Pulsar Signal Processing: A Machine Learning Perspective

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Background

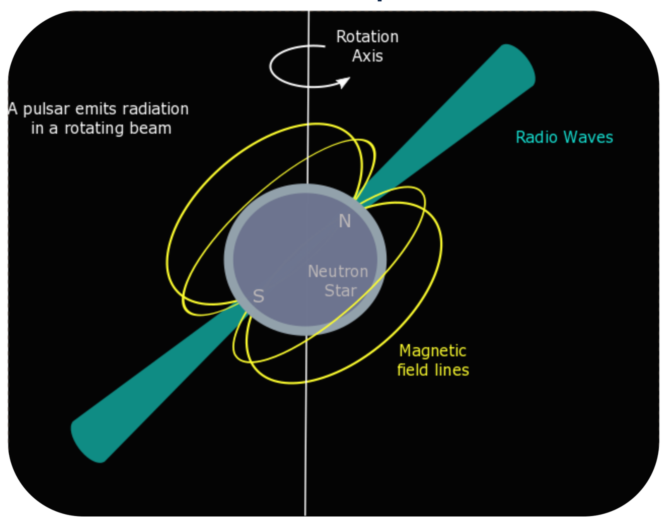
The next generation of radio telescopes will have unprecedented sensitivity and time-resolution offering exciting new capabilities in time-domain science. However, this will result in very large numbers of potential pulsar and transient event candidates and the associated data rates will be technically challenging in terms of data storage and signal processing. Automated detection and classification techniques are therefore required and must be optimized to allow high-throughput data processing in real time.

Signal Features

Automated detection methods exploit the signal feature space to identify data representations which maximize separation between noise and candidate events. Features can be extracted from diagnostic plots resulting from various stages of the signal processing pipeline. In particular, parameters derived from the dispersion measure search stage and the final integrated pulse profile are commonly used in classification algorithms.

Factors affecting the received signal:

Intrinsic Properties



- Emission Mechanism
- Rotational Properties

Propagation through the ISM

Image Credit: Serge Brunier

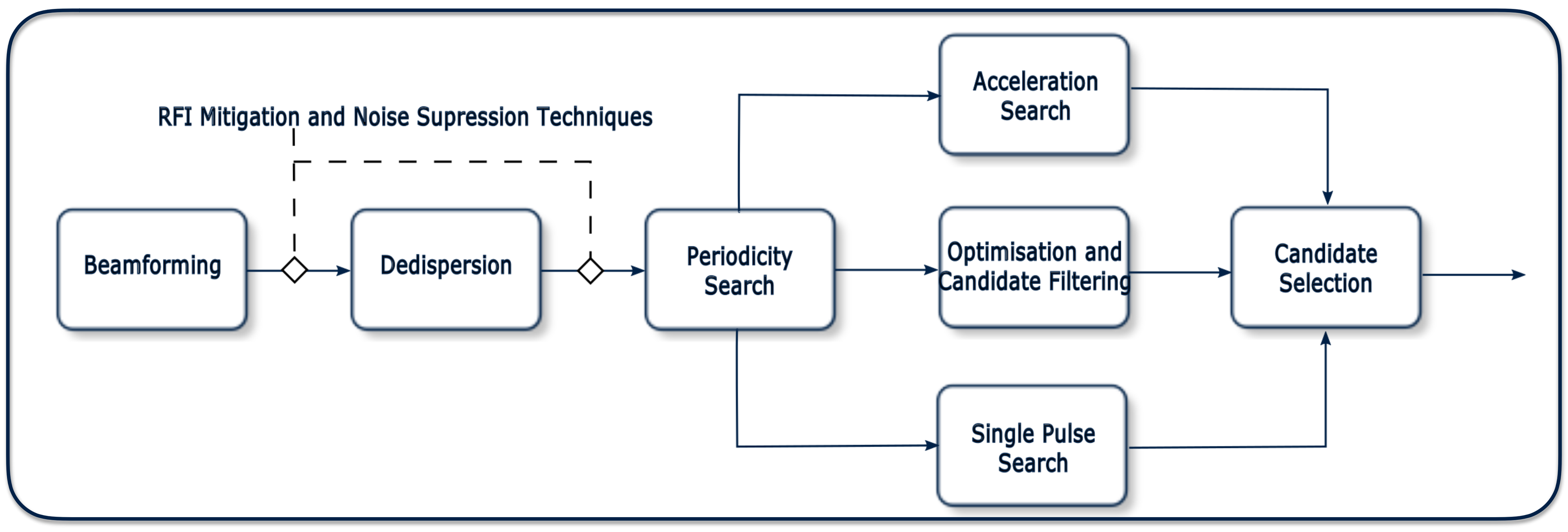
- Plasma dispersion
- Scattering
- Scintillation

Hardware Effects

Image Credit: CSIRO

- Analogue to Digital Conversion
- Polyphase Filtering
- Optional Detection, Integration, Decimation or Normalisation Stages

Signal Processing Pipeline



Important Considerations:

- How does each stage affect the signal?
- Which features can be extracted for classification?

Literature

The evolution of automated candidate selection techniques.

Publication	Method	Details
Faulkner 2004	Graphical Selection Tool	128 new pulsars
Keith 2009	Graphical Selection Tool and Scoring Algorithm	28 new pulsars
Eatough 2010	ANN	8 to 12 features, 1 new pulsar
Bates 2012	ANN	up to 22 features
Lee 2013	Scoring Algorithm	6 `quality factors' 47 new pulsars
Morello 2014	ANN	Feature-based
Zhu 2014	ANN, CNN and SVM	Image-based Algorithms combined in Deep Neural Network
Lyon 2016	Hellinger Decision Tree	Feature-based
Devine 2016	ANN, SVM, Direct Rule Learner, Standard Tree Learner, Hybrid Rule-and-Tree Learner and Ensemble Tree Learner	Algorithms combined optimally for binary and multi-class classification
Bethapudi 2017	ANN, Adaboost, GBC and XGBoost	Comparative Study of 4 Algorithms

Remarks

Automated detection methods have reduced the amount of processing time required for pulsar discoveries, however, most are only applied at the final candidate selection stage. This leaves scope to re-examine earlier modules in the signal processing chain and identify areas which could be optimised by modern machine learning techniques. Extending algorithms to integrate physics more fully into the models is also a current challenge, as is the ever-present issue of scalability, particularly for the next generation of radio telescopes.

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