Hidden Markov Model-based Gesture Recognition with FMCW Radar

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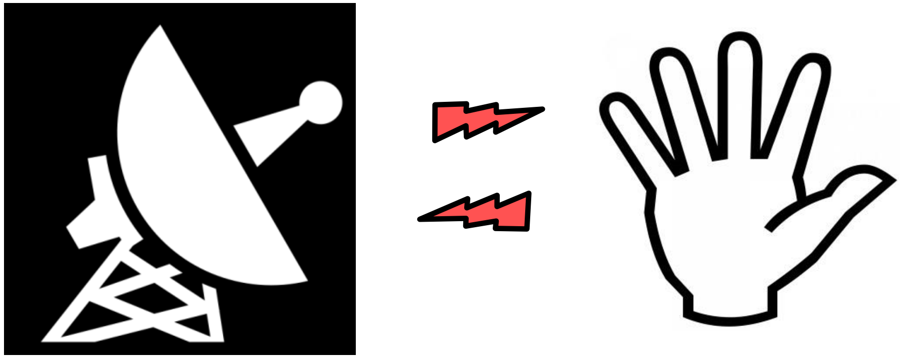
Our Goal

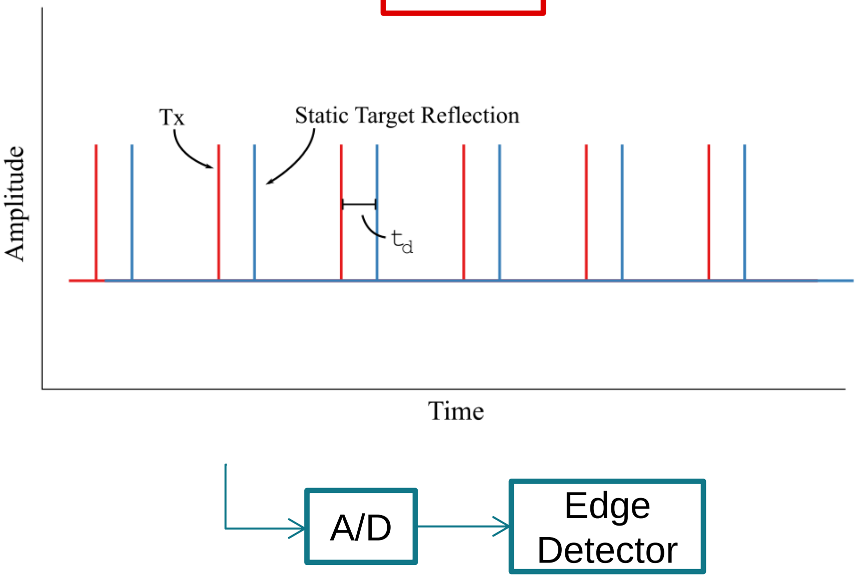


- Detect and classify coarse hand gestures using RADAR
  - Compact, low power
  - All-lighting, all-weather performance
  - NLOS capable operation
- Targeting distinct hand gestures involving motion

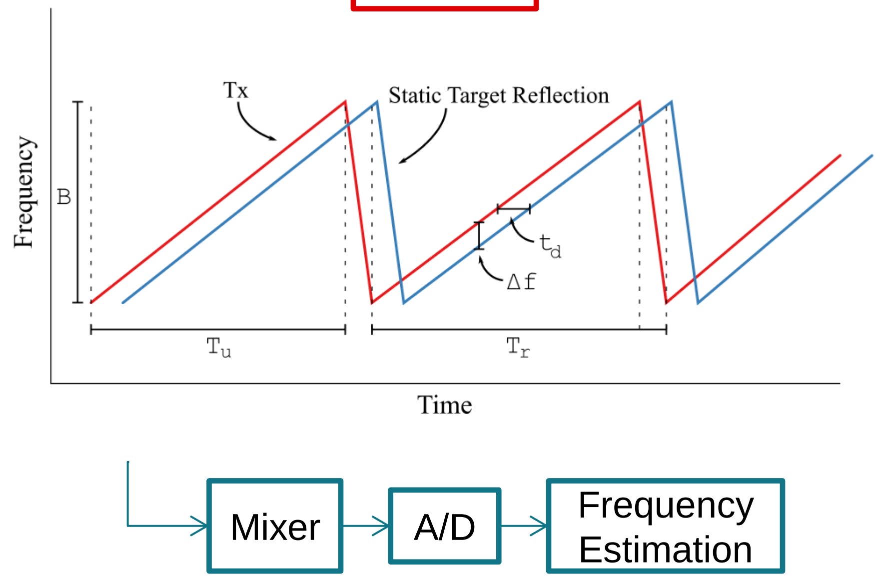
Types of Radar

- Two broad categories: pulsed and continuous wave (CW)
  - Pulsed radar directly measures time-of-flight to compute distance
  - CW radar indirectly measures distance through phase or frequency changes

Pulsed



FMCW



FMCW Radar

- Single chirp

$$s(t) = \exp(j2\pi f_c t + j\pi B T_r t^2)$$

- Down-converted response of a **point target** with moving with constant velocity v starting at some range R_0.

$$x(n,m) = \Gamma \exp\left(j\frac{4\pi}{c_0}\left(\frac{BR_0}{T_r}nT_s + vf_c mT_r\right)\right)$$

  - For nth sample in mth chirp

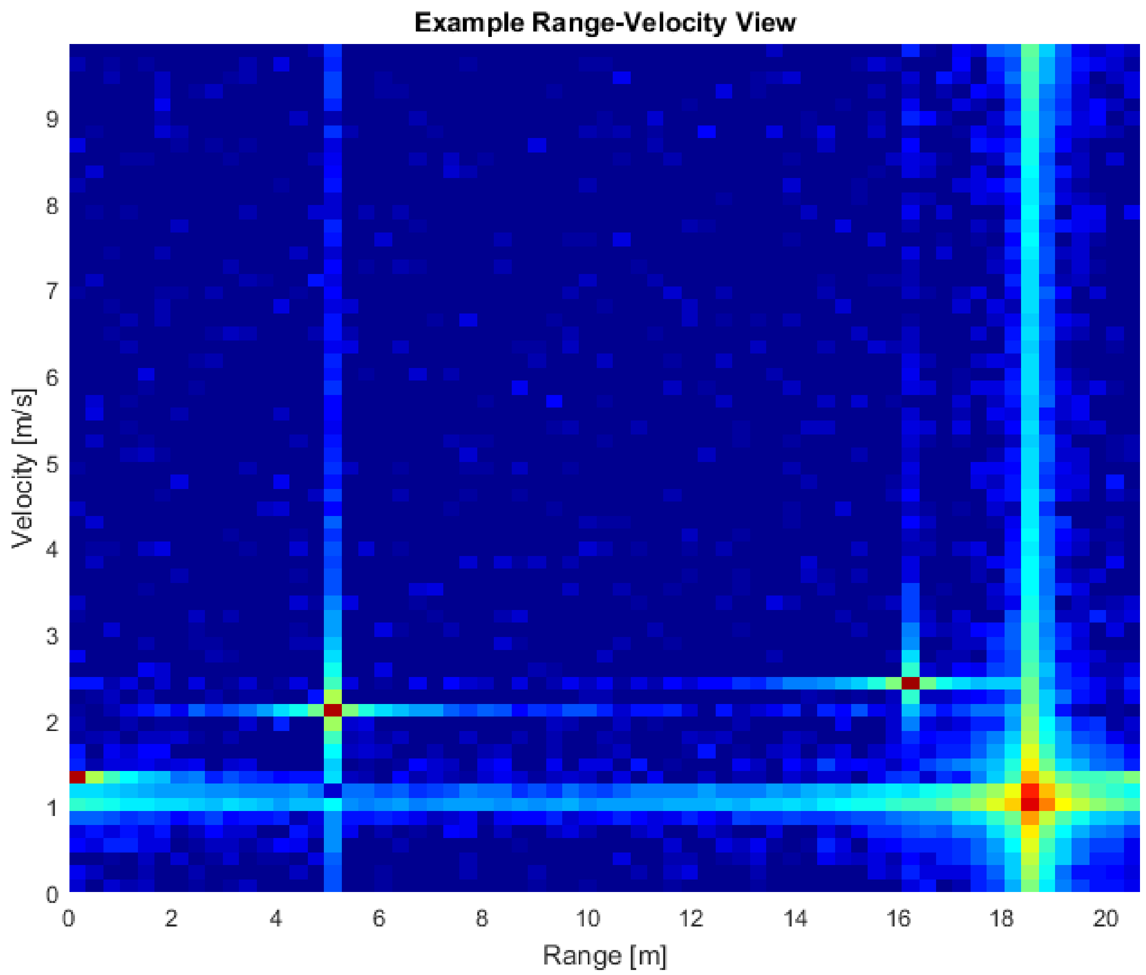
- Describe a group of point targets via 2D DFT:

$$X(k,w) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x(n,m)\exp\left(j2\pi\frac{nk}{N}\right)\exp\left(j2\pi\frac{mw}{M}\right)$$

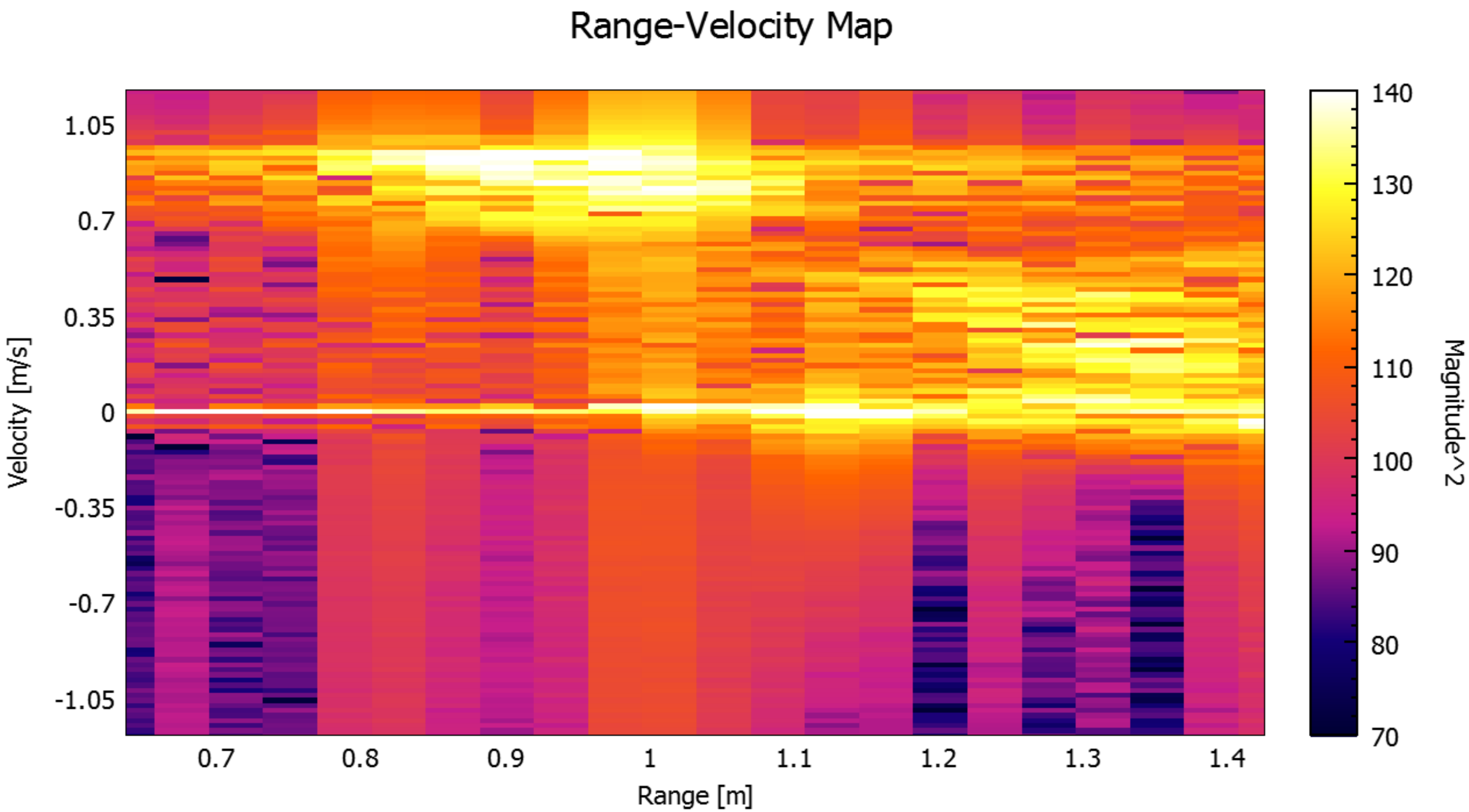
- Resulting pixel resolution

$$\Delta R = \frac{c_0}{2B} \qquad \Delta v = \frac{c_0}{2f_c M T_r}$$

Model Signature



Real Signature

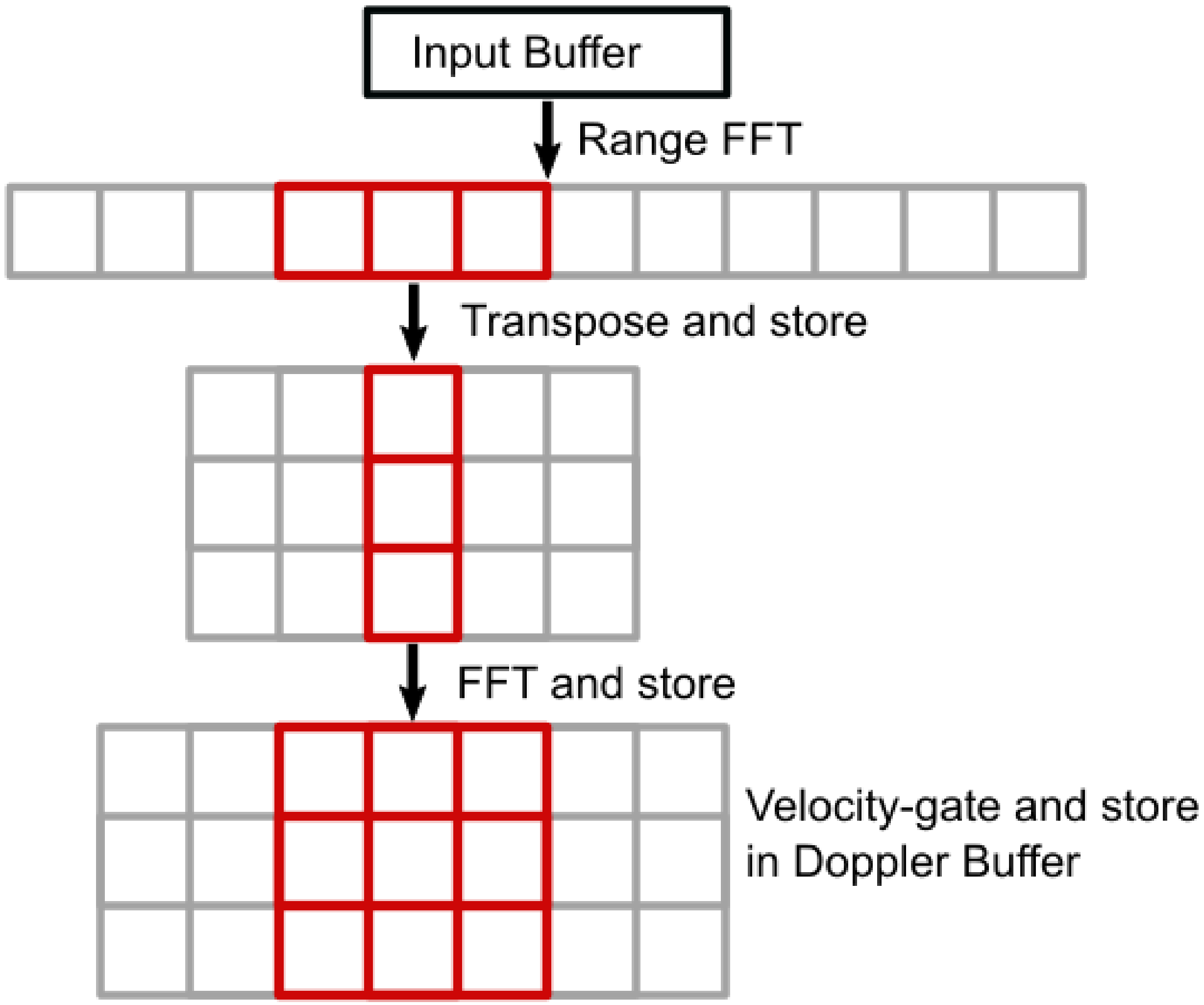


Micro-Doppler

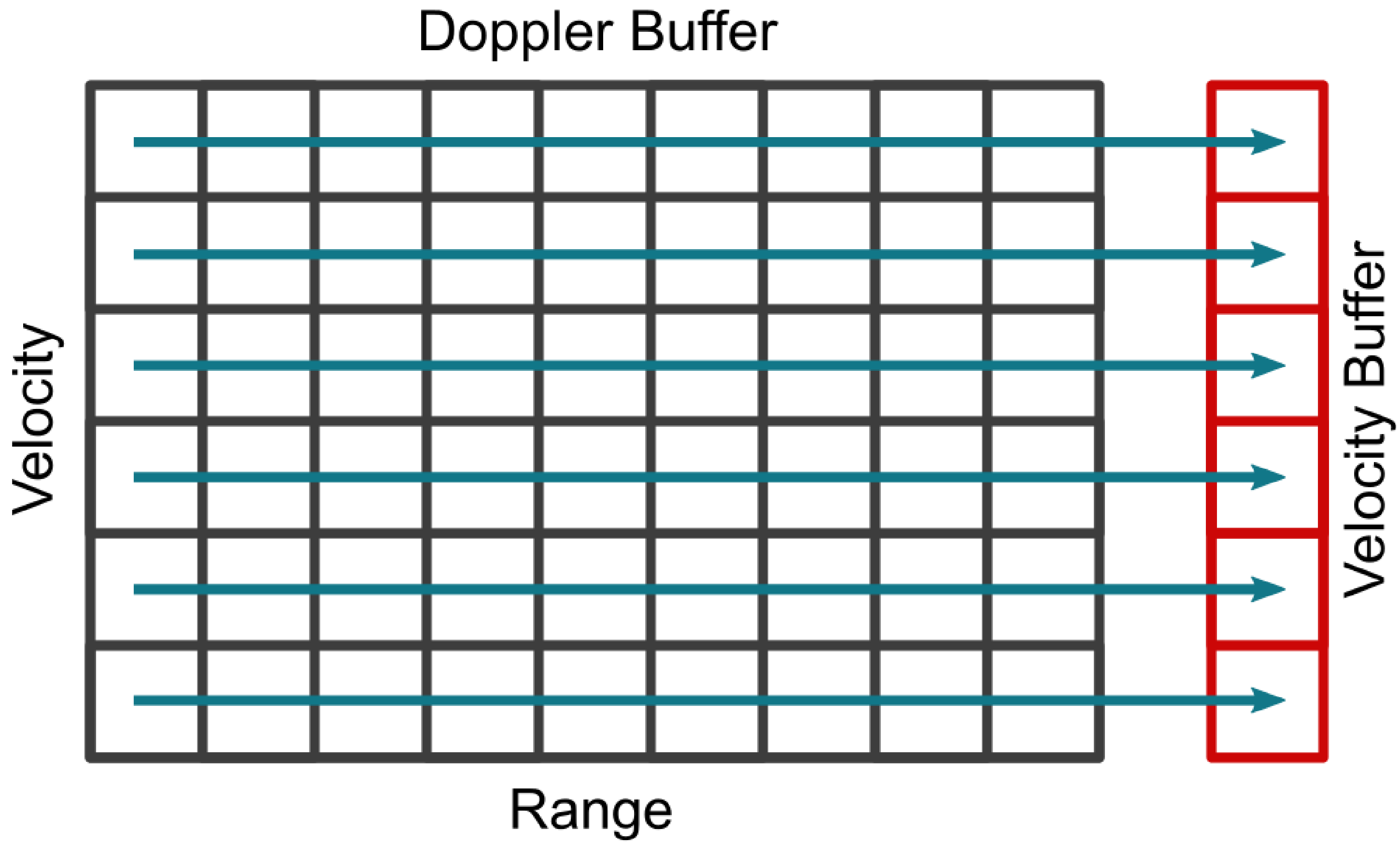
- Reality complicates matters
  - **Surface** composed of point targets
  - Multiple reflections, continuous internal scattering
  - Time-varying configuration, spatially diverse parameters

- Most relevant effect: micro-Doppler
  - Velocity signature associated with composite targets experiencing non-uniform motion
  - Difficult to characterize for all but the most trivial of configurations

Processing Step 1

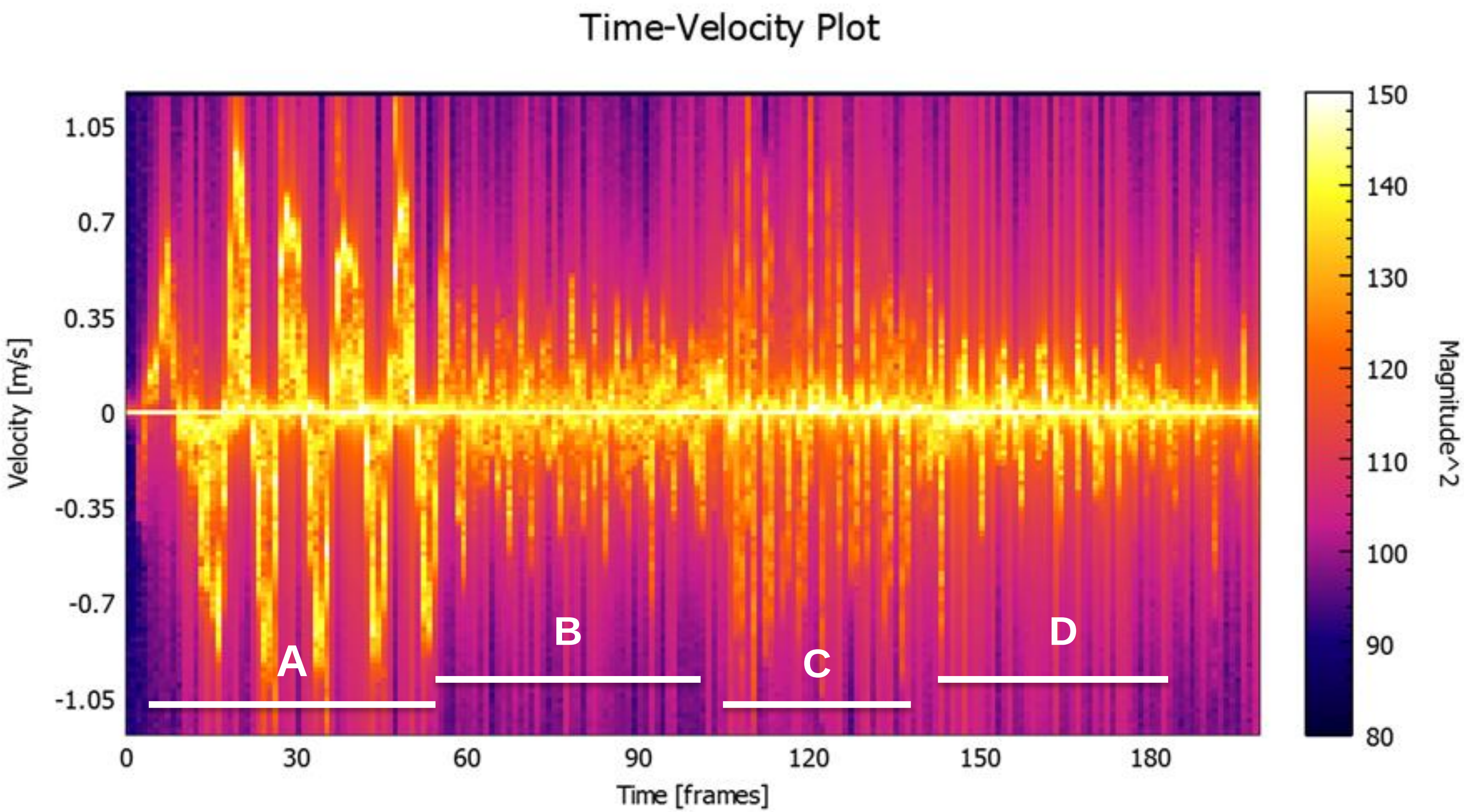


Processing Step 2

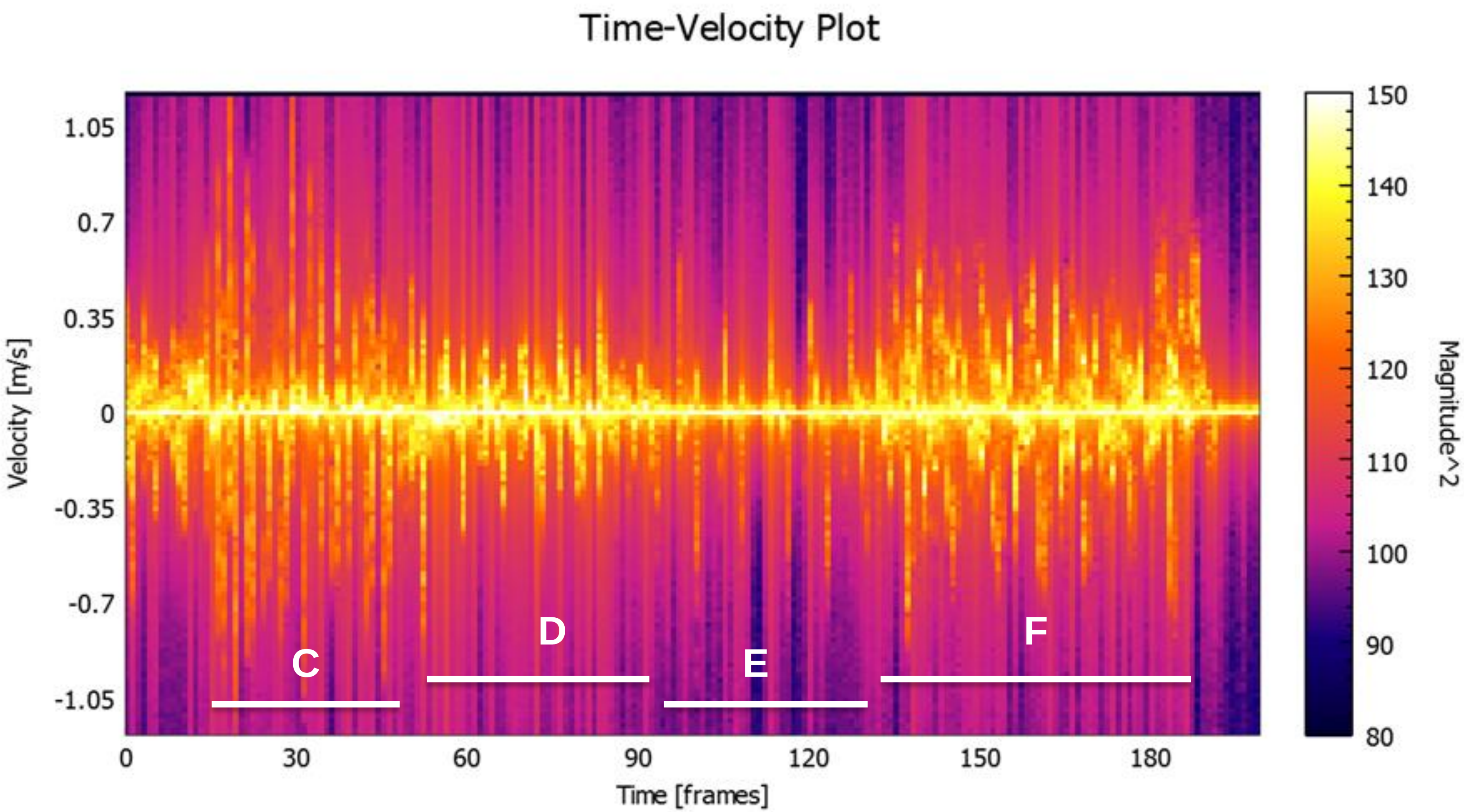


Resulting data forms “Velocity-Energy” measurement for recognition

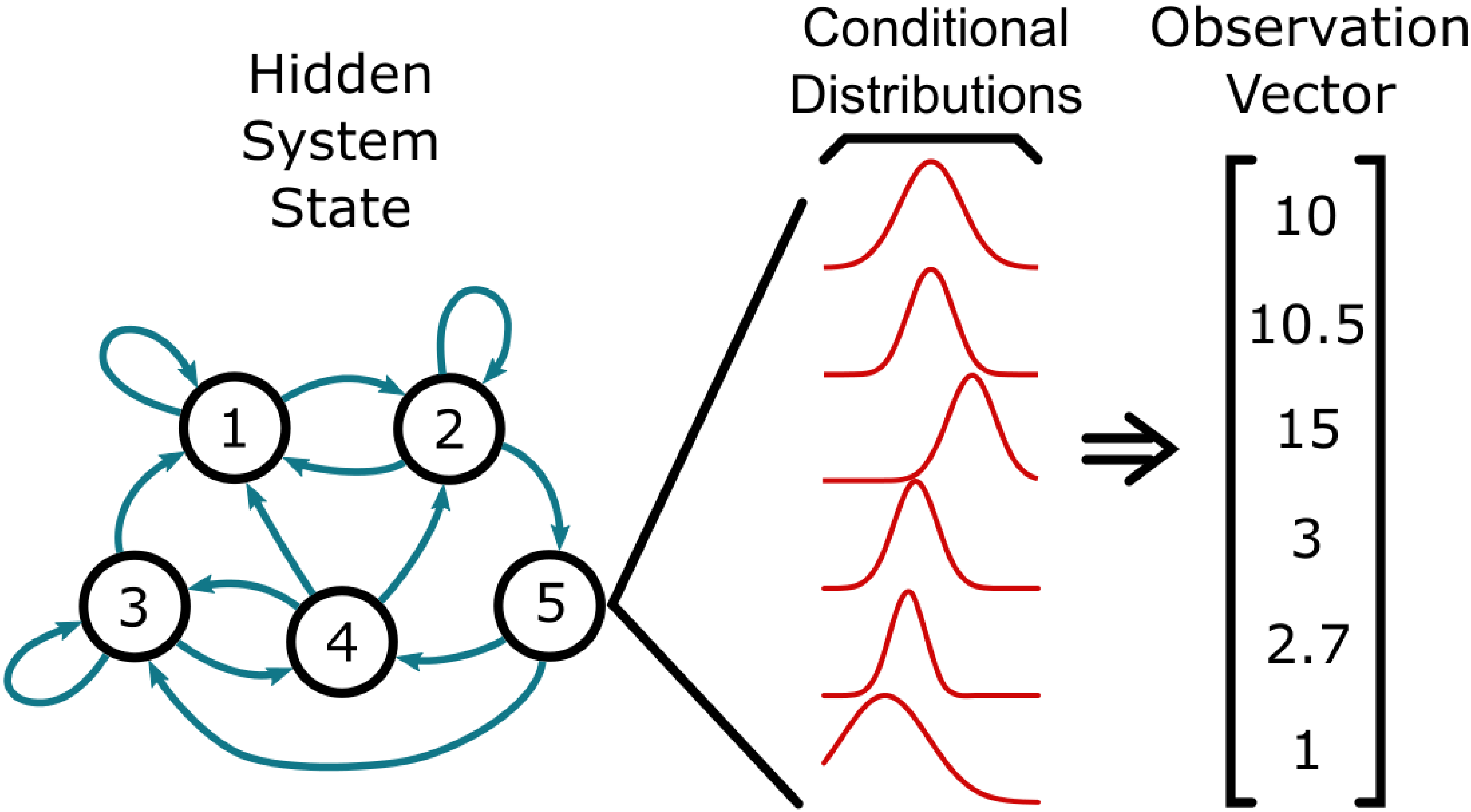
Gesture Dictionary



Gesture Dictionary (2)



Hidden Markov Models



Data Collection Parameters

- 4 GHz bandwidth starting at 76 GHz (3.75 cm range resolution)
- 1022 chirps with ~100μs chirp interval per **frame** (0.1 sec)
  - Plus ~0.2 sec dead time between frames
- 128-point velocity vector, one for each bin (~2 cm/s velocity resolution)
- 30, 15, or 10 frame “chunks”
  - Arbitrary segmentation used for both training and classification
  - Uninformed segmentation, no “markers” or silence detection
  - ~3,000 chunks per gesture collected
- Markov Model parameters
  - 5 states for each gesture model
  - 1 or 2 gaussian mixtures for each state
  - Diagonal covariance matrix for observation vector (implies independence)
- Optional feature extraction/lossy compression algorithm

Feature Extraction

- 128-point observation vectors (one velocity-energy buffer)
- Lower dimension observation vector is cheaper to classify
  - Good results if $I\left(Y; f(Y)\right)$ is suitably large
- Due to PSF, FFT windowing, and hand structure, V-E vectors have spatial correlation
  - V-E vectors might be seen as a sum of Gaussian functions,

$$f[n] = \sum_{l=1}^{L} w_l \exp\left(-\frac{(n-\mu_l)^2}{\sigma_l^2}\right)$$

$$v[n] = \eta[n] + f[n]$$

  - Then, the feature vector $\vec{z}$ is found as the parameters $\{w_l, \mu_l, \sigma_l\}$ that minimize the L2 distance between $\vec{f}(\vec{z})$ and the observation vector,

$$e^2 = \left(\vec{v} - \vec{f}\right)^T \left(\vec{v} - \vec{f}\right)$$

Classification Results

128-point vectors

- 30 frames
  - 1 GMM: 82.3%
  - 2 GMMs: 87.9%
- 15 frames:
  - 1 GMM: 81.5%
  - 2 GMMs: 84.8%
- 10 frames:
  - 1 GMM: 79.0%
  - 2 GMMs: 83.1%

10-point vectors

- 30 frames
  - 1 GMM: 83.3%
  - 2 GMMs: 88.9%
- 15 frames:
  - 1 GMM: 82.4%
  - 2 GMMS: 87.5%
- 10 frames:
  - 1 GMM: 75.85%
  - 2 GMMs: 81.7%

Conclusions

- Radar-based gesture recognition is feasible
- Learn from speech recognition
  - Previous work in activity classification focused on classification without modeling
  - Gestures can be explained using Hidden Markov Models
- Future work
  - More gesture data collection
  - Informed HMM design for gestures
  - Dealing with variation (physical size, gesture speed, viewing angle)

Extra Slides

Micro-Doppler in FMCW

- Bjorklund, S.; Johansson, T.; Petersson, H., **Evaluation of a micro-Doppler classification method on mm-wave data**, *2012 IEEE Radar Conference (RADAR)*, pp.0934,0939, 7-11 May 2012

- Gait identification at 77 GHz (150 MHz BW)
- Uses STFT to compute micro-Doppler signature
- Compute “Cadence Velocity Diagram (CVD)” by Fourier Transform over time for each velocity
- Construct feature vector from M peaks in CVD and corresponding velocities
- Use SVM classifier to match against training set

Micro-Doppler Signatures

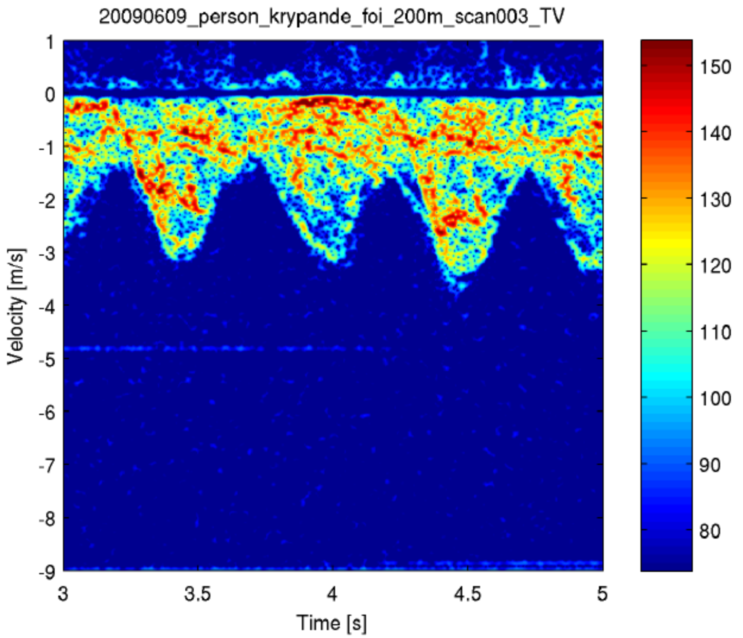


Fig. 2: A person creeping with negative Doppler. The 77 GHz SIRS 77 radar. The color shows power in dB. [runatr1019d2]

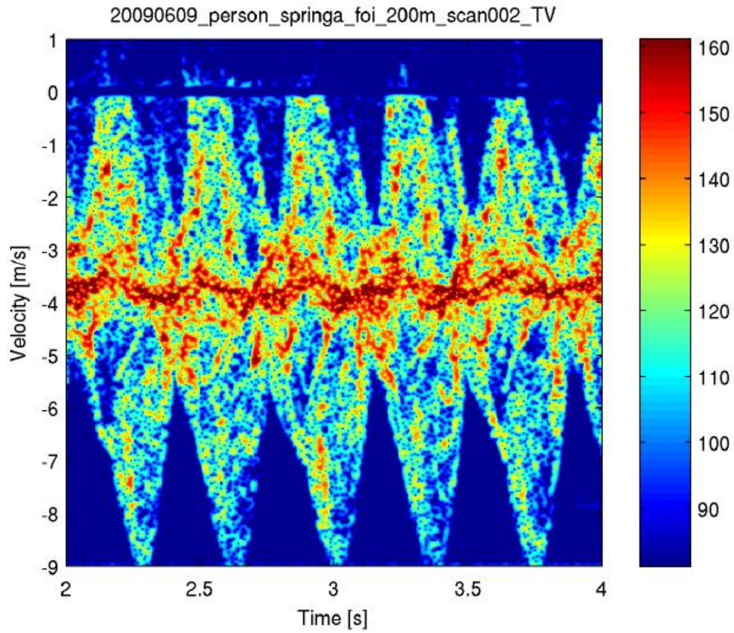


Fig. 4: A person running with negative Doppler. The 77 GHz SIRS 77 radar. The color shows power in dB. [runatr1019d2]

From "Evaluation of a micro-Doppler classification method on mm-Wave data"

Published Classification Results

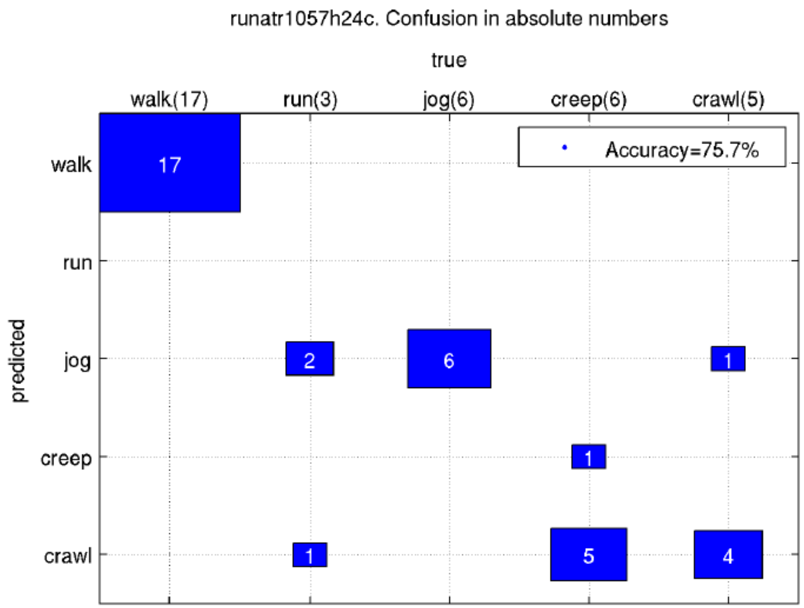


Fig. 10: Classification result (confusion matrix) with true and estimated classes. Number of training sequences: 41 (walk), 8 (run), 14 (jog), 14 (creep), 12 (crawl).

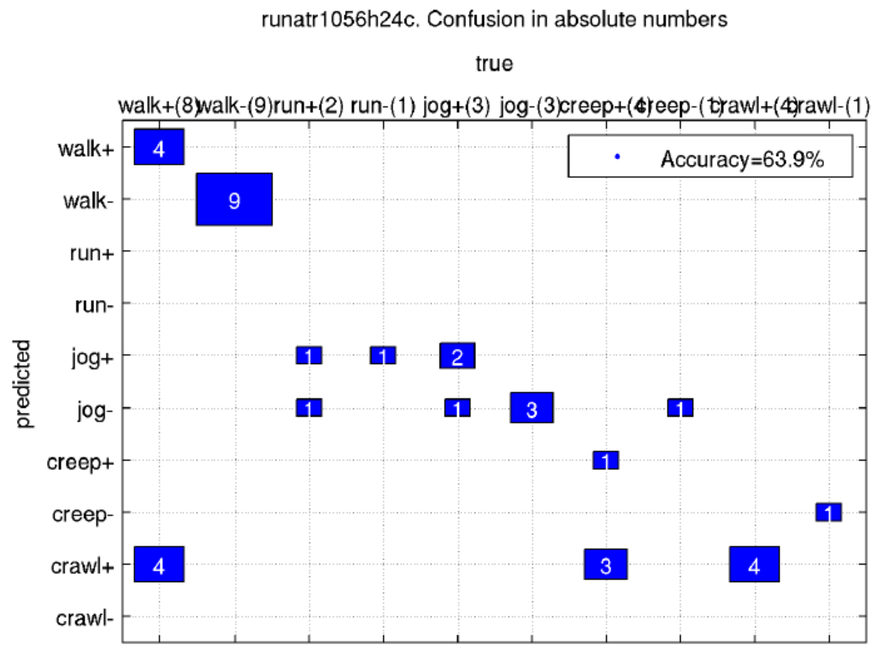


Fig. 11: Classification result (confusion matrix) with true and estimated classes. The labels above the plot should be "walk+(9) walk-(9) run+(2) run-(2) jog+(3) jog-(3) creep+(4) creep-(2) crawl+(4) crawl-(1)". Number of training sequences: 20, 21, 4, 4, 7, 7, 11, 4, 10, 2.

From "Evaluation of a micro-Doppler classification method on mm-Wave data"

Feature Extraction Algorithm

Find Largest Peak

↓

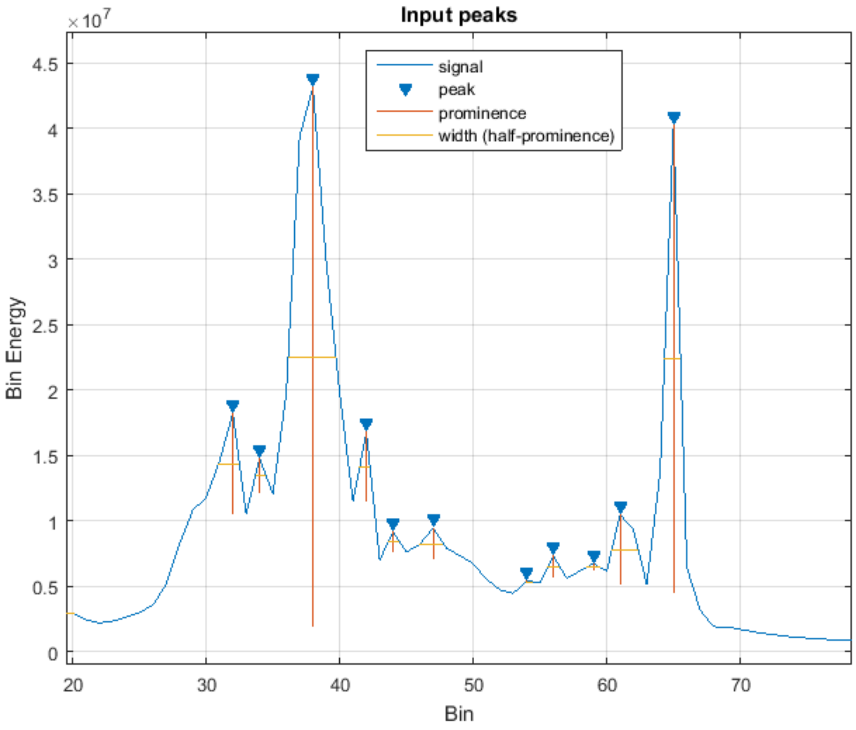
Newton Refinement for Matching

↓

Subtract Model Signal

↓

Repeat



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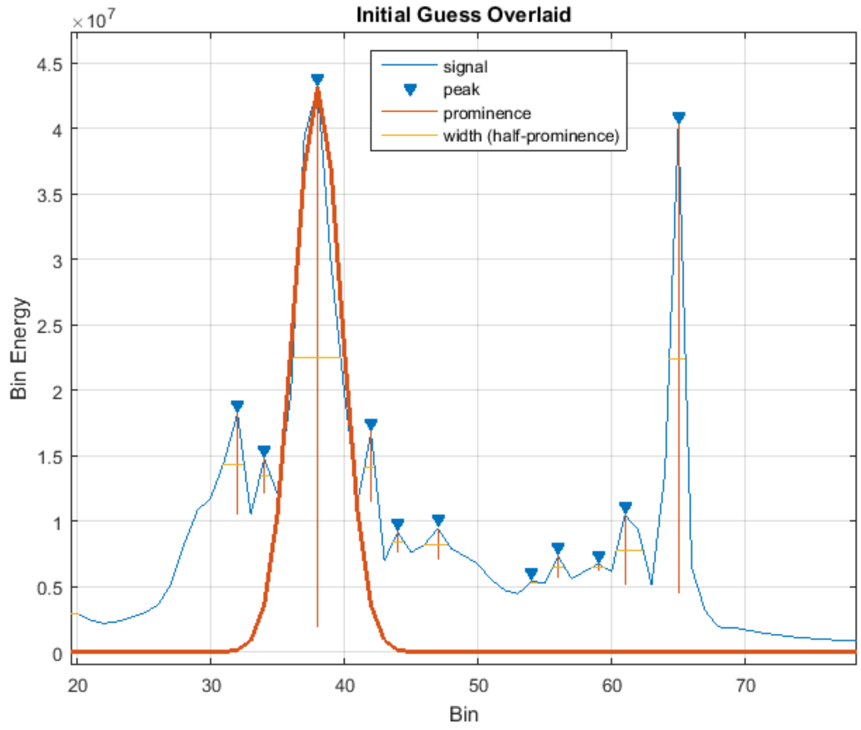
Subtract Model Signal

Repeat



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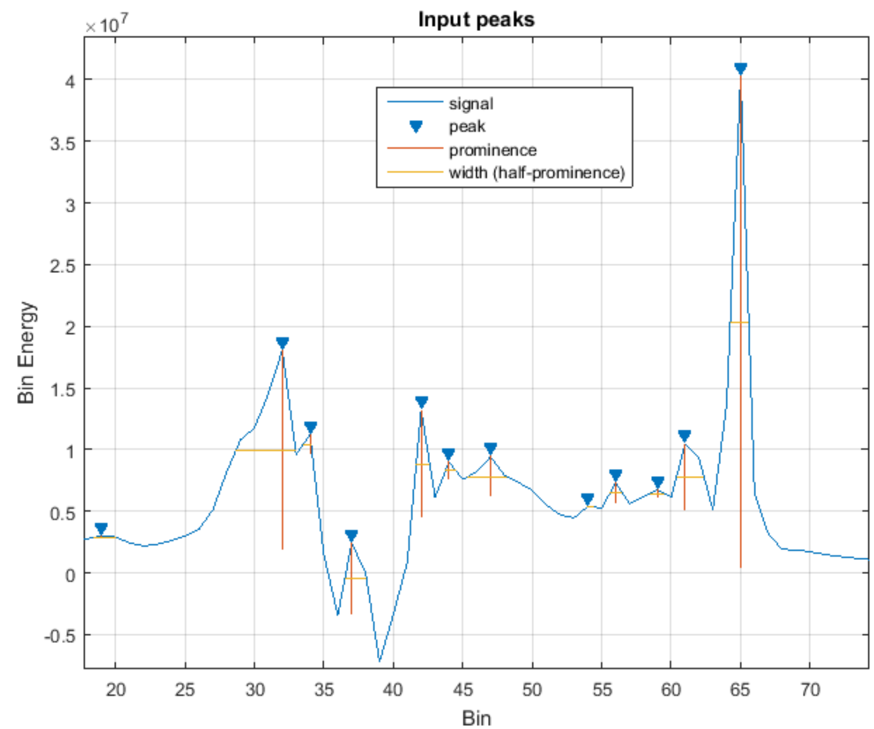

Feature Extraction Algorithm

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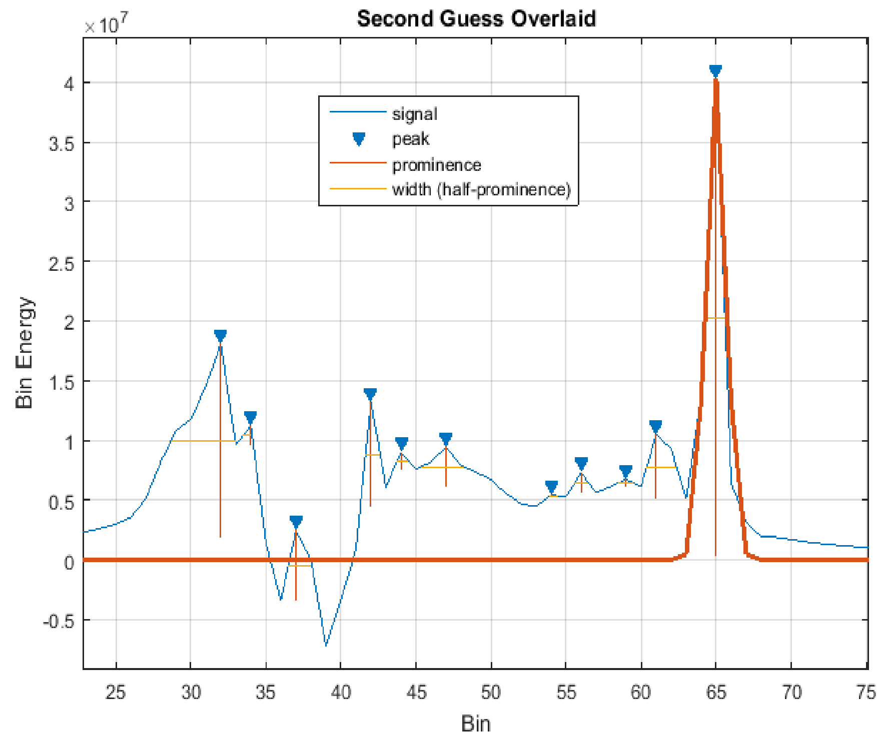
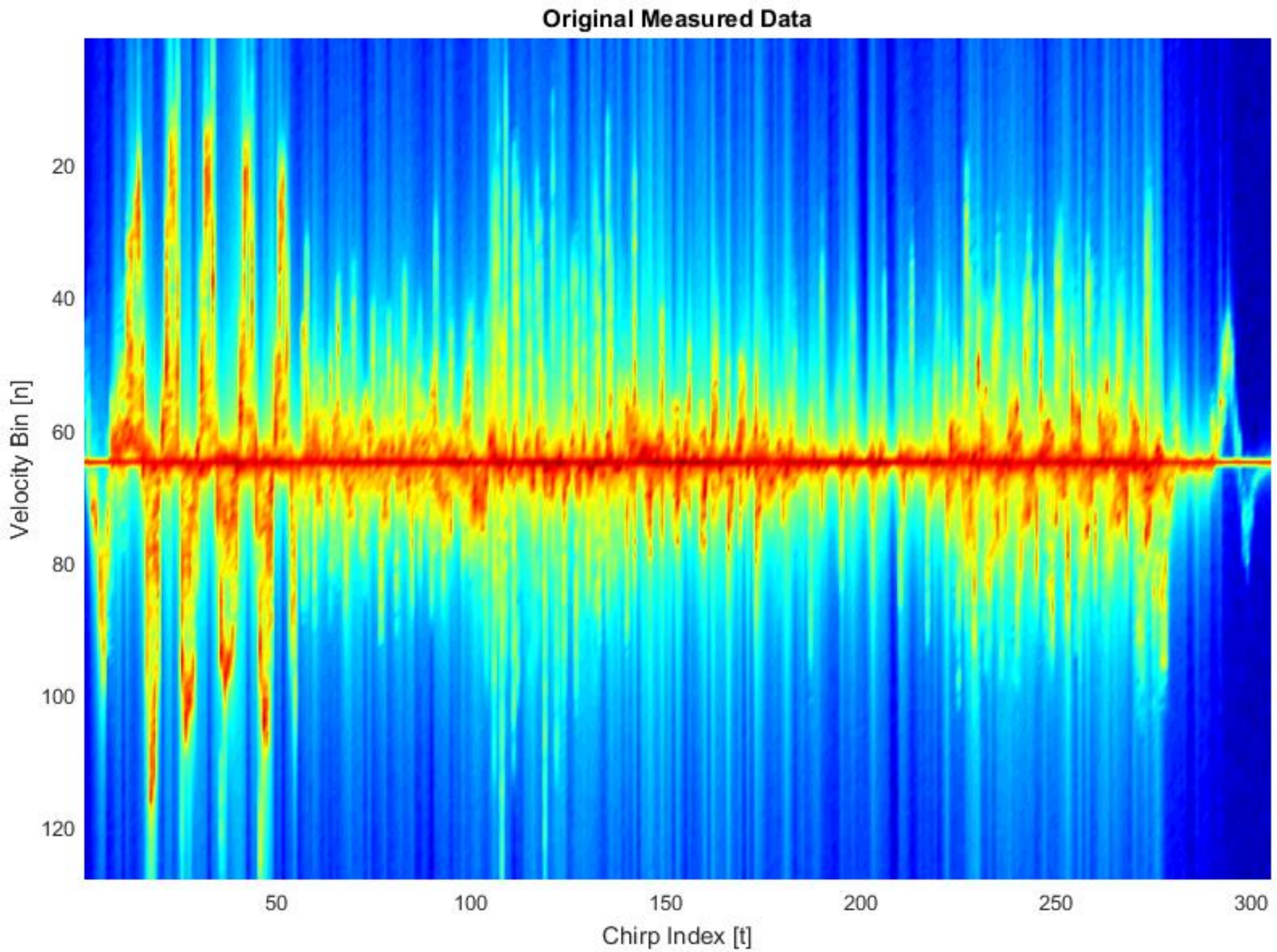


Original V-E Plot



Reconstructed V-E Plot