ISAR cross-range scaling based on the MUSIC technique

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Abstract: Cross-range scaling plays an important role in the inverse synthetic aperture radar (ISAR) imaging. Many of the published cross-range scaling algorithms are based on the fast Fourier transformation (FFT). However, the FFT technique is resolution limited, so that the FFT-based algorithms will fail in the rotation velocity (RV) estimation of the slow rotation target. In this paper, we propose an accurate cross-range scaling algorithm based on the multiple signal classification (MUSIC) method. We first select some range bins with the mono-component linear frequency modulated (LFM) signal model. Then, we dechirp the signal of each selected range bin into the form of sinusoidal signal, and utilize the super-resolution MUSIC technique to accurately estimate the frequency. After processing all the range bins, a linear relationship related to the RV can be obtained. Eventually, the ISAR image can be scaled. The proposal can precisely estimate the small RV of the slow rotation target with low computational complexity. Furthermore, the proposal can also be used in the case of cross-range scaling for the sparse aperture data. Experimental results with the simulated and raw data validate the superiority of the novel method.

Keywords: inverse synthetic aperture radar (ISAR) imaging, cross-range scaling, multiple signal classification (MUSIC) method, slow rotation target, sparse aperture.

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1. Introduction

Inverse synthetic aperture radar (ISAR) system has shown its wide applications in various fields because it can provide high-focused images of the desired moving targets [1 – 7]. From the obtained unscaled ISAR image, we can have a rough understanding of the type, the shape, and the gesture of the objective. However, for further accurate information, the ISAR image has to be scaled, such as the size, the detailed structure, the feature, and so on. The range scaling can be easily achieved with the already known bandwidth of the radar signal. However, the cross-range scaling factor is related with the rotation angle of the target which is determined by the unknown rotation velocity (RV) during the coherent processing interval (CPI) [8,9]. The cross-range scaling can only be done once the RV is estimated.

Plenty of researches about the cross-range scaling have been carried out recently. Algorithms proposed in [10] and [11] can be categorized as image correlation ones because they estimated the RV by rotating the range-Doppler images obtained by two adjacent data sequences. The algorithm in [10] assumed the rotation centers of the images are already known, but this is always unavailable in practice. The algorithm in [11] jointly estimated the rotation center and the RV, but its iteration procedure for searching the RV is time-consuming. The polar format algorithm [12] obtained the RV by optimizing the image quality. This method is also computational expensive because of the optimizing iteration. The image-based algorithms are always of high computational burden, because they need to process the image and many of them have the optimizing procedure. The proposals in [13 – 16] and many other phase-based algorithms extracted the phase coefficient to estimate the RV. Nevertheless, most of those methods have the accuracy limitation, because they are always based on the fast Fourier transformation (FFT). The FFT is not precise enough for a precise estimation of the RV of the desired target, especially for the slow rotation targets with small RVs. The algorithm in [17] can estimate small RVs, however, its involved iterative adaptive approach (IAA) is of high computational complexity. Thus, our paper focuses on proposing a highly accurate RV estimation method for the slow rotation target with a low computational burden.

In reality, the processing data in ISAR imaging is not always the full aperture data. For example, sometimes the radar needs to implement several functions simultaneously, or the radar needs to detect and image multi-targets simultaneously, or sometimes the received data are contaminated because of the interference. Under those situations, the processing data are discontinuous sparse aperture (SA) data. Recently, there are a lot of algorithms focusing on

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the SA. The algorithm in [18] achieved high resolution SAR imaging by recovering the SA data. The authors of [19] used the complex deconvolution to restore the SA data. The algorithm in [20] used the relax technique for the super-resolution ISAR imaging with the SA data. However, papers seldom studied the algorithms suitable for the SA cross-range scaling.

In this paper, an accurate ISAR image cross-range scaling algorithm based on the multiple signal classification (MUSIC) method is proposed. The novel method can successfully scale the slow rotation target with a low computational burden. In the proposal, we first employ the amplitude normalized variance (ANV) [13] to select the range bins with one dominant scatterer. The signal of each selected range bin can be seen as a mono-component linear frequency modulated (LFM) signal. Then, we dechirp the LFM signal of each selected range bin into the sinusoidal one, and employ the MUSIC method [21,22] to precisely estimate the frequency of the sinusoidal signal. And eventually, the RV can be obtained by analyzing the relationship between the selected range bins and the frequencies of the sinusoidal signals. The proposal is superior to many other phase-based algorithms. Firstly, it has a high accuracy of the RV estimation, and it can successfully scale the slow rotation target rotating with small RV. Most of the phase-based methods have poor estimation accuracy and will fail to estimate the small RV, because they are always based on the FFT technique which is resolution limited. In the proposal, the involved MUSIC method can break the Rayleigh limitation to achieve highly accurate estimations. Secondly, the proposal has a low computational burden. One reason is that the novel method only needs to process several range bins to get the RV. However, many other cross-range scaling methods need to process all the range bins to obtain the estimation, which is quite computational expensive. Another reason is that the MUSIC technique has a lower computational complexity compared to other super-resolution methods, like the relax algorithm [20,23] and the IAA algorithm [17]. Those methods always include time-consuming iteration procedures. As widely known, to use the MUSIC technique, the number of signals in one range bin should be estimated previously, and the signals should be uncorrelated to each other. In our proposal, the range bins processed are those with mono-component LFM signal ones. Therefore, it is of big advantage to employ the MUSIC technique in the proposal, because there is no need to estimate the number of signals and decorrelate the signals.

Experiments with simulated and raw ship data prove that the proposal can precisely estimate the RV for the cross-range scaling of the slow rotation target. And the experimental results also verify the proposal can be successfully utilized in the SA situation.

This paper consists of five parts. Section 2 introduces the basic signal model. In Section 3, the novel accurate cross-range scaling method is proposed. In Section 4, the experiments are carried out. And Section 5 gives the conclusions.

2. Basic signal model

This paper focuses on the cross-range scaling, so we first give the related resolution formulas. The range resolution can be obtained as

\[
\delta_r = \frac{c}{2B}
\]  

(1)

where \(B\) is the bandwidth of the radar signal and \(c\) is the light speed.

The cross-range resolution is calculated by

\[
\delta_a = \frac{\lambda}{2\Delta \theta} = \frac{\lambda}{2wT}
\]  

(2)

where \(\lambda\) is the wavelength, \(\Delta \theta\) denotes the rotation angle during the CPI, \(w\) is the desired unknown RV of the target, and \(T\) represents the CPI. We can see that the estimation of the RV is the key for the cross-range scaling.

Having completed the motion compensation, we can regard the moving target as a turntable rotating around the center \(O\), as shown in Fig. 1. In Fig. 1, the radar line of sight is along the \(X\)-axis. The location of the scatterer \(P\) is \((x_p, y_p)\), \(R_r\) and \(R_p\) are the distances between the center \(O\) and the radar, and the center \(O\) and the scatterer \(P\), respectively. And \(R_r\) is much larger than the size of the target. The angle between \(Y\)-axis and \(PO\) is \(\theta_0\). The RV of the turntable target is \(w\).

Fig. 1 Model of the turntable target

The range \(\hat{R}\) between the scatterer \(P\) and the radar can be calculated as

\[
\hat{R}(t_m) = \sqrt{R_r^2 + R_p^2 + 2R_rR_p \sin(\theta_0 + wt_m)}
\]  

(3)

where \(t_m = m\Delta T\ (m = 0, 1, \ldots, M - 1)\) is the slow time in radar imaging, \(\Delta T\) denotes the pulse repetition interval, \(M\) represents the number of received pulses, and \(M\Delta T = T\).
As $R_\tau \gg R_p$, we have

$$
\hat{R}(t_m) \approx R_r + R_p \sin \theta_0 \cos(wt_m) + R_p \cos \theta_0 \sin(wt_m) = R_r + x_p \cos(wt_m) + y_p \sin(wt_m)
$$

(4)

where

$$
\begin{aligned}
x_p &= R_p \sin \theta_0 \\
y_p &= R_p \cos \theta_0
\end{aligned}
$$

(5)

The Doppler frequency of the received signal of the scatterer $P$ is

$$
f_d = \frac{2 \, d\hat{R}(t_m)}{\lambda \, dt_m} = \frac{2w}{\lambda} [\sin(wt_m) + y_p \cos(wt_m)].
$$

(6)

With the Taylor series, (6) can be further written as

$$
f_d \approx \frac{2w}{\lambda} (-x_p wt_m + y_p).
$$

(7)

Thus, the received signal of scatterer $P$ has the form of

$$
s_p(t_m) = a_p \exp\left[ j2\pi \left( \frac{2yg_p t_m}{\lambda} - \frac{1}{2} \frac{2x_p}{\lambda} t_m^2 \right) \right]
$$

(8)

where $a_p$ represents the amplitude of the signal.

In the SA situation, the signal shapes like

$$
\bar{s}_p(t_m) = \begin{cases} 
  s_p(t_m), & m \in \Psi; m \not\in \Phi \\
  0, & m \in \Phi
\end{cases}
$$

(9)

where $\Psi = \{0, 1, \ldots, M-1\}$, the elements in $\Phi$ represent the lost bins, and $\Phi$ is a subset of $\Psi$.

In ISAR imaging, the geometry of the SA data is as shown in Fig. 2. The red pulse represents the valid one and the white pulse means the lost one.

3. Novel cross-range scaling method

As formerly discussed in the introduction that most of the existing cross-range scaling algorithms have either a high computational burden or a low estimation accuracy of the small RV. In this section, we propose a novel cross-range scaling algorithm which can precisely estimate the RV of the objective and simultaneously has a low computational complexity.

Rewrite (8) as

$$
s_p(t_m) = a_p \exp\left[ j2\pi \left( f_p t_m - \frac{1}{2} \gamma_p t_m^2 \right) \right]
$$

(10)

where $f_p$ and $\gamma_p$ are the initial frequency and the chirp rate, respectively, with the forms of

$$
f_p = \frac{2yg_p w}{\lambda},
$$

(11)

$$
\gamma_p = \frac{2x_p w^2}{\lambda}.
$$

(12)

From (10) we can see that the received signal of scatterer $P$ is an LFM signal. Its chirp rate is related to the location with regard to the $X$-axis and the RV of the target which is the desired parameter for the cross-range scaling.

The Wigner-Ville distribution (WVD) [24,25] is a famous time-frequency analysis technique. The WVD of signal $s(t)$ is defined as

$$
W(t, f) = \int_{-\infty}^{t+\infty} s(t + \tau) s^*(t - \tau/2) e^{-j2\pi f \tau} d\tau.
$$

(13)

With this operation, the change of the frequency of $s(t)$ versus the time can be easily seen.

Inspired by the WVD technique, we implement the following multiplication to extract the chirp rate of $s_p(t_m)$:

$$
h_p(t_m) = s_p(t_m + \tau_m) s_p^*(t_m - \tau_m) = a_p^2 \exp[j2\pi(2f_p \tau_m - 2\gamma_p \tau_m t_m)]
$$

(14)

where $\tau_m$ is the time delay.

It can be seen that $h_p(t_m)$ is a sinusoidal signal with respect to $t_m$, and its frequency is

$$
F_p = -2\gamma_p \tau_m
$$

(15)

therein $\tau_m$ can be fixed as a certain value.

With the above operation, the LFM signal $s_p(t_m)$ is successfully dechirped into the sinusoidal signal $h_p(t_m)$.

After estimating the frequency of $h_p(t_m)$, the chirp rate of $s_p(t_m)$ can be obtained as

$$
\gamma_p = \frac{-F_p}{2\tau_m}
$$

(16)

And, from (12), we can get the relationship between the chirp rate $\gamma_p$ and the RV:

$$
\gamma_p = \frac{2w^2}{\lambda} x_p = kx_p.
$$

(17)

It can be seen that there is a linear relationship between $\gamma_p$ and $x_p$, and $k = 2w^2/\lambda$ is the slope. Having acquired the chirp rates of signals in different range bins, the slope
can be acquired by the least square error (LSE) technique [26].

Then, the RV can be estimated as

$$w = \sqrt{\frac{k\lambda}{2}}$$  \tag{18}

It should be noted that only the range bin with mono-component LFM signal can directly reduce the order of the signal as (14) shows. Thus, we use the ANV [13] to select the range bins with one dominant scatterer.

The signal of the range bin with L scatterers is multi-component LFM signal shaped like

$$s_n(t_m) = \sum_{p=1}^{L} s_p(t_m) = \sum_{p=1}^{L} \alpha_p \exp \left[ j2\pi \left( f_p t_m - \frac{1}{2} \gamma_p^2 t_m^2 \right) \right].$$  \tag{19}

And the ANV of this range bin can be calculated as

$$\delta_n = 1 - \frac{|E(|s_n(t_m)|)|^2}{E(|s_n(t_m)|^2)}$$  \tag{20}

where E(·) means the average operation, | · | represents taking the amplitude. A range bin is more likely to have one dominant scatterer when the ANV is a smaller value. Thus, we choose the range bins with the smallest ANVs to estimate the RV.

According to the experience, eight to ten range bins are always selected to acquire a good result of the RV estimation. If too few range bins are selected, the fitting result will not be accurate enough to reveal the linear relationship in (17). If too many range bins are selected, the computational burden will increase, and some unqualified range bins with several dominant scatterers may be chosen.

Similar as the proposal, the cross-range scaling algorithms in [15] and [16] also estimate the RV by analyzing the high-order phase coefficient. However, those algorithms have two big problems. One is that those algorithms need to artificially specify the scope of the range bins to be processed in advance, because only the range bins containing the target scatterers can be used to estimate the RV. The other problem is that it is time-consuming to process so many range bins. For our proposal, there is no need to prior-know the range bin scope of the target. And the computational burden is low owing to that only several range bins with the smallest ANVs need to be processed.

After selecting the range bins and dechirping the signal of every selected range bin, FFT is the conventional method to extract the frequency. However, the FFT technique has defect in the resolution, so that it is not accurate enough for the small RV estimation. The analysis is given below.

Substituting (12) into (15), we have

$$F_p = \frac{-4x_p w^2 \tau_m}{\lambda}.$$  \tag{21}

Denote the estimation error of $F_p$ and $w$ as $\Delta F_p$ and $\Delta w$, respectively. Thus,

$$w + \Delta w = \sqrt{\frac{-\lambda}{4x_p \tau_m}} (F_p + \Delta F_p).$$  \tag{22}

The estimation error of $F_p$ will result in the inaccuracy of the RV estimation. From (21) we can see that $F_p$ is a smaller value when the objective rotates with a small RV compared to the big RVs. Thus, the influence of $\Delta F_p$ is more serious on the RV estimation when dealing with the slow rotation target. The conventional FFT method does not have a small enough $\Delta F_p$ because of the resolution limitation. Thus, it is not precise enough for the RV estimation, especially for the small RV situations. To scale the slow rotation target, we need a super-resolution method to estimate the frequency $F_p$.

Thus, in our proposal we utilize the MUSIC method to obtain the frequency of the dechirped signal of each selected range bin. The MUSIC is a famous super-resolution direction of arrival (DOA) estimation algorithm. The formation of the processing signal in ISAR cross-range scaling is similar to the signal processed in the DOA estimation. Therefore, the MUSIC method can be employed in our cross-range scaling algorithm. To utilize the MUSIC algorithm, the number of signals in each range bin should be estimated in advance and the spatial smoothing technique is needed to decorrelate the signals in each range bin. However, in our proposal the signal of each processing range bin can be seen as a mono-component LFM signal model, so that there is no need to estimate the number of signals and there is also no need to decorrelate the signals. Thus, it is quite convenient and of low computational burden so that we can directly use the MUSIC to estimate the frequency of the dechirped signal. And served as a super-resolution technique, the MUSIC technique can achieve highly precise estimations.

The dechirped signal in one range bin is shaped like (14). Rewrite $h_p(t_m)$ ($m = 0, 1, \ldots, M - 1$) in the matrix form as

$$h_p = [h_p(t_0), h_p(t_1), \ldots, h_p(t_{M-1})]^T$$  \tag{23}

where $(·)^T$ is the transpose.

The covariance matrix of $h_p$ is calculated as

$$H_p = h_p h_p^H$$  \tag{24}

where $(·)^H$ represents the complex conjugate transpose.
The eigenvalue decomposition of the covariance matrix is expressed as

\[ H_p = E_s A_s E_s^H + E_n A_n E_n^H \]  \hfill (25)

where

\[ A_s = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_M \end{bmatrix} \]  \hfill (26)

\[ A_n = \begin{bmatrix} \lambda_2 \\ \lambda_3 \\ \vdots \\ \lambda_M \end{bmatrix} \]  \hfill (27)

Because there is only one dominant scatterer in the range bin, the signal subspace \( E_s \) is composed of the eigenvector corresponding to the biggest eigenvalue \( \lambda_1 \), and \( A_s \) is a matrix with only one element \( \lambda_1 \). \( A_n \) is a diagonal matrix with components of other smaller eigenvalues \( \lambda_2, \lambda_3, \ldots, \lambda_M \). The noise subspace \( E_n \) is composed of the eigenvectors corresponding to \( A_n \).

Thus, (25) can be written as

\[ H_p = \lambda_1 e_1 e_1^H + \sum_{i=2}^{M} \lambda_i e_i e_i^H \]  \hfill (28)

where \( E_s = e_1 \), \( E_n = [e_2, e_3, \ldots, e_M] \), \( e_1 \) is corresponding to \( \lambda_1 \), and \( e_2, e_3, \ldots, e_M \) are corresponding to \( \lambda_2, \lambda_3, \ldots, \lambda_M \).

The MUSIC method is based on the orthogonality of \( E_s \) and \( E_n \). Ideally, those two spaces are perfectly orthogonal, so that the MUSIC method can achieve highly accurate estimations.

Define the steering vector as

\[ a(f) = [e^{j2\pi f t_0}, e^{j2\pi f t_1}, \ldots, e^{j2\pi f t_{M-1}}]^T \]  \hfill (29)

where \( t_m = m\Delta T, m = 0, 1, \ldots, M - 1 \), and \( a(f) \) has a similar formation as \( h_p \).

Because \( a(f) \) shares the same space with \( E_s \),

\[ a^H(f) E_n = 0. \]  \hfill (30)

However, the above equation is not perfectly equal to zero because of the existence of noise.

Therefore, the MUSIC spectrum is defined as

\[ g(f) = \frac{1}{a^H(f) E_n E_n^H a(f)}. \]  \hfill (31)

Then, the frequency of the dechirped signal \( h_p(t_m) \) can be obtained by searching the maximum of the MUSIC spectrum as

\[ \hat{f}_p = \arg \max_f \{ g(f) \}. \]  \hfill (32)

Fig. 3 gives the detailed steps of the novel accurate cross-range scaling algorithm. First, the range bins with the smallest ANVs are selected. Then, we dechirp the LFM signal of each selected range bin into the sinusoidal form, and use the MUSIC technique to estimate the frequency of the dechirped signal. After this, a fitting line which reveals the linear relationship between the range bins and the chirp rates of the LFM signals can be obtained by the LSE technique. Eventually, the RV can be obtained with (18), and the ISAR image can be cross-range scaled. The proposal is an accurate method with low computational burden. It can successfully scale the slow rotation target.

![Fig. 3 Procedure of the proposed cross-range scaling method](image)

4. Experimental results

We implement the experiments with simulated and raw data to demonstrate the superiority of our proposed cross-range scaling algorithm so that it can achieve highly accurate estimation of the small RV and can work efficiently with SA data. The traditional dechirp method [14,27] which is based on the FFT technique is employed as comparison here.

4.1 Experiments with simulated data

Fig. 4 shows the scatterer model of the simulated turntable ship target which rotates around the rotation center with the RV of 0.01 rad/s. The length of the simulated ship in the cross-range direction is 25.5 m. Table 1 gives the simulation parameters. The signal to noise ratio (SNR) is 10 dB. We select 10 range bins with the smallest ANVs in this
simulation. The time delay is $\tau_m = T/6$. The search step of the MUSIC technique involved in the proposal is $\Delta f = 0.001$ Hz. The search step of the dechirp method is $\Delta w = 0.0001$ rad/s.

Table 1 Parameters of the simulated ship data

| Parameter                  | Value   |
|----------------------------|---------|
| Carrier frequency/GHz      | 10      |
| Bandwidth/MHz              | 400     |
| Pulse repetition frequency/Hz | 125     |
| Pulse accumulation number  | 256     |
| Range bins number          | 1000    |

Fig. 5 shows the fitting linear relationships between the range and the chirp rate of the signal of the selected range bin obtained via the dechirp method and the proposal. From the slopes of two linear lines, we can obtain the RV estimated via the dechirp method is 0.0136 rad/s, and the RV estimated via the proposal is 0.0101 rad/s. We can see from the results that the proposed method achieves an accurate estimation of the small RV, while the dechirp method fails to get the right result, although the searching step of it is small enough, we can also conclude our proposal has a high accuracy from the fitting results of the dechirp method and the proposal. We have derived in Section 3 that the chirp rate has a linear relationship with the range. Thus, in the ideal situation, the estimated chirp rates should distribute along the fitting line. In Fig. 5(a), the estimated chirp rates have big fluctuations. It is because the FFT method is resolution limited to have a precise estimation of the chirp rates.

In Fig. 5(b), the estimated results are very close to the fitting line, which demonstrates the proposal has a high estimation accuracy of the chirp rates. The results demonstrate that the novel algorithm can achieve a precise estimation of the small RV.

Fig. 6(a) and Fig. 6(b) are the ISAR images of the simulated ship after cross-range scaling via the dechirp method and the proposal, respectively. The length of the scaled ship via the dechirp method in the cross-range domain is 18.75 m, which is quite different from the actual 25.5 m. The scaled ship via the proposal has a length of 25.25 m in the cross-range domain. The scaled ship via the proposal is very similar to the scatterer model.

The scaled results indicate that the proposed method can precisely estimate the RV of the slow rotation ship target.
while the dechirp method cannot. Because only the RV is right estimated, the ISAR image can be accurately cross-range scaled, and eventually the scaled ship target can be close to the scatterer model. The scaled images prove that our proposal is superior to the dechirp method.

Fig. 7 shows the root mean square errors (RMSEs) of the dechirp method and the proposed method under different RVs. The results are obtained by doing 20 Monte Carlo simulations. We can see that the proposal has a better estimation accuracy than the dechirp method, especially when dealing with small RVs. The proposed method can still work effectively even \( w = 0.005 \text{ rad/s} \). However, the dechirp method fails to get the right estimation faced with small RVs. The simulation results accord with (22) which is derived in Section 3. The estimation error of the chirp rate of the signal of each range bin will result in the inaccuracy of the RV estimation, especially when the RV is small. The proposal has a high estimation accuracy about the chirp rate, so it can well estimate the small RV. The obtained result demonstrates that the proposal is an accurate cross-range scaling method and it can successfully scale the slow rotation target.

The results are obtained by doing 20 Monte Carlo simulations. The experimental result shows that the estimation accuracy of the novel method is better than the dechirp method and it improves with the increase of the SNR. From the result we can see that the proposal can work efficiently even with low SNR.

Fig. 9 shows the experimental results with respect to two SAs. Fig. 9(a) is the SA with 25% sparsity, which means 25% of the data is lost.
Fig. 9 Experimental results of the simulated ship data with respect to two SAs

Fig. 9(b) is the fitting result corresponding to the SA with 25% sparsity, and the estimated RV is 0.010 1 rad/s. Fig. 9(c) is the SA with 50% sparsity. Fig. 9(d) is the fitting result corresponding to the SA with 50% sparsity, and the estimated RV is 0.010 2 rad/s. The obtained RVs under two SAs are both close to the real RV. And we can see from the fitting results that the estimated chirp rates all distribute close to the fitting line. The obtained results indicate that our proposal can be used in the SA situation for the cross-range scaling. Even with 50% sparsity, our proposed method can still successfully estimate the RV.

Fig. 10 shows the scaled ISAR images of the simulated ship with respect to the SAs in Fig. 9.

4.2 Experiments with raw data

We do the experiments with raw ship data in this part. Table 2 shows the related parameters. Ten range bins with the smallest ANVs are selected in the experiment. The time delay is $\tau_n = T/6$. The search step of the MUSIC technique involved in the proposal is $\Delta f = 0.001$ Hz. The search step of the dechirp method is $\Delta w = 0.000 1$ rad/s.

Table 2 Parameters of the raw ship data

| Parameter                  | Value |
|----------------------------|-------|
| Working band               | X band|
| Bandwidth/MHz              | 400   |
| Pulse accumulation number  | 512   |
| Range bins number          | 2 048 |

We use two different raw ship data sequences to demonstrate the efficiency and superiority of the proposal. Let us denote the two data sequences as data 1 and data 2. The unscaled ISAR images of two data sequences are shown in Fig. 11.

Fig. 12 and Fig. 13 show the fitting results of the two raw data sequences via the dechirp method and the proposal respectively. The RVs estimated via the dechirp method with respect to data 1 and data 2 are 0.005 4 rad/s and 0.006 1 rad/s, respectively. The RVs estimated via the proposal with respect to data 1 and data 2 are 0.007 1 rad/s and 0.004 7 rad/s, respectively. In Fig. 13, the distribution of the estimated chirp rates is close to the fitting line. While the estimated chirp rates in Fig. 12 have big fluctuations. In Section 3, we have derived that the chirp rate and the range have a linear relationship. Thus, for an accurate estimation method, the estimated chirp rates should distribute near the...
fitting line. From the fitting results we can deduce that the proposal has a high estimation accuracy. The ship target is a slow rotation target, which can be known from the estimated RV. Faced with the slow rotation target, the proposal can well estimate the small RV. Nevertheless, the dechirp method fails to get the right estimation. Experimental results of both two data sequences validate the superiority of the proposal.

Fig. 12 Fitting results of two raw data sequences via the dechirp method

Fig. 13 Fitting results of two raw data sequences via the proposal

Fig. 14 shows the ISAR images of the two different raw data sequences after cross-range scaling via the proposal. With the estimated RVs, the images can be cross-range scaled. In Fig. 14(a), the ship target has a length of 16.5 m in the cross-range direction. And in Fig. 14(b), the length is 16 m. The two results are different from each other. It is because the obtained ISAR images are the projections on different imaging planes. Scaling is of significant importance in the practice. Only after scaling, the ISAR image can reflect the target in the realistic situation.

To validate the proposal is suitable for the SA cross-range scaling, we do the experiments with two SAs. One is of 25% sparsity, and the other is of 50% sparsity. The raw ship data 1 is employed for an example here. The SA with 25% sparsity is shown in Fig. 15(a). The fitting result in Fig. 15(b) corresponds to the SA with 25% sparsity, and the estimated RV is 0.006 9 rad/s. The SA with 50% sparsity is shown in Fig. 15(c). Fig. 15(d) is the fitting result corresponding to the SA with 50% sparsity, and the estimated RV is 0.007 3 rad/s.

Fig. 14 Scaled ISAR images of two raw data sequences via the proposal

Fig. 15 Experimental results of the raw ship data with respect to two SAs

The two obtained RVs are both close to the estimated 0.007 1 rad/s with full aperture data. And from the fitting results, we can see the estimated chirp rates all distribute close to the fitting line. The results demonstrate that our proposal can be successfully employed in the SA cross-range scaling.
Fig. 16 shows the scaled ship images with respect to two SAs shown in Fig. 15. In Fig. 16(a), the length of the scaled ship in the cross-range domain is 16.9 m. And in Fig. 16(b) it is 16 m. They are both close to the length of 16.5 m in the full aperture data situation, which indicates that the proposal is suitable for the SA cross-range scaling.

5. Conclusions

This paper proposes a novel accurate cross-range scaling algorithm based on the MUSIC technique for the slow rotation target. Because the involved MUSIC method is a super-resolution technique, the proposal is superior to the FFT-based cross-range scaling algorithms and it can achieve accurate estimations of the small RVs. The proposed algorithm has a low computational complexity for it only needs to process several range bins. The experimental results demonstrate that our proposal can accurately scale the slow rotation target, and it can work efficiently in the SA situation.

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