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Parameter estimation of weak space-based ADS-B signals using genetic algorithm

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Space-based automatic dependent surveillance-broadcast (ADS-B) is an important emerging augmentation of existing ground-based ADS-B systems. In this paper, the problem of space-based ultra-long-range reception processing of ADS-B signals is described. We first introduce a header detection method for accurately determining the pulse position of a weak ADS-B signal. We designed a signal encoding method, shaping method, and fitness function. We then employed a genetic algorithm to perform high-precision frequency and phase estimations of the detected weak signal. The advantage of this algorithm is that it can simultaneously estimate the frequency and phase, meaning a direct coherent demodulation can be implemented. To address the computational complexity of the genetic algorithm, we improved the ratio algorithm for frequency estimation and raised the accuracy beyond that of the original ratio algorithm with only a slight increase in the computational complexity using relatively few sampling points.

KEYWORDS
automatic dependent surveillance-broadcast, genetic algorithm, space-based, weak signal

1 | INTRODUCTION

The automatic dependent surveillance-broadcast (ADS-B) system obtains air traffic status information, such as the position (latitude, longitude, and altitude), velocity, and operating status, of an aircraft through the global navigation satellite system (GNSS), inertial navigation system (INS), inertial reference system (IRS), and other airborne sensors. This air traffic status information is then combined with the aircraft's identity and category information in a fixed format to form an ADS-B information frame, which is subsequently broadcast at a certain rate through the onboard ADS-B transmitting device [1]. All ADS-B ground stations and aircraft within 200 nautical miles receive these signals and then re-transmit the information. Through monitoring of the aircraft with the above process, conflict detection and avoidance can further be realized. The ADS-B system is an automatic broadcasting system that does not require inquiry or response. Therefore, when compared with conventional secondary surveillance radar, the ADS-B system is a simplified process and can effectively improve the efficiency of air traffic status information transmission. Therefore, it has become an extremely widely used air traffic management technology.

The ground receiving station is one of the core components of the current ADS-B system. Most of the world's surface is covered by ocean, where the construction of ground-based ADS-B receiving stations is precluded for a variety of reasons, including cost and engineering constraints. Similar constraints apply to vast deserts and other special areas. Because of these constraints, the current ground-based ADS-B system cannot feasibly achieve the desired comprehensive surveillance capability. A potential solution for this problem is space-based ADS-B technology. In a space-based ADS-B system, high-sensitivity ADS-B receivers are installed on low-orbit satellites to receive and analyze the broadcast information transmitted by the aircraft through the satellite. Such information is transmitted to ground stations in real time and incorporated into the air traffic control system [2]. With the large coverage area of satellites, surveillance of aircraft in remote areas becomes possible.

Although the advantages of space-based ADS-B systems are obvious, the signal must be transmitted over a vast distance. Thus, it is necessary to solve the key technical problems of receiving and processing weak ADS-B signals transmitted through ultra-long ranges. Current airborne ADS-B transmitter systems have not been modified accordingly to meet the needs of space-based ADS-B systems. As a result, a signal received by the satellites will have a very low power. The power loss, "los," can be calculated as follows:

$$\mathrm{los}\,(\mathrm{dB}) = 32.44 + 20\log D\,(\mathrm{km}) + 20\log F\,(\mathrm{MHz}), \quad (1)$$

where D is the signal transmission distance and F is the signal frequency, which are 3000 km and 1090 MHz, respectively, in this study. Based on this equation, the maximum loss can be greater than 160 dB, and the minimum received power is only −109 dBm. In this case, the signal-to-noise ratio (SNR) is very low, and designing a signal demodulation algorithm in a space-based environment is one of the key technical challenges faced by space-based systems [3]. In addition, given the advantage of the large area covered by a space-based ADS-B system, the number of aircraft in the coverage area is high. Thus, there will be significant signal overlap, and an effective de-interlacing algorithm must be designed. However, a set of high-performance signal demodulation algorithms must first be designed.

Coherent demodulation can effectively suppress noise, making it an effective way to demodulate weak signals. While implementing the coherent demodulation algorithm, it is necessary to estimate the parameters of the received signal (including frequency and phase) accurately. This is more difficult to achieve when the SNR is low. The commonly used signal frequency estimation method in recent years is a two-step method involving rough estimation followed by fine estimation. The rough estimation is achieved through discrete Fourier transform (DFT) of the signal and the fine estimation is achieved by modifying the rough estimation using the ratio method or other methods [4–7]. There are many other methods directly based on time-domain signals, such as the autocorrelation algorithm and linear prediction algorithm [8,9]. These methods perform well in frequency estimation; however, the phase of the signal cannot be estimated in the meantime.

In this paper, based on the characteristics of ADS-B signals, we first introduce a header detection method for weak ADS-B signals to determine their pulse position accurately. We subsequently use a genetic algorithm to estimate the frequency and phase of the detected signal and achieve higher accuracy. However, the disadvantage of using a genetic algorithm is that it is computationally intensive. To address this shortcoming, we improve the ratio algorithm used in frequency estimation and increase its accuracy by increasing the computational volume only slightly and using a small number of sampling points in the simulation verification of the algorithm.

2 | ESTIMATION METHOD FOR WEAK SIGNAL PARAMETERS

2.1 | ADS-B signal format

The three signal systems of the current ADS-B system are the 1090ES data link, VDL-4, and UAT data link. The 1090ES data link is the most widely used signal system, and it is the standardized signal system of the International Civil Aviation Organization (ICAO). Therefore, we studied the ADS-B signal for the 1090ES data link.

The ADS-B signal of the 1090ES data link used in our analysis had a transmission frequency of 1090 MHz, with allowable deviations within 1 MHz. The frame length of the signal was 120 μs, and the pulse-position modulation (PPM) scheme was used. The 120 μs signal frame length was divided into a header signal of 8 μs and a data field of 112 μs. The header contained four leading pulses, located at 0 μs, 1.0 μs, 3.5 μs, and 4.5 μs. The data bit began at 8 μs and had a length of 112 μs for a total of 112 bits. Each bit contained two elements. If the pulse was located at the lead element, the bit was 1, and if the pulse was located at the trailing element, the bit was 0 [10], as illustrated in Figure 1.

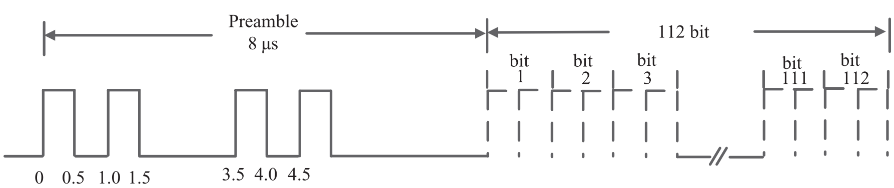

FIGURE 1 ADS-B signal format

2.2 | Header detection for weak ADS-B signal

In the demodulation of weak signals by space-based ADS-B high-sensitivity receivers, the key technology is correlation. The two most important steps in completing the ADS-B message extraction are the header extraction and extraction of the 112-bit data bit.

The header extraction requires an accurate determination of the leading pulse position of the weak ADS-B signal. The keys to accurate extraction of the timing information from the four leading pulses of the ADS-B signal are high sensitivity and low jitter. To improve the SNR, not only the amplitude information of the signal but also the phase relationship is introduced in the space-based ADS-B receiver. The principle is analyzed as follows.

The baseband $S(t)$ of the ADS-B signal is equally divided into four branches. The first branch $S_1(t)$ is not time delayed, the second branch $S_2(t)$ is delayed by time T_{12}, the third branch $S_3(t)$ is delayed by time T_{13}, and the fourth branch S_4(t) is delayed by time T_{14}, as illustrated in Figure 2. It follows that the first pulse of the second branch occurs simultaneously with the second pulse of the first branch, the first pulse of the third branch occurs simultaneously with the third pulse of the first branch, and the first header of the fourth branch occurs simultaneously with the fourth header pulse of the first branch.

The SNR is effectively improved using the correlation of the four pulses:

$$S_c(t) = \left\{S_1(t) \times S_2(t)\right\} \times \left\{S_3(t) \times S_4(t)\right\}. \qquad (2)$$

Finally, we obtain the signal

$$S_c(t) = A^4 + n_0'(t), \qquad (3)$$

where A is the amplitude of the signal, and $n_0'(t)$ is the error caused by the noise. Thus, a threshold may be set to detect the header.

2.3 | Signal parameter estimation based on genetic algorithm

A genetic algorithm is a search algorithm based on the principles of biological individual inheritance, gene cross-compilation, and natural environmental selection in the process of natural evolution. The algorithm is widely used in various fields. Several researchers have systematically elaborated on the basic theories and methods of genetic algorithms and summarized their theoretical bases. Furthermore, it has been pointed out that all adaptation problems can be expressed as genetic problems through appropriate modeling, and their solutions can be found through continuous evolution [11].

After the header detection is complete in the processing of the space-based ADS-B signal, the frequency and phase of the signal must be accurately estimated if the coherent demodulation algorithm is to be used for the pulses. The use of genetic algorithms to estimate signal parameters requires several major processes, including chromosome encoding, individual fitness assessment, and genetic manipulation.

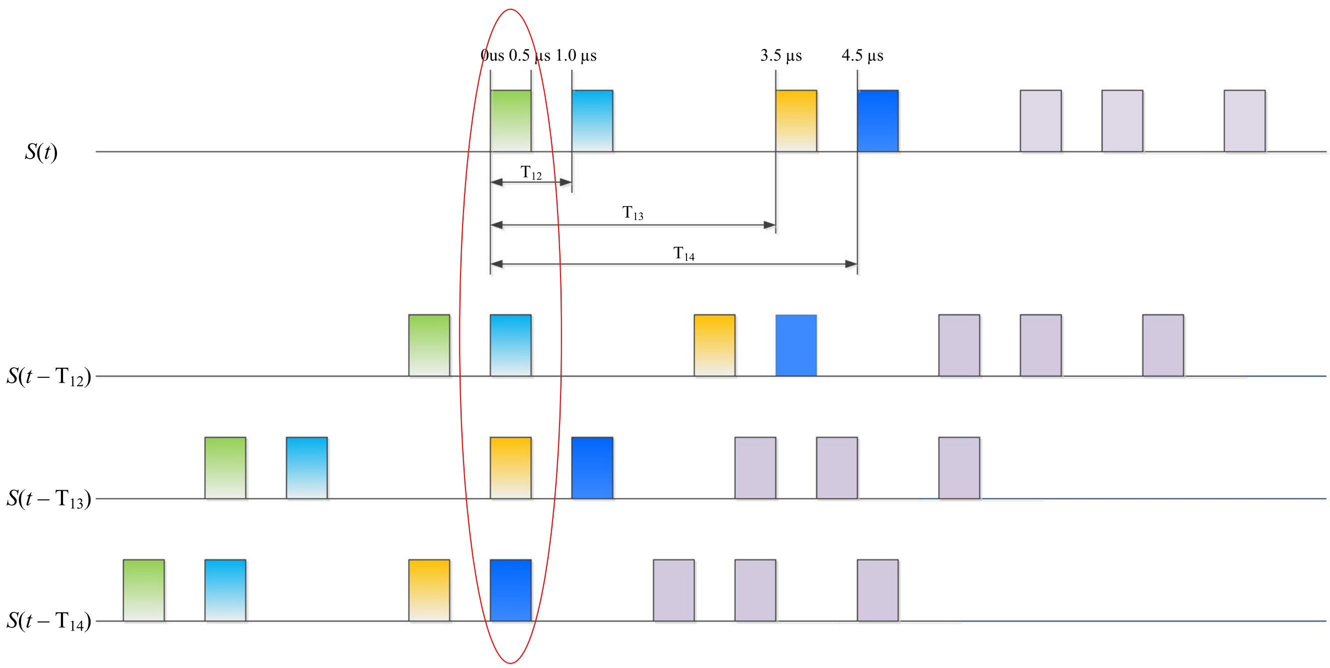

FIGURE 2 Phase relationship in correlation calculation of weak ADS-B signal

2.3.1 | Chromosome encoding

The process of chromosome encoding is an encoding method for determining a feasible solution domain of a specific problem. Using the encoding method, each solution of the feasible solution domain can be represented by a numerical value or string. Common encoding methods include binary encoding, floating point encoding, Gray code encoding, and symbol encoding.

A commonly used signal frequency estimation method in recent years is a two-step method involving rough estimation followed by fine estimation. Rough estimation is used to obtain the amplitude spectrum of the acquired signal by DFT, and the peak frequency is chosen as the estimated frequency in the rough estimation. The fine estimation in some ways nudges the rough frequency estimation toward the true frequency. Commonly used fine estimation methods include the interpolation method and ratio method [12–17]. In a low SNR environment, the interpolation and ratio methods are prone to errors due to distortion of the spectrum, and the phase of the signal cannot be estimated. In this study, we also used a two-step method to estimate the signal parameters. The rough estimation process performs a DFT on the acquired signal $x(n)$ as follows:

$$R(k)=\sum_{n=0}^{N-1} x(n)\, e^{-j2\pi nk/N}, \tag{4}$$

where N is the length of the signal, $k = 0, 1, 2, \ldots, N - 1$, and the indexed value of the discrete frequency at the maximum amplitude $R(k)$ is denoted as k_0. Thus, the rough estimation of the frequency is $k_0\Delta f$, where

$$\Delta f = f_s/N, \tag{5}$$

and f_s is the sampling rate. Because $k_0\Delta f$ is the rough estimate of the signal frequency and the actual frequency of the signal should be located at $\left[\left(k_0-0.5\right)\Delta f,\ \left(k_0+0.5\right)\Delta f\right]$, the actual frequency of the signal f_0 can be expressed as follows:

$$f_0=\sum_{i=1}^{Q} w_i f_i, \tag{6}$$

where $w_i \in [0, 1]$ and $w_1+w_2+\cdots+w_Q=1$. The interval $\left[\left(k_0-0.5\right)\Delta f,\ \left(k_0+0.5\right)\Delta f\right]$ is divided equally into $i - 1$ parts by interpolation points $f_i\,(i=1, 2, \ldots, Q)$. Thus, the chromosome of f_0 is encoded as $w_1w_2\cdots w_Q$. Similarly, for the phase of the signal, the interval $[-\pi, \pi]$ is divided into $S - 1$ equal parts, and the actual phase is encoded as $v_1v_2 \cdots v_S$. Therefore, the entire parameter of the chromosome code of the signal is $w_1w_2 \cdots w_Qv_1v_2 \cdots v_S$.

Following the idea described above, the first generation of the chromosome is encoded, where $w_1w_2 \cdots w_Qv_1v_2 \cdots v_S$ are generated randomly.

2.3.2 | Selection of fitness function

The fitness function is a measure of the merit for each set of solutions in the feasible domain. Because each set of encoded and mutated solutions can determine a frequency f and phase φ, it can determine a signal as follows:

$$y(n)=\cos(2\pi fn+\varphi). \tag{7}$$

Letting $e(n)=x(n)-y(n)$ be the error sequence of each set of solutions and assuming the correlation function of $r(\tau)$ is $e(n)$, the fitness function of $y(n)$ will be as follows:

$$s(y)=|r(0)|+|r(1)|, \tag{8}$$

where $|\cdot|$ denotes the norm.

A smaller value of the fitness function denotes a better solution. The value $|r(0)|$ is minimized to ensure that the frequency and phase after the approximation are closer to their true values, and $|r(1)|$ is minimized to ensure that the errors are Gaussian (ie, the noise is Gaussian).

2.3.3 | Crossover and mutation

The recombination of chromosomes is the basis for evolution. The crossover operator can simulate the recombination process of biological chromosomes. In this study, for the above coding method, the frequency and phase coding were performed with random single point crossings, after which coding shaping was performed (ie, $w_1 + w_2 + \cdots + w_Q = 1$) to ensure the stability of the solution. A new chromosome generated after the intersection was encoded as $w_1'w_2'w_3' \cdots w_Q'v_1'v_2'v_3' \cdots v_S'$. Thus, the revised frequency code was $w_1'w_2'w_3' \cdots w_Q'/\sum_{i=1}^{Q} w_i'$. Similarly, the revised phase code was $v_1'v_2'v_3' \cdots v_S'/\sum_{i=1}^{S} v_i'$.

Mutation is a process in which new biological traits are produced due to chromosomal alterations caused by certain accidental factors. In a genetic algorithm, mutation can improve the local search ability of the algorithm and prevent the algorithm from falling into a local minimum solution. Additionally, the mutation algorithm can ensure diversity of the population. In this study, the next generation of mutated individuals was generated from multi-chromosome random crossover of the previous generation. The mutation probability is a parameter of the algorithm, which is generally taken to be small.

2.3.4 | Algorithm steps

In summary, the steps to estimate the signal parameters using a genetic algorithm are as follows:

Step 1: Set the algorithm parameters, such as the population size of each generation, total number of generations, and mutation probability.

Step 2: Create a first-generation population $P(k = 1)$ according to a certain chromosome encoding scheme.

Step 3: Calculate the fitness of each member in $P(k)$ based on the fitness function $s(y)$. Select a high-quality member and determine whether to abort the algorithm based on the parameters.

Step 4: Subject the population to crossover and mutation to generate the next generation. Set k to $k + 1$ and return to Step 3.

The advantage of estimating the parameters of a weak ADS-B signal is that the frequency and initial phase can be estimated directly and with high precision, and thus, coherent demodulation can be performed. The disadvantage is that the process is computationally intensive and not conducive to real-time processing. If there are five generations in the algorithm and the population size is 100 in each generation, the genetic algorithm is more than five times more computationally expensive than the ratio algorithm introduced in the next section.

2.4 | Improved ratio algorithm

In the two-step estimation of signal frequency, the Quinn ratio [12] algorithm is often used for fine estimation. Denoting the indexed discrete frequency at the maximum amplitude of the DFT $R(k)$ of signal $x(n)$ as k_0 and the difference between the true frequency and the coarse estimated frequency as $\delta\Delta f$, where Δf is defined in Section 2.3 and δ is between -0.5 and 0.5, the steps of the Quinn ratio algorithm are as follows. Let

$$a_1 = \text{real}\left(R\left(k_0 - 1\right)/R\left(k_0\right)\right), \tag{9}$$

$$a_2 = \text{real}\left(R\left(k_0 + 1\right)/R\left(k_0\right)\right), \tag{10}$$

where "real" indicates the real part of the complex number. Furthermore, let

$$\delta_1 = a_1/\left(1 - a_1\right), \tag{11}$$

$$\delta_2 = -a_2/\left(1 - a_2\right). \tag{12}$$

If δ_1 and δ_2 are both positive, the estimate of δ is δ_2; otherwise, the estimate of δ is δ_1.

The Quinn ratio algorithm has a higher accuracy when the SNR is high. However, when the SNR is low, the accuracy is unstable due to the distortion of $R(k_0 - 1)$ and $R(k_0 + 1)$. Furthermore, when changes occur in the sampling numbers or δ, the performance of the algorithm is different. Therefore, we designed an iteration algorithm based on the Quinn ratio algorithm and paid special attention to changes in spectrum amplitudes of the newly estimated frequencies during the iterative process. In this way, the improved algorithm can always achieve optimal performance of the Quinn algorithm regardless of the value of δ. The iterative algorithm is as follows.

Letting $\delta_0 = 0$ and assuming Q iterations, the following loop operation is performed at each step, as i changes from 1 to Q:

$$X_{-1} = \sum_{n=0}^{N-1} x(n)\, e^{-j2\pi n\left(k_0 + \delta_{i-1} - 1\right)/N},$$

$$X_1 = \sum_{n=0}^{N-1} x(n)\, e^{-j2\pi n\left(k_0 + \delta_{i-1} + 1\right)/N},$$

$$a_1 = \text{real}\left(X_{-1}/R\left(k_0\right)\right),$$

$$a_2 = \text{real}\left(X_1/R\left(k_0\right)\right),$$

$$\text{new\_}\delta_1 = a_1/\left(1 - a_1\right),$$

$$\text{new\_}\delta_2 = -a_2/\left(1 - a_2\right).$$

If δ_1 and δ_2 are both greater than 0, then

$$\delta_i = \delta_{i-1} + \text{new\_}\delta_2.$$

Otherwise,

$$\delta_i = \delta_{i-1} + \text{new\_}\delta_{1.}$$

At the end of the loop, δ is estimated with the following formula:

$$\delta = \underset{\delta_i}{\text{argmax}}\left(\left|\sum_{n=0}^{N-1} x(n)\, e^{-\frac{j2\pi n\left(k_0 + \delta_i\right)}{N}}\right|\right).$$

The number of iterations, Q, is usually fewer than 5, and thus, the volume of computations is only increased slightly. Simulation analysis showed that the accuracy of the modified algorithm was substantially improved when the number of samples was low.

3 | SIMULATION ANALYSIS

To verify the performance of the genetic algorithm for estimating the parameters of the ADS-B signal, 50 independent experiments were performed for each parameter. There

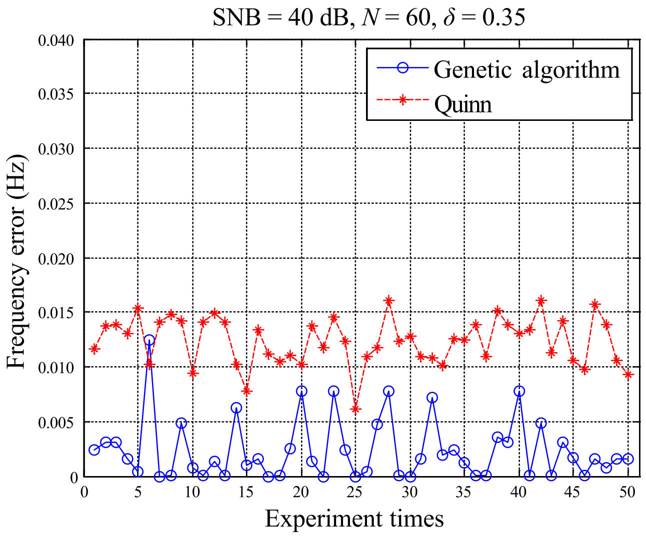

FIGURE 3 Performance of genetic algorithm when signal-to-noise ratio was high

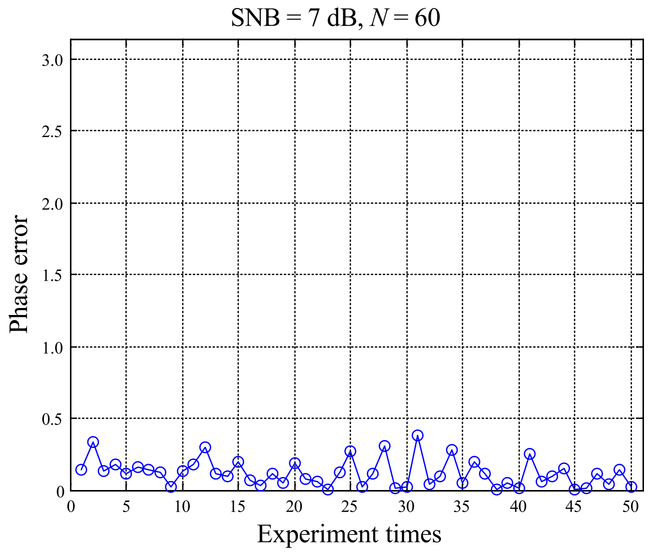

FIGURE 5 Phase estimation performance of genetic algorithm when signal-to-noise ratio was low

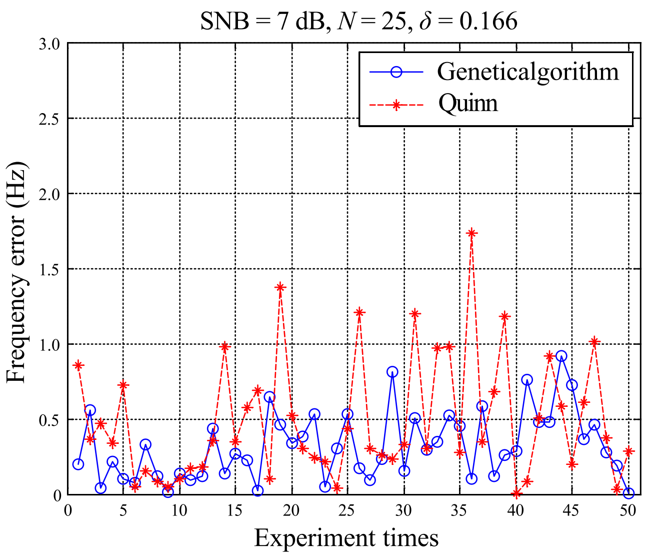

FIGURE 4 Performance of genetic algorithm when signal-to-noise ratio was low

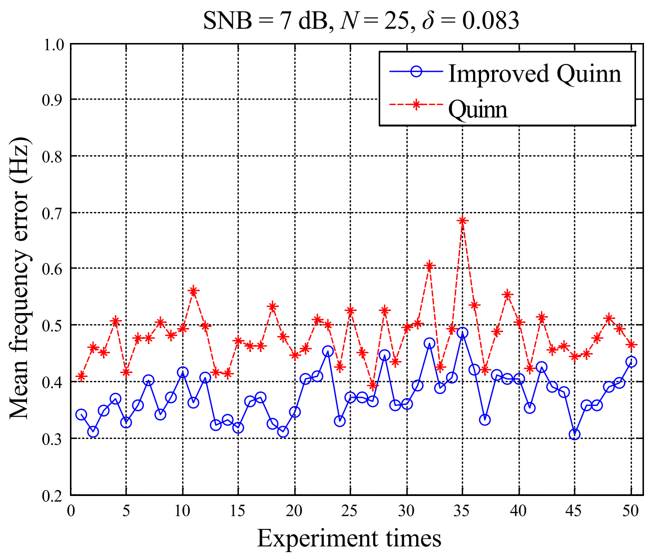

FIGURE 6 Estimation performance of improved ratio algorithm with δ close to 0

were five generations in the algorithm and the population size was 100 in each generation. We assumed a sampling rate of f_s = 120 Hz, 60 sampling points (the number of points after one pulse conversion of the ADS-B system), and a SNR of 40 dB. A comparison of the errors of the signal frequency estimated directly with the genetic algorithm and the frequency estimated directly using the conventional method is shown in Figure 3 (δ in this figure was described in Section 2.4).

Figure 3 shows that the error of the frequency estimated by the genetic algorithm was greatly reduced compared with the conventional algorithm when the SNR was high. Figure 4 shows the results when the SNR was reduced to 7 dB (the SNR of the signal received by the space-based system) and when the number of sampling points was reduced to 25.

At lower SNRs, the algorithm designed in this study was still better than the conventional estimation algorithm. In addition, the algorithm could directly estimate the initial phase and thereby directly perform coherent demodulation. At a low SNR of 7 dB, the accuracy of the direct phase estimation was higher. The errors are shown in Figure 5.

Genetic algorithms exhibit poor real-time performance because they are computationally intensive. In this study, we estimated the signal frequency with the improved Quinn

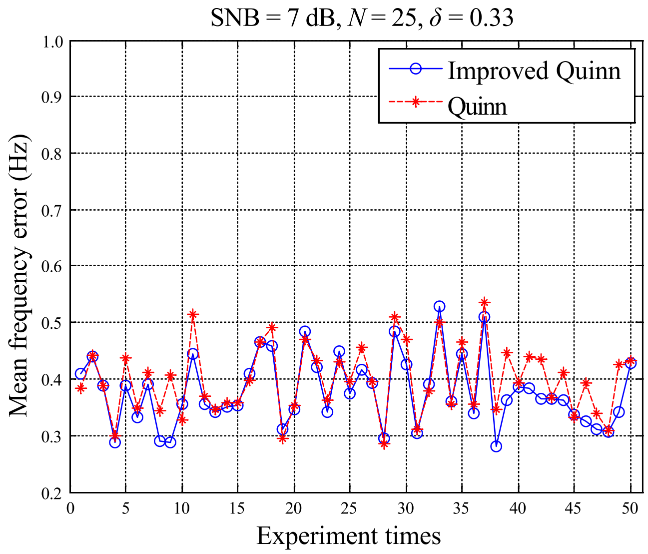

FIGURE 7 Estimation performance of improved ratio algorithm with δ not close to 0

ratio algorithm, which is less computationally intensive. Our proposed algorithm improved the accuracy of the original algorithm when δ was close to 0, but the improvement was less substantial when $|\delta|$ was close to 0.5. The errors of the algorithm in different environments are shown in Figures 6 and 7.

4 | CONCLUSION

The space-based ADS-B system is an important development direction for the ADS-B system. Compared with the conventional system, the space-based ADS-B system can provide continuous and stable aircraft surveillance capabilities covering the whole world. Therefore, it can provide better support for air traffic safety management while also making great progress in efficiency and cost-effectiveness. Faced with the challenges of space-based systems, we proposed the idea of detecting weak ADS-B signals by coherent demodulation and designed a practical implementation method. We first presented a header detection method for accurately detecting the pulse position in a weak ADS-B signal. We designed an encoding method, shaping method, and fitness function so that the genetic algorithm could be used to estimate the frequency and phase of the detected signal and achieve higher precision. The advantage of this algorithm is that the frequency and phase can be estimated simultaneously, and coherent demodulation can be performed directly. To address the computational intensiveness of the genetic algorithm, we improved the ratio algorithm to estimate the signal frequency with higher precision while increasing the volume of computations only slightly and using a small number of sample points.

The algorithm described in this article performs well in a simulated environment, and future research should extend it to more general situations. In addition to signal demodulation, de-interlacing also remains an important challenge for space-based systems, and requires further study.

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