ABSTRACT This paper studies the application of compact polarimetric (CP) SAR in the detection and identification of ocean internal solitary waves (ISWs). First, based on full-polarimetric ALOS PALSAR images, we construct CP SAR images and extract 26 CP features. Then, the ISWS-sea surface differentiation capability for the different polarization features is analyzed by using the Jeffries and Euclidean distances. The results show that $\lambda_1$, Entropy ($H$), Lambda, the polarimetric total power ($\text{Span}$) and the Stokes parameters ($\text{Stokes}_g^0$, and $\text{Stokes}_g^3$) improve the ISWs detection results. On this basis, a $k$-means clustering algorithm based on CP features is introduced, and the results show that the ISWs detection and identification performance of the algorithm are superior to that of the traditional Wishart polarization clustering algorithm, which suggests that CP SAR has good application prospects in the detection and identification of ocean ISWs.

INDEX TERMS Internal solitary waves, compact polarimetric SAR, detection, polarization features.
distribution characteristics of ISWs in the Georgia Strait, and analyzed the relationships between ISWs and tidal and wind fields. In [9], Pisoni et al. used Advanced Land Observing Satellite (ALOS) Phase Array type L-band SAR (PALSAR) images to study ISWs on the Argentine inner Patagonian shelf and evaluated their generation mechanism and propagation speed. In [10], Nadimpalli et al. used Envisat and TerraSAR-X images to study the potential generation locations of ISWs in the Andaman Sea.

The SAR imaging mechanisms of ISWs mainly consist of three complex physical processes [11]. These physical processes cause ISWs to produce special electromagnetic scattering characteristics at the ocean surface, which in turn cause peaks and troughs to appear as alternating bright and dark bands in SAR images [12]. However, polarimetric SAR has sensitive electromagnetic wave response characteristics [13], so it can be used to detect and characterize targets with abundant polarimetric information, such as ISWs.

SAR systems have developed from single-polarization to dual-polarization (DP) and even full-polarization (FP) observation modes. Compared with single-polarization SAR, FP SAR can completely describe the vector relationship between an incident wave and the scattered wave of the target, and the acquired target information is abundant. In [14], Schuler et al. first applied FP SAR for ISWs detection, and studied the influence of ISWs fronts on the polarization orientation angle, thus providing a new way to identify these marine features. In [15], based on FP SAR images, Li et al. comparatively analyzed the visibility of ISWs in 11 polarization feature images. However, due to the narrow width of FP SAR images (for example, the width of an FP RADARSAT-2 SAR image is only 25-50 km), such images cannot meet the requirements of large-scale ISWs survey applications.

To solve the problem of FP SAR systems, Souyris and Mingot proposed the concept of compact polarimetric (CP) SAR [16]. Compared with FP SAR, CP SAR can not only reduce the design complexity and improve the coverage width of the image but also maintain the polarization capability of an FP SAR system to a certain extent [17]. Preliminary studies, such as that of Shirvany et al., who detected ships on the sea surface based on the polarization degree extracted from CP SAR, have been conducted in the field of target detection [18]. In [19], Cao et al. constructed CP SAR data based on FP RADARSAT-2 data and compared the ship detection capabilities of FP, CP and DP SAR systems. In [20], Salberg et al. introduced some CP features for the detection of oil spills; additionally, the polarization degree and ellipticity, which were obtained from \( \lambda - m \) decomposition, were used for oil spill detection. However, in the field of ISWs, research using CP SAR technology for detection is still lacking.

Considering the above problems, this paper uses FP ALOS PALSAR images to construct CP images. Then, we extract some features through polarization decomposition and other processing steps and analyze the ISWs detection and identification characteristics of these features in detail. We discuss the feasibility of using CP SAR technology for ISWs detection and identification and for the selection of polarization features that can be effectively used for ISWs detection. This work improves the general scientific understanding of ISWs and provides a reference for follow-up work on the detection and automatic extraction of SAR ISWs.

### II. DATA

#### A. DATA INTRODUCTION

In this paper, FP ALOS PALSAR SAR images are used. PALSAR is an L-band SAR sensor carried by the Japanese ALOS-1 satellite. The Level 1.1 products provided by PALSAR are all complex single-look data sets. The images have undergone azimuth and range compression, with an azimuth resolution of approximately 24 m and a range resolution of approximately 10 m. In total, 145 scenes of ALOS PALSAR Level 1.1 images are selected to perform the research presented in this paper. Five scenes were selected to screen the features for compact polarization. These images were acquired in the Andaman Sea and the Sulu Sea because the ISWs in these two areas have obvious characteristics, with large amplitude and spatial scale. Another 140 scenes were used for subsequent ISWs classification and identification analysis, and they were obtained from different ocean regions of the world, such as the South China Sea and the waters near Colón Island.

Figure 1 shows the Pauli-based pseudocolor composite images (PauliRGB) of the above 5 scenes. The ISWs in images #1-3 propagate in the range direction, and the ISWs in images #4-5 propagate in the azimuth direction.

#### B. DATA PROCESSING

The CP SAR system considered in this paper is essentially a special DP SAR system. Due to the lack of real CP data, most studies use FP images reconstruction to generate CP images. In this paper, CP SAR images are also constructed based on ALOS PALSAR images. Since the original FP images include single-look complex data and the images are narrow and long, ISWs information is difficult to obtain. Therefore, during data processing, the original SAR data are first processed with a multilook method in the azimuth direction, and the number of looks is 6. Then, the FP images are filtered after multilook processing because the single-frequency electromagnetic wave emitted by the SAR system is scattered by distributed ground objects, the echoes of different scattering surface elements contain wave path differences, and the coherent superposition of echoes generates coherent

### TABLE 1. The specific information of the 5 SAR images.

| Image Number | Image Name           | Imaging Area   | Incidence Angle |
|--------------|----------------------|----------------|-----------------|
| #1           | ALPSRP065000120      | Andaman Sea    | 23.93°          |
| #2           | ALPSRP233480140      | Andaman Sea    | 25.73°          |
| #3           | ALPSRP274470120      | Andaman Sea    | 23.95°          |
| #4           | ALPSRP229970140      | Sulu Sea       | 25.73°          |
| #5           | ALPSRP229970180      | Sulu Sea       | 25.72°          |
At present, there are three main modes of CP SAR: horizontal and vertical echoes or circularly polarized waves. Both directions are received at the same time, namely, as horizontal linear polarization reception methods to reconstruct waves are generally linear polarization waves or circular magnetic waves. Compared with the FP SAR system, the CP SAR system emits electromagnetic waves only in one direction, and the features are generally 45°. However, the echo signals from both directions are received at the same time, namely, as horizontal and vertical echoes or circularly polarized waves. At present, there are three main modes of CP SAR: π/4, circular-to-circular (CC) and hybrid-polarity (HP) modes. In this paper, we choose the HP mode. This mode uses right-hand circular polarization transmission and horizontal and vertical linear polarization reception methods to reconstruct fully polarimetric information. The polarization scattering vector is expressed as follows:

\[
\mathbf{k} = \begin{bmatrix} E_{HC} \\ E_{VC} \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \begin{bmatrix} 1 \\ \pm i \end{bmatrix}
\]

In the above formula, the subscript ‘C’ indicates circular polarization, and ‘+’ and ‘-’ represent right-hand and left-hand circular polarization, respectively. ‘H’ and ‘V’ indicate horizontal and vertical polarization, respectively. From (1), the covariance matrix of CP SAR is expressed as:

\[
C = \mathbf{k}^\dagger \mathbf{k} = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} \langle |S_{RH}|^2 \rangle & \langle S_{RH}^* S_{RV} \rangle \\ \langle S_{RV} S_{RH}^* \rangle & \langle |S_{RV}|^2 \rangle \end{bmatrix},
\]

where ‘R’ denotes right circular polarization, ‘T’ is a matrix transpose operation, ‘∗’ denotes the complex conjugate, and <> is the spatial average.

The polarization features commonly used for target detection in SAR images can generally be divided into two categories: one category is based on the information obtained from the original SAR data, such as the elements of the polarization coherence matrix or their linear combinations, and the other category is the information obtained through various polarization decompositions. Such information includes polarization entropy and average scattering angle information. Table 2 lists all the polarization features used in this article, which includes 26 CP features and σ₀ images of 4 different polarization channels. Among these features, f₁ and f₂ correspond to the amplitudes of C₁₁ and C₂₂, respectively, in (2) [23], and f₃ represents the total polarization power (Span) [24], which is expressed as:

\[
\text{Span} = |S_{RH}|^2 + |S_{RV}|^2
\]

Similar to the theory of fully polarized HAA decomposition, in 2012, Cloude et al proposed a compact polarized HAA decomposition method based on the covariance matrix C [23]. This decomposition can obtain the eigenvalues λᵢ of the covariance matrix, and the eigenvalues satisfy λ₁ ≥ λ₂ ≥ ... ≥ λₘ. Using λᵢ, a series of features can be obtained, such as the compact polarization entropy (Hᵢ fᵢ), anisotropy (Aᵢ fᵢ) and average scattering angle (αᵢ fᵢ) [23], [24]. In addition, feature f₀ is the Lambda value, which characterizes the ability of the sea surface to reflect electromagnetic waves [13].

In addition to the scattering vector kᵢ, CP SAR can also be expressed by Stokes vectors [24]:

\[
g_{HP} = \begin{bmatrix} g_0 \\ g_1 \\ g_2 \\ g_3 \end{bmatrix} = \begin{bmatrix} \langle |S_{RH}|^2 + |S_{RV}|^2 \rangle \\ 2\text{Im} \langle S_{RH}^* S_{RV} \rangle \\ -2\text{Re} \langle S_{RH} S_{RV}^* \rangle \end{bmatrix}
\]

The features Stokes gᵢ are Stokes vectors (f₁₀ − f₁₃) [25], where g₀ represents the total power of an electromagnetic
wave, $g_1$ represents the horizontal or vertical linear polarization component power, $g_2$ represents the value of linear polarization component power at $45^\circ$ or $135^\circ$, and $g_3$ is the circularly polarized component power. Based on Stokes vectors, we further obtain the features $f_{14} - f_{20}$, which are the linear polarization ratio and circular polarization ratio ($LPR, f_{14}$; $CPR, f_{15}$), the degree of linear polarization and degree of circular polarization ($DoLP, f_{16}$; $DoCP, f_{17}$), the ellipticity Angle ($\tau_s$, $f_{18}$), the orientation angle ($\phi$, $f_{19}$) and the contrast ($\text{Con}, f_{20}$) [25].

Features $f_{21} - f_{23}$ are the roundness ($\chi$, $f_{21}$), the degree of polarization ($m$, $f_{22}$) and the relative phase ($\delta$, $f_{23}$) extracted from Raney’s decomposition, respectively [25]. The corresponding formulas are:

\[
m = \sqrt{\frac{g_1^2 + g_2^2 + g_3^2}{g_0}}, \quad \delta = -\tan\left(\frac{-g_3}{m g_0}\right), \quad \sin 2\chi = \frac{-g_3}{m g_0} \tag{5}
\]

The polarization features $f_{24} - f_{26}$ characterize the ability of the SAR system to detect surface scattering (Odd, $f_{24}$), double scattering (Dbl, $f_{25}$) and volume scattering (Vol, $f_{26}$) of objects.

Finally, $f_{27} - f_{30}$ represent $\sigma_0$ images of the copolarization and cross-polarization, respectively.

**B. FEATURE SELECTION**

The features extracted above have a certain ocean background and ISWs target discrimination ability, but because of their different physical characteristics, their “sensitivity” to ISWs varies. In this paper, based on the differences between the scattering characteristics of ISWs areas and clear sea surface areas, ISWs and sea clutter samples are selected. Then, two detection indexes, the Jeffries distance [26] and Euclidean distance [19], are constructed to evaluate the ISW-sea surface discrimination ability of SAR images for different polarization features. Finally, the CP features that yield the best detection performance for ISWs are selected. To ensure the accuracy of the samples and avoid misjudgments as much as possible, we choose the pixels with the most obvious ISWs characteristics as ISWs samples and clear uniform seawater pixels as sea surface samples. It should be noted that when select ISWs samples, we mainly choose the pixels of the leading wave in the wave packet. The pixels that are spatially scattered and from different regions are selected at the largest possible distances to make the results representative. The 5 images shown in Fig. 1 were used for feature selection, and each image yielded an average of approximately 93,000 ISWs and sea surface pixels. The statistical ISWs and sea surface pixels are marked with red and blue boxes, respectively, in Fig. 6a.

The Jeffries distance and the Euclidean distance between ISWs and the sea surface are defined as:

\[
J = \frac{1}{8} (M_{IW} - M_{sea})^2 - \frac{\sigma_{IW}^2 + \sigma_{sea}^2}{2} + \frac{1}{2} \ln \frac{\sigma_{IW}^2 + \sigma_{sea}^2}{2\sigma_{IW}\sigma_{sea}} \tag{6}
\]

\[
D = \frac{|M_{IW} - M_{sea}|}{\sqrt{\sigma_{IW}^2 + \sigma_{sea}^2}} \tag{7}
\]

In the above formulas, $M_{IW}$ and $M_{sea}$ represent the mean value of the ISWs and sea surface statistical samples, respectively; $\sigma_{IW}^2$ and $\sigma_{sea}^2$ represent the variance of the ISWs and sea surface statistical samples, respectively. In the formulas, the two detection indexes are dimensionless because the means and variances of the samples are considered. When $J$ and $D$ are large, ISWs are generally easily distinguishable from the sea surface.

Figure 3 shows the calculation results for the ISWs-sea surface Jeffries distances of the 5 images used in this paper.

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**TABLE 2.** The compact polarimetric features used in this paper.

| Number | Polarization Features |
|--------|-----------------------|
| $f_1 - f_2$ | $|C_{11}|, |C_{22}|$ |
| $f_3$ | $\text{span}$ |
| $f_4 - f_5$ | $\lambda_1, \lambda_2$ |
| $f_6 - f_8$ | $\text{Entropy}(H), \text{Anisotropy}(A), \text{Alpha}(\alpha)$ |
| $f_9$ | $\text{Lambda}$ |
| $f_{10} - f_{12}$ | $\text{Stokes}_g, \text{Stokes}_s, \text{Stokes}_e, \text{Stokes}_t$ |
| $f_{13}$ | $\text{LPR}, \text{CPR}, \text{DoLP}, \text{DoCP}$ |
| $f_{14}$ | $\text{Ellipticity Angle}(\tau_s)$ |
| $f_{15}$ | $\text{Orientation Angle}(\phi)$ |
| $f_{16}$ | $\text{Contrast}(\text{Con})$ |
| $f_{17} - f_{19}$ | $\chi, m, \delta$ |
| $f_{20} - f_{22}$ | $\text{Odd}, \text{Dbl}, \text{Vol}$ |
| $f_{23} - f_{26}$ | $\sigma_{0}^{v}, \sigma_{0}^{o}, \sigma_{0}^{ee}, \sigma_{0}^{mm}$ |

**FIGURE 2.** Flowchart of the data processing step.
The solid black line represents the average value. According to the statistical results, the evaluation index $J$ has the same trend for the 5 images, and the only difference is related to the size of the relative value. From the average result, we can see that the Jeffries distances of $Stokes_g^0$, $Stokes_g^3$, $\lambda_1$, $Lambda$, $Entropy (H)$, and $Stokes_g^1$ are high, and the ISWs discrimination effect in these images is better than the original images. The Jeffries distances of other features are all less than 2, and their ISWs detection performance is relatively poor.

Similar to the Jeffries distance, the Euclidean distance can reflect the difference between ISWs and the uniform sea surface scattering intensity, and can be used as a measure of the detectability of ISWs. Figure 4 shows the ISWs-sea surface Euclidean distances. In general, the detection results are consistent with those of the Jeffries distance, but unlike in the previous case, the $Span$ feature also displays good ISWs-sea surface background discrimination ability.

A comprehensive analysis of the Euclidean distance and Jeffries distance results was performed. Table 3 summarizes the ISWs detection capabilities of the features used in this paper.

Excellent performance in ISWs detection and identification. The average value of features in Level II is between 1 and 2, and the ISWs recognition ability based on these features is relatively poor. The features in Level III represent unrecognizable ISWs, and the average values of the Euclidean distance and Jeffries distance are less than 1. In addition, we should note that the original copolarization $\sigma_0$ images and cross-polarization $\sigma_\phi$ images are in Level II and Level III, respectively.

In Table 1, we have listed the specific information of 5 scene images, and we can find that images #1 and #3 have relatively close incident angles of 23.99°, while images #2, #4 and #5 have the same incident angle, that is, 25.72°. To analyze the influence of the radar incidence angle on the selection of polarization features, this paper displays 7 features in Level I. As shown in Fig. 5, the ordinate represents the average Jeffries distance and Euclidean distance. The dashed lines represent the result values of the 5 scene images, and the solid green line represents the average value of images.
#1 and #3, whose incident angles are small; the solid red line represents the average of 3 scenes with larger incident angles. It can be seen from the figure that the incidence angle increases, the distance value increases in the different polarization feature images, that is, the distinguishability between ISWs and the sea surface increases. This finding is consistent with the ship detection results by CP features indicated in [27]. However, for images with the same incidence angle, the distance value does not change much, and the overall trend is relatively stable, as shown by the solid line in the figure. The above analysis shows that the incident angle has a reference role in the selection of the polarization features but does not play a decisive role, because for each scene image, the incident angle is fixed. Under this condition, the CP features selected in this paper are better than the ISWs detection performance of the original $\sigma_0$ images.

Figure 6 shows seven features in image #3, all of which are categorized as Level 1. Compared with the results based on the original PauliRGB images, the visual interpretation results for the ISWs of most of the features in the images are improved, and the features of the ISWs region are highlighted. However, in the $Stokes_g1$ image, the ISWs features are fuzzy and cannot be effectively recognized, as will be verified and explained in the following section. In addition, it should be mentioned that in the feature images shown in Fig. 6, $\lambda_1$, Entropy($H$) and Lambda have no units, because they are linear indexes. The remaining 4 features are all displayed in dB, and the pixel values in the $Stokes_g1$ and $Stokes_g3$ images need to be logarithmically converted to achieve dB as the unit.

IV. CLASSIFICATION

To identify ISWs in remote sensing images, ISWs and the sea background are classified. Based on this principle, the CP features selected above are used as the basis for establishing a simple unsupervised classification method to further study the potential of using such features to detect and identify ISWs at the sea surface. We mainly use the $k$-means clustering algorithm based on the features selected above and the traditional Wishart clustering algorithm. The Wishart clustering algorithm based on the polarimetric covariance matrix $C_2$ is regarded as the standard clustering method for processing polarimetric data [28], [29]. When using CP features for $k$-means classification, the features are first logarithmically transformed to enhance the contrast of the data and thus improve the performance of the $k$-means clustering algorithm [29]. Additionally, in $k$-means classification, the number of classes ($k$) must be determined in advance. In the two cases used in this section, we set the number of classes to 2; that is, only the target type and the sea background type are considered.

A. PERFORMANCE ANALYSIS

To analyze the ISWs identification performance of the above two clustering algorithms, the ISWs identification accuracy of each approach is analyzed, and the results are compared. However, there is no accurate and feasible standard for evaluating the accuracy of ISWs detection in remote sensing images. Therefore, when we evaluate the accuracy of ISWs identification, the standard this paper used is the number of ISWs detected. First, the ISWs were manually identified in the original PauliRGB images and the leading waves were marked with a solid red line in the figure (seen in Fig. 7). Then, the $k$-means clustering algorithm and the Wishart algorithm are used to classify the polarization feature images and
the $C_2$ matrix, respectively, and the classification result is obtained (the ISWs pixels are equal to 1, and the sea pixels are equal to 0). Finally, the artificially marked ISWs areas in the original image were compared pixel by pixel with the corresponding ISWs areas in the classification results. If the pixel coincidence rate reaches 70%, that is, at least 70% of the pixels in the artificially marked area are consistent with the ISWs area detected in the feature images, then the ISWs detection is considered successful.

In this paper, 140 fully polarized ALOS PALSAR images were selected, and 250 ISWs were identified from the images. It should be noted that because ISWs are large-scale marine features, they appear as light and dark bands in the form of wave packets in remote sensing images. Therefore, in this paper, when the ISWs are calibrated, the large connected area at the front of waves is the main area selected.

Table 4 shows that the Wishart clustering method is able to identify 194 ISWs with a recognition accuracy of 77.6%. However, the $k$-means clustering algorithm based on compact polarization features yields an excellent ISWs identification performance. $\lambda_1$, $\text{Lambda}$, $\text{Entropy}(H)$ and $\text{Span}$ of ISWs identification are greater than 80%. The ISWs identification accuracies for the $\text{Stokes}_0$ and $\text{Stokes}_3$ features are close to those obtained with the Wishart algorithm at 77% and 79%, respectively. However, only 142 ISWs can be identified in the image of $\text{Stokes}_1$ feature, with a detection accuracy of 57%, suggesting that the ISWs identification ability is poor; therefore, this feature is not suitable for the detection of ocean ISWs. In summary, the partial CP features selected based on the Euclidean distance and Jeffries distance in this paper can be effectively used for the detection and identification of
ocean ISWs, and such features include $\lambda_1$, Lambda, Entropy ($H$), $\text{Stokes}_0$, $\text{Stokes}_3$, and Span.

### B. SAMPLE FINDINGS

Figure 8 shows the results of the two clustering algorithms on the ISWs in image #1. This section mainly analyzes Figure 8 indicates that with both classification methods, the ISWs can be easily distinguished from the background environment, but there is a certain difference between the results of the Wishart clustering algorithm and those of the feature-based clustering algorithm. Notably, the k-means clustering algorithm based on CP features can highlight the characteristics of the ISWs regions, has a significant denoising effect and effectively maintains the edge features of the ISWs. Thus, the ISWs detection and recognition effects are more accurate than those of the standard Wishart classification algorithm. This finding supports the conclusion that the CP features selected in this paper can be used to effectively distinguish ISWs and the ocean background. Although these features do not contain complete polarization information, they contain sufficient information for the purpose of this study.

### V. CONCLUSION

CP SAR is an emerging polarization mode that can not only achieve wide swath observations but also fully retain the polarization information of a detected target; therefore, this approach has great potential in the observation and analysis of large-scale marine phenomena. However, in the field of CP SAR, current research on the detection of ocean ISWs is still lacking, and the use of CP SAR technology for the detection and identification of ocean ISWs has become an increasingly popular issue. Therefore, this paper focuses on the detection and identification of marine ISWs with spaceborne CP SAR.

In this paper, based on the reconstruction of FP ALOS PALSAR images, CP SAR data in HP mode are obtained. On the basis of the proposed extraction method for CP features, the ISWs and sea background discrimination abilities obtained with different polarization features are systematically analyzed based on the Jeffries distance and Euclidean distance. The results show that some CP features can be effectively used for ISWs detection and identification research, such as $\lambda_1$, Lambda, Entropy ($H$), $\text{Stokes}_0$, $\text{Stokes}_3$ and Span, and their ISWs detection capabilities exceed the original copolarization and cross-polarization $\theta_0$ images.

By using the selected features as the basis of simple unsupervised classification, the $k$-means clustering algorithm proposed in this paper outperforms the traditional Wishart polarization clustering algorithm and has advantages in the identification of ISWs and the determination of the characteristics of ISWs regions. Combined with an accuracy evaluation based on expert interpretation, the results show that the accuracy of the Wishart clustering algorithm in ISWs identification is 77.6%, and $\lambda_1$, Lambda, Entropy ($H$) and Span yield accuracies greater than 80% in ISWs identification. The identification accuracies of $\text{Stokes}_0$ and $\text{Stokes}_3$ are close to those achieved by the Wishart algorithm at 77% and 79% respectively. In other words, these features contain sufficient information to detect and identify ISWs.

This paper explores the potential of ISWs detection using CP SAR technology. The polarization scattering characteristics of ISWs are beyond the scope of this article and require further research to improve the overall understanding of ISWs and promote the automatic detection and extraction of ISWs in SAR images.

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