ARMY SCIENCE & TECHNOLOGY

SYMPOSIUM AND SHOWCASE

EMPOWERING A SOLDIER'S SUCCESS

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Walter E. Washington Convention Center

http://www.ndia.org/army-science

INTELLIGENT SYSTEMS

Tactical short range radar for personnel tracking with split-brain autoencoders

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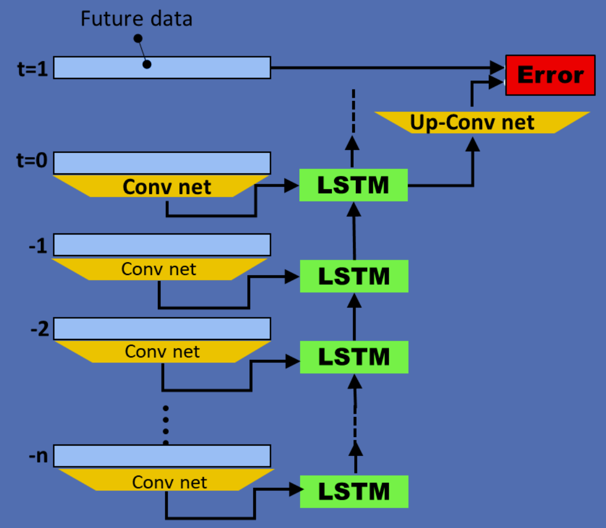

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INTRODUCTION

We use **AI** to enhance the efficiency of radar detection, tracking, and **classification** in complex clutter environments.

As a stand-in for conventional signal processing, AI has potential benefits: it reduces computational overhead, enables detection in low SNR, and improves classification.

We explore **representation learning** using a convolutional architecture with actual unlabeled data, perform experiments to establish usefulness of new data mining techniques, and apply them to our radar target classification system.

- **convolutional auto encoder with split-brain** structure and L1 sparsity regularization
- **convolutional recurrent neural network** (to predict future Doppler spectrum)
- **linear classifier** (to classify tracks from learned representations)

Finding: the network **learned unsupervised representations** for a moving human target and for clutter, with an underlying ability to discriminate them.

Speculation: a single network can stand in for a large number of different processing steps to simplify a system.

APPLICATION

MOTIVATION

ARCHITECTURE

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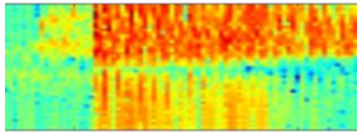
GOAL

- Our radar prototype demonstrated capability to **track personnel** moving **behind three walls**; however, the multi-path returns and other moving objects in the scene create complications.

- The user desires include
  - an **improved classification** capability
  - a capability to discriminate men from women and children

- Tremendous success of ML in object classification in images for disparate applications suggest a **potential applicability of such AI tech** for our classification problem.

- We can shape radar data as **images** with
  - dimensions: time, Doppler, range, azimuth, etc.
  - features depending on the chosen dimensions, relative location/orientation of the radar face to the structures, and on the choice of Doppler resolution.



- Our goal is to **examine utility** of ML for improved classification.

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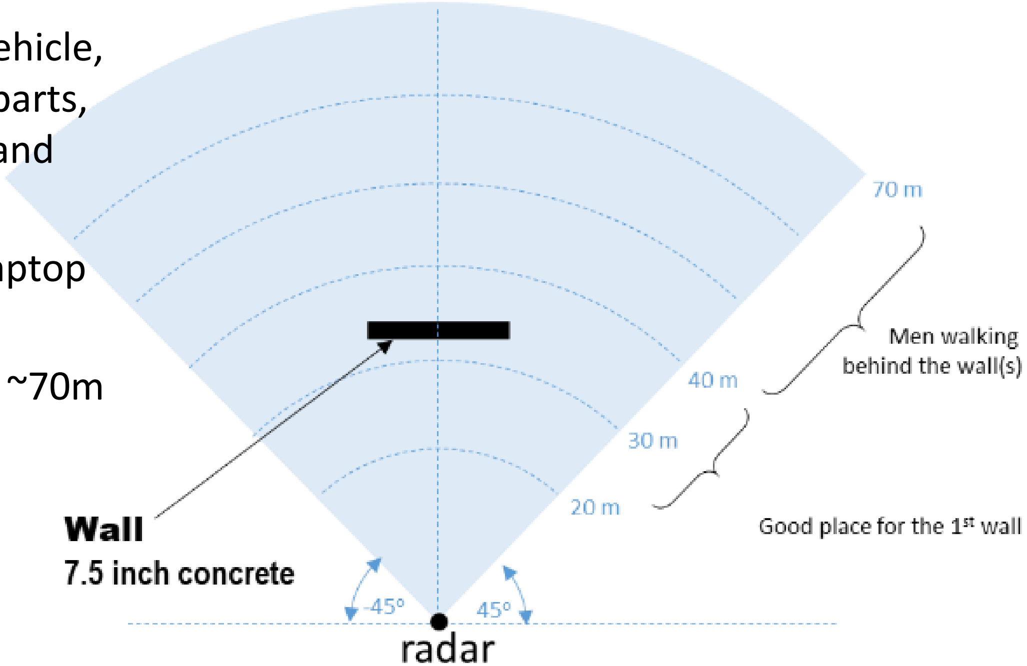
ALION RADAR Findr™

Alion Findr™ is a man-portable battery-powered multi-mode FMCW radar for foliage penetration, **sense through the wall (STTW)** surveillance of personnel, and tracking of autonomous vehicles both on the ground and in the air.

The **STTW mode**

- detects and tracks people moving within structures and behind obstructions
- provides operators the ability to identify **the number of personnel and their location** inside buildings from up to 150m standoff distance
- detects **all moving objects** (vehicle, stationary equipment with moving parts, aircraft, animals, birds, vegetation, and humans) and **classifies them**
- tracks are delivered real-time to a laptop with COP via 4G LTE wireless link
- a typical standoff detection range is ~70m with 1.5m range resolution



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NEED TRAINING-DATA FOR ML

Radar datacube: 3D FFT (range, Doppler, azimuth/beam) of the time domain data from the radar from various US DoD sponsored events, including

- 2018 Urban 5th Generation Marine (**U5G**) Advanced Naval Technology Exercise (**ANTX**), Camp Pendleton, CA
- US Army Special Ops Command (USASOC) 2018 **Thunderstorm** Technology Demonstration and Evaluation, Fayetteville, NC

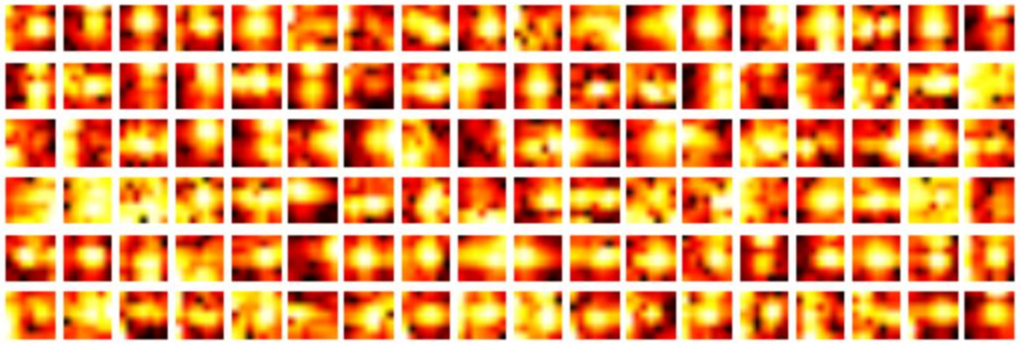
Plan

- create a semi-annotated dataset (from actual data)
- classify ‘target’ from ‘no-targets’ in small regions of range-Doppler preprocessed data fields (images)

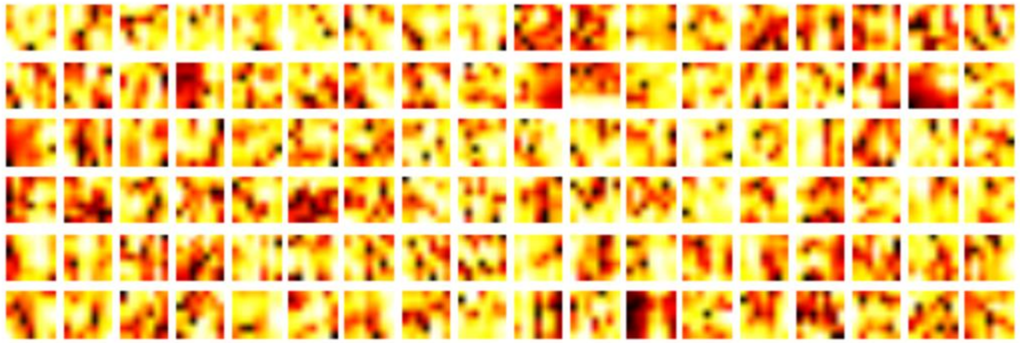
Dataset

- dataset shape (2368, 7, 7, 3)
- labels shape (2368, 2) using one-hot encoding
  - 1184 examples of each class, and each example is a complex 7x7x3 cube slice of the datacube
  - ‘target’ examples generated using detections from CFAR
  - ‘no-targets’ - random selections from the datacube

Target



No-target



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ML ARCHITECTURE USED

Supervised feed-forward convolutional network

- Trained a simple network to classify target/no-target
- Achieved **92% classification accuracy**
- Computed on low-cost GeForce GTX 970, using tensorflow
- Training time depends on dataset and hyper parameters (ranging from hours to days)

Need to do better!

Convolutional split-brain

- Divide an unlabeled dataset into two: use one as labels and the other as input
- Let the neural network learn a representation without labeled data
- This technique works as a feature extraction on images with similar spatial structure to radar images

Long Short Term Memory (LSTM) with convolutional layers

Add time dimension

- Run inference by processing each new row of data as it arrives (more efficient than the convolution-over-time approach, processing larger amount of history at each time step)
- Train to predict future frames from past frames. Use a variable amount of history for the prediction. The long term memory is promising for **learning a running representation**

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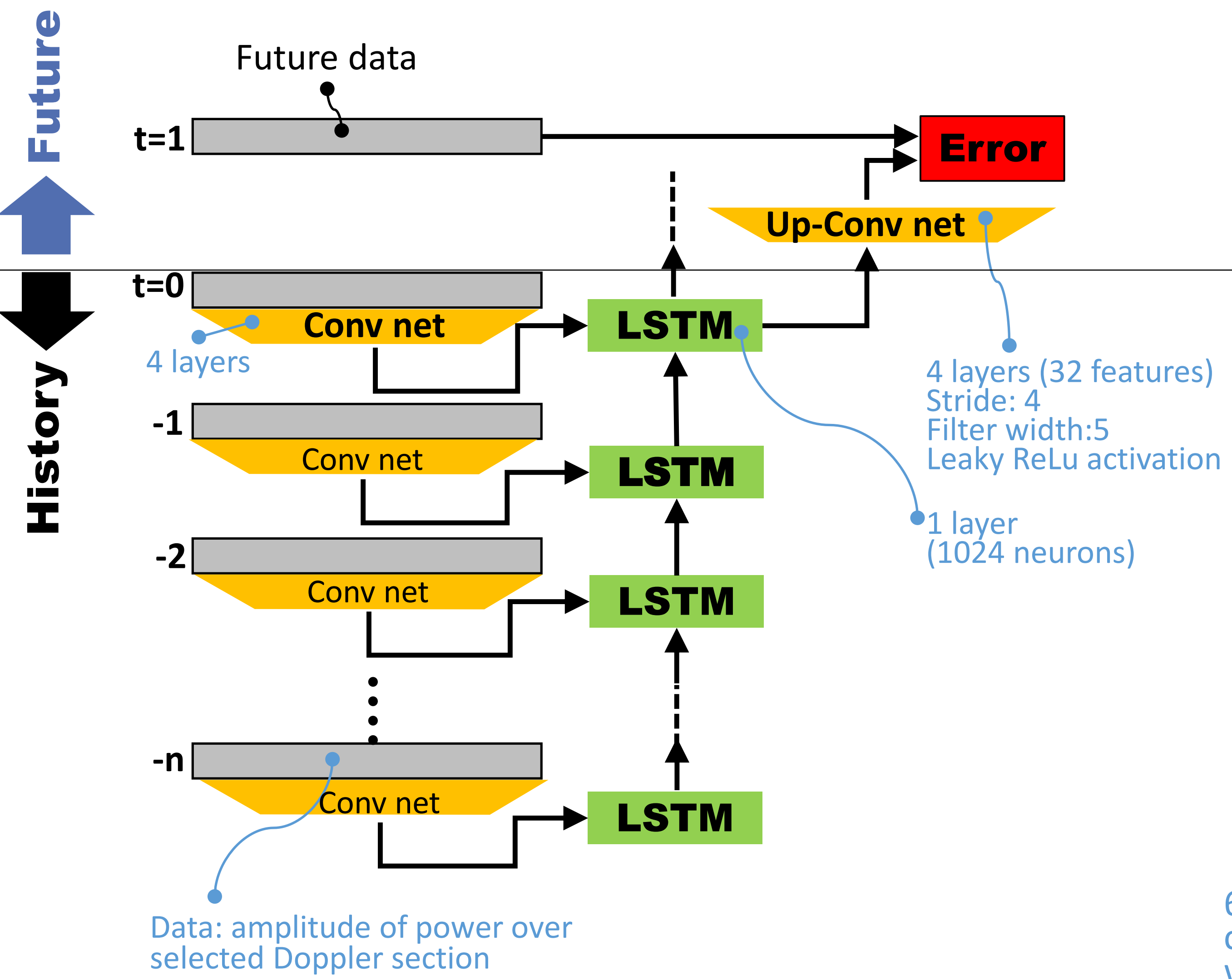
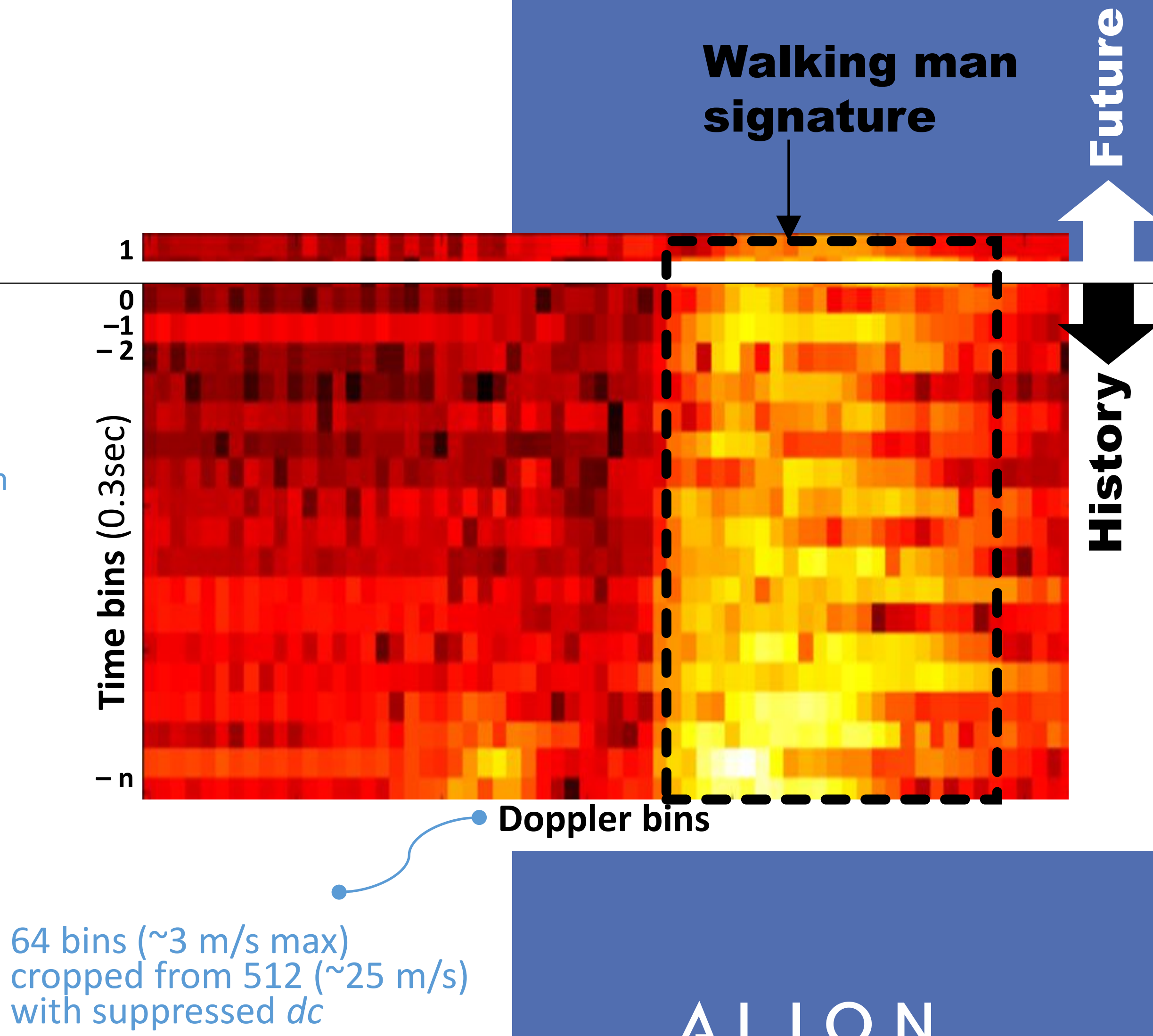
LSTM WITH CONVOLUTIONAL LAYER





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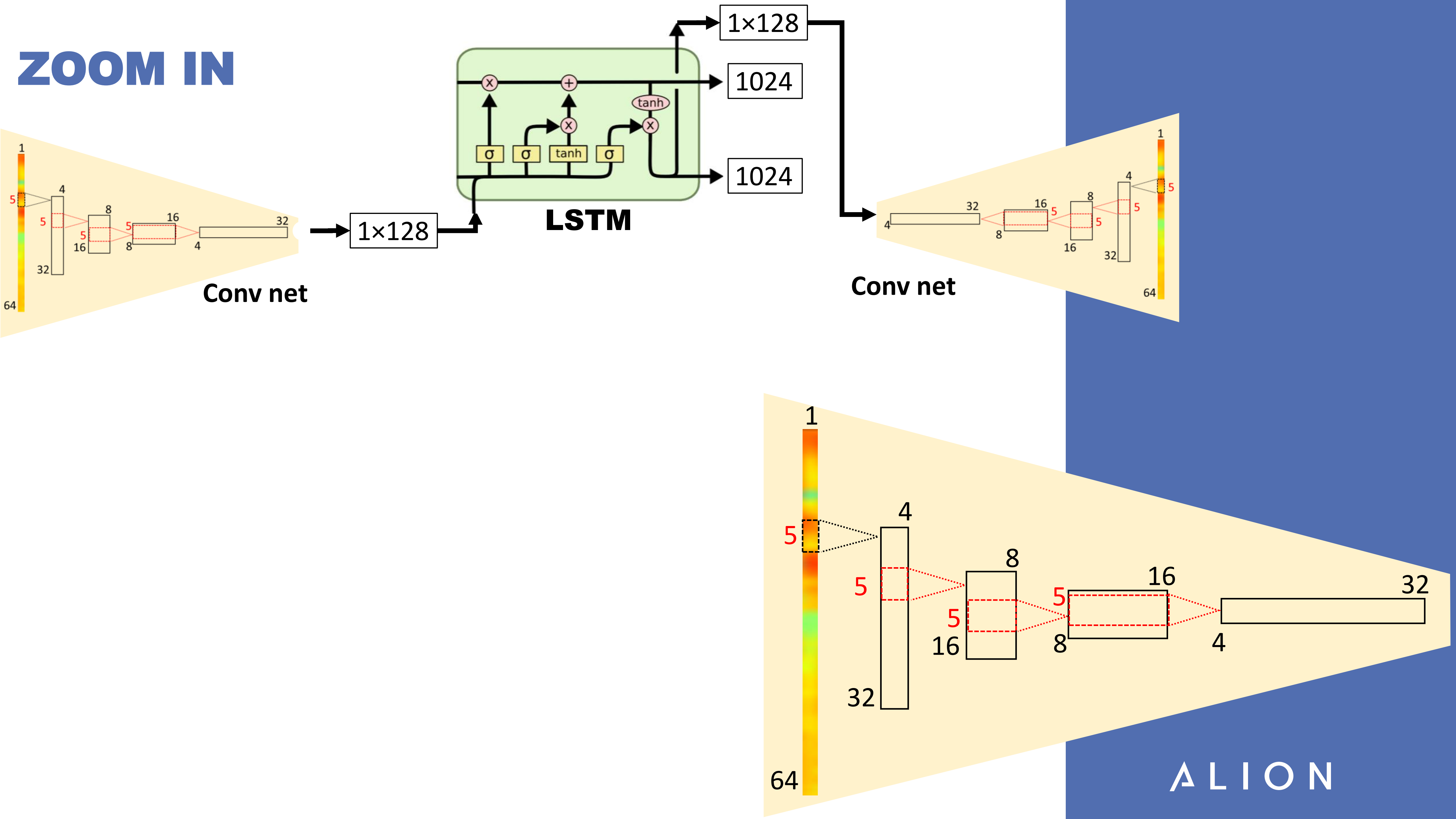
ZOOM IN



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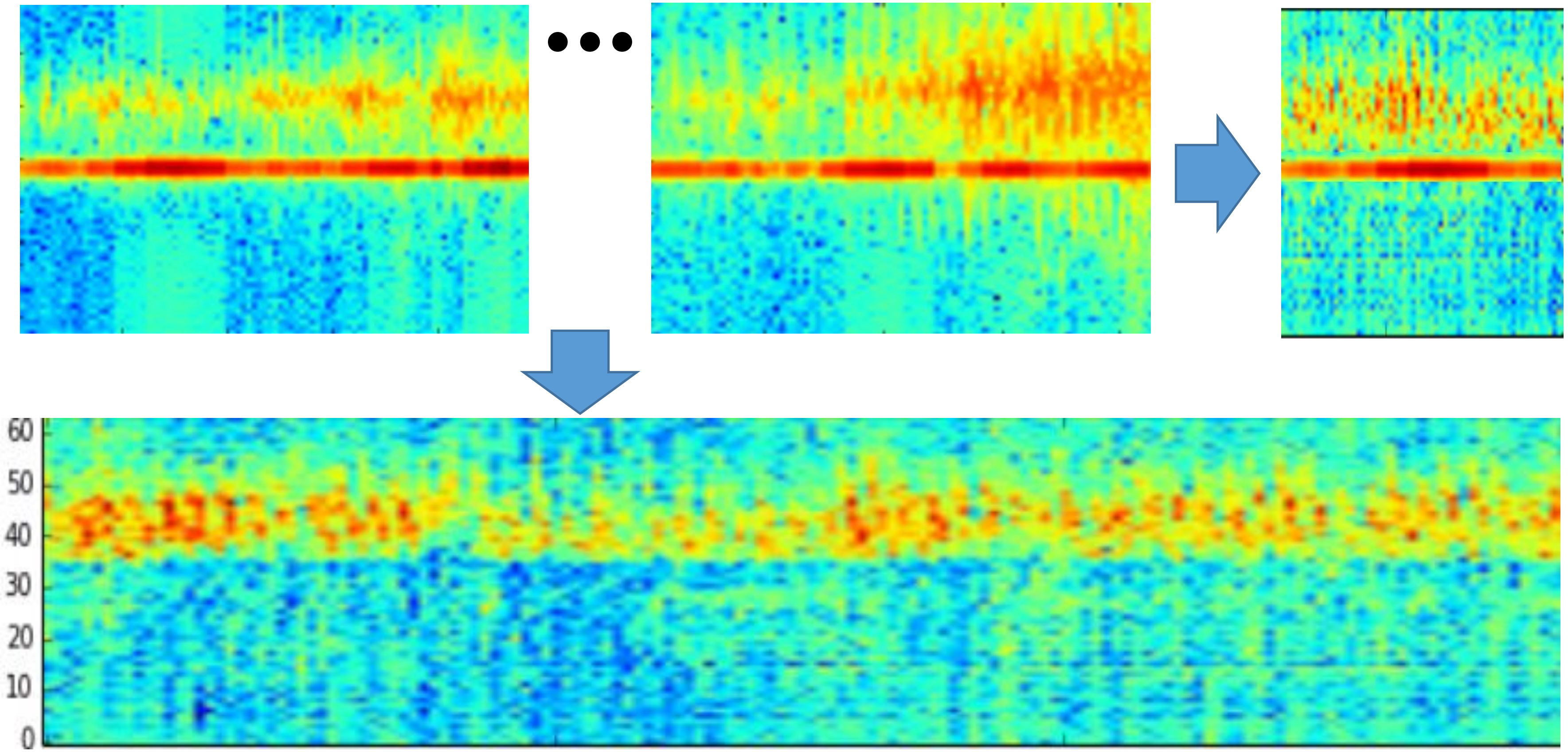
RESULTS

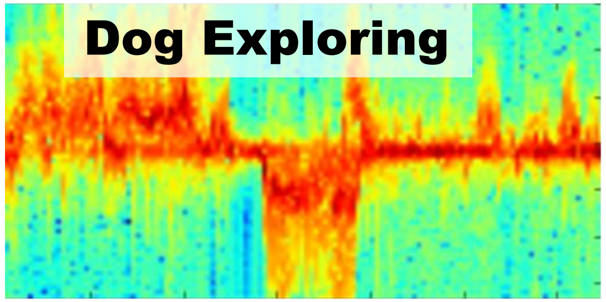
To verify that the LSTM has learned the structure of the training data, it’s predictions can be fed back into it’s input to create a possible Doppler history.
The arm swing Doppler patterns appearing in the generated Doppler history provide proof that the network has learned an internal representation of these patterns.

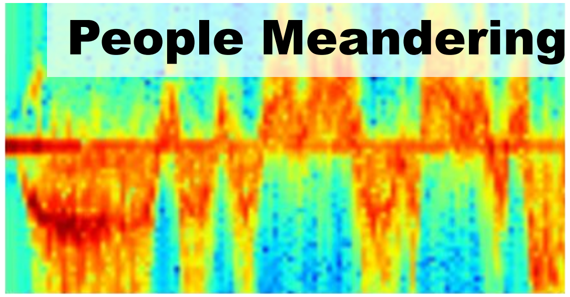
From radar **From model**

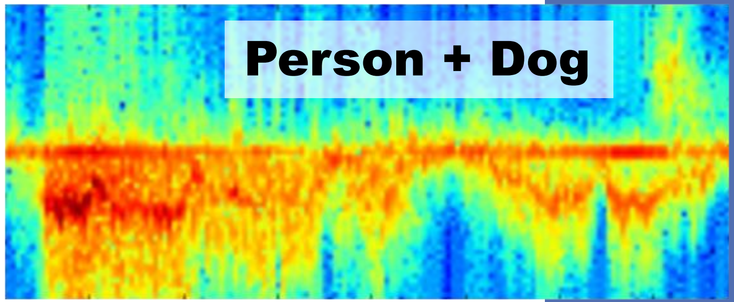


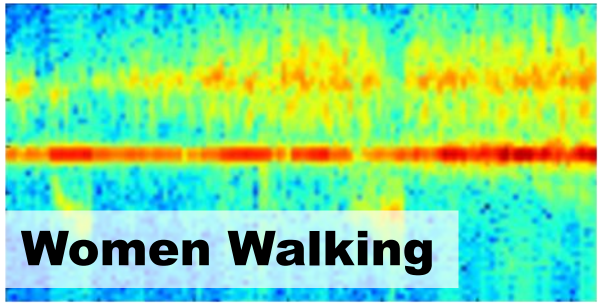
From model with removed stationary clutter

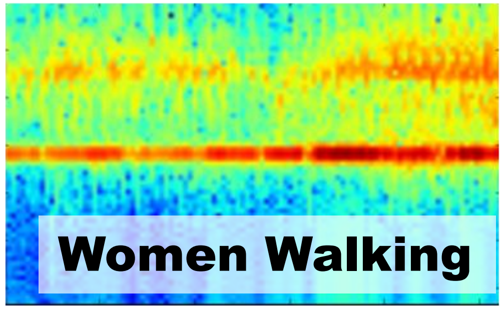
EXAMPLES OF POTENTIAL CLASSES

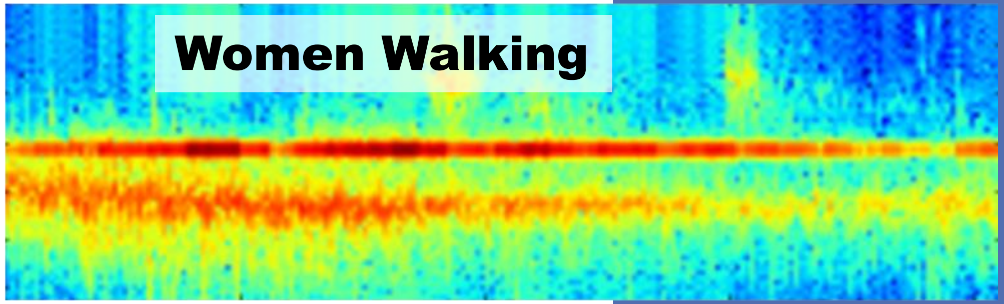


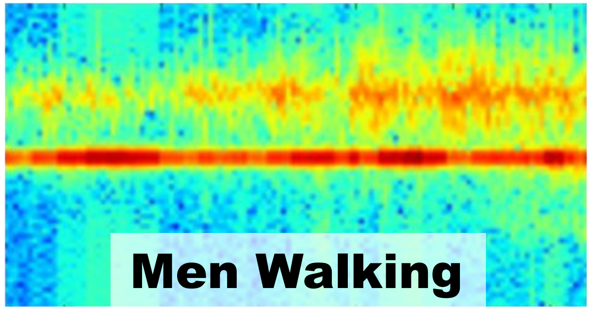


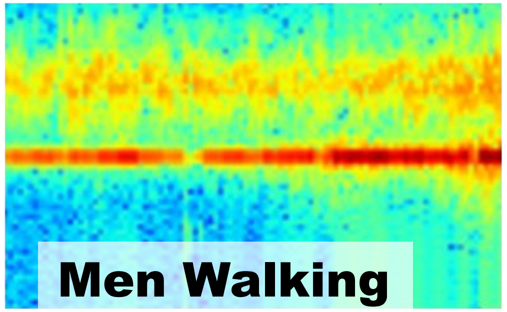


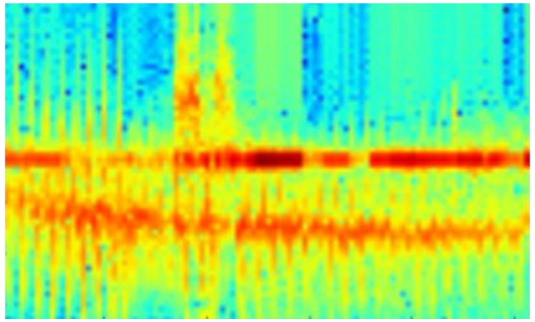












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CONCLUSIONS

- There is **clear feature extraction** however better performance is likely possible.
- We tested several architectures.
  - Can **improve classification** with traditional conv net by using **more labeled data and deeper net** architecture
  - Can pair a **linear classifier** with a net trained using unsupervised learning
- We found that shallow configuration (4 layers) can be adequate for feature extraction and feature representation on our radar data.
- We apply our representation as training data for a linear classifier and find that the classifier is effective on small amounts of labeled data. With additional data, we expect generalization to unseen targets.
- Speculations:
  - Using conv net over time appears to be equivalent to using LSTM with memory periodically erased
  - unlabeled data may be sufficient

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CLOSING

The practical applications of the research is in creating a learned representation of radar images, which includes detecting, tracking, and classifying the radar targets in complex environments.

The following are anticipated changes to existing practice resulting from this research:

- The change in design and signal processing philosophy: there is no longer a need to engineer algorithms based on known statistics to discriminate targets because the neural network organizes data from an existing dataset, finds a process that extracts features, and approximates a classification function. Subsequently, we can use the neural network as a substitute for the engineered algorithm.

The unique finding of this research is the confirmation that the network is capable of learning an unsupervised representation for a moving human target and for clutter with an underlying ability to discriminate them.

Thank You!

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