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Overview of Vehicle-mounted 4D Millimetre Wave Radar Technology

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Abstract: In response to the urgent need for ranging resolution, real-time target detection, and point cloud clustering in high-precision 4D millimeter-wave radar imaging, this paper systematically reviews the research progress of key signal processing algorithms. Regarding ranging accuracy, while spectrum refinement algorithms (such as ZFFT and CZT) and super-resolution algorithms (such as MUSIC and compressed sensing) improve resolution, they generally suffer from high computational complexity and insufficient utilization of phase information. In the field of constant false alarm rate (CFAR), mean-value algorithms (CA-CFAR) offer excellent real-time performance but weak multi-target detection capabilities, while ordered statistics algorithms (OS-CFAR) offer strong interference tolerance but require optimization of the adaptive range threshold. Among clustering algorithms, the improved 3D PG-DBSCAN overcomes the global density limitations of traditional DBSCAN, but its static grid parameter setting still restricts its adaptability to dynamic scenes. Based on this, this paper proposes a coherent information-fused CZT-Rife joint ranging algorithm, a range-adaptive ED-CFAR detection strategy, and a 3D PG-DBSCAN optimization scheme with dynamic grid parameters, providing theoretical support for high-precision real-time processing in automotive millimeter-wave radars.

Keywords: 4D millimeter-wave radar, super-resolution ranging, constant false alarm rate (CFAR), DBSCAN clustering algorithm, adaptive parameter optimization.

1. Introduction

With the development of autonomous driving and intelligent transportation systems, 4D imaging millimeter-wave radars must simultaneously meet three core requirements: centimeter-level ranging accuracy, real-time multi-target detection, and robust clustering in dynamic scenes. On the hardware side, TDM-MIMO technology improves resolution by expanding the aperture through a virtual array. On the software side, high-resolution signal processing algorithms are crucial for overcoming performance bottlenecks. However, existing research suffers from three contradictions: First, there is an imbalance between accuracy and efficiency: Spectral refinement algorithms (such as CZT) and super-resolution algorithms (such as compressed sensing) improve ranging accuracy but significantly increase computational complexity; second, there is insufficient environmental adaptability: Among CFAR detectors, CA-CFAR offers excellent real-time performance but struggles to withstand multi-target interference, while OS-CFAR offers strong interference tolerance but suffers from range-attenuation errors due to its fixed threshold; third, clustering generalization is weak: The improved DBSCAN algorithm relies on static parameters, making it difficult to adapt to the density distribution characteristics of radar point clouds that vary with distance. This article focuses on the aforementioned challenges, systematically elaborating on the technical context for improving ranging accuracy, CFAR detection, and clustering algorithms. It also proposes an innovative solution that integrates coherent information, distance adaptation, and dynamic grids to promote the practical application of automotive millimeter-wave radar in complex scenarios.

2. Improve Ranging Accuracy Algorithm

(1) Improving the current status of ranging algorithm research

Currently, millimeter-wave radar research focuses primarily on 4D imaging, with a growing demand for high-performance, high-precision ranging. To meet the requirements for high-performance, high-precision ranging for high-precision imaging, 4D millimeter-wave radars often employ time-division multiplexing-multiple input, multiple output (TDM-MIMO) technology in hardware. This technology, without increasing the number of receiving antennas, allows for a larger equivalent virtual array at the receiver by adding transmitting antennas. This results in a larger aperture, improving ranging accuracy and the resolution and accuracy of the Direction of Arrival (DOA) estimation algorithm, enabling better 4D imaging.

In radar measurement, sampling an intermediate frequency signal yields a discrete sequence of intermediate frequency signals. This sequence is a set of fixed-frequency signals. Estimating the frequency of these signals converts them into target ranges. Therefore, the accuracy of the frequency estimation directly impacts radar ranging accuracy. In addition to hardware improvements, the introduction of high-resolution ranging algorithms to enhance ranging resolution and accuracy is also an important solution. In a 4D millimeter-wave radar signal processing system, echo signals undergo baseband mixing and sampling. The output analog-to-digital converter (ADC) data undergoes two discrete Fourier transform (DFT) compressions to form a range-Doppler (RD) spectrum. Adaptive threshold detection is then used to extract target velocity and distance information. While this process improves processing speed, it also reduces the ability to resolve small targets and accurately estimate target distance.

Currently, the demand for precise target imaging in 4D millimeter-wave radar is growing. Achieving both fast and accurate measurement places higher demands on the real-time performance and accuracy of ranging algorithms. Improving ranging accuracy relies on three key aspects: increasing the number of sampling points, improving spectral resolution, and ensuring that sampling points correspond precisely to peaks in the spectrum. This is particularly important for recognizing complex targets in high-resolution scenarios. With the increasing demand for high-precision ranging resolution, research is rapidly developing, and a variety of methods for improving resolution have emerged.

As early as 1997, M. Vossiek proposed a method that combines scanning linearization, predistortion modulation signal and constant phase initial sampling, and introduced the autoregressive moving average (ARMA) model for high-resolution spectrum estimation. In addition, he also proposed to use the phase error in the nonlinear frequency modulation signal for velocity measurement, which can obtain the best range resolution independent of Doppler resolution under a given sweep bandwidth [1]. In 2010, F. Ali and M. Vossiek proposed a method to improve the range-Doppler two-dimensional resolution, and achieved high-precision target separation in short-range radar systems through long-term phase coherent accumulation [2]. In 2016, B. Al-Qudsi proposed a three-way ranging synchronization protocol to address the frequency deviation problem between crystal oscillators in FMCW radar, effectively compensating for frequency deviation and improving ranging accuracy [3]. M. Altmann et al. used confocal radar combined with lens focal length information to successfully separate coherent targets below the basic resolution [4]. S. D. Kim achieved accurate positioning of human targets by using an extrapolation algorithm combined with a fixed filter and a high-pass filter [5]. Among frequency domain methods, DFT is an important foundation. In 1999, Qi Guoqing proposed a frequency refinement and interpolation method to improve the frequency resolution of the difference frequency signal and used the linear relationship between the peak phase of the DFT spectrum and the frequency to perform phase correction. However, due to the spectrum leakage problem caused by the fence effect, the resolution of the DFT method is limited [6]. To this end, Liu Jinming proposed a continuous refinement Fourier spectrum correction algorithm, which became the basis for subsequent improvements [7]. Zheng Wenbin combined FFT and DFT to refine the spectrum analysis within the rough estimation frequency band, taking into account both computational efficiency and spectrum accuracy [8]. Zhong Peng proposed a method combining FFT with Chirp-Z transform to significantly improve ranging accuracy [9]. Other improvements include: He Xingchen proposed an FFT+Chirp-Z algorithm based on energy center of gravity for target estimation [10]; Cunlong Li achieved multi-target high-precision ranging [11]; Yuyong Xiong proposed a PDA algorithm, combined with an improved ICCD, to achieve centimeter-level accuracy [12]. J. Ran applied two-dimensional CZT to perform spectrum decomposition of SAR signals to achieve high-resolution analysis [13]. In the direction of spectrum refinement, the Zoom-FFT (ZFFT) algorithm can magnify and analyze any frequency region. B. Runqing improved its structure, reduced the amount of calculation and suppressed mode aliasing [14]. N. Fernandes combined ZFFT with the MUSIC algorithm and proposed Zoom MUSIC to achieve high-resolution detection of dense frequency signals [15]. In terms of sparse spectrum estimation, in 2020, B. Park proposed sparse fast Fourier transform (SFFT), which extracts key frequency points through hash mapping, effectively reducing the computational complexity [16]. Liao Ran further integrated the advantages of ZFFT and SFFT, taking into account both high resolution and high efficiency [17]. On the other hand, the use of radar signal phase information is also an important direction for improving accuracy. Liu Yu proposed a method of improving frequency estimation by sequence shifting and phase difference correction [18]. Xie Ming and Zhang Xiaofei further proposed a universal phase difference correction model to enhance the applicability and stability of the algorithm [19]. In addition to frequency domain optimization, waveform design has also been widely studied. Y. Son combined sawtooth waves and triangle waves to improve the distance and speed resolution in stages [20]; W.S. Kouzeiha proposed single-step and double-step modulation waveforms, using slope difference analysis to improve the ranging capability, simplify the system structure and achieve higher accuracy [21].

In order to alleviate the fence effect, the most common solution is to fill in the time domain with zeros, which is equivalent to interpolation in the frequency domain, so that the number of frequency domain points increases, making the spectrum curve smoother, thus achieving spectrum refinement. Reference [22] proposed to fill in zeros after the sampling sequence to improve the ranging accuracy. Secondly, ZFFT (ZOOM-FFT) is a targeted analysis of any local frequency band, so this algorithm can improve the measurement accuracy in the set frequency band. The essence of the ZFFT algorithm is to move a broadband signal to zero frequency, filter it into a narrowband signal through a low-pass filter, and then downsample it to extract the signal, so as to achieve the purpose of obtaining high frequency resolution at a low sampling rate. In addition to the above algorithms evolved from fast Fourier transform, the MUSIC super-resolution algorithm is also one of the most effective algorithms for spatial spectrum estimation. The principle of this algorithm is: first, the covariance matrix of the signal receiving matrix is calculated, and then the eigenvalues of the covariance matrix are solved; based on the result of eigendecomposition, the original signal matrix is divided into two mutually orthogonal matrices, namely the signal subspace and the noise subspace. Finally, by utilizing its orthogonality, that is, the projection of any vector in the signal subspace in the noise subspace is zero, the super-resolution information about the target can be solved. In addition to being used to obtain the spatial information of the target in DOA estimation, the MUSIC super-resolution algorithm is also applicable to super-resolution ranging.

In addition, the literature [9] proposed the use of linear frequency modulation Z transform, namely Chirp-Z (CZT) transform, which is a spectrum refinement algorithm on the Z plane. The essence of the algorithm is to perform equal-interval sampling on a section of the spiral line of interest to the researcher on the Z plane to achieve spectrum refinement. Unlike the time domain zero-filling method introduced above, the CZT algorithm does not need to analyze the global spectrum, but selects any section of the spectrum containing valid information for analysis. Therefore, the CZT algorithm has a smaller computational load and better real-time performance of the signal. The literature [23] proposed applying the compressed sensing algorithm used in the DOA field to the ranging field. Sparse signal models are often used to solve parameter estimation problems such as spectrum estimation and azimuth estimation, and are therefore also applicable to the distance estimation field. In the compressed sensing framework, signals are sampled discretely. A dictionary is then formed by collecting observations corresponding to the sampled parameter values as dictionary elements. Therefore, the parameter estimation problem is simplified to representing the actual observations as a linear combination of the smallest possible dictionary elements. These selected elements are then mapped to corresponding sample values in the parameter space, which serve as the final output parameter estimate. The compressed sensing algorithm also operates in this way. When the signal is compressible or sparse, the original high-dimensional signal can be projected into a low-dimensional space without losing any effective information. Finally, by solving the nonlinear optimization problem through convex optimization or other algorithms, the original signal can be accurately reconstructed. Because radar signals have scattering properties and can be fitted by a small number of scattering centers, they are sparse, meeting the requirements of compressed sensing algorithms.

However, these aforementioned methods rarely address two key aspects: improving spectral resolution by incorporating phase information and using spectral correction algorithms to ensure that the sampling points correspond precisely to the highest peaks of the spectrum. Regarding the principle of using coherent information to improve the ranging algorithm, the literature [23] proposed a super-resolution CS improved algorithm and a CZT improved algorithm based on coherent spectrum. In the article, it was proved that there is a clear functional relationship between the phase and frequency in the FMCW millimeter wave radar signal, indicating that the phase change is correlated with the frequency. In order to fully extract the effective information in the signal, this study adopts a phase modulation compensation method: by introducing a phase compensation factor related to the frequency, the phase component of the original signal that changes with the frequency is eliminated. The specific implementation method is to use the phase coherence characteristics of the signal for compensation processing during the Fourier transform process. Its mathematical essence is to modulate a time-varying cosine function based on the amplitude of the original signal. This improves its spectral resolution.

Regarding the use of spectrum correction algorithm to make the sampling point correspond exactly to the highest peak point of the spectrum peak. The reason for the error is that after performing N-point discrete Fourier transform on the signal, when the frequency of the original signal happens to be an integer multiple of the spectrum line interval, the frequency of the original signal can be accurately estimated. When the frequency of the original signal is not an integer multiple of the spectrum line interval, there is an error between the frequency estimated by discrete Fourier transform and the true frequency. In academic research and engineering practice, researchers have developed a variety of effective spectrum correction algorithms, mainly including: ratio correction method: an interpolation algorithm based on the ratio of adjacent spectral line amplitudes; energy centroid method [24]: a weighted average method using the spectrum energy distribution characteristics; Based on this, reference [25] proposed to use one of the ratio correction methods, the Rife frequency estimation optimization algorithm, to optimize this part of the error. Reference [26] combines these two algorithms and uses the CZT algorithm in the spectral line part and the parabola fitting algorithm in the spectral line correction algorithm for correction. In this paper, only single target distance measurement is performed, and its accuracy can reach the millimeter level.

(2) Literature Review

In the study of spectrum refinement algorithms, the time domain zero-filling method can reduce the amplitude and phase errors caused by the fence effect by increasing the number of sampling points, but its computational complexity is high and there is a problem of memory waste. The ZFFT algorithm uses a finite-length unit impulse response filter to achieve local frequency band refinement, which can effectively improve the ranging resolution of FMCW millimeter-wave radar, but there are still three limitations: first, the spectrum distortion introduced by the filter affects the measurement accuracy; second, the intermediate data storage requirements are large; and third, the algorithm implementation complexity is high. Although the MUSIC algorithm can achieve super-resolution detection in the spatial domain and distance dimension, it has insufficient ability to distinguish coherent signal sources, and the global spectrum peak search leads to a surge in computational complexity. The improved CS algorithm based on coherent spectrum proposed in reference [23] increases the extreme ranging resolution to 10 times the basic value, and the relative error is stable below 0.5%. It has excellent noise resistance and measurement accuracy, but its super-resolution performance comes at the cost of higher computational complexity, which limits its practical application. In comparison, the improved CZT algorithm based on coherent spectrum only achieves a 3-fold resolution improvement and maintains the error below 1%, but because it does not introduce a spectral line correction algorithm, its accuracy still has room for improvement. The Rife frequency estimation algorithm proposed in reference [25] optimizes the distance dimension and Doppler dimension estimation, but lacks the spectrum subdivision capability, and the single spectral line correction has limited improvement on the ranging accuracy. Reference [26] achieved significant results by combining CZT and Rife algorithms, but did not fully utilize the phase information, and the parabola fitting algorithm significantly increased the complexity compared to the Rife algorithm with limited performance improvement.

To address the above problems, this paper proposes a CZT-Rife joint algorithm based on coherent information fusion, which combines FFT, Chirp-Z transform based on coherent spectrum, and Rife algorithm for spectrum correction. The algorithm first uses FFT to calculate the rough frequency, and then performs spectrum subdivision and correction through the coherent spectrum to obtain more accurate measurement results.

3. Constant False Alarm Rate (CFAR)

(1) Current Status of Constant False Alarm Algorithm

The RD matrix can characterize the power spectrum distribution characteristics of the target and the environment in the detection scene. However, in actual road scenes, the interference intensity of clutter and noise will change dynamically with the environment. To cope with this time-varying interference condition, radar signal processing systems usually use constant false alarm rate (CFAR) technology to achieve adaptive target detection.

If a fixed threshold is used for radar target detection in a non-stationary background, the false alarm rate (P_{fa}) will increase sharply with the increase of clutter power. The false alarm rate is an important indicator for measuring the detection performance of radar signals. The constant false alarm rate (CFAR) target detection technology adaptively changes the detection threshold according to the change of clutter level to obtain the maximum detection probability under the condition of constant false alarm rate [27]. The criterion used is the Neyman-person criterion, because it makes the detector reach suboptimal without knowing the prior probability.

Different CFAR detection strategies should be adopted for different clutter environment models to approach the optimal detection performance as much as possible. Clutter models are mainly divided into two categories: Gaussian and non-Gaussian clutter. The current main model of non-Gaussian clutter is the sea clutter model, but in the environment used by vehicle-borne millimeter-wave radar, the main clutter environment is still Gaussian clutter environment, so the research on CFAR technology is still based on the Gaussian clutter model. The experimental environment set up for general vehicle-borne millimeter-wave radar algorithms is also a uniform clutter distribution environment.

In detection, two effects may occur. When the target is in the detection unit and there are other targets in the surrounding reference units, the detection unit target may be missed, that is, the shielding effect. When the clutter power difference between the front and rear edge reference sliding windows is large, when using certain algorithms for detection, the false alarm at the clutter edge will increase. This is the clutter edge effect.

The more common algorithm in vehicle-borne millimeter-wave radar is the unit average constant false alarm (CA-CFAR) detection algorithm first proposed in the literature [28]. The data of the adjacent reference units around the unit to be detected are averaged and used as the background clutter power estimate to obtain the detection threshold. To improve the masking effect, the smaller of the sum of the front and back half windows can be selected and then averaged as the background clutter estimate to prevent the background estimate from being too large and thus avoid missing the target, that is, the minimum cell selection (SO-CFAR). To improve the false alarm caused by the clutter edge, the maximum cell selection (GO-CFAR) can be used. The above CFAR algorithms are all based on the average processing of the reference sliding window, so they are called mean-type CFAR. Reference [29] conducted a detailed analysis of the performance of the three types of algorithms, CA, SO, and GO, under different clutter environments. Later, some scholars proposed the weighted cell averaging (WCA)-CFAR [30] improved algorithm, which weighted the front and back windows according to the clutter intensity to obtain the clutter estimate, that is $z=\alpha x+\beta y$, α and β are obtained by P_{d} maximizing while keeping P_{fa} constant. Reference [31] conducted a comprehensive analysis and comparison of the constant false alarm rate (CFAR) loss of the CA algorithm under both linear and square-law detection modes in the context of Gaussian noise. The conclusion was that at the same false alarm rate, the CFAR loss of linear detection is higher than that of square-law detection, and that the CFAR loss decreases with the increase in the number of reference units. For the mean-based algorithm, the larger the reference window N, the better the detection performance. The mean-based CFAR has the best detection performance in a uniform background, but performs poorly in a multi-target environment.

In order to improve the problem of the deterioration of detection performance of the mean-type CFAR in multi-target environments, Rohling first proposed the ordered statistics (OS)-CFAR [32]. The data in the reference unit is sorted and the kth value after sorting is taken as the background clutter power estimate to calculate the detection threshold. Therefore, the appropriateness of k selection is related to the quality of the detection results. Rohling summarized the impact of the bilateral reference window length N and the value of k on the detector performance of OS. That is, when k < 1/2N, the influence of the clutter edge effect will be greater. It is recommended that k should be taken at about 3/4N to obtain comprehensive performance in multi-target or mixed clutter environments [33]. Reference [34] proposed a modified k OS-CFAR. Under the condition of known data prior information, the accurate k value can be calculated to obtain better detection performance.

The essence of OS-CFAR still depends on all sample data in the reference window, but because only one reference data value is retained, its CFAR loss is higher than that of the mean class. Therefore, based on the OS-CFAR detector, OS-CFAR detectors such as the deleted mean CMLD-CFAR and the reduced mean TM-CFAR were derived. The deleted mean (CMLD-CFAR) algorithm first sorts, then deletes r larger values, and finally selects the remaining reference unit samples for weighted averaging. However, some scholars have proposed two improved algorithms. The first one is to delete not only the r maximum values but also the r minimum values [27]. The second one is the equipartition deletion (ED)-CFAR algorithm, which aims to reduce the influence of the target within the reference unit, that is, to reduce the shielding effect [35]. CMLD and TM can retain more ordered reference samples by pre-selecting deletion points, while taking into account the advantages in multi-target environments and smaller CFAR loss. In response to the problem of long response time caused by sorting in OS-type CFAR, reference [36] proposed a repeated sorting algorithm to reduce the response time. That is, the sliding window repeatedly sorts the sliding window of n consecutive reference units in order around the unit to be tested. The computational complexity of this algorithm is reduced by n/4 times compared with the traditional sorting. In addition, the GOS-type method with automatic screening technology can also improve the sorting time problem [37]. In the multi-target environment, the performance of OS-type CFAR is better than that of mean-type CFAR, but its performance also decreases to a certain extent in the clutter edge environment.

The above-mentioned CFAR detectors can only approach the optimal detection performance in a certain clutter environment, and require prior information of the data. Adaptive CFAR can adaptively select algorithms and parameters. For example, cell averaging (CCA-CFAR), adaptive clutter edge position (HCE-CFAR), variation index (VI-CFAR), etc. Among them, VI-CFAR and HCE-CFAR algorithms are more studied as conventional adaptive constant false alarm. The VI algorithm first calculates the VI value and MR value of the reference window. The VI value is used to determine whether the reference window sampling value is uniform, and the MR value is used to determine whether the power mean of the front and back reference windows is consistent. After calculating the VI value and MR value, the clutter type is determined. After obtaining the clutter background type, the optimal CFAR algorithm under each type is adopted. Reference [38] proposed a strategy for calculating the VI and MR threshold values, that is, the error probability of misjudging a uniform environment as a non-uniform environment should be of the same order of magnitude as the preset false alarm rate, and the error probability of misjudging the front and back window means in a uniform environment is required to be no more than 0.1. Reference [39] proposed an I-VI detector using automatic screening technology. When the VI algorithm determines that there are targets in both reference windows, it adopts the OSCMCA strategy, using the OS algorithm to make a local estimate of the leading sliding window and the CMLD algorithm to make a local estimate of the trailing sliding window. The sum of the two local estimates is then used as the clutter estimate of the total sliding window background. Similar detectors include VIHCEOS-CFAR [40], VIEHCE-CFAR, MALVI-CFAR [41], etc., all of which fine-tune the detection strategy after the VI determines the clutter background type.

The HCE-CFAR algorithm first estimates the clutter edge position, obtains the clutter area in which the unit to be tested is located, and then calculates the background power of the clutter area as the corresponding background estimate. The HCE-CFAR algorithm can accurately determine the clutter edge position and has a good control capability compared to the false alarm improvement of the CA algorithm in high clutter areas. However, if the HCE detection algorithm is used in a uniform background, it will bring additional CFAR detection loss. Reference [40] proposed an improved HCE detector, which first determines whether the clutter background is uniform. If it is uniform, the CA algorithm is used. Otherwise, the HCE-CFAR algorithm is used for detection, which makes up for a defect of the HCE-CFAR algorithm.

(2) Literature Review

When selecting a constant false alarm (CFAR) algorithm for automotive millimeter-wave radar, factors such as real-time performance, multi-target detection capabilities, and environmental adaptability must be comprehensively considered. Currently, CA-CFAR (cell-averaged CFAR) is widely used in practical applications due to its low algorithmic complexity and high computational efficiency, which enables it to meet the stringent real-time requirements of automotive environments. However, with the advancement of automotive millimeter-wave radar hardware performance, the limitations of average-based CFAR algorithms (such as CA-CFAR) in multi-target environments have become increasingly apparent, and their detection performance is significantly inferior to that of OS-CFAR (ordered statistical CFAR).

Among adaptive CFAR algorithms, VI-CFAR (variable exponential CFAR) can adapt to varying clutter environments, but its "judgment first, then detection" mechanism results in high algorithmic complexity, making it difficult to meet the real-time requirements of automotive millimeter-wave radars. HCE-CFAR (high clutter environment CFAR) is more suitable for high-clutter scenarios, but the uniform clutter distribution in automotive environments makes this algorithm unsuitable. Overall, the improved OS-CFAR algorithm is more suitable for automotive millimeter-wave radar applications. Among improved OS-CFAR algorithms, ED-CFAR (exponentially weighted CFAR) effectively mitigates the "target shadowing" problem that can easily occur with mean-valued CFAR in multi-target environments, while also offering better detection performance than CMLD-CFAR (truncated mean CFAR). However, ED-CFAR uses a fixed threshold parameter, and the echo intensity of radar targets decreases with increasing detection range. Therefore, a fixed threshold can result in overdetection of short-range targets and underdetection of long-range targets. To address this issue, ED-CFAR needs to be optimized to adaptively adjust its parameters to meet the detection requirements of targets at varying distances, thereby further improving the detection performance of automotive millimeter-wave radars.

4. Clustering Algorithms

(1) Current status of clustering algorithms

With the widespread application of high-resolution radar, more and more high-resolution radar data processing requires matching a group (cluster) of scattering points with a target. Therefore, clustering algorithms are increasingly used in radar data processing. Clustering algorithms are essentially a typical unsupervised learning [42], that is, there is no prior information and category corresponding labels. The goal of clustering analysis is to divide different data objects into several different sets based on the similarity between data objects. Corresponding to the vehicle-mounted millimeter-wave radar scene, it is to divide the point cloud data detected by the radar into their respective actual targets [43]. In the process of studying clustering algorithms, a large number of clustering algorithms have been proposed and are almost widely used in the field of information science and other fields. These clustering algorithms can be roughly divided into several types [44]: one is the partition-based clustering method, the second is the hierarchical clustering method, and the third is the density-based clustering method. Both the partition-based clustering method and the hierarchical clustering method require the final number of clusters to be set in advance.

However, in actual applications, the road environment is complex and changeable, and the number of targets in the next frame time period cannot be predicted. Therefore, the above two algorithms have inevitable defects. At this time, the DBSCAN algorithm based on density clustering can be used. This algorithm does not require the number of clusters to be specified in advance. It clusters according to the density between data objects, finds clusters of any shape, and can filter out abnormal points caused by noise and clutter. The number of clusters finally obtained is the number of targets in this radar scanning frame [45].

The main idea of the DBSCAN density clustering algorithm is to use a set of "neighborhoods" to describe the density of sample distribution [46]. The parameters include the neighborhood distance Eps and the minimum number of neighborhood samples MinPts. The effectiveness of DBSCAN mainly depends on the parameters Eps and MinPts. Appropriate parameters can just distinguish different clusters and identify noise; too large Eps parameters may cause clusters to be incorrectly connected or noise objects to be added to the cluster; too small Eps parameters will split a cluster. If MinPts is set too large, clusters with fewer real points will be regarded as noise, and if MinPts is set too small, noise may be clustered into one class.

There are two major issues with the current application of the DBSCAN algorithm in automotive millimeter-wave radars. The first is the global density threshold. The radar's azimuth resolution unit increases linearly with distance. For automotive targets, the closer they are to the radar, the more traces they detect, while the farther they are, the fewer traces they detect. Consequently, on the radar's range-azimuth diagram, the trace density for near and far targets is inconsistent, with sparse density at distant locations and high density near them. The DBSCAN algorithm, which uses a global density threshold, clusters clutter close to the radar as targets, while targets farther away are not, significantly limiting the radar's detection range. The second issue is algorithmic complexity. The algorithm's time complexity primarily depends on the number of neighborhood queries. The algorithm must traverse all data points in the dataset, performing N neighborhood queries for each point. Therefore, the time complexity of the DBSCAN algorithm is O(N*N). To avoid repeated distance calculations, the algorithm generates an N-order symmetric distance matrix, resulting in an O(N*N) space complexity.

Many scholars have discussed these two issues and proposed many improvement measures. Reference [47] proposed to change the distance calculation from Gaussian function to kernel function for problem 2, and proposed a method to automatically locate the position of Eps when obtaining the neighborhood distance Eps based on the K-distance map, that is, to obtain the quadratic slope after filtering the mean of the K-distance map. Reference [48] proposed to use polar coordinate grid (PG) that conforms to the characteristics of radar data instead of equal-interval grid based on problems 1 and 2. The grid size at different distances corresponds to the density distribution of radar traces, solving the clustering problem of different density point clusters. In order to make full use of three-dimensional information, polar coordinate grid of distance-angle dimension and equal-interval grid of velocity dimension are used for three-dimensional grid clustering. Grid clustering is first used for coarse clustering, and then DBSCAN is used for fine clustering. Reference [49] proposed to use Mahalanobis distance to describe point cloud similarity in close-range detection to eliminate variable correlation and dimensional influence; in medium and long-range detection, multi-parameter Euclidean distance is used to describe point cloud relationship. It can better reflect the real similarity between data points in a large number of point clouds, and adaptively set the threshold by the target point cloud distance and radar angle resolution. Reference [50] proposed to process the point cloud with less than 60 points by multi-frame joint processing based on problems one and two. The core idea of multi-frame merging is to reduce the number of calculations by processing multiple frames of data at the same time, thereby optimizing the execution efficiency of the algorithm, and creating an adaptive mechanism for the parameter minPts. The parameter of the scaling factor is the distance value. Reference [51] proposed to use distance, horizontal angle and pitch angle to construct a three-dimensional polar coordinate ellipsoid area based on problem one, select adjacent point clusters (center distance is less than the set value) for fuzzy C-means algorithm (FCM) correction, and use the membership matrix and Sigmoid function to weight the correlation between point clusters to achieve more accurate clustering.

(2) Literature Review

The algorithm proposed in [47] improves detection accuracy while enhancing adaptability and reducing computational complexity. However, it does not quantitatively analyze the optimization effect of algorithm complexity and processing speed. Its core contribution is still focused on improving detection accuracy. The three-dimensional PG-DBSCAN algorithm proposed in [48] overcomes the limitation of traditional DBSCAN relying on global density threshold by utilizing the three-dimensional spatial information of radar point cloud, significantly improves clustering accuracy and computational efficiency, and is suitable for large-scale real-time point cloud processing of high-resolution vehicle-mounted anti-collision radar. However, the clustering performance of this algorithm is greatly affected by the grid division parameters, and the parameter selection strategy needs to be further optimized. The method in [49] performs well in improving clustering accuracy and robustness, but this is at the cost of increasing algorithm complexity. The improved algorithm in [50] achieves an accuracy of 92.6% in target detection tasks, which is 1.1% higher than the original algorithm. At the same time, the detection speed is also improved. However, its experimental data is mainly based on human targets, and its generalization in complex road environments still needs to be verified. Reference [51] improves clustering accuracy by introducing angle information, but also faces the problem of high algorithm complexity.

Comprehensive comparison shows that the 3D PG-DBSCAN algorithm (reference [48]) has more advantages in accuracy and efficiency, but its fixed grid parameter setting limits the adaptability of the algorithm in dynamic scenes. Therefore, this paper proposes an improved strategy to adjust the static grid parameters to dynamic parameters that change adaptively with the detection distance, so as to further improve the performance of the algorithm in vehicle-mounted millimeter-wave radar point cloud clustering.

5. Conclusion

This review reveals the evolutionary trends and current limitations of millimeter-wave radar signal processing algorithms:

Ranging accuracy optimization requires a balanced approach to spectrum refinement and phase correction. Methods such as time-domain zero-padding and ZFFT are limited by computational efficiency. While CZT and compressed sensing offer significant local optimization, they do not fully integrate phase information. The proposed CZT-Rife joint algorithm, through coherent information fusion and spectral line correction, promises to achieve a balance between accuracy and efficiency.

CFAR detection is evolving from mean-based to ordered statistics-based detection. ED-CFAR mitigates target shadowing effects, but fixed thresholds struggle to adapt to range attenuation. Introducing a distance-adaptive threshold mechanism can improve robustness across multiple scenarios.

Innovative clustering algorithms are exemplified by the three-dimensional PG-DBSCAN. Its polar coordinate grid design overcomes the density sensitivity of traditional DBSCAN, but static grid parameters limit dynamic adaptability. Adaptive adjustment of grid parameters with distance will be a breakthrough.

Future research needs to further explore: low-complexity phase-spectrum joint optimization architecture; hardware-friendly implementation of CFAR detectors; and deep learning-based parameter adaptive clustering framework to promote the practical application of 4D imaging radar in complex vehicular environments.

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