Meteor Head Echo Detection at Multiple High-Power Radar Facilities via a Convolutional Neural Network Trained on Synthetic Data

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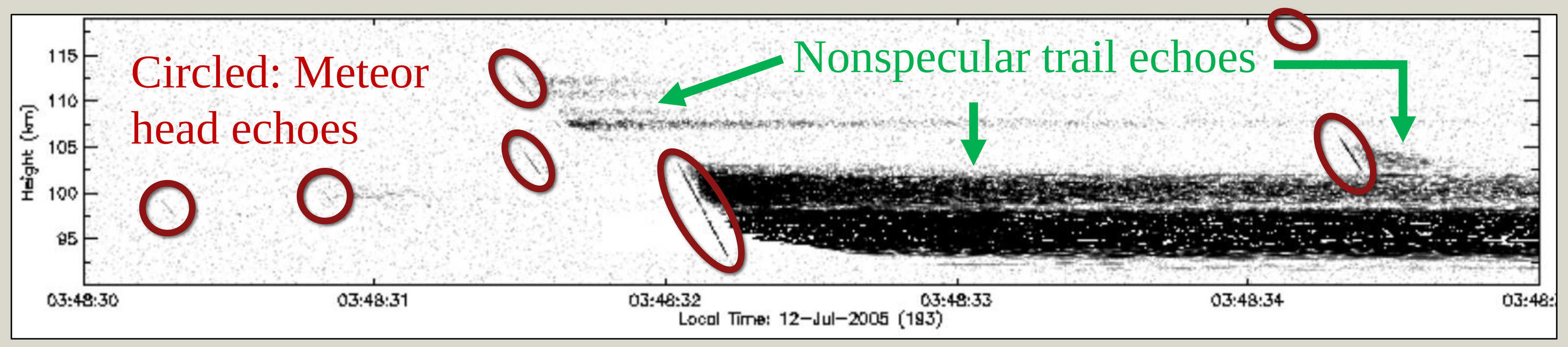
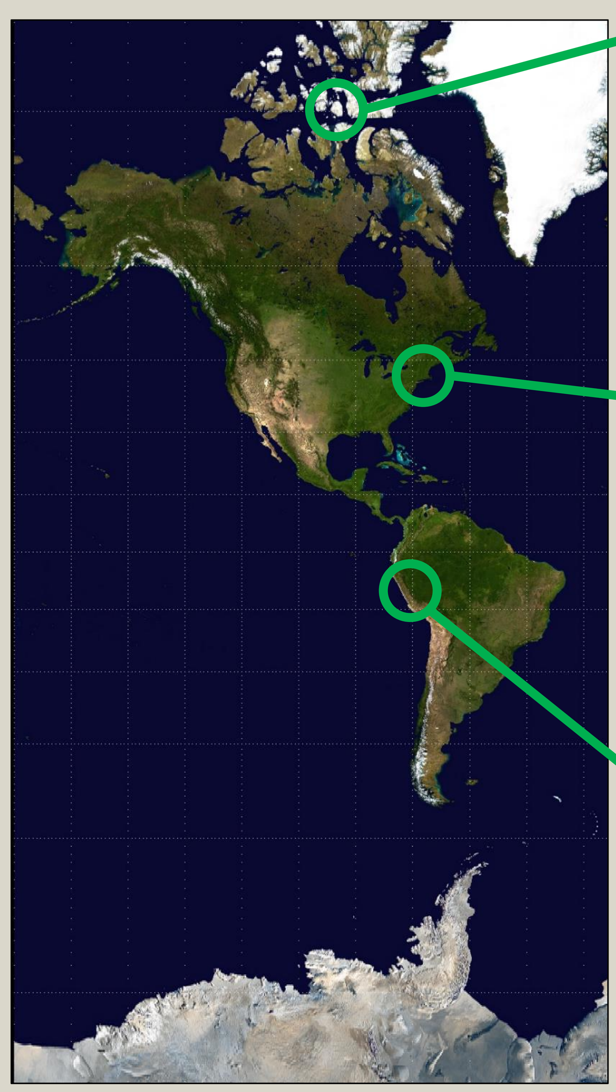
Motivation

- Meteor head echoes abundant in high-power large-aperture (HPLA) radar data: up to thousands/hour
- Want to identify head echoes without searching through clutter
- Want method that works on **any** radar facility or pulse code
  - Existing method only works at Jicamarca with short pulse[1]
  - Head echoes can be observed at non-HPLA facilities, albeit more infrequently[2,3], and technique would be valuable there



Meteor Experiment

Simultaneous head echo observations at three high-power radar facilities were taken before dawn on October 10th & 11th, 2019.



Resolute Bay Incoherent Scatter Radar (RISR-N)
~120 head echoes/hour

Frequency: 442.5 MHz
Pulse code: Min. Sidelobe 51, 51 µs with 1 µs baud
Pulse period: 1.4 ms
Beam angle: 26° azimuth, 86° elevation

Millstone Hill Observatory (MHO)
~600 head echoes/hour

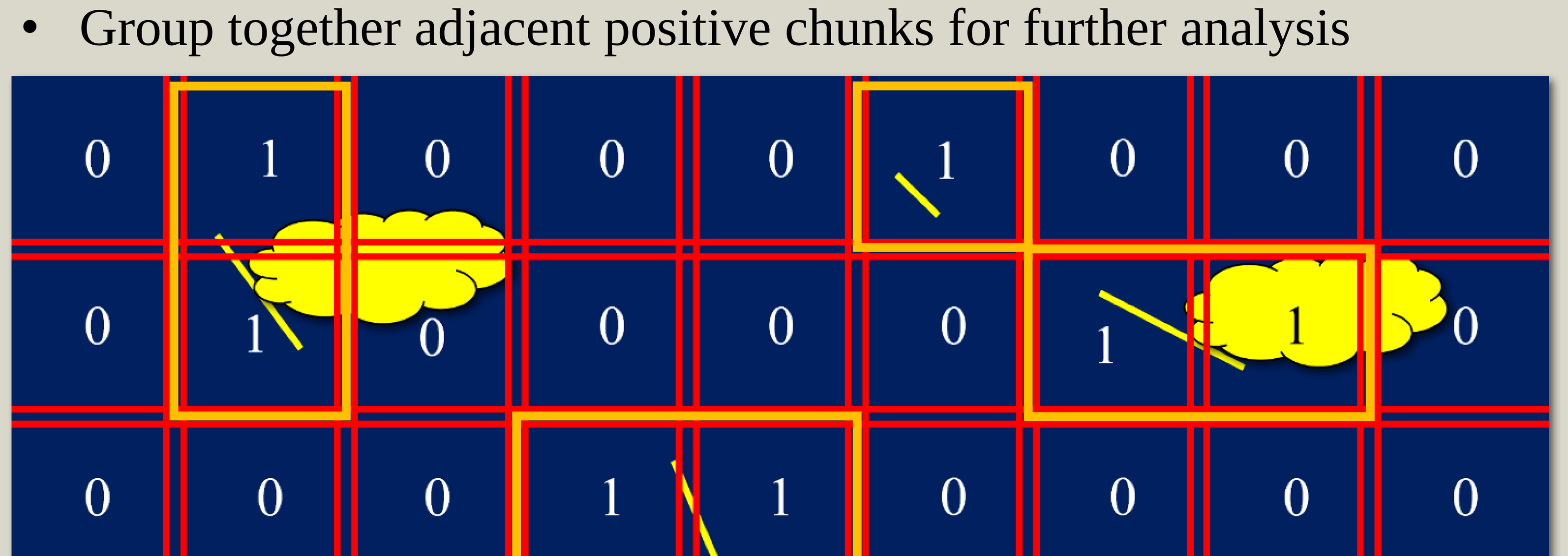
Frequency: 442.9 MHz
Pulse code: Barker-7, 42 µs with 6 µs baud
Pulse period: 2 ms
Beam angle: 270° azimuth, 45° elevation

Jicamarca Radio Observatory (JRO)
~5000 head echoes/hour

Frequency: 50 MHz
Pulse code: Min. Sidelobe 51, 51 µs with 1 µs baud
Pulse period: 1.25 ms
Beam angle: 90° elevation

General Approach

- Split raw data into chunks of size 2×150×150 (or similar) with some overlap
- Real and imaginary components form separate channels
- Classify chunks as head echo (label = 1) or non head echo (label = 0)
- Group together adjacent positive chunks for further analysis



Training via Synthetic Data

- **Problem: Need O(10000) head echoes to train the network for a specific meteor radar experiment!**
- Solution: generating synthetic head echoes
- Head echoes reflect pulse code + Doppler shift → easy to synthesize
- We assume meteoroid range is exponential, and received power curve is a sinc function, with some random parameters…

Observed head echo range:

$$r(t) = \left(r_0 - \frac{v_0^2}{a_0}\right) + \frac{v_0^2}{a_0} e^{(a_0/v_0)t}$$

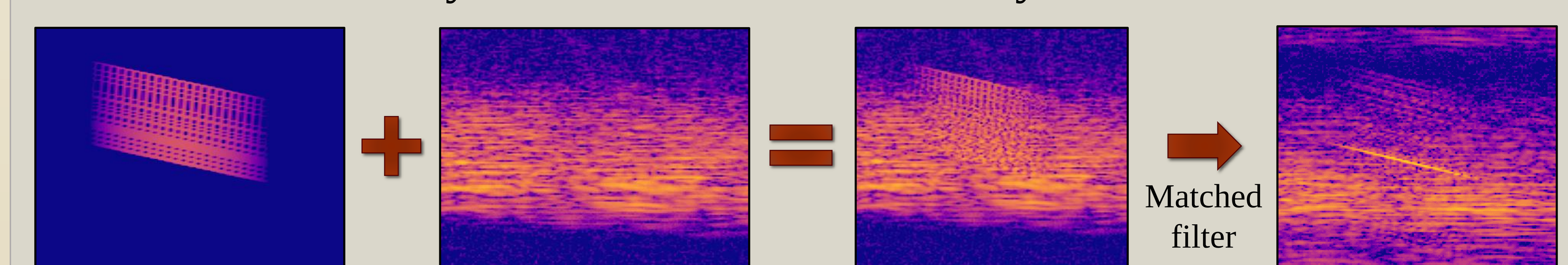
Received voltage signal (complex):

$$rx(t) = 10^{\frac{1}{20}(SNR+nf)} c(t) e^{i\phi(t)} \mathrm{sinc}(a+bt)$$

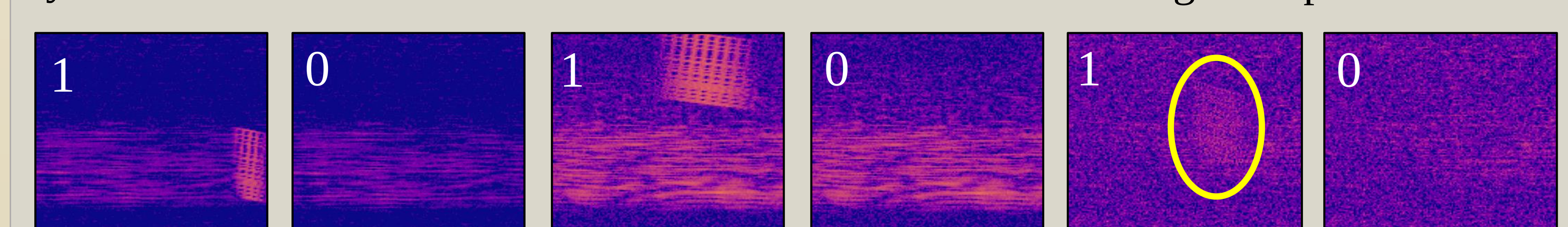
$$\phi(t) = \frac{4\pi f}{c} \int_0^t v(t)dt + \phi_o$$

$r_0 \in [75,130]$ km
$v_0 \in [12,73]$ km/s
$a_0 \in [0,70]$ km/s^2
$SNR \in \sim[10,40]$ dB
$c(t) \in \mathbb{C}$ (pulse code)
$\phi(t) \in \mathbb{R}$ (Doppler phase)
$nf \in \mathbb{R}$ (noise floor)
$a, b, \phi_0 \in \mathbb{R}$ (constants)

Radar clutter is hard to synthesize but is more abundant than head echoes. Can identify clutter in data and add to synthetic head echoes:

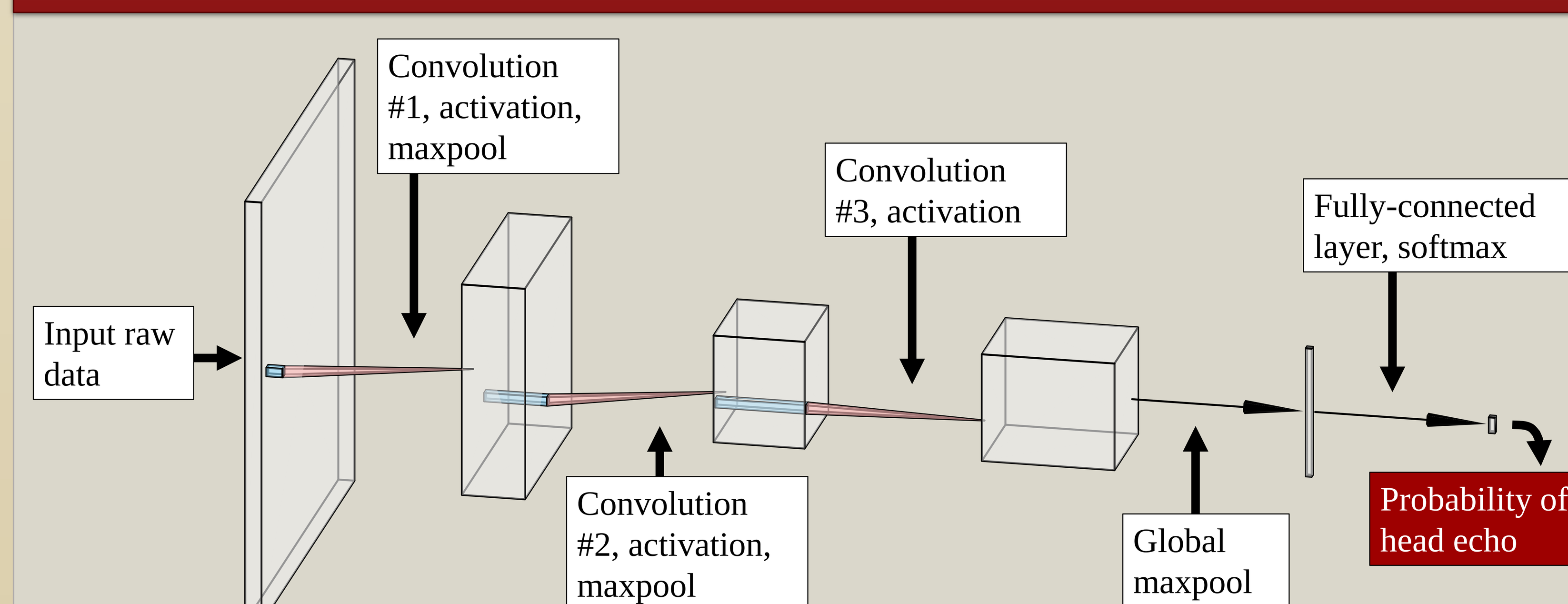


Synthetic head echo Real clutter Training example



Examples of synthetic training examples generated in pairs with and without head echo

Convolutional Neural Network Architecture



- 3 convolutional layers with leaky rectified linear unit (ReLU) activation function, 2×2 max pool
- Global maxpool after final convolutional layer
- Fully-connected layer with softmax performs final classification

Optimization Algorithm	Adam
Loss function	Cross-entropy
Batch size	100
# training examples	25000 positive/25000 negative
Learning rate	0.001 initially, 5e-5 near convergence
Weight decay coefficient	1/10*(learning rate)
Total number of parameters	142987

Results: Performance Metrics

We manually labelled "truth" data at each facility and excluded inconclusive streak-like objects from analysis. Training set statistics:

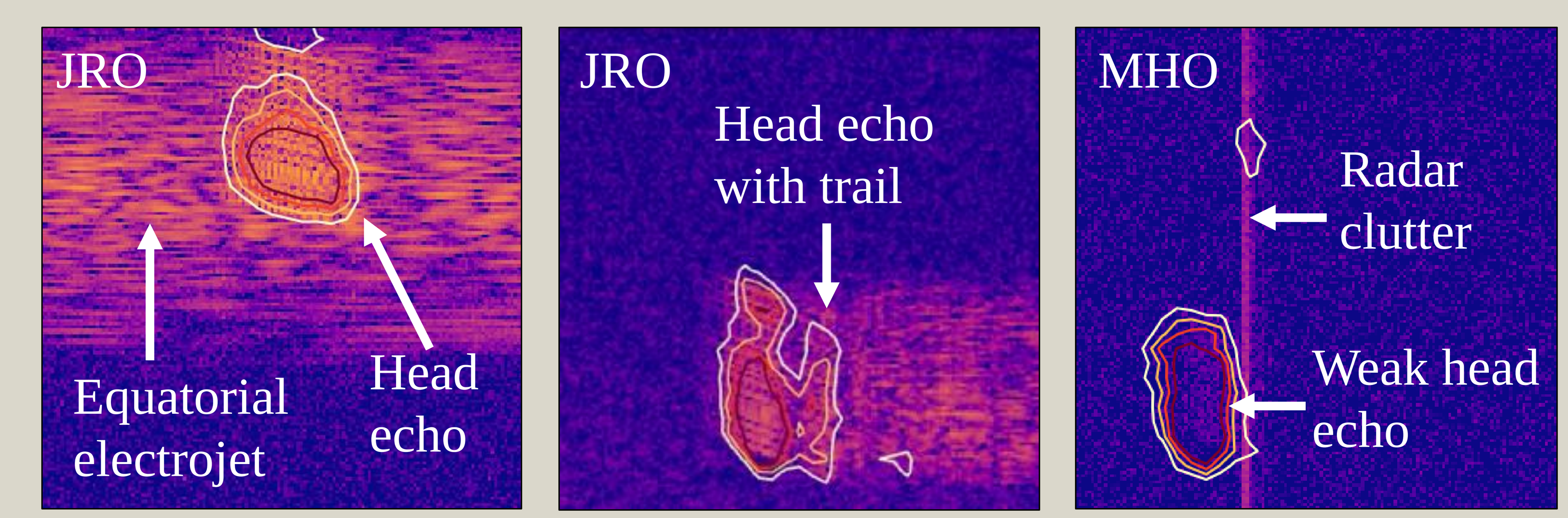
	RISR-N	MHO	JRO (non-EEJ)	JRO (EEJ)
Total test set size	11868	7140	4836	4836
# positive (truth)	157	148	290	122
# negative (truth)	11631	6848	4373	4574
# inconclusive (truth)	80	144	173	140

Each neural network corresponding to each facility is tested against truth data. Results at each facility:

	RISR-N	MHO	JRO (non-EEJ)	JRO (EEJ)
Classification accuracy (% of chunks correctly classified)	99.6	99.4	96.2	97.4
Sensitivity (% of head echo chunks that are identified)	75.8	80.8	77.4	71.3
Sensitivity to ≥15 dB echoes	93.4	97.0	91.7	77.8
Sensitivity to ≤15 dB echoes	51.5	65.3	59.4	58.5
Precision (% of head echo classifications that are correct)	96.7	88.1	66.4	50.3

Overall sensitivities greater than 70% demonstrate the technique's capability to discriminate between head echoes and clutter. Sensitivities greater than 50% for head echoes less than 15 dB demonstrate detection of a non-exhaustive selection of the weakest head echoes.

Class activation maps for some head echoes in raw data…



Conclusions and Future Work

- Convolutional neural networks (CNNs) are highly capable of distinguishing head echoes from other radar signatures
- The CNN technique is sensitive to the weakest head echoes, which may be missed by the human eye when manually searching
- Can apply technique at any facility and pulse code to greatly speed up population analyses
- Future meteor experiments can benefit from improved meteor shower identification and estimation of neutral densities[4] with the technique
- Future work will more accurately quantify sensitivity biases of the method, and refine the synthetic data model and CNN architecture to improve sensitivity to the weakest head echoes

References:
[1] Li et al., 2022
[2] Janches et al., 2014
[3] Panka et al., 2021
[4] Li et al., 2016

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