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Clutter Suppression for GPS-Signal-Based Passive Radar

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Abstract

To improve target detection in GPS-signal-based passive radar under strong interference and noise, this paper develops a time-frequency-scale-domain adaptive clutter suppression method that uses the scale-domain feature difference between target echoes and clutter. The manuscript first reviews representative clutter suppression methods for passive radar, including adaptive filtering, subspace-projection methods, extensive cancellation algorithms, CLEAN-type methods, and time-frequency methods. It then introduces the GPS passive reception scenario and the proposed wavelet and empirical mode decomposition (EMD) reconstruction framework. Measured data collected under weak clutter, strong noise, and strong interference conditions are used to evaluate the method. The results show that both reconstruction methods improve the range-Doppler map. Wavelet reconstruction gives the strongest overall performance, with an average signal-to-interference ratio improvement of 8.07 dB and an average signal-to-noise ratio improvement of 6.83 dB under strong clutter conditions. The results also show that the method is most effective when the target and clutter have distinct scale-domain features.

Keywords: passive radar; GPS signal; clutter suppression; target detection; adaptive signal processing; wavelet transform; empirical mode decomposition

1. Introduction

Active radar detects, locates, and identifies targets by transmitting electromagnetic waves and receiving the echoes. Because its transmitter and receiver are controlled by the same system, active radar usually provides strong autonomy, all-weather operation, and high measurement accuracy. Its transmitted high-power signal, however, can also expose the radar platform. Passive radar uses a third-party non-cooperative illuminator to illuminate the target and receives the scattered signal to estimate target information such as range, azimuth, and velocity^[1-4]. This operating mode reduces spectrum demand and improves concealment. The history of passive radar dates back to 1935, when Willis^[5] built an early bistatic radar experiment in the United Kingdom and detected an aircraft with BBC shortwave radio signals. In 1943, the German Klein Heidelberg system became an early practical passive radar system and showed useful resistance to jamming^[6]. After a long period of slow development, passive radar research accelerated in the 1990s. Griffiths^[7] used simulated television signals for aircraft detection in 1994, and several practical passive radar systems were then reported, including Silent Sentry^[8,9], PAPADE^[10,11], Thales HA100^[12], TAMARA KRTP-86^[13], YLC-20, and DWL002.

Passive radar can be classified by the type of illuminator. Ground-based illuminators, such as FM radio, television, and communication signals, have been widely studied and have reached a relatively mature stage^[15,16]. Their coverage is still limited by transmitter locations and the curvature of the Earth. Satellite illuminators provide a different option^[17,18]. GPS satellites offer continuous global coverage, stable carrier frequencies, accurate timing, and recoverable direct-path signals^[19-21]. These features help reduce the coverage and synchronization limits that appear in many ground-based passive radar systems. Even so, GPS-based passive radar remains difficult because the satellite orbit is high, the reflected target echo is weak, and the received data often contain strong background noise, direct-path interference, multipath, and ground clutter. Existing work on GPS passive radar mainly studies signal ambiguity, detection range, coherent integration, and tracking. Fewer studies focus on measured-data clutter suppression for weak ground targets. This gap motivates the present study.

Clutter suppression is a central step in passive radar because the target echo is usually much weaker than the direct-path signal, multipath, and stationary or slowly varying clutter. Early and widely used methods include adaptive filters such as Least Mean Square (LMS), Normalized Least Mean Squares (NLMS), and Recursive Least Squares (RLS). These methods estimate a clutter replica from a reference signal and subtract it from the surveillance channel. They are simple and can track slow changes, but their performance depends strongly on

filter length, step size, convergence behavior, and the quality of the reference signal. Least-squares and subspace-projection methods provide a more direct way to remove clutter. The extensive cancellation algorithm (ECA) and its variants build a clutter subspace from delayed and Doppler-shifted copies of the reference signal and project the surveillance signal onto the orthogonal complement of this subspace^[31,32]. ECA is effective for direct-path and multipath cancellation and has also been applied to GNSS-based passive bistatic radar^[31]. Variants such as batch ECA, sliding ECA, and sequential cancellation reduce the computational burden or improve the handling of time-varying clutter^[33]. Their main limitation in the present scenario is that they rely on an explicit clutter model and a reliable reference channel. When clutter is not well represented by the constructed subspace, residual interference may remain. CLEAN and matching-pursuit methods estimate strong clutter components iteratively and remove them from the received signal^[34]. They can be effective when a small number of strong components dominate the data. Batch-based CLEAN further improves efficiency for long data records. These methods, however, usually require a proper dictionary, stopping rule, and component-selection strategy. Their performance may also degrade when weak target echoes are close to strong clutter components. Time-frequency and image-based methods process the range-Doppler or time-frequency representation directly. They are useful for nonstationary interference and can exploit local differences between target and clutter. Wavelet and empirical mode decomposition (EMD) methods belong to this family because they describe the signal at multiple scales and can represent local transient features^[25-30]. The method proposed in this paper follows this idea but focuses on GPS passive radar. It uses the measured scale-domain feature difference between the target and clutter to guide weighted reconstruction.

This paper studies target detection with passively received GPS satellite signals. The main goal is to suppress clutter and noise in range-Doppler maps when the target echo is weak and when ground clutter and direct-path interference are present. The proposed method first forms a time-frequency representation and then reconstructs the signal in the wavelet or EMD scale domain according to the feature difference between the target and clutter. Compared with methods that mainly estimate and cancel a direct-path or multipath subspace, the proposed method focuses on scale-domain energy distribution. This choice is useful when the target and clutter overlap in the time-frequency domain but remain separable in the scale domain. The paper introduces the reception scenario, reviews related clutter suppression methods, describes the proposed algorithm, analyzes measured range-Doppler maps before and after processing, and summarizes the SNR and SIR improvement under weak and strong clutter conditions.

2. Target Detection Scenario and Clutter Suppression Algorithm

2.1. Target detection scenario

The original dataset used in this paper is collected from May 28 to 29, 2025. The detection scenario is shown in Figure 1. Two receivers separated by a fixed baseline receive GPS satellite signals reflected by the target. The target is a corner reflector mounted on a vehicle. The distance from the target to each receiver is approximately 200 m, and the lateral velocity of the target relative to the receivers is approximately 20 m/s. The receiver sampling rate is 10.23 MHz. The maximum number of range gates is 170, and the range span is 0 to 4952.58 m.

For each receiver, the GPS signals in the antenna main-lobe coverage are first reconstructed in sequence. Each reconstructed signal is then convolved with the received signal, which is equivalent to pulse compression, and coherent integration is performed with an integration time of 2 s. This process produces range-Doppler maps for different GPS reference signals. As shown in Figure 1, the direct-path signals from low-Earth-orbit satellites and other satellites can form clutter in the range-Doppler map. These two types of clutter are the main suppression targets in this paper. Because the system uses a bistatic receiving geometry, the target Doppler is not fixed at 20 m/s but may fall between 1 m/s and 20 m/s. Similarly, the target range bin is not simply 200 m but may fall between 20 m and 200 m.

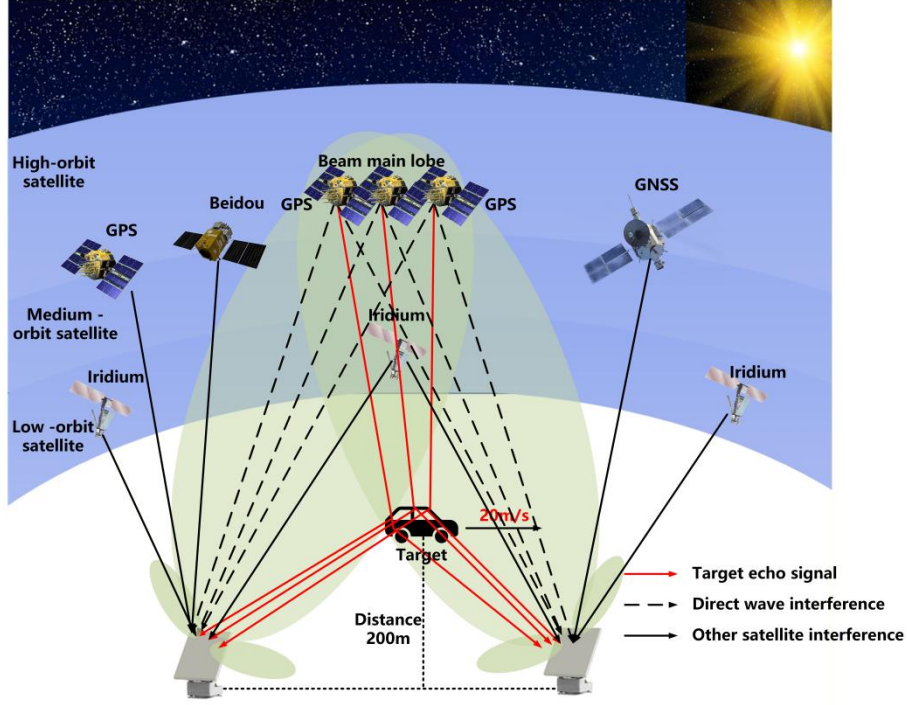


Figure 1. Target detection scenario for the passive receiver based on satellite signals.

2.2 Time-Frequency-Scale-Domain Adaptive Clutter Suppression Based on Target-Clutter Feature Differences

In weak-target scenarios, conventional time-frequency analysis has difficulty providing both high resolution and strong adaptability to nonstationary interference. In passively received GPS signals, the target echo and clutter may overlap in the time-frequency domain, but their energy distributions can still differ in the wavelet or EMD scale domain. The proposed algorithm uses this difference to suppress clutter while preserving the target echo.

The processing chain starts from the raw I/Q data and contains two main stages. The first stage performs time-frequency analysis and basic interference suppression. The second stage decomposes, reconstructs, and adaptively suppresses clutter in the wavelet or EMD scale domain under a sparse regularization constraint.

2.2.1 Signal Processing and Clutter Suppression in the Time-Frequency Domain

For the raw I/Q data, coherent integration and the short-time Fourier transform (STFT) are performed first. The STFT of the received signal is expressed as follows:

$$X(t, f) = \int_{-\infty}^{+\infty} x(\tau) \omega(\tau - t) e^{-j2\pi f\tau} d\tau, \quad (1)$$

where f is the frequency, which is also the Doppler frequency, and the window function is centered at time t . In practical processing, the STFT is implemented in the discrete domain. For a discrete signal, the STFT is expressed as follows:

$$X[m, k] = \sum_{n=0}^N x[n] \omega[n - m] e^{-j2\pi kn/N}, \quad (2)$$

where the window function is a Hamming window in this paper.

The processing yields a range-Doppler matrix for the received signal. In this matrix, the range dimension is the fast-time dimension and the Doppler dimension is the slow-time dimension. Displaying this matrix as a two-dimensional pseudo-color image gives the range-Doppler map. The zero-Doppler column is then set to zero to reduce direct-path interference and DC components.

2.2.2 Scale-Domain Reconstruction with Sparse Regularization

This stage is the main part of the proposed method. It contains wavelet or EMD decomposition, extraction

and statistical analysis of target scale features from measured data, adaptive matching of scale features under sparse regularization, and weighted reconstruction in the time-frequency domain.

(a) Wavelet and EMD decomposition

The wavelet transform and EMD [14,25,26] are time-scale analysis methods with multi-resolution properties. They decompose a one-dimensional signal into several components at different scales. Both methods provide lower time resolution and higher frequency resolution at low frequencies, and higher time resolution and lower frequency resolution at high frequencies. They are therefore suitable for nonstationary signals and local feature extraction. Similar scale-domain ideas have been used for ionospheric clutter suppression, sea clutter suppression, and signal denoising [27-30].

The wavelet transform is written as follows:

$$W_a^b(t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(\tau) \psi\left(\frac{\tau-b}{a}\right) d\tau, \quad (3)$$

where the scale and translation parameters describe the scale and time location of the wavelet basis function. Different wavelet bases can be selected for different signal analysis tasks. This paper uses db3 as the wavelet basis.

The range-Doppler matrix is transformed by applying the wavelet transform along the range dimension. Because the matrix is discrete, the discrete wavelet transform is used, and the forward and inverse transforms are expressed as follows:

$$W_\psi(a, b) = \frac{1}{\sqrt{a}} \sum_k x_i(n) \psi(2^a k - b), \quad (4)$$

$$x_i(n) = \frac{1}{C_\psi} \sum_k W_\psi(a, b) \psi(2^a k - b), \quad (5)$$

where the selected row denotes the Doppler sequence of one range gate, the scale and translation parameters are integers, and the wavelet coefficient represents the component at the corresponding scale.

The EMD decomposition is expressed as follows:

$$x_i(n) = \sum_{j=1}^N c_j(n) + r_N(n), \quad (6)$$

where IMF denotes the intrinsic mode function and the last term denotes the trend component. To keep the notation consistent with the wavelet transform, the IMF components are treated as EMD coefficients.

After decomposition, the discrete Doppler sequence is represented in the wavelet or EMD domain. The normalized amplitude of the Doppler cell containing the target or clutter in each coefficient component is defined as the scale-domain feature of the target or clutter.

If the energy distribution of a pure target in the wavelet domain is given, the target scale in the wavelet domain is expressed as follows:

$$\omega_{k, target} = C_{target}(k) / \max[C_{target}(k)], \quad (7)$$

where the coefficient denotes the wavelet component at the corresponding scale.

(b) Extraction and statistical analysis of target scale features from measured data

Frequency-domain filtering can separate a target from clutter when their frequency difference is large enough. In the same way, scale-domain filtering can separate them when their wavelet or EMD scale features are sufficiently different. The proposed method uses this scale difference to suppress clutter.

Figure 2 shows the scale curves of the target and clutter extracted from measured data. The curves show clear differences in the wavelet and EMD domains. In the EMD domain, the target signal is mainly concentrated near the second-level EMD coefficient, while clutter is mainly concentrated around the fourth and fifth coefficients. In the wavelet domain, the target signal is mainly concentrated near the second-level coefficient, while clutter is concentrated on the first-level coefficient and the residual component. The ninth-level wavelet coefficient is the residual component.

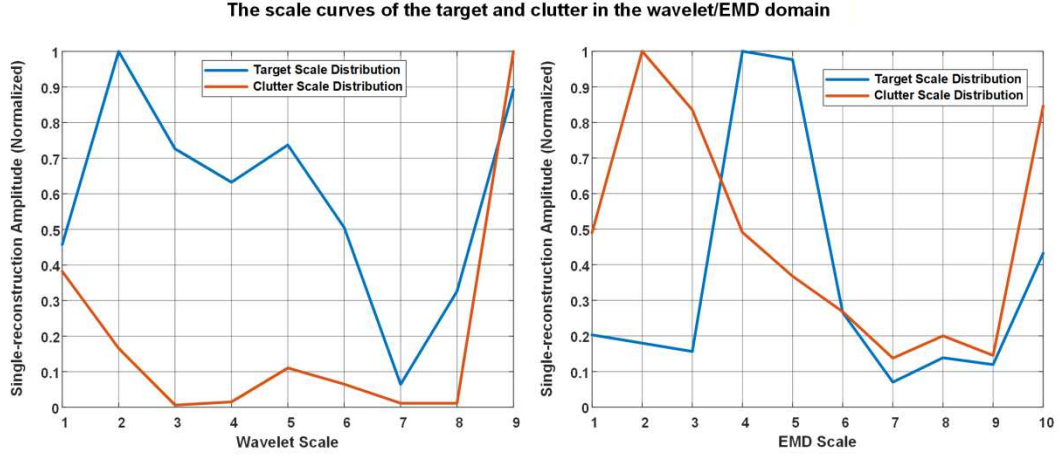


Figure 2. Scale-difference curves in the wavelet domain (left) and EMD domain (right) for Doppler cells containing the target (blue) and clutter (red) in measured data.

(c) Adaptive matching of scale features under sparse regularization

Using the target scale-domain feature as a reconstruction weight can preserve the target-related component and reduce the clutter-related component. In measured data, however, this feature is not fixed. It changes with the signal-to-interference-plus-noise ratio, target velocity, and receiver condition. Since the reflected GPS signal is very weak, the target can also be buried by noise and interference.

To address this problem, many measured-data samples are used to obtain the relation between scale-domain features and signal-to-noise ratio. During processing, the preliminary estimate of the measured signal-to-interference-plus-noise ratio is used to select the corresponding mean scale-domain feature as the reconstruction weight. An L1-norm sparse regularization constraint is also introduced to enhance target sparsity in the scale domain and suppress Gaussian white noise and low-energy clutter. The constraint is expressed as follows:

$$\hat{\omega}_k = \bar{\omega}_{k, target} \max \{0, |\Omega_{k, target}| - \lambda\}, \quad (8)$$

where the threshold can be set according to the sample variance and the number of samples, or adjusted for specific measurement conditions. This constraint suppresses background noise and interference while preserving the transient feature of the target.

(d) Weighted reconstruction in the time-frequency domain

With the final weight coefficient vector, the weighted and combined Doppler spectrum of each range gate is expressed as follows:

$$NRD(r_0, f_d) = \Omega^T D = [\omega_1, \omega_2, \dots, \omega_A] \begin{bmatrix} \frac{1}{C_\psi} \sum_k W_\psi(1, b) \psi_{1,b}(f_d) \\ \frac{1}{C_\psi} \sum_k W_\psi(2, b) \psi_{2,b}(f_d) \\ \frac{1}{C_\psi} \sum_k W_\psi(3, b) \psi_{3,b}(f_d) \\ \vdots \\ \frac{1}{C_\psi} \sum_k W_\psi(A, b) \psi_{A,b}(f_d) \end{bmatrix}_{A \times 1}, \quad (9)$$

where the reconstruction vector contains the single-branch reconstructed signals at all scales. Combining the Doppler spectra of all range gates gives the range-Doppler map after clutter suppression.

Figure 3 shows the complete processing flow from the receiver I/Q output to the range-Doppler map after clutter suppression.

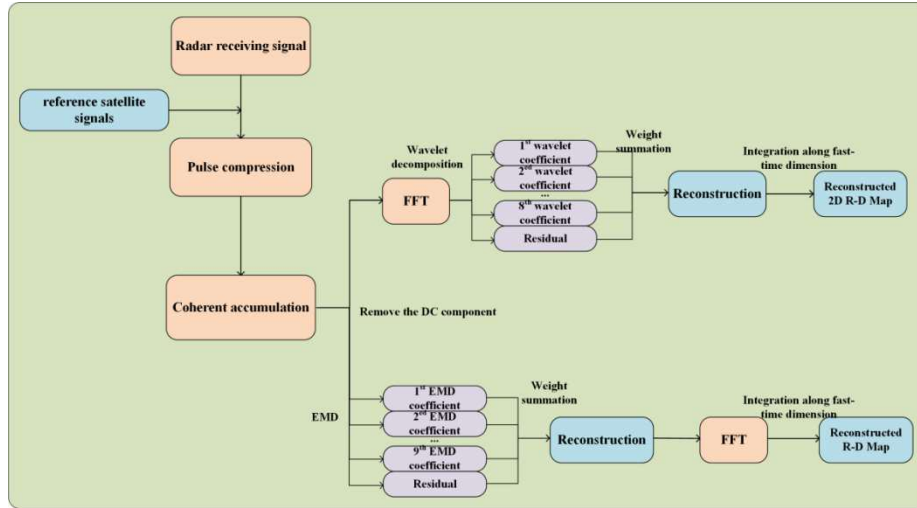


Figure 3. Processing flow of the time-frequency-scale-domain adaptive clutter suppression algorithm based on target-clutter feature differences.

3. Results and Analysis

3.1 Preliminary Evaluation with Simulation Data

Simulation data are first used to evaluate the clutter suppression capability of the algorithm. The original simulated radar reception data contain two satellite signals and background noise, but no sea clutter. To model interference from other satellites, the energy of the non-reference satellite signals is increased by a factor of 10. To model ground clutter, a clutter component is added near the target range gate. Its energy is similar to the target energy, and its Doppler frequency is 30 Hz. The simulated target is approximately 5000 m from the radar, and its component velocities in the Cartesian coordinate system are [20 m/s, -30 m/s, 20 m/s]. Figures 4 to 7 show the range-Doppler maps and Doppler-domain amplitude curves before and after wavelet and EMD processing.

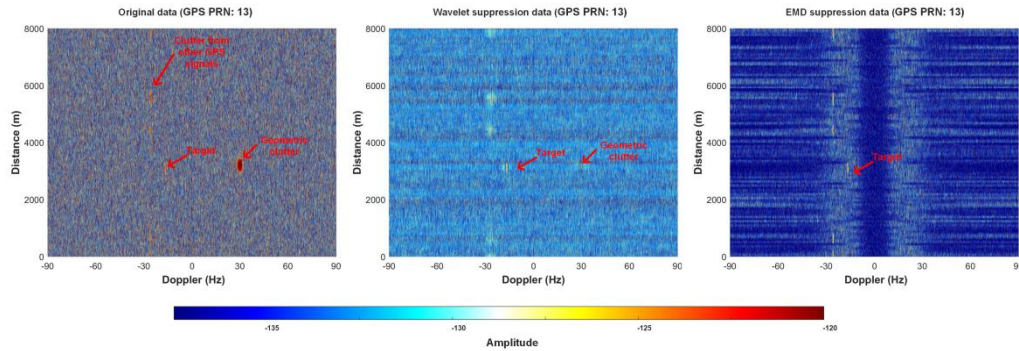


Figure 4. Range-Doppler maps before and after wavelet and EMD clutter suppression with simulation data. The selected GPS satellite PRN is 13.

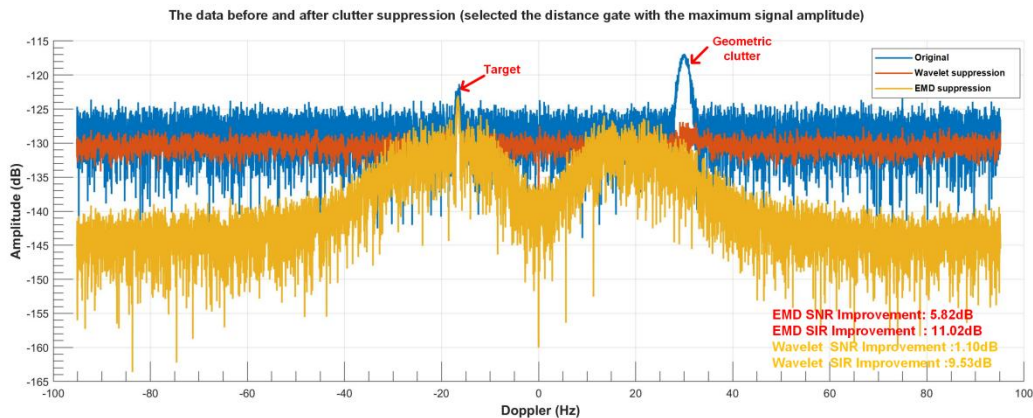


Figure 5. Doppler-domain amplitude curves before and after clutter suppression for the strongest target range cell in Figure 4.

Figure 4 compares the original range-Doppler map with the maps obtained after wavelet and EMD suppression. The color represents energy, and red indicates higher energy. In the original map, the bright point near 3000 m and -17 m/s is the target. A bright point at the same range gate and 30 m/s is ground clutter. Direct-path interference from other satellites also appears across several range gates. After clutter suppression, the ground clutter is removed effectively, while the direct-path interference is reduced only slightly. Figure 5 shows that wavelet processing improves the SNR by 1.10 dB and improves the SIR of the ground-clutter component by 11.02 dB. EMD processing improves the SNR by 5.82 dB and improves the ground-clutter SIR by 9.53 dB.

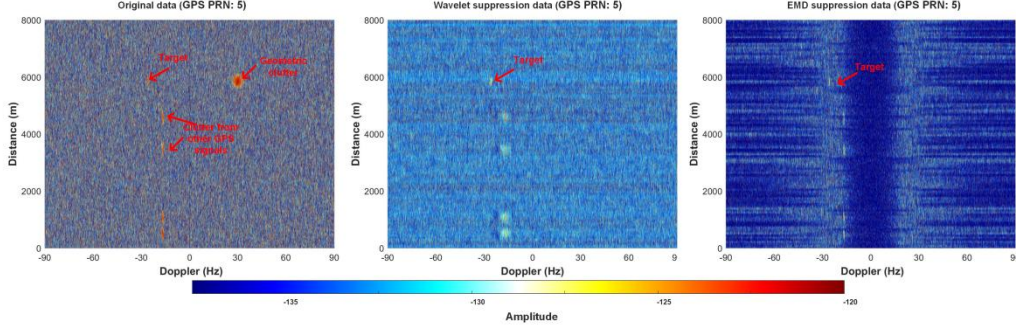


Figure 6. Range-Doppler maps before and after wavelet and EMD clutter suppression with simulation data. The selected GPS satellite PRN is 5.

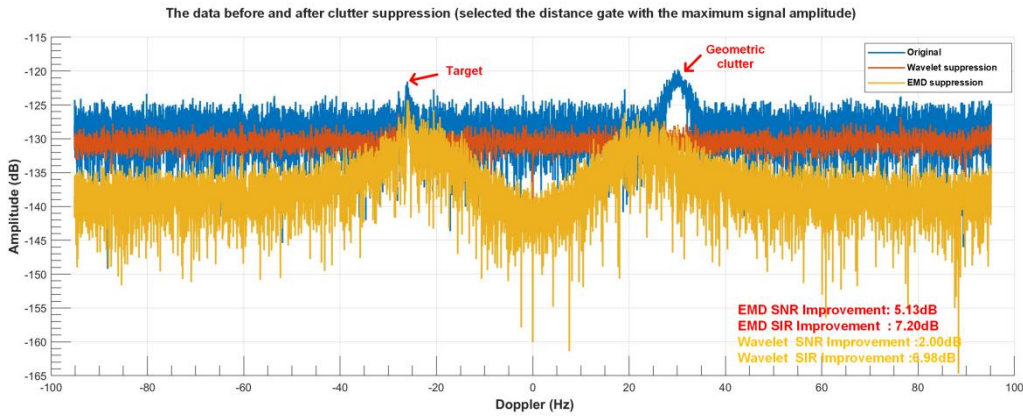


Figure 7. Doppler-domain amplitude curves before and after clutter suppression for the strongest target range cell in Figure 6.

Figures 6 and 7 give the results for another GPS satellite, PRN 5, as the reference signal for pulse compression. In Figure 6, the target is located near 6000 m and -30 m/s. Direct-path interference from other satellites appears near -17 m/s, while ground clutter appears near 6000 m and 30 m/s. After suppression, the background noise is clearly reduced, and the ground clutter is removed effectively. The direct-path interference is only slightly reduced. Figure 7 shows that wavelet processing improves the SNR by 2.00 dB and the ground-clutter SIR by 6.98 dB. EMD processing improves the SNR by 5.13 dB and the ground-clutter SIR by 7.20 dB.

The simulation results show that EMD improves the SNR by about 5 to 6 dB and improves the SIR of ground clutter by about 7 to 10 dB. Wavelet reconstruction improves the SNR by about 1 to 2 dB and improves the SIR of ground clutter by about 7 to 11 dB. The results indicate that both methods are effective when clutter and target echoes have different scale-domain features.

The results also show a limitation of the proposed scale-domain method. Direct-path interference from other satellites has features that are similar to the target echo, so it has a similar scale distribution in the wavelet and EMD domains. As a result, the suppression of this type of clutter is weaker, and the SNR improvement for target-like clutter is less than 3 dB. In contrast, ground clutter has a scale distribution that differs clearly from the target. The wavelet and EMD methods therefore remove it more effectively.

3.2 Typical Measured-Data Scene

The data received at 17:23 local time on May 28, 2025 are selected as a typical measured-data case. The received signals are processed according to the flowchart in Figure 3. Figures 8 and 9 show the results obtained by using the No. 3 GPS satellite signal, among eight GPS satellites within the antenna main lobe, as the reference signal for pulse compression. Figure 8 shows the range-Doppler maps before and after clutter suppression, and Figure 9 shows the Doppler-domain amplitude curves extracted from the strongest target range cell.

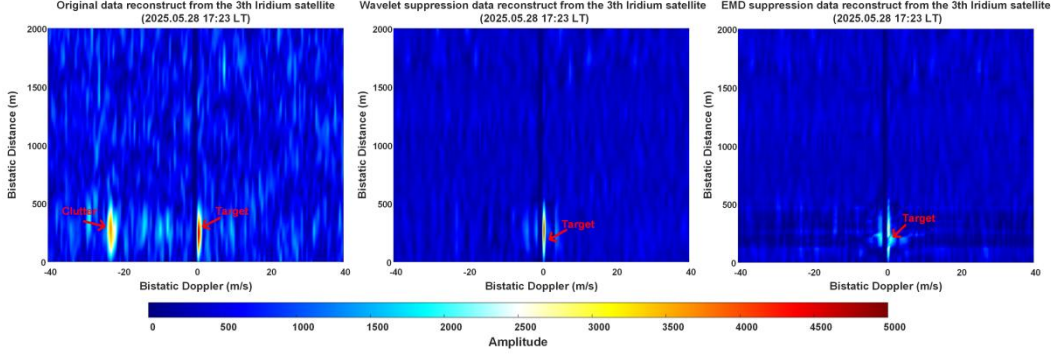


Figure 8. Range-Doppler maps before and after clutter suppression. The data are received at 17:23 LT on May 28, 2025, and the No. 3 GPS satellite signal is used as the reference channel signal for pulse compression. The panels show the original map (left), the wavelet result (middle), and the EMD result (right). Red indicates higher energy.

In Figure 8, the original range-Doppler map contains a bright point within 20 to 200 m and 1 to 20 m/s, which corresponds to the target. The original map also contains a clutter component with energy comparable to the target at approximately -20 to -30 m/s. The clutter and target appear in similar range gates, so this case represents strong interference with weak noise.

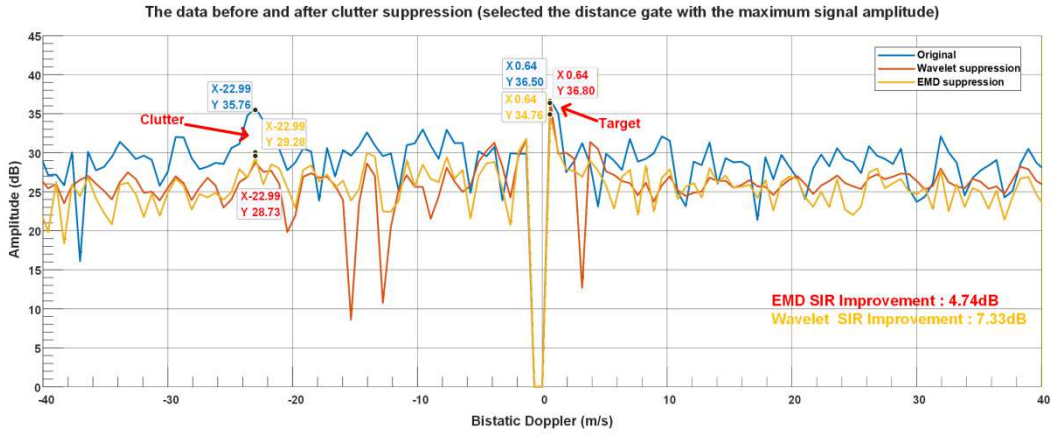


Figure 9. Doppler-domain amplitude curves before and after clutter suppression for the strongest target range cell in Figure 8. The data are received at 17:23 LT on May 28, 2025, and the No. 3 GPS satellite signal is used as the reference channel signal for pulse compression. The curves show the original data (blue), the wavelet result (red), and the EMD result (yellow).

After clutter suppression, the clutter energy is reduced in both processed maps. Figure 9 shows that the original SIR is 0.74 dB. EMD processing increases the SIR to 5.48 dB, and wavelet processing increases it to 8.07 dB. The corresponding SIR improvements are 4.74 dB and 7.33 dB, respectively.

Figures 10 and 11 show the results obtained from the same data at 17:23 LT on May 28, 2025, using the No. 2 GPS satellite signal for convolutional reconstruction.

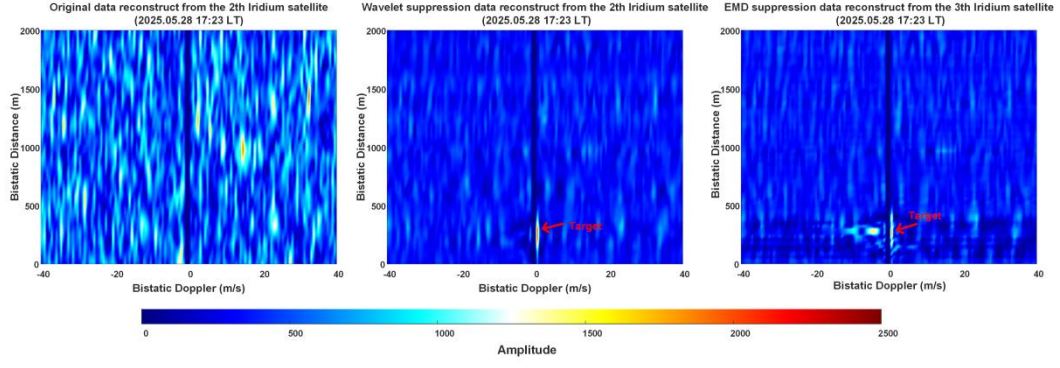


Figure 10. Range-Doppler maps before and after clutter suppression. The data are received at 17:23 LT on May 28, 2025, and the No. 2 GPS satellite signal is used as the reference channel signal for pulse compression.

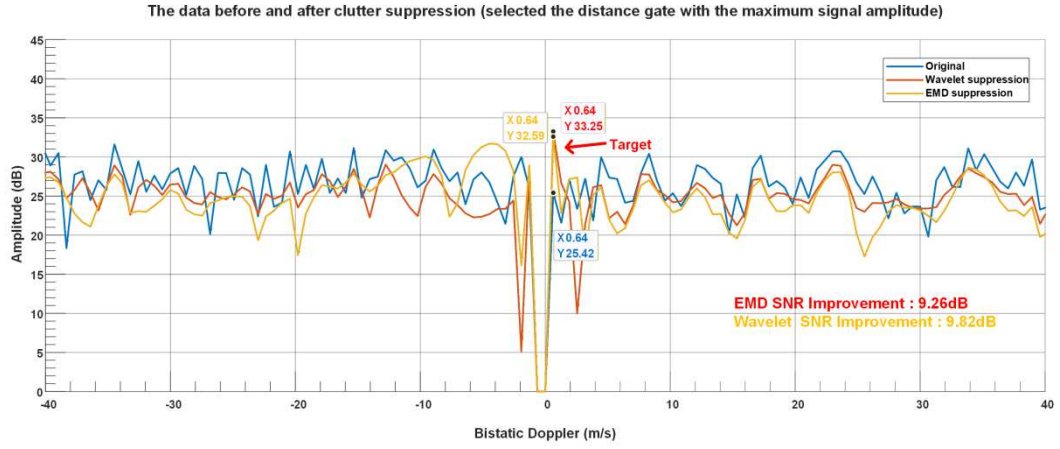


Figure 11. Doppler-domain amplitude curves before and after clutter suppression. The data are received at 17:23 LT on May 28, 2025, and the No. 2 GPS satellite signal is used as the reference channel signal for pulse compression.

In the original range-Doppler map in Figure 10, the target is buried in noise. No high-amplitude interference appears between 0 and 200 m, so this dataset represents weak interference with strong noise.

After clutter suppression, the target becomes visible in the wavelet and EMD results. Figure 11 shows that EMD processing improves the SNR by 9.26 dB, and wavelet processing improves the SNR by 9.82 dB.

Figures 12 and 13 show the results obtained from the same data at 17:23 LT on May 28, 2025, using the No. 8 GPS satellite signal for convolutional reconstruction.

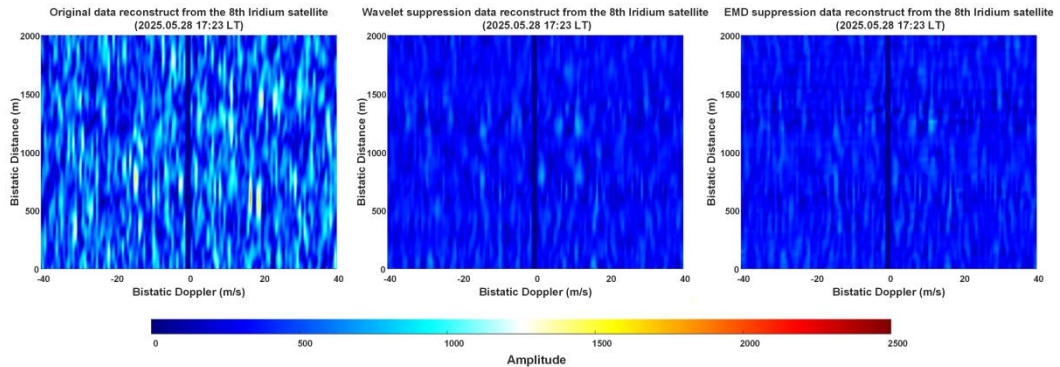


Figure 12. Range-Doppler maps before and after clutter suppression. The data are received at 17:23 LT on May 28, 2025, and the No. 8 GPS satellite signal is used as the reference channel signal for pulse compression.

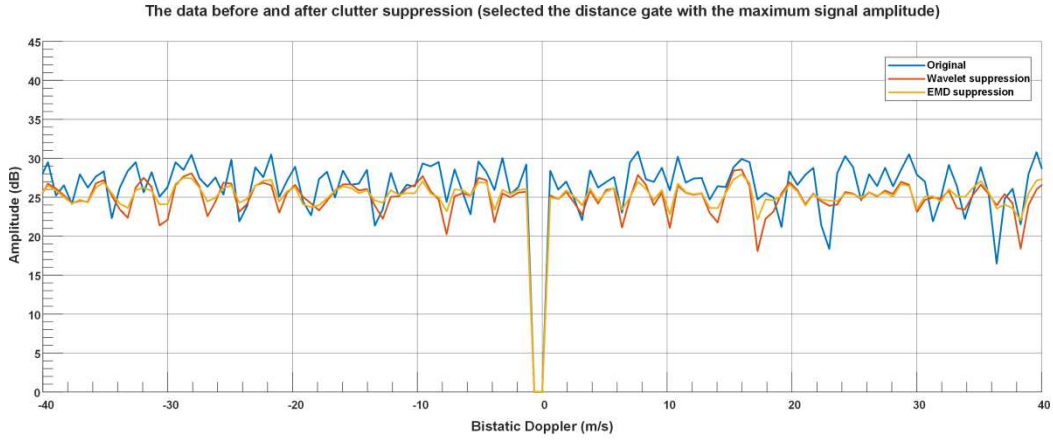


Figure 13. Doppler-domain amplitude curves before and after clutter suppression. The data are received at 17:23 LT on May 28, 2025, and the No. 8 GPS satellite signal is used as the reference channel signal for pulse compression.

The target is not visible in Figures 12 and 13. This result indicates that the target echo reflected from the No. 8 GPS satellite signal is too weak for effective detection. In this case, wavelet and EMD processing can reduce part of the noise-like background, but they cannot recover a target component that is below the usable signal level.

3.3 Strong-Noise Scene

To evaluate the method under strong noise, the data received at 11:56 LT on May 29, 2025 are selected for signal processing and clutter suppression. Figure 14 shows the results obtained by using the No. 1 GPS satellite signal for convolutional reconstruction. In the original range-Doppler map, the noise is too strong for reliable target detection, so this dataset represents a typical strong-noise case.

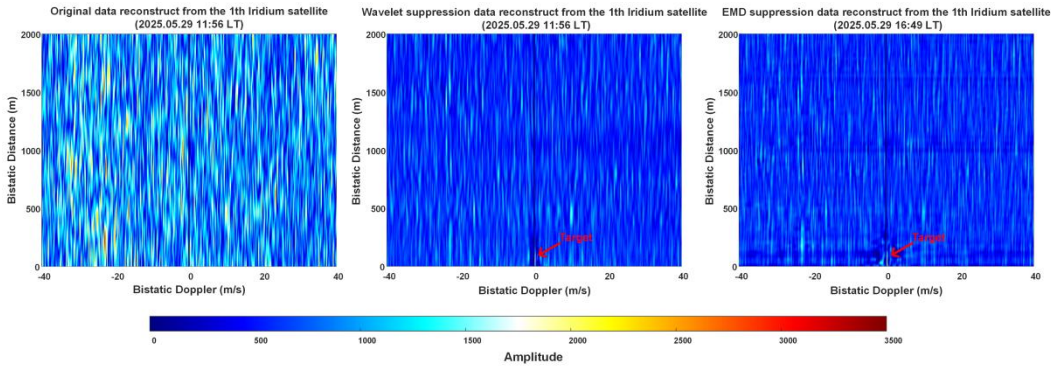


Figure 14. Range-Doppler maps before and after clutter suppression. The data are received at 11:56 LT on May 29, 2025, and the No. 1 GPS satellite signal is used as the reference channel signal for pulse compression.

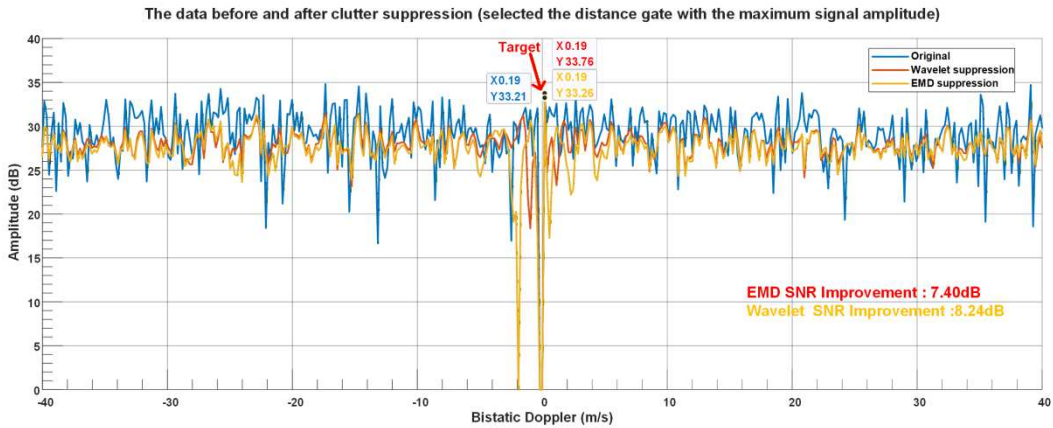


Figure 15. Doppler-domain amplitude curves before and after clutter suppression. The data are received at 11:56 LT on May

29, 2025, and the No. 1 GPS satellite signal is used as the reference channel signal for pulse compression.

After clutter suppression, a small bright point with a narrow Doppler spread appears in the processed maps in Figure 14. This point corresponds to the target. Figure 15 shows that EMD processing improves the SNR by 7.40 dB, and wavelet processing improves the SNR by 8.24 dB. The result shows that both methods remain effective under strong noise.

3.4 Strong-Interference Scene

To evaluate the method under strong interference, the data received at 16:49 LT on May 29, 2025 are selected for signal processing and clutter suppression. Figure 16 shows the results obtained by using the No. 1 GPS satellite signal for convolutional reconstruction. In the original range-Doppler map, strong clutter appears from -20 to -40 m/s and from 0 to 1500 m. This dataset therefore represents a typical strong-interference case.

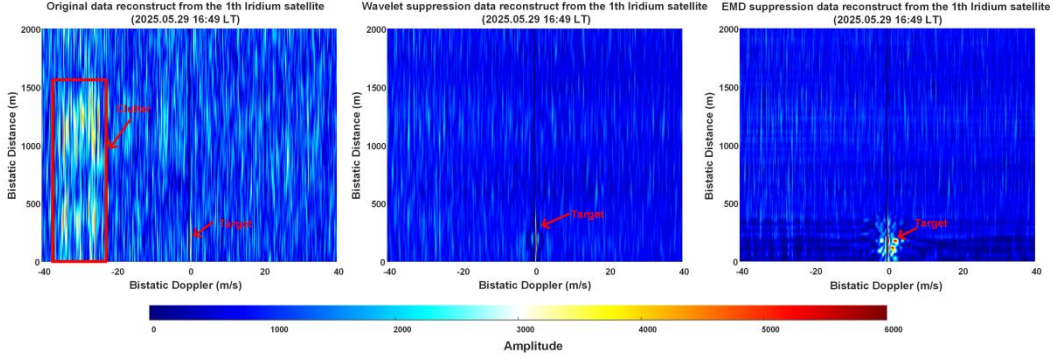


Figure 16. Range-Doppler maps before and after clutter suppression. The data are received at 16:49 LT on May 29, 2025, and the No. 1 GPS satellite signal is used as the reference channel signal for pulse compression.

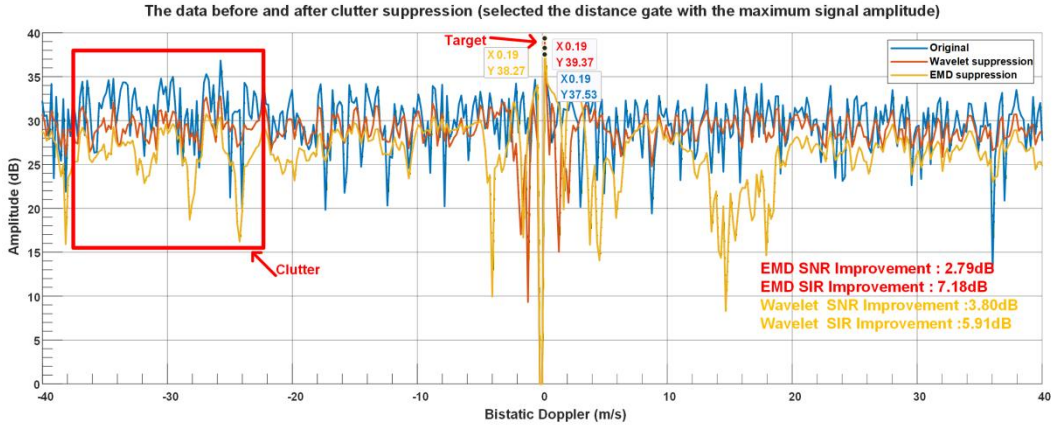


Figure 17. Doppler-domain amplitude curves before and after clutter suppression. The data are received at 16:49 LT on May 29, 2025, and the No. 1 GPS satellite signal is used as the reference channel signal for pulse compression.

After clutter suppression, a small bright point with a narrow Doppler spread appears in the processed maps in Figure 16. Figure 17 shows that EMD processing improves the SNR by 2.79 dB and the SIR by 7.18 dB. Wavelet processing improves the SNR by 3.80 dB and the SIR by 5.91 dB. These results show that both methods suppress strong interference, although the improvement depends on the scale-domain difference between the target and the interference.

4. Statistical and Comparative Analysis of SNR and SIR Improvement

To avoid relying on individual examples, the average SNR and SIR improvements are calculated from the data collected from May 28 to 29, 2025.

The improvement generally increases when the background noise or interference energy becomes stronger, provided that the target and clutter have different scale-domain features. The data are therefore divided into weak-clutter and strong-clutter conditions. Strong clutter contains two cases. In the first case, strong noise makes the target invisible in the original range-Doppler map. In the second case, strong interference exists when the

clutter amplitude is greater than half of the signal amplitude, which means that the clutter amplitude in dB is higher than the signal amplitude minus 3 dB. Figure 18 gives the average SNR and SIR improvements for these conditions.

Figure 18 shows the average SNR and SIR improvements of the two algorithms. The left panel gives the results under weak clutter, and the right panel gives the results under strong clutter. In each panel, the first two bars show the average SIR improvement, and the last two bars show the average SNR improvement. The orange bars represent EMD, and the purple bars represent wavelet reconstruction.

Under weak clutter, EMD gives limited improvement, with an average SIR improvement of 3.53 dB and an average SNR improvement of 1.17 dB. Under strong clutter, its performance is better, with average SIR and SNR improvements of 6.39 dB and 6.00 dB. Wavelet reconstruction gives stronger overall performance. Under weak clutter, it improves the SIR by 6.37 dB and the SNR by 2.48 dB. Under strong clutter, it improves the SIR by 8.07 dB and the SNR by 6.83 dB. These results show that the wavelet method is more stable in the measured scenes, while EMD is more sensitive to weak-clutter conditions.

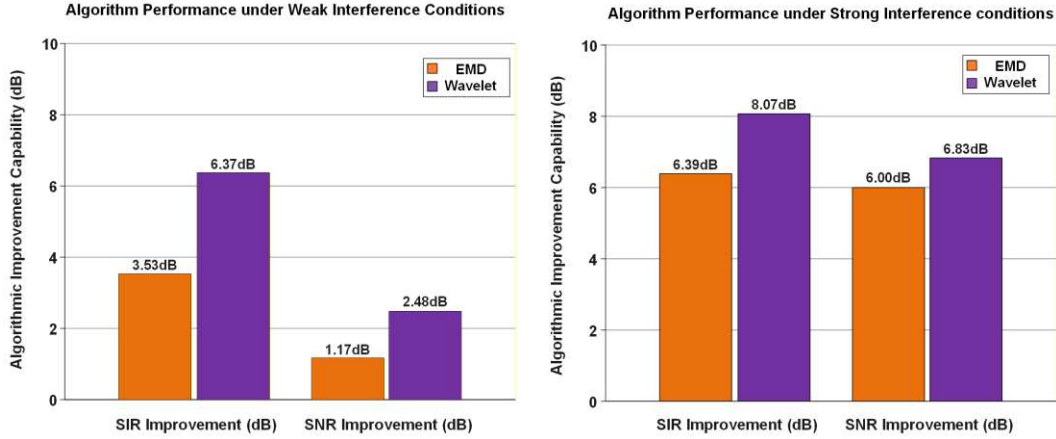


Figure 18. Statistical analysis of clutter suppression performance under weak clutter (left) and strong clutter (right). Orange represents EMD, and purple represents wavelet reconstruction.

The measured and simulated results show that the proposed method is most effective for clutter whose scale-domain distribution differs from the target echo. This behavior differs from ECA, least-squares cancellation, and CLEAN-type methods. Those methods mainly estimate direct-path, multipath, or other strong clutter components from a reference signal and remove them before target detection. They are strong choices when the clutter can be well modeled by delayed or Doppler-shifted copies of the reference signal. The proposed method instead works after range-Doppler formation and uses scale-domain feature separation. It is therefore complementary to subspace and CLEAN methods rather than a complete replacement for them.

For the GPS passive radar data used in this paper, the wavelet method gives better average measured performance than EMD. The simulation cases also show that both methods remove ground clutter more effectively than direct-path interference from other satellites. This result is consistent with the method principle. Ground clutter has a scale distribution that differs from the target echo, while direct-path interference from other satellites can have a target-like scale distribution. The comparison indicates that scale-domain reconstruction is suitable for suppressing ground clutter and noise-like interference, but it should be combined with ECA or CLEAN-type cancellation when target-like direct-path interference dominates.

5. Conclusions

This paper studies clutter suppression for GPS-signal-based passive radar. A time-frequency-scale-domain adaptive clutter suppression method is proposed and evaluated with measured data. The method uses the scale-domain feature difference between target echoes and clutter and performs weighted reconstruction with wavelet or EMD components. The study also reviews representative passive radar clutter suppression methods and compares their processing principles with the proposed scale-domain approach.

The results show that GPS passive radar can detect a weak ground target, but the target echo is easily buried by background noise, direct-path interference, and other clutter. The proposed wavelet and EMD reconstruction methods improve the visibility of the target in range-Doppler maps when the target and clutter have different scale-domain energy distributions.

Both algorithms improve the SNR and SIR under weak and strong clutter conditions. Wavelet reconstruction gives the best overall performance in the measured data. It reaches an average SIR improvement of 8.07 dB and an average SNR improvement of 6.83 dB under strong clutter. EMD improves the SIR and SNR by 6.39 dB and 6.00 dB under strong clutter, but its improvement under weak clutter is lower, with 3.53 dB for SIR and 1.17 dB for SNR.

The comparison with existing clutter suppression methods shows that the proposed method has a different role from direct-path cancellation methods such as ECA and CLEAN. ECA and its variants are well suited for removing direct-path and multipath components when a reliable reference channel is available and the clutter subspace can be modeled. CLEAN-type methods can also remove strong components iteratively, but they often require careful dictionary or stopping-rule design. The proposed scale-domain reconstruction does not mainly depend on direct-path subspace estimation. It is more useful when clutter and target have distinct scale features, especially for ground clutter and noise-like interference in the measured GPS passive radar data.

The method also has clear limits. If direct-path interference from other satellites has a scale distribution similar to the target echo, the suppression effect is weak. If the reflected GPS signal is too weak, as in the No. 8 satellite case, scale-domain reconstruction cannot recover an effective target. Future work should add direct quantitative comparisons with ECA, ECA-B, CLEAN, and adaptive filtering on the same measured data and should combine subspace cancellation with scale-domain reconstruction to improve suppression of target-like interference.

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