT-based crypto-watermarking scheme that employs multiplicative and transposition-based encryption mechanisms to enhance security for multispectral images. The 3-level DWT decomposition for watermarking provides better visual, perceptual, and structural quality in multispectral images. However, key management is difficult and increases the system's computational complexity. Bhatti

et al. [21] proposed a watermarking technique based on Speeded-Up Robust Features (SURF), incorporating an integer wavelet transform and a sampling pyramid decomposition. This approach is quite robust against geometric attacks such as scaling, rotation, and translation, making it well-suited for remote sensing images. It also maintains a high level of reversibility, meaning the original picture can be reconstructed with minimal loss of quality. Even though this approach has certain benefits, it is computationally expensive and may be vulnerable to advanced attacks targeting the feature extraction process.

Xu et al. [22] used a zero-watermarking method together with blockchain technology. This method uses K-L transform, Nonsubsampled Contourlet Transform (NSCT), and SVD to create a watermark that is stored on a blockchain to protect copyright. The best thing about this method is that it doesn't require adding a watermark to the picture, which helps keep the original data safe. Also, using blockchain ensures that copyright management is decentralized and immutable.

But this technique is not very useful for real-time applications, as it is expensive to run due to the blockchain infrastructure and complex arithmetic operations. Serra-Ruiz and Megias [23] developed a semi-fragile forensic watermarking system that employs tree-structured vector quantization. This approach is specifically designed for multispectral and hyperspectral images. Its goal is to find tampering while keeping the watermark intact during lossy compression. This method makes it possible to detect any unauthorized changes to the image, which is helpful for forensic purposes.

But it isn't very robust against image scaling, which might cause the watermark to be lost in some cases. Also, the difficulty of implementation makes it less useful in real-world applications. Devi et al. [24] explored the Redundant DWT-SVD (RDWT-SVD) method, where the embedding scale factor is optimized using the Grasshopper-BAT algorithm. The effectiveness of the RDWT-SVD is analyzed for aerial RSHIs that have shown greater robustness in image imperceptibility and watermarking. However, the effectiveness of the system is limited for various geometric attacks such as clipping and rotation, which limits the deployment flexibility for real-time.

From the extensive literature survey, the following major gaps are identified from the survey:

- HSI water-making is challenging due to higher spatial and spectral variability in the spectral bands of RSIs.
- The computational complexity of the existing watermarking technique increases the watermarking time.
- The existing spatial domain watermarking techniques show low robustness against different geometrical and non-geometrical watermarking attacks.
- The band selection algorithms face challenges due to greater computational complexity, reduced solution diversity, an imbalance between exploration and exploitation, and poor convergence.
- Less focus is given on preserving the security, integrity, privacy, and authenticity of the HSIs.

### 3. Methodology

The flow diagram of the crypto-watermarking framework for RSHIs is shown in Figure 1.

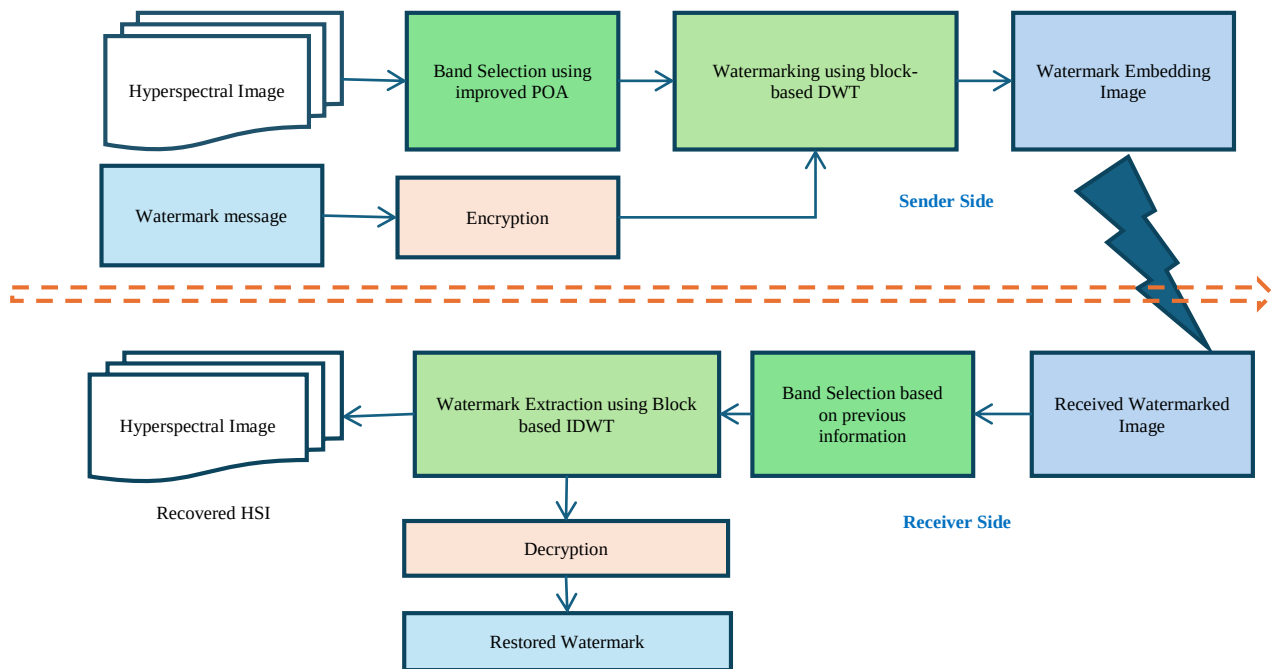


Fig. 1 Flow diagram of proposed crypto-watermarking framework

The proposed crypto-watermarking scheme comprises watermark embedding and watermark extraction to ensure the privacy, security, integrity, and authenticity of the HSIs. The SLIS-POA scheme for the band selection based on the maximum variance and entropy of the spectral bands to retain the visual and structural quality of the HSI bands. The message is encrypted using the ATM method to ensure its privacy and security.

The encrypted message is embedded in HIS bands using block-based DWT [26, 27]. The watermarked band is inserted into HSI images at its original position. The watermarked HSI is propagated over the channel. On the receiver side, the watermarked band is selected based on earlier information from the watermarked HIS. The message is retrieved using watermark extraction. The extracted watermark is decrypted using inverse ATM to acquire the original message.

### 3.1. Band Selection using SLIS-POA

The POA algorithm is a simple optimization method that models a perfumer's behavior and processes during perfume

preparation [25]. The traditional POA suffers from poor convergence, a lower search space, and an inferior balance between exploitation and exploration. The proposed improved POA considers the LCM for improving the population diversity of the POA, Levy's flight for updating the perfume scent stepwise to enhance the search space and avoid random exploration. It provides a novel SLIS that improves the population with lower fitness relative to the population with the highest fitness before proceeding to the next iteration, thereby enhancing exploitation of the PAO. The flow of the SLIS-POA is presented in Figure 2.

The SLIS-POA selects the 5 bands having higher variance and entropy. One band is selected from the optimized bands for the watermarking. Higher variance yields a better invisible embedding, and high entropy ensures less information loss across the bands during watermarking. Higher variance and entropy help select complex regions with texture and edge variations, making watermarking more robust and invisible. It ensures the preservation of the spatial and spectral content of the RSHIs while embedding the secret message in bands.

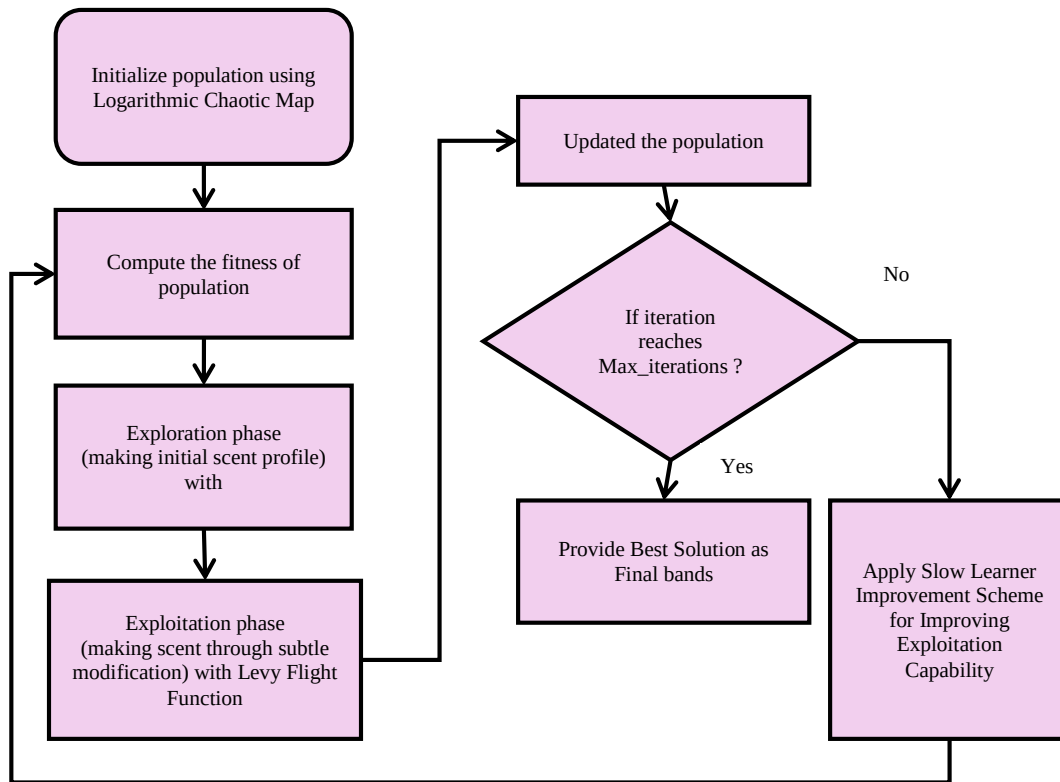


Fig. 2 Flowchart of SLIS-POA

The steps in the SLIS-POA-based band selection are summarized as follows:

*Step 1: Initialization of the Population of Perfume Composition using LCM*

The initialization phase randomly generates perfume compositions to produce the specific scent. To improve

compositional diversity, the LCM is used, thereby increasing the population diversity of POA algorithms. The Perfume Compositions (PC) are provided using Equations (1) and (2), where D denotes the number of spectral bands to be selected (elements of perfume composition), and N denotes the total population (possible perfume compositions). Here, LB and

UB denote lower bound, which is equivalent to 1 and upper bound, which is equivalent to total bands.

$$PC = \begin{bmatrix} PC_{11} & PC_{12} & \cdots & PC_{1B} \\ PC_{21} & PC_{22} & \cdots & PC_{2B} \\ \vdots & \vdots & \ddots & \vdots \\ PC & PC_{N2} & \cdots & PC_{NB} \end{bmatrix}_{N \times B} \quad (1)$$

$$PC_{ij} = LB_j + LCM_n * (UB_j - LB_j), \quad i=1, 2, \dots, N, j=1, 2, \dots, D \quad (2)$$

The population diversity is increased to improve the solution diversity as given in Equations (3) and (4), respectively. Here,  $LCM_n$  denotes the current state of the variable,  $\beta$  denotes a chaotic control variable, and  $LCM_{n+1}$  signifies the next value in the chaotic sequence. The  $\beta$  is considered dynamically to enhance the randomness of the population, considering  $\beta_{max} = 0.8$ ,  $\beta_{min} = 0.2$ , maximum iterations ( $T_{max}$ ), and current iterations ( $T$ ). The value of  $\beta$  increases as iteration increases to reduce premature convergence.

$$LCM_{n+1} = \beta \cdot \log(1 + LCM_n) \quad (3)$$

$$\beta = \beta_{max} + (\beta_{max} - \beta_{min}) * \frac{T}{T_{max}} \quad (4)$$

#### Step 2: Fitness Computation of Population

Compute the fitness of each population, which is analogous to smelling the scent of the perfume. Here, fitness is computed based on higher variance ( $Var$ ) and higher entropy ( $Ent$ ) to preserve the perceptual and visual quality of the spectral bands as given in Equation (5).

$$fitness = w_1 * (1/Ent) + w_2 * (1/Var) \quad (5)$$

#### Step 3: Exploration Phase (Broad Scent Discovery of Perfume)

In this stage, the scent is produced randomly, considering different combinations of aromatic molecules, oils, and fixatives to create the promising fragrance. For every perfume composition, the reference scent is identified from the worst and best compositions, randomly selected based on fitness value. The reference scent ( $ref_i$ ) is provided by Equation (6), where  $PC_{Best}$  denotes population with the highest fitness,  $PC_{Worst}$  indicate the population with the lowest fitness,  $r_1$  is a random number between 0 and 1,  $I$  is a random number chosen between 1 and 2, and  $PC_i$  indicates perfume combination considered for update.

$$ref_i = PC_i + r_1 * (PC_{Best} - I * PC_{Worst}) \quad (6)$$

A new perfume composition is created using this reference as given in Equation (7). If the new composition yields higher fitness (scent) than the existing one, the new

solution is accepted; otherwise, it is discarded.

Here,  $PC_{ij}^{new1}$  denotes updated perfume, and  $PC_{ij}$  signifies  $i^{th}$  perfume composition for  $j^{th}$  ingredient.

$$PC_{ij}^{new1} = PC_{ij} + I * r_1 * (Ref_i - I * PC_{ij}) \quad (7)$$

$$PC_i = \begin{cases} PC_{ij}^{new1} & \text{if } fitness(PC_{ij}^{new1}) > fitness(PC_{ij}) \\ PC_i & \text{Otherwise} \end{cases} \quad (8)$$

#### Step 4: Exploitation Phase (Fine-Tuning of Fragrance Properties)

Once the general scent is achieved, the scent is refined meticulously to enhance fragrance balance, silage, and longevity. It deals with local exploitation to fine-tune the solutions as given in Equation (9). If the fitness of the refined solution is greater than that of the existing solution, then it is accepted in the population as given in Equation (10).

$$PC_{ij}^{new2} = PC_{ij} + (1 - 2 * I * r_1) * \frac{(UB-LB)}{T} \quad (9)$$

$$PC_i = \begin{cases} PC_{ij}^{new2} & \text{if } fitness(PC_{ij}^{new2}) > fitness(PC_{ij}) \\ PC_i & \text{Otherwise} \end{cases} \quad (10)$$

#### Step 5: Apply a Slow Learner Improvement Scheme

The SLIS helps update the population with the lowest fitness to improve exploitation and expand the search space, as given in Equation (11). Here,  $PC_{new}$  is updated worst population using SLIS scheme,  $\eta$  denotes learning rate, and  $\eta$  stands for mutation rate, which helps to improve convergence and exploitation capability of POA.

$$PC_{new} = PC_{weak} + \eta \cdot (PC_{Best} - PC_{weak}) + \eta \quad (11)$$

#### Step 6: Repeat Steps 2-5 until the Maximum Number of Iterations is Reached.

### 4. Novel Slow Learner Improvement Scheme

The traditional POA directly passes the lower-performing population to the next iteration, which reduces the algorithm's search space, as this weak population often fails to provide optimal solutions and has limited capability to reach the best solution. In SLIS, we consider the weakest population member, with the lowest fitness, analogous to a weak student in a classroom. The weak member is updated based on the best-fitness member, analogous to the topper of the class. The week's update to the member ensures improvement in the search space before proceeding to the next iteration. The weak student has a chance to improve his performance if he collaborates with the topper for information sharing and learning. The algorithm for the SLIS is provided as follows:

Algorithm: Slow learner improvement scheme

Input: Weak Population

Output: Enhanced solution

Step 1: Consider 5-15% weak population having lowest fitness

Step 2: Consider Learning rate ( $\eta$ ) and mutation rate ( $\eta$ )

Step 3: update each population using equation

$$P_{new} = P_{weak} + \eta \cdot (P_{Best} - P_{weal}) + \eta$$

Step 4: Compute fitness of each  $P_{new}$

Step 5: If fitness( $P_{new}$ ) > fitness( $P_{weak}$ )

$P'_{new} = P_{new}$

else

$P'_{new} = P_{weak}$

end

Step 6: update overall population

Step 7: repeat step 2-6 for all weak members

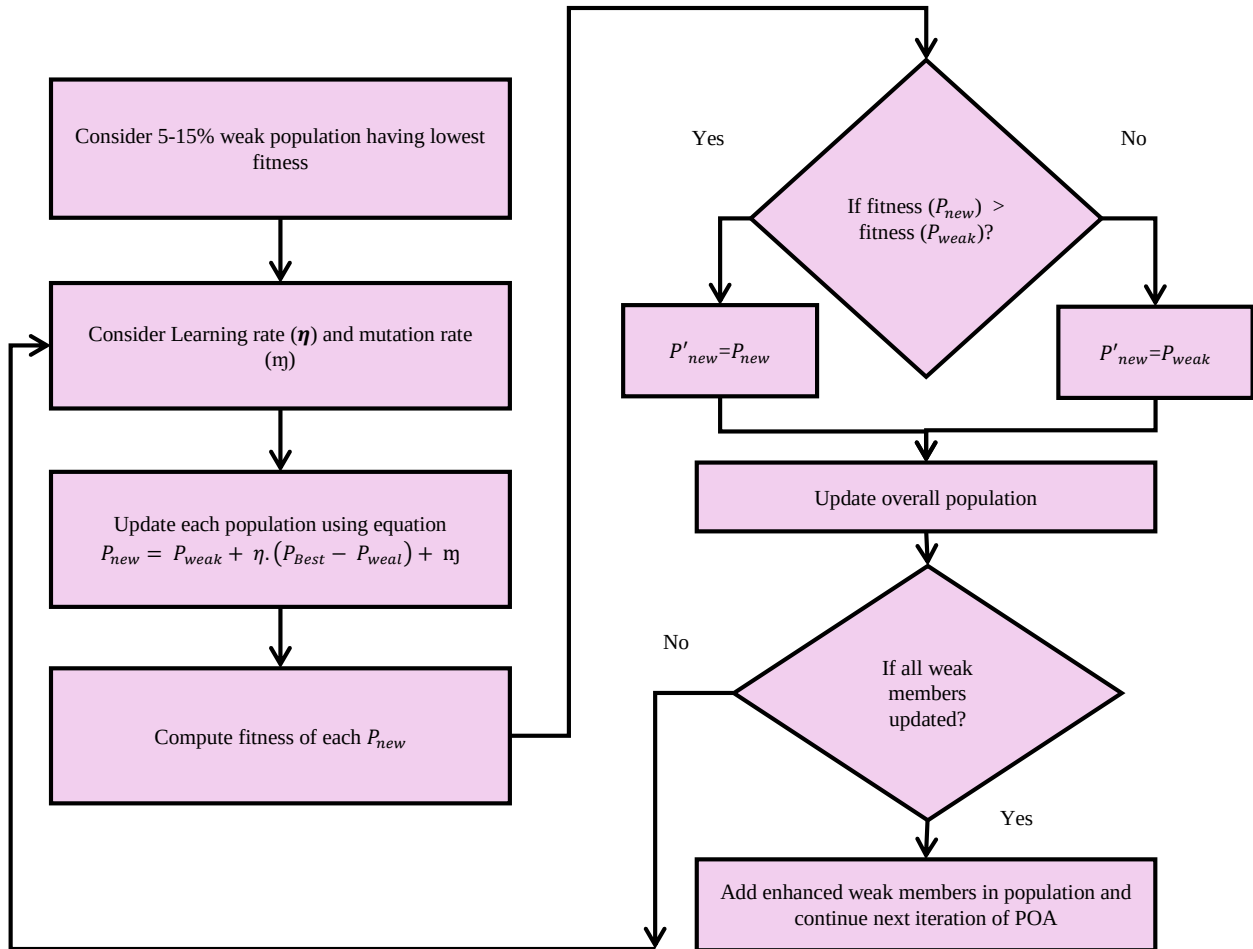


Fig. 3 Flowchart of SLIS scheme

## 5. Experimental Results and Discussion

The crypto-watermarking system is implemented in MATLAB R2025 on a personal computer with 16 GB of RAM in a Windows environment.

### 5.1. Dataset

The system's performance is evaluated on the public Indian Pines (IP) and Salinas datasets. The IP and Salinas are captured using the AVRIS sensor. The details of the IP and Salinas dataset are provided in Table 1.

Table 1. RSHI dataset details

| Parameter          | Indian Pines                        | Salinas            |
|--------------------|-------------------------------------|--------------------|
| Sensor             | AVRIS                               | AVRIS              |
| Spatial Size       | 145×145 pixels                      | 512×217 pixels     |
| Total Bands        | 220                                 | 224                |
| Spatial Resolution | ~20m                                | ~3.7 meters        |
| Image Content      | Vegetation, Agriculture, and Forest | Agriculture Fields |

## 5.2. Visualization of Results

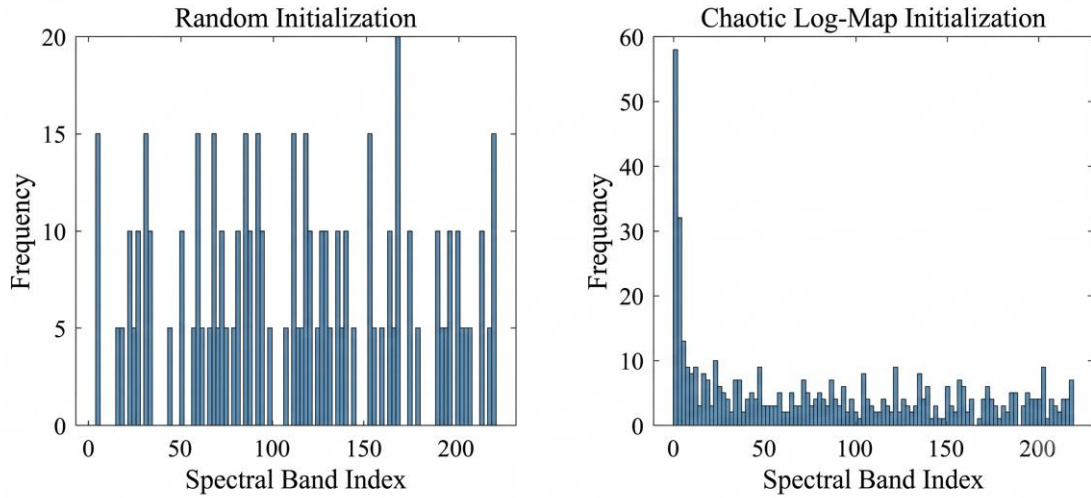
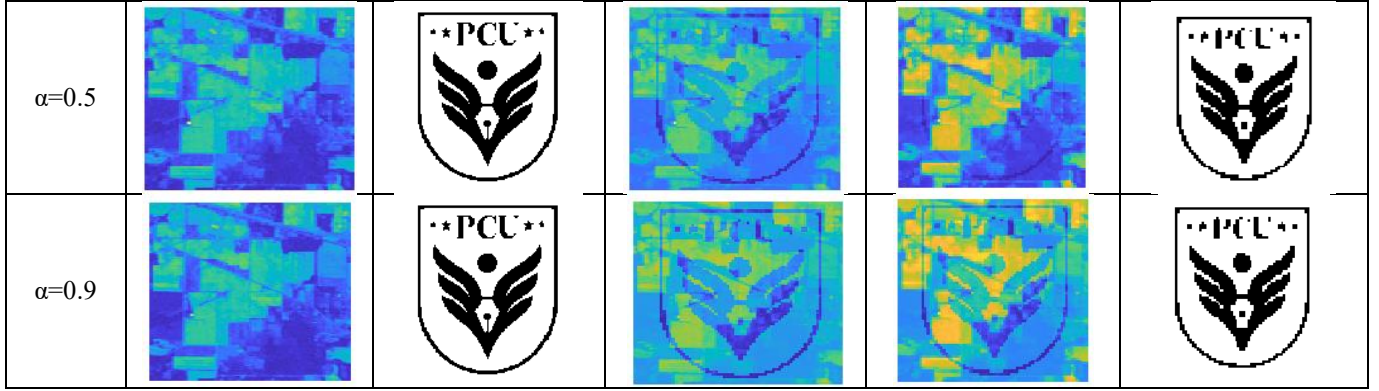


Fig. 4 Effect of LCM for distribution of band in initial population for 100 iterations for SLIS-POA-based band selection

The LCM increases population diversity in SLIS-POA-based band selection by providing a uniform distribution across the population. Figure 4 shows that LCM provides a uniform distribution of the selected band frequency in the population over 100 iterations for band selection, compared with traditional random population generation.

The visualizations of the results for various values of  $\alpha$  for IP and Salinas are shown in Figure 5. The visualizations show that the watermark band is invisible and that the structural and visual quality of the images is maintained. The retrieved message confirms ownership of the images and shows strong preservation of content.

| $\alpha$ value | Original Band | Original Message | Watermarked Band | Extracted Band | Extracted Message |
|----------------|---------------|------------------|------------------|----------------|-------------------|
| $\alpha=0.001$ |               |                  |                  |                |                   |
| $\alpha=0.01$  |               |                  |                  |                |                   |
| $\alpha=0.1$   |               |                  |                  |                |                   |

Fig. 5 Visualizations of watermarking for different value  $\alpha$  for the IndianPines dataset

### 5.3. Results Comparison for Original and Recovered Image

The effectiveness of the SLIS-POA-based band selection is compared with traditional algorithms like POA, FBIAO, and PSO for the original cover and recovered cover bands of the HIS for IndianPines and Salinas, as given in Tables 2 and 3, respectively. The DWT-based watermarking shows better results for the  $\alpha=0.001$ , showing robustness in invisible watermarking. The DWT and proper selection of bands for watermarking helps to retain the perceptual, structural and

visual quality of the hyperspectral bands. The SLIS-POA-DWT shows the PSNR of 52.26 dB and 52.18 dB for IndianPines and Salinas dataset respectively. The structural content preservation is depicted by higher SSIM of 0.9998 and 0.9999 for the IndianPines and Salinas, respectively for SLIS-POA algorithm. The band selection helps to improve the watermarking performance by selecting the bands to hide the watermark message without degrading the quality and content of images.

Table 2. Results comparison for original and recovered image for IndianPines dataset

| Alpha | PSO       |        |        | FBIAO     |        |        | POA       |        |        | SLIS-POA  |        |        |
|-------|-----------|--------|--------|-----------|--------|--------|-----------|--------|--------|-----------|--------|--------|
|       | PSNR (dB) | SSIM   | NC     | PSNR (dB) | SSIM   | NC     | PSNR (dB) | SSIM   | NC     | PSNR (dB) | SSIM   | NC     |
| 0.001 | 47.4223   | 0.9508 | 0.9619 | 49.1773   | 0.9696 | 0.9763 | 50.7163   | 0.9853 | 0.9886 | 52.2603   | 0.9998 | 0.9999 |
| 0.01  | 42.6738   | 0.9573 | 0.9583 | 43.7878   | 0.9710 | 0.9722 | 45.0268   | 0.9883 | 0.9861 | 46.6438   | 0.9994 | 0.9997 |
| 0.1   | 38.3980   | 0.9477 | 0.9573 | 39.9180   | 0.9662 | 0.9683 | 41.5760   | 0.9762 | 0.9807 | 43.2610   | 0.9896 | 0.9922 |
| 0.5   | 36.3705   | 0.9286 | 0.9415 | 37.9205   | 0.9452 | 0.9524 | 39.0995   | 0.9559 | 0.9684 | 40.8325   | 0.9737 | 0.9799 |
| 0.9   | 34.7568   | 0.9131 | 0.9152 | 35.9928   | 0.9241 | 0.9278 | 37.6188   | 0.9402 | 0.9461 | 38.9368   | 0.9562 | 0.9654 |

Table 3. Results comparison for original and recovered image for Salinas dataset

| Alpha | PSO       |        |        | FBIAO     |        |        | POA       |        |        | SLIS-POA  |        |        |
|-------|-----------|--------|--------|-----------|--------|--------|-----------|--------|--------|-----------|--------|--------|
|       | PSNR (dB) | SSIM   | NC     | PSNR (dB) | SSIM   | NC     | PSNR (dB) | SSIM   | NC     | PSNR (dB) | SSIM   | NC     |
| 0.001 | 48.0297   | 0.9463 | 0.9527 | 49.4147   | 0.9659 | 0.9634 | 50.8117   | 0.9849 | 0.9831 | 52.1817   | 0.9999 | 0.9999 |
| 0.01  | 42.2735   | 0.9415 | 0.9478 | 43.9155   | 0.9536 | 0.9647 | 45.4605   | 0.9689 | 0.9757 | 46.6025   | 0.9877 | 0.9908 |
| 0.1   | 38.5810   | 0.9304 | 0.9382 | 40.1580   | 0.9490 | 0.9530 | 41.5460   | 0.9622 | 0.9645 | 43.2330   | 0.9789 | 0.9840 |
| 0.5   | 36.9064   | 0.9180 | 0.9188 | 38.0604   | 0.9376 | 0.9387 | 39.3224   | 0.9518 | 0.9581 | 40.8114   | 0.9653 | 0.9731 |
| 0.9   | 34.3618   | 0.9060 | 0.9103 | 35.5188   | 0.9172 | 0.9300 | 37.2698   | 0.9365 | 0.9442 | 38.9198   | 0.9530 | 0.9626 |

### 5.4. Results Comparison for Original and Watermarked Image

Table 4. Results comparison for original and watermarked image for IndianPines dataset

| Alpha | PSO     |        |        | FBIAO [14] |        |        | POA     |        |        | SLIS-POA |        |        |
|-------|---------|--------|--------|------------|--------|--------|---------|--------|--------|----------|--------|--------|
|       | PSNR    | SSIM   | NC     | PSNR       | SSIM   | NC     | PSNR    | SSIM   | NC     | PSNR     | SSIM   | NC     |
| 0.001 | 33.4656 | 0.9460 | 0.9393 | 34.6086    | 0.9596 | 0.9562 | 35.9576 | 0.9764 | 0.9759 | 37.3816  | 0.9877 | 0.9908 |
| 0.01  | 31.5350 | 0.9367 | 0.9439 | 33.0500    | 0.9470 | 0.9546 | 34.5750 | 0.9653 | 0.9675 | 36.0630  | 0.9789 | 0.9840 |
| 0.1   | 31.0265 | 0.9091 | 0.9280 | 32.4175    | 0.9282 | 0.9411 | 33.7655 | 0.9462 | 0.9524 | 34.9185  | 0.9593 | 0.9680 |
| 0.5   | 29.9204 | 0.8927 | 0.9023 | 31.0244    | 0.9066 | 0.9214 | 32.3894 | 0.9235 | 0.9356 | 33.9074  | 0.9363 | 0.9478 |
| 0.9   | 27.9117 | 0.8798 | 0.8909 | 29.4717    | 0.8900 | 0.9023 | 30.7917 | 0.9056 | 0.9139 | 32.1817  | 0.9187 | 0.9312 |

The results for the original and watermarked band for IndianPines and Salinas dataset are shown in Figures 4 and 5, respectively, for different optimization algorithms. The embedding of the message increases the errors in the pixel values and thus results in lower PSNR. However, DWT-based watermarking for  $\alpha=0.001$  manages to retain the visual and structural quality of the bands where the message is totally invisible and hard to predict watermarking by naked eyes. The SLIS-POA-based shows higher PSNR of 37.38 dB and 36.05

dB for IndianPines and Salinas compared with POA (35.95 dB for IndianPines and 34.87 dB for Salinas), FBIAO (34.60 dB for IndianPines and 33.65 dB for Salinas), and PSO (33.46 dB for IndianPines and 32.49 dB for Salinas) for  $\alpha=0.001$ . Effective band election of using SLIS-POA supports to preserve the visual quality of watermarked bands, offering improved SSIM of 0.9877 and 0.9835 for the IndianPines and Salinas dataset respectively.

**Table 5. Results comparison for original and watermarked image for Salinas dataset**

| Alpha | PSO     |        |        | FBIAO [14] |        |        | POA     |        |        | SLIS-POA |        |        |
|-------|---------|--------|--------|------------|--------|--------|---------|--------|--------|----------|--------|--------|
|       | PSNR    | SSIM   | NC     | PSNR       | SSIM   | NC     | PSNR    | SSIM   | NC     | PSNR     | SSIM   | NC     |
| 0.001 | 32.4998 | 0.9356 | 0.9455 | 33.6598    | 0.9493 | 0.9640 | 34.8748 | 0.9660 | 0.9770 | 36.0508  | 0.9835 | 0.9876 |
| 0.01  | 30.9468 | 0.9346 | 0.9406 | 32.3228    | 0.9477 | 0.9572 | 33.5378 | 0.9622 | 0.9681 | 34.9078  | 0.9764 | 0.9820 |
| 0.1   | 29.0948 | 0.9095 | 0.9115 | 30.8038    | 0.9229 | 0.9271 | 32.2498 | 0.9388 | 0.9446 | 33.8978  | 0.9530 | 0.9626 |
| 0.5   | 28.3182 | 0.8935 | 0.9071 | 29.8082    | 0.9037 | 0.9228 | 31.3592 | 0.9219 | 0.9341 | 32.9932  | 0.9328 | 0.9446 |
| 0.9   | 26.1891 | 0.8773 | 0.8751 | 27.7441    | 0.8905 | 0.8916 | 29.0531 | 0.9010 | 0.9061 | 30.7361  | 0.9115 | 0.9241 |

##### 5.5. Results Comparison for Original and Recovered Message

The SLIS-POA-based shows higher PSNR of 63.5458 dB and 62.2068 dB for IndianPines and Salinas compared with POA (62.01 dB for IndianPines and 60.56 dB for Salinas), FBIAO (60.65 dB for IndianPines and 59.21 dB for Salinas), and PSO (59.09 dB for IndianPines and 57.92 dB for Salinas) for  $\alpha=0.001$ . Selection of proper band using SLIS-POA helps

to maintain the information preservation of the message image, offering improved SSIM of 0.9915 and 0.9929 for the IndianPines and Salinas datasets, respectively. The visualizations of the PSNR, SSIM and NC for the different band selection techniques for DWT-based watermarking for original band vs recovered band, original band vs watermarked band, and original message vs recovered message are shown in Figures 6 - 8 respectively.

**Table 6. Results comparison for original and recovered message for IndianPines dataset**

| Alpha | PSO     |        |        | FBIAO [14] |        |        | POA     |        |        | SLIS-POA |          |          |
|-------|---------|--------|--------|------------|--------|--------|---------|--------|--------|----------|----------|----------|
|       | PSNR    | SSIM   | NC     | PSNR       | SSIM   | NC     | PSNR    | SSIM   | NC     | PSNR     | SSIM     | NC       |
| 0.001 | 59.0928 | 0.9433 | 0.9516 | 60.6598    | 0.9548 | 0.9677 | 62.0158 | 0.9748 | 0.9834 | 63.5458  | 0.991534 | 0.99551  |
| 0.01  | 59.2030 | 0.9452 | 0.9559 | 60.6530    | 0.9572 | 0.9738 | 61.8980 | 0.9746 | 0.9839 | 63.2610  | 0.989395 | 0.994327 |
| 0.1   | 58.6922 | 0.9330 | 0.9370 | 60.2122    | 0.9449 | 0.9489 | 61.8352 | 0.9557 | 0.9680 | 62.9852  | 0.975741 | 0.986339 |
| 0.5   | 58.0219 | 0.9361 | 0.9273 | 59.4879    | 0.9487 | 0.9461 | 61.0739 | 0.9592 | 0.9654 | 62.7179  | 0.972496 | 0.984333 |
| 0.9   | 58.0046 | 0.9223 | 0.9381 | 59.2066    | 0.9373 | 0.9516 | 60.8906 | 0.9509 | 0.9675 | 62.4586  | 0.969107 | 0.982194 |

**Table 7. Results comparison for original and recovered message for Salinas dataset**

| Alpha | PSO     |        |        | FBIAO [14] |        |        | POA     |        |        | SLIS-POA |          |          |
|-------|---------|--------|--------|------------|--------|--------|---------|--------|--------|----------|----------|----------|
|       | PSNR    | SSIM   | NC     | PSNR       | SSIM   | NC     | PSNR    | SSIM   | NC     | PSNR     | SSIM     | NC       |
| 0.001 | 57.9238 | 0.9475 | 0.9552 | 59.2198    | 0.9633 | 0.9669 | 60.5608 | 0.9762 | 0.9785 | 62.2068  | 0.992908 | 0.994752 |
| 0.01  | 56.9311 | 0.9389 | 0.9470 | 58.6861    | 0.9553 | 0.9585 | 60.1941 | 0.9722 | 0.9756 | 61.9621  | 0.991313 | 0.993554 |
| 0.1   | 57.6352 | 0.9321 | 0.9355 | 59.1892    | 0.9513 | 0.9520 | 60.4352 | 0.9613 | 0.9681 | 61.7242  | 0.981252 | 0.985839 |
| 0.5   | 57.0585 | 0.9277 | 0.9337 | 58.3995    | 0.9439 | 0.9526 | 59.8705 | 0.9613 | 0.9655 | 61.4925  | 0.976358 | 0.981983 |
| 0.9   | 56.7619 | 0.9241 | 0.9332 | 58.1249    | 0.9345 | 0.9488 | 59.8849 | 0.9541 | 0.9639 | 61.2669  | 0.97375  | 0.979899 |

The simulation results for the original and recovered message embedded into IndianPines and Salinas dataset are

shown in Figures 6 and 7, respectively for distinct optimization algorithms.

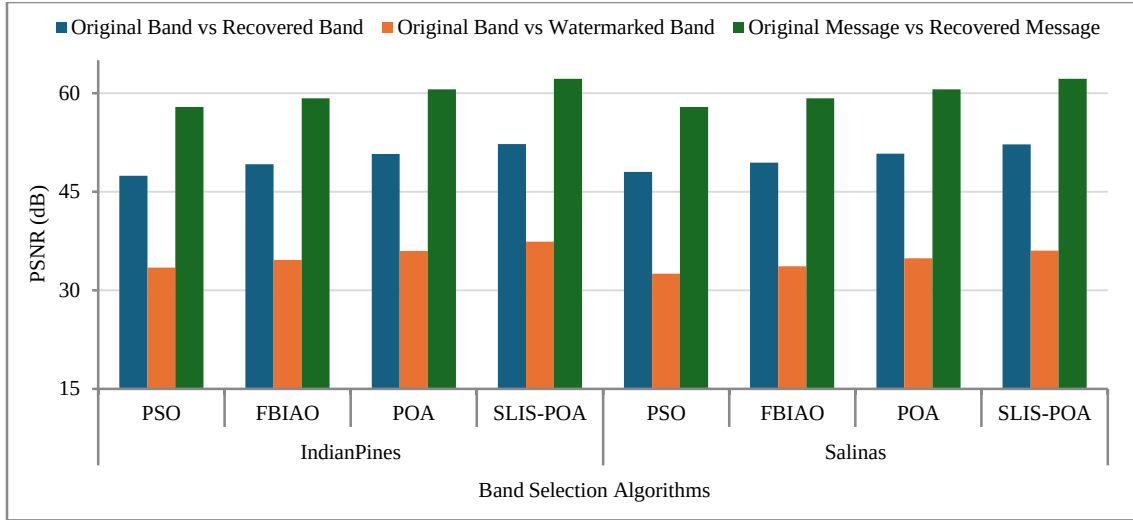


Fig. 6 PSNR visualization for proposed crypto watermarking technique

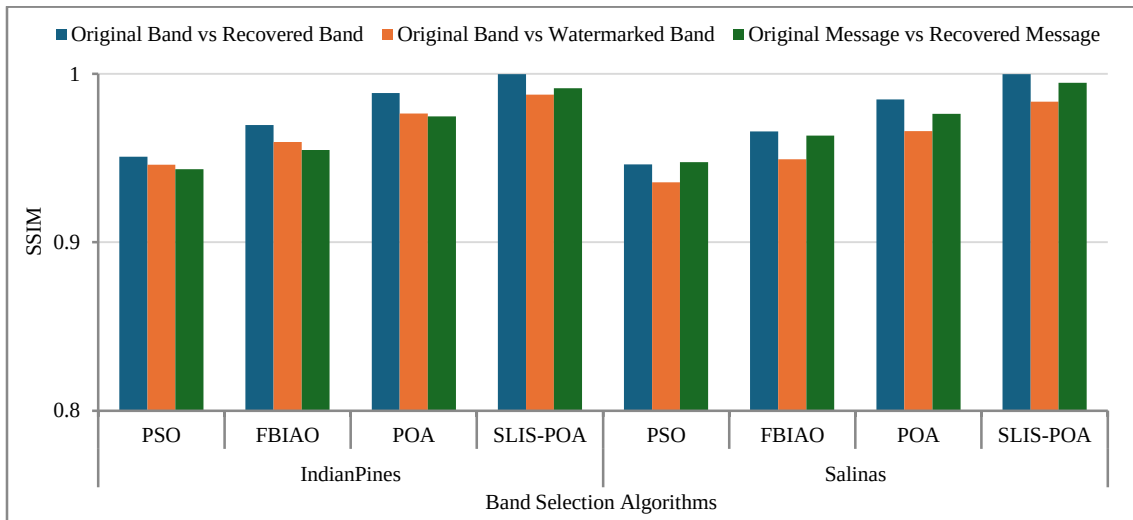


Fig. 7 SSIM visualization for proposed crypto watermarking technique

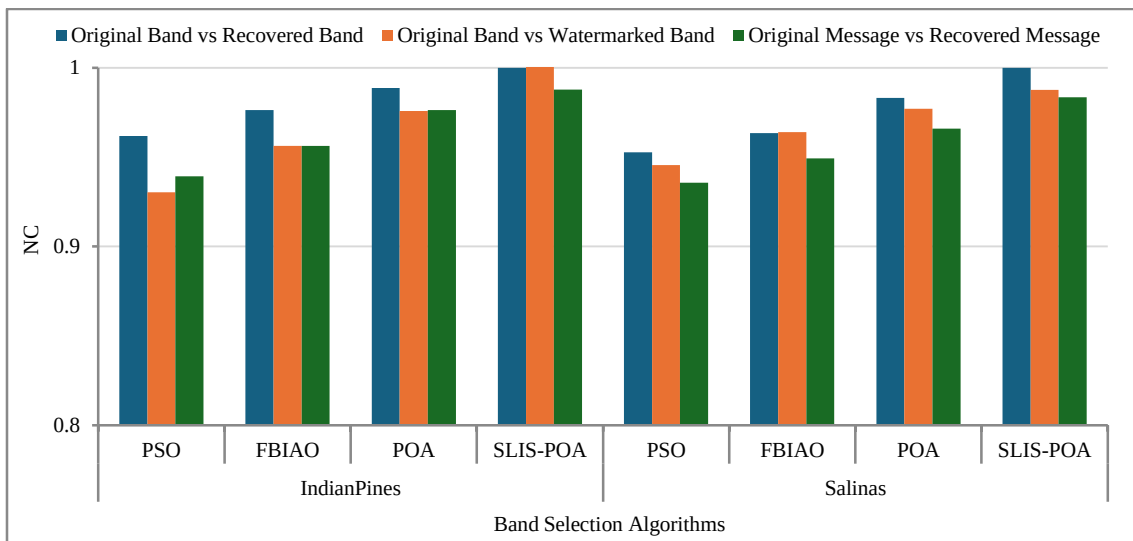


Fig. 8 NC visualization for proposed crypto watermarking technique

### 5.6. Impact of Attacks on Watermarking

The experimental results on the IndianPines hyperspectral dataset demonstrate that the proposed SLIS-POA-based spectral band selection significantly enhances watermark robustness across different transform domains, with DWT consistently achieving superior performance compared to DCT and DFT as given in Table 8 and Figures 9 - 11 respectively. Under median filtering, the SLIS-POA-DWT method attains a PSNR of 40.8114 dB, SSIM of 0.9034, and NC of 0.9314 for a 3×3 kernel, which decreases to 38.9198 dB, 0.8990, and 0.9273 for 5×5, and further to 37.3674 dB, 0.8682, and 0.8964 for 7×7. In comparison, the DCT-based method records 38.9014 dB, 0.8776, and 0.9065 for 3×3 filtering, while DFT shows lower values of 36.3334 dB, 0.8535, and 0.8797. A similar trend is observed for average filtering, where SLIS-POA-DWT achieves 37.3816 dB, 0.8901, and 0.9189 for 3×3, reducing to 36.1630 dB, 0.8725, and 0.9011 for 5×5, and 36.0630 dB, 0.8682, and 0.8964 for 7×7, outperforming both DCT and DFT counterparts.

Under noise and enhancement attacks, such as salt-and-pepper noise and histogram equalization, DWT maintains higher robustness with PSNR values of 34.9185 dB and 33.0018 dB, SSIM of 0.7687 and 0.7479, and NC of 0.7407 and 0.7354, respectively, whereas DCT and DFT exhibit comparatively lower performance.

Furthermore, under compression, rotation, and cropping attacks, the DWT-based method continues to demonstrate improved resilience, achieving 32.1817 dB, 0.7581, and 0.7513 for compression, 31.4325 dB, 0.7252, and 0.6986 for rotation, and 30.7428 dB, 0.7190, and 0.7090 for cropping. These values are consistently higher than those obtained using DCT and DFT. Overall, the results confirm that the integration of SLIS-POA with the DWT domain provides enhanced imperceptibility and robustness for hyperspectral image watermarking under diverse signal processing and geometric attacks.

Table 8. Performance of SLIS-POA-DWT for different attacks for the IndianPines dataset

| Attacks                | Parameter | SLIS-POA-DFT |        |        | SLIS-POA-DCT |        |        | SLIS-POA-DWT |        |        |
|------------------------|-----------|--------------|--------|--------|--------------|--------|--------|--------------|--------|--------|
|                        |           | PSNR (dB)    | SSIM   | NC     | PSNR (dB)    | SSIM   | NC     | PSNR (dB)    | SSIM   | NC     |
| Median Filtering       | 3x3       | 36.3334      | 0.8535 | 0.8797 | 38.9014      | 0.8776 | 0.9065 | 40.8114      | 0.9034 | 0.9314 |
|                        | 5x5       | 35.3278      | 0.8460 | 0.8723 | 36.9358      | 0.8725 | 0.9002 | 38.9198      | 0.8990 | 0.9273 |
|                        | 7x7       | 32.5324      | 0.8198 | 0.8493 | 34.6954      | 0.8460 | 0.8723 | 37.3674      | 0.8682 | 0.8964 |
| Average Filtering      | 3x3       | 33.5706      | 0.8366 | 0.8686 | 34.9176      | 0.8656 | 0.8926 | 37.3816      | 0.8901 | 0.9189 |
|                        | 5x5       | 31.8770      | 0.8229 | 0.8492 | 33.4900      | 0.8467 | 0.8735 | 36.1630      | 0.8725 | 0.9011 |
|                        | 7x7       | 31.3610      | 0.8171 | 0.8488 | 33.4700      | 0.8457 | 0.8731 | 36.0630      | 0.8682 | 0.8964 |
| Salt and Pepper Noise  |           | 30.8185      | 0.7238 | 0.6902 | 32.5405      | 0.7464 | 0.7178 | 34.9185      | 0.7687 | 0.7407 |
| Histogram Equalization |           | 28.8708      | 0.6997 | 0.6868 | 30.5958      | 0.7219 | 0.7103 | 33.0018      | 0.7479 | 0.7354 |
| Compression            |           | 28.6007      | 0.7041 | 0.7019 | 30.4957      | 0.7299 | 0.7245 | 32.1817      | 0.7581 | 0.7513 |
| Rotation               |           | 26.9225      | 0.6752 | 0.6445 | 29.2525      | 0.7005 | 0.6728 | 31.4325      | 0.7252 | 0.6986 |
| Cropping               |           | 26.4958      | 0.6709 | 0.6574 | 28.1578      | 0.6952 | 0.6823 | 30.7428      | 0.7190 | 0.7090 |

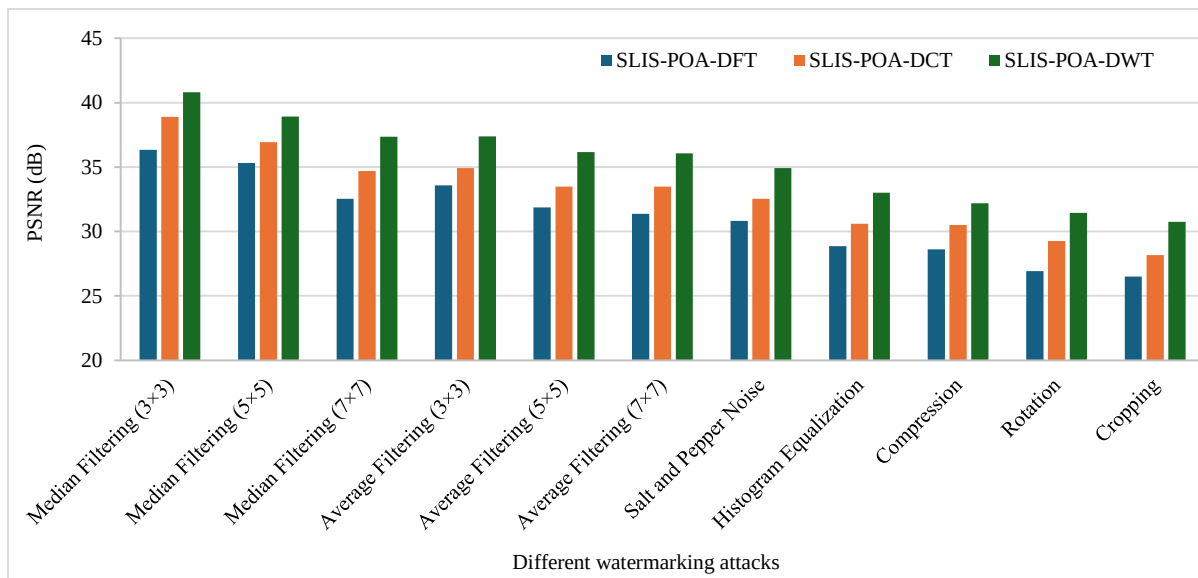


Fig. 9 PSNR visualization for proposed crypto watermarking technique under different attacks for IndianPines

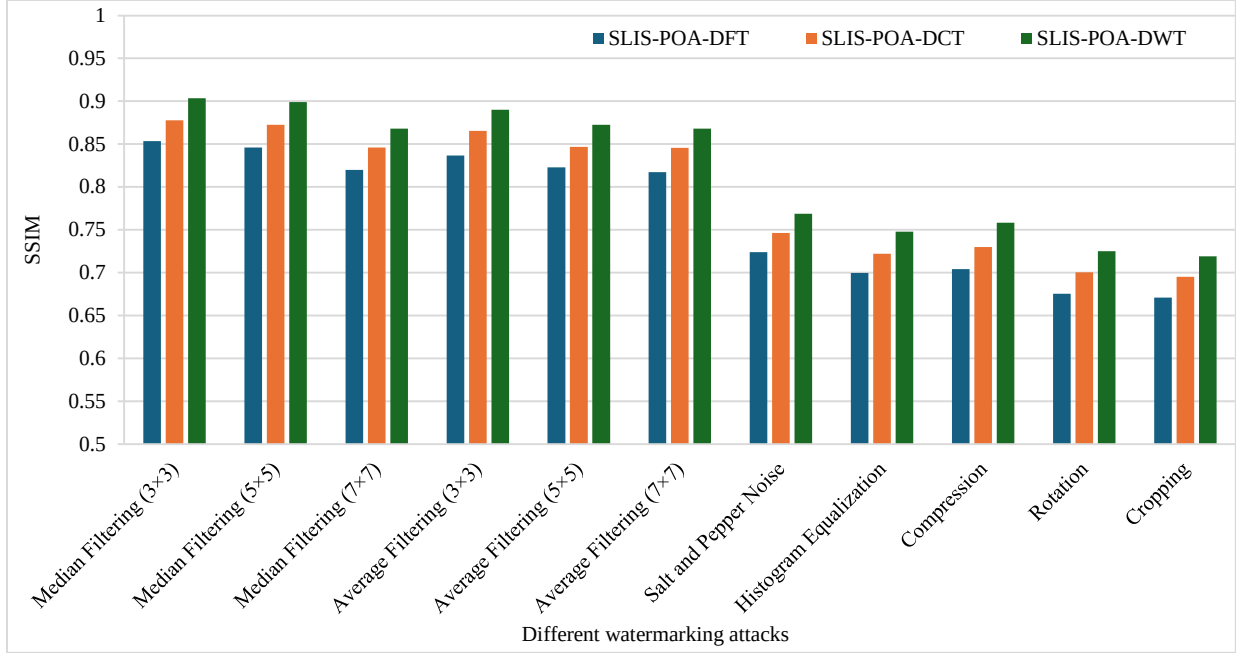


Fig. 10 SSIM visualization for proposed crypto watermarking technique under different attacks for IndianPines

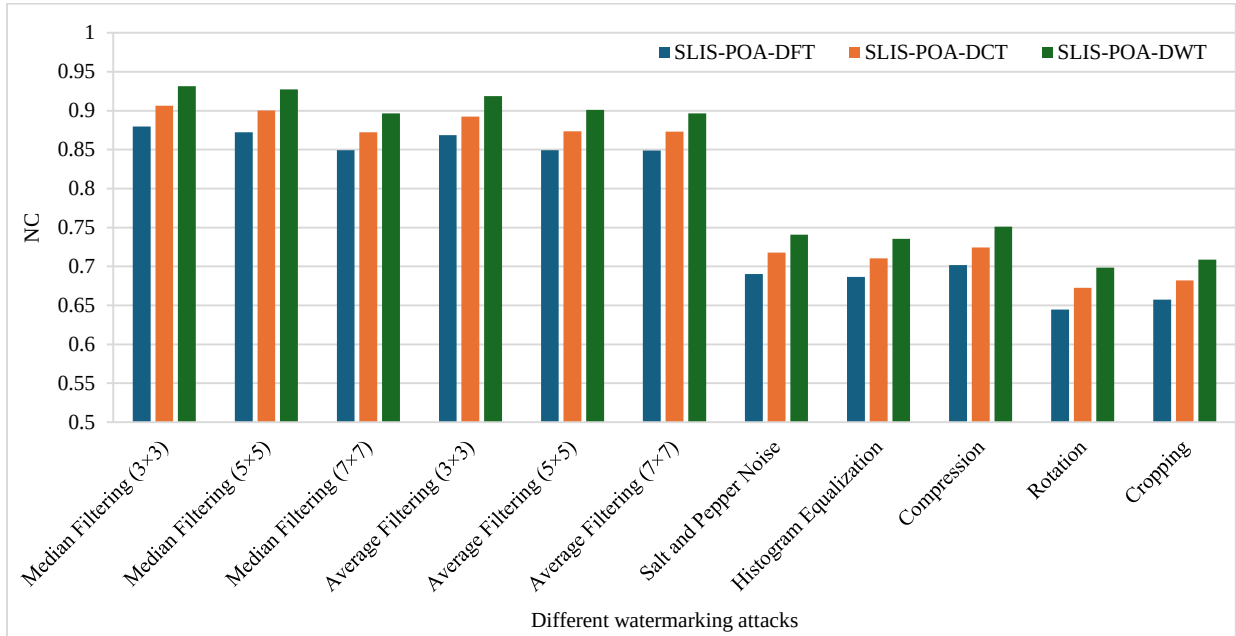


Fig. 11 NC visualization for proposed crypto watermarking technique under different attacks for IndianPines

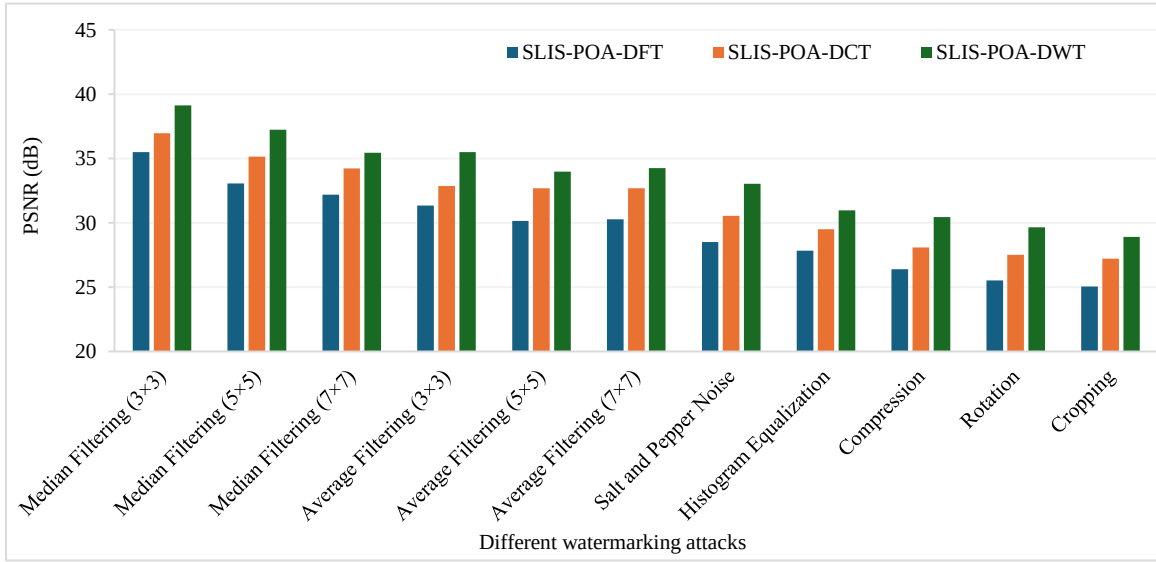
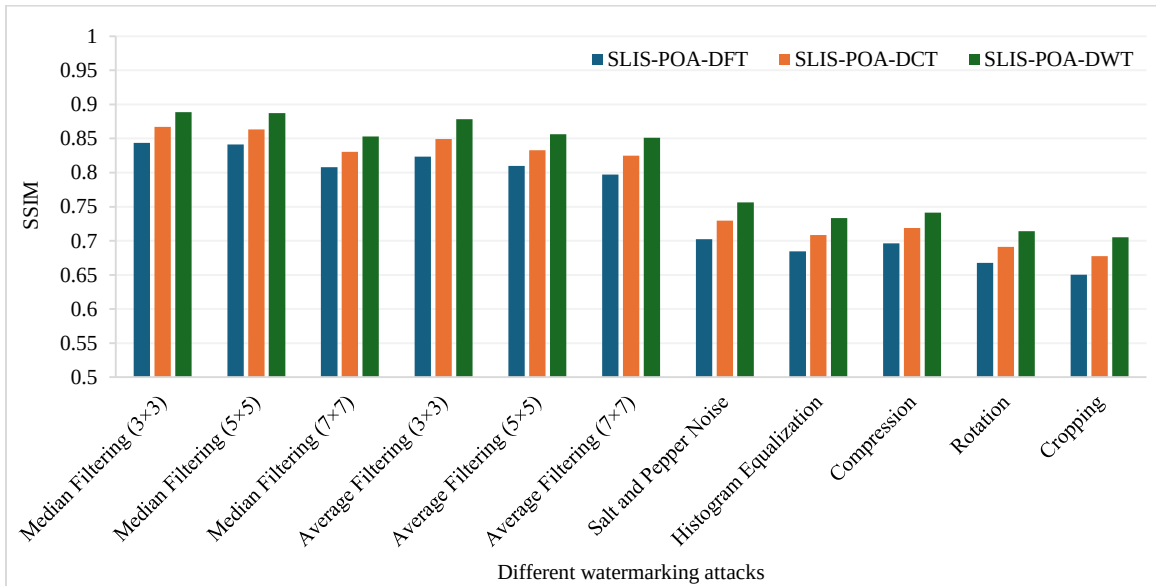
The results on the Salinas hyperspectral dataset further validate the effectiveness of the proposed SLIS-POA method, where the DWT domain consistently achieves superior robustness compared to DCT and DFT, as given in Table 9 and Figures 12 - 14 respectively.

Under median filtering, SLIS-POA-DWT records PSNR values of 39.1484 dB, 37.2568 dB, and 35.4554 dB with corresponding SSIM of 0.8888, 0.8875, 0.8528, and NC of 0.9204, 0.9135, 0.8785 for 3x3, 5x5, and 7x7 filters,

outperforming DCT and DFT. For average filtering, DWT maintains higher performance with PSNR ranging from 35.5016 dB to 33.9990 dB, SSIM from 0.8783 to 0.8561, and NC from 0.9039 to 0.8886. In the presence of salt-and-pepper noise and histogram equalization, DWT achieves 33.0345 dB and 30.9768 dB PSNR, with improved SSIM (0.7565, 0.7335) and NC (0.7273, 0.7180) compared to other transforms. Similarly, for compression, rotation, and cropping attacks, DWT shows better resilience with PSNR values of 30.4557 dB, 29.6515 dB, and 28.9098 dB, respectively.

**Table 9. Performance of SLIS-POA-DWT for different attacks for Salinas dataset**

| Attacks                | Parameter | SLIS-POA-DFT |        |        | SLIS-POA-DCT |        |        | SLIS-POA-DWT |        |        |
|------------------------|-----------|--------------|--------|--------|--------------|--------|--------|--------------|--------|--------|
|                        |           | PSNR (dB)    | SSIM   | NC     | PSNR (dB)    | SSIM   | NC     | PSNR (dB)    | SSIM   | NC     |
| Median Filtering       | 3x3       | 35.4984      | 0.8435 | 0.8698 | 36.9834      | 0.8672 | 0.8939 | 39.1484      | 0.8888 | 0.9204 |
|                        | 5x5       | 33.0688      | 0.8412 | 0.8667 | 35.1638      | 0.8632 | 0.8890 | 37.2568      | 0.8875 | 0.9135 |
|                        | 7x7       | 32.1974      | 0.8079 | 0.8230 | 34.2454      | 0.8305 | 0.8515 | 35.4554      | 0.8528 | 0.8785 |
| Average Filtering      | 3x3       | 31.3606      | 0.8234 | 0.8522 | 32.8816      | 0.8495 | 0.8755 | 35.5016      | 0.8783 | 0.9039 |
|                        | 5x5       | 30.1530      | 0.8098 | 0.8314 | 32.6930      | 0.8327 | 0.8599 | 33.9990      | 0.8561 | 0.8886 |
|                        | 7x7       | 30.2780      | 0.7972 | 0.8373 | 32.6900      | 0.8251 | 0.8583 | 34.2690      | 0.8510 | 0.8833 |
| Salt and Pepper Noise  |           | 28.5285      | 0.7023 | 0.6747 | 30.5555      | 0.7297 | 0.7001 | 33.0345      | 0.7565 | 0.7273 |
| Histogram Equalization |           | 27.8538      | 0.6846 | 0.6662 | 29.5208      | 0.7086 | 0.6945 | 30.9768      | 0.7335 | 0.7180 |
| Compression            |           | 26.4097      | 0.6961 | 0.6832 | 28.1017      | 0.7186 | 0.7116 | 30.4557      | 0.7412 | 0.7335 |
| Rotation               |           | 25.5255      | 0.6678 | 0.6299 | 27.5235      | 0.6910 | 0.6584 | 29.6515      | 0.7139 | 0.6844 |
| Cropping               |           | 25.0498      | 0.6503 | 0.6350 | 27.2318      | 0.6775 | 0.6638 | 28.9098      | 0.7054 | 0.6910 |


**Fig. 12 PSNR visualization for proposed crypto watermarking technique under different attacks for Salinas**

**Fig. 13 SSIM visualization for proposed crypto watermarking technique under different attacks for Salinas**

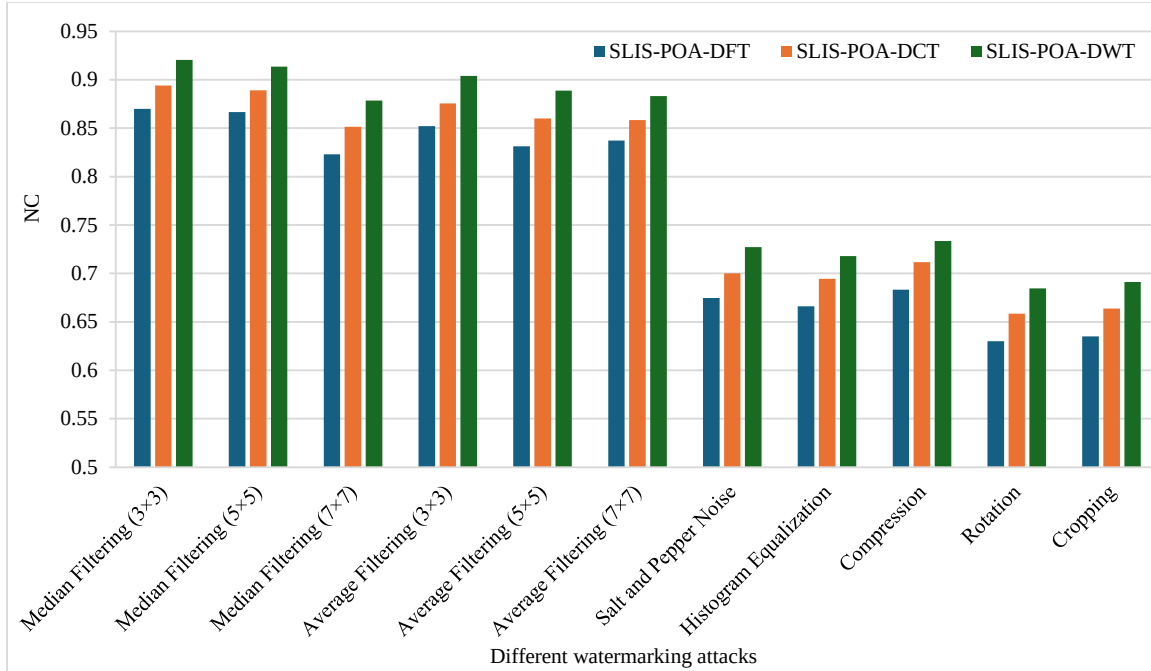


Fig. 14 NC visualization for proposed crypto watermarking technique under different attacks for Salinas

## 6. Conclusion and Future Scope

Thus, this paper presents RSHI crypto-watermarking using DWT, with SLIS-POA-based hyperspectral band selection to improve the system's robustness, reliability, privacy, authenticity, and integrity of the system. The performance of the proposed method is evaluated on the IP and Salinas datasets using various metrics, demonstrating significant improvements in MSE, PSNR, SSIM, and CC compared with traditional techniques. The SLIS-based band selection helps to improve the convergence, exploitation-exploration balance and solution diversity of the band population. For different attack conditions, the SLIS-POA-

DWT-based cryptowatermarking scheme provides PSNR in the range of 28.90 dB to 39.14 dB, SSIM in the range of 0.7054 to 0.8888, and NC in the range of 0.691 to 0.9204, which shows robustness in the scheme. The effectiveness of cryptowatermarking can be improved in the future by providing a more robust encryption framework to handle various attacks on the image. The focus can be on providing robustness against adversarial attacks and optimizing the algorithms' parameters. The results of the system can be validated for the deep learning-enabled chaotic encryption technique to improve the robustness against different deepfake attacks.

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