An Animation and Chirplet-Based Approach to Developing a PIR Sensing Intrusion Detection System for an Outdoor Setting

Raviteja Upadrashta

ECE Department

Thesis Advisor: Prof. P. Vijay Kumar

EECS Research Students Symposium - 2016

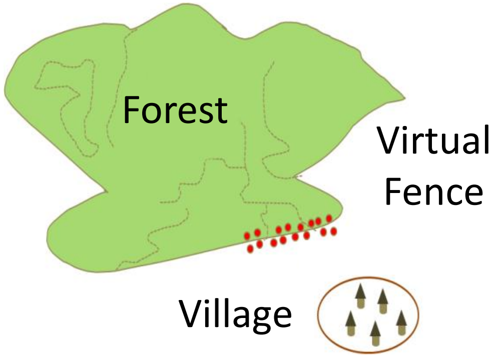
April 28-29, 2016

Motivation: Mitigation of Human-Wildlife Conflicts

Leopard attacks a man in a village in Bengal.

Leopard attacks a man in a school at Bengaluru.

Police display tiger and leopard skins that were seized at Ghaziabad, New Delhi.

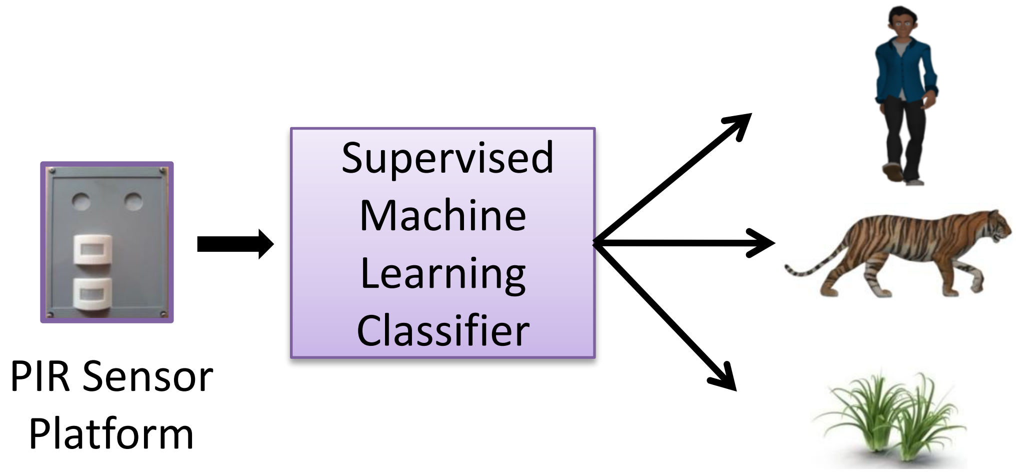


Early warning systems: Virtual fence

* Work part of a project jointly funded by NSF & DeitY (June 2012-August 2015)

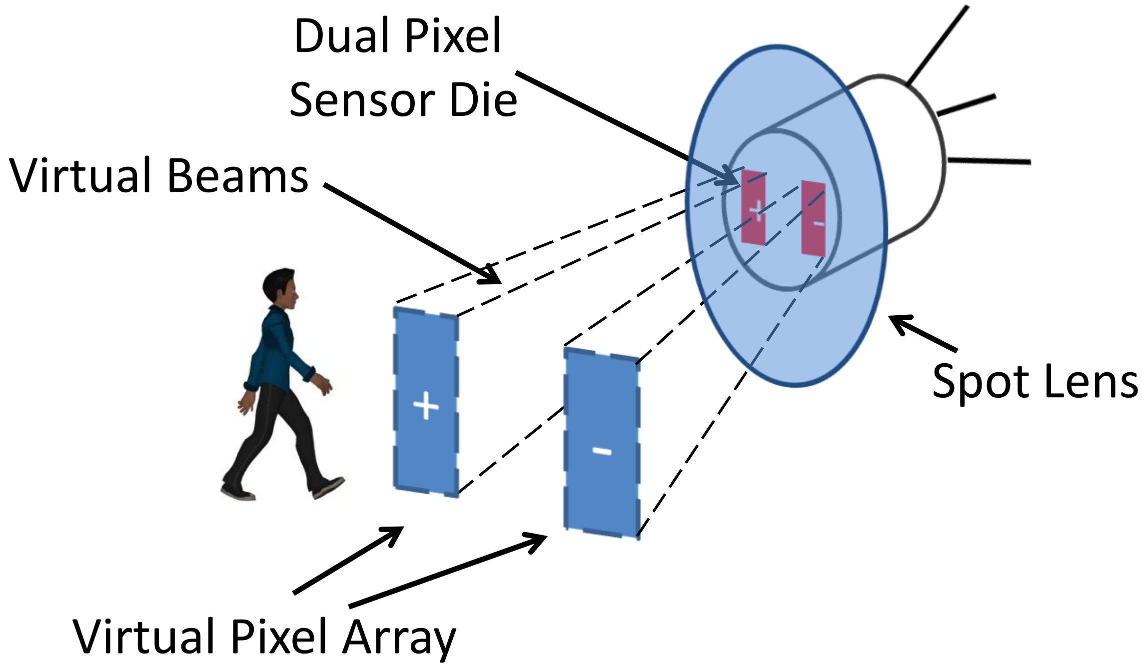
- Animal excursions
  - Results in killing of livestock and crop destruction
  - Sometimes animals themselves are injured/killed
  - Leopard attacks routinely make headlines
- Human intrusions
  - Results in poaching and forest destruction
  - Tiger killings in India average two per week
- Goal: Investigate efficacy of low-power WSN-based early warning systems to manage human-animal conflicts
  - PIR sensors (motion sensors) are passive devices, inexpensive and widely available commercially

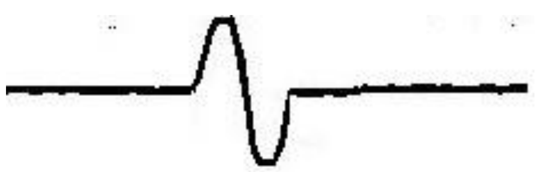
PIR-Based Sensor Platform for Intruder Classification



- Designed and developed Indigenous PIR-based sensor platform that makes use of inexpensive commercially available components
- Challenges:
  - False alarms generated by wind-blown vegetative motion
  - Need to classify intrusions: Humans Versus Animals
  - Animal data collection is hard
- Restricted problem setting with the following assumptions:
  - Intruder moves in straight lines at a uniform velocity that is typically observed
  - No multiple intrusions
  - Only intrusions from humans, dogs, leopards, tigers and wolves

Virtual Pixel Array: Single Lens

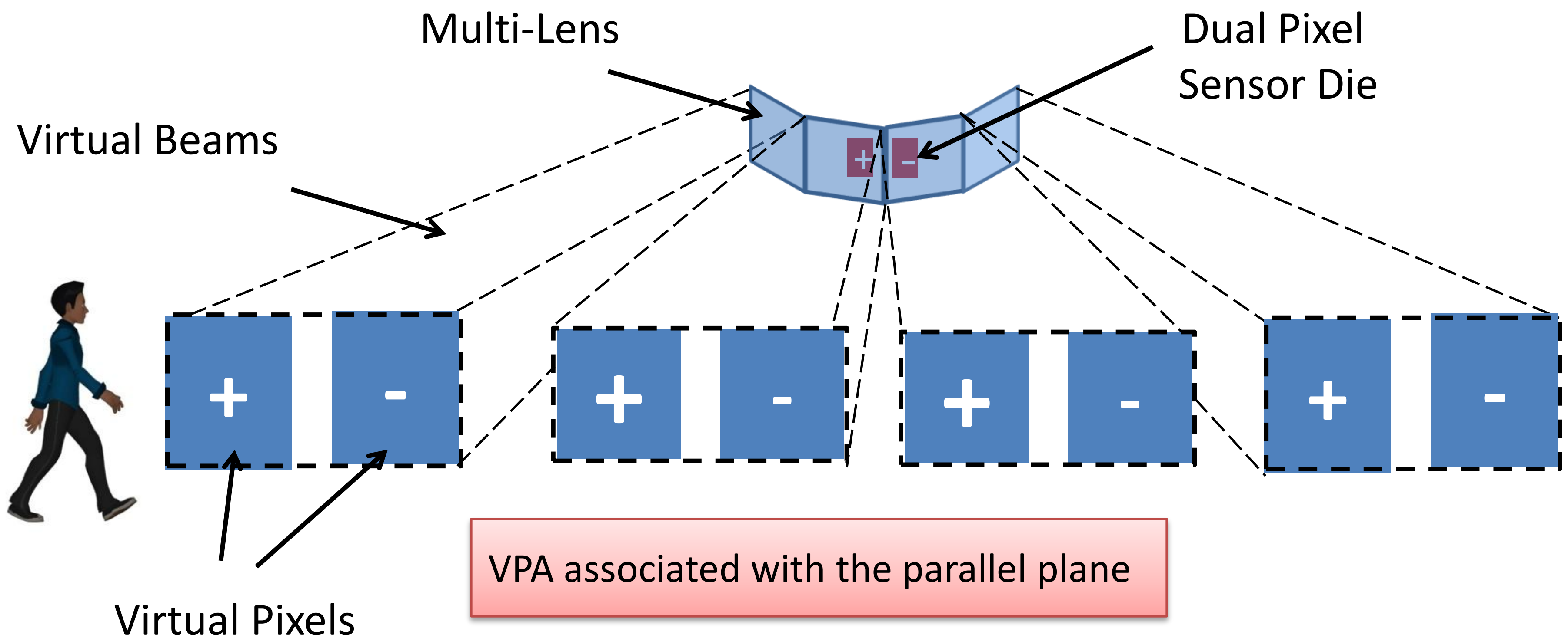




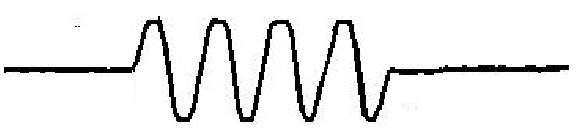
Signal output for an human moving across the VPA

- PIR sensors detect changes in radiation
  - Typically used in conjunction with a lens
- Field of View (FoV) of the sensor
  - Set of diverging virtual beams along which radiation is received by the pixels
- Virtual Pixel Array (VPA) associated with a plane:
  - Intersection of the FoV of the sensor with a plane
  - Signal generated when an object enters and exits the pixels (hence, suitable for motion detection)

Virtual Pixel Array : Multi-lens

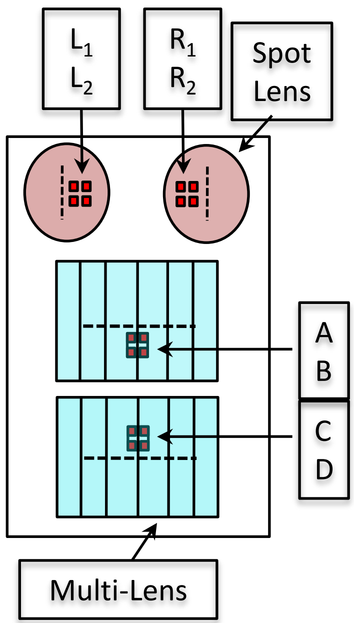


VPA associated with the parallel plane



Signal output for an human moving across the VPA

VPA Design

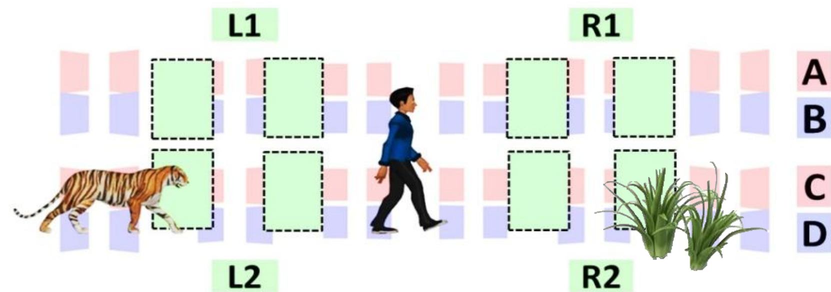


Sensor-lens arrangement

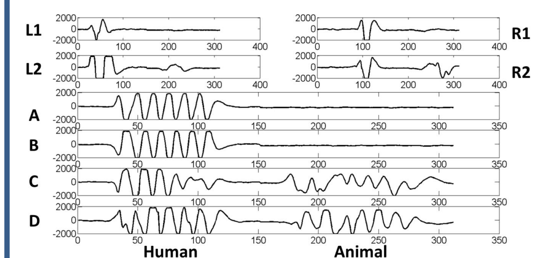
Outside View

Inside View

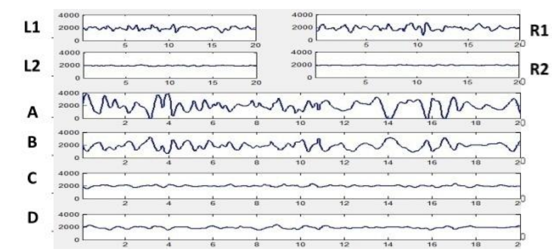
Indigenous sensor platform developed



Corresponding VPA generated at 5 m



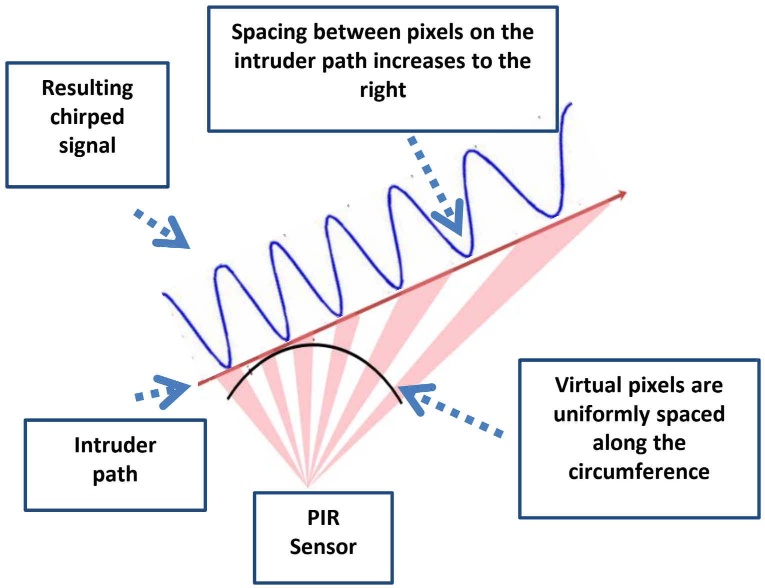
Waveforms for human and animal walking back-to-back



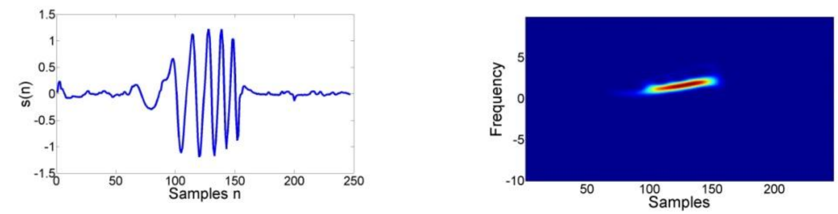
Waveform for clutter arising from wind-blown vegetation

- Sensors A, B, C and D provide vertical spatial resolution
  - Helps classify intrusions by exploiting difference in their height
  - Human cuts more rows compared to animals
- Sensors L_1, L_2, R_1 & R_2 provide horizontal spatial resolution
  - Helps discriminates between intruder and clutter based on type of motion
  - L and R signals will be highly correlated for an intruder
- Energy and correlation based features can be used for discrimination
  - Can be computed easily even on processors with modest computational resources (known as a mote)

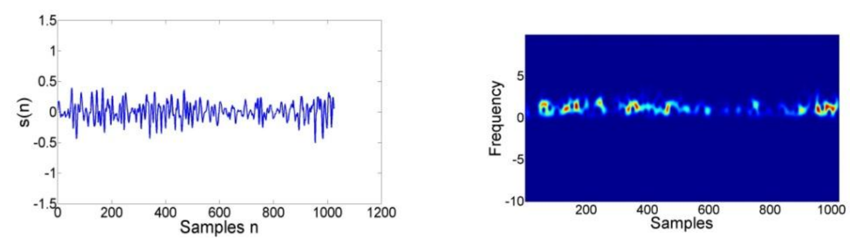
Chirplet-Based Model For Intruder Detection



Explaining Chirp in the Intruder Signals



Intruder signal & its corresponding Short-Time Fourier Transform

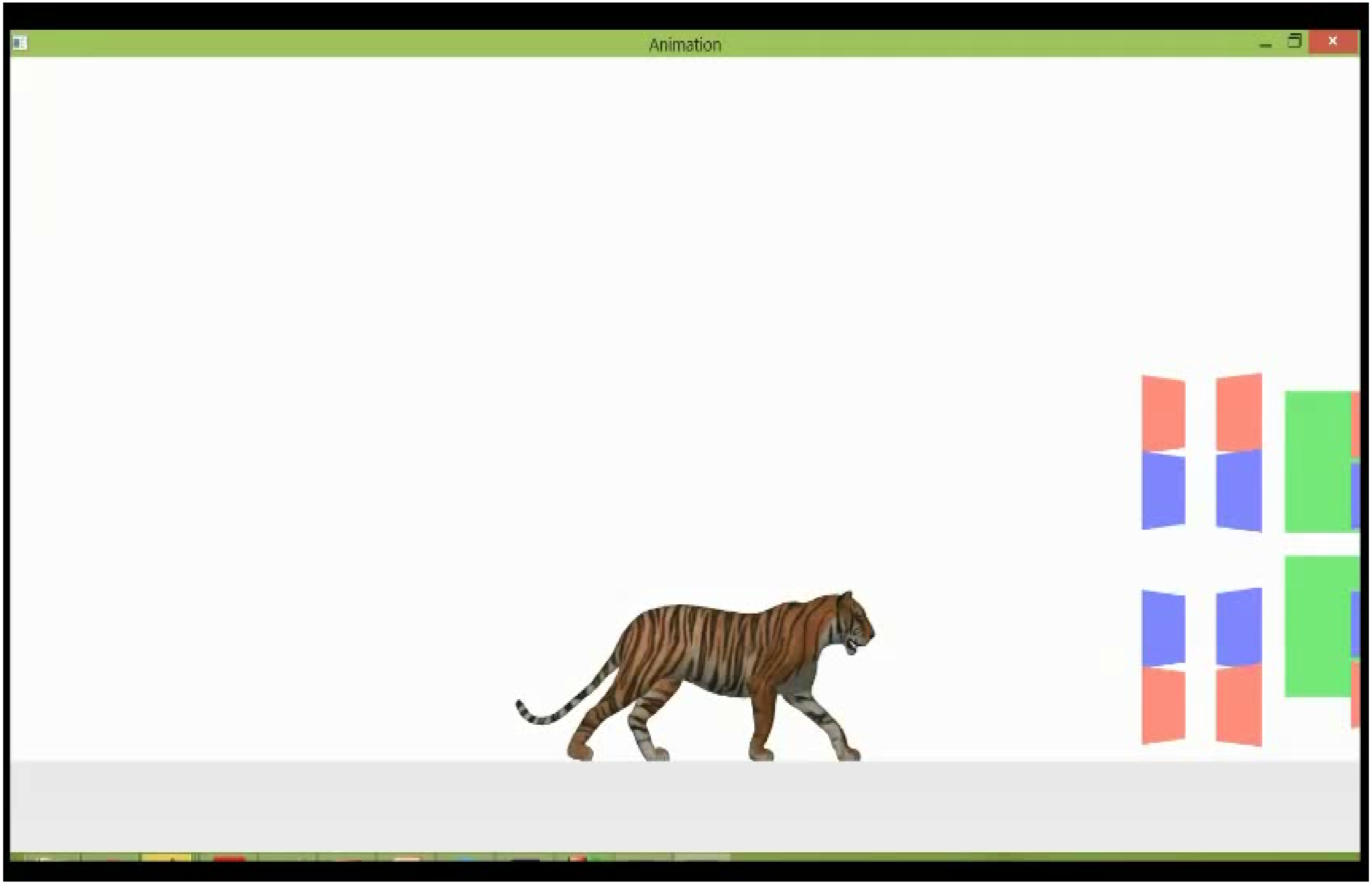


Clutter signal & its corresponding Short-Time Fourier Transform

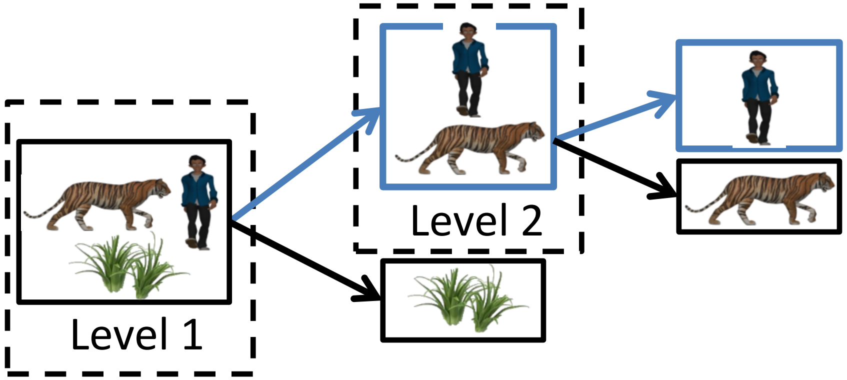
- Intruder Detection:
  - Exploit fact that signals in sensors A, B, C and D corresponding to intrusions exhibit chirp while clutter signals do not.

Video: Data Collection

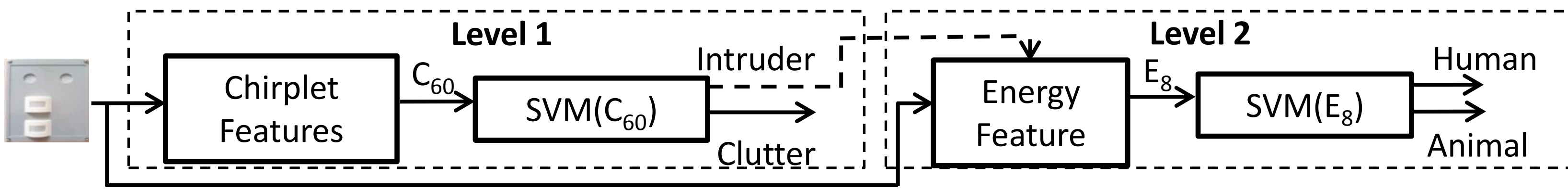
Video: Signal Generation via 3D Animation



Final Classifier: Classification Accuracy



Two-Level Classifier



Notation:

SVM(f): SVM classifier that employs feature vector f.

Feature vectors employed:

C_{60} $\leftrightarrow$ 60-D Chirplet parameters

E_8 $\leftrightarrow$ Energy in all 8 sensors

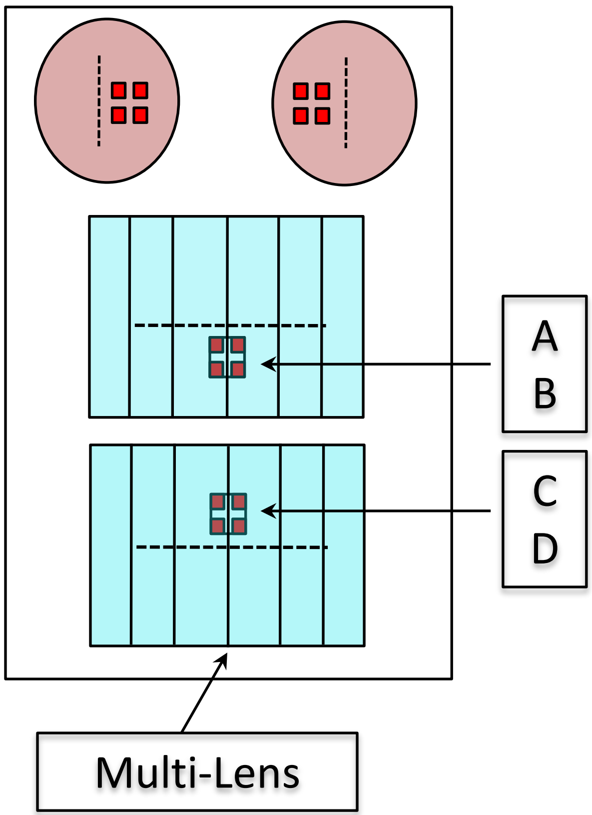
	Real-World Data		Simulated Data	
	Minimum Accuracy	Average Accuracy	Minimum Accuracy	Average Accuracy
Clutter	96.3	98.3	96.4	99.2
Intruder	100	98.6	98.7	99.2
Human	95.0	98.0	100.0	100.0
Animal	100.0	99.5	100.0	100.0
Overall	98.8	99.9	99.4	99.9

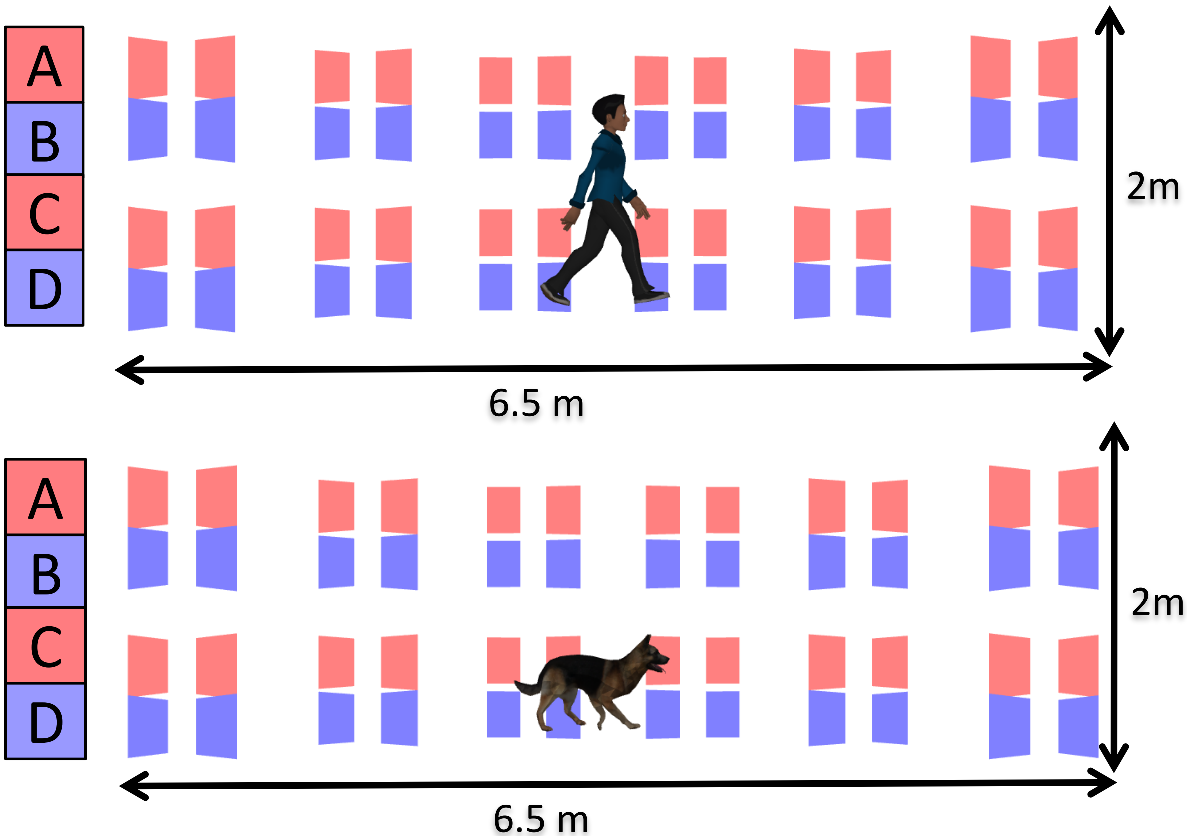
Thank You!!

Questions???

Backup Slides

VPA: Rows A, B, C & D

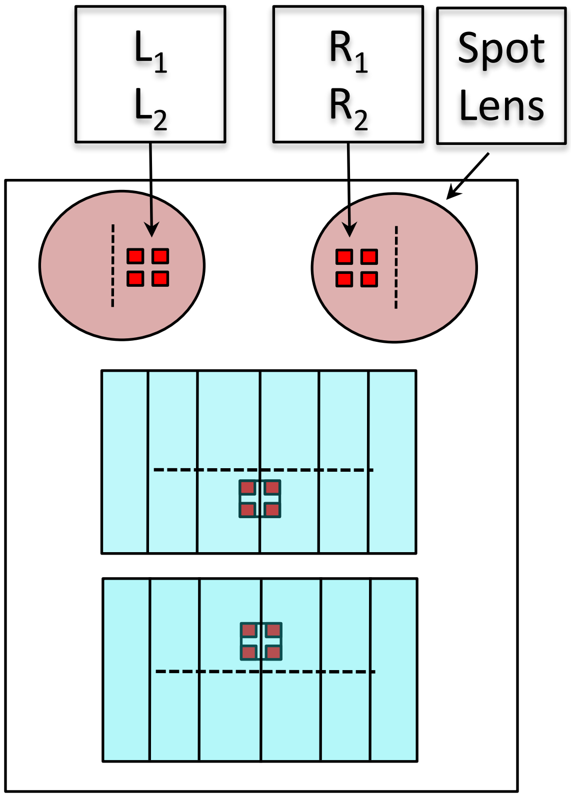




Exploiting difference in geometry for classification at 5m

- Sensors A, B, C and D provide vertical spatial resolution
  - Classify intrusions by exploiting difference in their height
  - Energy features useful

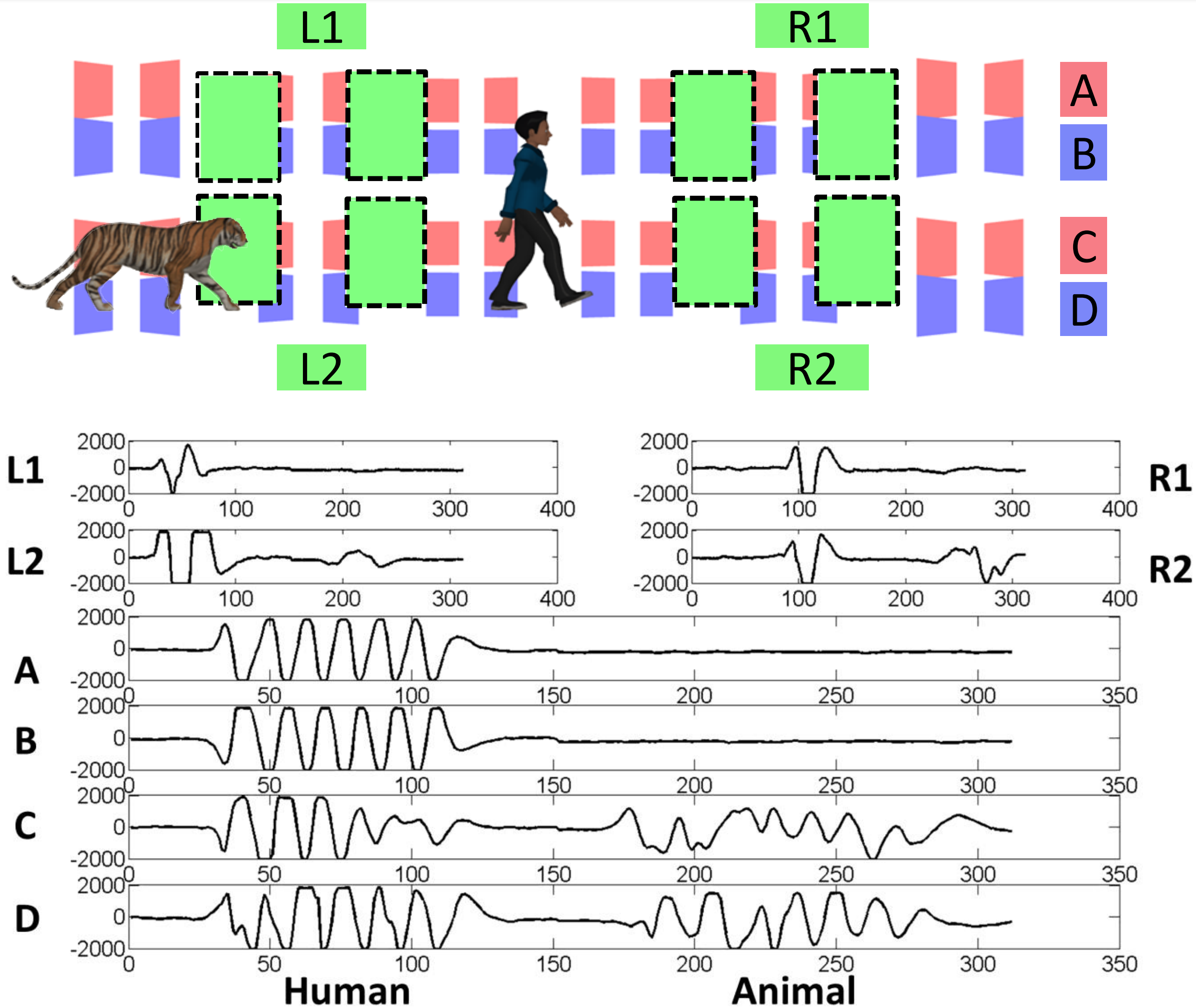
VPA: L_1, L_2, R_1 & R_2



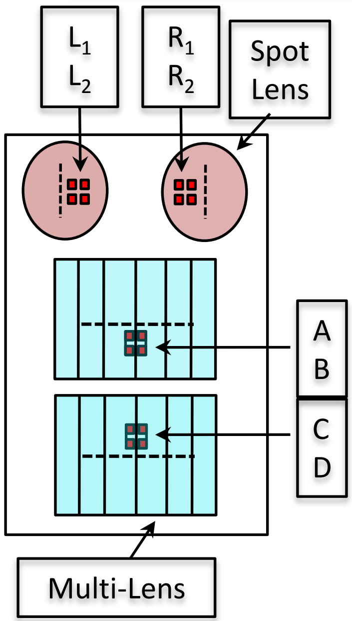
Exploiting difference in motion for classification

- Sensors L_1, L_2, R_1 & R_2
  - Discriminates between intruder and clutter based on type of motion
  - (oscillatory vs translational motion)
  - Left and right sensors will have similar signals for intrusion (will exhibit a high correlation)

Human vs Animal: Comparing the Signals Generated



VPA Design

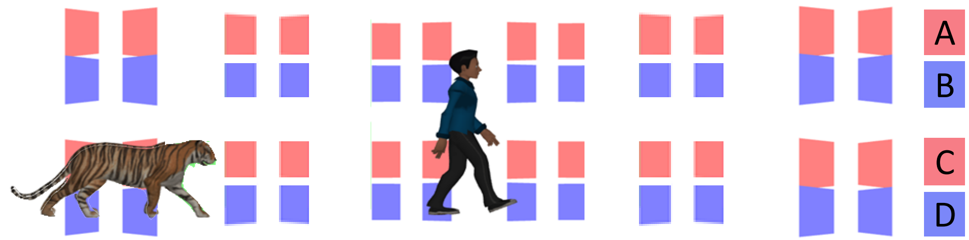


Sensor-lens arrangement

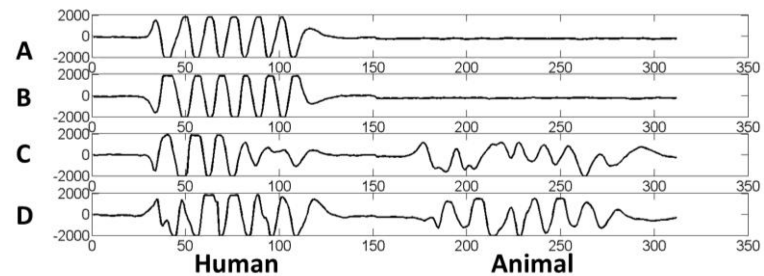
Outside View

Inside View

Indigenous sensor platform developed



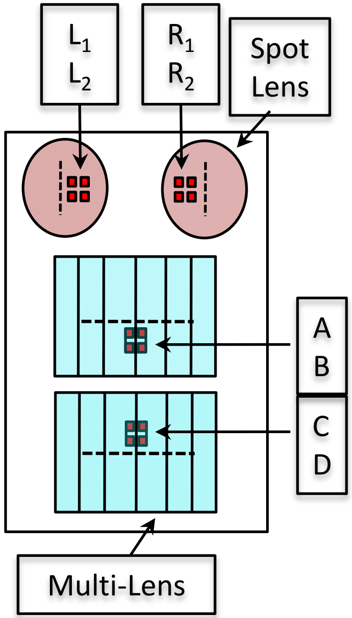
Corresponding VPA generated



Waveform generated by human and animal

- Sensors A, B, C and D provide vertical spatial resolution
  - Classify intrusions by exploiting difference in their height
  - Human cuts more rows compared to animals
- Sensors L_1, L_2, R_1 & R_2
  - Discriminates between intruder and clutter based on type of motion
  - L and R signals will be highly correlated for an intruder

VPA Design

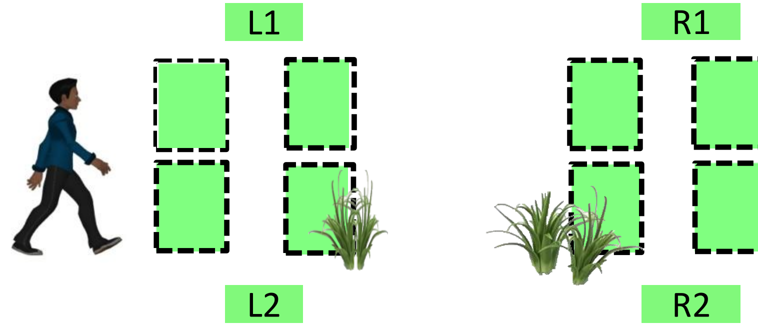


Sensor-lens arrangement

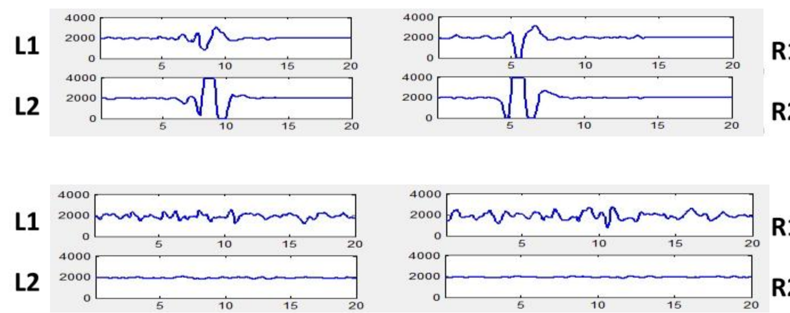
Outside View

Inside View

Indigenous sensor platform developed



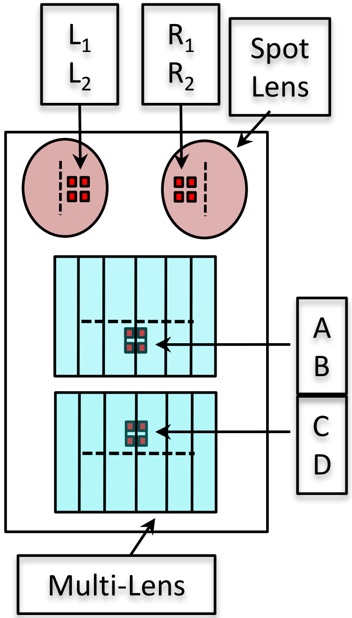
Corresponding VPA generated



Waveform generated by human and clutter

- Sensors A, B, C and D provide vertical spatial resolution
  - Classify intrusions by exploiting difference in their height
  - Human cuts more rows compared to animals
- Sensors L_1, L_2, R_1 & R_2
  - Discriminates between intruder and clutter based on type of motion
  - L and R signals will be highly correlated for an intruder

VPA Design

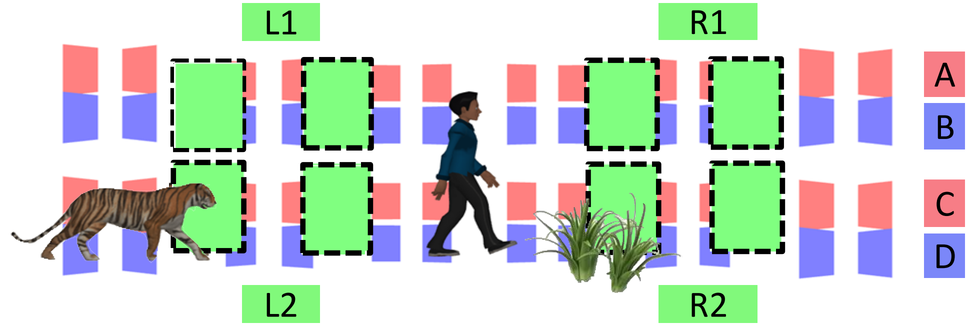


Sensor-lens arrangement

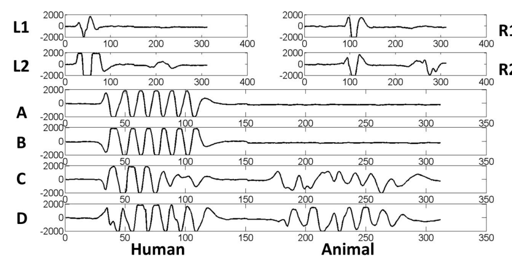
Outside View

Inside View

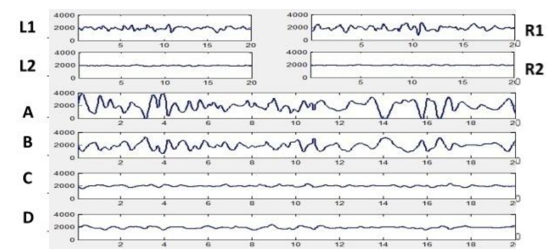
Indigenous sensor platform developed



Corresponding VPA generated



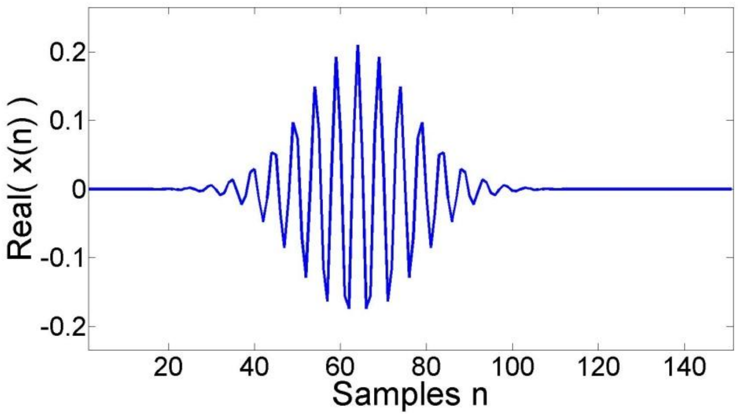
Waveforms for human and animal walking back-to-back



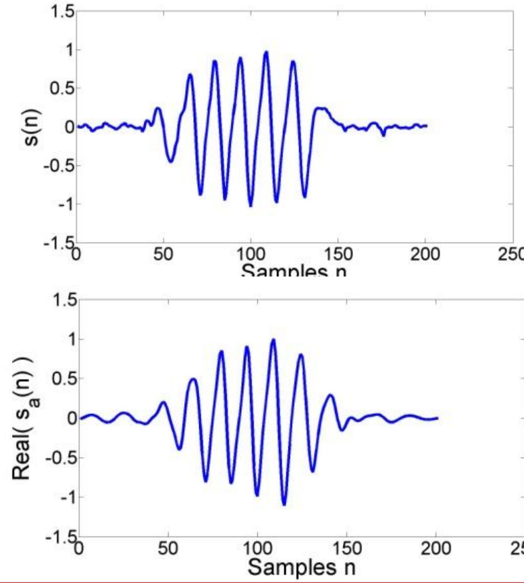
Waveforms for clutter

- Sensors A, B, C and D provide vertical spatial resolution
  - Classify intrusions by exploiting difference in their height
  - Human cuts more rows compared to animals
- Sensors L_1, L_2, R_1 & R_2
  - Discriminates between intruder and clutter based on type of motion
  - L and R signals will be highly correlated for an intruder

Intruder Detection via Chirplet Decomposition



Example chirplet



Real signal approximated by 3 chirplets

- Chirplet $$x(n;m,\omega,c,d) = (2\pi d^2)^{-\frac{1}{4}} \exp\left\{-\frac{(n-m)}{4d^2}\right\} \times \exp\left\{ j\frac{c}{2}(n-m)^2 + j\omega(n-m)\right\}$$
- Complex analytic representation of signal $s_a(n) = s(n) + j\hat{s}(n)$
- Intruder signal well approximated by sum of 3 chirplets: $s_a(n) = \sum_{i=1}^{3} a_i e^{j\phi} x_i(n; m_i, \omega_i, c_i, d_i)$
- Chirplet–based feature vector C_{60} : Append ML estimates $(\hat{a}_i, \hat{m}_i, \hat{\omega}_i, \hat{c}_i, \hat{d}_i)$ corresponding to 3 chirplets
- C_{60} has dimension 60: (5 Parameters per Chirplet * 3 Chirplets per Signal * 4 Signals)

Reference : J. C. O'Neill, P. Flandrin and W. C. Karl, *"Sparse representations with chirplets via maximum likelihood Estimation"*

Chirplet Decomposition for Human and Clutter