

Article

Machine Learning-Based Extraction of Authorized GPS M Code Stream Using Time-Frequency Domain Features

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Abstract

Modern Global Navigation Satellite System (GNSS) architectures incorporate authorized signals like GPS M-code; however, conventional extraction methods suffer from performance degradation under low signal-to-noise-ratio (SNR) conditions and exhibit strong dependence on high-gain antennas and precise synchronization. This paper proposes a machine learning-based end-to-end extraction framework leveraging time-frequency domain feature fusion. This method breaks through the constraint of relying solely on either time-domain or frequency-domain features. It jointly feeds the time-domain waveforms and spectral features of baseband signals into models such as Multi-Layer Perceptron (MLP) and Transformer, enabling automatic learning of the nonlinear time-frequency characteristics of M-code. This approach effectively suppresses interference from P(Y) code sidelobes and fully exploits the information contained in both the main and side lobes of the M code spectrum. Experimental results demonstrate that under the extremely low SNR condition of -10 dB, the extraction accuracy of the proposed method is improved by 13.7% compared with conventional methods. Systematic accuracy–efficiency trade-off analysis shows that the lightweight MLP model achieves comparable accuracy to the complex Transformer model, with only 6.8% of the parameter scale and 6.2 times faster inference speed, making it the most competitive solution for real-time engineering deployment. In the real-world measurement scenario using a 7.5-m antenna, an extraction accuracy of 94.7% is achieved with only 10 ms of small-sample training data. This method significantly enhances the extraction performance of authorized signals under low-SNR non-cooperative reception conditions.

Keywords: machine learning; GPS M-code; authorized signal extraction; non-cooperative signal processing



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1. Introduction

With the development of the Global Navigation Satellite System (GNSS), it has become increasingly integrated with domains such as national defense security, economy, and modern infrastructures. Modern GNSS signals typically adopt a multiplexed method where open signals and authorized signals are broadcast together. Authorized signal code streams extracted under non-cooperative conditions are critical foundational data, which have potential application value in research fields including signal quality monitoring,

satellite operation status assessment, and navigation anti-spoofing [1–3]. In the field of signal quality monitoring, authorized signal, as part of the satellite navigation signal system, given its quality parameters such as correlation curves [4], correlation loss [5], and S-curve zero-crossing bias [6], can reflect the operational status of the satellite and enable rapid identification of satellite payload anomalies. Furthermore, utilizing authorized signals extracted under non-cooperative conditions helps establish a multi-system navigation signal quality monitoring framework [7], providing information assurance for the integrity and reliability of navigation services. Simultaneously, given that authorized signals are difficult to forge [8,9], they possess inherent advantages in anti-spoofing capabilities and can serve as trusted reference sources [10,11], providing prior references for navigation signal spoofing detection [12,13]. As the prerequisite for the practical application of authorized signals across various fields, the successful recovery and extraction of their pseudo-random noise (PRN) code sequences with minimal bit errors and stable performance is of great importance. Therefore, it is necessary to research methods for extracting navigation authorized signal code sequences under non-cooperative conditions, achieving stable and high-precision extraction of authorized signal code streams. This will provide extracted authorized signal code streams for related research such as signal quality monitoring and anti-spoofing technologies. As an essential component of the modernized GPS architecture, the GPS M-code authorized signal, a typical representative of such authorized signals, employs a signal structure that combines Binary Offset Carrier (BOC) modulation [14] with an encrypted direct-sequence spread spectrum, achieving co-frequency but out-of-band modulation for the authorized signal [15]. This authorized signal modulation approach is common in satellite navigation systems like GPS and Galileo, exemplified by signals such as L1M, L2M, E1A, and E6A [16]. While these modulation methods enhance anti-jamming, anti-spoofing, and anti-multipath performance [17,18], they also render traditional extraction methods ineffective. Therefore, it is particularly necessary to research methods for extracting GPS M-code and other co-frequency, out-of-band navigation authorized signal code sequences under non-cooperative conditions, and against this background, this paper focuses on the extraction of GPS M-code, aiming to propose effective extraction methods to achieve stable and high-precision extraction of GPS M-code streams, thereby providing support for related research such as signal quality monitoring and anti-spoofing technologies.

Focusing on co-frequency, out-of-band authorized signals represented by the GPS M-code and existing extraction methods can be categorized into two branches according to the utilized information dimension: time-domain-based methods and frequency-domain-based methods.

In the field of time-domain authorized signal extraction, methods are generally built on the mapping between baseband signal features and chip polarity, covering three typical technical routes. First, the amplitude-based polarity discrimination method: Rui et al. [19] determined M-code chip polarity directly from the power distribution of the M-code component on the baseband I-channel, and validated the method with a 7.3 m receiving antenna. This method is simple in principle but requires distinct power differences between signal components, and its accuracy drops sharply under low SNR due to noise-induced amplitude blurring. Second, the constellation matching method for constant-envelope multiplexed signals: Xiao et al. [20,21] recovered the M-code sequence by matching baseband in-phase/quadrature (I/Q) phase points against the theoretical constellation template based on the CASM modulation mapping rule, and realized GPS L1 M-code extraction with a 7.5 m antenna. This method depends on standard constant-envelope signal structures and high received SNR; it is invalid for non-constant-envelope signals and gains limited support from public signal components. Third, the zero-threshold chip decision method with blind sequence generation: Merwe et al. [22] extracted M-code sequences with the

assistance of public auxiliary signals and known modulation parameter candidate sets, using a 1.8 m active directional antenna. This method still relies on high-gain receiving devices and is affected by synchronization errors from auxiliary signals.

For frequency-domain authorized signal extraction, methods mainly exploit the split-spectrum characteristic of BOC modulation, including two mainstream schemes. The first is the bandpass filtering method for the M-code main lobe [23]. Li et al. [24] performed chip alignment and coherent enhancement with the assistance of the C/A code, and extracted the M-code main lobe in the 5–15 MHz band via a bandpass finite impulse response (FIR) filter to realize blind M-code demodulation. Nevertheless, hard frequency truncation in bandpass filtering introduces inter-symbol interference and energy loss, and the method requires precise estimation of the BOC subcarrier initial phase, which restricts real-time performance. The second is the frequency-domain correlation method with locally generated sequences [23], which is mainly used for fast long-code acquisition in authorized receiver scenarios. This scheme is only applicable when the local authorized signal sequence is available and cannot be adopted in non-cooperative extraction scenarios.

The applicable conditions, core limitations, and corresponding references of the above representative methods are systematically summarized in Table 1.

Table 1. Methods and Comparative Analysis for Authorized Signal Extraction Methods.

Category	Specific Approach	Applicable Conditions	Limitation	References
Time-Domain	Amplitude-based polarity discrimination.	High received SNR (7.3 m antenna); Components on the baseband branch with distinct power levels.	Rapid performance degradation under low SNR conditions; Reliance of component power differences.	Rui et al. [19]
Time-Domain	Constellation matching for constant-envelope multiplexing.	High received SNR; (7.5 m antenna) Signals with standard constant-envelope multiplexing.	Only applicable to high SNR scenarios; Invalid for non-constant-envelope signal structures; Auxiliary role of public signals in authorized signal recovery is limited.	Xiao et al. [20,21]
Time-Domain	Zero-threshold chip decision with blind sequence generation.	Public auxiliary signal available; High-gain receiving antenna (1.8 m active directional antenna); Candidate set of modulation parameters known.	High gain antenna required; Synchronization errors from auxiliary signals.	Merwe et al. [22]
Frequency-Domain	Bandpass filter of M code main lobe.	High received SNR; (10 m parabolic antenna) BOC-modulated authorized signals; Stable tracking of public auxiliary signals available.	Bandpass filtering introduces inter-symbol interference and energy loss; Requires precise estimation of BOC subcarrier initial phase.	Li et al. [24]
Frequency-Domain	Frequency domain correlation with locally generated sequence.	Long-code fast acquisition scenarios; Locally generated authorized signal available.	Applicable only to the acquisition scenario of authorized receivers.	Li et al. [23]

In summary, existing methods are primarily based on high SNR data from high-gain antennas. Some approaches utilize the BOC modulation characteristics of the GPS M-code for coherent enhancement [24], and this method estimates the starting position of the sub-

carrier chips over a period of observation data to determine the initial phase of the M-code subcarrier, thereby compromising the real-time performance of authorized signal extraction, which requires precise time alignment. Furthermore, the accuracy of time alignment is significantly affected by the SNR, making it difficult to precisely determine the chip starting position under low SNR conditions, which limits the accuracy of code extraction. In terms of utilizing frequency-domain information, existing methods only employ bandpass filters to extract the M-code within its main lobe region, without considering the utilization of the M-code spectral sidelobes or addressing the interference caused by the overlap between the P(Y)-code sidelobes and the M-code main lobe. This results in insufficient exploitation of spectral information. Additionally, current M-code extraction methods rely solely on either baseband time-domain sequence information or spectral distribution information, failing to achieve multi-dimensional fusion of time-domain and frequency-domain information for M-code signal extraction.

To address the mentioned issues, this paper introduces a machine learning approach that integrates time-frequency domain features for the extraction of the authorized M-code sequence, aiming to resolve current limitations such as insufficient real-time performance, inadequate utilization of frequency-domain features, and underutilized time-frequency domain information. As an end-to-end method that maps sample features to results, machine learning establishes the mapping relationship between input time-domain/frequency-domain features and authorized signal chips. This enables direct transformation from baseband signal input features to authorized code signals, thereby achieving enhanced real-time performance in signal processing and authorized code stream extraction. Regarding frequency-domain information utilization, the machine learning model autonomously extracts and constructs features from the spectrum without being confined to the M-code main lobe frequency band, allowing for more comprehensive utilization of spectral information [25]. By employing joint time-frequency domain features to construct the M-code extraction model, multi-dimensional characteristics can be effectively fused. M-code extraction based on multi-dimensional features can be accomplished through this end-to-end machine learning framework.

2. Structure Overview of GPS-IIF Signals

2.1. CASM Constant Envelope Modulation

Modern GPS-IIF L1 band signals consist of three signal components: C/A code, P(Y) code, and M-code. The M-code signal employs a Binary Offset Carrier (BOC) modulation, specifically BOC(10,5) [26], and utilizes the Coherent Adaptive Subcarrier Modulation (CASM) technique to achieve six-phase constant envelope multiplexing of the three signal components [27]. The CASM method synthesizes a constant envelope signal by adjusting the phase and power allocation of multiple subcarriers to combine multiple signal components. The normalized baseband signal can be expressed as:

$$S(t) = I(t) \cos(2\pi f_d t) + jQ(t) \sin(2\pi f_d t) \quad (1)$$

where f_d is the carrier frequency. Under the CASM modulation scheme, the in-phase component $I(t)$ and the quadrature-phase component $Q(t)$ can be expressed as:

$$\begin{cases} I(t) = \sin \theta_2 \cos \theta_3 \cdot s_2 + \cos \theta_2 \sin \theta_3 \cdot s_3 \\ Q(t) = -\cos \theta_2 \cos \theta_3 \cdot s_1 + \sin \theta_2 \sin \theta_3 \cdot s_1 s_2 s_3 \end{cases} \quad (2)$$

In the equations above, s_1 , s_2 , s_3 correspond to the C/A code, P(Y) code, and M-code, respectively. θ_2 and θ_3 correspond to the modulation angle for the CASM signal. Specifically, in the modern GPS L1 band, the P(Y) code and M-code are modulated on the in-phase

branch I(t), while the C/A code and an intermodulation component are modulated on the quadrature branch Q(t) [28]. By considering the code polarity combinations of these three signal components, the resulting baseband signal amplitudes can be derived as shown in Table 2 [20]. It can be observed that the constant envelope multiplexing of the three signal components generates up to eight distinct phase points, while the overall energy of the baseband signal remains constant. This demonstrates that CASM modulation achieves both multi-signal multiplexing and a constant envelope characteristic for the baseband signal.

Table 2. Baseband I/Q Branch Amplitude for Various Polarity Combinations.

s_1	s_2	s_3	I-Branch Amplitude	Q-Branch Amplitude
1	1	1	$\sin(\theta_2 + \theta_3)$	$-\cos(\theta_2 + \theta_3)$
1	1	-1	$\sin(\theta_2 - \theta_3)$	$-\cos(\theta_2 - \theta_3)$
1	-1	1	$-\sin(\theta_2 - \theta_3)$	$-\cos(\theta_2 - \theta_3)$
1	-1	-1	$-\sin(\theta_2 + \theta_3)$	$-\cos(\theta_2 + \theta_3)$
-1	1	1	$\sin(\theta_2 + \theta_3)$	$\cos(\theta_2 + \theta_3)$
-1	1	-1	$\sin(\theta_2 - \theta_3)$	$\cos(\theta_2 - \theta_3)$
-1	-1	1	$-\sin(\theta_2 - \theta_3)$	$\cos(\theta_2 - \theta_3)$
-1	-1	-1	$-\sin(\theta_2 + \theta_3)$	$\cos(\theta_2 + \theta_3)$

2.2. BOC Modulation

The GPS M-code employs BOC modulation, a spread-spectrum modulation technique that utilizes a square wave as the subcarrier. The generation of the subcarrier is governed by two fundamental parameters: the subcarrier frequency f_s and the code rate f_0 . In the GPS-IIF L1 signal structure, f_s is 10 times the reference frequency of 1.023 MHz, while the M-code rate f_0 is 5 times the reference frequency, resulting in a modulation denoted as BOC(10,5). The subcarrier is a square wave that varies regularly between +1 and -1. In summary, each M-code chip contains four square wave chips.

After employing BOC modulation, the M-code signal exhibits a split-spectrum characteristic, as illustrated in Figure 1. In the baseband signal spectrum, energy is distributed into upper and lower sidebands, while the power spectral density of the M-code becomes null at the central frequency. This spectral configuration effectively separates the M-code from C/A and P(Y) codes, preventing overlapping and interference among signal components. Furthermore, the two symmetrically distributed main lobes of the M-code in the frequency domain facilitate straightforward signal separation from a spectral perspective, making frequency-domain features suitable as distinctive features for machine learning-based authorized signal extraction.

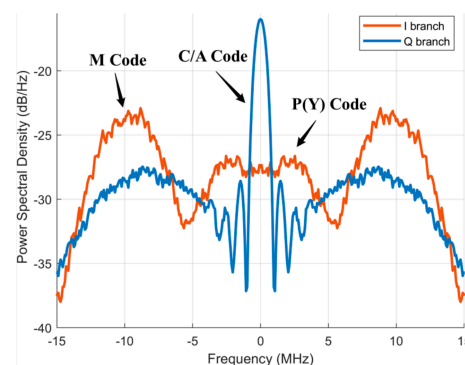


Figure 1. Power spectral density of the baseband signal after BOC(10,5) modulation.

2.3. GPS L1 Simulated Baseband Signal Generation

Based on the modernized GPS baseband signal structure described above, a simulation of GPS baseband signals is conducted. The GPS L1 frequency band contains the publicly available C/A code, the authorized P(Y) code, and M-code signals. These three signal components are multiplexed into a constant-envelope composite signal using the CASK technique. The specific modulation phase for each chip interval in the baseband signal is determined by the binary combination of the code polarities from these three signals, enabling the distinction between different chip combinations.

In this work, the C/A code signal is directly obtained via its known generation method. For the P(Y) code and M-code, pseudo-random sequences are generated according to their respective code rates and subcarrier modulation schemes to represent the authorized signals. It should be noted that the genuine P(Y)-code and M-code sequences are encrypted and not publicly available, which is a common constraint for non-cooperative GNSS signal processing research. Since the core task of this work is chip-level polarity extraction, the performance of the extraction method mainly depends on the modulation structure, statistical characteristics, and power distribution of the signal, rather than the specific coding pattern of the pseudo-random sequence. The random binary sequences used in simulation strictly follow the same chip rate, BOC(10,5) subcarrier modulation, and CASK power allocation ratio as the real GPS M-code. Therefore, the time-domain and frequency-domain characteristics of the simulated baseband signal are statistically equivalent to those of the real signal.

The methodology for generating the baseband signal is illustrated in Figure 2.

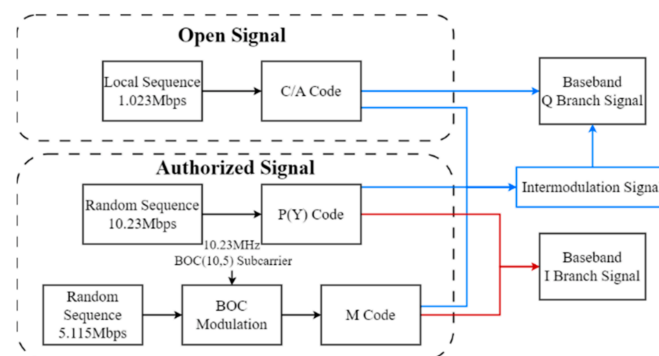


Figure 2. Process of simulated baseband signal generation.

Following the generation of the three simulated signal codes, the power ratios of different GPS signal components are obtained from measured data according to Xiao et al. [21], shown in Table 3. Based on these power ratios, the modulation coefficient ratio between the C/A code component and the intermodulation (IM) component in the Q branch is 1:1, while the ratio between the P(Y) code and the M-code modulation coefficients in the I branch is 1:1.69. so $\frac{\cos \theta_2 \sin \theta_3}{\sin \theta_2 \cos \theta_3} = 1.69$, $\frac{\cos \theta_2 \cos \theta_3}{\sin \theta_2 \sin \theta_3} = 1$. From these ratios, a feasible set of CASK modulation angles is derived: $\theta_2 = 37.5688^\circ$ and $\theta_3 = 52.4314^\circ$. Using these modulation angles, CASK modulation is performed to generate the simulated GPS L1 baseband signal.

Table 3. Power Ratio of different Components in GPS IIF Signals.

Signal Component	C/A	P(Y)	M	IM
Power Ratio	25%	13%	37%	25%

The simulated baseband signal is subsequently analyzed. Its ideal constellation diagram is shown in Figure 3, which reveals that the baseband constellation for the GPS L1 frequency band employs a constant envelope modulation scheme characterized by a three-code, six-phase distribution. This observation is consistent with the findings derived from measured data of GPS Block IIF satellites.

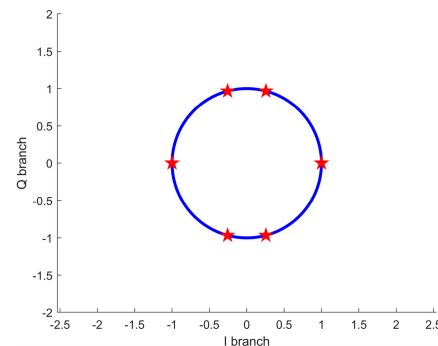


Figure 3. Constellation Diagram of the Simulated GPS-IIF L1 Baseband Signal.

Furthermore, the power spectrum of the simulated baseband signal is analyzed and presented in Figure 1. It can be observed that the I-branch, modulated with the M-code signal, exhibits distinct features of a BOC(10,5) modulated signal. Specifically, pronounced spectral peaks appear within the 5–15 MHz frequency band. This clearly demonstrates the spectral splitting and energy dispersion characteristics inherent to M-code BOC modulation.

3. M-Code Extraction Methods

3.1. Conventional M-Code Extraction Machine Learning Model

Conventional methods for GPS M-code extraction can be broadly categorized into two classes: those based on time-domain information and those based on frequency-domain information, as shown in Figure 4.

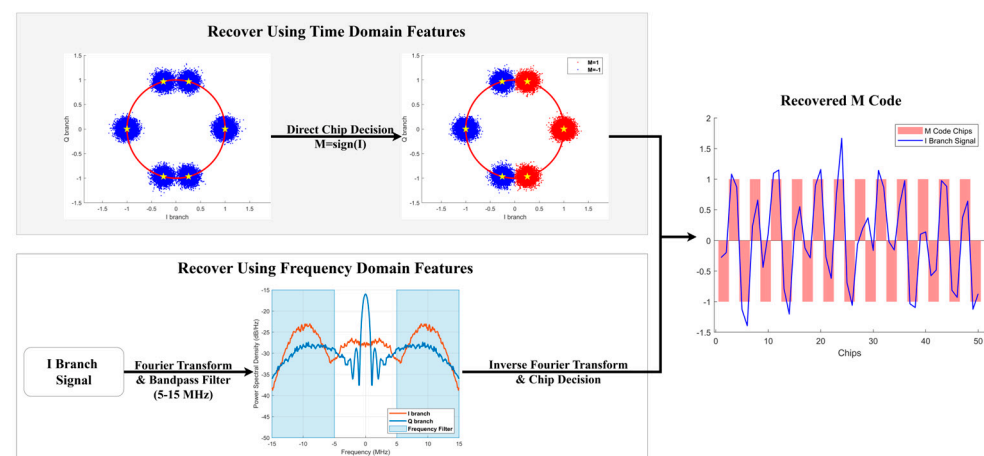


Figure 4. M-Code Extraction Method.

For time-domain extraction, as informed by the modernized GPS signal structure described earlier, the L1 signal modulated using CASM technique exhibits a direct relationship where the binary combination of chip polarities of the C/A code, P(Y) code, and M-code determines the amplitude relationship of the in-phase (I) and quadrature (Q) baseband components. This relationship is manifested in the I-Q constellation diagram as distinct phase points corresponding to different chip polarity combinations.

Regarding frequency-domain extraction, since the GPS M-code employs BOC subcarrier modulation, the I-branch of the baseband signal demonstrates pronounced spectral splitting characteristic. This property allows for M-code extraction in the frequency domain by utilizing the information from the main lobes of the M-code spectrum.

Focusing on time-domain-based GPS M code extraction, practitioners can leverage the direct correlation between the I-Q time-series sequences and the chip polarities. The Constellation Diagram Matching method can be applied, which recovers the M-code signal by identifying the nearest phase point in the constellation diagram template. Given that the C/A code is publicly available and can be directly acquired during signal recovery, and with its information known a priori, the recovery of the M code sequence simplifies to matching against just four possible phase points within the constellation diagram. Furthermore, due to the specified GPS signal power ratio, the power of the M code in the I-branch is significantly higher than that of the P(Y) code. Consequently, the polarity of the I-branch signal directly reflects the polarity of the M code. Thus, the problem of M code extraction can be treated as directly discriminating the polarity of the I-branch signal. In this approach, the sign (positive or negative) of the I-branch baseband signal is directly interpreted as the M-code polarity. Under favorable SNR conditions, the M code polarity can be recovered directly using this method. In this paper, both the constellation matching method and the polarity discriminant method are employed to represent the capabilities of conventional time-domain-based approaches for M code extraction.

These traditional time-domain M-code extraction methods, which rely on the relationship between the position of the I-Q time-series in the constellation diagram and the M code polarity, are characterized by their straightforward principle and high extraction efficiency. However, their performance is contingent upon having clearly separable phase points in the constellation diagram to achieve reliable matching with the ideal phase points and subsequent M-code extraction. Nevertheless, under low SNR conditions, as illustrated in Figure 5, the phase points in the constellation diagram inevitably exhibit overlap and ambiguity under the conditions of low SNR such as 5 dB. Attempting to match these ambiguous points to the ideal phase points leads to significant degradation in accuracy, making it challenging to achieve high-precision M-code extraction directly under such conditions.

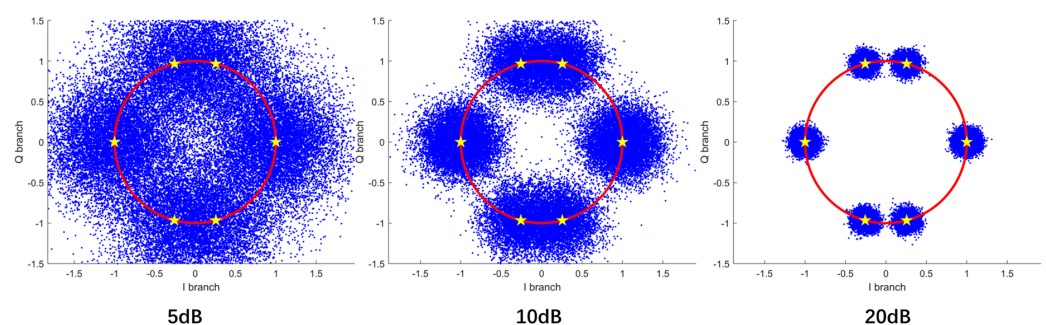


Figure 5. Baseband Signal Constellation under different SNR.

For M-code extraction from the frequency domain features, the utilization of BOC(10,5) subcarrier modulation for the M-code causes the I-branch signal spectrum to exhibit the characteristic BOC modulation features of spectral splitting and energy dispersion. This results in the main lobes of the M-code being distributed within the 5–15 MHz frequency range. Consequently, traditional methods often employ a frequency-domain filtering approach. This involves applying a bandpass filter to the I-branch spectrum to isolate the M-code main lobes, followed by an inverse Fourier transform to recover the M-code signal.

However, this method, which relies solely on information within the main lobe range for extraction, overlooks the potential information contained in the M-code side-lobes, leading to insufficient utilization of the available spectral data. Furthermore, the direct use of a bandpass filter to extract the main lobe components is susceptible to aliasing between the P(Y) code side-lobes and the M code side-lobes, indicating room for improvement in M code extraction accuracy.

Simultaneously, traditional approaches often leverage the short-code characteristic of BOC-modulated signals to perform coherent integration and subcarrier stripping, aiming to mitigate the impact of P(Y) code side-lobes on M code extraction. However, this technique requires precise estimation of the starting position of the BOC modulation subcarrier chips, which subsequently compromises the real-time performance of the M code extraction process.

3.2. Time-Frequency Fused Machine Learning Method for M-Code Extraction

3.2.1. Construction of Time-Frequency Domain Fused Input Features

Single-dimensional features suffer from inherent performance limitations; extraction methods relying exclusively on time-domain I/Q sequences essentially perform discrimination based on the instantaneous correspondence between chip polarity and branch amplitude. Under low SNR conditions, noise directly blurs the distinguishability of constellation phase points. Furthermore, such methods fail to exploit the prior information of frequency-domain energy distribution introduced by BOC modulation, rendering it difficult to break the accuracy bottleneck in low-SNR scenarios. Given that the M code signal is based on BOC modulation and its main lobe exists within the 5–15 MHz frequency band of the I branch signal, it is feasible to consider the frequency-domain feature of the I branch as an additional feature input to assist the machine learning model in M-code extraction.

The workflow for the time-frequency feature fusion is shown in Algorithm 1. The time-domain sequences of the baseband I/Q components and the real and imaginary parts of the I component were concatenated as inputs, while the corresponding M-code sequences were designated as the expected output for the M code signal extraction machine learning models. Considering the distinct spectral distribution characteristics of the P(Y) code and the M-code within the I-branch, a segmented sampling strategy is employed for sample feature extraction. First, a segment sequence of length n is extracted from the I and Q branches, forming the initial time-domain features of the sample. Subsequently, the I-branch segment signal containing the M code undergoes a Fourier transform to obtain the frequency spectrum of the segment sequence, thereby extracting its frequency-domain features. The acquired time-domain and frequency-domain features are then concatenated to form the input features X for the machine learning model, while the corresponding M-code sequence of the segment serves as the ground truth output Y .

3.2.2. Model Selection and Architecture Design

To extract the M code sequences from baseband signals by a machine learning model, this study utilizes various machine learning models to realize the end-to-end M-code chip extraction. As illustrated in Figure 6, the model takes fixed-length time sequences and spectrum sequences of the I/Q baseband signal as input and outputs the corresponding M-code sequences. By fusing temporal domain and spectral features through the feature concatenating in the model input layer, this architecture directly establishes a nonlinear mapping from baseband signal segments to authorized M code sequences, thereby avoiding the detailed and complex multi-stage processing pipelines of traditional methods that separately handle time and frequency domains. The machine learning models offer the following advantages:

Algorithm 1: the procedure of I, Q baseband signals processing into machine learning training and testing data

Input: baseband signal I and Q , ground truth M -code sequence, number of points n for each sample of the machine learning models.

Output: input sample X and expected output Y for MLP model with numbers of samples s

1. split I , Q , and M into s slices with n points for each.

$$[I_1, I_2, \dots, I_s], [Q_1, Q_2, \dots, Q_s], [M_1, M_2, \dots, M_s]$$

2. for each sample index $k \in [1, s]$ do:

3. Perform Fast Fourier Transform on the k -th I-branch slice:

$$F_k = \text{FFT}(I_k)$$

4. Extract the real and imaginary parts of the spectrum:

$$F_{k,real} = \text{Re}\{\text{FFT}(I_k)\}$$

$$F_{k,imag} = \text{Im}\{\text{FFT}(I_k)\}$$

5. Concatenate time-domain and frequency-domain features to form the input sample:

$$x_k = [I_k, Q_k, F_{k,real}, F_{k,imag}]$$

6. Set the corresponding label:

$$y_k = M_k$$

7. end for

8. Construct the Dataset: $X = [x_1, x_2, \dots, x_s]$, $Y = [y_1, y_2, \dots, y_s]$

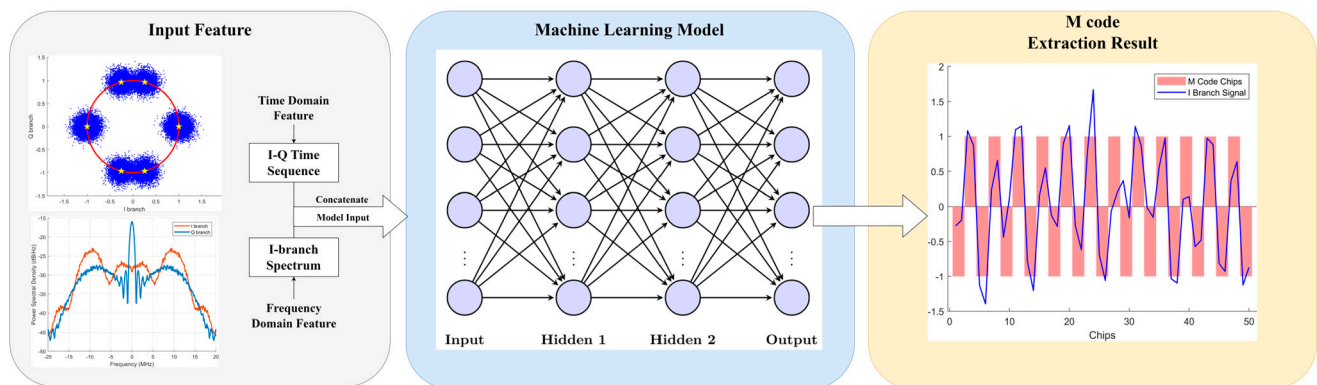


Figure 6. Structure for M-code Extraction Machine Learning Models.

(1) High computational efficiency and real-time performance: Owing to its simple structure, models such as MLP consists solely of a neural network with multiple fully connected layers, involving only simple matrix operations and activation functions. This results in high efficiency and enables it to meet real-time computing requirements.

(2) Learning nonlinear data correlations: By taking the concatenated time sequences and spectrum sequences as input and the corresponding M code sequence as output, the machine learning models can achieve data correlation and fusion between the time and frequency domains through updating the weights of the fully connected layers, thereby realizing more comprehensive M code extraction.

(3) Compatibility with sequence labeling tasks: M code extraction can be treated as a sequence labeling task and machine learning model such as MLP, Transformer, and Convolutional Neural Network (CNN) is inherently compatible with the input and output of fixed-length sequences. The end-to-end nonlinear mapping process of the machine models is capable of satisfying the task requirements for M-code sequences extraction.

To systematically validate the effectiveness of machine learning for M-code extraction and evaluate the performance boundaries of different modeling paradigms, in this study, four types of models, MLP, CNN, Residual Network (ResNet), and Transformer, are selected to cover four mainstream sequence modeling paradigms: global nonlinear mapping, local feature extraction, deep convolutional modeling, and global attention modeling, so as to establish a complete comparison gradient of performance and complexity spanning from simple to complex architectures and from local to global modeling scopes. The core network structure and hyper parameter are listed in Tables 4 and 5.

Table 4. Network Structure of Machine Learning Models.

Model Name	Core Network Structure
MLP	512-dim input $\rightarrow$ $2 \times$ 512-dim Full Connect $\rightarrow$ 128-dim output
CNN	512-dim input $\rightarrow$ 2-stage Conv ($2 \times$ 1 Max Pooling per stage) (channels: $16 \rightarrow 32$, $3 \times$ 1 kernel) $\rightarrow$ $3 \times$ Full Connect ($4096 \rightarrow 512 \rightarrow 512 \rightarrow 128$) $\rightarrow$ 128-dim output
ResNet1d	512-dim input $\rightarrow$ $2 \times$ ResBlock ($3 \times$ 1 kernel, channels: $16 \rightarrow 32$) + $2 \times$ 1 Max Pooling per block $\rightarrow$ $3 \times$ Full Connect ($4096 \rightarrow 512 \rightarrow 512 \rightarrow 128$) $\rightarrow$ 128-dim output
Transformer	512-dim input $\rightarrow$ $4 \times$ Encoder (8-head self-attention, 512-dim) $\rightarrow$ 128-dim projection $\rightarrow$ 128-dim output

MLP serves as the baseline model, which enables pure verification of the fundamental performance gains brought by time-frequency feature fusion, and boasts a lightweight structure with high computational efficiency. CNN and ResNet1d represent the convolutional modeling paradigm and are applied to verify the performance boundary of local feature extraction capability for this task. Transformer, as the representative of the cutting-edge global dependency modeling paradigm, is employed to explore the upper performance limit of long-range context modeling.

Such multi-architecture comparison not only clarifies the core technical characteristics of the M-code extraction task, but also provides a hierarchical model selection basis for deployment scenarios with varying computing power constraints.

Table 5. Hyper Parameters of M-code Extraction Machine Learning Model.

Parameters	Values
Signal Duration	200 ms (100 ms for training, 100 ms for testing)
Sampling Rate	4×10.23 MHz
Input Sequence Size (I/Q branch sequence + I branch spectrum)	512
Output Sequence Size (M Code Sequence)	128
Optimizer	Adam
Activation	Sigmoid
Loss Function	Mean Squared Error (MSE)
Epoch	30
Learning Rate	0.001

4. Experimental Results

4.1. Simulation Results

4.1.1. Time-Domain Feature-Based M Code Extraction

Machine learning methods facilitate authorized signal extraction by establishing a functional mapping relationship between time-domain information and chip polarity. This process can be formulated as a classification problem. The model takes the baseband I/Q time-series and the known C/A code sequence as inputs. By learning the mapping relationship between the input features and the corresponding M-code chips, the machine learning algorithm trains a classification model based on temporal information to discriminate M-code chips, thereby enabling the extraction of the M-code sequence.

The machine learning extraction method utilizing only time-domain feature can directly employ the I and Q values as inputs and the corresponding M-code polarity as the output for model training. The process of establishing this chip polarity mapping can be viewed as constructing a binary classification model based on the input feature, where the M-code chip polarities of -1 and 1 correspond to the two classes. Consequently, various classic machine learning classification models can be directly applied for M-code extraction. In this experiment, we consider using Random Forest, Support Vector Machine (SVM), and MLP classification models to achieve M-code extraction utilizing time-domain features.

A high-SNR of 20 dB baseband signal sequence with a duration of 100 ms and a sampling rate of 4×10.23 MHz was generated through simulation to serve as the training dataset. We use the I/Q component as model input and the corresponding M code as the model expected output.

For M-code sequence extraction, both conventional and machine learning approaches were employed. Conventional methods included constellation diagram matching and I brand polarity discrimination, while machine learning techniques involved Random Forest, SVM, and MLP models. Test datasets under various SNR conditions were generated by adding white Gaussian noise to evaluate the performance of these methods across different noise levels. The accuracy of M-code extraction from time-domain features is summarized in Table 6.

Table 6. M-Code Extraction Accuracy only with Time-Domain Features.

SNR	I-Polarity Discrimination	Constellation Matching	SVM	Random Forest	MLP (Time-Domain Feature)
−10	0.606	0.608	0.533	0.609	0.608
−5	0.679	0.680	0.637	0.679	0.679
0	0.776	0.774	0.768	0.774	0.774
5	0.866	0.864	0.863	0.864	0.863
10	0.932	0.933	0.932	0.932	0.931
15	0.988	0.989	0.988	0.988	0.988
20	1.000	1.000	1.000	1.000	1.000

It can be observed from Table 6 that all machine learning methods yield almost identical accuracy compared to the conventional extraction methods of constellation matching and I-polarity discrimination. Among various machine learning models, Random Forest and MLP slightly outperform SVM; the accuracy of SVM is about 7% lower than the other method under low SNR conditions of -10 dB. This can be attributed to the fact that SVM exhibits poor robustness against high-dimensional noisy data. Moreover, when using I/Q time-domain features for M-code extraction, the machine learning methods did not exhibit significant performance variations across different SNR conditions. The best-performing Random Forest and MLP only yield an accuracy improvement of approximately 0.1% com-

pared to the conventional constellation matching method. Such a marginal improvement is practically negligible in real-world applications. This result conclusively demonstrates that machine learning methods relying exclusively on time-domain features cannot overcome the performance bottleneck of traditional methods, necessitating the introduction of additional information dimensions.

4.1.2. Frequency-Domain Feature-Based M-Code Extraction

The BOC(10,5) modulation of M-code results in the two symmetrically distributed main lobes in the frequency band of 5–15 MHz domain, which facilitate straightforward signal separation from a spectral perspective, making frequency-domain features suitable as distinctive features for conventional methods such as bandpass filter and machine learning-based authorized signal extraction.

To quantitatively evaluate the independent contribution of frequency-domain information for M-code extraction and verify the effectiveness of full-spectrum utilization, we conduct experiments using only frequency-domain features as model input. Conventional bandpass filtering method covering the 5–15 MHz main lobe band of the M-code spectrum is applied to the I-branch signal represents as the traditional frequency-domain extraction paradigm. As for the machine learning methods, three input feature concatenation strategies of frequency spectrum main lobe, full frequency spectrum, and time-frequency fused features are adopted to explicitly decompose the performance gain brought by spectral information.

The extraction accuracy results are summarized in Table 7. Under all SNR conditions, both main-lobe and full-spectrum MLP methods achieve higher accuracy than the conventional bandpass filtering approach. At -10 dB, the main-lobe MLP improves accuracy by 4.5% over bandpass filtering, and the full-spectrum MLP improves by 8.2%. Experiment results demonstrate that conventional bandpass filter relies on hard truncation in the frequency domain, which not only causes inter-symbol interference and energy loss of the M-code, but also cannot effectively separate the aliased components between P(Y)-code sidelobes and the M-code main lobe. The MLP model establishes a nonlinear mapping between spectral features and M-code chip polarity, which can adaptively suppress sidelobe interference and retain more valid information, thus achieving better extraction performance.

Table 7. M-Code Extraction Accuracy only with Frequency-Domain Features.

SNR	Bandpass Filter (I Branch Spectrum)	MLP (Frequency-Main Lobe 5–15 MHz)	MLP (Full Spectrum 0–20 MHz)	MLP (Time-Frequency-Fused Features)
−10	0.646	0.691	0.728	0.745
−5	0.732	0.771	0.836	0.858
0	0.848	0.863	0.933	0.960
5	0.939	0.974	0.973	0.994
10	0.978	0.983	0.987	0.999
15	0.990	0.994	0.997	1.000
20	0.994	1.000	1.000	1.000

4.1.3. Time-Frequency-Domain Fused Feature-Based M-Code Extraction

Furthermore, unlike the scenario using only time-domain features for M-code extraction where one sample corresponds to a single M-code chip, the input of a frequency spectrum necessitates the model output to be a segment of the M-code sequence. This requirement for multi-dimensional output poses a challenge for models like Random Forest, which are not naturally suited to such tasks. In contrast, models like MLP, CNN, and

Transformer are capable of capturing both the global and local characteristics of signal sequences, making them inherently well-suited for sequence-to-sequence signal extraction tasks. Therefore, this experiment adopts the MLP, CNN, ResNet1d, and Transformer to perform the machine learning-based extraction of the M code by fusing time-domain and frequency-domain features.

The extraction accuracy results are summarized in Table 8. After incorporating frequency-domain features, the M code extraction performance demonstrated notable improvement compared to the conventional time-domain-based method such as constellation matching, particularly under low SNR conditions such as -10 dB, -5 dB, and 0 dB. The accuracy of code extraction for the machine learning models such as MLP, ResNet1d, and Transformer increased by more than 10%. Under the low SNR condition of -10 dB, MLP and Transformer exhibited the optimal performance of 74.5% and 74.3% respectively, surpassing the traditional low-pass filter and constellation matching methods by over 10%. This notable improvement indicates that the machine learning models can effectively learn code-related information from the frequency spectrum, thereby further enhancing extraction performance beyond what is achievable with time-domain information alone. Machine learning models can more comprehensively utilize information from both the main and side lobes of the M-code while suppressing the interference from P(Y)-code side lobes, thereby achieving a more thorough extraction of M-code information in the frequency domain.

Table 8. M-Code Extraction Accuracy of Time-Frequency-Domain fused Features.

SNR	Constellation Matching	Bandpass Filter (I Branch Spectrum)	MLP (Time-Frequency-Fused Features)	ResNet1d	CNN	Transformer
-10	0.608	0.646	0.745	0.707	0.691	0.743
-5	0.680	0.732	0.858	0.827	0.795	0.866
0	0.774	0.848	0.960	0.938	0.870	0.964
5	0.864	0.939	0.994	0.985	0.915	0.997
10	0.933	0.978	0.999	0.997	0.926	0.999
15	0.989	0.990	1.000	0.999	0.935	1.000
20	1.000	0.994	1.000	0.998	0.930	1.000

Experimental results also demonstrate that M-code chip polarity discrimination based on time-frequency domain fused information relies more on global spectrum-time domain information fusion and the nonlinear mapping relationship of M-code chips, whereas local neighborhood detail features yield no significant gain for the discrimination of surrounding chips.

The fully-connected architecture of MLP enables each output chip to directly access all time-domain sampling points and full-band spectral information, which is inherently compatible with the global weighted fusion of time-frequency heterogeneous features. It can autonomously learn the contribution weights of different frequency bins and time-domain positions to M-code polarity without layer-by-layer information propagation. Transformer realizes information interaction across all global positions via the self-attention mechanism and can adaptively focus on the valid main-lobe information of M-code and suppress side-lobe interference from the P(Y) code. Both models fall into the global modeling paradigm and are highly aligned with task requirements.

In contrast, CNN and ResNet1d are essentially local modeling paradigms that depend on local neighborhood feature extraction and weight sharing of convolutional kernels. On the one hand, constrained by the receptive field range, they can hardly make efficient use of full-band spectral distribution information. On the other hand, spectral features do not con-

form to the convolutional assumption that “adjacent positions have stronger correlation”, and weight sharing in turn restricts the model’s adaptive weighting capability for different frequency points. Although ResNet1d deepens the network and expands the receptive field through residual connections, it does not break away from the essential framework of local modeling. Its global information propagation efficiency is still lower than that of fully-connected and attention-based structures, resulting in inferior performance compared with the two aforementioned models.

As shown in Figure 7, the extraction accuracy of M code methods is positively correlated with SNR. Conventional method such as constellation matching fails under low SNR conditions. However, the machine learning methods incorporating time-frequency-domain features significantly enhance M-code extraction accuracy under low SNR conditions. This reflects the effectiveness of the machine learning model in improving M-code extraction through time-frequency feature fusion and nonlinear modeling of input signal characteristics and verifies its robustness under low SNR conditions.

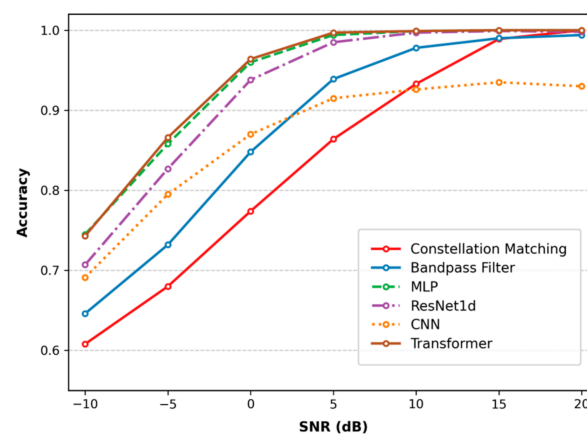


Figure 7. Accuracy of Different Methods under Varying SNR.

To further evaluate the practical deployability and engineering value of the proposed time-frequency fused extraction framework, we conduct a systematic accuracy–efficiency trade-off analysis based on the parameter scale and time consumption statistics in Table 9. From the perspective of model scale, the MLP model features the most lightweight architecture, much lighter than the other models of CNN, ResNet1d, and Transformer. In terms of training and testing efficiency, MLP exhibits the highest training and testing efficiency. Its inference speed is approximately 5.9 times faster than that of CNN, 9.4 times faster than that of ResNet1d, and 6.2 times faster than that of Transformer. Such high training efficiency is of great practical significance in non-cooperative reception scenarios. Combining the accuracy results in Table 6 with the complexity metrics in Table 7, it can be found that for the majority of practical non-cooperative reception scenarios, especially those with limited computing resources and real-time processing requirements, the MLP-based time-frequency fused method is the most competitive solution. The Transformer model can serve as an alternative for high-precision offline analysis scenarios with sufficient computing power.

Table 9. Parameter Scale and Time Consumption of M code extraction models.

Model	Parameters	Training Time (Seconds)	Inferencing Time (Seconds)
MLP	590,976	14.01	1.46
CNN	2,427,616	30.73	8.59
ResNet1d	2,432,080	57.57	13.70
Transformer	8,739,456	77.25	9.05

4.2. Generalization Experiments

The above simulation experiments are all conducted under the condition that the training and test data follow consistent signal distributions. To further verify the robustness and practical applicability of the proposed time-frequency fused M-code extraction method, generalization experiments are carried out from two dimensions: different satellite PRN numbers and different SNR conditions. The experiments aim to verify whether the machine learning model learns the universal modulation characteristics of GPS M-code signals, rather than overfitting to the sequence features of a specific satellite or a specific SNR environment, so as to provide experimental support for the deployment of the method in complex non-cooperative reception scenarios.

4.2.1. Cross-PRN Generalization

In this experiment, the time-frequency fused MLP model is trained exclusively using the simulated signal data of PRN 1 satellite, with a training SNR of 20 dB and a training data duration of 100 ms. All signal parameters including sampling rate, power allocation ratio and modulation mode are consistent with the simulation settings in Section 4.1. The trained model is then tested on the test sets of PRN 1, PRN 8, and PRN 29, respectively.

The correlation functions of the C/A code and simulated M code sequences are illustrated in Figures 8 and 9. It can be observed that the auto-correlation reaches a peak when fully synchronized and the cross-correlation between different PRN sequences remains at a low level, which can fully represent the sequence correlation characteristic of the C/A code and simulated M code in the experiments.

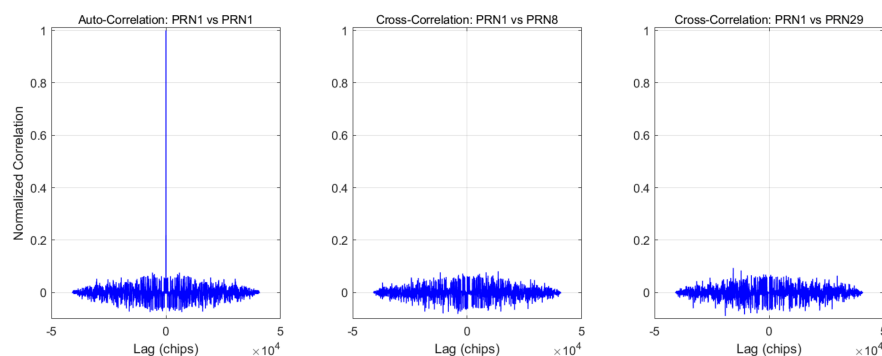


Figure 8. Normalized Correlation Functions of C/A code of Various Satellite PRN.

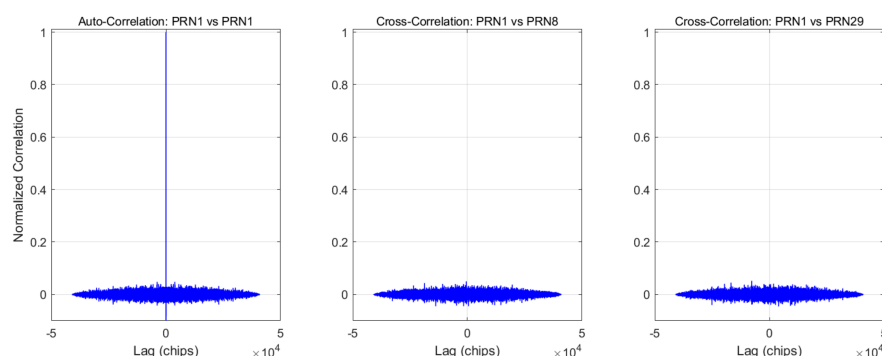


Figure 9. Normalized Correlation Functions of Simulated M code of Various Satellite PRN.

The extraction accuracy results of cross-PRN testing are summarized in Table 10. The experimental results show that the model trained on PRN 1 data has no obvious performance degradation when tested on PRN 8 and PRN 29 datasets. Under the extremely low SNR condition of -10 dB, the extraction accuracy of cross-PRN test is only about 0.5%

lower than that of the same-PRN test, and the maximum accuracy difference under all SNR conditions does not exceed 0.8%. When the SNR is above 15 dB, all test groups achieve nearly 100% extraction accuracy. This phenomenon indicates that the proposed method does not rely on the specific pseudo-random code sequence of a single satellite. The model essentially learns the nonlinear mapping relationship between the time-frequency domain characteristics of baseband signals and M-code chip polarity under the CASM constant envelope multiplexing and BOC(10,5) modulation framework. Therefore, the model trained on a single satellite can be directly generalized to other satellites of the same system, which verifies the excellent cross-satellite generalization capability of the proposed method.

Table 10. M-Code Extraction Accuracy under cross-PRN conditions.

SNR	MLP (Train on PRN1, Test on PRN1)	MLP (Train on PRN1, Test on PRN8)	MLP (Train on PRN1, Test on PRN29)
−10	0.745	0.740	0.743
−5	0.858	0.852	0.859
0	0.960	0.952	0.956
5	0.994	0.989	0.989
10	0.999	0.996	0.999
15	1.000	1.000	1.00
20	1.000	1.000	1.00

4.2.2. Cross-SNR Generalization

To explore the impact of training SNR on model performance and verify the generalization ability under the different training–testing SNR, four groups of experiments are set up in this section. Four MLP models with identical structure are trained using training sets with SNR of 20 dB, 10 dB, 0 dB, and −10 dB, respectively. The training data duration and other signal parameters remain completely consistent. All four models are tested on test sets covering seven SNR levels from −10 dB to 20 dB, and the extraction accuracy is shown in Table 11.

Table 11. M-Code Extraction Accuracy under cross-SNR conditions.

Testing SNR	MLP (Training SNR = 20 dB)	MLP (Training SNR = 10 dB)	MLP (Training SNR = 0 dB)	MLP (Training SNR = −10 dB)
−10	0.745	0.752	0.756	0.692
−5	0.858	0.885	0.966	0.785
0	0.960	0.973	0.997	0.885
5	0.994	0.998	0.998	0.943
10	0.999	1.000	1.000	0.966
15	1.000	1.000	1.000	0.974
20	1.000	1.000	1.000	0.975

The models trained at 20 dB and 10 dB maintain high extraction accuracy in test scenarios where the test SNR is higher than or close to the training SNR. When the test SNR is significantly lower than the training SNR, the accuracy decreases gradually with the deterioration of noise, but still significantly outperforms traditional constellation matching and bandpass filtering methods. Compared with high-SNR trained models, the model trained at 0 dB SNR achieves better performance under low SNR test conditions. At −10 dB test SNR, its extraction accuracy reaches 75.6%, which is 1.1% higher than that of the model trained on 20 dB data. Meanwhile, the model achieves an accuracy improvement up to

10% at -5 dB test SNR compared to the model trained on 20 dB SNR. This phenomenon indicates that training data containing moderate noise enables the model to learn the feature distribution law of signals under noise interference in advance, and enhances the adaptation to signal distortion caused by noise. However, when the training SNR drops to -10 dB, the overall performance of the model degrades significantly across all test SNR intervals. Even under the high SNR test condition of 20 dB, the extraction accuracy is only 97.5%. This is because under extremely low SNR, strong noise submerges the inherent time-frequency characteristics of M-code signals, and the model cannot learn a stable and general mapping relationship between input features and chip polarity, resulting in the decline of overall generalization ability.

In general, the proposed method exhibits favorable SNR generalization capability, and the core advantage lies in that the model can effectively learn the noise characteristics embedded in training data, so as to further improve the M-code extraction performance under low-SNR conditions. By training the model with medium-SNR data with reliable ground truth M code, the model can autonomously learn the noise distribution pattern and the nonlinear mapping between time-frequency features and M-code chip polarity and thus deliver significant performance gains in even lower-SNR reception scenarios. Notably, however, obtaining reliable ground truth of M-code sequences under low-SNR conditions is an inherent and long-standing bottleneck in non-cooperative reception scenarios, which fundamentally restricts the engineering deployment of data-driven M-code extraction methods.

4.3. Real-World Experiments

To further validate the usability of the proposed machine learning-based M-code extraction method, experiments were conducted on GPS II-F signals collected by a 7.5-m antenna. The signal acquisition parameters are presented in Table 12. The constellation diagram of the field-measured baseband signals is shown in Figure 10.

Table 12. Acquisition Parameters for Measured Signals.

Experiment Parameters	Values
Antenna Type	7.5 m narrow beam antenna
Center Frequency	1575.42 MHz
Acquisition Time	26 February 2019
Satellite PRN	GPS 31
Signal Duration	20 ms (10 ms for training, 10 ms for testing)

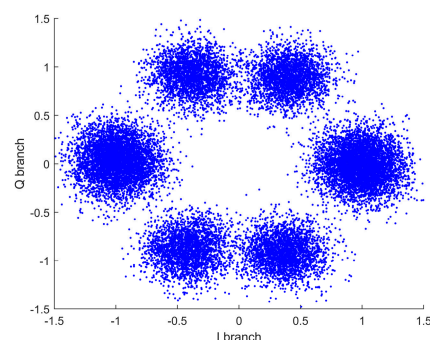


Figure 10. Baseband Signal Constellation of Measured Signal.

From the constellation diagram in Figure 10, the constellation phase points of the measured signal based on the 7.5 m antenna are relatively clear and distinguishable under the received SNR of approximately 12 dB. Since the authentic encrypted M-code sequence

is not publicly accessible as an authorized signal, the M-code sequence extracted via the constellation template matching method is adopted as the pseudo-ground truth for model training and performance evaluation. Based on the constellation template for high-gain M-code extraction, 20 ms of measured baseband IQ signals along with the corresponding M-code ground truth were acquired. The first 10 ms of the measured data were used for model training, while the remaining 10 ms were reserved for validation.

Based on the simulation experiments, we select the MLP as the extraction model for the real-world experiment. MLP can achieve extraction performance comparable to the complex models such as Transformer with fewer parameters and higher computational efficiency, which can meet the requirements for real-time and efficient M code extraction. Meanwhile, due to the limitations imposed by the extraction conditions for high SNR signals, the 20 ms small sample data make it difficult to ensure that complex models like Transformer can achieve satisfactory data fitting. In contrast, small-parameter MLP models exhibit superior stability under small-sample conditions. Furthermore, the MLP model performs M code signal extraction using fully connected layers and possesses an intuitive structure. The contributions of input features can be directly reflected through the network weights, which facilitates subsequent signal analysis and research.

The recovery results are shown in Figure 11. For the measured signal with an SNR of approximately 12 dB, the machine learning model achieved an M-code extraction accuracy of 94.7%, which is close to the performance obtained in simulation. These results demonstrate that the machine learning approach can effectively recover the correct M code sequence from the baseband signal, confirming its validity in practical measurement scenarios.

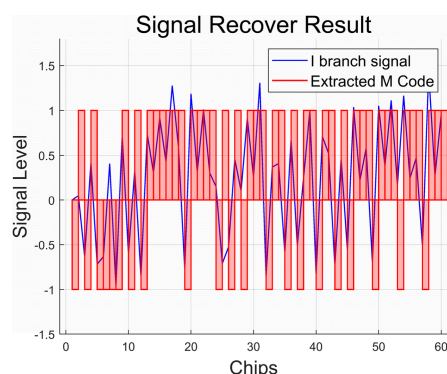


Figure 11. Time-Domain Waveform of I branch signal and extracted M code.

5. Discussion

This paper proposes a machine learning-based method for extracting GPS M code authorized code streams by integrating time-frequency domain features to construct an M code extraction model. By directly inputting the baseband signal spectrum and time-domain sequences into machine learning models such as MLP, ResNet1d, CNN, and Transformer, the approach achieves feature extraction and nonlinear modeling of time-domain and frequency-domain features, completing the process from time-frequency domain sequence input to M code sequence extraction. Under low SNR conditions, this method leverages frequency-domain information to achieve higher accuracy in M code extraction compared to conventional methods such as constellation matching and bandpass filters. This demonstrates that the machine learning approach can more effectively learn code extraction-related features from the signal spectrum, utilizing both the main and side lobes of the M code while suppressing interference from P(Y) code side lobes, thereby improving extraction precision. Additionally, this method does not rely on subcarrier chip

characteristics for signal enhancement, making it more adaptable to M-code extraction under low SNR conditions with better efficiency. Furthermore, the machine learning method enables automatic feature extraction and construction, is not limited to the M-code main lobe frequency band, and more fully utilizes frequency-domain information, further enhancing M-code extraction performance. Moreover, the method successfully achieved direct M-code extraction from high-gain measured baseband signals, validating its effectiveness. Therefore, the machine learning-based GPS M code extraction method provides a more effective approach for recovering authorized signal code streams in non-cooperative environments. As a fundamental signal processing method, it can provide data support for subsequent research on navigation anti-jamming, anti-spoofing [29–31], and satellite operation status monitoring. It should be noted that complete system-level verification in these application scenarios has not been carried out in this work, and will be further explored in future research.

The proposed machine learning-based GPS M code extraction method still has potential for further research. This study only used simulated signals for experiments, replacing real M code streams with random sequences, and the sample size was limited. Subsequent research could incorporate generative networks for code generation and extraction studies, using data generation models to provide high-quality sample data, enabling the model to further explore sample features and enhance extraction capabilities. Furthermore, future studies could conduct experimental validation in measured signal environments, further optimizing the model structure based on the characteristics of measured signals to develop a practically applicable machine learning-based authorized signal code extraction model. Moreover, complete system-level verification in these application scenarios has not been carried out in this work, and the practical value in specific application scenarios needs to be further verified by follow-up system-level research.

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