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Abstract

Fast Radio Bursts (FRBs) have emerged as one of the most intriguing and enigmatic phenomena in radio astronomy. The key to current research is obtaining sufficient FRB signals, necessitating computer-aided search methods. Given the scarcity of FRB signals and the massive volume of observational data, the primary challenges concern search speed, accuracy, and recall. In this paper, we propose a novel FRB search method based on Commensal Radio Astronomy FAST Survey (CRAFTS) data. The CRAFTS drift survey data provide extensive sky coverage and high sensitivity, which significantly enhance the probability of detecting transient signals such as FRBs. Leveraging knowledge of FRB signal structural isomorphism, the search process is divided into two stages, with a different deep learning model adopted in each stage. To evaluate the proposed method, we develop FRB signal datasets based on FAST observational data, combining both simulated and real FRB signals. Compared with the benchmark method, the proposed method achieves an F-score of 0.951 and a recall of 0.936. The method has been applied to search for FRB signals in raw FAST data. The code and datasets used in this paper are available at github.com/aoxipo.

Full Text

Preamble

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TSC: Efficient FRB Signal Search by a Two-stage Cascade Deep Learning Model on FAST

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Abstract

Fast Radio Bursts (FRBs) have emerged as one of the most intriguing and enigmatic phenomena in radio astronomy. A key challenge in current research is obtaining a sufficient number of FRB signals, necessitating computer-aided search methods. Given the scarcity of FRB signals amid massive observational datasets, the primary challenges lie in achieving high search speed, accuracy, and recall. In this paper, we propose a novel FRB search method based on Comensal Radio Astronomy FAST Survey (CRAFTS) data. The CRAFTS drift survey data provide extensive sky coverage and high sensitivity, significantly enhancing the probability of detecting transient signals like FRBs. Leveraging the structural isomorphism of FRB signals, our search process is separated into two stages, with a different deep learning model adopted in each stage. To evaluate the proposed method, we developed FRB signal datasets combining simulated and real FRB signals based on FAST observation data. Compared with benchmark methods, our approach achieved an F-score of 0.951 and a recall of 0.936. The method has been successfully applied to search for FRB signals in raw FAST data. The code and datasets used in this paper are available at github.com/aoxipo.

Key words: techniques: image processing – techniques: high angular resolution – techniques: interferometric

1. Introduction

Since the first Fast Radio Burst (FRB) signal was discovered in 2007 (Lorimer et al. 2007), FRBs have garnered significant attention in astronomy. Many observatories, including the Green Bank Telescope (Prestage et al. 2009), Parkes Observatory (Hobbs et al. 2011; Bailes et al. 2017), and the Square Kilometre Array Pathfinder projects such as UTMOST (Dewdney et al. 2009), have conducted extensive observational research on FRBs. The Five-hundred-meter Aperture Spherical radio Telescope (FAST; Li et al. 2018), independently developed by China, offers unique advantages for FRB detection due to its high-precision detection capability and exceptional sensitivity.

Traditional machine learning search methods primarily employ de-dispersion-based approaches (Thompson et al. 2011; Wagstaff et al. 2016; Foster et al. 2017; Farah et al. 2018, 2019; Li et al. 2018; Michilli et al. 2018; Madison et al. 2019; Yatawatta et al. 2019; Gupta et al. 2021; Morello et al. 2021). These methods use various machine learning algorithms (such as support vector machines and random forests) for training and testing to compare model performance. While exhibiting notable advantages including high accuracy and effective signal recovery capabilities, making them suitable for high-precision FRB research, these approaches suffer from significant drawbacks, particularly regarding computational cost and processing speed.

In contrast, deep learning-based approaches offer substantial advantages in speed and have been widely adopted in recent years. These approaches can be divided into two categories based on whether they employ de-dispersion.

Regarding de-dispersion-based methods, Connor & Van Leeuwen (2018) utilized several types of input data, including dispersive dynamic spectra, dispersion measure (DM)–time series, and multibeam detection signal-to-noise arrays. These inputs were processed separately using a two-dimensional Convolutional Neural Network (2D CNN), a one-dimensional CNN (1D CNN), and a forward Neural Network (FNN) to extract features, which were then integrated into a fully connected layer for candidate classification. This approach achieved 99.7% recall and 99% accuracy for single-pulse identification of pulsars. Devansh et al. (2020) constructed a classification network using frequency and dispersion-time information, evaluating eleven different deep learning models for FRB signal identification in candidates. Their best method achieved 99.88% accuracy, 99.92% recall, and 99.87% F-score on the relevant dataset.

However, actual FRB samples are utilized less frequently in training; therefore, despite exceptional performance on test sets, model efficacy may diminish when applied to entirely novel data. Furthermore, these methods require de-dispersion, which significantly reduces processing speed—a limitation evident in the speed comparisons shown in Table 8. The common characteristic of these technologies lies in applying deep learning to search and detect dispersed candidate objects, demonstrating high reliability but suffering from the time cost of de-dispersion operations.

In this context, Zhang et al. (2020) proposed using saliency maps to improve model accuracy by enhancing brightness variations in images of transient features. By constructing a simple Deep Neural Network (DNN) model and influencing predicted probability scores through pixel-order low-mass pulse signaling, they performed gradient integration for given pixels to capture luminance variations of smooth pixels in pulses, thereby identifying FRB signals against complex background noise without requiring the complicated de-dispersion step.

Zhang et al. (2018) proposed a ResNet structure with 17 convolutional layers trained directly on raw signals without de-dispersion, achieving 88% recall and 98% precision. Liu et al. (2022) proposed a decentralized dynamic spectral

search (DDSS) pipeline that searches for FRB signals directly in raw data, using ResNetV2 and Xception Net models for feature extraction, achieving over 99.6% accuracy, though their targeted dataset had a limited DM range of 100–500 pc cm⁻³.

Despite this progress, these methods still face challenges including radio frequency interference (RFI) (Wu et al. 2021), sensitivity to training data distribution, and difficulties with high-resolution backgrounds. Prior research has focused on model architectures and lightweight networks to improve search efficiency but has overlooked the inherent isomorphism of FRB signals—where a portion of an FRB signal is structurally and characteristically similar to the whole signal. While learning FRB features enhances accuracy, existing methods lack flexibility to capture intricate details.

To enhance FRB signal search efficiency and accuracy, we present a two-stage cascade deep learning method that intuitively aligns with the search process. By leveraging the high time and frequency resolution of drift survey data, our method efficiently identifies FRB signals while addressing challenges such as RFI and baseline drift. Unlike traditional approaches, our method does not rely on de-dispersion and operates directly on raw data. By sequentially learning the signal’s intensity distribution and dispersion structure features, our approach exhibits remarkable flexibility and performance. In the first stage, we employ the Efficient-Net model to detect shape and intensity features of FRB signals. In the second stage, we utilize a global attention (GA) model to identify positional features. This cascade approach—initial detection followed by refinement—enables efficient and accurate FRB signal detection.

The main contributions of this paper are:

1. Development of three datasets by combining simulated and real FRB signals.
2. Proposal of a two-stage cascade deep learning search method with advantages in search speed, accuracy, and recall.

2. Datasets

To research deep learning-based FRB search algorithms, we developed three image datasets (Dataset-I, Dataset-II, Dataset-III) primarily from simulated FRB signals and partially from real FRB signals, annotated through a computer-aided approach.

2.1. FRB Signal Simulation

FAST-mode simulated FRB signals are obtained by superimposing simulated FRB signals onto FAST observation data backgrounds. The consistency between simulated and real FRB signals significantly impacts dataset quality. Simulated FRB signals are generated according to the method proposed by Niu

et al. (2021), incorporating parameters such as DM, peak signal-to-noise ratio, pulse width, and others. The dispersion estimation equation is defined as:

$$I(\text{DM}, t) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(t - \text{DM} \cdot \Delta t)^2}{2\sigma^2}\right)$$

Here, $I(\text{DM}, t)$ represents the equation of a plane wave at a given DM and sampling time t . The dispersion degree of each point in the simulated signal duration is constructed by estimating the maximum dispersion.

Using the simulated brightness of the FRB within the beam size and the beam response, we calculate the received peak flux density to simulate the intensity distribution of the FRB signal:

$$S_{\text{peak}} = \frac{l^*}{4\pi d^2} \cdot \frac{1}{\text{SN}}$$

Here, α represents the power-law index, l^* is luminosity, l is intrinsic luminosity of FRB, and SN is peak signal-to-noise ratio.

The pulse width can be defined as:

$$W = \frac{1}{\sqrt{f_s \cdot f_e}} \cdot T_{\text{samp}}$$

where $x \in (f_s, f_e)$, f_s represents initial frequency, f_e represents termination frequency, and T_{samp} represents the unit sampling time.

The final simulation generation is expressed below:

$$\frac{dN}{dl} \propto l^{-\alpha} dl$$

Here $x \in (f_s, f_e)$, and D represents a constant. FITS-format FAST observation data from the Commensal Radio Astronomy FAST Survey (CRAFTS) drift survey were chosen as the background for superimposing simulated signals. The CRAFTS drift survey data provide large sky coverage and high sensitivity, which are essential for detecting transient signals like FRBs. To avoid low-probability events such as real FRB signals accidentally appearing in the background, each background file was manually inspected.

Generally, each FAST observation data FITS file with a bandwidth of 500 MHz and 4096 channels can be transformed into an image with shape 4096×22144 , representing 12.8849 s total observation time and 4.9152×10^{-5} s sampling time. The parameters for simulating FRB signals are listed in Table 1. FITS images after superimposing simulated FRB signals on the background are displayed in Figure 1 [Figure 1: see original paper].

2.2. Collecting the Datasets

After superimposing simulated FRB signals onto FAST observation data backgrounds, Dataset-I with image shape 4096×4096 and Dataset-II with image shape 512×512 were produced by segmenting the FITS-format superimposed data into samples. By recording the superimposed position combined with the frequency range from simulation, a computer-aided approach was used to label samples after calculating segmentation positions, duration, sampling time, and image dimensions.

For Dataset-I, image samples were generated by dividing the entire image every 4096 pixels along the time axis. For Dataset-II, image samples were obtained by further segmenting Dataset-I samples using the same production method. Each image sample in Dataset-I was segmented into eight equal parts in width and height individually, yielding image samples with shape 512×512 . Samples in Dataset-I and Dataset-II (partitioned from Dataset-I) are illustrated in Figures 2 [Figure 2: see original paper] and 3 [Figure 3: see original paper], respectively.

Dataset-III was created using currently discovered real FRB signals from FAST observation data, published on the FAST public signal platform CST-Cloud (<https://fast.cstcloud.cn/datavolume/10.1038.s41586-021-03878-5>) (Li et al. 2021). A total of 60 FITS files were selected. After separation from Dataset-I and manual labeling, 2661 data samples with size 4096×4096 were obtained, including 74 positive samples and 2587 negative samples.

The image sizes, simulation parameters, and sample counts for the three datasets are shown in Table 2 .

3. Methodology

3.1. Isomorphism of FRB Signals

FRB signals exhibit structural isomorphism. When a small portion is segmented from a complete FRB signal, it retains the main characteristics of FRB signals—such as high energy and dispersion—with only the duration becoming shorter. This feature provides significant advantages for FRB detection and analysis.

Based on this characteristic, we developed a two-stage cascade search method that integrates partial and overall recognition. In the initial stage, extensive observation data are segmented into smaller windows, and signal segments with FRB characteristics are searched within these small time windows. This approach efficiently filters potential FRB candidate signals, significantly reducing the amount of data requiring detailed analysis. In the second stage, comprehensive recognition is performed to analyze candidate signals filtered in the initial stage, reconstructing the complete signal to verify its classification as an FRB and performing in-depth feature extraction. This method enhances search speed through rapid local recognition while enabling quick elimination of irrelevant data. Meanwhile, the overall recognition stage effectively reduces false positives and improves FRB identification reliability, as shown in Figure

4 [Figure 4: see original paper]. When a portion of an FRB signal is extracted from a complete FRB signal, it will still be detected as an FRB signal.

3.2. Model Architecture

Leveraging the isomorphism of FRB signals, we propose a cascade model (TSC-Model) with two stages to search for FRB signals in FAST observation data. TSC-Model consists of two components: Model-I, trained to detect FRB signals in 512×512 images; and Model-II, trained to detect FRB signals in 8×8 2-bit images. The architecture of TSC-Model is illustrated in Figure 5 [Figure 5: see original paper].

When applying TSC-Model to search for FRB signals in FAST observation data, the process is separated into two stages, as shown in Figure 6 [Figure 6: see original paper] using a FITS file as an example.

In the first stage, a FAST observational image in FITS format is used as input. FITS data typically consist of multidimensional arrays, which we reshape into a two-dimensional array (time \times channel) for subsequent analysis. To mitigate baseline drift, baseline correction is performed by subtracting the mean value from each channel. Finally, the data are binarized using Otsu's thresholding method. This process enhances contrast between potential FRB signals and background noise, making subsequent analysis more efficient and accurate.

Following binarization, the data are divided into blocks of size 4096×4096 , which are further subdivided into 8×8 sub-blocks, each with dimensions of 512×512 pixels. These 64 sub-images are fed into Model-I to predict the presence of FRB signals. The prediction results are compiled into a list of length 64, which is subsequently reshaped into an 8×8 2-bit image for input to Model-II.

In the second stage, each 8×8 2-bit image is fed into Model-II for prediction. If the prediction result is positive, it indicates the presence of an FRB signal within the corresponding 4096×4096 image. As long as any segmented block is predicted to contain an FRB signal, the FAST observational image can be determined to include an FRB signal.

4. Experiments

4.1. Model-I

We evaluated ResNet, Inception-ResNet (Szegedy et al. 2017), DenseNet (Huang et al. 2011), and Efficient-Net (Tan & Le 2019) as candidate models for Model-I using Dataset-II. The training, validation, and test sets were split in a 40%, 10%, and 50% ratio, respectively. To prevent overfitting, we employed early stopping with patience set to 5 during training, meaning training stops if the model fails to converge on the validation set for 5 consecutive epochs.

The training processes for the four models are shown in Figure 7 [Figure 7: see original paper], with testing results presented in Table 3 .

4.2. Model-II

The goal of Model-II is to predict on 8×8 2-bit images—a relatively simple task. We employed the GA model (Abujar et al. 2021) for this purpose. To train the GA Model, we created a temporary dataset where positive samples were generated from Dataset-I and Dataset-II using their correspondence, and negative samples were generated as zero-matrices or random matrices manually. Example training samples are shown in Figure 8 [Figure 8: see original paper].

The temporary dataset contains 11,422 samples, with 5,711 positive and 5,711 negative samples. The training, validation, and test sets were split in a 40%, 10%, and 50% ratio, respectively. Training results for Model-II are shown in Table 4, with test results in Table 5.

4.3. TSC-Model

Based on the above results, we constructed TSC-Model using EfficientNet as Model-I and the GA Model as Model-II, evaluating its performance against EfficientNet, ResNet, Inception-ResNet, DenseNet, Conv17, and FETCH models using Dataset-I and Dataset-III. As mentioned, Dataset-III contains real FRB signals. For training, Dataset-I and Dataset-III were separated with 40% for training, 10% for validation, and 50% for testing. While Model-I and Model-II were trained separately, TSC-Model did not require further training on Dataset-I and Dataset-III, so only the test set was used for evaluation.

4.3.1. Accuracy Results We tested all models on Dataset-I and Dataset-III, with results shown in Tables 6 and 7. The area under the curve (AUC) and receiver operating characteristic (ROC) results are shown in Figure 9 [Figure 9: see original paper].

The experimental results provide compelling evidence of TSC-Model’s outstanding performance in FRB signal detection. TSC-Model not only achieves the highest accuracy but also attains the second-highest recall rate, which is particularly important for FRB detection as it reduces false positives while capturing more potential FRB signals. Although other models such as EfficientNet and FETCH demonstrate commendable precision, TSC-Model exhibits advantages across all metrics.

The model’s excellent discriminative capability is substantiated by its AUC score of 0.996, nearly equivalent to the perfect value of 1. This near-optimal AUC signifies remarkable proficiency in differentiating between positive (FRB signals) and negative (non-FRB signals) samples. The ROC curve for TSC-Model is closest to the upper left corner, indicating outstanding performance across various threshold settings. This characteristic underscores the model’s excellent equilibrium between sensitivity (capacity to detect true FRB signals) and specificity (ability to accurately identify non-FRB signals). These results convincingly demonstrate TSC-Model’s superiority in FRB signal detection, reflecting a commendable balance among accuracy, precision, and recall. The

AUC score and ROC curve demonstrate that this model is capable of delivering reliable, efficient, and sensitive FRB signal detection in practical applications.

4.3.2. Search Speed Results To evaluate average search speed, we recorded the time each model required to process a single FAST FITS file (4096×262144 pixels, 2.02 GB) on an Nvidia A100 graphics card, calculating the average across multiple files. The results are presented in Table 8, where bold indicates optimal performance and underline indicates sub-optimal. As shown, TSC-Model's average search time is quite competitive considering its accuracy.

4.3.3. Heat Map Results To analyze TSC-Model's effectiveness, we applied Class Activation Map (CAM) (Zhou et al. 2016) to visualize the detection process. As shown in Figure 10 [Figure 10: see original paper], red areas in CAM heat maps for samples (a) through (d) highlight Model-I's focal points when learning intensity distribution. These focal points serve as cornerstones for final predictions, particularly for samples (b), (c), and (d). Multiple red regions signify areas of interest identified by Model-I.

For sample (e), the heat map indicates that the red region, shaped by noise, is starkly at odds with FRB dispersion patterns. Consequently, despite Model-I flagging this region as significant, the final prediction—considering the dispersion structure learned by Model-II—classifies it as a negative sample. Model-II, which learns dispersion structure distribution, pays particular attention to temporal relationships among multiple red regions identified by Model-I. This approach aligns perfectly with our proposed methodology, demonstrating the effectiveness of the cascaded Model-I and Model-II combination. Additional experimental results are available at <https://doi.org/10.57760/sciencedb.j00167.00010>.

5. Summary and Discussion

Reviewing existing FRB signal identification research reveals that despite progress, these methods still encounter significant challenges including RFI, sensitivity to training data distribution, and difficulties posed by high-resolution backgrounds. Notably, these methods tend to overlook the intrinsic isomorphism of FRB signals, which may limit recognition performance in complex environments.

Our approach analyzes FRB signals utilizing observational structure isomorphism. Through rigorous experimental validation, we discovered that the two-stage cascade search method based on structural isomorphism significantly enhances predictive accuracy and effectively reduces false positives caused by noise. Our method achieved 96.6% accuracy and 0.963 F1 score on simulated data. On real data, it achieved 93.6% accuracy, 98.8% recall, and 0.951 F1 score. The main contributions are:

1. Generation of three datasets by combining simulated and real data.

2. Introduction of a two-stage cascade search method demonstrating advantages in search speed, accuracy, and recall.

In our experiments, the specific model versions employed were EfficientNet-B6, ResNet101, Inception-ResNetV2, and DenseNet121. While the selected EfficientNet-B6 version may not be optimal in all scenarios, it remains compatible with our proposed methodology. Ablation studies have rigorously demonstrated the flexibility and robustness of the two-stage architecture. When evaluating the trade-off between temporal efficiency and accuracy, we advocate selecting models that exhibit both robustness and reduced time complexity for Model-I, while recommending models sensitive to temporal relationships for Model-II.

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