Elevation Estimation Algorithm for Low-Altitude Targets in Multipath Environment

Daihyun Kwon · Hyunwoo Ko · Sungwon Hong · Kichul Yoon · Byunglae Cho · Kwan Sung Kim

Abstract

The algorithm proposed in this study estimates the multipath elevation of targets at low altitudes, including near-zero elevation. Although the double null algorithm is a maximum likelihood elevation estimation algorithm, it diverges when the target elevation is near zero. Addressing this issue, the selective double null algorithm improves the accuracy of multipath elevation at low altitudes by applying previously measured antenna near-field patterns. However, it cannot be applied to active electronically scanned array radars, since antenna beam patterns vary with the steered azimuth and elevation angles. In this paper, the proposed algorithm modifies the double null algorithm to estimate the elevation in the divergence state more accurately. Since it is based on the multipath energy function, the antenna near-field pattern is unnecessary. In addition, to increase the accuracy of elevation estimation, an operation method that selectively uses the estimated elevations according to several conditions is proposed. The proposed algorithm was verified through simulations.

Key Words: Elevation Estimation, Multipath, Maximum Likelihood, Radar, Signal Processing.

I. INTRODUCTION

A radar is a sensor that detects the three-dimensional position and radial velocity of a target, determining the target’s position by measuring its range, azimuth, and elevation in a spherical coordinate system. In particular, multibeam radar typically estimates the azimuth and elevation from the ratio of the amplitudes of the received signal between the sum beam and the difference beam—a process also known as monopulse processing [1].

However, the monopulse method has limitations, especially in the presence of multipath interference, which occurs when a target’s elevation is low. In such cases, the received signal is usually a combination of two signals reflected directly and indirectly from the target, resulting in constructive or destructive interference, depending on the phase relationship. This interference can distort the received signal’s amplitude, leading to errors in monopulse elevation estimation. This phenomenon is referred to as the multipath phenomenon [2–4].

To address this issue, researchers applied the maximum likelihood algorithm to simultaneously estimate the elevation of the received signals from both the direct and indirect paths in a multipath environment. This algorithm, which is based on the antenna reception model, aims to solve the problem caused by multipath interference. Two previous studies have been conducted in this condition [5, 6]. Notably, these methods are based on zero-forcing precoding [7].

In addition, research aimed at estimating the two-dimensional (2D) angle in array antennas has been performed. For
instance, one study proposed a method to simultaneously estimate the direction of arrival (DOA) and polarization information between near-field sources and multi-input multi-output (MIMO) sensors in the near-field area [8]. Another study moved a coprime linear array antenna in the vertical direction to operate it as a virtual coprime planar antenna [9], as a result of which, unlike the coprime linear antenna, 2D angle estimation could be conducted. Furthermore, 2D departure and arrival angle estimations using an L-shaped sparse MIMO radar have also been proposed [10].

Additionally, investigations into the DOA of coherent signals have been conducted. For example, a recent study presented a model that reliably simulated DOA using channel information [11]. This model, as mentioned in its corresponding study, offers versatility by not imposing any limitations on the number of radar channels, array arrangements, or the types of beamformers employed.

Along the same lines, another study focused on tackling the issue of DOA estimation in two dimensions for coherent sources when employing an electromagnetic vector sensor array configured with uniform rectangular array geometry [12]. To address this challenge, the researchers introduced three innovative parallel factor methods to effectively eliminate rank deficiency in the source matrix by reorganizing the data, ultimately leading to enhanced accuracy in DOA estimation.

Researchers have also explored the use of artificial intelligence-based techniques, such as convolutional neural networks (CNN) [13] and deep learning [14], to mitigate the effects of multipath interference on elevation estimation. Notably, CNNs have been employed to determine the disregarding receive beam.

Moreover, a minimax optimization approach was employed to improve the robustness of the maximum likelihood estimation [15], the results of which indicated that the optimization process aims to minimize the maximum error observed in the steering vector.

However, the system considered in this paper is a multifunctional phased-array radar that needs to perform multiple tasks simultaneously in real time. In this context, to meet the constraints of limited memory and computing power, an algorithm that ensures real-time performance is crucial.

A potential algorithm for estimating multipath elevation has been discussed in [6]. However, it is characterized by an issue in which the elevation estimation error increases rapidly as the target elevation approaches zero—a phenomenon also known as "divergence." This issue was addressed by Kim et al. [16], who proposed a real-time algorithm that utilized the previously measured near-field pattern of an antenna to estimate the elevation in the divergence region. However, this algorithm was designed for mechanically rotated radars and did not account for active electronically-steered array (AESA) radars, whose beam pattern is distorted by electronical steering for azimuth or elevation direction.

In response, Kwon et al. [17] introduced a novel algorithm to accurately estimate multipath elevation in the divergence region without relying on the antenna’s near-field pattern. However, this algorithm is not applicable to real-time systems.

In this paper, the authors propose a novel algorithm to estimate multipath elevation for low-altitude targets in real-time systems without encountering divergence or relying on pre-measured antenna near-field patterns.

The structure of this paper is outlined as follows: Section II discusses related multipath elevation estimation algorithms, Section III presents the proposed algorithm in detail, Section IV conducts simulations to compare the performance of the proposed method with that of the other approaches, and Section V provides the conclusions drawn regarding the proposed algorithm.

1. Notations

In this paper, the italicized lowercase letters (such as s), the italicized capital letters (such as M), and the bold lowercase letters (such as v), denote scalars, matrices, and vectors, respectively. Furthermore, \( \hat{v} \) denotes the estimation of vector v. Additionally, \((M)^H\) and \((M)^{-1}\) denote the conjugate transpose and inverse of matrix M, respectively. The \( s \times s \) identity matrix is denoted by \( I_s \), while \( \|v\| \) and \|v\| denote the \( L^2 \) norm and absolute values, respectively.

II. RELATED WORKS

1. Double Null Algorithm

In a multipath environment, an antenna receives the signals reflected by a target from a direct path and an indirect path. In this context, 3D beam domain maximum likelihood (BDML) [6] estimation uses reception models in a multipath environment for elevation estimation. Considering \( \theta_d \) as the elevation of the target in the direct path and \( \theta_l \) as the elevation of a target in the indirect path, the double null algorithm serves to minimize the estimation error of both \( \theta_d \) and \( \theta_l \).

![Fig. 1. The reception model in a multipath environment.](image-url)
tion model is shown in Fig. 1. The model uses a linear antenna array with \( l = 1, 2, 3, ..., N_l \), \( N_l \) being the number of antennas. Furthermore, the antenna is uniformly spaced by \( d \), assuming 5 receive beams.

For signal reception modeling, a beamforming matrix \( W[N_l \times 5] \) and a steering matrix \( A[N_l \times 2] \) are used, where \( W \) is a function of \( N_l \), \( d \), and the spacing of the receive beams. Notably, 5 columns of \( W \) are considered due to the 5 receive beams. Meanwhile, \( A \) is a function \( \theta_d \) and \( \theta_l \), with 2 columns of \( A \) referring to the two reception paths: \( \theta_d \) and \( \theta_l \). Considering \( c \) as the complex envelope of the received signal corresponding to \( \theta_d \) and \( \theta_l \), the modeled received signal is \( \tilde{x} \), it can be expressed as follows:

\[
\tilde{x} = W^H A c = F c. \tag{1}
\]

Additionally, considering that the radar measurement is \( x \), the optimization equation for minimizing the received signal estimation error is as follows:

\[
\min_{\theta_d, \theta_l, c} \| x - \tilde{x} \|^2. \tag{2}
\]

Furthermore, the optimal solution for \( c \), as mentioned above, can be obtained through zero forcing as follows:

\[
c_{\text{min}} = (F^H F)^{-1} F^H x, \tag{3}
\]

Finally, by substituting Eq. (1) and Eq. (3) into Eq. (2), the following equation is derived:

\[
\min_{\theta_d, \theta_l} \frac{1}{2} E = x^H P x,
\]

\[
P = I_5 - (F^H F)^{-1} F^H
\]

Eq. (4) represents the energy function of the double null algorithm, where \( I_5 \) is the identity matrix of size 5, corresponding to the 5 receive beams. In summary, the double null algorithm seeks to find the solution to \( \theta_d \) and \( \theta_l \) in the optimization problem.

In general, to use optimization algorithms, the entire energy function is generated, while the optimal value is found within the domain and constraints. However, in the case of the double null algorithm, 3D BDML must be performed to generate a single point value of the energy function. This means that the energy function can be obtained only when this process is performed for each point in the domain of the energy function.

The optimization algorithm should ideally be applied to the energy function generated by the abovementioned process. However, this is impossible due to the real-time limitations of the system considered in this study. Therefore, whenever the energy function value of each point is calculated, the minimum value is obtained by comparing it with the value of the previously calculated point. This is referred to as the double null algorithm.

The double null algorithm provides accurate elevation estimations in a multipath environment. It constructs the energy function using Eq. (4) and then finds the minimum value. This suggests that a unique minimum value must exist in the search area to make the algorithm converge to one value. Fig. 2 illustrates a scenario which has a unique minimum value. The blue area in Fig. 2 signifies the area with low energy, with the minimum value indicated using a white square.

The diagonal line in Fig. 2 appears when \( \theta_d = \theta_l \). It is evident that the energy values in the diagonal line, originating from calculating the inverse matrix of the energy function, diverge.

Fig. 3 compares the elevation estimation performance of the monopulse method and the double null algorithm. At target elevations less than 3.15°, the multipath phenomenon occurs, and the received signal level is distorted. Notably, Fig. 3 confirms that the elevation estimation error of the monopulse method increases as elevation decreases.

Compared to the monopulse method, the elevation estimation of the double null algorithm is significantly more accurate. The double null algorithm can be described in Algorithm 1.

**Algorithm 1. Double null algorithm**

\[
\theta_d = \theta_l
\]

![Fig. 2. Energy function of unique minimum value.](image2.png)

![Fig. 3. Comparison of the monopulse method and the double null algorithm in a multipath environment.](image3.png)
1. Perform 3D BDML to generate $E = x^H P x$ from all combinations of $\theta_d$ and $\theta_i$.

2. Find $\theta_D = \arg \min_{\theta_d, \theta_i} E(\theta_d, \theta_i)$.

2. Divergence of the Double Null Algorithm

In general, when a single energy function has a unique global minimum, the double null algorithm converges to the global minimum.

However, if the target elevation approaches 0, a region with low energy appears in the form of a cross in the energy function map, exhibiting more than one local minimum. This leads to divergence in the double null algorithm, as shown in Fig. 4. Although the true target elevation is near $0^\circ$, the double null algorithm diverges and estimates the elevation to be way over $1^\circ$. As a result, the elevation estimation error becomes larger than the monopulse results in the region, as shown in Fig. 5.

3. Selective Double Null Algorithm

To overcome the divergence phenomenon arising from the double null algorithm, Kim et al. [16] proposed a selective double null algorithm. Considering $D$ and $x$ as the signal magnitude for each receive beam obtained by measuring the near-field pattern and the target in a multipath environment, respectively, and $\beta$ as the elevation for each measured near-field point, the following discriminant equation can be formulated to determine the occurrence of the multipath phenomenon, as noted in [16]:

$$Q_d(\beta) = 1 - \left( \frac{|x^H D(\beta)|}{\|x\|\|D(\beta)\|} \right)^2. \quad (5)$$

If the multipath effect does not occur, $Q_d$ will appear to be close to 0. Conversely, as the multipath effect increases, $Q_d$ will gradually approach 1. Notably, in the selective double null algorithm, the double null algorithm is only used when $Q_d$ is greater than a certain value; the elevation is estimated using the monopulse method otherwise. The improved elevation estimation results obtained using the selective double null algorithm are shown in Fig. 6.

Fig. 6 confirms that the selective double null algorithm (Algorithm 2) shows better performance than the double null algorithm. However, it still suffers from the limitation of requiring the measurement of the antenna’s near-field pattern, which makes it difficult for application in AESA radars.

Algorithm 2. Selective double null algorithm

1. Calculate $Q_d(\beta) = 1 - \left( \frac{|x^H D(\beta)|}{\|x\|\|D(\beta)\|} \right)^2$

2. $\theta_S = \begin{cases} \theta_D, & Q_d > \alpha \\ \theta_M, & \text{otherwise} \end{cases}$ is the decision parameter. $\theta_M$ is the monopulse elevation.

III. PROPOSED ALGORITHM

1. Low-Altitude Double Null Algorithm

In this paper, an algorithm capable of estimating the elevation in a divergence region without the need for previously measured antenna near-field patterns is proposed, termed the low-elevation double null algorithm. The elevation range for the use of this method, with $\theta_{\text{min}}$ and $\theta_{\text{max}}$ being the minimum and maximum elevations, respectively, can be defined as follows:
The low-energy region is distributed in a rotated L-shape, represented by the blue-colored region in Fig. 7. Even though the true target elevation is near-zero degrees, the double null’s elevation estimation results show 2.65° (indicated by the white square mark).

To solve this case of divergence, the following assumption is made: the index of the low-energy region’s center is considered to be the elevation to be estimated. The proposed algorithm was then designed based on this assumption (Algorithm 3).

**Algorithm 3. Low-altitude double null algorithm**

1. Find \( \arg \min E(\theta_d, \theta_l) \) for all \( \theta_l \)
2. Save the minimum index \( i_m(\theta_l) \) of \( E(\theta_d, \theta_l) \) in the \( \theta_d \) direction while performing Algorithm 1
3. Condition (C): The values of \( i_m(\theta_l) \) differ by 1 or less for \( l \) times consecutively.
4. Calculate \( \theta_l = \theta_d(i_m(\theta_l)) \)
5. \( \theta_L = \begin{cases} \theta_l, & \text{for C} \\ \theta_D, & \text{otherwise} \end{cases} \)  

Notably, the proposed algorithm is a modification of the double null algorithm. Experimentally, \( l \) is determined to be 40%-50% of the number of \( \theta_d \) grids.

In this study, Algorithms 1 and 3 were both designed to be executed in the same main loop. After acquiring both \( \theta_D \) and \( \theta_L \), the elevation was selected based on the flow described in Fig. 8. Notably, since the proposed algorithm has been developed to attain more accurate estimations of elevation when the target elevation approaches near zero, it is needed to use this algorithm conditionally.

2. **Finding \( \theta_{Thr} \) for the Proposed Algorithm**

\( \theta_{Thr} \) signifies the boundary value above which multipath effects become negligible. More specifically, \( \theta_{Thr} \) is the starting point at which both the monopulse and multipath elevations begin to accurately estimate the target elevation. To calculate \( \theta_{Thr} \), the elevations of the monopulse method and the double null algorithm were compared to arrive at \( \theta_{Thr} = 3.15° \), based on Fig. 3.

3. **Selective Operation of the Elevation Estimation Algorithms**

Fig. 8 presents a flowchart describing the elevation estimation process using the low-altitude double null algorithm. The operational concept was developed to increase elevation estimation accuracy by selectively using elevation estimation values according to specific conditions. The first condition, shown at the top right corner of Fig. 8, involves a comparison of \( \theta_M \) and the decision parameter \( \theta_{Thr} \).

If \( \theta_M \) is larger than \( \theta_{Thr} \), \( \theta_M \) is selected. This means that the target elevation is high enough to neglect the multipath effect. The value of \( \theta_{Thr} \) is dealt with in the previous section.

The second condition, noted in the middle section of Fig. 8, pertains to checking for the divergence of \( \theta_D \). If \( \text{Condition R} \) is satisfied, it is determined that \( \theta_D \) diverges. Thus, \( \theta_M \) or \( \theta_L \) is selected. On the other hand, if \( \text{Condition R} \) is not satisfied, \( \theta_R \) is considered reliable. As a result, \( \theta_M \) or \( \theta_D \) is selected.

The third condition, presented at the bottom left of Fig. 8, is related to the reliability of \( \theta_L \). If \( \text{Condition L} \) is satisfied, \( \theta_L \) is selected, and \( \theta_M \) is selected otherwise.

The last condition at the bottom right corner of Fig. 8 pertains to the reliability of \( \theta_D \). If \( \text{Condition D} \) is satisfied, \( \theta_D \) is selected, and \( \theta_M \) is selected otherwise.

Each condition is summarized in Algorithm 4.

**Algorithm 4. Selective operation of elevation estimation algorithms**

\[ \text{Condition R} \]
1. Condition \( R_1 \): mean(\( \theta_m, 8 \)) > 0.03°.
   mean(\( \theta_m, 8 \)) refers to the moving average of \( \theta_m \) for 8 scans.

2. Condition \( R_2 \): std(\( \theta_L, 8 \)) < 0.1°
   std(\( \theta_L, 8 \)) refers to the standard deviation of \( \theta_L \) for 8 scans.

3. Condition \( R_3 \): std(\( \theta_D, 8 \)) < 2°
   std(\( \theta_D, 8 \)) refers to the standard deviation of \( \theta_D \) for 8 scans.

\[ \text{Condition } R = R_1 \cap R_2 \cap R_3 \]

<table>
<thead>
<tr>
<th>Condition</th>
<th>( \theta_{\min} &lt; \theta_L &lt; 1° )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_m )</td>
<td></td>
</tr>
</tbody>
</table>

This is the reliable condition for \( \theta_1 \).

Condition \( D \)

1. Condition \( D_1 \): \( \theta_{\min} < \theta_D < \theta_{rhr} \).
   This is the reliable condition for \( \theta_D \).

2. Condition \( D_2 \): \( \theta_D - \theta_L < 1° \).
   This is the condition to check if \( \theta_D \) is divergent.

\[ \text{Condition } D = D_1 \cap D_2 \]

IV. SIMULATION

1. Simulation Settings
   Simulations were performed considering a scenario where the low-altitude target approached the radar, maintaining a constant altitude (Table 1).

<table>
<thead>
<tr>
<th>Target parameters for the simulation</th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range (km)</td>
<td>60</td>
<td>10</td>
</tr>
<tr>
<td>Velocity (m/s)</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Altitude1 (m)</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Altitude2 (m)</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Altitude3 (m)</td>
<td>300</td>
<td>300</td>
</tr>
<tr>
<td>Altitude4 (m)</td>
<td>400</td>
<td>400</td>
</tr>
<tr>
<td>Altitude5 (m)</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>SNR1 (dB)</td>
<td>15</td>
<td>−</td>
</tr>
<tr>
<td>SNR2 (dB)</td>
<td>20</td>
<td>−</td>
</tr>
<tr>
<td>SNR3 (dB)</td>
<td>25</td>
<td>−</td>
</tr>
<tr>
<td>SNR4 (dB)</td>
<td>30</td>
<td>−</td>
</tr>
<tr>
<td>SNR5 (dB)</td>
<td>35</td>
<td>−</td>
</tr>
</tbody>
</table>

The signal-to-noise ratio (SNR) is based on the value at the farthest distance, which increased by the factor of \( R^4 \) as the target got closer. A total of 25 scenarios were analyzed by performing 5 types of SNRs for the 5 types of altitudes. Finally, 1,667 scan results were acquired for each scenario, after which the root mean square errors (RMSEs) for the four algorithms were obtained to compare their performances.

The simulation parameters—surface dielectric constant, surface conductivity, surface roughness, and vegetation—were optimized to simulate a marine environment.

2. Results of Elevation Estimation
   The performance results of SNR5 at Altitude1 are illustrated in Fig. 9, where the blue dotted line denotes the monopulse method, the red dotted line pertains to the double null algorithm, the light green solid line represents the selective double null algorithm, the purple solid line indicates the proposed algorithm, and the black solid line signifies the simulated target.

   It is evident that under the most severe conditions, all \( \theta_D \), \( \theta_M \) and \( \theta_1 \) values diverged by a distance of over 50 km. However, it can also be confirmed that the proposed algorithm achieved the most accurate results.

   The comparison results for SNR5 at Altitude5 are shown in Fig. 10. In this scenario, the distorted result of \( \theta_M \) resulting from the presence of the multipath effect is clearly revealed. In contrast, \( \theta_D \) and \( \theta_L \) show the most accurate results. In this case, the RMSE of the proposed algorithm is slightly higher than that of \( \theta_D \), which can be attributed to the fact that the proposed algorithm required 8 scans at the initial stage for calculating the
average

3. Performance Comparison of the Algorithms in Terms of RMSE

The RMSE results by altitude are shown in Figs. 11–15. Furthermore, a Cramer–Rao bound (CRB) was numerically calculated using the Monte Carlo simulation. Compared to the other algorithms, the proposed algorithm showed the results closest to the CRB. In Figs. 11–15, the blue dotted line denotes the results of the monopulse methods, the red line with an "x" marker indicates the double null algorithm, the light green solid line with an "o" marker represents the selective double null algorithm, the purple solid line with a "hexagon" marker refers to the proposed algorithm, and the light blue solid line with a "square" marker is the CRB. Except for one case, the proposed algorithm exhibited the best performance among all the compared algorithms.

The singular exception occurred in the SNR5 at Altitude5 scenario, illustrated in Fig. 10. To confirm the relative accuracy of the proposed algorithm, the relative RMSE value was defined in terms of the formula noted below:

\[
RMSE_{p,s} = \frac{|RMSE_p - RMSE_s|}{RMSE_s}. \tag{7}
\]

In this formula, \(RMSE_p\) refers to the RMSE of the proposed algorithm, \(RMSE_s\) is the RMSE of the selective double null algorithm, \(RMSE_m\) indicates the RMSE of the monopulse method, and \(RMSE_d\) denotes the RMSE of the double null algorithm. Furthermore, \(RMSE_{p,s}, RMSE_{p,m}, RMSE_{p,d}\) are the relative RMSEs of the proposed algorithm in terms of the RMSEs of the selective double null algorithm, monopulse method, and double null algorithm, respectively. In each of the 25 scenarios, the average RMSE was calculated to compare the relative performance, the results of which are shown in Table 2. Compared to the selective double null algorithm, the proposed algorithm exhibited an improvement in RMSE by 25.6743% on average.

V. CONCLUSION

This paper proposed a low-altitude double null algorithm and selective operation of elevation estimation algorithms to estimate the elevation of low-altitude targets in a multipath environment. The performances of popular elevation estimation algorithms, including monopulse, double null, and selective double null, were compared to those of the proposed algorithm through simulation. In most cases, the proposed algorithm showed the best performance. However, an exceptional case was also observed, resulting from the initialization process that calculated the average and standard deviation from the elevation values using 8 initial scans. This limitation of the proposed algorithm should be addressed by conducting further research.

This research was performed in 2024 with government funding.

Table 2. Average of the relative RMSE values

<table>
<thead>
<tr>
<th>RMSE (%)</th>
</tr>
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<tbody>
<tr>
<td>Mean ((RMSE_{p,s}))</td>
</tr>
<tr>
<td>Mean ((RMSE_{p,m}))</td>
</tr>
<tr>
<td>Mean ((RMSE_{p,d}))</td>
</tr>
</tbody>
</table>
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