An Improved Space-Time Joint Anti-jamming Algorithm Based on Variable Step LMS

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Recommended Citation
Dengao Li, Jinqiang Liu, Jumin Zhao et al. An Improved Space-Time Joint Anti-jamming Algorithm Based on Variable Step LMS. Tsinghua Science and Technology 2017, 22(5): 520-528.
An Improved Space-Time Joint Anti-jamming Algorithm Based on Variable Step LMS

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Abstract: In wireless communication, the space-time anti-jamming method is widely applied because it shows better performance than the pure airspace and pure temporal anti-jamming methods. However, its application is limited by its computational complexity, and it cannot suppress narrowband interference that is in the same direction as the navigation signal. To solve these problems, we propose improved frequency filter to filter the narrowband interference from the desired signal direction in advance, meanwhile, an improved variable step Least Mean Square (LMS) method is proposed to complete the space-time array weights with fast iteration, thereby reducing computational complexity. The simulation results show that, compared with conventional methods, the anti-jamming capability of the proposed algorithm is significantly enhanced; and its complexity is significantly reduced.

Key words: Space-Time Adaptive Processing (STAP); Least Mean Square (LMS); computational complexity; frequency domain filter

1 Introduction

With the development of wireless communication[1], the electromagnetic wave environment faced by navigation receivers has become more and more complex. It is necessary to enhance the anti-jamming capability of navigation receivers. The Space-Time Adaptive Processing (STAP) algorithm is widely used as the most important anti-jamming method[2–4]. The STAP algorithm adds the same number tap delays to each array element based on traditional antenna arrays and it can inhibit a variety of broadband and narrowband interferences without increasing the array elements[5, 6].

However, STAP involves the Sampling covariance Matrix Inverse (SMI) operation and requires a large amount of calculation, so it is difficult to guarantee interference suppression in real time. Domestic and foreign scholars have proposed many algorithms to reduce the dimension computation. Myrick et al.[7] carried out a Multi-Stage Nested Wiener Filter (MSNWF) GPS anti-jamming processing theory simulation in 1999. Sun et al.[8] used a minimum variance criterion to achieve an MSNWF that made the algorithm own the anti-multipath interference effect. Wang et al.[9] used compressed sensing principle to reduce the dimension of the sample matrix, but the algorithm complexity was large.

The classical Least Mean Square (LMS) error adaptive algorithm solves weights by using the iterative method, which avoids matrix inversion, and it is simple and requires less computation. But traditional LMS algorithm convergence speed is slow, and the convergence speed and steady-state error required to simultaneously achieve the optimal state cannot be guaranteed. To improve these shortcomings, we propose a variable step-size LMS algorithm with two different step-size iteration formulas based on error signal autocorrelation values[10–12]. Compared with the traditional variable step-size algorithm, the improved one achieves faster convergence speed and fewer

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Manuscript received: 2016-07-25; revised: 2016-10-17; accepted: 2016-10-20
convergence steady-state errors without increasing in complexity.

When the direction of the interference signal is the same as the navigation signal, it generates a deep zero in the direction of the navigation signal, resulting in a large number of navigation signals being suppressed\cite{13, 14}. STAP algorithm, combining an IIR notch filter and a space-time FIR filter, which can solve this problem, has been proposed in Ref. [15]. However, for narrowband interference spectrum with unknown statistical characteristics, this method is not suitable for capturing the fast-changing signal. Therefore, we propose an algorithm combining a space-time filter with a frequency domain narrowband interference filter, and introduce a weight leakage factor in the frequency domain filter structure to reduce the loss of navigation signal during the filtering process.

The rest of the paper is arranged as follows. The traditional STAP algorithm is introduced in Section 2. The improved frequency domain filter and the improved variable step LMS algorithm are introduced in Sections 3.1 and 3.2, respectively; the improved space-time adaptive processor architecture is introduced in Section 3.3. Section 4 presents the simulation, and the performance of the proposed algorithm is proved for four cases. Section 5 gives the conclusion.

2 Traditional STAP Algorithm

Figure 1 shows a two-dimensional space-time processor with \(M\) array elements and a \(P\) tap delay connected to the back of each element. The space-time weighted matrix \(W\) is \(MP \times 1\) dimensional, and can be expressed as

\[
W = (\omega_1, \omega_2, \ldots, \omega_1P, \omega_2, \ldots, \omega_2P, \ldots, \omega_MP)\text{T}
\]

(1)

The array input signal \(X\) can be expressed as

\[
X = (x_{11}, x_{12}, \ldots, x_{1P}, x_{21}, \ldots, x_{22P}, \ldots, x_{MP})\text{T}
\]

(2)

The space-time weighted vector optimal solution can be expressed as

\[
W_{opt} = R_x^{-1}R_{xd}
\]

(3)

where \(R_x\) and \(R_{xd}\) represent the correlation matrices of the input and reference signals, respectively. The space-time weighted vector output is

\[
y = W^H X
\]

(4)

3 Improved STAP Algorithm

3.1 Improved frequency domain filter

When the direction of narrowband interference signal is the same as that of the navigation signal, the anti-jamming performance of the space-time filter is greatly reduced. To effectively suppress the narrowband interference from the navigation signal direction and reduce the loss of useful signal during the filtering process, this paper uses an improved frequency domain narrowband filter to process the signal received by each array element, which filters out any narrowband interference that is the same as the navigation signal direction. Then, the processed signals are sent to the space-time filter to filter out the wideband interference. The structure of the frequency domain filter is shown in Figure 2.

Weighting coefficients in frequency domain is

\[
\omega_{mn}'(k + 1) = \gamma \omega_{mn}'(k) + 2\xi E^*_{mn}(k) Y^*_{mn}(k),
\]

\[
m = 1, 2, \ldots, M; n = 1, 2, \ldots, N
\]

(5)

where \(\omega_{mn}'(k + 1)\) and \(\omega_{mn}'(k)\) are the weighting coefficients of the \(m\)-th array element and the \(n\)-th frequency component from \(k\) to \(k + 1\) moment, respectively; \(\gamma\) is the weight value of the leakage factor; \(\xi\) is the convergence factor; and \(Y^*_{mn}(k)\) is the value

![Fig. 1 Structure of the traditional STAP algorithm.](image1)

![Fig. 2 Diagram of frequency domain filter structure.](image2)
of the $m$-th array element and the $n$-th frequency point of the input navigation signal $X'(i)$ after Fast Fourier Transform (FFT),

$$E'_m(k) = Y'_m(k) - \omega'_m(k)Y_m(k)$$

is the error signal, and the filter output signal $X_m(i)$ is obtained after $E_m(k)$ Inverse Fast Fourier Transform (IFFT); and “*$” is the conjugate operator. The weight coefficient value $\omega'_m(k + 1)$ can be expressed as

$$\omega'_m(k + 1) = \gamma \omega'_m(k) + 2\xi [1 - \omega'_m(k)]Y_m(k)Y'_m(k)$$

(6)

The mathematical expectation of $\omega'_m(k + 1)$ can be expressed as

$$E\{\omega'_m(k + 1)\} = \gamma E\{\omega'_m(k)\} + 2\xi E\{\|Y_m(k)\|^2\} - 2\xi E\{\omega'_m(k) \|Y_m(k)\|^2\}$$

(7)

where $E\{\|Y_m(k)\|^2\} = \sigma^2$, so Eq. (7) can be expressed as

$$E\{\omega'_m(k + 1)\} = 2\xi \sigma^2 + [\gamma - 2\xi \sigma^2]E\{\omega'_m(k)\}$$

(8)

$$\omega'_m(\infty) = \lim_{k \to \infty} \omega'_m(k) = \frac{2\gamma \sigma^2}{(1 - \gamma + 2\xi \sigma^2)}$$

(9)

We set energy threshold $B$ as

$$B = \frac{(1 - \gamma)^2}{4\xi}$$

(10)

$$\omega'_m(\infty) = \frac{\sigma^2}{\sigma^2 + B}$$

(11)

From Eq. (11), we find that: (1) If $\sigma^2 \geq B$, $\omega'_m(\infty) \approx 1$, the power spectrum is small, and the weight incremental tends to 0. If the leakage factor is $0 < \gamma < 1$, the weight tends to 0 after several iterations, thereby the loss of the desired signal tends to 0 after filtering. (2) If the power spectrum is large, the weight increment is also quite large, which makes the weight tend to 1 and offsets the leakage factor. Therefore, the weighting leakage factor value can inhibit the large power signal and protect the small power signal.

Based on the above analysis, if the signal power is very small, the weight increment tends to 0 and the leakage factor range is $0 < \gamma < 1$. After iteration the weight tends to 0, so the loss of useful signal in the filtering process tends to 0. If the signal power is large, the weight increment increases 1 to offset the leakage factor effect, so after several iterations the weight tends to 1 and the narrowband interference is almost completely inhibited.

### 3.2 Improved variable step LMS algorithm

Equation (3) is the weight calculation for an ideal case. It is difficult to achieve in practice, because the navigation signal power is very low. It is difficult to get the reference signal from the training sequence, and the computation of the covariance matrix and its inverse matrix is difficult[16]. Considering the above situation, we introduced the improved variable step-size LMS algorithm to solve the problem of space-time array weighted values.

Under practical application, the navigation signal power is low and almost submerged in noise and interference. To improve the array output Signal to Interference and Noise Ratio (SINR), we used white noise signal as the space time filter input reference signal. The uncorrelated characteristics between white noise and the interference signal means that the strong interference signal can be restrained. Therefore, the space-time filter output error signal can be expressed as

$$e(k) = \text{noise}(k - 1) - W(k - 1)X(k - 1)$$

(12)

The recursion equation deduced by the steepest descent method can be expressed as

$$W(k) = W(k - 1) + 2\mu e(k - 1)X(k - 1)$$

(13)

where $\mu$ is a constant defined as the convergence factor. The power spectral density function of the white noise is constant over the whole frequency domain, and its correlation with any signal is zero, thus it can be seen to inhibit any input signal. Meanwhile, the power of the interference signal is much higher than that of the noise and navigation signal, so the result will form a nulling in the direction of interference, and if the interference is stronger, the nulling will be deeper.

Equations (12) and (13) show the traditional recursive LMS algorithm, which cannot balance the convergence rate and the steady state error due to its fixed step-size. In order to improve this shortcoming, we propose a new variable step-size algorithm via the two-step iterative method. This is based on one proposed in Ref. [12] that reduces computation and improves the convergence performance. The step-size updating equations can be expressed as

$$\mu(k) = \alpha \tanh |\beta e(k)e(k - 1)|$$

(14)

$$\mu(k) = \beta e(k)e(k - 1) + \mu(k - 1)$$

(15)

where $\alpha$ is the amplitude weighting factor, and $\beta$ is the waveform constraint factor. In Eq. (14), we have

$$\left|\frac{e(k)}{e(k - 2)}\right| < 0.9$$

and at the same time in Eq. (15),
0.9 < \left| \frac{e(k)}{e(k-2)} \right| \leq 1.

The degree of similarity of the error signal between the k-th and k-2 moment is used as the judgment condition when deciding which kind of step-size iteration equation to be used. In the initial stage of convergence, the step changes with hyperbolic tangent functions of the input signal error autocorrelation values can realize fast converge when the input signal state is changed. When the input error signal meets the following conditions: 0.9 < \left| \frac{e(k)}{e(k-2)} \right| \leq 1, step changes with the previous step factor \( \mu(k-1) \), and input signal error autocorrelation value \( e(k)e(k-1) \), the uncorrelated values will be suppressed and the steady state error will be effectively reduced, thereby the convergence rate of the algorithm will be improved.

Therefore, the improved variable step-size LMS space-time filtering algorithm can be expressed as

\[
W(k + 1) = W(k) + 2\mu(k)e(k)X(k) \label{eq:16}
\]

\[
e(k) = \text{noise}(k) - W^H(k)X(k) \label{eq:17}
\]

\[
\mu(k) = \alpha \tanh(\beta e(k)e(k-1)) \label{eq:18}
\]

\[
\mu(k) = \beta e(k)e(k-1) + \mu(k-1) \label{eq:19}
\]

In this paper, we have \( \left| \frac{e(k)}{e(k-2)} \right| < 0.9 \) in Eq. (18) and 0.9 < \left| \frac{e(k)}{e(k-2)} \right| \leq 1 in Eq. (19). The effect of different \( \alpha \) and \( \beta \) on the iteration step is analyzed by using multiple simulations. Figures 3 and 4 show the relationship between \( \mu(k) \) and \( e(k) \). In Fig. 3, \( \beta \) changes and \( \alpha \) keeps constant, and in Fig. 4 the opposite occurs.

We used the Monte Carlo method to conduct a number of simulations and found that: (1) When the amplitude weighting factor \( \alpha \) is constant, and the waveform constraints factor \( \beta \) is higher, the convergence speed is faster. (2) When \( \beta > 20 \), a small error can cause a large fluctuation in the iteration step, which affects the stability of the convergence stage. (3) When the waveform constraints factor \( \beta \) is constant, \( \alpha \) affects the amplitude range of the iteration step. (4) When \( \alpha > 0.9 \), the initial iteration step is large, and the weighted value fails to converge. Therefore, we set \( \alpha > 0.9 \) and \( \beta > 20 \) when calculating the weighted values.

### 3.3 Improved space-time adaptive processor architecture

A schematic diagram of the improved space-time processing algorithm produced as a result of the above analysis is shown in Fig. 5. The improved algorithm consists of 6 steps, as follows:

**Step 1** The data received by each array is divided into \( N \)-point batches, according to the overlapping phase addition. The \( k \)-th batch data received by the \( m \)-th array element can be expressed as

\[
X'_m(k) = [x'_m(kN + 1), \ldots, x'_m(kN + N)]^T, \quad m = 1, 2, \ldots, M \label{eq:20}
\]

**Step 2** Send the received data \( X'_m(k) \) to the improved LMS frequency domain filter, transferring the signal to a frequency domain signal:
\[ Y_m(k) = [Y_{m1}(k), Y_{m2}(k), \ldots, Y_{mN}(k)] \] by FFT.

**Step 3** Update the frequency domain weight coefficients, update the \( n \)-th weight:
\[
\omega_{mn}'(k + 1) = \gamma \omega_{mn}'(k) + 2\varepsilon E_{mn}(k) Y_{mn}^*(k), \\
m = 1, 2, \ldots, M, n = 1, 2, \ldots, N
\] (21)

where \( E_{mn}(k) = Y_{mn}(k) - \omega_{mn}'(k) Y_{mn}^*(k) \).

**Step 4** Calculate the weight coefficient stability.
\[
d = \frac{1}{N} \sum_{n=1}^{N-1} \left[ \omega_{mn}(k + 1) - \omega_{mn}'(k) \right]^2,
\]
which comes out to be a very small value. We can determine whether the weight reaches the steady state according to \( d \). If the weight reaches the steady state, then the data enters Step 5, otherwise the data repeats Step 3.

**Step 5** Make the error signal \( X_m(i) = \text{IFFT}(E_{mn}(k)) \) be the output signal.

where
\[
\begin{align*}
E_{mn}(k) &= [E_{m1}(k), E_{m2}(k), \ldots, E_{mN}(k)], \\
X_m(k) &= [X_{m1}(k), X_{m2}(k), \ldots, X_{mN}(k)]
\end{align*}
\] (22)

**Step 6** The signal \( X_m(k), m = 1, 2, \ldots, M \), processed by the LMS frequency domain filter can be expressed as the space-time received signal:
\[
X = (x_{11}, x_{12}, \ldots, x_{1P}, x_{21}, \ldots, x_{2P}, \ldots, x_{MP})^T
\] (23)

Send the received signal \( X \) for space-time anti-jamming processing. Finally, we get the output signal,
\[
y(k) = W(k)^H X(k)
\] (24)

### 4 Simulation

#### 4.1 Computational complexity analysis

Firstly, we analyzed the computational complexity of several different updating algorithms, and the results are shown in Table 1. These algorithms are the algorithm proposed in this paper, the VSS-LMS algorithm in Ref. [17], the improved LMS algorithm proposed in Ref. [10], and the traditional RLS algorithm. It can be seen that the algorithm proposed here, the VSS-LMS algorithm, and the improved LMS algorithm require similar amounts of computation, which is far less than that required by the RLS algorithm. If we set the array element number to \( M = 8 \), the delay number of each array is 4, and results show that the number of multiplications required for proposed algorithm is 60, and the number of adders is 58, which is equivalent to 0.27% and 0.41% of the RLS algorithm. Therefore, the computational complexity is significantly reduced.

#### 4.2 Convergence performance simulation

In this section, we compared the convergence performance of the traditional LMS algorithm, the RLS algorithm, and the improved LMS algorithm. Simulation conditions of a uniform linear array were set up, where \( M = 8 \), \( P = 4 \), wavelength= 0.1 m, and the array element spacing= 0.05 m. The SNR of the navigation signal C/A code was −30 dB, and the SINR was 50 dB. The direction of the desired signal was 0°, the direction of the interference signal was 20°, and the snapshot number was 1000. The simulation results are shown in Fig. 6.

From the convergence curves, we found that:

1. The improved LMS algorithm converged in 50 iterations, the traditional LMS algorithm converged in

![Fig. 6 Convergence curve of the three algorithms.](image)

Table 1 Computational complexity of typical step iteration algorithms.

| Algorithm          | Step update algorithm                              | Number of multiplies | Number of pluses |
|--------------------|----------------------------------------------------|----------------------|-----------------|
| VSS-LMS[17]        | \( u(k) = a u(k-1) + y e^2 \)                     | \( 2 (M - 1) P + 5 \) | \( 2 (M - 1) P + 2 \) |
| Improved LMS[10]   | \( u(k) = a u(k-1) + (1 - a) x \) \( P(n-1)x(n) \) | \( 2 (M - 1) P + 9 \) | \( 2 (M - 1) P + 2 \) |
| RLS algorithm      | \( \mu(n) = \frac{\alpha + x^H(n) P(n-1) x(n)}{P(n-1) x(n) P(n-1) - \mu(n) x^H(n) P(n-1)} \) | \( (M - 1)^3 P^3 \) | \( (M - 2)^3 P \) |
| Proposed algorithm | \( \mu(n) = \alpha \left( 1 - \frac{1}{100} x(n) e(n-1) \right) + \mu(n-1) \) | \( 2 (M - 1) P + 4 \) | \( 2 (M - 1) P + 2 \) |
160 iterations, and the RLS algorithm converged in 70 iterations. Therefore, the convergence performance of the proposed algorithm was significantly better than the LMS algorithm and similar to the classic RLS algorithm. (2) The MSE of the improved LMS algorithm converged around 0.05, the LMS algorithm converged around 0.25, and the classical RLS algorithm converged around 0.06. From the perspective of the steady state error, the proposed algorithm also performed better than the classical LMS and RLS algorithms.

4.3 Simulation experiments for the suppression of narrowband interference

A navigation signal with a $0^\circ$ incidence angle was collected by the GNSS intermediate frequency sampling instrument. The frequency of the navigation signal was 2.5 MHz, and the sampling frequency was 10 MHz. In this paper, three different frequency narrowband signals with incident angles of $0^\circ$ were used as artificial interference. The interference signals at 2.81 MHz and 2.97 MHz were the fixed frequency interference, and the INRs are 41 dB and 42 dB, respectively. The other interference was the varied frequency narrowband interference in the range of 1.5 MHz–2 MHz, and the INR was 40 dB. The power spectrum of the input signal containing interference is shown in Fig. 7. The signal spectrum after processing with the proposed frequency domain LMS filter algorithm is shown in Fig. 8. The simulation results show that the improved algorithm can suppress fixed frequency and variable frequency narrowband interferences from the desired signal direction, and guarantee the desired signal gain.

4.4 Interference suppression performance simulation for the space time adaptive processing algorithm

A uniform linear array was used in the simulation experiment, the number of array elements was $M = 5$, the tap delay was $P = 4$, and the array element spacing was half a wavelength. The DOA desired signal was $0^\circ$ and the SNR was $-30$ dB. A narrowband interference frequency range was set to change over time in the range 1.5 Hz–2 Hz, the INR was 40 dB, and the DOA was $0^\circ$, the same direction as the desired signal. The DOA of two uncorrelated narrowband interferences were set as $-20^\circ$ and $-40^\circ$, and the INRs were 25 dB and 30 dB, respectively. A wideband interference was set to the Gaussian white noise with a bandwidth the same as the desired signal. The DOA was $60^\circ$, the INR 38 dB. Comparisons between our improved algorithm and the conventional STAP algorithm are shown in Figs. 9 and 10.

Figure 9 shows that the conventional STAP algorithm can suppress strong interference signals from different directions, and its ability to suppress strong interference power is about 50 dB. However, if the direction of the narrowband interference is the same as that of the desired signal, the latter’s power losses increased by about 20 dB. In this situation the traditional STAP algorithm cannot recognize the narrowband interference from the desired signal.
signal.

Figure 10 shows that our improved STAP algorithm has a better interference suppression performance. Its ability to suppress strong interference power is about 78 dB, which is higher than the conventional STAP algorithms at around 28 dB. In addition, the desired signal is not significantly attenuated, which means that the proposed algorithm can effectively identify the interference and desired signals when the direction of narrowband interference is the same as that of the desired signal; at the same time it can effectively suppress the interference signal. The output results of SINR from the traditional and improved STAP algorithms are shown in Figs. 11 and 12.

As can be seen from Fig. 11, the improved and traditional STAP algorithms both have good anti-jamming capabilities under the conditions of no narrowband interference, but the output SINR of the improved algorithm is better by around 5 dB compared with the conventional algorithm. Figure 12 shows the output SINR of the conventional STAP algorithm reduced by about 20 dB, however, the output SINR of the improved algorithm only reduced by about 5 dB.

We can conclude that the proposed algorithm can effectively suppress narrowband interference when its direction is the same as that of the desired signal, and can improve system output SINR.

5 Conclusion

The traditional STAP algorithm is complicated and cannot filter out narrowband interference with a direction the same as that of the desired signal. To solve the above problems, we introduced an improved frequency domain LMS filter to eliminate the narrowband interference in the desired signal direction. We then sent the processed navigation data to the space-time processing unit to eliminate other types of interference using the improved variable step-size LMS algorithm. Simulation results show that the proposed algorithm needs less computation, improves the convergence speed of the algorithm, distinguishes the interference and the useful signals in the same direction, and effectively improves the output SINR from STAP.

Acknowledgment

This paper was supported by the National High-Tech Research and Development (863) Program of China (No. 2015AA016901), the International Cooperation Project of Shanxi Province (No. 201603D421012), the National Natural Science Foundation of China (Nos. 61371062, 61572346, and 61303207).

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