Advances in GNSS-Based Ionospheric Scintillation Detection Methods: Postprint

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Abstract

Ionospheric scintillation is a physical phenomenon of radio waves caused by irregularities in the ionospheric electron density. Radio signals passing through ionospheric irregularities undergo random, rapid fluctuations in amplitude and phase, thereby degrading the propagation channel of radio signals. For global navigation satellite systems (GNSS), ionospheric irregularities can induce cycle slips in satellite signals and, in severe cases, lead to loss of lock. Scintillation detection is thus crucial for space-based applications such as GNSS. This paper introduces the calculation methods of GNSS scintillation indices, with a particular focus on the current research status of scintillation detection methods; it then discusses manual visual inspection methods, threshold-based detection methods, and non-scintillation-index-based detection methods, and analyzes the application of machine learning in scintillation detection; finally, for different application scenarios, it compares the advantages and disadvantages of various ionospheric scintillation detection methods.

Full Text

Preamble

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Advances in GNSS-based Ionospheric Scintillation Detection Methods

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Abstract

Ionospheric scintillation is a physical phenomenon affecting radio waves caused by irregularities in ionospheric electron density. Radio signals passing through ionospheric irregularities exhibit random and rapid fluctuations in amplitude and phase, thereby disrupting radio signal transmission channels. For Global Navigation Satellite Systems (GNSS), ionospheric irregularities can cause cycle slips in satellite signals and, in severe cases, lead to loss of lock. Detecting scintillation is crucial for space-based applications such as GNSS. This paper introduces the calculation methods for GNSS scintillation indices, focusing on analyzing the current research status of scintillation detection methods. We discuss manual visual detection, threshold detection, and non-scintillation-index detection methods, and analyze the application of machine learning in scintillation detection. Finally, we compare the advantages and disadvantages of various ionospheric scintillation detection methods for different application scenarios.

Keywords: ionospheric scintillation; GNSS; scintillation index; detection methods

1 Introduction

Ionospheric irregularities can severely affect radio signal propagation [?]. Radio signals passing through ionospheric irregularities produce random and rapid fluctuations in amplitude and phase, known as ionospheric scintillation [?, ?]. For Global Navigation Satellite Systems (GNSS), ionospheric scintillation can cause cycle slips in satellite signals and, in severe cases, lead to loss of lock [?]. Ionospheric scintillation events primarily occur in the magnetic equatorial and polar regions, which are key areas for human activities and scientific research [?]. Detecting ionospheric scintillation is vital for space weather research and satellite navigation and communication [?]. Accurate and timely detection helps develop algorithms and technologies to mitigate the adverse effects of scintillation on navigation accuracy. Scintillation detection enables GNSS users to proactively identify potential signal interruptions and implement strategies to maintain lock or accelerate recovery after loss of lock [?]. Ionospheric scintillation detection is equally important for navigation system applications, as detection results allow users to take preventive measures. Furthermore, continuous monitoring of scintillation helps refine models and algorithms related to ionospheric disturbances. Research on ionospheric scintillation detection can effectively enhance understanding of the Earth' s upper atmosphere and ensure the safety and reliability of space- and ground-based applications [?].

In recent years, ionospheric scintillation research has become a priority. Two GNSS receiver manufacturers have developed their own ionospheric scintillation receivers: NovAtel' s GPStation-6 and Septentrio' s PolaRx5S. These receivers incorporate amplitude scintillation index S_4 and phase scintillation index σ_ϕ to characterize ionospheric scintillation intensity. Ionospheric scintillation receivers are specifically designed for monitoring scintillation but are typically expensive due to their specialized design and technical requirements, limiting their widespread deployment. Research on ionospheric irregularities primarily utilizes widely distributed, low-cost geodetic receivers [?]. Based on Total Electron Content (TEC) retrieved from dual-frequency GNSS geodetic receiver observations, Aarons used the Rate of TEC (ROT) to study electron density irregularities. Pi et al. [?] standardized ROT and proposed monitoring ionospheric irregularities using the ROT Index (ROTI), which is the standard deviation of ROT over a time interval. Cai et al. [?] proposed a method for calculating amplitude scintillation index using 20 Hz GNSS carrier-to-noise ratio (C/N_0). Luo et al. [?] proposed calculating amplitude scintillation index S_{4c} using 1 Hz carrier-to-noise ratio data from geodetic receivers. Currently, the primary scintillation indices used for monitoring ionospheric irregularities in GNSS are ROTI and S_{4c}.

The main purpose of scintillation detection is to warn users and systems about potentially harmful ionospheric effects. Detection is a critical preparatory step for monitoring and mitigating impacts, a valuable source of information for understanding and modeling the upper atmosphere, and for applying countermeasures to reduce the effects of ionospheric scintillation on GNSS receiver performance. Therefore, this paper focuses on introducing different ionospheric scintillation detection methods.

2 GNSS Scintillation Index Calculation Methods

GNSS ionospheric scintillation indices are key parameters for measuring scintillation intensity, and their calculation methods are crucial for detecting and studying ionospheric scintillation phenomena. Ionospheric scintillation receivers primarily use amplitude scintillation index S_4 and phase scintillation index σ_ϕ. The scintillation indices calculated from geodetic receivers are mainly ROTI and S_{4c}.

2.1 Calculation Methods for Ionospheric Scintillation Receiver Indices

The amplitude scintillation index S_4 quantifies received signal amplitude variations [?], as shown in equation (1):

$$S_{4T} = \frac{\langle SI^2 \rangle - \langle SI_{\mathrm{det}} \rangle^2}{\langle SI_{\mathrm{det}} \rangle^2}$$

where S_{4T} represents the amplitude scintillation index including ambient noise,

$\langle\rangle$ denotes the averaging operator, and SI_{det} is the detrended signal intensity. SI_{det} is expressed as:

$$SI_{\text{det}} = \frac{(P_{NB} - P_{WB})_k}{(P_{NB} - P_{WB})_{\text{lpf},k}}$$

where subscript k denotes epoch number, subscript lpf is the abbreviation for low-pass filter, P_{NB} is narrowband power, P_{WB} is wideband power, and $(P_{NB} - P_{WB})_{\text{lpf},k}$ represents the trend component of raw signal intensity $(P_{NB} - P_{WB})_k$, typically obtained using a 6th-order Butterworth low-pass filter with a cutoff frequency of 0.1 Hz.

The amplitude scintillation index after removing ambient noise effects is:

$$S_4 = \sqrt{\frac{\langle SI^2\rangle - \langle SI_{\text{det}}\rangle^2}{\langle SI_{\text{det}}\rangle^2} - \frac{100}{\widehat{S}/\widehat{N}_0}\left(1 + \frac{500}{19}\frac{1}{\widehat{S}/\widehat{N}_0}\right)}$$

where $\widehat{S}/\widehat{N}_0$ is the mean signal-to-noise density ratio over 1 minute.

The phase scintillation index σ_ϕ is defined as the standard deviation of detrended phase observations ϕ (detrending is implemented using a 6th-order Butterworth high-pass filter with a cutoff frequency of 0.1 Hz), expressed as [**?**]:

$$\sigma_\phi = \sqrt{\langle\phi^2\rangle - \langle\phi\rangle^2}$$

2.2 Calculation Methods for Geodetic Receiver Scintillation Indices

GNSS geodetic receiver scintillation indices include the Rate of TEC Index (ROTI) and amplitude scintillation index S_{4c}. ROT represents the temporal rate of change of TEC, and ROTI is the standard deviation of ROT over a certain time interval, calculated as:

$$L_{GF}(i) = L_1(i) \times \lambda_1 - L_2(i) \times \lambda_2$$

$$\text{ROT}(i) = \frac{L_{GF}(i) - L_{GF}(i-1)}{\Delta t \times 10^{16} \times 40.3 \times \left(\frac{1}{f_1^2} - \frac{1}{f_2^2}\right)}$$

$$\text{ROTI}(i) = \sqrt{\frac{\sum_{j=i-N}^{i}[\text{ROT}(j) - \overline{\text{ROT}}]^2}{N}}$$

where $L_{GF}(i)$ is the geometry-free linear combination equation of GNSS dual-frequency observations at epoch i, L_1 and L_2 are phase observations, λ_1 and λ_2

are wavelengths corresponding to carrier frequencies, Δt is the time difference between adjacent epochs in minutes, f_1 and f_2 are frequencies corresponding to phase observations, and N is the number of epochs used in the calculation.

The amplitude scintillation index calculated from geodetic receiver carrier-to-noise ratio C/N_0 data is denoted as S_{4c} [?]. The ratio between signal intensity SI and noise power N_0 is denoted as S/N_0 (signal-to-noise ratio), which relates to carrier-to-noise ratio C/N_0 as shown in equation (6) [?]:

$$S/N_0 = 10^{0.1(C/N_0)}$$

From the above equation, signal intensity S can be calculated from C/N_0 and noise power N_0. The calculation method for S_{4c} is:

$$SI_{\mathrm{det}} = \frac{S(k)}{N_0(k)} - \left\langle \frac{S(k-i)}{N_0(k-i)} \right\rangle \quad (k > n)$$

$$S_{4\mathrm{c}} = \frac{\sqrt{\langle SI_{\mathrm{det}}^2 \rangle - \langle SI_{\mathrm{det}} \rangle^2}}{\langle SI_{\mathrm{det}} \rangle}$$

where SI_{det} is the detrended signal intensity, $\langle\rangle$ denotes the averaging operation, k is the current epoch, and n is the number of epochs used for calculating the mean. The noise density N_0 remains nearly constant over short periods (e.g., 1 minute), so $N_0(k)$ can be considered equal to $N_0(k-i)$.

3 Detection Methods

3.1 Manual Visual Detection Method

Numerous studies perform scintillation detection through manual visual inspection of scintillation indices [?]. By observing the time series of scintillation indices, empirical evaluations are conducted. To further discriminate, researchers typically also rely on carrier-to-noise ratio, satellite elevation angle, azimuth angle, and geomagnetic activity index data. Additionally, due to the unique characteristic patterns of ionospheric scintillation, comparisons with historical data can be made in certain cases. For example, since amplitude scintillation index is affected by multipath effects, ionospheric scintillation phenomena can be easily identified in GNSS signals by comparing time series at regular intervals of one sidereal day.

Taking the amplitude scintillation index S_{4c} from geodetic receivers as an example, the data sampling rate in this paper is 1 s with a sliding window of 60 epochs. Figure 1 shows the temporal variations of S_{4c}, elevation angle, azimuth angle, and geomagnetic activity index for satellite G04 on August 5, 2024. It can be observed that S_{4c} exhibits some fluctuations around 13:30 UT; however, due to the low elevation angle, short duration of only a few minutes, and the Dst index indicating a weak geomagnetic storm during this period, these fluctuations are identified as non-ionospheric scintillation. Starting from 16:00 UT, S_{4c} shows multiple fluctuations while other values such as elevation angle remain normal, indicating that ionospheric scintillation occurred during this period. Although manual visual detection lacks scientific rigor, this method ensures optimal detection performance. Its disadvantages are obvious: manual operation is extremely time-consuming and depends on the experience of the operator.

[FIGURE:1] Temporal series of S_{4c}, elevation angle, azimuth angle, and geomagnetic activity index for satellite G04 on DOY 218, 2024

3.2 Threshold Detection Method

The semi-automated threshold detection method relies on comparing predefined thresholds with scintillation index values. This method is called threshold triggering in Taylor et al. [?] and hard detection in Linty et al. [?]. It is an automated, objective determination method. Different thresholds are predefined according to the scintillation indices, and when a scintillation index exceeds its predefined threshold, an ionospheric scintillation event is identified. Taking the amplitude and phase scintillation indices S_4 and σ_ϕ from ionospheric scintillation receivers as examples, an ionospheric scintillation event is considered to occur if and only if:

$$S_4[n] > T_{S_4} \quad \text{or} \quad \sigma_\phi[n] > T_{\sigma_\phi}$$

where T_{S_4} and T_{σ_ϕ} are predefined thresholds for S_4 and σ_ϕ, respectively. When the above conditions are satisfied, ionospheric scintillation is deemed to have occurred.

The performance of this method clearly depends on threshold selection, which is influenced by location, time, observation environment, and receiver quality. Excessively large thresholds can lead to missed detection of scintillation events, while overly small thresholds can cause false alarms. Regarding amplitude scintillation index, many scholars use $T_{S_4} = 0.2$ as the judgment threshold for ionospheric scintillation [?, ?]; some consider S_4 between 0.2 and 0.5 as moderate scintillation and $S_4 > 0.5$ as strong scintillation [?]. For phase scintillation index, $T_{\sigma_\phi} = 0.25$ rad is commonly used [?, ?]. For ROTI, different sliding windows employ different thresholds for ionospheric scintillation event determination. With 1 s sampling and a 1 min sliding window, the ROTI threshold is generally 2.5 TECU/min [?]. In this paper, the observation data sampling interval is 1 s, Δt is 1 min, and the number of epochs N is 60.

In practical applications, threshold selection should be further adjusted according to station environment, signal quality, and other factors. As shown in Figure 2, ionospheric scintillation detection results based on the scintillation index threshold method indicate that many large scintillation index values are concentrated at both ends of the satellite scintillation index "U-shaped" curve, i.e., in

Figure 2

Figure 1: Figure 2

Figure 4

Figure 2: Figure 4

low elevation angle regions. To illustrate this in more detail, Figure 3 shows the temporal variation of amplitude scintillation index for one satellite (G05). Analysis reveals that this method yields a high false alarm rate because low elevation angle regions are affected by multipath effects [?]. It can therefore be inferred that many scintillation phenomena detected by this method are actually caused by multipath effects rather than genuine ionospheric scintillation.

Ionospheric scintillation detection results based on scintillation index threshold method for DOY 151, 2024

To reduce false alarms or missed detections of ionospheric scintillation events caused by multipath effects and other propagation errors, and to detect ionospheric scintillation phenomena more accurately, scholars have proposed the cutoff elevation angle method. Most false alarms caused by multipath effects can be eliminated by discarding data below a certain elevation angle, but this approach may also lead to loss of some useful information. The calculation method is as follows:

$$S_4[n] > T_{S_4} \quad \text{and} \quad \theta_{\text{el}}[n] > T_{\theta_{\text{el}}}$$

where θ_{el} is the elevation angle and $T_{\theta_{\text{el}}}$ is the elevation angle threshold, i.e., the cutoff elevation angle. The cutoff elevation angle is generally set to 30° [?, ?]. Figure 4 shows ionospheric scintillation detection results based on the cutoff elevation angle method. Compared with Figure 2, the cutoff elevation angle constraint in this method significantly eliminates multipath effects and additionally detects two ionospheric scintillation events, but it also loses a lot of valid information.

Ionospheric scintillation detection results based on cutoff elevation angle method for DOY 151, 2024

Restrictions can also be applied to carrier-to-noise ratio to exclude effects with excessive noise, or to azimuth angle to exclude environmental influences. However, defining the carrier-to-noise ratio threshold is relatively complex because it mainly depends on receiver performance. In related studies, 37 dB-Hz is generally used as the carrier-to-noise ratio threshold [?]. Pelgrum et al. [?] proposed a method that jointly considers carrier-to-noise ratio C/N_0 and amplitude scintillation index. Ionospheric scintillation is deemed to occur at a given moment when the following condition is satisfied:

$$S_4 > 1.075 - (C/N_0) \cdot 0.01875$$

Figure 5 shows ionospheric scintillation detection results based on the linear combination method of scintillation index and carrier-to-noise ratio. It can be clearly seen that this method has low accuracy, especially when phase scintillation exists. Vikram and Morton [?] analyzed the effectiveness of this method using data from 25 ionospheric scintillation events over 6 days, finding that only 4 scintillation events were detected. They subsequently proposed a scintillation event determination method combining cutoff elevation angle and scintillation index. Taking amplitude scintillation index as an example, the judgment condition is:

$$S_4 > -9.09 \times 10^{-4}\theta_{\mathrm{el}} + 0.1373$$

Figure 6 shows ionospheric scintillation detection results based on the linear combination method of scintillation index and elevation angle. This method fails to significantly eliminate multipath effects and exhibits numerous misjudgments. Taylor et al. [?] analyzed continuous five-day data from PRN 25 between February 27 and March 2, 2011, and found that fluctuations in scintillation index caused by multipath effects at low satellite elevation angles were mistakenly identified as ionospheric scintillation phenomena. After further optimization, they introduced a third condition in satellite azimuth angle, which selected appropriate thresholds based on a preset false alarm rate and manual visual scintillation detection. However, this method' s drawback is its reliance on a minimization process specific to data distribution, limiting its applicability under different spatial and temporal observation conditions. Since multipath effects are location-dependent, the receiver' s surrounding environment can be characterized to avoid losing valuable data by setting predetermined thresholds. Taylor et al. integrated data from December 20-26, 2011, and found that improving azimuth angle conditions and selecting appropriate scintillation index thresholds could avoid all false detections.

3.3 Non-Scintillation-Index Detection Methods

Scintillation-index-based detection methods have serious flaws. Although scintillation indices are widely used and validated, their calculation process reduces the order of raw information, thereby ignoring higher-order characteristics of the signal [?]. Their computation requires averaging and detrending operations, needs algorithms with complex adjustments, is time-consuming and computationally expensive, and may introduce serious errors that affect scintillation detection results [?]. Particularly, detrending data through Butterworth filters, though efficient, has limitations as many authors have found when processing polar scintillation, which relates to the choice of filter cutoff frequency and local ionospheric characteristics [?, ?]. Additionally, scintillation-index-threshold-based detection algorithms are complex and computationally costly. For these reasons, real-time detection is typically not feasible with this method.

To address this, Fu et al. [?] proposed a wavelet decomposition method that can effectively detect or extract scintillation-related signal features by converting signals into time-domain scintillation signals. Mushini et al. [?] also proposed a detrending detection method based on wavelet filters, which significantly outperforms Butterworth filters in terms of correlation between amplitude and phase scintillation indices and is more suitable for GPS scintillation signals. Ionospheric scintillation detection is a binary hypothesis testing problem. Let X represent the observed values of phase or amplitude scintillation $\Delta\phi$ or ΔA, or their corresponding wavelet coefficients d_j, which are assumed to follow a normal distribution and thus conform to two physical system models as follows:

$$H_0 : (X \sim N[m_0, \sigma^2], \text{no scintillation})$$
$$H_1 : (X \sim N[m_1, \sigma^2], \text{with scintillation})$$

Here, X is treated as a Gaussian process with known parameters m_0 and σ^2, while m_1 related to scintillation signals is unknown. Therefore, the detection problem constitutes a two-sided test with simple hypothesis H_0 and composite hypothesis H_1:

$$H_0 : (\theta = \theta_0), \quad H_i : (\theta = \theta_i \neq \theta_0)$$

where $\theta_i = m_i$ $(i = 0, 1)$. Due to the lack of prior probability information about scintillation occurrence, the Neyman-Pearson detector is an appropriate choice for solving this problem.

After a series of calculations on the logarithm of the likelihood ratio $L(x)$, the following test criterion can be obtained:

$$\text{When } |X| > X_t, \text{ select hypothesis } H_1$$
$$\text{When } |X| \leq X_t, \text{ select hypothesis } H_0$$

where the detection threshold X_t is determined by:

$$P_f = 2Q\left(\frac{X_t}{\sigma}\right)$$

and the detection probability P_d can be calculated as:

$$P_d = P(|X| > X_t|H_1) = Q\left[\frac{X_t - m_1}{\sigma}\right] + Q\left[\frac{X_t + m_1}{\sigma}\right]$$

$$Q(z) = \int_z^\infty \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$$

This test is commonly known as the UMPU (Uniformly Most Powerful Unbiased) test, which has the greatest detection power among all two-sided composite tests under specified P_f conditions. Unbiased means that for any value of the unknown parameter θ, the false alarm rate is less than the detection probability. When m_1 is close to m_0, the signal-to-noise ratio $m_1 m_0/\sigma$ is low, and $P_d = P_f$, representing the worst-case scenario. Scintillation detection can be effectively achieved by performing wavelet decomposition on scintillation signals. For each level of wavelet decomposition, a UMPU detector is constructed, with the layer detector defined as:

$$H_j = \{1 \text{ indicates scintillation}; 0 \text{ indicates no scintillation}\}$$

where H_j represents the binary detection result corresponding to the j-th level wavelet coefficients d_j.

Finally, by combining the results of each layer detector, a multiple binary detector is formed, expressed as:

$$H_M = \bigcup_{j=1}^{M} H_j$$

Ouasson et al. [?] proposed a new method based on nonparametric local regression, which reduces the computational load of wavelet analysis and handles discontinuities excellently, being more robust to discontinuous phase observations than traditional methods. The core of the nonparametric regression method is to construct density estimation or local regression models by selecting appropriate kernel functions and bandwidth parameters, then use Taylor expansion to obtain approximations of bias and variance, thereby deriving the Asymptotic Mean Integrated Squared Error (AMISE) and obtaining the optimal bandwidth.

The basic model formula for kernel density estimation is:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right)$$

where K is a kernel function satisfying non-negativity, symmetry, and normalization requirements, and h is a bandwidth parameter controlling the degree of smoothing. Next, to analyze the estimator' s error, this method uses Taylor expansion to decompose the mean squared error into bias and variance components, with the two main approximate formulas being:

$$\text{bias}\{\hat{f}_h(x)\} \approx \frac{1}{2}h^2 f''(x)\mu_2(K)$$

$$\text{var}\{\hat{f}_h(x)\} \approx \frac{1}{nh}\|K\|^2 f(x)$$

where $\mu_2(K) = \int u^2 K(u)du$ represents the second moment of the kernel function, and $\|K\|^2 = \int K^2(u)du$ is the L_2 norm of K. Combining bias and variance, the AMISE expression is:

$$\text{AMISE} = \frac{1}{4}h^4\mu_2^2(K)\int [f''(x)]^2 dx + \frac{1}{nh}\|K\|^2$$

The optimal bandwidth h_{opt} is then obtained by differentiating AMISE and setting the derivative to zero, with its analytical expression being:

$$h_{\text{opt}} \approx \left(\frac{\|K\|^2}{\mu_2^2(K)\int [f''(x)]^2 dx}\right)^{1/5} n^{-1/5}$$

In local polynomial kernel regression, the key idea is to perform local polynomial fitting of data near the target point x, with the basic model being:

$$P(x) = \beta_0 + \beta_1(X_i - x) + \cdots + \beta_p(X_i - x)^p$$

and the estimator obtained through weighted least squares:

$$\hat{\beta} = (X^T W X)^{-1} X^T W Y$$

where the diagonal elements of weight matrix W are $w_i = K_h(X_i - x) = \frac{1}{h}K\left(\frac{X_i - x}{h}\right)$. The final regression estimate at point x is the intercept $\hat{\beta}_0$. When $p = 0$, the method reduces to the Nadaraya-Watson kernel estimator, with the form:

$$\hat{f}_{\text{NW}}(x) = \frac{\sum_{i=1}^n K_h(X_i - x)Y_i}{\sum_{i=1}^n K_h(X_i - x)}$$

The connection between this method and traditional filters can be illustrated using a first-order Butterworth low-pass filter as an example, whose frequency response is:

$$H(f) = \frac{1}{1 + j(f/f_c)}$$

The time-domain kernel obtained through inverse Fourier transform is:

$$h(x) = 2\pi f_c K_0(2\pi f_c |x|)$$

where $K_0()$ represents the modified Bessel function of the second kind. This result shows that the Butterworth filter is essentially equivalent to smoothing using a Bessel kernel, and there is a direct relationship between the filter' s cutoff frequency f_c and the smoothing parameter in this method.

Piersanti et al. [?] proposed a new multiscale data analysis technique called Adaptive Local Iterative Filtering (ALIF), which can better describe the multiscale nature of studied geophysical signals than Fourier transform and improve the scale resolution of discrete wavelet transform. ALIF is an improved method based on Empirical Mode Decomposition (EMD) and Iterative Filtering (IF). The outer loop extracts Intrinsic Mode Components (IMC) layer by layer from the signal until the residual becomes a trend. The inner loop continuously detrends the current residual signal to extract the k-th IMC. Unlike EMD, ALIF no longer obtains local means through interpolation of upper and lower envelope lines but uses a local adaptive filter mask $h_n^{(t)}(x)$ to perform weighted integration of the signal. In practice, infinite iterations are not performed; instead, the relative change SD between adjacent iterations is monitored in the inner loop:

$$SD = \frac{\|g_{\text{ALIF}}^{1,n} - g_{\text{ALIF}}^{1,n-1}\|^2}{\|g_{\text{ALIF}}^{1,n-1}\|^2}$$

The inner loop stops when $SD < \varepsilon$ or the maximum number of iterations is reached.

When processing only amplitude scintillation, C/N_0 analysis can detect amplitude fluctuations in the signal. In this case, it is more difficult to distinguish genuine scintillation from other noise. Detecting ionospheric scintillation based on C/N_0 is a universal method applicable to any GNSS receiver, making C/N_0-based techniques low-cost and easily accessible. Miriyala et al. [?] proposed a new algorithm for detecting ionospheric irregularities based on Multifractal Detrended Fluctuation Analysis (MF-DFA), which uses multiple adaptive time-frequency methods to decompose GNSS satellite signal data affected by scintillation, providing better detection results. The algorithm first performs CEEMD decomposition, which decomposes the original C/N_0 signal into multiple IMF components through a complementary noise injection strategy: adding complementary Gaussian white noise (positive and negative paired noise) to the signal, generating two sets of IMF ensembles through multiple EMD decompositions, and taking the mean of the IMF ensembles to eliminate noise residuals and obtain the final IMF component set. This method requires performing multifractal detrended fluctuation analysis on each IMF component.

(1) Cumulative deviation sequence construction:

$$y(i) = \sum_{l=1}^{i} I(l) - \frac{1}{M} \sum_{k=1}^{M} I(k)$$

where $I(l)$ is the IMF component and M is the data length.

(2) Segmentation and detrending:

Divide $y(i)$ into $2M_s$ equal-length segments ($M_s = [M/s]$), perform linear fitting on each segment, and calculate variance:

$$F^2(s,u) = \frac{1}{s} \sum_{i=1}^{s} [y((u-1)s+i) - y_u(i)]^2$$

(3) q-order fluctuation function calculation:

$$F_q(s) = \left\{ \frac{1}{2M_s} \sum_{u=1}^{2M_s} [F^2(s,u)]^{q/2} \right\}^{1/q}$$

(4) Generalized Hurst exponent estimation:

Determine the fractal scaling through power-law relationship:

$$F_q(s) \sim s^{h(q)}$$

where $h(q)$ is the q-order generalized Hurst exponent.

Finally, noise detection is performed by setting a threshold $\varphi = 0.5$ (the theoretical Hurst value for white noise), and IMF components with $h(q) < \varphi$ are selected as ionospheric scintillation noise, with remaining IMFs reconstructed to achieve signal denoising.

3.4 Machine Learning Detection Methods

In recent years, researchers have proposed machine learning techniques for automatic detection of scintillation events. The machine learning process refers to building models trained on a set of historical data, with the ability to solve tasks by analyzing the correct features of the research target. Machine learning includes various algorithms aimed at constructing models from given datasets and applying them. These algorithms are divided into three categories: supervised learning, unsupervised learning, and semi-supervised learning. The difference between these categories lies in whether the dataset used is labeled, unlabeled, or a combination of both. The main goal of our research is to classify scintillation events, so the chosen method employs supervised learning algorithms. In the case of supervised learning, experimental data are pre-labeled through manual annotation. The supervised machine learning process is shown in Figure 7.

[FIGURE:7] Flowchart of supervised machine learning process

Selecting the feature set for training and classification tasks is key to machine learning algorithms, including GNSS scintillation indices, signal C/N_0, and satellite elevation and azimuth angles, thereby providing descriptive features of the data. The dataset is then labeled through manual annotation and used to train machine learning algorithms and validate their performance.

Support Vector Machine (SVM)-based detection methods have been widely studied. SVM is a popular classification and regression technique widely applied in handwriting recognition, database searching, classification, and many areas of machine intelligence. SVM is an optimization technique for structural risk minimization. Moreover, SVM is the optimal linear machine in kernel space. SVM can be configured as a back-propagation neural network or radial basis function machine, and it is also commonly used for nonlinear regression, formally known as Support Vector Regression. The core algorithms of SVM mainly cover the primal form for model training, the dual form, and the prediction decision function.

(1) Primal optimization problem:

When $y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 - \xi_i$, $\xi_i \geq 0$, the primal form of model training is:

$$\min_{\mathbf{w},b,\{\xi_i\}} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N}\xi_i$$

where $\mathbf{w}$ is the normal vector of the classification hyperplane, b is the bias term, ξ_i is the slack variable for the i-th sample to allow soft margin, and $C > 0$ controls the penalty intensity for margin violations.

(2) Dual optimization problem:

The dual form of model training is:

$$\max_{\alpha} \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)$$

where α_i are Lagrange multipliers corresponding to each training sample, and $K(\mathbf{x}_i, \mathbf{x}_j)$ is the kernel function, commonly including linear kernel and RBF kernel, etc. This dual form only involves inner products between samples and can be directly kernelized.

(3) Classification decision function:

The prediction decision function for model training is:

$$f(\mathbf{x}) = \sum_{i=1}^{N}\alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b, \quad \hat{y} = \mathrm{sign}(f(\mathbf{x}))$$

This function only relies on support vectors ($\alpha_i > 0$) to participate in the summation, completing nonlinear mapping in high-dimensional feature space through kernel function K. This algorithm uses a large amount of real scintillation data for training with manual labeling, achieving detection accuracy of 91%-96%, which is significantly better than other ionospheric scintillation detection methods [**?**, **?**].

Decision tree is one of the most commonly used classification techniques. It is based on a tree structure defined by recursively partitioning the input space: each internal node represents some feature of the domain; each branch emanating from a node represents the result of a decision made based on that feature at the node; each leaf represents a final classification decision corresponding to a combination of individual decisions made along the path from the root to the leaf. Learning occurs when the machine creates a set of rules that define the model, which are defined according to the branching and function order of decision criteria at each node [**?**, **?**]. Decision tree is a top-down, recursive splitting greedy algorithm used to partition the data space into several "pure" subregions. At each node to be split, the algorithm traverses all features and their possible thresholds, evaluates the "reduction in impurity after splitting," and selects the maximum for partitioning. Splitting criteria typically use entropy, Gini impurity, or classification error rate, aiming to improve the homogeneity of child nodes. Information entropy measures the confusion degree of sample category distribution in a node and can be expressed as:

$$H(t) = -\sum_{j=1}^{K} p_j \log_2 p_j$$

where p_j is the proportion of samples of class j in node t. Larger entropy indicates more mixed nodes. Gini impurity is a commonly used impurity measure, representing the probability of misclassifying two randomly drawn samples, expressed as:

$$I_{\text{Gini}}(t) = 1 - \sum_{j=1}^{K} p_j^2$$

When a node is completely pure (only one class proportion is 1), the Gini value is 0. When partitioning node D_p using feature A, information gain is defined as the difference in entropy before and after splitting, expressed as:

$$G(D_p, A) = H(D_p) - \frac{N_{\text{left}}}{N_p} H(D_{\text{left}}) - \frac{N_{\text{right}}}{N_p} H(D_{\text{right}})$$

where N_p, N_{left}, and N_{right} are the sample numbers of the parent node and left/right child nodes, respectively. Information gain essentially measures the improvement in purity after partitioning, and the above process is repeated for each newly formed child node until stopping conditions are met (e.g., node sample number is less than threshold or purity is sufficiently high). The output of leaf nodes is the category (taking the majority class) or regression value (taking the mean), and pruning can be further performed to prevent overfitting.

Random forest is an ensemble learning method for classification based on constructing a large number of decision trees during training. It helps overcome overfitting problems and reduces estimation variance through averaging. Random forest is a combination of tree predictors, where each tree depends on independently sampled random vector values, and all trees in the forest have the same distribution. As the number of trees in the forest increases, the forest' s generalization error converges to a limit that depends on the strength of individual trees in the forest and the correlation between them. When using only correlator outputs, the accuracy can reach 98.0%. When using the random forest algorithm at the cost of greater computational load, the result further improves to 99.7%. Relying on pre-trained machine learning decision tree algorithms, ionospheric amplitude scintillation events can also be accurately identified using measurements collected by geodetic GNSS receivers. Experimental results using real data show that scintillation detection accuracy can reach 99% [**?**].

The decision tree algorithm can also detect transient times before and after the strongest phase of an event, thereby providing early runtime warnings. Another advantage is that finer temporal resolution can be obtained in detection by utilizing high-rate correlator outputs. Additionally, avoiding scintillation indices prevents problems with detrending and filtering processes. Although the training phase for building models is computationally demanding, the decision phase is usually very simple and can be performed in real time without affecting performance.

4 Comparison of Ionospheric Scintillation Detection Methods

Accurate early detection and classification of scintillation events are crucial for space weather, atmospheric remote sensing, high-precision GNSS, and critical infrastructure and data collection systems that rely on GNSS. We summarize and compare the advantages and disadvantages of the detection techniques described above, as shown in Table 1 . In practical research, due to the impact of global stations and high resolution, manual visual detection methods, non-scintillation-index detection methods, and machine learning detection methods require significant manpower or complex algorithms. Therefore, the most commonly used method currently is the threshold detection method. The threshold plus cutoff elevation angle detection method yields results more consistent with manual visual detection.

5 Summary and Future Outlook

5.1 Summary

In this paper, we discuss the calculation of GNSS ionospheric scintillation indices, focusing on different detection methods for ionospheric scintillation events. Timely and accurate detection of scintillation events can provide scintillation warnings for high-precision applications and critical infrastructure, thereby improving GNSS user application performance. On the other hand, precise scintillation records help advance research on the upper atmosphere and space weather. Reducing false alarms caused by ionospheric scintillation can optimize the use of storage and bandwidth resources in monitoring station networks. Ionospheric scintillation indices are widely applied, mainly relying on manual visual inspection of scintillation index time series or threshold-based automatic determination, but these are limited by required manpower and threshold applicability, respectively. Machine learning algorithms have higher complexity and computational load but can achieve detection accuracy exceeding 98%. Current research is moving toward designing specialized receivers and advanced filtering and processing algorithms, which can ensure more accurate understanding of ionospheric scintillation characteristics for better detection performance.

5.2 Future Outlook

(1) Further Optimization of Detection Methods

Existing ionospheric scintillation detection methods, including manual visual inspection, threshold-based automatic determination, and machine learning algorithms, each have their advantages and limitations in their respective applications. Future research will overcome the limitations of existing methods by further developing automated, intelligent, and real-time detection methods to achieve more efficient and precise scintillation monitoring. Manual visual inspection, while intuitive, is inefficient and subject to human factors. Fixed threshold-based detection methods, though widely used, are prone to false alarms and missed detections in complex environments. Future research will focus on developing intelligent dynamic threshold setting methods using machine learning technology, which can automatically adjust detection thresholds based on data features rather than relying on static settings. Adaptive algorithms can adjust detection standards under different ionospheric conditions in different regions and time periods, thereby improving detection flexibility and accuracy. Although machine learning algorithms (such as Support Vector Machines, Random Forests, etc.) have achieved good results in scintillation detection, challenges remain, such as high computational load and real-time data processing. With the development of deep learning technology, future research can explore more efficient deep neural network structures and parallel processing of large-scale data.

(2) Precise Extraction of Scintillation Indices

GNSS ionospheric scintillation indices, as key parameters for measuring ionospheric scintillation intensity, are crucial for the detection and research of ionospheric scintillation phenomena. Although these methods have achieved initial success in ionospheric scintillation detection, how to further precisely extract scintillation indices remains a current research focus. Current calculation methods mainly rely on traditional statistical analysis of amplitude and phase variations. While these methods are relatively mature, they may have certain errors and limitations when facing complex ionospheric environments. Future research can focus on developing more precise calculation models that incorporate more signal features, such as multi-frequency and multipath effects, to improve the accuracy of scintillation indices. The real-time extraction and monitoring capability of scintillation indices are particularly important. Future development will focus on efficient real-time data processing and analysis platforms, combined with cloud computing and edge computing technologies, to achieve rapid response and dynamic monitoring of ionospheric scintillation. This will help achieve timely warnings of scintillation events and provide support for high-precision navigation, communication, and other applications.

(3) Multi-Source Data Fusion Detection

Current main detection equipment for ionospheric irregularities includes GNSS, ionospheric digital ionosondes, scatter radars, Low Earth Orbit (LEO) satellites, and optical equipment such as all-sky airglow imagers [?]. Based on various detection means, scholars have conducted extensive research on ionospheric irregularities, with different detection devices having their own advantages and limitations when analyzing ionospheric irregularities [?]. To improve monitoring comprehensiveness and accuracy, future research can develop multi-source data fusion detection methods that combine GNSS signals with other observation data to obtain more comprehensive information for detecting and analyzing ionospheric scintillation. Exploration can be made into fusing data from different sources of sensors (such as ground- and space-based observation data) to enhance the detection and analysis capabilities of scintillation events. Through multimodal learning algorithms, the complementarity and fusion effectiveness of different sensor data can be improved.

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