

Weak GPS signal tracking using block coherent integration based on NN discriminator

Zhiqiang Gong

National University of Defense Technology

honglei lin

linhonglei@nudt.edu.cn

National University of Defense Technology

Liu Zhe

National University of Defense Technology

Gang Ou

National University of Defense Technology

Research Article

Keywords: GNSS, Tracking loop, Phase-Locked Loop, Neural network

Posted Date: April 24th, 2025

DOI: <https://doi.org/10.21203/rs.3.rs-6350123/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Weak GPS signal tracking using block coherent integration based on NN discriminator

Zhiqiang Gong^{1,2}, honglei lin^{1,2*}, Liu Zhe^{1,2}, Gang Ou^{1,2}

¹ National University of Defense Technology, College of Electronic Science and Technology, Changsha, 410000, China

² National Key Laboratory for Positioning, Navigation and Timing Technology, Changsha, 410000, China

* Corresponding author: Honglei Lin (E-mail: linhonglei@nudt.edu.cn)

Abstract

High sensitivity carrier phase tracking is critical for intelligent unmanned mobile devices such as smart drones and autonomous vehicles. To address the issue of sensitivity degradation caused by signal amplitude attenuation in traditional coherent integration (CI) methods, this paper proposes a Blocked Coherent Integration Neural Phase-Locked Loop (BCI-NPLL) method. By constructing a Blocked Coherent Integration (BCI) matrix and integrating it with a hybrid neural network discriminator, the method achieves improved carrier phase estimation. Additionally, a novel sensitivity evaluation approach is proposed to quantitatively assess the sensitivity and accuracy of closed-loop tracking. Through semi-analytical simulations, the loop phase jitter model under the proposed BCI method is validated, and the

practical performance of the Neural Phase-Locked Loop (BCI-NPLL) method is tested using both simulations and real GNSS signals. The results show that the Blocked Coherent Integration BCI-NPLL improves the sensitivity by 2 to 3 dB under static conditions compared to traditional PLL methods. Under $1g$ and $2g$ acceleration conditions, sensitivity is improved by 4 dB and 5 dB respectively. In addition, BCI-NPLL achieves a 15% to 26% improvement in tracking accuracy as the Carrier-to-Noise Ratio (CNR) decreases.

Keywords GNSS · Tracking loop · Phase-Locked Loop · Neural network

Introduction

Navigation in urban environments is a critical area for the civil applications of Global Navigation Satellite Systems (GNSS), and robust positioning technology is a prerequisite for autonomous driving and intelligent transportation networks (Parekh et al. 2022). Furthermore, the application of reliable and low-cost consumer-grade GNSS chips in unmanned intelligent mobile devices such as smart drones and autonomous vehicles has become an increasingly prominent trend (Zhang et al. 2018; Niesen et al. 2018). However, in urban environments, GNSS signal energy can be severely degraded or even unavailable due to signal blockage, multipath interference and other problems (Yan et al. 2023). Currently, there are three main approaches to address this issue: 1. increasing the coherent integration time to improve the Signal-to-Noise Ratio (SNR) of the coherent integration signal (Zhong 2024); 2. improving loop filter design to enhance noise reduction capability (Jiang et al. 2017); and 3. improving the estimation accuracy of the discriminator (Yan et al. 2016; Han et al. 2022); These methods can be applied individually or in combination to achieve better performance. Additionally, A-GPS is often combined with the

aforementioned methods to further improve performance.

When increasing the coherent integration time of the signal, three main issues arise: unknown navigation data bit flips, user dynamics, and oscillator clock instability (Alban et al. 2003). For the issue of navigation data bit flips, in the presence of a reference station, this can be eliminated using Assisted GNSS (A-GNSS) technology (Van Diggelen 2009). In the absence of a reference station, standalone GNSS receivers typically employ navigation position prediction algorithms or non-coherent integration methods to address this problem (Ren and Petovello 2017; Borio and Lachapelle 2009). Moreover, new GNSS signals such as GPS L5 and B1C introduce pilot signals, which mitigate the issue of navigation data bit flips (Thoele et al. 2019). To eliminate the effects of relative motion between the receiver and the satellite, an Inertial Measurement Unit (IMU) is commonly used to assist the GNSS receiver (Hasan et al. 2009; Srinivas and Kumar 2017). Studies have shown that the tracking error of an INS-assisted GNSS tracking loop in high dynamic conditions is comparable to the tracking error under static testing (Pany et al. 2005; Bernal et al. 2008; Zhang et al. 2017). Regarding oscillator clock instability, Focal Point developed the ultra-correlation technology (Faragher et al. 2018), and Xin Feng proposed the LCI technique (Feng et al. 2023), both of which use external strong signals to assist in correcting the instability of the oscillator, thereby achieving ultra-long coherent integration. However, when the signals are weak, the effectiveness of the above methods remains limited and the problem has not been fully resolved.

There are currently two main approaches for improving loop filters. One approach is to use Kalman filtering as the loop filter to denoise the discriminator output (Klokov et al. 2022; Jiang et al. 2017; Niu et al. 2017). The advantage of this method lies in the simplicity of the design matrix, while the disadvantage is that the measurement noise covariance does not follow a Gaussian distribution. The other

approach is to use Extended Kalman Filtering (EKF) to directly process the coherent integration values of the I and Q branches (Ziedan and Garrison 2004; Tang et al. 2013; Chen et al. 2018). The advantage of this method is that the noise characteristics of the I and Q branch coherent integration values satisfy the white Gaussian noise assumption, which is a key assumption in the EKF algorithm. On this basis, it has been further developed into vector tracking, the advantages of which in terms of high sensitivity have been demonstrated by mathematical derivation and theoretical analysis (Lashley et al. 2009). In recent years, vector tracking has been extensively studied for applications in harsh environments, such as under weak signal (Petovello et al. 2008), multipath (Hsu et al. 2013) and non-line-of-sight (NLOS) conditions (Hsu et al. 2015). Vector tracking can also be combined with IMU assistance to construct ultra-tight INS/GNSS based on vector tracking loops (Zeng et al. 2016; Yan et al. 2020). However, the drawback of vector tracking is that it is more complex than standard tracking, and the data between loops is highly interrelated, meaning that errors in any one channel will propagate through the system (Yan et al. 2017).

In improving the discriminator to enhance sensitivity, research has mainly focused on improving Frequency Lock Loop (FLL) discriminators, such as Differential Amplitude (DA) discriminators and FFT-based discriminators. The DA discriminator was first proposed by Wenfei Guo using multiple NCOs to implement a structure similar to early delay, thereby enabling frequency discrimination using the DA discriminator. Experimental results verified its effectiveness under weak signal conditions (Guo et al. 2014). Subsequently, Ji Li combined the DA method with a moving window to propose the memory discriminator, which improves Doppler estimation quality by reducing the variance of the measurements, thus mitigating noise effects and achieving better tracking performance (Li et al. 2018). Compared to tracking based on traditional discriminators, FFT processing provides a more ideal way to obtain linear measurements and a lower tracking signal-to-noise ratio threshold (Palmer 1974). Kunlun Yan developed

a tracking architecture using an FFT-based carrier frequency discriminator and an INS-assisted tracking method based on an FFT discriminator, processing I/Q coherent integration results with FFT to improve tracking sensitivity. In addition, this approach reduces the computational load of the tracking loop compared to processing intermediate frequency signals with FFT (Yan et al. 2017). Building on this, Xinlong Wang implemented a dynamic segmentation tracking loop based on FFT, which uses a multi-NCO structure and multi-correlator design. By selecting the optimal values for dynamic frequency step and FFT size, the signal-to-noise ratio gain is maximized, thus improving tracking sensitivity (Wang et al. 2015).

Although the above methods have made some progress in improving weak signal processing capabilities, they are essentially open-loop architectures. When frequency discrimination errors occur, these methods cannot compensate for them, making it easy to lose lock directly (Borovic et al. 2005). Moreover, the receivers mentioned above can only rely on pseudorange measurements, which have much lower accuracy than carrier phase measurements. In contrast, the Phase-Locked Loop (PLL) not only provides more precise carrier phase measurements but also offers better weak signal tracking capabilities (Ziedan and Garrison 2004). However, when dealing with weak signals, the frequency mismatch between the local signal and the satellite signal significantly reduces the energy of the coherent integration signal, which is a major obstacle to further improving sensitivity.

To address the above issues, this paper proposes an Blocked Coherent Integration (BCI) method along with a corresponding neural network (NN) discriminator. Compared to existing coherent integration methods and the atan discriminator, the tracking sensitivity is improved by 2 to 3 dB and the tracking accuracy is improved by 15% to 26% under static conditions. Under $1g$ and $2g$ acceleration conditions, the tracking sensitivity is improved by 4 dB and 5 dB respectively. The

innovations and contributions of this paper are summarized as follows:

- An Blocked Coherent Integration (BCI) method is proposed. By dividing the continuous coherent integration (CI) into multiple shorter coherent integration blocks, and keeping the total integration time constant, the effect of the frequency mismatch on the signal is effectively mitigated by shortening the duration of each integration block.
- Based on the characteristics of the BCI method, a neural network discriminator is designed to match it. The BCI values are treated as two-dimensional images and input into the NN discriminator for joint estimation. This design fully exploits the performance of the BCI signal and improves the estimation accuracy of the discriminator.
- A new evaluation method is proposed to assess the closed-loop tracking sensitivity and accuracy. First, Cramér-Rao Lower Bound (CRLB) for the BCI method and the CI method is calculated. Then, the relationship between the phase jitter of the tracking loop and the CRLB is derived. Finally, experimental results verify the correctness of the proposed method.

The remainder of this paper is organized as follows: First, the signal processing flow of the receiver's tracking section are introduced, and the BCI method along with its corresponding NN discriminator are further explained. Next, the estimation and tracking performance of the BCI method are analyzed, including the impact of the number of blocks on performance. Then, the experimental design and result analysis are discussed in detail. Finally, a conclusion is drawn and the future work is outlined.

BCI-NPLL tracking methodology

In this section, the signal processing of the receiver, the coherent integration signal and the problems it

faces are described. Then, the BCI method proposed in this paper and its corresponding NN discriminator are described in detail.

Traditional tracking methods

Satellite signals propagate in space in the form of high-frequency carrier waves, which can be expressed as:

$$s(t) = \sqrt{2P} d(t) c(t) \cos(2\pi f_c t + \phi) \quad (1)$$

Where P represents the average power of the satellite signal, f_c is the carrier frequency, ϕ is the carrier phase, and $c(t)$ and $d(t)$ represent the ranging code and navigation data code, respectively.

When the signal reaches the receiver, it undergoes front-end processing and is converted to an intermediate frequency signal, which is expressed as:

$$y(t) = \sqrt{2C} d(t - \tau_0) c(t - \tau_0) \cos[2\pi t(f_{IF} + f_d) + \phi_0] + \eta(t) \quad (2)$$

- C is the average power of the intermediate frequency (IF) signal;
- f_{IF} is the frequency of the intermediate frequency signal;
- f_d is the Doppler frequency shift relative to f_{IF} ;
- τ_0 is the signal propagation delay;
- ϕ_0 is the initial phase;
- $\eta(t)$ is zero-mean additive white Gaussian noise (AWGN).

The received intermediate frequency (IF) signal $y(t)$ is tracked by the receiver using a Phase-Locked Loop (PLL) to lock precisely to the phase and frequency of the signal. The PLL achieves frequency and phase locking by synchronizing the received signal with the local signal phase. The operation of the PLL involves five key modules, as shown in Figure 1:

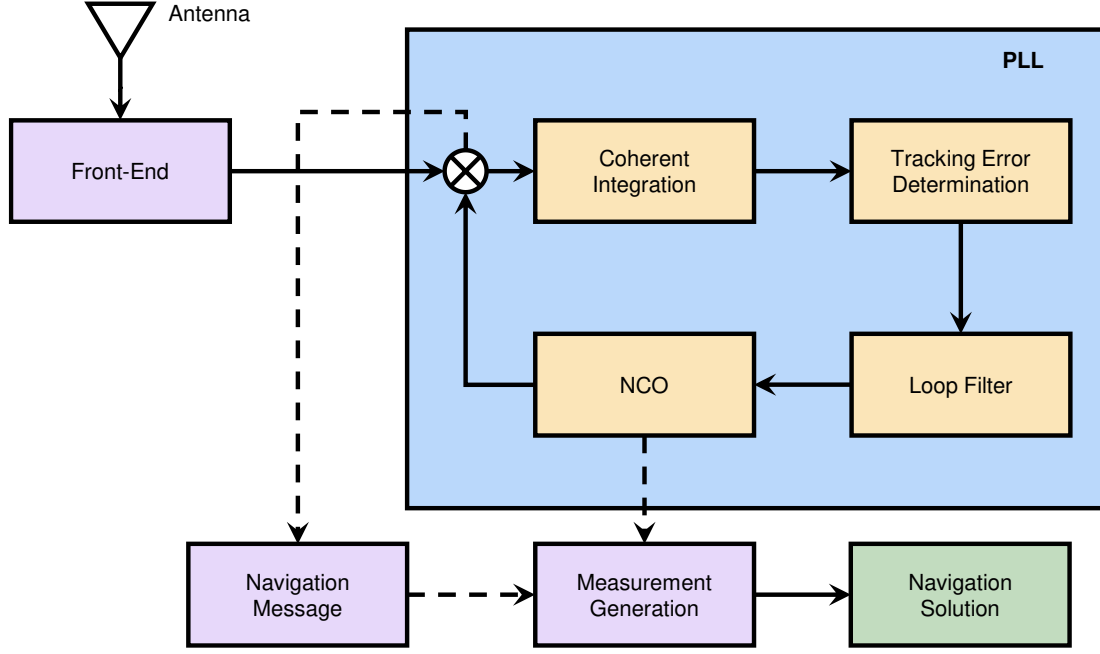


Fig. 1 Structure of the GNSS Receiver. The section enclosed in the blue box represents the specific modules of the PLL.

- Multiplier: Multiplies the received signal with the local reference signal to generate the error signal.
- Coherent Integration Module: Integrates the error signal to improve the SNR.
- Phase Comparator: Performs phase estimation on the integrated error signal.
- Loop Filter: Filters high-frequency noise, smooths the error signal, and ensures a stable control signal output.
- Numerically Controlled Oscillator (NCO): Adjusts the local oscillator frequency based on the output of the loop filter to maintain synchronization with the received signal.

After passing through the multiplier and coherent integration, the signal can be expressed as:

$$r_p(t) = \sqrt{\frac{C}{2}} R(\tau_e) \frac{\sin(\pi f_e T_{\text{coh}})}{\pi f_e T_{\text{coh}}} \exp[j(\pi f_e T_{\text{coh}} + \theta_0)] + \eta'(t) \quad (3)$$

In the equation:

- $R(\tau)$ is the autocorrelation function of the ranging code;
- τ_e is the ranging code phase error;
- f_e is the carrier frequency deviation;
- θ_0 is the initial phase error;
- $\eta'(t)$ is the AWGN after integration processing.

Under the assumption of perfect synchronization of the pseudocode, i.e., $R(\tau_e) = R(0) = 1$ the amplitude of the coherent integration signal will be attenuated if there is a frequency mismatch between the local signal and the received signal. Figure 2 shows how the signal amplitude varies with frequency offset for different coherent integration times (20 ms, 10 ms, and 5 ms). It can be seen that for a fixed frequency offset, the signal energy attenuation becomes more significant as the coherent integration time increases.

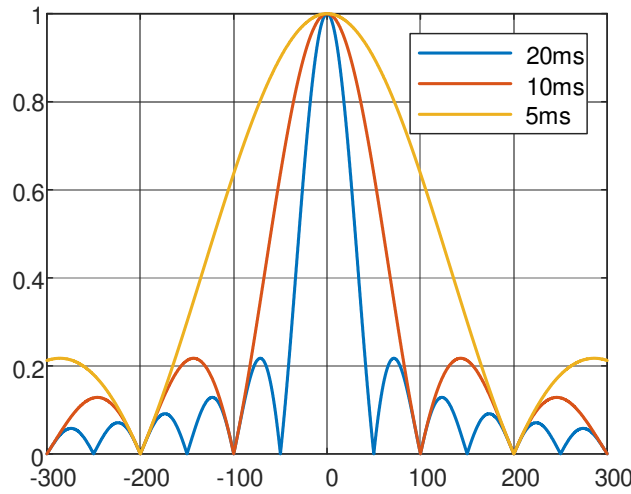


Fig. 2 Amplitude of the Coherently Integrated Signal, where the blue, red, and yellow lines represent integration times of 20 ms, 10 ms, and 5 ms, respectively.

To mitigate this energy attenuation, a common approach is to shorten the coherent integration time or reduce the loop bandwidth. However, shortening the coherent integration time reduces the integration gain, which negatively impacts the performance of the tracking loop. On the other hand, reducing the

loop bandwidth can effectively decrease the loop noise and minimize the frequency offset, thereby mitigating the impact of frequency offset on the coherent integration signal. However, reducing the loop bandwidth also limits the dynamic response capability of the tracking loop, leading to degraded tracking performance under dynamic conditions. Therefore, the trade-off between gain and attenuation and the effect of loop bandwidth on dynamic response is a key design issue. Existing research has not yet found an effective solution that simultaneously addresses the energy attenuation problem while ensuring dynamic tracking performance.

To solve this issue, this paper proposes a method that divides the coherent integration (CI) into multiple shorter integration blocks. By keeping the total integration time constant and shortening the duration of each integration block, the method effectively reduces the impact of frequency offset on the coherent integration signal and avoids the problem of decreased dynamic response caused by reducing loop bandwidth.

BCI-NPLL methods

Figure 3 shows the improved PLL structure. This PLL-based structure adopts BCI method and uses a NN discriminator instead of the atan discriminator. The working principle of the BCI-NPLL local tracking is detailed within the blue dashed box above Figure 3. The innovative method proposed in this paper divides the coherent integration data into multiple time blocks for processing and constructs a two-dimensional processing matrix. A hybrid NN discriminator is designed, combining Convolutional Neural Networks (CNN) and Feedforward Neural Networks (FNN). CNN is used to extract key features from the two-dimensional matrix, while FNN further analyzes these features to precisely estimate the phase error of the signal. This method not only accumulates the same energy as long coherent integration overall, but also significantly reduces the energy attenuation within a single coherent cycle, thereby

increasing the total energy of the coherent integration signal. This optimization improves the adaptability of the system to signal variations.

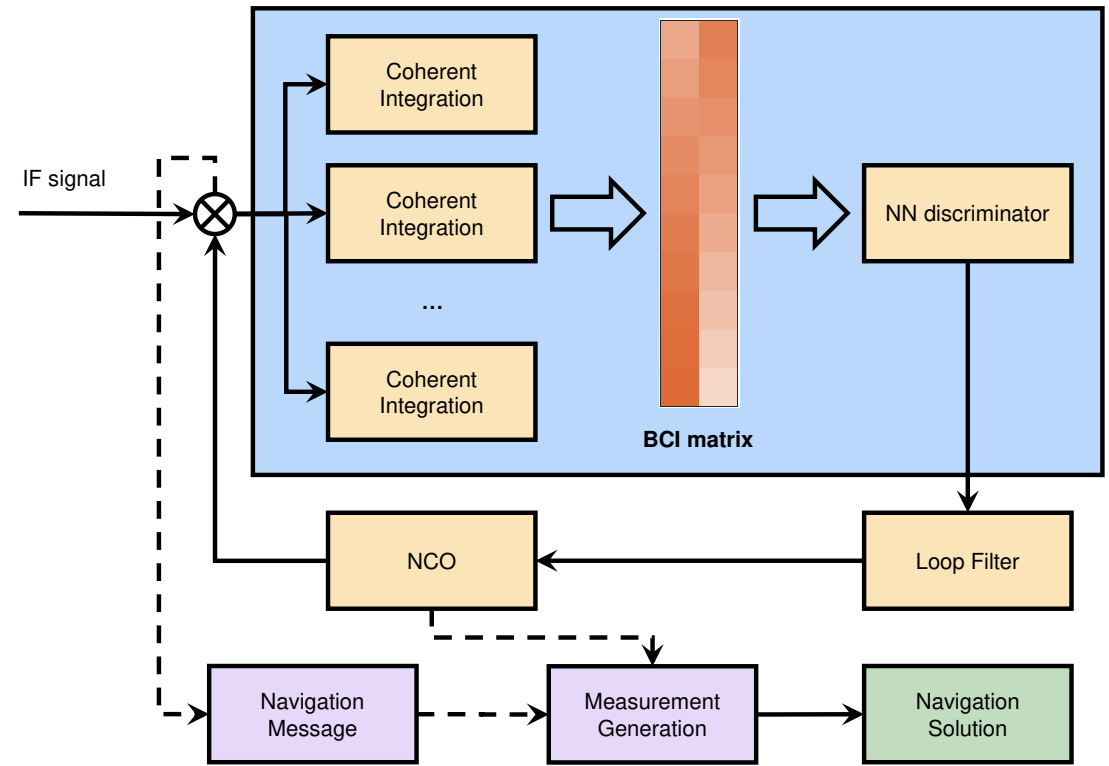


Fig. 3 BCI-NPLL Tracking Loop Model, where the blue region represents the specific optimization method.

BCI signal methods

Figure 4 visually illustrates the relationship between the BCI and CI methods in the time domain. Compared to the CI method, the BCI method mitigates the effect of frequency offset by reducing the coherent integration time of each coherent integration signal block, thereby maintaining a higher overall signal energy. This characteristic allows the BCI method to demonstrate superior tracking performance. The mathematical expression of the BCI method is as follows:

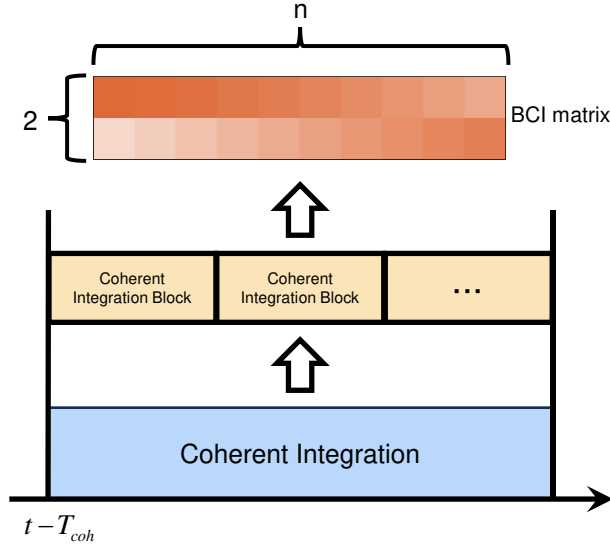


Fig. 4 Relationship between the BCI and CI Methods in the Time Domain, with the orange section

representing the BCI matrix.

$$\begin{aligned}
 x(t) &= \sqrt{\frac{C}{2}} R(\tau_e) \begin{bmatrix} \frac{\sin\left(\frac{\pi f_e T_{coh}}{n}\right)}{\frac{\pi f_e T_{coh}}{n}} \cos\left(\frac{\pi f_e T_{coh}}{n} + \theta_0\right) & \dots & \frac{\sin\left(\frac{\pi f_e T_{coh}}{n}\right)}{\frac{\pi f_e T_{coh}}{n}} \cos\left(\frac{\pi f_e T_{coh}}{n} + \theta_n\right) \\ \frac{\sin\left(\frac{\pi f_e T_{coh}}{n}\right)}{\frac{\pi f_e T_{coh}}{n}} \sin\left(\frac{\pi f_e T_{coh}}{n} + \theta_0\right) & \dots & \frac{\sin\left(\frac{\pi f_e T_{coh}}{n}\right)}{\frac{\pi f_e T_{coh}}{n}} \sin\left(\frac{\pi f_e T_{coh}}{n} + \theta_n\right) \end{bmatrix} \\
 &= \sqrt{\frac{C}{2}} R(\tau_e) \frac{\sin\left(\frac{\pi f_e T_{coh}}{n}\right)}{\frac{\pi f_e T_{coh}}{n}} \begin{bmatrix} \cos\left(\frac{\pi f_e T_{coh}}{n} + \theta_0\right) & \dots & \cos\left(\frac{\pi f_e T_{coh}}{n} + \theta_n\right) \\ \sin\left(\frac{\pi f_e T_{coh}}{n} + \theta_0\right) & \dots & \sin\left(\frac{\pi f_e T_{coh}}{n} + \theta_n\right) \end{bmatrix}
 \end{aligned} \quad (4)$$

Under the same total integration time, the noise suppression capability of the BCI method and the CI method is the same. However, by comparing Equation (3) and Equation (4), it can be observed that the signal amplitude of the BCI method is higher. This indicates that the main advantage of the BCI method is the enhance in signal amplitude, and with the noise level unchanged, the increase in signal amplitude effectively results in an indirect improvement in the SNR.

To further analyze the amplitude difference between the two methods, the signal portion is removed from the model to obtain the amplitude expressions for the BCI method and the CI method, respectively:

$$A = \text{sinc}(\pi f_e T_{\text{coh}}) \quad (5)$$

$$A' = \text{sinc}\left(\frac{\pi f_e T_{\text{coh}}}{n}\right) \quad (6)$$

Comparing Equation (5) and Equation (6), it can be observed that the amplitude improvement of the BCI signal relative to the CI signal is closely related to the number of blocks n , the frequency offset f_e , and the coherent integration time T_{coh} . The BCI method exhibits more significant performance advantages under larger values of f_e and T_{coh} . However, it should be noted that in a locked loop, there is an inherent balance between f_e and T_{coh} , i.e., $f_e < 1/2T_{\text{coh}}$. Therefore, the performance improvement of the BCI method over the CI method does not depend on f_e or T_{coh} alone, but is determined by the joint effect of both.

Additionally, by fixing the relationship between the parameters f_e and T_{coh} , the amplitude comparison for different values of n can be obtained, as shown in Figure 5. The results show that as n increases, the amplitude of the BCI signal also increases correspondingly. However, increasing n also significantly increases the computational complexity, which needs to be balanced in practical applications. From the figure, it can be observed that under the condition of $f_e < 1/2T_{\text{coh}}$, the maximum improvement of the BCI signal relative to the CI signal can reach 4 dB. However, since in real loops f_e is usually smaller than $1/2T_{\text{coh}}$, this implies that the performance improvement of the BCI method relative to the CI method is between 0 and 4 dB.

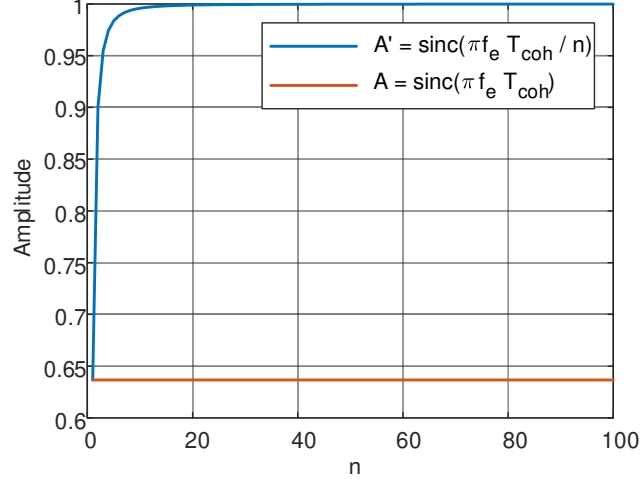


Fig. 5 Amplitude of the CI and BCI Methods for Different n Values, with the blue line and red line representing the BCI and CI methods, respectively.

It is important to emphasize that the atan phase estimation method struggles to reach the estimation lower bound of the BCI signal. This is because the atan method is unable to fully estimate the joint characteristics in the BCI signal, and joint estimation of the BCI signal is crucial for fully exploiting its performance. To address this issue, this paper develops a NN discriminator that matches the characteristics of the BCI signal.

Neural Network-Based Phase Estimator

To approximate the phase estimation lower bound of the BCI method, this paper proposes a neural network-based carrier phase estimator. The framework relies on NN by training on IF signal datasets. The NN consists of a series of layered structures, with each layer containing multiple neurons. Each neuron can be viewed as a function that performs a weighted sum of the input signals, followed by a transformation through a predefined nonlinear activation function. This structure of weighted summation and nonlinear transformation provides neurons with the ability to process and transmit information.

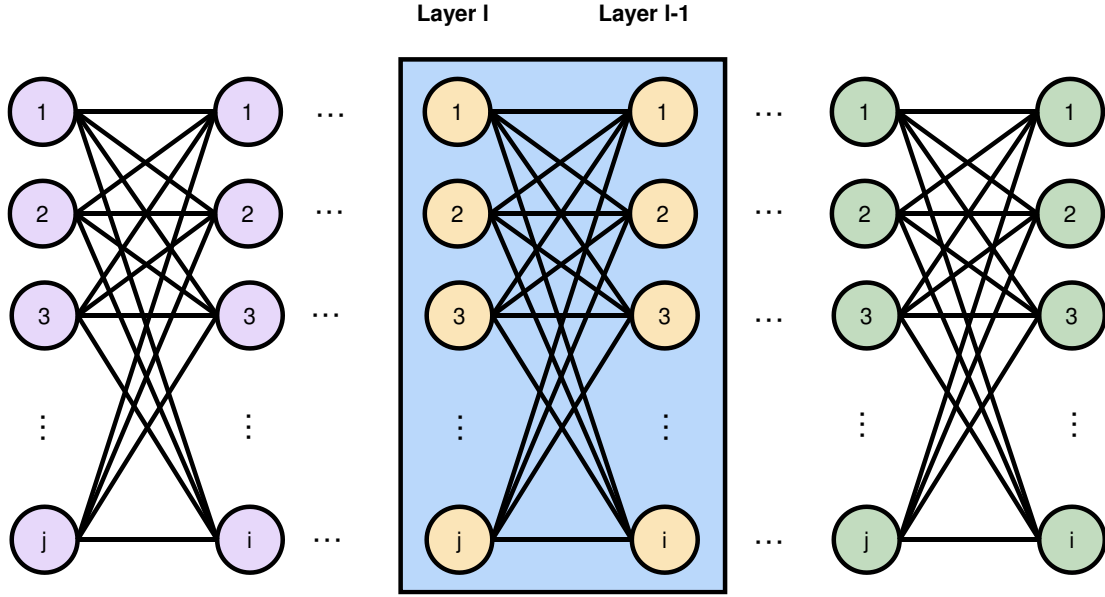


Fig. 6 General Structure of the Neural Network Method.

A typical NN consists of an input layer, an output layer, and multiple hidden layers. The general structure of an NN is shown in Figure 6, where the connection between the i neuron in the l layer and the j neuron in the $(l-1)$ layer is characterized by the weight parameter w_{ij} . The weight w_{ij} quantifies the influence of the $(l-1)$ layer's neuron j on the input to the l layer's neuron i . Furthermore, by introducing a bias term b_i , the x_i^l is adjusted, and the final result is obtained:

$$x_i^l = f \left(b_i + \sum_{j=0}^D w_{ij}^l x_j^{l-1} \right) \quad (7)$$

In the equation, $f(\cdot)$ is the activation function, and D is the number of neurons in the $(l-1)$ layer. Based on the above formula, the output of the l layer can be expressed as:

$$\mathbf{x}^l = \mathbf{f}(\mathbf{b}_l + \mathbf{W}_l \mathbf{x}^{l-1}) = \mathbf{f}_l(\mathbf{x}^{l-1}) \quad (8)$$

Therefore, the output of the NN can be expressed as:

$$\mathbf{y} = \mathbf{f}_L(\mathbf{f}_{L-1}(\cdots \mathbf{f}_1(\mathbf{x}))) \quad (9)$$

Given that the atan discriminator module is not well suited for the BCI method, this paper introduces a hybrid NN discriminator as an alternative to the discriminator in the PLL. The hybrid NN

model consists of two key modules: CNN and FNN. CNN simulates the biological visual perception mechanism and performs feature extraction on the input data through its convolutional layers. The CNN is trained using both supervised and unsupervised learning strategies and learns through layer-by-layer forward propagation, effectively overcoming challenges in training deep networks. CNN was originally developed for two-dimensional image recognition, and its input is typically a two-dimensional image. Therefore, in this paper, the segmented coherent integration signal, which varies with time and frequency offset, is treated as a two-dimensional image, as shown in Figure 7, so that CNN can be applied to process it. In this way, CNN extracts key features from the input two-dimensional matrix, and then FNN performs nonlinear regression on the extracted features to generate accurate estimates.

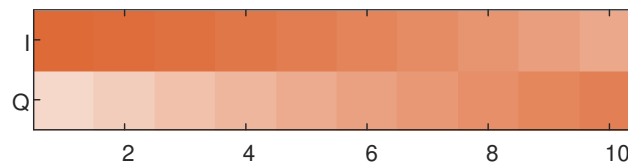


Fig. 7 BCI Matrix, where the color intensity indicates the magnitude of the values.

For real-time tracking of satellite signals, the estimation speed of the model is crucial. Although CNN significantly reduce computational load and accelerate processing speed through parameter sharing and local connections, this paper still adopts a structurally simplified neural network model to ensure efficiency in real-time signal tracking. As shown in Figure 8, the hybrid neural network model used in this paper consists of an input layer, three convolutional layers, three pooling layers, two fully connected layers, and an output layer. This design retains the fast processing advantages of CNN while further reducing model complexity by decreasing the number of network layers, thereby ensuring efficiency in real-time signal tracking applications. The simplified network architecture not only meets real-time requirements but also provides a solid foundation for future optimization and expansion.

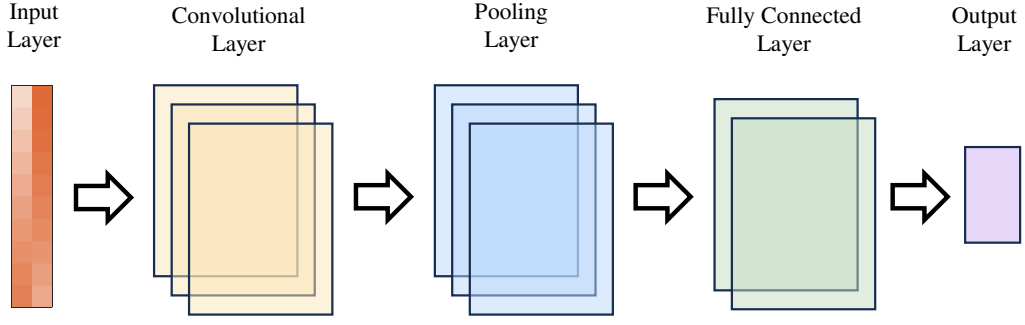


Fig. 8 Internal Structure of the NN Discriminator, where the input is the BCI matrix and the output is the phase error.

The CNN unit is typically composed of convolutional layers and pooling layers, and can be described by the following equation:

$$\mathbf{x}^l = \mathbf{f}(\mathbf{b}_l + \mathbf{W}_l * \mathbf{x}^{l-1}) = \mathbf{f}_l(\mathbf{x}^{l-1}) \quad (10)$$

$$y_{ij} = \frac{1}{h \times w} \sum_{a=0}^{h-1} \sum_{b=0}^{w-1} x_{i+a, j+b} \quad (11)$$

In the equation, $*$ denotes the convolution operation, $\mathbf{W}_l$ is the weight matrix of the l layer, h is the height of the pooling layer window, and w is the width of the pooling layer window. The computational formula for FNN is the same as that of a standard neural network framework and will not be described in detail here.

Before training, the training data is divided into training and testing sets. Adjustable parameters that affect the network performance include epoch, activation function, loss function, optimizer, learning rate, etc. (see Table 1).

Table 1. Adjustable Parameters Affecting Network Performance

No	Parameter	Value
1	Loss function	MSE
2	Optimizer	Adam

3	Activation function	ReLU
4	Learning rate	0.01
5	Epoch	200
6	Input size	$n \times 2 \times 1$
7	Kernel size	(2, 2)

Figure 9 shows the phase estimation results of the atan discriminator and the NN discriminator in the BCI method under simulated signal conditions. In the simulation, a coherent integration time of 10 ms and a satellite signal tracking loop with a bandwidth of 10 Hz were set. The figure compares the outputs of the atan discriminator and the NN discriminator with the true phase values. The results show that, although both discriminators are able to effectively identify phase errors, the NN discriminator performs better in terms of accuracy. This not only verifies the effectiveness of the NN discriminator, but also demonstrates its potential in complex signal processing tasks, laying the foundation for future applications in complex environments.

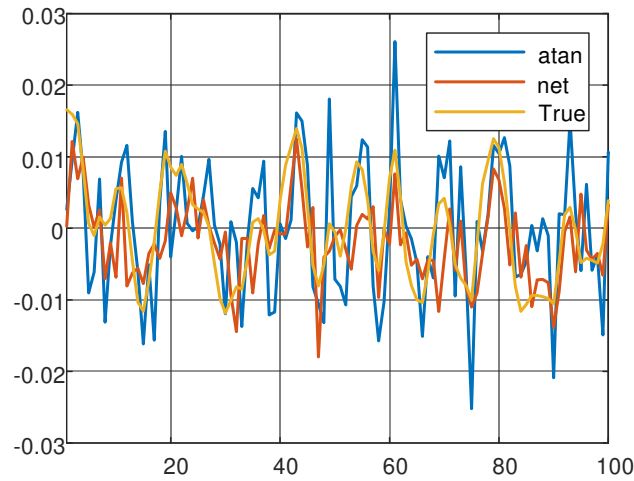


Fig. 9 Outputs of different discriminators under the BCI Method, where the blue, red, and yellow lines represent the outputs of the atan discriminator, the NN discriminator, and the true phase error, respectively.

Methods Performance Analysis and Comparison

In this section, the Cramér-Rao Lower Bound (CRLB) of the BCI method is first analyzed, and based on this, the closed-loop tracking error of the BCI method is studied. Then the effect of the choice of the number of blocks n on the performance is discussed.

Cramér-Rao of BCI methods

In this subsection, the CRLB of the phase estimation of the BCI method under different CNR is analysed in order to quantitatively assess the performance of the BCI method in phase estimation. In the calculations presented in this paper, the outputs of the correlator values I and Q are treated as complex numbers, i.e., $(I + jQ) = \exp[j(\pi f_e T_{\text{coh}} + \theta_0)] = \exp(j\varphi)$. In combination with the CI method and the BCI method, we will model the observations as follows:

$$x_1(i) = R(\tau_e) \text{sinc}(\pi f_e T_{\text{coh}}) \exp[j(\pi f_e T_{\text{coh}} i + \theta_0)] + \eta(i), \quad i = 1 \quad (12)$$

$$x_2(i) = R(\tau_e) \text{sinc}\left(\frac{\pi f_e T_{\text{coh}}}{n}\right) \exp\left\{j\left[\frac{\pi f_e T_{\text{coh}}(1+2i)}{n} + \theta_0\right]\right\} + \eta'(i), \quad i = 0, 1, \dots, n-1 \quad (13)$$

Since this paper mainly focuses on the impact of frequency offset on estimation accuracy, the effect of the code loop is neglected and it is assumed that the code phase is perfectly aligned. During the satellite tracking process, the CI signal model exhibits amplitude attenuation due to the carrier frequency offset. However, this attenuation primarily affects the SNR of the coherent integration signal and does not influence the core process of phase estimation. To simplify the model, the amplitude is not considered as part of the estimate but is instead correlated only with the SNR of the integrated signal. Based on the above assumptions, the observation model is adjusted accordingly, and the final observation model suitable for loop estimation is established:

$$x_1(i) = A \exp[j(\pi f_e T_{\text{coh}} i + \theta_0)] + \eta(i), \quad i = 1 \quad (14)$$

$$x_2(i) = A' \exp\left\{j\left[\frac{\pi f_e T_{\text{coh}}(1+2i)}{n} + \theta_0\right]\right\} + \eta'(i), \quad i = 0, 1, \dots, n-1 \quad (15)$$

$$\bullet \quad A = \text{sinc}(\pi f_e T_{\text{coh}});$$

- 345 • $A' = \text{sinc}\left(\frac{\pi f_e T_{\text{coh}}}{n}\right)$;
- 346 • $\eta(i) \sim \mathcal{N}\left(0, \frac{1}{2\text{CNR} \cdot T_{\text{coh}}}\right)$, which is zero-mean Gaussian noise.
- 347 • $\eta'(i) \sim \mathcal{N}\left(0, \frac{n}{2\text{CNR} \cdot T_{\text{coh}}}\right)$, which is zero-mean Gaussian noise.

348 For the above observation model, this paper defines the estimation vector as $\boldsymbol{\theta} = [f_e \ \theta_0]^T$.

349 The Fisher information matrix for this model is calculated as:

$$350 \quad [\mathbf{I}(\boldsymbol{\theta})]_{ij} = \frac{2}{\sigma^2} \text{Re} \left[\sum_{n=0}^{N-1} \frac{\partial s[n; \boldsymbol{\theta}]}{\partial \theta_i} \frac{\partial s[n; \boldsymbol{\theta}]}{\partial \theta_j} \right] \quad (16)$$

351 Where $s[n; \boldsymbol{\theta}] = A \exp[j(\pi f_e T_{\text{coh}} n + \theta_0)]$. Combining equations (15) and (16) gives the Fisher
 352 information matrix and the CRLB of the estimation vector.

$$353 \quad \mathbf{I}(\boldsymbol{\theta}) = \begin{bmatrix} \frac{(2n+1)(2n-1)(\pi T_{\text{coh}} A)^2}{3n\sigma^2} & \frac{n\pi T_{\text{coh}} A^2}{\sigma^2} \\ \frac{n\pi T_{\text{coh}} A^2}{\sigma^2} & \frac{nA^2}{\sigma^2} \end{bmatrix} \quad (17)$$

$$354 \quad \text{var}(\hat{f}_e) = \frac{3n^2}{2(n^2-1) \left(\pi T_{\text{coh}} \text{sinc}\left(\frac{\pi f_e T_{\text{coh}}}{n}\right) \right)^2 \text{CNR} \times T_{\text{coh}}} \quad (18)$$

$$355 \quad \text{var}(\hat{\theta}_0) = \frac{(4n^2-1)}{2(n^2-1) \left(\text{sinc}\left(\frac{\pi f_e T_{\text{coh}}}{n}\right) \right)^2 \text{CNR} \times T_{\text{coh}}} \quad (19)$$

356 Since $\boldsymbol{\varphi}$ is a composite estimator composed of two estimators, let $\mathbf{g}(\boldsymbol{\theta}) = (\pi f_e T_{\text{coh}} + \theta_0)$. The
 357 CRLB for $\boldsymbol{\varphi}$ can be estimated as:

$$358 \quad \text{var}(\hat{\boldsymbol{\varphi}}) = \frac{\partial \mathbf{g}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \mathbf{I}(\boldsymbol{\theta})^{-1} \frac{\partial \mathbf{g}(\boldsymbol{\theta})^T}{\partial \boldsymbol{\theta}} \quad (20)$$

359 By combining Equation (18), Equation (19), and Equation (20), the phase estimation CRLB for
 360 the BCI method under different CNR values can be obtained:

$$361 \quad \text{var}(\hat{\boldsymbol{\varphi}}) = \frac{1}{2 \text{sinc}^2\left(\frac{\pi f_e T_{\text{coh}}}{n}\right) \text{CNR} \times T_{\text{coh}}} \quad (21)$$

For the CI method, its CRLB can be directly derived and is given by the following equation

(Kay 1995):

$$\text{var}(\hat{\phi}) = \frac{1}{2\text{sinc}^2(\pi f_e T_{\text{coh}}) \text{CNR} \times T_{\text{coh}}} \quad (22)$$

Comparing Equation (21) and Equation (22), it is clear that as the CNR decreases and the frequency offset increases, the lower bound of the CI method gradually exceeds that of the BCI method and shows an increasing trend. This indicates that the BCI method outperforms the CI method under low CNR conditions. This result further verifies the effectiveness of the BCI method in handling frequency offset.

Tracking error

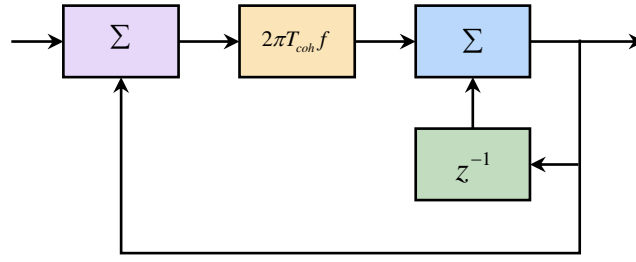


Fig. 10 Digital Model of the First-Order Loop.

In this subsection, the tracking error of the BCI method will be further studied. Figure 10 shows the digital block diagram of a first-order loop, from which the error transfer function can be derived as:

$$\Delta\hat{\phi}_{n+1} = \Delta\hat{\phi}_n + 2\pi f_e T_{\text{coh}} (\Delta\varphi_n + \varepsilon_n - \Delta\hat{\phi}_n) \quad (23)$$

- $\Delta\hat{\phi}$ is the loop estimated phase error;
- $\Delta\varphi$ is the true phase error;
- ε_n is the discriminator phase estimation error.

Based on the above, the loop phase jitter under the phase estimation error can be easily derived

as:

$$\begin{aligned}
\text{var}(\Delta\hat{\phi}_{n+1}) &= E\{(\Delta\hat{\phi}_{n+1} - \Delta\phi_{n+1})^2\} \\
&= E\{\Delta\hat{\phi}_{n+1}^2 - 2\Delta\hat{\phi}_{n+1}\Delta\phi_{n+1} + \Delta\phi_{n+1}^2\} \\
&= E\{\Delta\hat{\phi}_{n+1}^2\} \\
&= E\{\Delta\hat{\phi}_n^2\}(1 - 2\pi f_e T_{\text{coh}})^2 + E\{\Delta\varepsilon_n^2\}(2\pi f_e T_{\text{coh}})^2
\end{aligned} \tag{24}$$

The steady-state noise variance is:

$$E\{\Delta\hat{\phi}_{n+1}^2\} = E\{\Delta\hat{\phi}_n^2\} = \text{var}(\Delta\hat{\phi}) \tag{25}$$

Thus, the loop tracking error caused by thermal noise is:

$$\text{var}(\Delta\hat{\phi}_{n+1}) = 2 \text{var}(\varepsilon_n) B_l T_{\text{coh}} = 2 \text{var}(\hat{\phi}) B_l T_{\text{coh}} \tag{26}$$

Substituting into Equation (22) and simplifying, the thermal noise induced tracking error for the BCI-NPLL is obtained as:

$$\text{var}(\Delta\hat{\phi}_{n+1}) = \frac{B_l T_{\text{coh}}}{\text{sinc}^2\left(\frac{\pi f_e T_{\text{coh}}}{n}\right) \text{CNR} \times T_{\text{coh}}} \tag{27}$$

In addition to errors caused by thermal noise, dynamic factors also contribute to additional tracking errors. Dynamic errors mainly arise from the relative motion between the satellite and the receiver. This relative motion induces the Doppler effect, leading to changes in frequency and phase. Although only the impact of thermal noise was considered in the theoretical derivation, subsequent experiments have demonstrated the effect of dynamic factors on the BCI-NPLL.

Impact of Segment Number

From Equation (27), it can be seen that as the number of blocks n increases, the tracking error caused by thermal noise gradually decreases. This is because higher values of n improve the estimation accuracy, thereby reducing the error. However, increasing n also leads to an increase in computational overhead, which in turn extends the estimation time. Therefore, how to balance estimation accuracy and computational efficiency, and choose an optimal value for n becomes a key issue. In this subsection, This will be further explored, and a reasonable selection strategy will be provided.

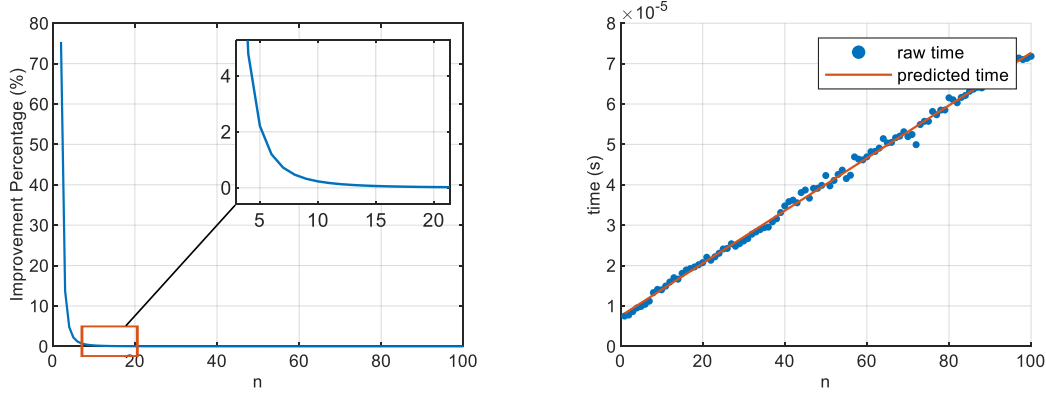


Fig. 11 Impact of n on Tracking Performance. The left panel shows the relationship between the improvement percentage and n , and the right panel illustrates the relationship between estimation time and n .

From Equation (27), it can be seen that the impact of the number of blocks n on tracking error is mainly reflected in the term $\frac{1}{\text{sinc}^2\left(\frac{\pi f_e T_{\text{coh}}}{n}\right)}$ in Equation (27). In this expression, the frequency offset uses the estimated loop frequency offset under thermal noise conditions (Rycroft 1997), and B_l is taken as $0.1/T_{\text{coh}}$ based on empirical values. Meanwhile, the CNR is obtained from the corresponding tracking threshold based on T_{coh} and B_l . The percentage improvement in tracking error due to n is shown in the left part of Figure 11. It can be observed that as n increases, the improvement in tracking error gradually decreases and eventually stabilizes. However, considering that as n increases, the required data for estimation also increases, which raises the complexity of the neural network model, the right part of Figure 11 shows that the runtime increases linearly with n .

Considering account both the impact of n on tracking error and estimation time, the optimal value of n should be between 8 and 15, as shown in the figure. Specifically, when n is less than 8, the increase in tracking error is significant as n increases. When n is greater than 15, the improvement in tracking error becomes very small and can be almost ignored. Based on this analysis, this paper suggests that the optimal range for n should be between 8 and 15. For validation in subsequent experiments, this study chooses $n=10$ as the validation example.

After determining the value of n , based on the above analysis, the theoretical performance comparison of tracking sensitivity between BCI method and CI method is shown in Figure 12. In the simulation, the number of blocks is set to $n = 10$, and the coherent integration times T_{coh} are set to 1 ms, 5 ms, 10 ms, and 20 ms. The bandwidth B_l is set to 100 Hz, 50 Hz, 10 Hz, and 5 Hz. The frequency offset uses the loop frequency offset estimated under thermal noise conditions (Rycroft 1997). The green and red lines in the figure represent the phase jitter of the CI and BCI methods under different CNR conditions. The figure clearly shows that under the same CNR conditions, the phase jitter of the BCI method is always lower than that of the CI method. Furthermore, the sensitivity of the BCI method is improved by approximately 2dB compared to the CI method, indicating that the BCI method has a significant advantage in tracking sensitivity over the CI method.

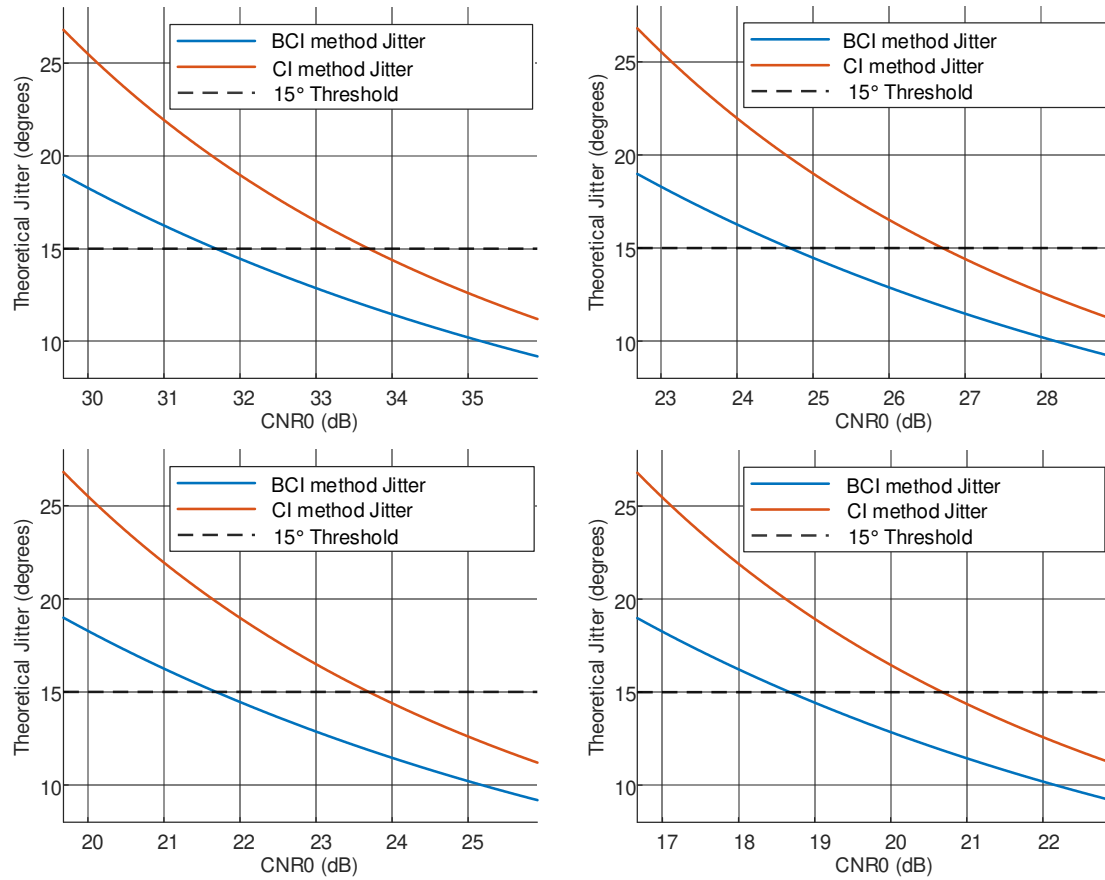


Fig. 12 Tracking Jitter of the CI and BCI Methods for Different Integration Times. From left to right and

top to bottom, the integration times are 1 ms, 5 ms, 10 ms, and 20 ms, respectively. The red line, blue line, and black dashed line represent the BCI method, CI method, and tracking threshold, respectively.

Figure 13 shows the theoretical performance comparison of tracking accuracy between BCI method and CI method. The red, blue, yellow, and green lines represent the tracking accuracy improvement of BCI-NPLL under different CNR conditions for coherent integration times of 1 ms, 5 ms, 10 ms, and 20 ms, respectively. From the figure, it can be seen that BCI method improves tracking accuracy by approximately 15% compared to CI method at higher CNR. As the CNR decreases, the improvement in tracking accuracy becomes more significant, with a maximum improvement of 26%. This indicates that the carrier phase tracking accuracy of the BCI method is also superior to that of the CI method.

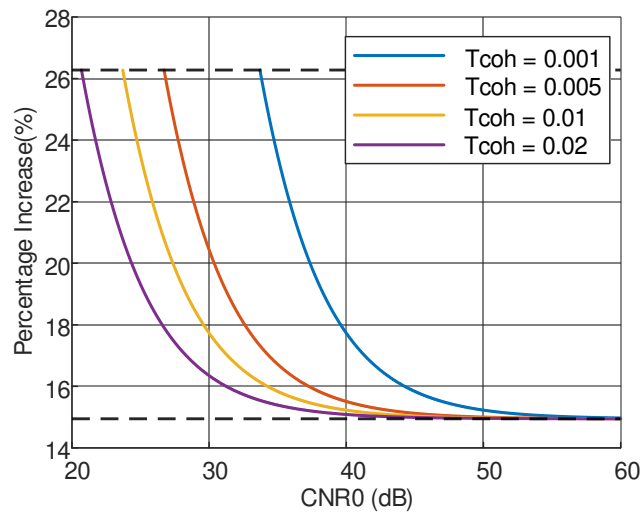


Fig. 13 Improvement in Tracking Accuracy of the BCI Method Relative to the CI Method.

Overall, these results indicate that, compared to the CI method, the BCI method can provide more stable and precise carrier phase tracking under low CNR and larger frequency offset conditions. This performance advantage gives the BCI method a distinct edge in complex GNSS environments, especially in scenarios with low signal-to-noise ratios and large frequency offsets.

BCI-NPLL performance tests and analysis

This section will tests and analyzes the performance of BCI-NPLL through semi-simulation, static, and dynamic GPS L1 signal experiments. The correctness of the theoretical model analysis of BCI method from the previous section is verified, and the performance of BCI-NPLL is discussed.

Semi-analytic simulation

To validate the BCI-NPLL theoretical model, single-carrier simulations are performed in this subsection to compare and analyse the BCI-NPLL with the PLL. The simulation is developed based on the SATLSim software simulation platform, and a schematic diagram of the simulation framework is shown in Figure 14 (Borio 2011). The BCI-NPLL simulation framework includes signal generation, blocked coherent integration, NN discriminator, loop filter, and local oscillator modules. Based on the output data of the NN discriminator, the loop filter further updates the NCO of BCI-NPLL and PLL to ensure that the system can accurately track the input signal. Coherent integration and blocked coherent integration are directly generated using Equations (12) and (13).

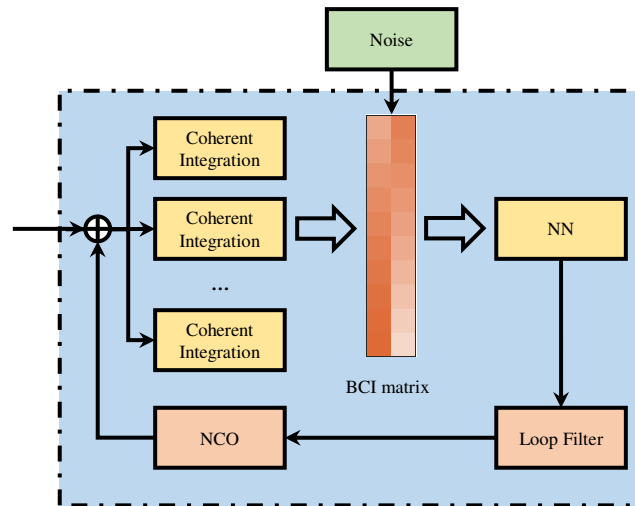


Fig. 14 Semi-Analytical Simulation of the BCI-PLL Tracking Loop, with noise directly added to the BCI

matrix.

The simulation results are shown in Figure 15, where coherent integration times of 1 ms , 5 ms ,

464 10 ms , and 20 ms are used, with bandwidths set to 100 Hz , 20 Hz , 10 Hz , and 5 Hz ,
465 respectively. The blue and red lines represent the phase jitter values of PLL and BCI-NPLL under
466 different CNR conditions, with solid lines indicating theoretical calculation results and dashed lines
467 indicating single-carrier simulation results. Under high CNR conditions, both BCI-NPLL and PLL can
468 achieve their respective lower bounds. Comparing the BCI-NPLL curve with the theoretical PLL curve,
469 it can be observed that under different coherent integration times, BCI-NPLL shows a performance
470 improvement of 2dB over PLL in the theoretical calculations. However, the actual simulation results
471 show that the sensitivity of PLL is improved by 2dB. This is because when the phase jitter approaches
472 15° , the PLL can lose lock under different coherent integration times, while the BCI-NPLL only loses
473 lock when the jitter exceeds 15° . Overall, the results show that the single-carrier simulation results are
474 in agreement with the theoretical calculations and that the BCI-NPLL shows higher stability compared
475 to the PLL.

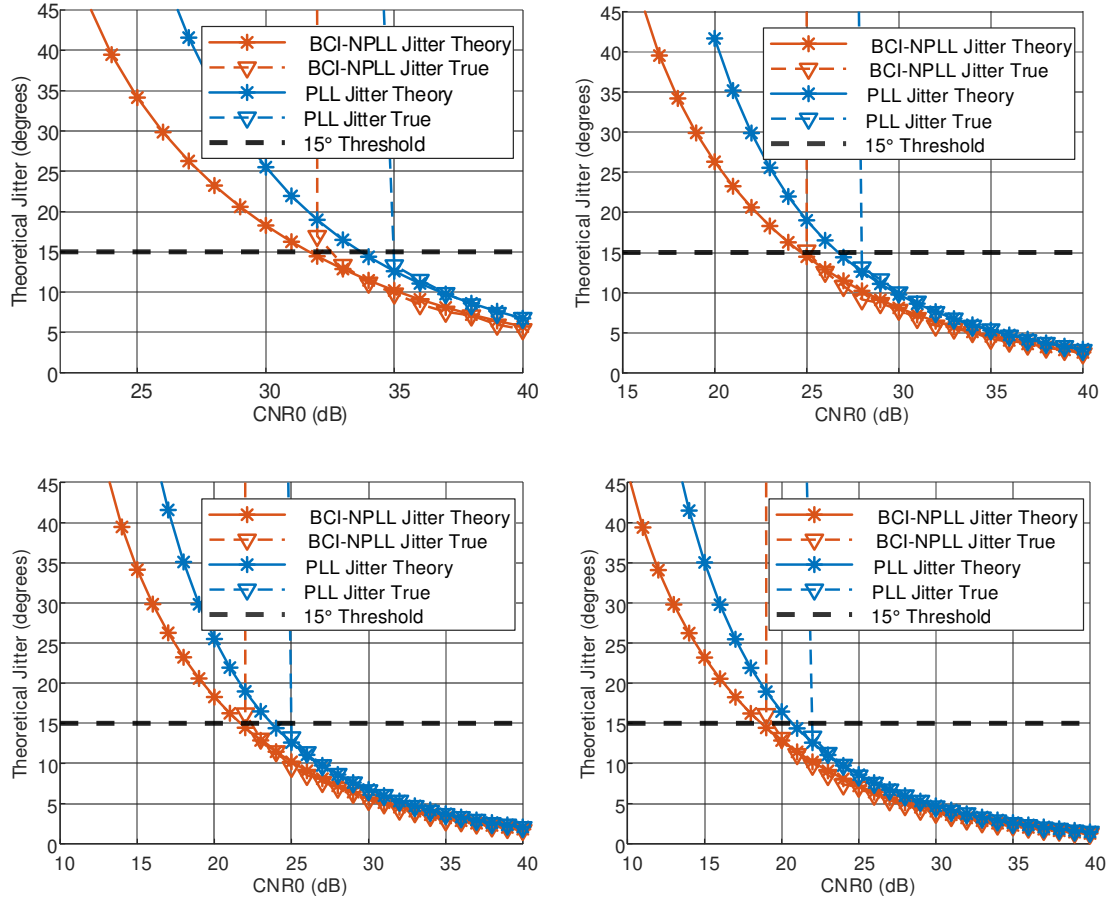


Fig. 15 Tracking Jitter of the PLL and BCI-PLL for Different Integration Times. From left to right and top to bottom, the integration times are 1 ms, 5 ms, 10 ms, and 20 ms, respectively. The red line, blue line, and black dashed line represent the BCI-NPLL, PLL, and tracking threshold, respectively.

The left part of Figure 16 shows the difference between the local carrier phase and the true carrier phase under different CNR conditions when the coherent integration time is 10 ms. The figure shows that the phase jitter of BCI-NPLL is always smaller than that of PLL under all CNR conditions, indicating that BCI-NPLL outperforms PLL in terms of carrier phase tracking accuracy. The right part of Figure 16 demonstrates the improvement of BCI-NPLL over PLL in terms of the mean square error of coherent phase difference under different CNR conditions for different coherent integration times. The figure shows that the improvement in tracking accuracy of BCI-NPLL over PLL is between 17% to 30% under various CNR values, and as the CNR decreases, the improvement in tracking accuracy

becomes more significant, which is consistent with the theoretical results derived earlier.

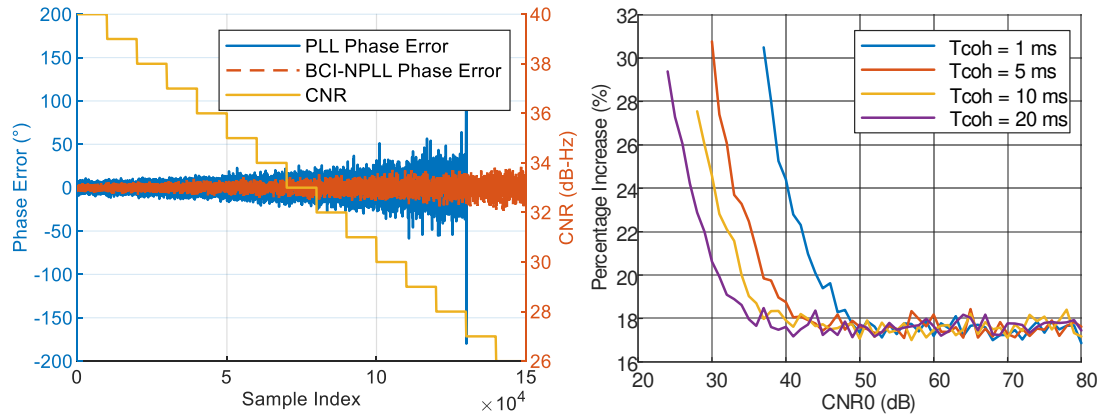


Fig. 16 Improvement in Tracking Accuracy of the BCI-NPLL in Semi-Analytical Simulation. The left panel shows the phase difference between the local signal and the true signal, and the right panel illustrates the improvement in tracking accuracy of the BCI-NPLL relative to the PLL.

To verify the versatility of the BCI method, three different neural network models were used for comparison: CNN+FNN, LSTM, and FNN. The results are shown in Figure 17, which shows the performance of various networks in the BCI-NPLL is displayed. It can be observed that all the neural network models effectively estimate the BCI method, thereby demonstrating the applicability and robustness of the BCI method across different neural network models. This result indicates that the BCI method is highly versatile.

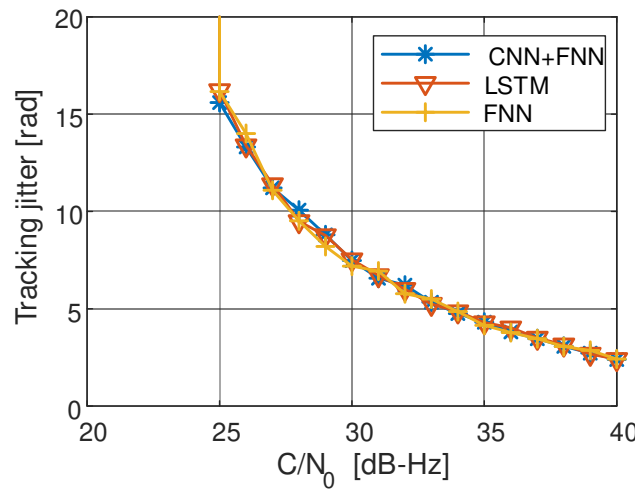


Fig. 17 Tracking Jitter for Different Neural Network Discriminators.

Hardware Simulation

This subsection evaluates the performance of BCI-NPLL through satellite signal tests conducted with both static and dynamic receiver terminals. The experimental setup is introduced first, followed by an analysis of the test results based on the zero-baseline three-difference carrier phase, tracking loop Doppler, and equivalent CNR (Rycroft 1997).

Experiment setup

This paper uses a GNSS simulator to generate a high fidelity synthetic dataset. The NSS8900 is a multi-frequency, multi-constellation GNSS simulator capable of generating pseudoranges for various satellite positioning systems, including GPS, GLONASS, BeiDou, and Galileo. The generated RF signals are sent to the N310 for data acquisition, with a rubidium clock used as the external clock source for the N310 to eliminate the effects of receiver clock instability. The experimental setup is shown in Figure 18.



Fig. 18 Equipment Configuration for the Test. The left panel includes the receiving equipment-comprising the receiving device, receiving computer, software radio, and rubidium atomic clock-while the right panel shows the transmitting equipment, which consists of the transmitting computer and NSS8900.

In this experiment, the NSS8900 is used to generate approximately 10 minutes of satellite signals for simulation, aiming to explore the performance of the BCI-NPLL tracking system in terms of GNSS carrier phase tracking sensitivity and tracking accuracy. The experiment uses a software-defined

GNSS receiver as the test platform, and Gaussian white noise of varying intensities is added to the intermediate frequency signals to generate signals with different CNR values. The noise intensity is set by the noise generation software to quantitatively assess the tracking sensitivity of BCI-NPLL and its performance under dynamic conditions. This section will conduct two types of tests: the first is to test the sensitivity improvement and tracking accuracy improvement of BCI-NPLL relative to PLL under different coherent integration times; the second is to test the sensitivity degradation of BCI-NPLL under different dynamic conditions.

Sensitivity test of BCI-NPLL

In this experiment, the improvement in sensitivity and tracking accuracy of BCI-NPLL compared to PLL under different coherent integration times is investigated and compared to PLL. To validate the versatility of BCI-NPLL for tracking satellites at different elevation angles, the simulation experiment uses a low-elevation satellite (Satellite 2) and a high-elevation satellite (Satellite 17) for tracking sensitivity and tracking accuracy tests with a coherent integration time of 5 ms and a loop bandwidth of 20 Hz. The equivalent CNR, Doppler frequency, and zero baseline three difference carrier phase are evaluated.

Figure 19 shows the variation of the equivalent CNR and Doppler output in the tracking loop for Satellites 2 and 17 as the CNR changes. The upper half of the figure shows the input signal CNR and the equivalent CNR calculated in the tracking loop. The lower half of the figure presents the Doppler output results of the tracking loop. The figure shows that as the CNR decreases, the Doppler output fluctuation of BCI-NPLL is consistently smaller than that of PLL. For Satellite 2, when the CNR drops to $-27\text{ dB}\cdot\text{Hz}$, PLL experiences a significant frequency error jump, while BCI-NPLL only shows a similar jump when the CNR drops to $-25\text{ dB}\cdot\text{Hz}$ and the equivalent CNR follows the same trend. For Satellite 17, the sensitivity threshold for PLL is $-25\text{ dB}\cdot\text{Hz}$, while the threshold for BCI-NPLL is

28 dB·Hz . These results are consistent with the theoretical derivations and semi-analytical simulation results presented earlier, confirming the advantages of BCI-NPLL in improving sensitivity and versatility of satellite tracking.

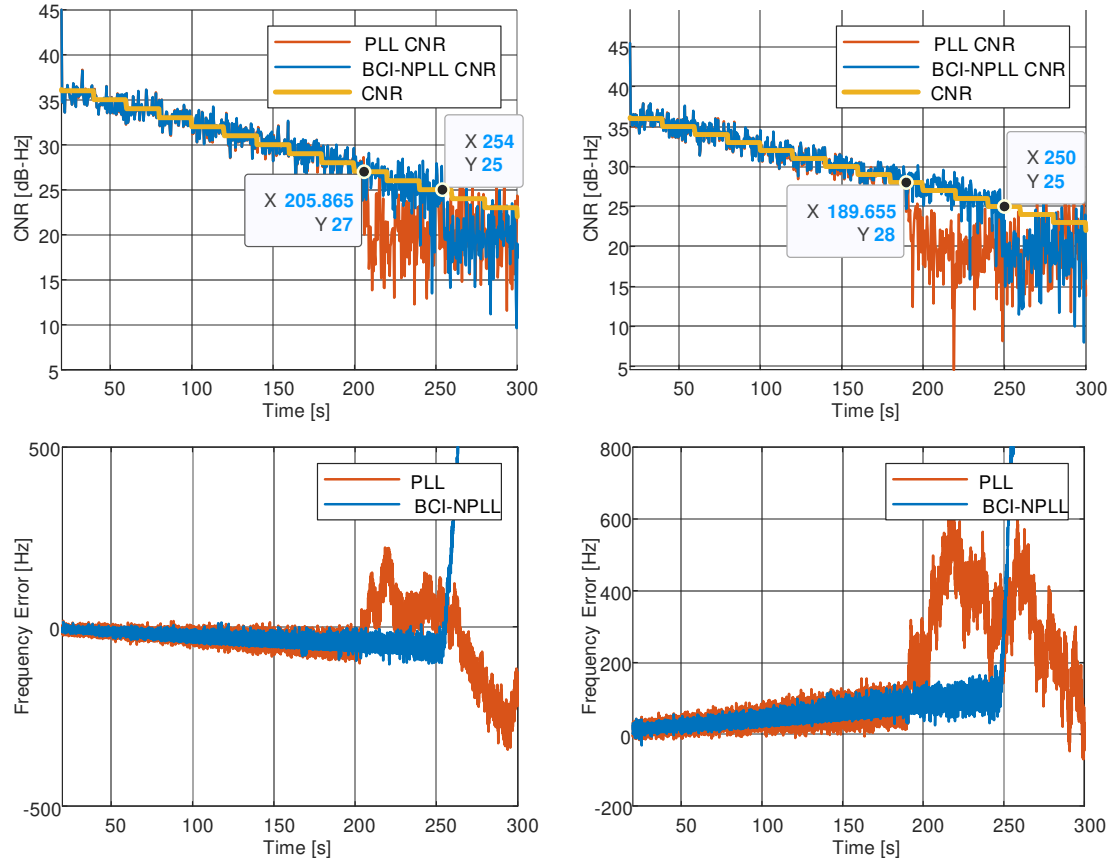


Fig. 19 Tracking doppler output and equivalent CNR of the PLL and BCI-NPLL for different elevation

Satellites. The left panel corresponds to satellite 2, while the right panel corresponds to satellite 17. The red and blue lines represent the PLL and BCI-NPLL, respectively.

Figure 20 shows the variation of the zero-baseline three-difference carrier phase results for Satellites 2 and 17 as the CNR changes, with a coherent integration time of 5 ms. The results show that as the CNR decreases, the zero-baseline three-difference carrier phase results of BCI-NPLL are always lower than those of PLL, and as the CNR decreases further, the phase fluctuation difference between BCI-NPLL and PLL becomes more significant. This indicates that the carrier phase tracking accuracy of BCI-NPLL is consistently better than PLL under different CNR conditions, and as the CNR decreases,

the accuracy improvement becomes more pronounced, which is consistent with the previous simulation results.

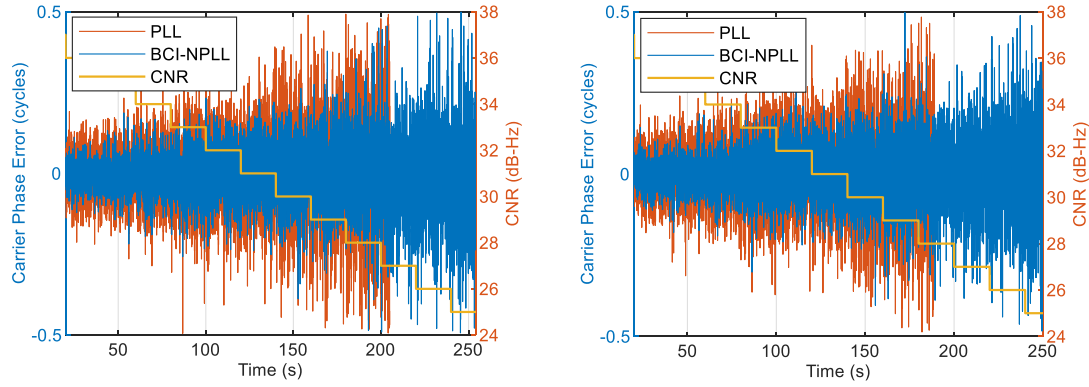


Fig. 20 Tracking zero baseline three difference carrier phase of the PLL and BCI-PLL for different elevation satellites. The left panel corresponds to satellite 2, while the right panel corresponds to satellite 17. The red and blue lines represent the PLL and BCI-NPLL, respectively.

Additionally, simulation experiments were conducted by adjusting the coherent integration time of the tracking loop, with values of 1 ms, 5 ms, 10 ms, and 20 ms, and corresponding loop bandwidths of 100 Hz, 20 Hz, 10 Hz, and 5 Hz. The results are shown in Figure 21. The experimental results indicate that BCI-NPLL exhibits higher tracking sensitivity than PLL under different integration times. These results are consistent with the theoretical analysis and the conclusions from the earlier single-carrier simulation experiments, further validating the advantages and potential of BCI-NPLL in enhancing GNSS receiver tracking performance.

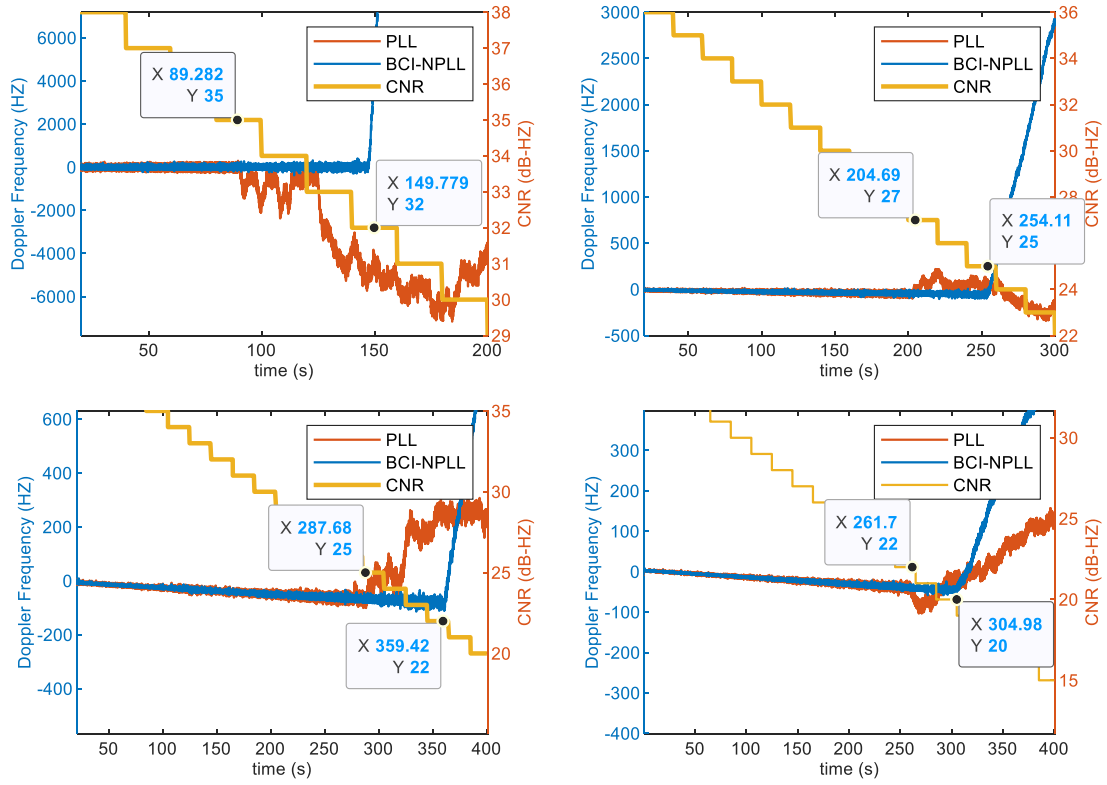


Fig. 21 Tracking doppler output of the PLL and BCI-NPLL for different Integration Times. From left to right and top to bottom, the integration times are 1 ms, 5 ms, 10 ms, and 20 ms, respectively. The red line, blue line, and black dashed line represent the PLL, BCI-NPLL, and tracking threshold, respectively.

Dynamic performance of BCI-NPLL

This subsection examines the effect of dynamic conditions on the sensitivity of the BCI-NPLL. A simulation experiment was conducted using satellite signals with receiver terminal accelerations of $1g$ and $2g$ generated by the signal simulation source for approximately 10 minutes (Tesla, Inc. 2024; DJI 2024). The experimental platform uses a software-defined receiver, with a coherent integration time of 5 ms and a bandwidth of 20 Hz. Doppler frequency shift and equivalent CNR were used as comparison metrics.

Figure 22 shows the tracking results of BCI-NPLL and PLL under dynamic conditions. The upper half of the figure shows the CNR of the input signal and the equivalent CNR calculated in the

tracking loop, while the lower half displays the Doppler output results of the tracking loop. The tracking results under $1g$ acceleration are shown in the left panel, where the sensitivity of BCI-NPLL remains unchanged compared to the stationary state, while the sensitivity of PLL decreases by $2 \text{ dB} \cdot \text{Hz}$. The right panel shows the tracking results under $2g$ acceleration, where the sensitivity of BCI-NPLL only decreases by $1 \text{ dB} \cdot \text{Hz}$, while the sensitivity of PLL decreases by $3 \text{ dB} \cdot \text{Hz}$. This indicates that BCI-NPLL not only outperforms PLL in sensitivity but also demonstrates stronger tracking capability under dynamic conditions.

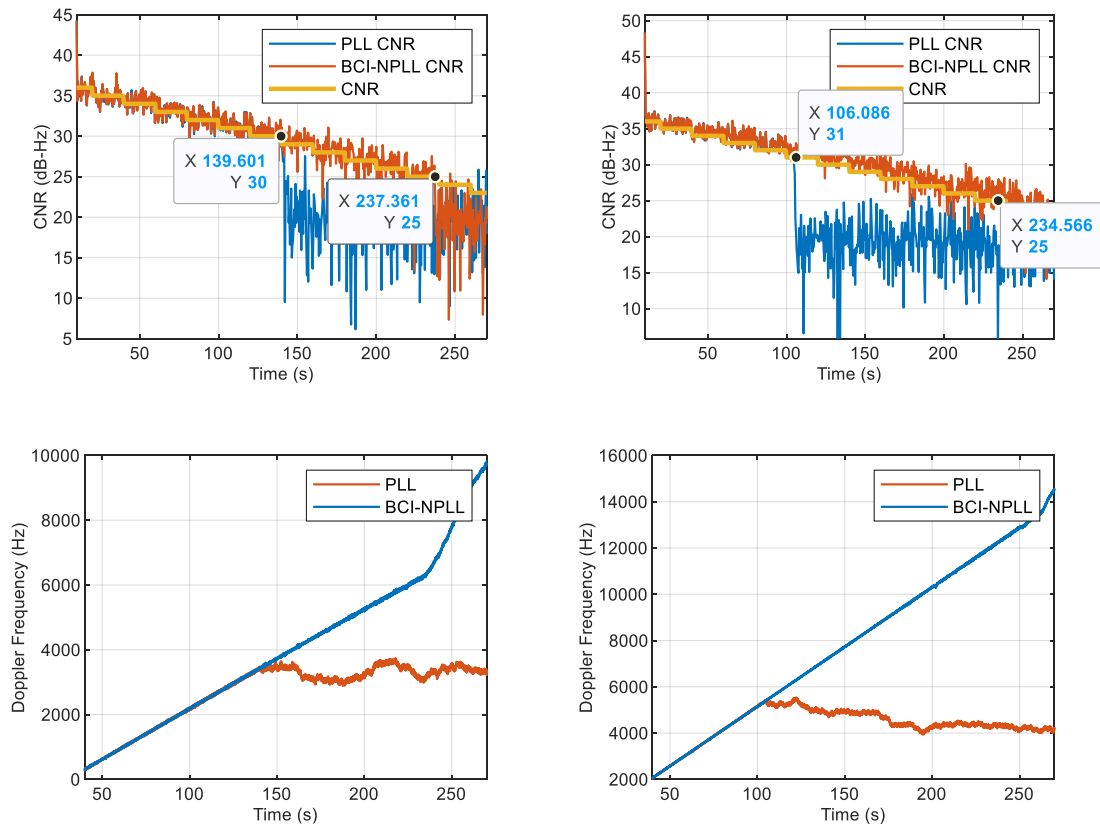


Fig. 22 Tracking doppler output and equivalent CNR of the PLL and BCI-PLL for different acceleration.

The left panel shows an acceleration of $1g$, while the right panel shows an acceleration of $2g$. The red and blue lines represent the PLL and BCI-NPLL, respectively.

To explore more intuitively the performance improvement of BCI-NPLL over PLL, the NSS8000 was used to generate satellite signal data while the receiver accelerated, moved at constant

speed and decelerated with accelerations of $1g$, $2g$ and $3g$. The CNR of the signal was set to $30\text{ dB}\cdot\text{Hz}$ to simulate typical environmental conditions such as urban canyons or tree obstructions (Rycroft 1997). The experimental results are shown in Figure 23, which clearly shows that for a CNR of $30\text{ dB}\cdot\text{Hz}$, BCI-NPLL remains stable at $3g$ acceleration, whereas PLL loses lock at $2g$ acceleration. This result visually demonstrates the significant advantage of BCI-NPLL in dynamic environments, showing higher stability throughout the tracking process.

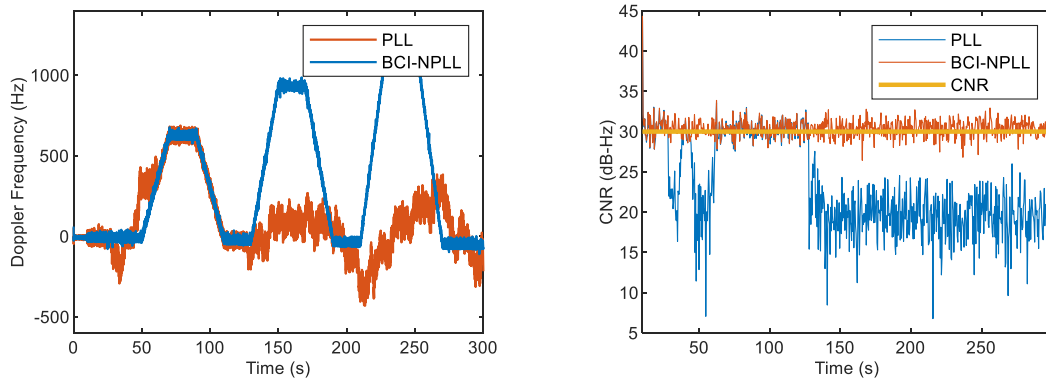


Fig. 23 Tracking doppler output and equivalent CNR of the PLL and BCI-PLL for different acceleration.

The left panel shows doppler output, while the right panel shows equivalent CNR. The red and blue lines represent the PLL and BCI-NPLL, respectively.

Conclusion

To address the attenuation of coherent integration signals caused by frequency offset, this paper proposes a novel GNSS carrier phase tracking method—BCI-NPLL, which combines the BCI method and NN discriminator. By dividing the signal into multiple short coherent integration blocks, the BCI method effectively improves the SNR of the coherent integration signal, thereby enhancing tracking accuracy and sensitivity. For the characteristics of the BCI method, this paper also designs a corresponding NN discriminator that performs nonlinear regression based on the features of the BCI signal, further improving the phase estimation accuracy. Additionally, a new evaluation method is proposed, where the

performance improvement of the BCI signal in closed-loop tracking is quantified based on the CRLB. To validate and test this tracking method, semi-analytical simulations and real GPS L1 signal experiments were conducted. The results show that, under static conditions, BCI-NPLL improves tracking sensitivity by 2dB to 3dB and tracking accuracy by 15% to 26% compared to PLL. Under 1g and 2g acceleration conditions, sensitivity is improved by 4 dB and 5 dB, respectively. Furthermore, the neural network discriminator in BCI-NPLL demonstrates good flexibility and can be replaced with various types of networks, further proving the broad applicability of the BCI method. Future research will further explore the performance of BCI-NPLL under high dynamic conditions and its potential for multipath suppression.

Acknowledgement This study is funded by the National Natural Science Foundation of China (U20A20193).

Data Availability

The data used in this manuscript are available from the corresponding author upon request.

References

- Alban S, Akos DM, Rock SM (2003) Performance analysis and architectures for INS-aided GPS tracking loops. In: Proceedings of the 2003 National Technical Meeting of The Institute of Navigation, 611–622.
- Bernal D, Closas P, Fernandez-Rubio JA (2008) Particle filtering algorithm for ultra-tight GNSS/INS integration. In: Proceedings of the 21st International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2008), 2137–2144.
- Borio D, Lachapelle G (2009) A non-coherent architecture for GNSS digital tracking loops. Ann

633 Telecommun 64(9):601–614. <https://doi.org/10.1007/s12243-009-0114-1>

634 Borovic B, Liu AQ, Popa D, Cai H, Lewis FL (2005) Open-loop versus closed-loop control of MEMS
635 devices: choices and issues. J Micromech Microeng 15(10):1917–1924. [https://doi.org/10.1088/0960-](https://doi.org/10.1088/0960-1317/15/10/018)
636 1317/15/10/018

637 Borio D (2011) SATLSim: A semi-analytic framework for fast GNSS tracking loop simulations. GPS
638 Solutions 15(4):427–431. <https://doi.org/10.1007/s10291-011-0221-0>

639 Chen Q, Wu X, Liang J, et al (2018) An EKF-based tracking loop filter algorithm in GNSS receiver for
640 ultra-high dynamic environment: The experiment results. In: IECON 2018-44th Annual Conference of
641 the IEEE Industrial Electronics Society, IEEE, 2802–2808.
642 <https://doi.org/10.1109/IECON.2018.8591337>

643 DJI (2024) DJI Mavic 3 Pro User Manual. DJI. <https://www.dji.com/mavic-3-pro>. Accessed 15 August
644 2024.

645 Faragher R, Couronneau N, Powe M, et al (2018) Supercorrelation: Enhancing the accuracy and
646 sensitivity of consumer GNSS receivers with a DSP upgrade. In: Proceedings of the 31st International
647 Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2018), 357–375.

648 Feng X, Zhang T, Niu XJ, Pany T, Liu JN (2023) Improving GNSS carrier phase tracking using a long
649 coherent integration architecture. GPS Solutions 27(1). <https://doi.org/10.1007/s10291-022-01361-w>

650 Guo WF, Yan KL, Zhang HP, Niu XJ, Shi C (2014) Double stage NCO-based carrier tracking loop in
651 GNSS receivers for city environmental applications. IEEE Commun Lett 18(10):1747–1750.
652 <https://doi.org/10.1109/LCOMM.2014.2350489>

653 Han Z, Liu D, Wei Z, et al (2022) A carrier phase tracking method for vector tracking loops. GPS
654 Solutions 26:111. <https://doi.org/10.1007/s10291-022-01302-7>

655 Hasan AM, Samsudin K, Ramli AR, et al (2009) A review of navigation systems (integration and
 656 algorithms). *Aust J Basic Appl Sci* 3(2):943–959.

657 Hsu LT, Groves PD, Jan SS (2013) Assessment of the multipath mitigation effect of vector tracking in
 658 an urban environment. In: *Proceedings of the ION 2013 Pacific PNT Meeting*, 498–509.

659 Hsu LT, Jan SS, Groves PD, Kubo N (2015) Multipath mitigation and NLOS detection using vector
 660 tracking in urban environments. *GPS Solutions* 19(2):249–262. [https://doi.org/10.1007/s10291-014-](https://doi.org/10.1007/s10291-014-0384-6)
 661 0384-6

662 Jiang R, Wang KD, Liu SH, Li Y (2017) Performance analysis of a Kalman filter carrier phase tracking
 663 loop. *GPS Solutions* 21(2):551–559. <https://doi.org/10.1007/s10291-016-0546-9>

664 Kay SM (1995) Fundamentals of statistical signal processing. *Technometrics* 37(4):465–466.

665 Klovov A, Kanouj M, Mironchev A (2022) A novel carrier tracking approach for GPS signals based on
 666 Gauss–Hermite Kalman filter. *Electronics* 11(14):2215. <https://doi.org/10.3390/electronics11142215>

667 Lashley M, Bevely DM, Hung JY (2009) Performance analysis of vector tracking algorithms for weak
 668 GPS signals in high dynamics. *IEEE J Sel Top Signal Process* 3(4):661–673.
 669 <https://doi.org/10.1109/JSTSP.2009.2023341>

670 Li J, Zhao L, Hou Y, et al (2018) A new tracking technique with the memory discriminator for high
 671 sensitivity GNSS receivers. In: *Proceedings of the 2018 IEEE 4th International Conference on Computer*
 672 *and Communications (ICCC)*, 959–962. <https://doi.org/10.1109/compcomm.2018.8780830>

673 Niesen U, Jose J, Wu X (2018) Accurate positioning in GNSS-challenged environments with consumer-
 674 grade sensors. In: *Proceedings of the 31st International Technical Meeting of the Satellite Division of*
 675 *The Institute of Navigation (ION GNSS+ 2018)*, 503–514. <https://doi.org/10.33012/2018.15998>

676 Niu XJ, Li B, Ziedan NI, Guo WF, Liu JN (2017) Analytical and simulation-based comparison between

677 traditional and Kalman filter-based phase-locked loops. *GPS Solutions* 21(1):123–135.
678 <https://doi.org/10.1007/s10291-015-0509-6>

679 Palmer L (1974) Coarse frequency estimation using the discrete Fourier transform (Corresp.). *IEEE Trans*
680 *Inf Theory* 20(1):104–109. <https://doi.org/10.1109/TIT.1974.1055156>

681 Pany T, Kaniuth R, Eissfeller B (2005) Deep integration of navigation solution and signal processing. In:
682 *Proceedings of the 18th International Technical Meeting of the Satellite Division of The Institute of*
683 *Navigation (ION GNSS 2005)*, 1095–1102.

684 Parekh D, Poddar N, Rajpurkar A, Chahal M, Kumar N, Joshi GP, Cho W (2022) A Review on
685 *Autonomous Vehicles: Progress, Methods and Challenges. Electronics* 11(14):2162.
686 <https://doi.org/10.3390/electronics11142162>

687 Petovello MG, O'Driscoll C, Lachapelle G (2008) Carrier phase tracking of weak signals using different
688 receiver architectures. In: *Proceedings of the 2008 National Technical Meeting of The Institute of*
689 *Navigation*, 781–791.

690 Ren T, Petovello MG (2017) A stand-alone approach for high-sensitivity GNSS receivers in signal-
691 challenged environments. *IEEE Trans Aerosp Electron Syst* 53(5):1.
692 <https://doi.org/10.1109/TAES.2017.2699539>

693 Rycroft MJ (1997) *Understanding GPS. Principles and applications*: Kaplan ED (ed.), 1996, 554 pp.
694 Artech House, £75, hb, ISBN 0-89006-793-7. *J Atmos Solar-Terrestrial Phys* 59(5):598–599.
695 [https://doi.org/10.1016/S1364-6826\(97\)83337-8](https://doi.org/10.1016/S1364-6826(97)83337-8)

696 Srinivas P, Kumar A (2017) Overview of architecture for GPS-INS integration. In: *2017 Recent*
697 *Developments in Control, Automation & Power Engineering (RDCAPE)*, 433–438.
698 <https://doi.org/10.1109/RDCAPE.2017.8358310>

699 Thoelet S, Steigenberger P, Montenbruck O, Meurer M (2019) Signal analysis of the first GPS III
 700 satellite. *GPS Solutions* 23(4):92. <https://doi.org/10.1007/s10291-019-0882-7>
 701 Tang X, Falco G, Falletti E, et al (2013) Practical implementation and performance assessment of an
 702 Extended Kalman Filter-based signal tracking loop. In: 2013 International Conference on Localization
 703 and GNSS (ICL-GNSS), IEEE, 1–6. <https://doi.org/10.1109/ICL-GNSS.2013.6577275>
 704 Tesla, Inc. (2024) Model X Owner's Manual. Tesla, Inc. Available at: <https://www.tesla.com/modelx>.
 705 Accessed 30 December 2024.
 706 Van Diggelen F (2009) A-GPS: Assisted GPS, GNSS, and SBAS. Artech House, Boston.
 707 Wang X, Ji X, Feng S, Calmettes V (2015) A high-sensitivity GPS receiver carrier-tracking loop design
 708 for high-dynamic applications. *GPS Solutions* 19(2):225–236. [https://doi.org/10.1007/s10291-014-](https://doi.org/10.1007/s10291-014-0382-8)
 709 [0382-8](https://doi.org/10.1007/s10291-014-0382-8)
 710 Xie G (2009) GPS Principles and Receiver Design. Beijing: Electronics Industry Press.
 711 Yang C (2003) Tracking of GPS code phase and carrier frequency in the frequency domain. In:
 712 Proceedings of the 16th International Technical Meeting of the Satellite Division of The Institute of
 713 Navigation (ION GPS/GNSS 2003), 628–637.
 714 Yan K, Ziedan NI, Zhang H, et al (2016) Weak GPS signal tracking using FFT discriminator in open loop
 715 receiver. *GPS Solutions* 20:225–237. <https://doi.org/10.1007/s10291-014-0431-3>
 716 Yan KL, Zhang TS, Niu XJ, Zhang HP, Zhang PH, Liu JN (2017) INS-aided tracking with FFT frequency
 717 discriminator for weak GPS signal under dynamic environments. *GPS Solutions* 21(3):917–926.
 718 <https://doi.org/10.1007/s10291-016-0579-0>
 719 Yan Z, Chen X, Tang X (2020) A novel linear model based on code approximation for GNSS/INS ultra-
 720 tight integration system. *Sensors (Basel)* 20(11):E3192. <https://doi.org/10.3390/s20113192>

Yan Z, Ruotsalainen L, Chen X, et al (2023) An INS-assisted vector tracking receiver with multipath error estimation for dense urban canyons. *GPS Solutions* 27(2):88. <https://doi.org/10.1007/s10291-023-01431-7>

Zhang TS, Ban YL, Niu XJ, Guo WF, Liu JN (2017) Improving the design of MEMS INS-aided PLLs for GNSS carrier phase measurement under high dynamics. *Micromachines* 8(5):135. <https://doi.org/10.3390/mi8050135>

Zhang XH, Tao XL, Zhu F, Shi X, Wang FH (2018) Quality assessment of GNSS observations from an Android N smartphone and positioning performance analysis using time-differenced filtering approach. *GPS Solutions* 22(3):1. <https://doi.org/10.1007/s10291-018-0736-8>

Zeng Q, Meng Q, Liu J, Feng S, Wang H (2016) Acquisition and loop control of ultra-tight INS/BeiDou integration system. *Optik* 127(19):8082–8089. <https://doi.org/10.1016/j.ijleo.2016.06.009>

Zhong Q (2024) Investigation of 3D-mapping-aided GNSS navigation in urban canyons. Dissertation, UCL (University College London).

Ziedan NI, Garrison JL (2004) Extended Kalman filter-based tracking of weak GPS signals under high dynamic conditions. In: Proceedings of the 17th International Technical Meeting of the Satellite Division of the Institute of Navigation (ION GNSS 2004), 20–31.

Author Biographies

Zhiqiang Gong is currently a PH.D. candidate at College of Electronic Science and Technology, National University of Defense Technology. Her current research focuses on GNSS signal processing and receiver design.

Honglei Lin was born in 1989. He received the Ph.D. degree from National University of Defense Technology, Changsha, in 2018. He has been an associate researcher with the College of Electronic Science and Technology, National University of Defense Technology. His research interests include GNSS signal processing, receiver design, and integrated communication and navigation.

Gang Ou was born in 1969. He is a professor at College of Electronic Science and Technology, National University of Defense Technology, Changsha. He has over 25 years of experience in satellite navigation system research areas including high-performance GNSS baseband chip, receiver design, GNSS test, and evaluation technology.

Zhe Liu was born in 1988, received the Ph.D. degree from National University of Defense Technology, Changsha, in 2015. He has been an associate researcher with the College of Electronic Science and Technology, National University of Defense Technology. His research interests include GNSS signal processing, receiver design, and multipath mitigation.

765 **Statements and Declarations**

766 **Conflict of Interest** The authors declare that they have no known competing financial interests or
767 personal relationships that could have appeared to influence the work reported in this paper.

768 **Author contributions** All authors contributed to the study conception and design. Zhiqiang Gong and
769 Honglei Lin designed the experiments. Zhiqiang Gong performed the experiments, analyzed the data,
770 and wrote the paper. Gang Ou and Zhe Liu contributed to discussions and revisions. All authors reviewed
771 and approved the manuscript.

772 **Funding** This study is funded by the National Natural Science Foundation of China (U20A20193)..

773