A Method for Removing Outlier Noise from ArrayInSAR Point Clouds based on Hybrid Filtering

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Abstract

Array Interferometric Synthetic Aperture Radar (ArrayInSAR) point cloud is a point cloud obtained by three-dimensional imaging of two-dimensional Synthetic Aperture Radar (SAR) images using array interferometric synthetic aperture radar technology, which can eliminate the phenomenon of layover in two-dimensional images and provide new data support for intelligent mapping. However, due to the influence of system thermal noise, baseline error and environment interference, there are noise points in the ArrayInSAR point cloud with uneven distribution and large elevation error, which bring a lot of gross errors to the 3D terrain results. To solve the problem that discrete points in ArrayInSAR point cloud data seriously affect the quality of three-dimensional data, this paper proposes an ArrayInSAR point cloud outlier noise removal method based on hybrid filtering. According to the distribution pattern of noise points, the outlier noise is divided into discrete outlier noise points and clusters of outlier noise. Firstly, the adaptive segmentation of point cloud dispersion coefficient within the k-neighborhood is used to remove discrete outlier noise points, and then the adaptive threshold segmentation algorithm based on the number of in-class points after K-means clustering is used to remove the cluster outlier noise of ArrayInSAR point cloud data. In order to verify the effectiveness, the proposed method is compared with other classical outlier noise removal methods. The experimental results show that the method proposed in this paper can effectively remove outlier noise in ArrayInSAR point cloud data and improve the quality of ArrayInSAR point clouds.

1. Introduction

Synthetic Aperture Radar (SAR), as a means of all-day and all-weather earth observation, has been widely used in terrain mapping, environmental monitoring, geological exploration, disaster investigation and so on. However, traditional SAR only has the ability of azimuth and ground range resolution, and can only obtain two-dimensional images. Although Interferometric Synthetic Aperture Radar (InSAR) has high elevation resolution, in the area of steep terrain change and complex environment, the three-dimensional targets will overlayer seriously on the two-dimensional image, resulting in a large number of areas can not be interpreted (Hadj-Sahraoui et al., 2019).

On the basis of directly obtaining the three-dimensional electromagnetic scattering structure of the target, SAR three-dimensional imaging technology can eliminate the phenomena of shrinkage, layover and top-to-bottom inversion caused by the imaging mechanism in SAR two-dimensional data (Knaell, 1995). It is of great significance for intelligent surveying, three-dimensional environment construction, target refinement interpretation, and disaster assessment (Rambour et al., 2020). Therefore, multiple countries have developed SAR Tomography (TomoSAR) three-dimensional imaging technology, and in order to solve the problem of low timeliness of TomoSAR technology (Zhang et al., 2015), array interferometric SAR three-dimensional imaging technology has emerged (Budillon et al., 2011 and Hu et al., 2022). Array interferometric SAR system uses array antennas across the flight, virtual equivalent phase centers of multiple antennas based on Multi-Input Multi-Output (MIMO) technology, and obtains multi-channel coherent SAR images by receiving ground object echoes. Multi-angle observation data can be obtained in one flight, and three-dimensional imaging can be achieved in a single flight.

However, the system thermal noise, baseline error, environmental interference and other factors in the imaging process of array interferometric SAR data can result in a large number of outliers in the obtained three-dimensional point cloud data of the observation scene, bringing a lot of gross errors to applications such as terrain surveying. In order to eliminate this gross error, the research team of array interferometric SAR three-dimensional imaging tried to eliminate noise points from the preliminary processing, which could suppress the noise generated by the building corner reflection to a certain extent (Zhang et al., 2020), but there were still a lot of outlier noise in the produced point cloud data, as shown in Figure 1 (a). Considerable efforts have also been made to eliminate amplitude-phase inconsistencies, thereby reducing noise in ArrayInSAR point clouds, but the effect is not significant (Wang et al., 2023).

Therefore, in order to effectively improve the quality of ArrayInSAR point cloud data, this paper presents a method to eliminate outlier noise in ArrayInSAR point cloud by using hybrid filtering. Firstly, according to the distribution form of outlier noise points, they are divided into discrete outlier noise and cluster outlier noise. Then, the adaptive segmentation of point cloud dispersion coefficient within the k-neighborhood is used to remove discrete outlier noise points, and finally, the adaptive segmentation of the number of intra class points after K-means clustering is used to remove outlier noise clusters.

2. Related Work

Due to the scattering characteristics of microwave and the side-looking mode of array interferometric SAR, the array interferometric SAR point cloud can obtain more scattering point information and scattering characteristics of complex terrain areas and building facades, which can make up for the data loss caused by layover in two-dimensional SAR images. Therefore, processing ArrayInSAR point cloud data can make better use of this data achievement. However, there is a big difference between the imaging mechanism of array interferometric SAR and the acquisition principle of Light Detection And Ranging (LiDAR) point cloud. The noise distribution of ArrayInSAR point cloud is different from that of LiDAR point cloud, and the conventional LiDAR point cloud data processing method is not suitable for the processing of array interferometric SAR point cloud. Therefore, it is important to study the denoising method of ArrayInSAR point cloud.

The technology of terrain mapping using three-dimensional point cloud data has been widely used in Light Detection And Ranging (LiDAR) technology. In terrain mapping, the LiDAR point cloud data is preprocessed by using clustering, filtering, registration and other operations, and the high-dimensional feature information of point cloud and convolutional neural network are used to obtain the classification results of large-scale point cloud data, providing ground points for fine classification of terrain products. A large number of statistical analysis methods, unsupervised clustering methods, region growth segmentation algorithms, key point detection techniques are widely used in point cloud denoising, segmentation and registration.

At present, relevant researches are mainly focused on the denoising of LiDAR point cloud data, the core of which is to distinguish noise points and ground object points, and adopt different methods to denoise according to different distribution modes of noise and ground object points. In order to remove the noise points quickly and efficiently, and retain the detailed characteristics of the point cloud as much as possible, the relevant researchers at home and abroad have carried out a lot of research. Some researchers combined the least square method and Lagrange multiplier method to carry out elliptic fitting of tunnel point cloud, and applied it to circular tunnel point cloud filtering, and realized the noise removal of tunnel point cloud data (Li and Wu, 2021). Some researchers propose to use dynamic radius filter to denoise the agricultural navigation laser point cloud, which can obtain good denoising effect while retaining details (Bi and Wang, 2021). Using the spectral information of multi-spectral lidar point cloud to reverse the point cloud containing color information, a multi-spectral lidar point cloud denoising algorithm based on color clustering is proposed, which is also an effective denoising model (Cao et al., 2021). Some researchers have also removed Gaussian noise and Laplacian noise in three-dimensional point clouds by means of a feature graph Laplacian regularizer that depends on signal features, combined with mean and median filters (Chinthaka et al., 2020). There are researchers used the correlation between color and geometry of the point cloud to construct a graph-based convex optimization method to obtain the point cloud after noise removal (Irfan et al., 2021). The above algorithm takes all the noise into consideration and achieves a good noise reduction effect visually, but it may also cause some areas to be over-processed, resulting in the loss of point cloud detail features.

In view of the above problems, many researchers have proposed a variety of noise removal methods based on the distribution characteristics of noise. Some researchers have proposed a hierarchical point cloud denoising algorithm from coarse to fine, by calculating the eigenvalues and eigenvectors of the tensor voting matrix of points and their neighbors to carry out coarse denoising, and using curvature features to carry out fine denoising (Zhao and Zhou, 2020). Some research institutions classify the noise according to the Euclidean distance between the noise point and the non-noise point, and use different denoising methods to make the denoising accuracy meet the application requirements (Ren et al., 2022). In order to obtain a point cloud model that meets the requirement of model reconstruction accuracy, some researchers proposed to de-noise and smooth the noise points in the point cloud of curved parts obtained by laser scanning according to noise classification (Liu et al., 2023). In order to remove the dense noise and large-scale noise caused by object reflection, some researchers compare and analyze the data of multi-position LiDAR sensor to achieve a better denoising effect (Gao et al., 2021). In order to have a better denoising effect on the point cloud with severe noise or irregular distribution, some researchers use the feature aggregation method of random screening to fuse the features of dense points and sparse points (Wang et al., 2023.).

Although there are many point cloud denoising methods at present, the noise distribution of ArrayInSAR point cloud data is not considered by the existing denoising methods when de-noising the ArrayInSAR point cloud data, which is easy to miss many noise points, which brings a lot of errors to the subsequent point cloud registration fusion and affects the quality of intelligent mapping results. In order to better process the ArrayInSAR point cloud, this study analyzed the outlier noise in the data. The discrete outlier noise and the cluster outlier noise are identified by the adaptive threshold segmentation algorithm based on the point cloud dispersion coefficient in the k neighborhood and the points number in the class after K-means clustering, so as to better eliminate the outlier noise in the ArrayInSAR point cloud.

3. Experimental data

The point cloud data used in this article is an airborne ArrayInSAR point cloud obtained through three-dimensional imaging using an ArrayInSAR system. The original data is Ku band airborne ArrayInSAR data. A point cloud data with obvious noise was selected from result obtained through array interferometry three-dimensional imaging as the research data of this article. It is about 550m long, 500m wide, and has a total area of about 275000m^2, including 3813546 points with a point density of about 16.2647 points/m^2.

3.1 Airborne array interferometric SAR 3D imaging model

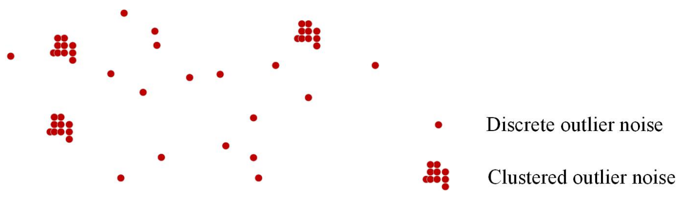
The array interferometric SAR system obtains high resolution in slant distance direction by pulse compression, high resolution in azimuth direction by platform movement to form large virtual aperture, and high resolution in elevation direction by array antenna. Because of the layover phenomenon, scattering points with the same slant distance overlap in the same resolution unit. After image registration, the signal in the azimuth resolution unit of the same slant distance between different channels can be expressed as Equation (1):

$$g_i = \int r(s) \exp\left(-j2\pi \frac{2b_i}{\lambda r_0} s\right) ds + w_i, i = 1,2,\cdots N \quad (1)$$

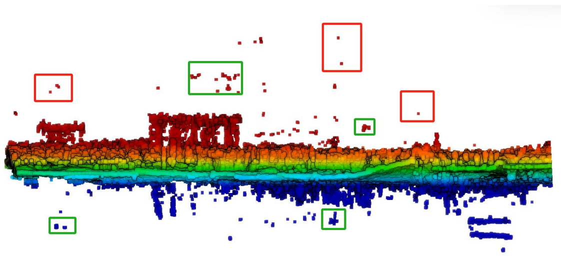
Where, g_i is the signal value of channel i, $r(s)$ is the scattering distribution of the target along the elevation direction, b_i is the orthogonal baseline of the i SAR interference fringe, λ is the wavelength, and r_0 is the slant distance.

3.2 Outlier noise distribution of array interferometric SAR point cloud

After observing and analyzing the experimental data, it can be seen that as shown in Figure1(b), the outlier noise contained in the ArrayInSAR point cloud data obtained by ArrayInSAR three-dimensional imaging technology includes discrete outlier noise points floating in the air and clustered outlier noise. The red discrete points in Figure 1 (a) are the outlier noise points, and the red cluster is the outlier noise cluster. In Figure 1 (b), the points in the red box are outlier noise points, and the points in the green box are outlier noise clusters. They float around buildings or ground point clouds in the ArrayInSAR point cloud, interfering with the identification of real point clouds.



(a) Simulated outlier noise distribution



(b) Outlier noise distribution in real ArrayInSAR point clouds

Figure 1. Outlier noise schematic diagram

4. Methodology

Due to the irregular distribution of outlier noise in the ArrayInSAR point cloud, this paper combines point cloud dispersion coefficient, K-means algorithm, and adaptive threshold algorithm as a hybrid filtering algorithm to remove outlier noise points and clusters. The hybrid filtering algorithm based on adaptive threshold first calculates the point cloud dispersion coefficient within the neighborhood, and based on the adaptive threshold method, the point cloud dispersion coefficient is binary classified to remove outliers floating around the main point cloud to reduce the number of clusters. Then, the K-means clustering algorithm and adaptive threshold algorithm are combined to remove outlier noise clusters, thereby quickly and effectively removing outlier noise in the ArrayInSAR point cloud. The technical process of removing outlier noise proposed in this paper is shown in Figure 2.

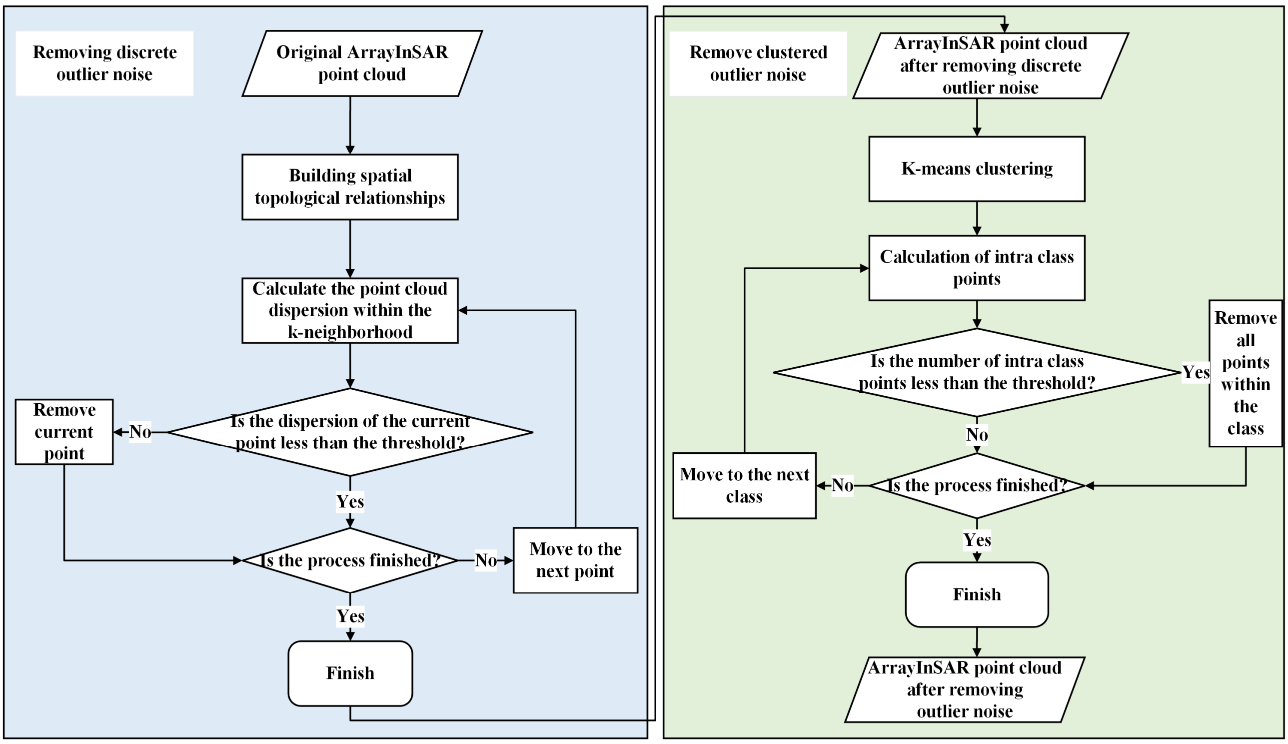


Figure 2. Flow chart of removing outlier noise from ArrayInSAR point clouds based on hybrid filtering

4.1 Remove outlier noise points

The outlier noise points in the ArrayInSAR point cloud refer to the discrete points floating in the air and far away from the object. According to the characteristics of outlier noise points, this paper uses an adaptive threshold segmentation algorithm based on the point cloud dispersion coefficient to remove the noise. The spatial topological relationship of disordered ArrayInSAR point cloud is constructed by using kd-tree. The average distance between the nearest neighbor points containing outlier noise is greater than the average distance between the nearest neighbor points without outlier noise. Therefore, the point cloud dispersion coefficient (PCDC) of the points in the neighborhood is defined according to this feature. The larger the PCDC is, the more discrete and sparse the point cloud distribution in the neighborhood is, and the higher the probability of the nearest neighbor containing outlier noise points is. According to the point cloud dispersion coefficient, the outlier noise points are separated from terrain and feature points by adaptive threshold segmentation.

(1) Determine the neighborhood size

The selection of neighborhood size directly affects the noise removal effect of point cloud. Before using kd-tree to search neighborhood points, the neighborhood value needs to be set. In this study, different neighborhood values are used to compare the denoising effect of the selected sample data, so as to determine the best neighborhood value.

(2) Calculate the point cloud dispersion coefficient

The average distance between the current sampling point and all points in its optimal neighborhood is taken as the point cloud dispersion coefficient (PCDC) of the current sampling point.

(3) Adaptive segmentation algorithm based on PCDC to remove outlier noise points

The sequence of point cloud dispersion coefficient (PCDC) values is defined as $P=\{P_i \mid i=1,2,\ldots,n\}$. Let the threshold for separating outlier noise points and object points be $P_t = th$. t indicates the serial number index corresponding to the PCDC value, then t can divide i into $1<i\le t$ and $t<i\le n$ parts.

Where, when $1<i\le t$, P_i represents the PCDC value of the ground object point cloud; when $t<i\le n$, P_i represents the PCDC value of the outlier noise point. The proportion of each PCDC value to all PCDC sequences is defined as $Q_i = P_i \big/ \sum_{i=1}^{n} P_i$, then the total proportion of PCDC value of ground object point cloud is $Q_1 = \sum_{i=1}^{k} Q_i$, and the total proportion of PCDC value of outlier noise points is $Q_1 = \sum_{i=k+1}^{n} Q_i$.

The PCDC average value of ground object point cloud is $b_1 = \left(\sum_{i=1}^{k} P_i Q_i\right) \big/ Q_1$, and the PCDC average value of outlier noise point is $b_1 = \left(\sum_{i=k+1}^{n} P_i Q_i\right) \big/ Q_2$. The outlier noise point and ground object point of the original point cloud are divided and evaluated by Equation (2):

$$M = Q_1\left(b_1 - b_G\right)^2 + Q_2\left(b_2 - b_G\right)^2 \tag{2}$$

Assuming $b_1 < b_G < b_2$, $\Delta b = b_2 - b_1$, the farther the outlier noise points are from the interval where the ground object point cloud is located, the better the evaluation effect of Equation (2) is, and the more accurate the identification of outlier noise points is. The objective function values of all separated evaluation criteria form set $\{M_i \mid i=1,2,\ldots,t,\ldots,n\}$. There is an optimal separation point k^*, that is $M\left(k^*\right) = \max\left(M\left(k\right)\right)$, and there is a separation threshold $th = P_{k^*}$, which makes the removal of outlier noise points best.

4.2 Remove outlier noise clusters

The outlier noise cluster in the ArrayInSAR point cloud data refers to the cluster of points floating in the air far away from the object. Unlike the outlier noise cluster, the outlier noise cluster is a series of dense point clusters, as shown in Figure 3 (a). In this paper, according to the dense distribution characteristics of outlier noise cluster, K-means clustering is carried out for point cloud data, and the outlier noise cluster is removed by adaptive threshold segmentation of points within the class.

(1) K-means clustering is performed on ArrayInSAR point clouds with outlier noise points removed.

(2) Calculate the number of points in the category of all clustering results.

(3) Adaptive threshold segmentation is carried out for the number of points in all classes to remove outlier noise clusters. The number of points in the clustering results of ground objects such as buildings and trees is large, while the number of points in the noise cluster is small. According to this, the cluster with a small number of points in the class is removed.

4.3 Denoising effect evaluation index

In order to verify the effectiveness of the method proposed in this paper, the experimental data are used as the ArrayInSAR point cloud data described above, and evaluation indicators are selected based on the distribution of target and non-target ground objects in the de-noised ArrayInSAR point cloud. The performance of ArrayInSAR point cloud denoising algorithm based on hybrid filter is compared with KNN filter and radius filter.

In this paper, the points in the de-noised ArrayInSAR point cloud are divided into two types through human-computer interaction: target object points or non-target object points. The 3D points belonging to the target object obtained after denoising are defined as Tp, the 3D points belonging to the non-target object are defined as Fp, and the 3D points belonging to the non-target object but detected as the target object are defined as F_N. The performance evaluation of the denoising algorithm is carried out according to the evaluation criteria in Equation (3-5):

Integrity *comp* represents the removal rate of noise points, the higher the integrity, the cleaner the noise removal:

$$comp = \frac{T_p}{T_p + F_N} \tag{3}$$

Corr represents the probability of correct denoising. The higher the accuracy rate, the more accurate the recognition of noise points:

$$corr = \frac{T_p}{T_p + F_p} \tag{4}$$

Quality evaluation Q represents the completion quality of the overall algorithm, that is, the integrity and accuracy information are integrated. The higher the quality evaluation value, the better the accuracy and integrity of noise removal:

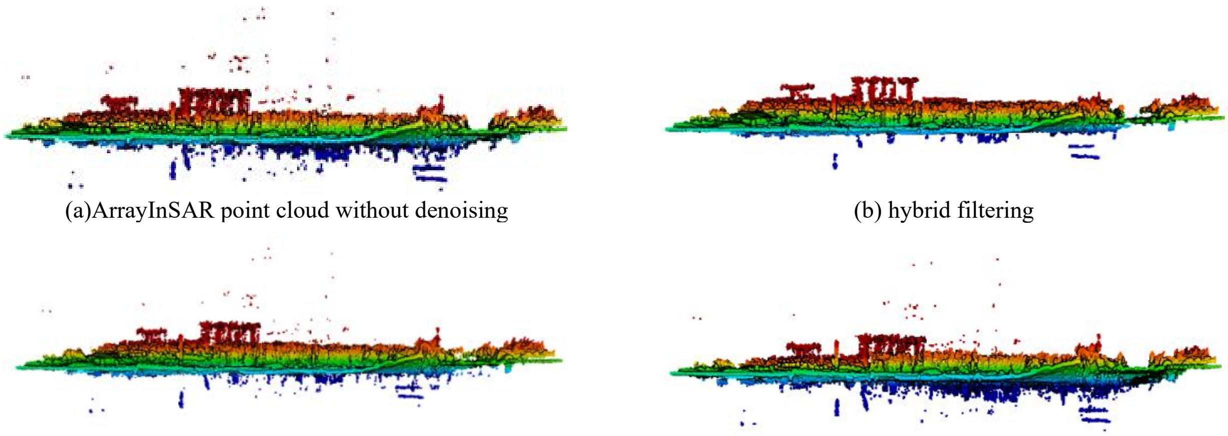
$$Q = \frac{comp \times corr}{comp + corr - comp \times corr} = \frac{T_p}{T_p + F_N + F_p} \tag{5}$$

5. Results

In order to evaluate the ability of the hybrid filtering algorithm used in this article to handle outlier noise in all ArrayInSAR point clouds, the results of removing outlier noise from experimental data were compared with other denoising algorithms(KNN filtering and Radius filtering).

Figure 3 (a) is the original array interferometric SAR point cloud. By comparing figure 3 (a) with Figure 3 (b), it can be clearly seen that the proposed method has a good effect on removing outlier noise, and there are almost no outlier noise points in the air. While there are still obvious noises in the point cloud data after being denoised by KNN filter and Radius filtering denoising methods, which shows the effectiveness of the proposed method for removing outlier noise.

Similarly, it can be seen from Table 1 that the three noise evaluation indexes after the removal of outlier noise by the hybrid filtering method proposed in this paper are all higher than KNN filter and Radius filtering, the ability of the proposed hybrid filtering algorithm to remove outlier noise in ArrayInSAR point cloud is proved again.



(a)ArrayInSAR point cloud without denoising (b) hybrid filtering

(c) KNN filtering (d) Radius filtering

Figure 3. Comparison of denoising effects between our method and other denoising methods

Denoising algorithm	The number of points after noise removal	T_p	F_p	F_N	Comp (100%)	Corr (100%)	Q (100%)
KNN filtering	2602819	2043889	558930	18233	99.1	78.5	77.9
Radius filtering	2798134	1999156	798978	19647	99.0	71.4	70.9
hybrid filtering	2761654	2551887	209767	2526	99.9	92.4	92.3

Table 1. Comparison of outlier noise removal effect

6. Conclusion

The outlier noise in airborne array interferometric SAR point cloud is a kind of gross error, which seriously affects the 3D reconstruction effect using array interferometric SAR point cloud. In order to remove the outlier noise floating in the air in the ArrayInSAR point cloud, a method based on hybrid filtering is proposed in this paper. The outlier noise points and outlier noise clusters are sequentially removed by the combination of point cloud dispersion coefficient, K-means clustering and adaptive threshold segmentation algorithm. Experimental results show that the proposed algorithm has higher denoising ability than other traditional denoising algorithms. At the same time, the hybrid filtering algorithm in this paper can eliminate the coarse error point in the ArrayInSAR point cloud by removing outlier noise, and provide high-quality ArrayInSAR point cloud data for subsequent registration, modeling and other processing, and provide data support for intelligent mapping.

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