Efficient PSS Detection Algorithm Aided by CNN

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Abstract: In a 5G mobile communication system, cell search is the initial step in establishing downlink synchronization between user equipment (UE) and base stations (BS). Primary synchronization signal (PSS) detection is a crucial part of this process, and enhancing PSS detection speed can reduce communication latency and improve overall quality. This paper proposes a fast PSS detection algorithm based on the correlation characteristics of PSS time-domain superposition signals. Conducting PSS signal correlation within a smaller range can reduce computational complexity and accelerates communication speed. Additionally, frequency offset can impact the accuracy of calculations during the PSS detection process. To address this issue, we propose applying convolutional neural networks (CNN) for frequency offset estimation of synchronization signals. By compensating for the frequency of related signals, the accuracy of PSS detection is improved. Finally, the analysis and simulation results demonstrate the effectiveness of the proposed approach.

Keywords: 5G; CNN; cell search; PSS detection

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1 Introduction

The communication between user equipment (UE) and the base station (BS) is established via wireless signals, where cell search serves as the initial step for terminal devices to access the 5G network. After power on, users need to perform a cell search to quickly identify their current cell, obtain the cell ID, and achieve time-frequency synchronization. The detection of the primary synchronization signal (PSS) in 5G is an important process in wireless communication, involving the identification and decoding of the PSS from received signals. PSS is one of the signals that help the UE synchronize with base stations, enabling devices to determine the start of wireless frames and decode additional signals. It also plays a key role in identifying 5G cells; when combined with the secondary synchronization signal (SSS), it can uniquely identify a cell. Through effective algorithms and techniques, efficient PSS detection can be achieved under various channel conditions, ensuring reliable synchronization and network access capabilities for the UE.

Several research findings regarding PSS detection algorithms have been proposed. Starting from the basic principles of the 5G initial access process, JEON et al.[1] proposed the cell search process and the PSS structure of the 5G communication system. CHAKRAPANI[2] proposed the composition of the synchronization signal block (SSB) carrying PSSes. BALASUBRAMANYA et al.[3] proposed a design scheme for 4G PSS in the evolution of 5G technology. A new method for rapid detection of PSS by UE was introduced in Ref. [4], which improved fast synchronization between terminals and networks. YOU[5] proposed a sequential integer carrier frequency offset (ICFO) and edge master synchronization signal (S-PSS) detection scheme to reduce complexity in the 5G new wireless vehicular Internet of Things system. There are also various solutions to the frequency offset problem in PSS detection[6]. In Ref. [7], the authors described a program for synchronizing 5G networks and proposed two methods to estimate frequency offset (FFO). The first method utilizes the carried information, and the second method involves partial cross-correlation of PSS, which is applied to each orthogonal frequency division multiplexing (OFDM) symbol in the SSB, with the phase of the auto-correlation peak used to estimate the value of FFO. However, synchronization errors can reduce the performance of maximum likelihood (ML) methods[8]. Some researchers have adopted joint detection and estimation methods for initial downlink access, as described in Refs. [9] and [10]. The second technique for estimating FFO is based on replicating the correlation signal between the partial input PSS and the PSS over more than half of the symbol length duration[11]. It is also noted that synchronization errors can diminish the performance of the FFO estimation method. In the past two years, significant advancement has been made in 5G PSS detection and the application of convolutional neural networks

(CNN) in physical layer algorithms. ASSAF et al.[12] evaluated 5G New Radio (NR) frequency synchronization in the downlink initial access, and proposed and investigated a reduced-complexity FFO estimation method. In Ref. [13], a novel approach to enhancing the detection of PSS sequences in 5G NR systems was proposed. ZHANG et al.[14] proposed a scheme to estimate the energy per resource element (EPRE) ratio of PSS to SSS/demodulation reference signal (DMRS) and demonstrated the proposed scheme can estimate the EPRE ratio accurately when the signal-to-noise ratio (SNR) is above −4 dB through simulation results. COUTINHO et al.[15] proposed a CNN-based algorithm for channel estimation in the presence of phase noise and carrier frequency offset (CFO) in 5G and beyond systems. ZHENG et al.[16] proposed a decomposed CNN for the sub-Nyquist tensor-based 2D direction of arrival (DoA) estimation.

The main motivation and novelties of this paper are summarized as follows.

• This paper proposes a fast PSS detection algorithm assisted by a CNN neural network, which can quickly complete the PSS detection process after the 5G terminal device is turned on, thereby reducing communication latency.

• In the fast PSS detection algorithm, the sum sequence, obtained by superimposing three frequency domain PSS sequences, is cross-correlated with the received signal in the time domain. A shorter time-domain sequence is determined based on the correlation peak and then transformed into the frequency domain to cross-correlate with the received signal. The cell ID required for PSS detection is determined from the correlation peak.

• Local received signals typically have a frequency offset. Using CNN-assisted frequency offset correction algorithms can yield corrected received signals, thereby enhancing the accuracy of PSS detection results.

2 Background Description

2.1 5G Cell Search Procedure

The 5G NR cell search process is a key step for UE to find and access suitable serving cells in the network when it is turned on or needs to reconnect. The specific steps of the 5G NR cell search are as follows:

Step 1: The NR terminal adjusts the radio frequency (RF) receiver to the designated receiving frequency to capture the signal;

Step 2: The PSS synchronization detection is performed to obtain time slot timing information and retrieve the sector number $N_{ID}^{(2)}$ within the cell group;

Step 3: Frequency offset compensation is applied;

Step 4: Based on the relationship between PSS and SSS in the synchronization signal and the physical broadcast channel (PBCH) block, the NR terminal performs frequency domain correlation detection on the SSS to obtain the cell group number $N_{ID}^{(1)}$;

Step 5: The NR terminal obtains the cell ID using the previously obtained cell group ID $N_{\mathrm{ID}}^{(2)}$ and cell group ID $N_{\mathrm{ID}}^{(1)}$. Then, retrieve the corresponding DMRS information from the PBCH based on the cell ID to obtain the SSB index, which corresponds to the beam ID[17];

Step 6: The PBCH symbol is decoded to obtain the master information block (MIB) information;

Step 7: The cell search process is completed, enabling the UE to perform a random signal access process for uplink synchronization.

2.2 PSS Detection

From the cell search process described above, it is evident that the PSS synchronization detection process is the initial step for mobile terminals to access the network. This step enables terminal devices to perform tasks such as sector identification $N_{\mathrm{ID}}^{(2)}$ recognition, frequency synchronization, neighbor cell search, and fast locking. Specifically, after several steps, such as coarse time synchronization, frequency offset estimation, fine synchronization, SSS detection, and beam ID detection, users can receive and interpret the physical broadcast information of the cell, obtain MIB and system information block (SIB), and complete cell access through random access and other processes based on the system messages received. In these steps, coarse time synchronization involves positioning the timing synchronization within the cyclic prefix range, which is accomplished using PSS signals. 5G PSS has strong autocorrelation and cross-correlation properties, which are leveraged for coarse time synchronization. Since there are only three sets of PSS sequences and the generation of SSS signals is linked to both cell group identification and sector identification, performing PSS detection first reduces synchronization complexity and facilitates the retrieval of necessary physical cell information. By utilizing the correlation characteristics of the PSS to demodulate the PSS in the received signal, the starting position of OFDM symbols and the sector ID, $N_{\mathrm{ID}}^{(2)}$, carried by PSS can be determined. Based on the fixed time-frequency position of SSB, once the time-frequency position of PSS is established, the time-frequency position of SSS can be determined. The frequency domain position of the SSS matches that of the PSS, while in the time domain, the SSS is shifted by two OFDM symbols from the position of the PSS. Using the generation rules or cross-correlation characteristics of SSS, the SSS sequence can be demodulated to determine the cell group ID, $N_{\mathrm{ID}}^{(1)}$, carried by SSS. The cell identification number can be calculated from the relationship between the cell group ID and the sector ID, completing the downlink synchronization process and allowing the terminal to access the base station's network. From the above process, it is clear that quickly determining the frequency domain position of PSS can improve the speed of cell search, enabling terminals to access the network more rapidly.

The traditional PSS detection algorithm generates a local

PSS time-domain sequence and performs cross-correlation calculations with the received signal. The PSS sequence has good correlation characteristics, and sliding cross-correlation can fully leverage these properties.

First, three sets of local PSS time-domain signals are generated, followed by point-by-point sliding cross-correlation with the received signal. Significant peaks occur only when the local PSS sequence matches the PSS sequence in the received signal. The maximum correlation value is identified, and the position of this maximum value serves as the synchronization point for the PSS. Simultaneously, the PSS sequence that detects the peak corresponds to the sector ID number it carries.

The sliding cross-correlation detection process is shown in Fig. 1.

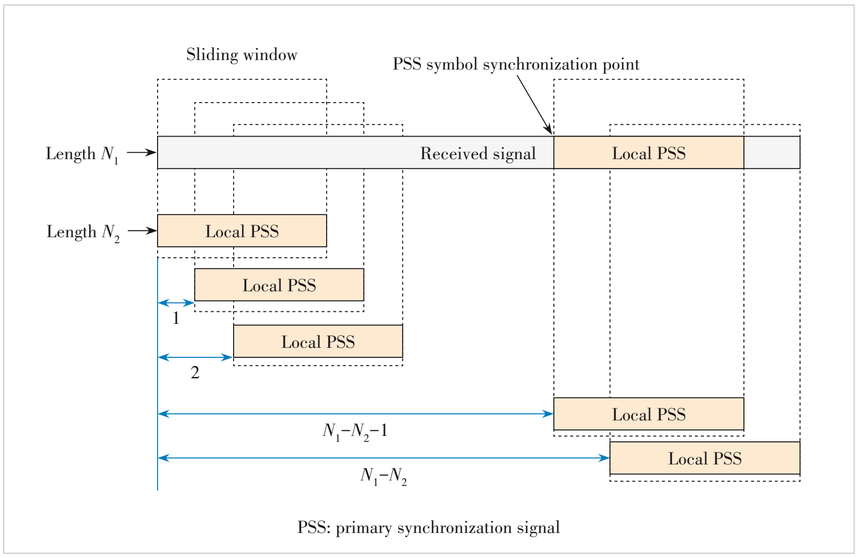


Figure 1. Traditional PSS detection algorithm

Table 1. Global synchronization grid

Frequency Range/MHz	SSB	GSCN	GSCN Range
0 – 3 000	N*1 200 kHz+M*50 kHz, N=1:2 499, M∈(1,3,5)	3N+(M−3)/2	2 – 7 498
3 000 – 24 250	3 000 MHz+N*1.44 MHz, N=0:14 756	7 499+N	7 498 – 22 255

GSCN: global synchronization channel number
SSB: synchronization signal block

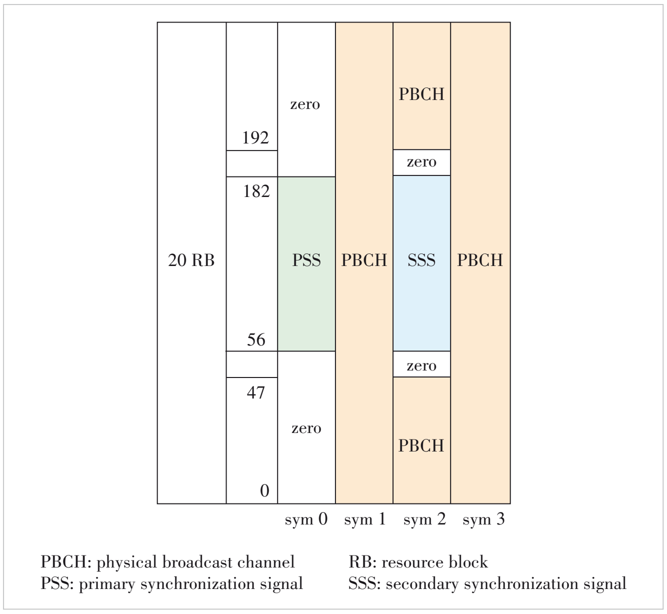


Figure 2. Structure of synchronization signal block

The frequency band occupied by 5G communications is relatively broad, encompassing a total of 29 frequency bands. They are primarily divided into two spectrum ranges: 26 frequency bands below 6 GHz (collectively referred to as sub-6 GHz) and 3 millimeter wave frequency bands. Currently, sub-6 GHz is primarily used in China, and it includes 7 frequency bands: n1, n3, n28, n41, n77, n78, and n79. 5G supports a maximum bandwidth configuration of 400 MHz. In the standalone (SA) mode, the SSB frequency domain location where the PSS is located must be determined by the global synchronization channel number (GSCN). Due to the extensive bandwidth of 5G NR, the concepts of GSCN and the Global Synchronization Grid have been introduced. The SSB frequency domain is positioned at integer intervals of the Global Synchronization Grid and terminals search for synchronization signals at these intervals. For frequencies below 3 GHz, the frequency scanning interval is 1.2 MHz; for frequencies between 3 GHz and 24.25 GHz, the interval is 1.44 MHz; for frequencies between 24.25 GHz and 100 GHz, the scanning interval is 17.28 MHz. The frequency range, SSB position, and GSCN determination are outlined in Table 1.

In the non-standalone (NSA) mode, the SSB frequency domain position is also uncertain, and the terminal is notified of the SSB frequency point position through high-level signaling. This introduces uncertainty in the SSB position across the entire bandwidth. The PSS sequence is a part of the SSB, as shown in Fig. 2, and the frequency-domain position of the PSS sequence is similarly uncertain across the entire bandwidth.

PSS sequences at different frequency domain positions may generate distinct time-domain sequences through the inverse fast Fourier transform (IFFT), leading to a rapid increase in computational complexity, which is unsuitable for 5G NR systems. Additionally, the large volume of received data further exacerbates computational complexity. This combination results in higher computational complexity, causing significant computation delays, longer communication delays, and reduced network communication quality. To address these challenges, this paper proposes a CNN-assisted PSS detection method to quickly determine the frequency domain position of the PSS, thereby shortening synchronization time and accelerating the cell search process. The existing PSS signal synchronization detection algorithm performs correlation operations on PSS sequences at various frequency points within the working frequency band in the time domain. Due to the lengthy PSS sequence (and consequently, the received signal), correlating the three PSS sequences with the received signal leads to high algorithm complexity and considerable computational demands, resulting in prolonged communication delays. Moreover, unlike 4G technology, the SSB in 5G NR is no longer fixed in the middle of the frequency band. The flexible placement of SSB time-frequency positions increases the initial blind detection computation of PSS, impacting the speed at which users can decode base station broadcast information and ultimately diminishing network communication quality.

2.3 System Model

During propagation, the transmitted signal is first corrupted by multi-path fading and additive white Gaussian noise (AWGN). CFO is introduced owing to the oscillator mismatch between BS and UE. The received signal is then modeled as[19]:

$$r(n) = s(n)e^{j\frac{2\pi\varepsilon n}{N}} + \omega(n) \tag{1},$$

where $s(n)$ is the transmitted signal, $\omega(n)$ is the zero mean AWGN with unity variance, and ε denotes the relative CFO normalized by the sub-carrier frequency spacing.

3 CNN-Assisted Fast PSS Detection Algorithm

Given the high complexity of traditional PSS detection algorithms and their limited resistance to frequency offset and noise[20], there is a pressing need for a new algorithm that offers fast processing speed, anti-frequency offset capabilities, and effective correlation utilization. To address this, this paper proposes an algorithm based on the CNN method to process the received signal sequence in the presence of frequency offset. It further leverages the cross-correlation features of frequency-domain superimposed signals to optimize PSS detection. This approach not only enhances the resistance to frequency offset but also significantly improves the PSS detection speed, thereby reducing communication latency. The processing flow of the proposed PSS detection optimization algorithm consists of the following steps.

1) Step 1: Generate a polynomial based on the PSS sequence. The specific implementation method is as follows. There are 1 008 physical layer cells in NR, and the formula for calculating NR cell IDs is:

$$N_{ID}^{cell} = 3N_{ID}^{(1)} + N_{ID}^{(2)} \tag{2},$$

where $N_{ID}^{(1)} \in \{0,1,\cdots,335\}$, carried by SSS, and $N_{ID}^{(2)} \in \{0,1,2\}$, carried by the PSS. The primary synchronization signal is defined in 3GPP protocol TS38.211 and utilizes three m-sequences of length 127 to represent the three values of $N_{ID}^{(2)}$.

To construct the PSS sequence, zeros are inserted at both ends of the $d_{PSS,i}(k)$ sequence (where i = 0,1,2 and k= 56, 57,⋯,182) for a local sequence length of 127. This process extends the sequence to a total length of 256, resulting in $PSS_i(k)$, which is expressed as:

$$PSS_i(k) = \begin{cases} 0, & k = 0,1,2,\cdots,55,183,\cdots,255 \\ d_{PSS,i}(k), & k = 56,57,\cdots,182 \end{cases} \tag{3},$$

where i=0, 1, and 2. The generation formula maps $PSS_i(k), i \in \{0,1,2\}$ to the corresponding $N_{ID}^{(2)}$.

2) Step 2: Overlay three frequency-domain PSS sequences. In the second step, the three frequency-domain PSS sequences are overlaid to create a sum sequence PSS_{sum}. An IFFT is then applied to convert the frequency-domain sequence into a time-domain sequence $pss\_t_{sum}(k), k = 0,1,2,\cdots,255$. The specific implementation method is as follows. Denote the three frequency-domain PSS sequences as $PSS_i(k)$, where $i = 0,1,2$. We compute the element-wise sum of the three sequences to obtain the sum sequence $PSS_{sum}(k)$ and represent it as:

$$PSS_{sum}(k) = \sum_{i=0}^{2} PSS_i(k), k = 0,1,2,\cdots, 255 \tag{4}.$$

The sequence shown above is transformed from a frequency domain sequence to a time domain sequence $pss\_t_{sum}(k)$ through the IFFT process, which can be expressed as:

$$pss\_t_{sum}(k) = IFFT\left(PSS_{sum}(k)\right), k = 0,1,2,\cdots, 255 \tag{5}.$$

3) Step 3: Estimate signal reception and frequency offset using CNN. In the third step, the terminal receives the time-domain signal $\tilde{r}(k)$ transmitted by the base station. A CNN model is then employed to correct the received signal and estimate the carrier frequency offset, yielding $r(k)$. The CNN-based carrier frequency offset estimation consists of two stages: offline training and online estimation. Firstly, the offline training process involves generating a network training dataset through MATLAB simulation based on the statistical characteristics of the signal used for frequency offset estimation. The dataset is processed from complex to real numbers and then used for offline training of the model. Finally, the trained network model parameters are saved. When estimated online, the received OFDM system signal $\tilde{r}(k)$ is converted into real numbers and transmitted to the trained CNN model. The estimation result $r(k)$ can be directly output based on the trained network parameters.

4) Step 4: Determine the peak value and time offset using correlation operation. A correlation operation is performed between the sequence and the time-domain received signal $r(k)$ to determine the peak value and corresponding time offset value k_0. The specific implementation process is as follows.

• Cross-correlation operation

We cross-correlate the time-domain sequence $pss\_t_{sum}(k), k = 0,1,2,\cdots,255$ with the local received signal $r(k)$, where k=0, 1, 2,⋯, 255. The cross-correlation function $C(k)$ is defined as:

$$C(k) = \left| \sum_{n=0}^{N-1} pss\_t_{sum}^{*}(n) r(k+n) \right|^2 \tag{6}$$

Here, $pss\_t_{sum}^{*}(n)$ is the complex conjugate of $pss\_t_{sum}(n)$, and N is the length of the sequence.

• Synchronization position determination

The position k_0 corresponding to the maximum value of the correlation peak is calculated as :

$$k_0 = \arg\max_{k} \{C(k), k = 0,1,2,\cdots\} \tag{7}$$

• Visualization of cross-correlation results

Fig. 3 illustrates the cross-correlation results among the time-domain received signals, the three local time-domain PSS sequences, and their superimposed and constructed sequences. The time-domain signals are obtained by applying an IFFT to the frequency-domain representations of the PSS sequences and their superposition. These time-domain signals are then cross-correlated with the received signal to calculate their correlation peak values.

• Analysis of correlation peak results

From Fig. 3, it is evident that the correlation peak values of the superimposed sequence $PSS_{sum}(k)$ in the time domain align with the trend of the correlation peak values of the individual PSS sequences, e.g., $pss\_t_3(k)$. While the peak magnitude of $PSS_{sum}(k)$ is slightly lower than that of a specific PSS sequence, and the difference is negligible. This demonstrates the feasibility of using the superimposed PSS to determine correlation peak values and derive the corresponding time offset k_0.

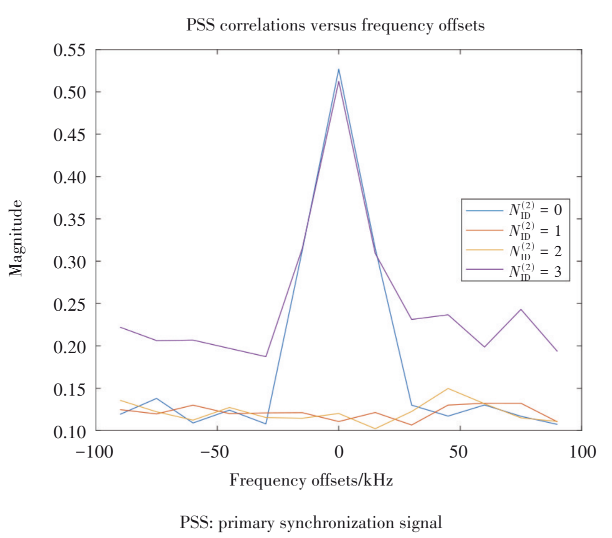


Figure 3. Correlation peaks of superimposed signals

• Example of cell ID correlation

Fig. 3 shows the three time-domain sequences $pss\_t_i(k), i = 1,2,3$, where i=1, 2, and 3 correspond to cell IDs 1, 2, and 3, respectively. The correlation results confirm that the superimposed sequence can reliably achieve time-domain synchronization for these cell IDs.

5) Step 5: Extract and transform the time-domain signal to frequency domain. In this step, a portion of the time-domain received signal is extracted from the corresponding time offset position k_0 to obtain a shorter time-domain signal sequence. The signal is then transformed into the frequency domain using FFT to obtain the frequency-domain signal segment $R0(k)$. The specific implementation method is as follows.

• Signal extraction

Starting from the corresponding time offset position k_0, we intercept a segment of the time-domain signal $r(k)$. The extracted signal segment is denoted as $r0(k)$, and its length corresponds to the OFDM symbol length L that depends on the number of sampling points, represented as intercept(k).

• Frequency-domain transformation and output

The extracted frequency domain representation of the received signal is obtained as $R0(k), k = 1,2,\cdots,L$. The signal $r0(k)$ is transformed by FFT into the frequency domain signal $R0$, denoted as $R0(k)$, where $R0(k) = \text{FFT}(r0(k)), k = 1,2,\cdots,L$.

6) Step 6: Perform correlation to determine the PSS sequence ID. Here, the received signal is correlated with the three possible PSS sequences $PSS_i, i = 1,2,3$, to determine the ID of the PSS sequence. The specific implementation method is as follows. The frequency domain signal $R0(k)$ is then correlated with three local frequency domain sequences $PSS_i(k), i = 0,1,2$. The maximum peak of the correlation value for each possibility of i is taken, and these three correlation values are compared to obtain the maximum value. Based on the corresponding frequency domain signal $PSS_i(k), i = 0,1,2$, the corresponding small cell group number N_{ID}^2 can be obtained, and the corresponding PSS sequence ID can be further determined. The mathematical expression for the above process is:

$$\text{corr}_i = \sum_n R0(n+k) + PSS_i(n) \tag{8}$$

$$PSS_{id} = \max_i (\text{abs}(\text{corr}_i)) \tag{9}$$

4 Simulation and Analysis

To evaluate the performance of the proposed PSS search algorithm, a 5G cell search link was constructed using MATLAB 2021a. The channel environment was modeled using the tapped delay line-A (TDL-A) model channel. The simulation parameters for cell search are shown in Table 2. This section simulates the main synchronization process of the 5G NR system using MATLAB.

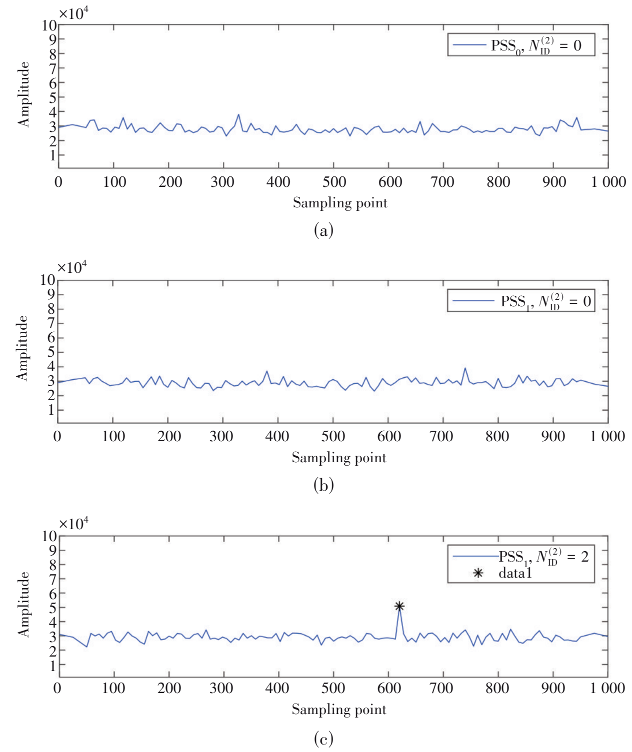
The simulation steps are as follows. First, according to 3GPP TS38.211[18], a downlink signal containing SSB is generated for a cell with a cell identifier of 2 (N_{ID}^{2} = 2), using parameters in Table 2. Next, the generated signal is passed through a channel model to simulate the received signal. The 5G NR channel model used in the simulation is a TDL. Finally, different PSS detection algorithms are applied using the received 5G signals for performance evaluation.

Fig. 4 shows the peak values obtained using the proposed algorithm under the aforementioned simulation conditions. The three subgraphs are calculated using the three local sets $\{N_{ID}^{2}, \mathrm{ID} \in (0,1,2)\}$ of PSS. The proposed algorithm successfully identifies the correct N_{ID}^{2} and PSS synchronization points.

Fig. 5 shows the comparison of PSS detection results between the improved algorithm and the existing algorithm with different frequency offset parameters. The accuracy of PSS detection by the improved algorithm is higher than that of the existing algorithm. Especially, when the frequency offset is large, the PSS detection accuracy of the improved algorithm is significantly improved compared with existing algorithms. The proposed superimposed cross-correlation method can mitigate the frequency offset accumulation of sliding cross-correlation. Combined with the CNN method for frequency offset correction of the received signal, it offers better detection performance and lower computational complexity than the traditional sliding cross-correlation method.

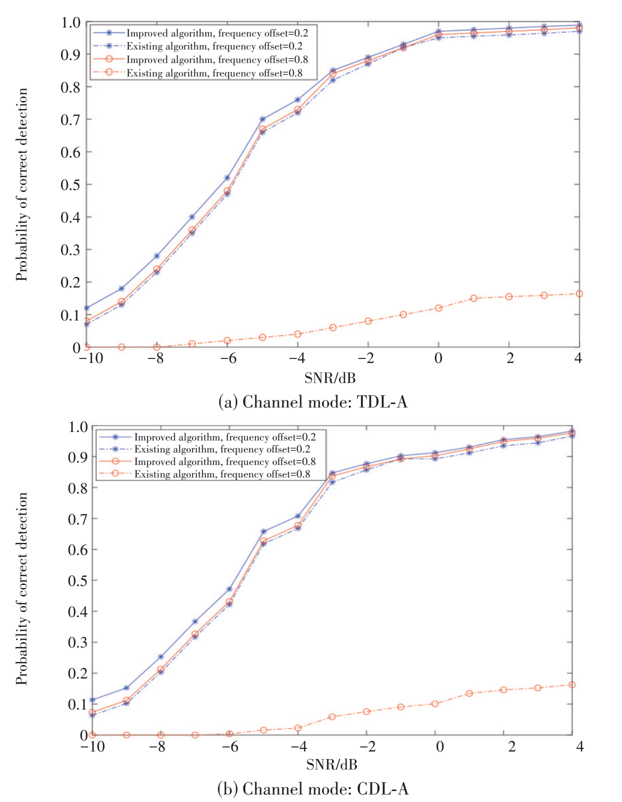
Fig. 6 shows when the SNR is low, the time consumption difference between the proposed algorithm and the baseline algorithm is not significant; on the contrary, when the SNR is high, using the proposed algorithm to perform PSS detection takes much less time than the baseline algorithm, indicating that the proposed algorithm is more suitable for scenarios with high SNRs.

Fig. 7 illustrates the accuracy of PSS synchronization under various frequency offsets. As the frequency offset increases,



PSS: primary synchronization signal

Figure 4. Correlation peak plot calculated by proposed algorithm



CDL-A: clustered delay line-A TDL-A: tapped delay line-A SNR: signal-to-noise ratio

Figure 5. Probability of primary synchronization signal search algorithm

Table 2. Simulation parameters for cell search

Simulation Parameter Types	Configuration Parameters
Channel bandwidth/MHz	100
Subcarrier spacing/kHz	15, 30
The number of FFT points	1 024, 4 096
Channel mode	TDL-A, CDL-A
Sampling frequency/MHz	122.88
Frequency offset/kHz	0.2, 0.8, 2.8
SSB block type	Case C
CP type	Standard

CDL-A: clustered delay line-A
CP: cyclic prefix
FFT: fast Fourier transform
SSB: synchronization signal block
TDL-A: tapped delay line-A

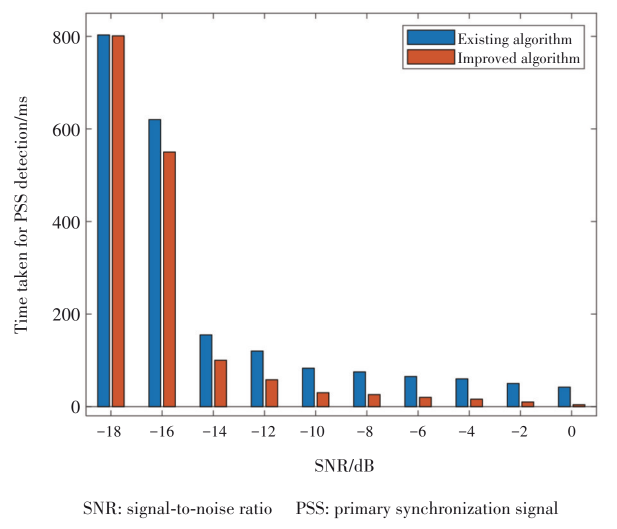


Figure 6. Time consumption difference between proposed algorithm and existing algorithm

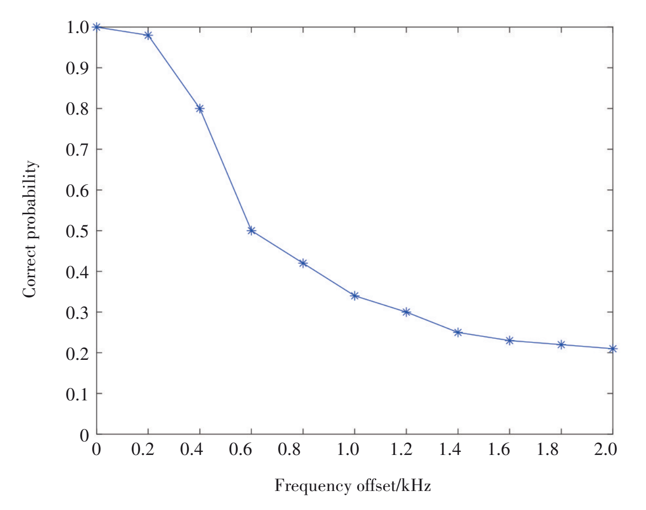


Figure 7. Accuracy of synchronization under different frequency offsets

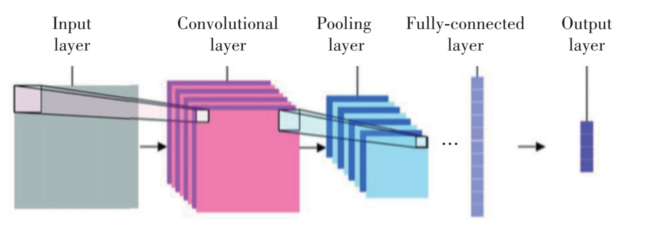


Figure 8. Basic structure of convolutional neural networks

the algorithm performs well and tends to stabilize.

Fig. 8 illustrates the CNN neural network architecture, which consists of several key layers designed to optimize PSS detection in 5G NR systems. The architecture begins with an input layer that processes the received signal data, followed by a series of convolutional layers that extract relevant features from the signal. Each convolutional layer is paired with activation functions, such as the rectified linear unit (ReLU), to introduce non-linearities. These layers are followed by pooling layers that reduce the dimensionality of the feature maps, which decreases computational complexity and improves generalization. The final layers include fully connected layers that aggregate the features and output a classification decision or prediction, such as the PSS sequence's position or the sector ID. This CNN architecture is tailored to enhance detection accuracy and robustness against frequency offsets and noise, making it suitable for high-performance PSS detection in dynamic 5G environments.

In the conventional method, the main complexity comes from the correlation operations, while in our proposed method, it comes from correlation operations and convolution layers in the CNN block. Unlike existing algorithms, our proposed algorithm exhibits higher complexity, primarily due to the operations of the CNN. Suppose the length of a data frame is L. After downsampling, the length of the received signal is K. The length of a downsampling time-domain PSS sequence is N. Using the traditional sliding correlation method, the sliding window length is $K-N+1$, representing the number of correlations required for a set of local PSS signals to complete synchronization detection. Each correlation operation involves N complex multiplications and $N-1$ complex additions. Therefore, sliding cross-correlation requires $3N(K-N+1)$ complex multiplications and $3(N-1)(K-N+1)$ complex additions. The order of magnitude of the calculation is $3O(NK)$. The proposed superimposed correlation method requires $N(K-N+1)+3N(L-N+1)$ complex multiplications and $N(K-N+1)+2N+3N(L-N+1)$ complex additions, where $L \ll K$. Given P is the number of transmitting antennas, M is the number of receiving antennas, and N_c is the number of subcarriers, with the CNN network comprising two convolutional layers of kernel size 3 (see Fig. 8), the additional complexity introduced by the algorithm is $O\left(2P \times M \times 2 \times 3^2\right)$. The proposed algorithm enhances detection and estimation performance, especially in the presence of a CFO. Considering the computational load of the CNN algorithm, the order of magnitude of the calculation is $O(NK)$. The total computational complexity is less than that of the traditional sliding correlation method.

Integrating AI modules and data processing units into 5G base stations enables the implementation of AI-related algorithms. This architecture can be guided by relevant patents[21].

5 Conclusions

This paper analyzes existing PSS synchronization detection algorithms and their characteristics in 5G NR systems, verifying the relationship between the autocorrelation peaks and frequency offset of three superimposed PSS signals compared with a single PSS signal through experimental results. The accuracy of the CNN-assisted frequency offset estimation algorithm is examined, leading to the proposal of a new fast PSS synchronization detection algorithm that offers resistance to frequency offset and noise. In the cell search process, a method is introduced to determine a shorter synchronization signal sequence based on the frequency domain offset consistency between the autocorrelation peak of the superimposed PSS signals and the correlation peak of non-superimposed signals. This approach reduces the computational load of PSS synchronization detection and enhances the efficiency of the NR communication system's cell search. The simulation results demonstrate that the improved algorithm effectively enhances synchronization detection performance under large CFO conditions in the TDL-A or CDL-A channel. Future research will focus on developing PSS detection algorithms suitable for low SNR scenarios. The performance of the CNN model in highly dynamic or interference-heavy environments, along with the computational burden on terminals and the energy consumption of running CNN models on resource-constrained devices, will be studied in future research.

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