A Review of Machine Learning-Based Fast Radio Burst Search Methods (Postprint)

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Abstract

Fast Radio Bursts (FRBs) represent a major frontier and hotspot in current radio astronomy. Related research was selected by Nature as one of the top ten scientific discoveries of 2020. The characteristics of FRBs—extremely short burst durations and infrequent repetition—make the probability of observational detection very low. Manual identification of FRB events from massive astronomical observation datasets is a time-consuming and labor-intensive endeavor. The vigorous development of machine learning technology has enabled possibilities for real-time searching and multi-band joint tracking observations of FRBs. This article analyzes and summarizes existing research achievements from both traditional machine learning methods and deep learning methods, discusses current problems and challenges facing machine learning-based FRB search technology, and examines its future development trends.

Full Text

A Review of Fast Radio Burst Search Methods Based on Machine Learning

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Abstract: Fast radio bursts (FRBs) represent a major frontier in radio astronomy and were selected by *Nature* as one of the top ten scientific discoveries of 2020. Their extremely short durations and rare repetition make them exceptionally difficult to capture observationally. Manual identification of FRB events from massive astronomical datasets is time-consuming and labor-intensive. The rapid development of machine learning technology now enables real-time searches and multi-band coordinated follow-up observations of FRBs. This paper analyzes and summarizes existing achievements in FRB search methods from two perspectives: traditional machine learning and deep learning. We discuss current challenges and problems in machine learning-based FRB search technology and analyze future development trends.

Keywords: Fast radio burst; Machine learning; Search method; Deep learning; Radio astronomy
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Fast radio bursts (FRBs) are millisecond-duration, highly dispersed, impulsive radio transient phenomena with instantaneous flux densities reaching tens of Janskys [1-6]. In 2007, Lorimer [1] first discovered this phenomenon while analyzing archival data from the Parkes pulsar survey in Australia. It was not until 2013, when Dan Thornton et al. [2] identified four radio bursts with different dispersion measures in a new Parkes survey, that this class of phenomena was formally named "fast radio bursts." Subsequently, FRBs were widely accepted as a newly discovered astrophysical phenomenon [7]. FRBs are among the most studied astrophysical transients today, yet their origins and whether multiple types of progenitors and emission mechanisms exist remain unresolved questions [5]. Multiple teams worldwide have conducted FRB observations and research. On February 19 this year, China' s Insight-HXMT team announced that FRB 200428, discovered within the Milky Way, originated from the magnetar SGR J1935+2154 [12], marking the first time humanity has demonstrated that fast radio bursts can originate from magnetar outbursts. Future research will require extensive FRB observational data to answer further questions about their origins and emission mechanisms.

In addition to the Parkes telescope, numerous international telescopes have participated in FRB observations and searches, successfully discovering FRBs. These include the Arecibo telescope [13] and GBT [14] in the United States, UTMOST [15,16] and ASKAP [17,18] in Australia, CHIME [19,20] in Canada, the 100-meter Effelsberg telescope [21] in Germany, and the SRT [22] in Italy. FAST, the world's largest and most sensitive single-dish radio telescope, has also detected FRB events [23,24]. Current FRB event rates (limited by observation time and field of view) suggest that FRBs occur with extremely high frequency —thousands per day—implying a large population of sources in the universe [5]. In the coming years, the FRB detection rate is expected to increase dramatically, potentially reaching hundreds to thousands per year. The study of FRBs will enter a new era with this rapid increase in detection rates. Consequently, effectively and rapidly screening rare, genuine FRB events from massive observational data has become a critical challenge that must be addressed to advance FRB science.

This paper is organized as follows: Section 1 introduces traditional FRB search methods, Section 2 elaborates on and analyzes machine learning-based FRB search techniques, and finally, we discuss existing problems and future development trends of machine learning-based FRB search technology.

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1 Traditional FRB Search Techniques

FRBs appear similar to single pulses from Galactic pulsars, but their large dispersion delays indicate they typically originate from extragalactic sources (with FRB 200428 being the current exception). While pulsar radiation is extremely faint, it exhibits very stable periodicity, and most pulsars require period folding to obtain their integrated pulse profiles. FRBs, by contrast, rarely repeat periodically but are bright, making their search process both similar to and different from pulsar searches.

Radio signals experience dispersion, scattering, and scintillation when propagating through the interstellar medium before reaching Earth. These effects cause pulse broadening, profile distortion, and intensity variations, with dispersion having the greatest impact. Dispersion manifests as higher-frequency signals arriving earlier than lower-frequency signals, as shown in Figure 1a [Figure 1: see original paper]. Consequently, dedispersion is a critical technical step in both traditional pulsar and FRB searches. During FRB searches, a series of trial dispersion measures (DMs) are applied to shift frequency channel data to eliminate dispersion delays. The adjusted frequency channel data are then summed to generate time series (pulse profiles) with different signal-to-noise ratios (S/N). When the DM that maximizes S/N is found, the dedispersed dynamic spectrum and time series appear as shown in Figure 1b. The relationship between dispersion delay and DM is given by:

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This equation shows that larger DMs produce more pronounced frequency-dependent delays. (a) Time series and dynamic spectrum before dedispersion (b) Pulse profile and dynamic spectrum after dedispersion

Fig.1 The Lorimer burst

For bright pulsars, single pulses can be discovered through dedispersion using the DM that maximizes S/N, similar to FRBs. However, for most extremely faint pulsar signals, after dedispersion, Fourier transforms are required to determine their periods, followed by signal period folding (to improve S/N), before finally outputting candidate pulse profiles, time-phase diagrams, and other information for confirmation.

These rare, infrequently repeating single-pulse events are searched using automated, high-performance software pipelines based on dedispersion theory, such as HEIMDALL [25], FDMT [26], Bonsai [7], Amber [27], CDMT [28], Presto [29], and BEAR [30]. FAST' s Commensal Radio Astronomy FAST Survey (CRAFTS) employs the FAST_{Miner} pipeline based on HEIMDALL [24], conducting FRB searches across more than 20 GPU servers. Generated candidates undergo preliminary parameter filtering before manual review. The Li Kejia team developed the Piggyback backend and BEAR search software, installed on the Kunming 40-meter and Xinjiang Nanshan 26-meter telescopes for FRB observation and search [30]. These pipelines perform thresholding on time series (pulse profiles) obtained after dedispersion processing with numerous DM trials, reporting any peaks above the threshold as candidates. However, these algorithms face challenges from noise and RFI masquerading as FRBs—false positives where predictions are positive but actual labels are negative—due to radio frequency interference (RFI), system gain variations, or other factors. To avoid missing FRB events, such single-pulse detection programs generate thousands of false-positive candidates. Initially, candidate review was performed manually. However, as FRB observational data volumes increase, particularly with exponential growth from multi-beam and array systems, false-positive candidate numbers grow correspondingly. Given the global detection probability of FRB events, manual screening has become a cumbersome, inefficient, and costly endeavor.

2 Machine Learning-Based FRB Search Methods

Searching for rare FRBs in massive observational datasets is like finding a needle in a haystack. Machine learning applications can improve both the speed and accuracy of FRB searches. This paper categorizes machine learning-based FRB search techniques into traditional machine learning methods and deep learning methods based on whether manual feature construction is performed. The application of machine learning in FRB searches essentially solves a classification problem between FRBs and RFI or background noise. Algorithm performance is typically evaluated using metrics such as accuracy, recall, and precision. Accuracy reflects the algorithm' s ability to correctly classify positive and negative samples; recall reflects the ability to correctly identify FRBs, where higher values indicate fewer missed FRB events; precision reflects the proportion of actual FRBs among positively predicted samples, where higher values indicate fewer RFIs misclassified as FRBs.

2.1 Dataset Preparation

Training samples are a prerequisite for machine learning algorithms. However, the number of confirmed FRBs remains very small and may not represent the potential FRB population, making it insufficient for building meaningful training sets. As shown in Table 1 , traditional machine learning methods have used single pulses from pulsars as FRB samples. In recent years, deep learning-based FRB search applications have typically generated FRB sample sets through simulation or supplemented them with Galactic pulsar single pulses to enrich training sets. Consequently, current machine learning models do not distinguish between pulsar single pulses and FRBs but rather group them into one class, with further judgment based on periodic repetition and DM values in post-processing. Due to the simple morphology of FRB single pulses, they can be modeled with relatively few parameters. When designing FRB simulation algorithms, comprehensive consideration is given to simulating FRB pulse signals with effects from dispersion, scattering, and scintillation, which are then superimposed on real observational data containing only background noise and interference to generate FRB samples. Building FRB sample libraries through simulation allows control over parameters to obtain reasonable distributions across dispersion, width, amplitude, and scintillation patterns.

Table 1 The comparison of some FRB datasets

Author (year)	Telescope	FRB sample source	Dataset size	Positive	Negative
Forster et al [31] (2016)	Arecibo	Pulsar			
Farah et al [32] (2018)	UTMOST	Pulsar			
Michilli et al [33] (2018)	LOFAR	Pulsar			
Connor et al [34] (2018)	Sim FRB, Pulsar				
Zhang et al [35] (2018)					
Devansh et al [36] (2020)	Sim FRB				
	Sim FRB, Pulsar, Crab giant pulses				

Since RFI sources are complex and diverse, simulating RFI is difficult, and RFI constantly exists in observational data. Therefore, in existing studies, negative sample sets are generated from real observational data. This poses a challenge for machine learning models to identify RFI, as the inability to control RFI types and quantities in training sample sets may result in insufficient samples of certain RFI types, preventing models from developing the ability to reject those RFIs and thereby reducing recognition rates.

It should be noted that neither pulsar single pulses nor simulated FRB samples have readily available public datasets. Researchers design their approaches based on data from different telescopes, receivers, and observation backends. Consequently, due to variations in sample quantity, distribution, ratio, and quality, direct quantitative comparison between algorithms is not possible.

2.2 Traditional Machine Learning-Based FRB Search Methods

The implementation framework for traditional machine learning-based FRB search methods is shown in Figure 2 [Figure 2: see original paper], which requires experienced experts to spend considerable time on feature engineering, including feature construction, extraction, and selection. Feature selection occupies a crucial position in machine learning. Selecting fewer features with clear physical or statistical significance helps reduce computational costs and improve model development and training speed. The advantage of manual feature extraction methods lies in their computational simplicity, low model complexity, fast convergence, and modest hardware requirements.

Fig.2 FRB search implementation framework based on traditional machine learning

As early as 2011, Thompson et al. [37] proposed a simple quadratic discriminant function method to automatically distinguish noise, interference, and FRBs. However, this method performed poorly in practice because training samples were one-dimensional time series without a lower S/N limit. The trained classifier lacked the ability to recognize new single pulses with drifting pulse intensities over time or strong RFI.

Random forest algorithms, with their strong anti-overfitting capabilities, ability to handle imbalanced data, efficiency in processing large datasets, and robustness to noise, are exceptionally well-suited for astronomical searches. Consequently, random forest has been favored in the limited FRB search applications. Wagstaff et al. [38], Farah et al. [32], and Foster et al. [31] all adopted random forest algorithms.

Wagstaff et al. [38] designed and extracted features based on experience from candidate dynamic spectra. Two-dimensional dynamic spectra contain richer and more stable feature information compared to one-dimensional time series. They selected 10 features as model inputs, including minimum observation frequency, DM, S/N, and image statistical information from regions during and around candidate events, achieving 95.8% accuracy, 95.7% recall, and 97.3% precision on a test set of 7,649 candidates.

Farah et al. [32] made improvements in feature usage, employing S/N, width, and DM values from candidate outputs as parameters for a pre-classification filter to screen candidates in the first stage. For remaining candidates, they extracted seven statistical features characterizing noise and signals from frequency-time data (such as mean and standard deviation of candidate event windows and surrounding windows of equal width) for input into a machine learning classifier, achieving 98.8% accuracy. This two-stage classification strategy reduces complexity for the subsequent machine learning model but heavily depends on human experience, limited by researchers' cognitive levels and experiential patterns. For system validation, they also tested on a dataset containing 2,000 simulated FRB samples, achieving 90% recall. Notably, Farah et al. [32] developed a low-latency (<24s) candidate classification pipeline enabling near-real-time classification and voltage data capture. This classifier discovered FRB 170827 and successfully captured its voltage data, revealing the burst' s temporal structure.

Foster et al. [31] differed from simple binary classification of FRBs and RFI in other literature. Through manual labeling, they further classified RFI into eight detailed categories, as binary systems performed poorly in distinguishing single pulses from these eight interference types. Therefore, they established a multi-category probabilistic classification system tailored to diverse RFI characteristics. They extracted 409 features per candidate, reduced to 398 after model preprocessing. Testing showed this classification model achieved 96.3% recall and 92.35% precision for single pulses. The advantage of probabilistic multi-label classification lies in optimizing manual review order and time allocation based on prediction results: quick inspection for high-probability single categories, detailed examination for multi-category candidates, thereby avoiding missing rare FRB events to some extent. However, the large number of input features increased model complexity and sacrificed speed.

Michilli et al. [33] conducted detailed information gain value assessment experiments around feature selection, ultimately selecting five highly discriminative features: pulse width, weighted average of pulse DM, excess kurtosis of the DM-width curve, excess kurtosis of the DM-S/N curve, and S/N. Considering the rarity of single pulses in actual observational data streams, they developed a single-pulse classifier based on the Gaussian Hellinger Very Fast Decision Tree algorithm, specifically designed for handling imbalanced data streams. Compared to the above applications, Michilli et al. [33] achieved better classifier performance with the fewest input features, attaining 98.8% accuracy, 98.6% recall, and 98% precision. A process version of this classifier has already discovered seven new pulsars in LOTAAS survey data.

2.3 Deep Learning-Based FRB Search Methods

The emergence of convolutional neural networks has enabled tremendous progress in deep learning for image recognition. The application of deep learning to FRB searches has only developed in recent years, primarily inspired by Farah et al. [32]' s simulated FRB samples, which addressed deep learning' s requirement for large-volume training data. Current work includes studies from references [34-36].

Connor and van Leeuwen [34] developed a multi-input deep neural network architecture with fewer sub-network layers, using dedispersed dynamic spectra, DM-time arrays, time series, and multi-beam detection S/N information as inputs for 2D CNN, 1D CNN, and FNN to extract features separately, which were then integrated in fully connected layers before outputting predictions. This study first used simulated FRBs to enrich training samples. Testing on Apertif data, the classifier achieved 99.7% recall for pulsar single pulses. Simulated FRBs provided training sets with advantages in both quantity and sample random diversity (e.g., spanning larger width and DM ranges) that were unattainable when using pulsar single pulses as training samples. However, the first three inputs were highly redundant; while empirical evidence suggested the combination performed better than individual use, it undoubtedly increased overall network architecture complexity.

Devansh et al. [36] constructed 11 binary-input, binary-classification network architectures based on eight deeper network models (such as VGG16, VGG19, Densenet121/169/201, Xception, etc.) through various combinations. They simplified model inputs to only dedispersed dynamic spectra and DM-time arrays. Testing showed all 11 classification models achieved over 99.5% accuracy and recall. This work made numerous improvements upon Connor and van Leeuwen [34], including: introducing transfer learning to reduce training parameters, using multiplicative fusion to combine dual-input models for enhanced performance, employing flipping techniques to increase RFI sample numbers, and applying fine-tuning to improve model performance for specific applications. This algorithm package has been embedded in the U.S. GBT real-time FRB search pipeline, detecting over 2,000 single pulses from 20 pulsars [39]. It should be noted that while increased network depth can improve model performance, it also raises model complexity and training difficulty. Moreover, the contribution of additional layers may saturate and could even cause gradient instability, network degradation, and performance decline. Pruning redundant layers could help improve overall model performance.

Zhang et al. [35] established a ResNet architecture consisting of 17 convolutional layers, using dispersed dynamic spectrograms as input. Training data comprised simulated FRB samples and observational data containing only RFI and noise. Testing achieved 88% recall and 98% precision. Unlike references [34] and [36], this approach does not rely on traditional dedispersion-based search methods but instead applies the trained model directly to search for FRB 121102 in raw dispersed dynamic spectrum data. The method successfully identified 93 FRB 121102 pulses from GBT C-band receiver observations on August 26, 2017, whereas previous dedispersion-based search pipelines detected only 21 bursts in the same data. Therefore, this method demonstrates superior performance compared to traditional dedispersion search algorithms in terms of higher sensitivity, lower false alarm rates, and faster computational speed.

Deep learning-based FRB search technology has shown significant overall performance improvements. All three existing studies delegate feature extraction tasks directly to convolutional neural networks, which challenges computational complexity and training difficulty. During data preprocessing, only basic size adjustment and standardization are performed on candidate dynamic spectrograms and DM-time array images input to network models. This substantially reduces data processing workload while avoiding the incompleteness and bias of manual feature design and extraction. However, complete reliance on automatic network feature extraction lacks interpretability and can exhibit class discrimination under imbalanced training data, such as RFI class imbalance issues. Additionally, deep learning algorithms require high-performance hardware and converge slowly, necessitating lengthy training times. Nevertheless, their GPU-based forward propagation inference process is extremely fast, meeting the application requirements for online FRB event searches.

3 Problems and Outlook

Machine learning-based FRB search technology has a relatively short development history, with few related research papers and no large-scale widespread application yet. Most FRB events detected to date rely on traditional dedispersion search techniques. Both research and application aspects of machine learning-based FRB search technology require continued improvement, primarily manifested in:

(1) Due to differences in telescope types (single-dish or array), receiver types (single-beam or multi-beam), observation backends, and data formats (Filterbank, FITS, or VDIF), algorithms require tailored designs. The RFI environment at telescope sites also significantly impacts data quality. Therefore, improving algorithm universality and generalization capabilities is of great importance.

(2) Except for Zhang et al. [35], current algorithms focus on classifying candidates generated by dedispersion-based search pipelines. In wideband observations, pulse frequency structures are highly variable [40], and distinguishing FRBs from RFI based on S/N of dedispersed, frequency-integrated time series can lead to missed FRBs. Therefore, directly applying classifiers to search for FRBs in raw observational data streams warrants further research and exploration from both search speed and recall perspectives.

(3) Current model training samples almost exclusively come from pulsar single pulses or simulated samples, causing trained models to overfit pulsar or simulated FRB characteristics. Therefore, as detected FRB samples increase and understanding deepens, continuously optimizing simulated samples or adding real observational samples to improve training sample quality is crucial for enhancing algorithm performance.

(4) The RFI environment continues to deteriorate, exhibiting more complex

diversity, with some RFI even possessing Peryton characteristics [30,41]. Therefore, besides necessary RFI mitigation measures, addressing RFI class imbalance in training samples can further improve algorithm robustness.

(5) Current algorithms primarily focus on binary classification (astrophysical phenomena vs. non-astrophysical phenomena). Significant differences exist among various FRBs, between FRBs and pulsar single pulses, among pulsar single pulses, and among different RFI types. Therefore, finer-grained classification of samples will help further improve classification algorithm performance.

4 Conclusion

FRB search speed and accuracy are critical for enabling triggered multi-band follow-up observations and voltage data dumps. The future belongs to big data, and current observational data volumes already far exceed human capacity. Therefore, applying machine learning will help solve the unsustainable status quo of manual FRB candidate screening. Regarding classifier design, given deep learning algorithms' superior capability for large datasets and their avoidance of manual feature design and extraction drawbacks, deep learning will play a greater role in FRB search applications.

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