Application of Machine Learning-Based Single Pulse Search Candidate Identification to FAST CRAFTS Observational Data: Postprint

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Abstract

Single-pulse search serves as a powerful tool for pulsar detection and plays an important role in detecting rotating radio transients and fast radio bursts. To rapidly screen the most valuable single-pulse search candidates from massive radio survey data, candidate identification has evolved from early heuristic threshold-based judgment to machine learning-based automatic recognition. For FAST observations, we studied the performance of machine learning-based single-pulse search candidate identification applied to ultra-wideband pulsar data from CRAFTS (the commensal radio astronomy FAST survey). During the evaluation process, two types of automatic identification methods—Single-Pulse Event Group IDentification (SPEGID) and Single-Pulse Searcher (SPS)—were used to automatically identify single-pulse search candidates generated from the CRAFTS benchmark dataset through seven different machine learning classifiers; for comparison, heuristic threshold-based methods (RRATtrap and Clusterrank) were also employed. The results demonstrate that SPEGID achieves the best performance (highest F1-score of 95.1%, second-highest recall rate of 95.4%, lowest false positive rate of 4.7%), while SPS offers the fastest screening speed (averaging 4,010 candidates per hour). Through comparative analysis of the results, we discuss how to conduct efficient single-pulse search candidate identification based on FAST observational data.

Full Text

Preamble

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Application of Machine Learning-Based Single-Pulse Search Candidate Identification to FAST CRAFTS Observations: A Performance Study

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Abstract

Single-pulse search serves as a powerful tool for pulsar detection and plays a crucial role in discovering rotating radio transients (RRATs) and fast radio bursts (FRBs). To rapidly screen the most valuable candidates from massive radio survey datasets, identification methodologies have evolved from early heuristic threshold-based approaches to automated recognition powered by machine learning. This study evaluates the performance of machine learning-based single-pulse search candidate identification when applied to ultra-wideband pulsar data from the Commensal Radio Astronomy FAST Survey (CRAFTS). In our assessment, we employ two automated recognition methods—Single-Pulse Event Group Identification (SPEGID) and Single-Pulse Searcher (SPS)—to automatically classify candidates generated from a CRAFTS benchmark dataset using seven distinct machine learning classifiers. For comparative purposes, we also utilize heuristic threshold-based methods (RRATtrap and Clusterrank). The results demonstrate that SPEGID achieves the best overall performance (highest F1-score of 95.1%, second-highest recall of 95.4%, and lowest false positive rate of 4.7%), while SPS delivers the fastest screening speed (averaging 4,010 candidates per hour). Through comparative analysis, we discuss strategies for

conducting efficient single-pulse search candidate identification with FAST observational data.

Keywords: single-pulse search; candidate identification; machine learning; pulsar; FAST; CRAFTS

1 Introduction

Pulsar search methods primarily fall into two categories: periodicity searches and single-pulse searches [?]. Periodicity searches identify periodic signals by transforming time series into the frequency domain using Fast Fourier Transforms (FFT) [?]. Traditionally, pulsar detection has relied mainly on periodicity searches that exploit the intrinsic periodic nature of pulsar signals. Single-pulse searches, in contrast, focus on detecting strong, non-periodic pulses and are particularly well-suited for discovering isolated bursts that periodicity searches cannot detect [?]. This approach led to the discoveries of rotating radio transients (RRATs) and fast radio bursts (FRBs). In 2006, McLaughlin et al. [?] first identified RRATs, which are considered a special class of intermittent pulsars. In 2007, Lorimer et al. [?] discovered the first FRB in data from the Parkes Multibeam Pulsar Survey (PMPS).

Since Cordes and McLaughlin [?] first proposed single-pulse searching for pulsar detection in 2003, this technique has generated massive numbers of candidates. To rapidly identify the most promising candidates from radio survey data, various identification methods have been developed for specific pulsar surveys [?, ?, ?, ?, ?, ?]. Candidate identification has progressed from early heuristic threshold-based approaches to automated recognition using machine learning [?]. Heuristic methods leverage characteristic properties of pulsars to guide searches and filter candidates. For example, Deneva et al. [?] discovered seven new pulsars through single-pulse searches of the Pulsar Arecibo L-band Feed Array Survey (PALFA). Keane et al. [?] identified ten RRATs in the PMPS, while Burke-Spolaor et al. [?] found eleven RRATs in the High Time Resolution Universe Survey (HTRU) data. In 2015, Karako-Argaman et al. [?] developed RRATtrap, a tool for detecting pulsars and RRATs that assigns numerical scores based on adherence to predefined rules, enabling discrimination between pulsar and radio frequency interference (RFI) candidates by examining only those exceeding a given threshold. This approach yielded 21 RRATs in data from the Green Bank Telescope 350-MHz Drift-Scan Survey (GBT350Drift) and the Green Bank North Celestial Cap Survey (GBNCC). In 2016, Deneva et al. [?] created Clusterrank, which quantifies how well a candidate' s dispersion measure (DM) versus signal-to-noise ratio (S/N) curve matches the theoretical predictions of Cordes and McLaughlin [?], thereby assessing pulsar likelihood. This method discovered 14 pulsars and eight RRATs in the Arecibo 327 MHz Drift Pulsar Survey (AO327). However, heuristic threshold methods primarily construct rules based on pulsar characteristics without specifically targeting

RFI, often generating numerous false candidates and struggling to cope with large-scale data processing.

Artificial intelligence techniques have been widely applied to periodicity search candidate identification [?, ?, ?, ?], but research in the single-pulse search domain remains relatively limited. As pulsar surveys produce exponentially growing numbers of candidates, manual screening alone cannot meet timeliness requirements. Machine learning and other AI technologies are gradually being adopted for single-pulse search candidate identification. Machine learning-based approaches (hereafter "ML methods") exploit the intrinsic properties of pulsars and RFI to develop feature engineering that maximizes discrimination between them, then employ classifiers for automated candidate recognition. In 2016, Devine et al. [?] first applied machine learning to single-pulse candidate identification, achieving automated screening. In 2018, Pang et al. [?] from the same group proposed SPEGID, constructing 18 features to describe aggregated single-pulse event groups (SPEGs) and combining them with machine learning classifiers for automated recognition of PALFA data. Subsequently, the SPEGID feature set was expanded to 23 features [?] and applied to GBTDrift. Meanwhile, in 2018, Michilli et al. [?] designed SPS, which uses five features to statistically model SPEGs and employs machine learning classifiers to distinguish pulsars from RFI in the LOFAR Tied-Array All-Sky Survey (LOTAAS) data, even under strong interference conditions.

The Five-hundred-meter Aperture Spherical radio Telescope (FAST) is currently the world's most sensitive single-dish radio telescope. FAST's Commensal Radio Astronomy FAST Survey (CRAFTS) simultaneously collects data for multiple scientific objectives—including pulsars, neutral hydrogen, molecular lines, transients, and FRBs—using multiple digital backends [?]. CRAFTS pulsar searches are estimated to generate tens to hundreds of thousands of candidates per 24-hour scanning session [?], with manual diagnosis revealing that the vast majority are false candidates caused by RFI or cosmic noise [?]. Conducting single-pulse searches for new pulsars in FAST' s massive datasets requires rapidly identifying scientifically valuable candidates for prioritized storage to avoid accumulation delays, while employing robust identification methods to accurately and efficiently distinguish pulsars from RFI.

From August 2017 to May 2018, FAST operated in drift-scan mode using an ultra-wideband receiver (270–1620 MHz), continuously observing multiple sky regions. During this period, 2,760 hours of pulsar survey data were collected, comprising 317,497 data files known as the CRAFTS ultra-wideband pulsar survey dataset (hereafter "CRAFTS data"), stored at the NAOC-GZNU FAST Early Science Data Center. This study evaluates the performance of ML methods on single-pulse search candidates from CRAFTS data to identify solutions for rapid and efficient candidate screening. The paper is organized as follows: Section 2 introduces the fundamental theory of ML-based single-pulse search candidate identification; Section 3 tests ML methods (SPEGID and SPS) and heuristic methods (RRATtrap and Clusterrank) on a CRAFTS benchmark dataset, comparing their performance and speed; Section 4 provides a summary and discussion.

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2 Fundamental Theory of Machine Learning-Based Single-Pulse Search Candidate Identification

Pulsar detection from radio astronomical data typically involves five stages [?]: data collection, RFI mitigation, dedispersion, periodicity or single-pulse search, and manual diagnosis. First, radio signals collected by telescope backends are stored as voltage time series. Second, RFI mitigation eliminates or reduces interference effects on search results. Third, dedispersion removes frequency-dependent delay effects. Fourth, periodicity or single-pulse searches identify pulsar candidates from the observational data. Finally, each candidate undergoes manual diagnosis to determine its authenticity. Currently, FAST data primarily uses the parallelized PRESTO (Pulsar Exploration and Search Toolkit) for pulsar search research [?]. The data flow diagram for astrophysical signal detection using PRESTO-based single-pulse search includes: data collection, RFI mitigation, dedispersion, single-pulse search, candidate identification, and manual diagnosis (Figure 1 [Figure 1: see original paper]).

In the candidate identification module of Figure 1, both heuristic threshold-based methods (RRATtrap and Clusterrank) and ML methods (SPEGID and SPS) are listed. Table 1 provides basic information for these four identification methods. To compare their ability to distinguish pulsar from non-pulsar candidates, performance can be quantified using evaluation metrics. In candidate identification, we seek methods that accurately identify all pulsar candidates while minimizing false positives. Therefore, the primary evaluation metrics are recall and false positive rate [?]: recall quantifies the proportion of true pulsar candidates correctly identified, while false positive rate quantifies the proportion of false candidates generated. The optimal method exhibits high recall and low false positive rate. F1-score and G-mean provide comprehensive assessments of a method' s ability to correctly identify pulsars while controlling false positives, with balanced methods showing high values for both metrics. As shown in Table 1, ML methods generally achieve higher recall and lower false positive rates compared to heuristic approaches.

Single-pulse searches typically generate one or more diagnostic plots per observation, and the process of isolating pulsars from these plots is called candidate identification. Figure 2 [Figure 2: see original paper] shows diagnostic plots for PSR B0540+23 detected via single-pulse search of CRAFTS data using PRESTO. PRESTO-based candidate identification methods process the `single_{{{pulse}}_{{search}}}.py` results file (which records DM, arrival time, S/N, and pulse width for each single-pulse event) to perform identification and classification. Operating under the assumption that pulsar signals possess distinctive features that allow them to stand out from numerous false detections, these methods are designed to uncover these hidden characteristics [?]. Since pulsar signals are typically associated with groups of single-pulse events (SPEs) appearing at approximately the same time across a certain DM range, identification methods generally: (1) use clustering algorithms to aggregate SPEs within specific DM and time thresholds into single-pulse event groups (SPEGs); (2) construct heuristic rules or perform feature engineering to discriminate between pulsar and non-pulsar candidates; and (3) apply these rules or ML classifiers to SPEGs for candidate classification.

ML-based identification methods typically operate in two stages for automated candidate recognition (see magnified region in Figure 1). The first stage clusters related SPEs into SPEGs and develops feature engineering. The second stage combines ML algorithms to create a fully labeled feature dataset for training multiple classifiers. In the first stage, SPEGID employs the density-based spatial clustering algorithm DBSCAN [?] to aggregate related SPEs into SPEGs of arbitrary shape, then constructs 18 features to characterize them. SPS uses the Friends-of-Friends clustering algorithm [?] to group neighboring SPEs within time and DM thresholds, then models SPEGs statistically using five features. In the second stage, SPEGID selects six classifiers implemented in the WEKA data mining software, ultimately using the best classifier (RandomForest) for automated identification of unlabeled observations. SPS selects the Gaussian Hellinger Very Fast Decision Tree (GH-VFDT) [?] as its optimal classifier and further filters SPEGs labeled as pulsars based on spatial information to generate final candidate diagnostic plots for manual inspection.

For ML classifiers to automatically identify and classify single-pulse search candidates, they must learn general patterns of "pulsars" from training data—a supervised learning application that infers a target function for distinguishing pulsars from RFI from labeled training sets [?]. This function accurately maps observational data feature values to corresponding categories (pulsar or non-pulsar). However, radio astronomical data exhibits severe class imbalance, with the vast majority being useless data caused by RFI or cosmic noise and only a tiny fraction containing actual pulsar signals [?]. When trained on imbalanced datasets, ML classifiers tend to be "over-trained" on the majority class (non-pulsar), causing them to bias predictions toward the majority class and misclassify many minority class instances (pulsars) of interest [?]. To mitigate this performance degradation, benchmark datasets must undergo imbalance treatment. Previous studies [?, ?] have shown that SMOTE (Synthetic Minority Over-sampling Technique) [?] outperforms other methods for handling data imbalance in this context.

3 Application and Comparative Analysis of Machine Learning Methods on CRAFTS Data

This study evaluates the overall performance of ML methods on FAST data by testing four single-pulse search candidate identification approaches on CRAFTS data. We first construct a CRAFTS benchmark dataset, then preprocess it using PRESTO for RFI mitigation, dedispersion, and single-pulse search. Next, we apply ML methods (SPEGID and SPS) to identify candidates, and for comparison, also use heuristic threshold-based methods (RRATtrap and Clusterrank). To comprehensively compare different ML classifiers, we employ seven classifiers from the Scikit-learn library: Gaussian Naive Bayes (GaussianNB) [?], Logistic Regression (LR) [?], Support Vector Machine (SVM) [?], Decision Tree (DT) [?], Random Forest (RF) [?], Gradient Boosting Decision Tree (GBDT) [?], and Multi-Layer Perceptron (MLP) [?]. We apply SMOTE to create synthetic instances for the minority class (pulsars), building balanced training datasets.

To evaluate identification method performance, we construct a benchmark dataset comprising 823 pulsar and 1,023 non-pulsar candidates. Pulsar candidates are samples confirmed to contain pulsar signals through preliminary RRATtrap screening of CRAFTS data, while non-pulsar candidates represent major RFI types identified during manual diagnosis as primary sources of false candidates. ML methods require a fully labeled feature dataset for classifier training. We manually annotate each feature data entry from benchmark candidates using the following criteria: for pulsar candidates, each feature entry is compared against diagnostic plots (Figures 2a, 2b). SPEGs are labeled as pulsar if their DM satisfies: (1) a spindle-shaped distribution in time-DM space (Figure 2c), (2) a Gaussian curve in DM-S/N space (Figure 2d), and (3) presence of SPEGs at different times within a $\pm 2pc \cdot cm^{-3}$ DM range. All non-pulsar candidate feature entries are labeled as non-pulsar.

3.1 SPEGID Method: Automated Identification and Classification of Benchmark Candidates

To apply SPEGID to the CRAFTS benchmark dataset, we collect feature data for each candidate following the SPEGID methodology: first clustering candidates into SPEGs using DBSCAN, then extracting feature values for each SPEG using SPEGID' s feature engineering. This yields 227,632 feature entries, each corresponding to one SPEG. Manual annotation following the above criteria results in 27,521 SPEGs labeled as pulsar and 200,111 as non-pulsar. To study classifier performance, we split the SPEGID feature dataset into training and test sets. The training set contains 5,772 pulsar SPEGs and 87,898 non-pulsar SPEGs (corresponding to 240 pulsar and 260 non-pulsar candidates), while the test set contains the remaining 21,749 pulsar SPEGs and 112,213 non-pulsar SPEGs (corresponding to 583 pulsar and 763 non-pulsar candidates). To address class imbalance, we apply SMOTE to synthesize pulsar SPEG samples, creating a balanced training set for training all seven classifiers. During training, we use 5-fold cross-validation and Scikit-learn's GridSearchCV to determine optimal hyperparameters for each classifier by evaluating all possible hyperparameter combinations. Finally, we evaluate the trained classifiers on the test set and compute performance metrics based on classification results and manual labels.

Table 2 presents evaluation metrics for the seven classifiers on the SPEGID test set. Key findings include: (1) All classifiers trained on SMOTE-balanced datasets show higher recall but also higher false positive rates, indicating that imbalance treatment enables correct classification of more pulsar SPEGs while also misclassifying more non-pulsar SPEGs as pulsars. (2) Except for SVM, which exhibits severe overfitting (recall below 2% across multiple hyperparameter settings), all other classifiers achieve performance metrics above 80%, demonstrating that SPEGID' s feature engineering effectively separates pulsars from RFI. (3) Among the 14 classifier configurations, LR-smote achieves the highest recall, while GBDT and LR yield the lowest false positive rates (SVM' s overfitting makes its false positive rate non-comparable). GBDT-smote achieves the highest F1-score and G-mean, indicating the best overall balance. In summary, SPEGID applied to the benchmark dataset achieves high evaluation metrics even with simple classifiers like GaussianNB, confirming its effectiveness for CRAFTS data single-pulse search candidate identification.

3.2 SPS Method: Automated Identification and Classification of Benchmark Candidates

For SPS-based identification of CRAFTS benchmark candidates, we follow the SPS methodology to collect feature data: clustering candidates into SPEGs using the Friends-of-Friends algorithm, then extracting feature values for each SPEG using SPS' s feature engineering. This yields 90,494 entries, with 14,779 SPEGs labeled as pulsar and 75,715 as non-pulsar following manual annotation. We similarly split the SPS feature dataset into training and test sets. The training set contains 2,821 pulsar SPEGs and 37,896 non-pulsar SPEGs (corresponding to 240 pulsar and 260 non-pulsar candidates), while the test set contains the remaining 11,958 pulsar SPEGs and 37,819 non-pulsar SPEGs (corresponding to 583 pulsar and 763 non-pulsar candidates). We train seven classifiers on the training set with GridSearchCV-determined optimal hyperparameters and apply SMOTE for imbalance treatment before training. Finally, we evaluate the trained classifiers on the test set and compute performance metrics.

Table 3 summarizes evaluation metrics for the seven classifiers on the SPS test set. Observations include: (1) Compared to classifiers trained on imbalanced data, SMOTE-balanced training improves recall but also increases false positive rates (GaussianNB and LR perform poorly across hyperparameter settings with F1-scores below 50%, making their false positive rates non-comparable). (2) For MLP, SMOTE treatment increases recall by nearly 0.4. (3) Tree-based classifiers (DT, RF, GBDT) consistently outperform the other four classifiers across all metrics. (4) Among the 14 configurations, GBDT-smote achieves the highest recall (with the caveat about GaussianNB' s poor performance), while

GBDT yields the lowest false positive rate. GBDT achieves the highest F1-score, and GBDT-smote achieves the highest G-mean. Overall, SPS applied to the benchmark dataset achieves high evaluation metrics only with tree-based classifiers (DT, RF, GBDT).

3.3 Comparative Analysis of Performance and Screening Speed

To compare performance across method categories, we also apply heuristic threshold-based methods (RRATtrap and Clusterrank) to the benchmark dataset. Since heuristic methods return overall scores representing pulsar probability, their classification results are candidate-dependent. ML methods, however, classify SPEGs, with each candidate typically containing multiple SPEGs (Figure 2a). For fair comparison, we define that any candidate containing at least one SPEG classified as pulsar is marked as pulsar; otherwise, it is marked as non-pulsar. We then compute performance metrics for SPEGID and SPS at the candidate level. Notably, SPEGID and SPS results are tested on the complete feature dataset (without train-test splitting) to enable fair comparison with heuristic methods. For RRATtrap and Clusterrank, we test multiple threshold combinations and select those yielding the highest F1-score for comparison. For ML methods, we similarly select classifiers with the highest F1-score.

Table 4 presents performance metrics for the four identification methods at the candidate level, with the final two rows summarizing SPEGID and SPS performance at the SPEG level. Findings reveal: (1) All four methods achieve high recall (above 90%), meaning most pulsar signals in the benchmark dataset are correctly identified. However, RRATtrap, Clusterrank, and SPS exhibit high false positive rates, indicating numerous false candidates in their results. Clusterrank shows the highest recall (97.7%) but also the highest false positive rate (60.3%). (2) When measured at the candidate level, SPEGID and SPS maintain recall similar to their SPEG-level results, but false positive rates increase significantly (SPS from 9.9% to 46.1%; SPEGID from 0.1% to 4.7%). This increase indicates that misclassified pulsar SPEGs are distributed across many candidates. (3) SPEGID achieves the best scores across multiple metrics with a false positive rate of only 4.7%, far lower than the other three methods. Its F1-score and G-mean exceed 95%, demonstrating superior performance (high recall, low false positive rate) on the CRAFTS benchmark dataset. The four methods show similar recall, but SPEGID' s lower false positive rate stems from its feature engineering, which effectively captures unique pulsar characteristics in DM-time and DM-S/N spaces to distinguish pulsars from RFI [?]. Compared to other radio telescopes (Table 1), CRAFTS data covers a broader frequency range (270–1620 MHz), and all four methods exhibit higher false positive rates on CRAFTS data, suggesting it contains substantial RFI mimicking pulsar signals. Future work should collect representative RFI samples from CRAFTS data, conduct targeted time/frequency domain analyses, and develop effective RFI-mitigation features to reduce false candidates and alleviate manual diagnostic workload and storage pressure.

Finally, we examine the screening speed of the four methods. Processing time per candidate generally increases with the number of single-pulse events (SPEs). To clearly illustrate this effect, we record the time each method spends screening pulsar candidates in the benchmark dataset. Note that SPEGID and SPS timings only include feature extraction, excluding manual annotation and classifier training. The average screening speeds are: SPS: 4,010 candidates/hour, SPEGID: 51 candidates/hour, Clusterrank: 147 candidates/hour, RRATtrap: 112 candidates/hour. As shown in Figure 3 [Figure 3: see original paper], RRATtrap and SPEGID times are strongly affected by SPE count, while Clusterrank and SPS times show little variation with event number. Overall, SPS is the fastest, with the speed advantage becoming more pronounced as SPE count increases, primarily because SPS does not construct peak-detection algorithms to verify DM-S/N curve peaks, unlike the other three methods.

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4 Summary and Discussion

This study investigates the performance and screening speed of ML-based single-pulse search candidate identification methods (SPEGID and SPS) applied to CRAFTS ultra-wideband pulsar survey data, with heuristic threshold-based methods (RRATtrap and Clusterrank) included for comparison. We construct a benchmark dataset comprising pulsar and non-pulsar candidates from CRAFTS data, collect feature values for each candidate according to ML method feature engineering, manually annotate each entry, split the data into training and test sets, train seven ML classifiers, and evaluate their performance. SMOTE imbalance treatment is applied to training data. The results demonstrate that SPEGID achieves the best performance (high recall, low false positive rate), while SPS offers the fastest screening speed.

Based on comparative analysis, we discuss future directions for efficient single-pulse search candidate identification in FAST data. Both identification paradigms construct target functions that maximize separation between pulsars and RFI. Heuristic methods build rules based solely on pulsar characteristics in DM-time and DM-S/N spaces, limiting their ability to identify diverse pulsars and filter RFI effectively. Studies [**?**] show that incorrect DM values, mismatched filter values, and source position relative to the main beam can cause S/N losses, while pulsar signals exhibit significant variations in intensity, width, and profile [**?**], making universal heuristic rules difficult to establish. ML methods, trained on fully labeled feature datasets, learn characteristics of both pulsars and RFI simultaneously, demonstrating superior performance in pulsar identification and RFI rejection. Moreover, as ML methods are iterative processes involving result analysis, data augmentation, classifier updates, and repeated application [**?**], their performance should improve with accumulating training data. Therefore, ML methods are recommended for automated identification and classification of single-pulse search candidates in FAST data.

Notably, deep learning has recently been applied to candidate identification. For example, Connor and Van Leeuwen [?] proposed a tree-structured deep neural network for classifying single-pulse search diagnostic plots; Agarwal et al. [?] developed FETCH for real-time classification of candidates from ASKAP and Parkes data; and Liu et al. [?] used convolutional neural networks for automated candidate identification and pulsar-FRB classification. Future work will analyze unique features of ML (including deep learning) applications to FAST data compared to other telescopes and address data processing considerations specific to CRAFTS candidate identification.

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Note: Figure translations are in progress. See original paper for figures.