Design, development, study and deployment of a passivE InfraRed based Intrusion System for an outdoor environment

Tarun Choubisa, Raviteja Upadrashta, A. Praneeth, Tony G.   Advisor: Prof. P. Vijay Kumar

Human-Animal Conflicts

Long-Range Goal

Exploring the use of WSN for the minimization of human-animal conflicts

Different Sensing Modalities

Pyroelectric Infra-Red (PIR)

Pulse Doppler Radar

Fiber Optics

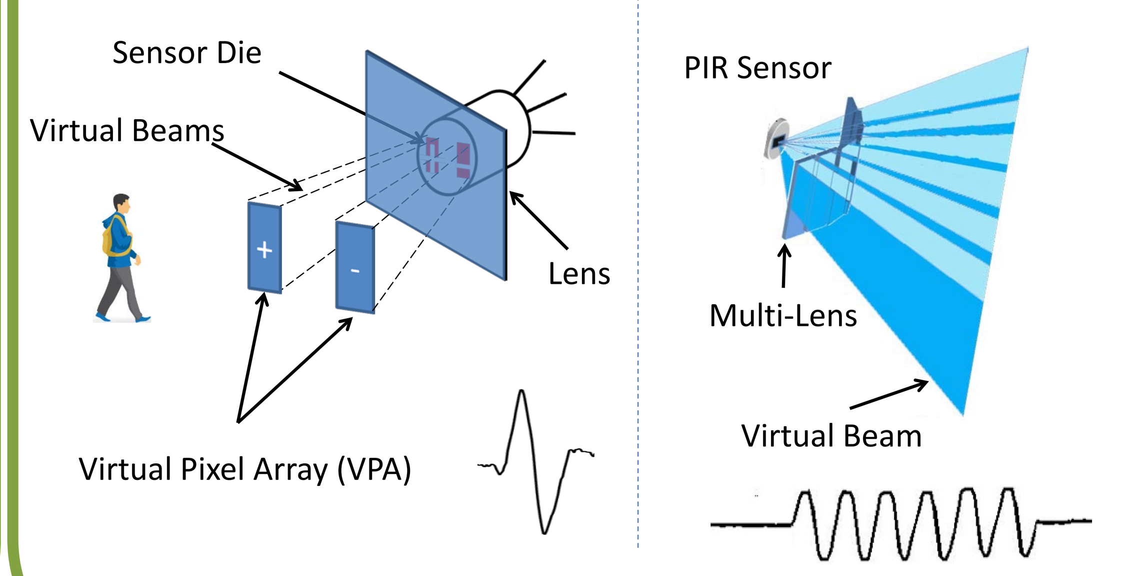
Our Focus

PIR

PIR | Pulse Doppler Radar | Fiber Optics

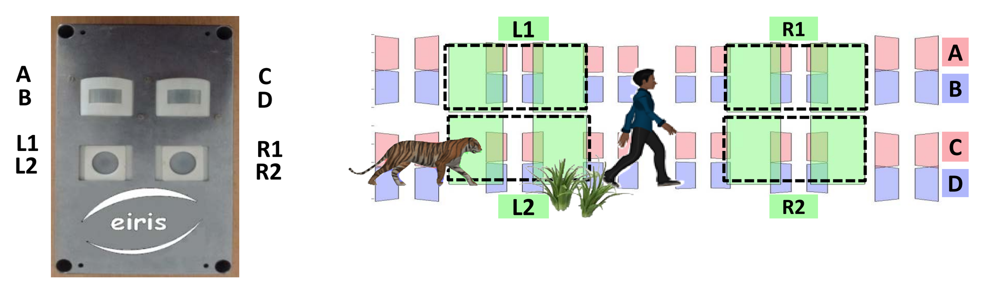
Working of PIR Sensor System

Spot Lens | Multi-lens

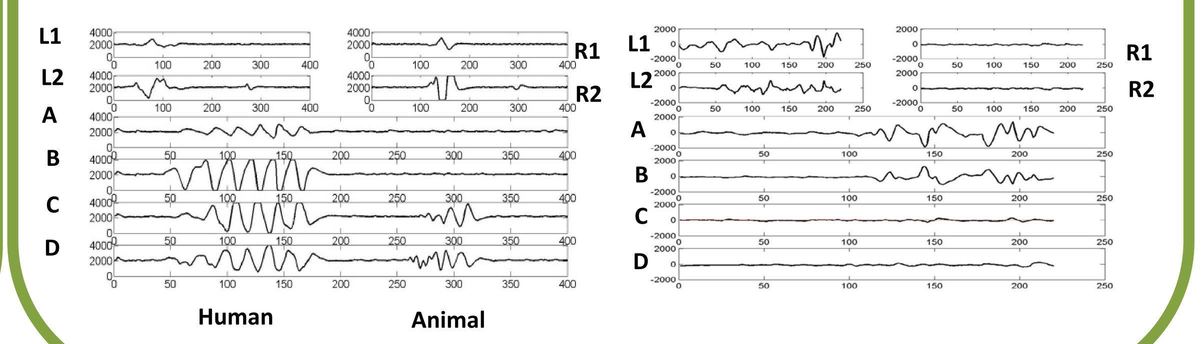


VPA : Intersection of virtual beams with a plane

Height and Motion based Classification

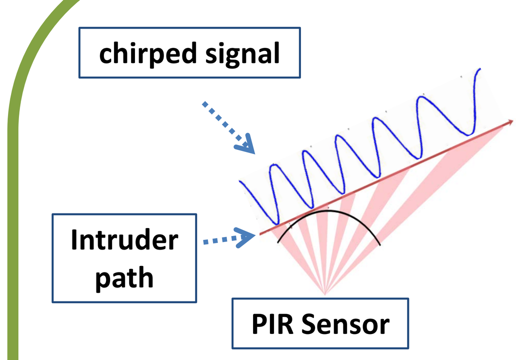


Difference in height | Vegetation: oscillatory motion



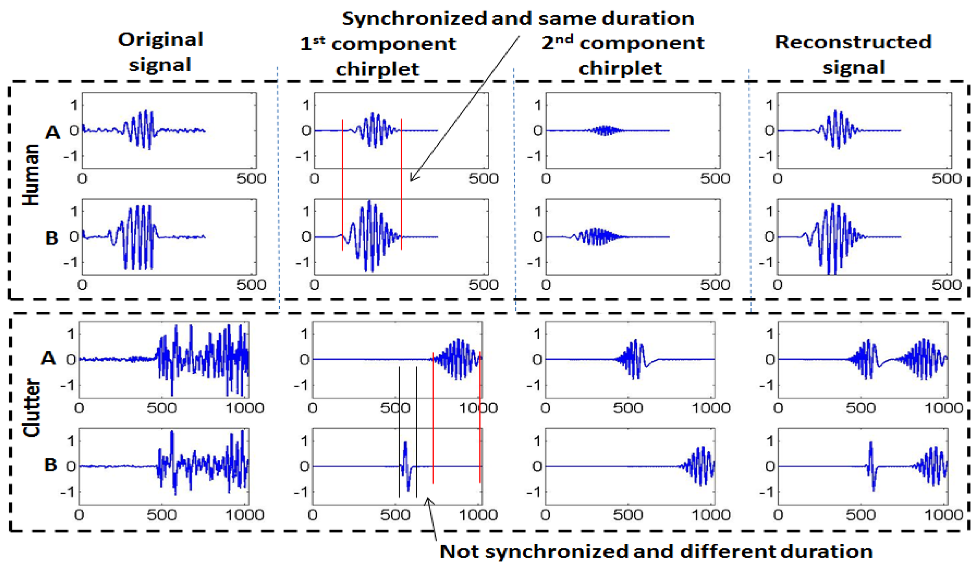
EIRIS: a passivE InfraRed based Intrusion System

Chirplet-Based Algorithm for Intrusion Detection

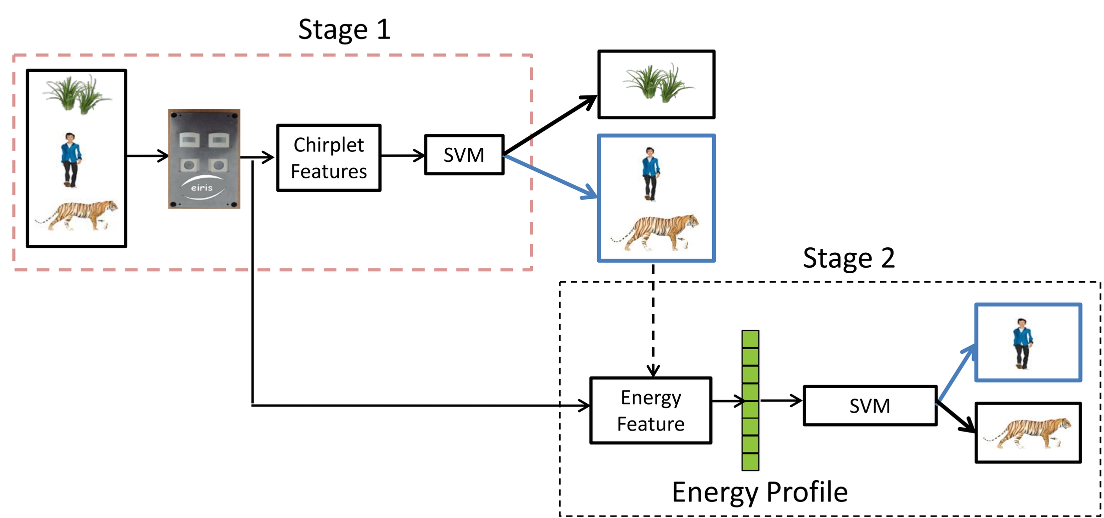


Intruder Signal | Clutter Signal

$$x(n;m,\omega,c,d) = (2\pi d^2)^{-\frac{1}{4}} \exp\left\{-\left(\frac{n-m}{2d}\right)^2\right\} \times \exp\left\{j\omega(n-m) + j\frac{c}{2}(n-m)^2\right\}$$



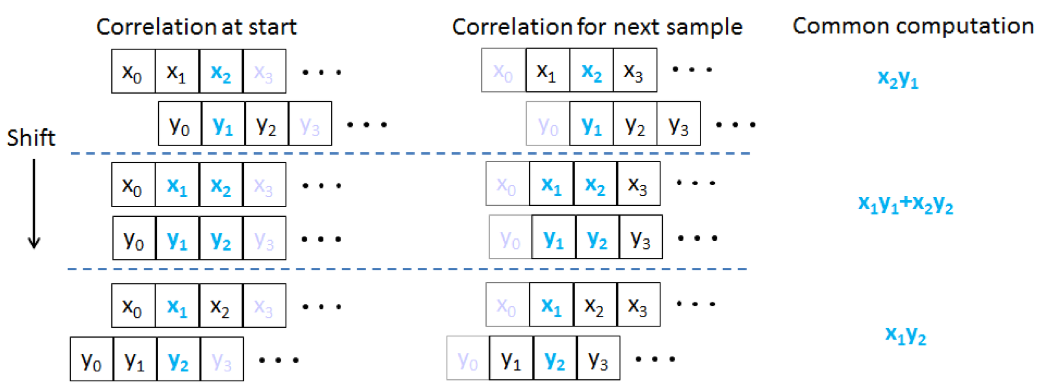
Final 2-Stage Classifier



Classification Accuracy

	Clutter	Intruder	Human	Animal	Overall
Average Accuracy	98.5 %	99.4 %	98.0 %	98.7 %	97.9 %
Standard Deviation	1.8 %	0.7 %	1.9 %	1.6 %	1.3 %

Simplified Correlation and Energy



$C(-2,0) = x_2y_0$
$C(-1,0) = x_1y_0 + x_2y_1$
$C(0,0) = x_0y_0 + x_1y_1 + x_2y_2$
$C(1,0) = x_0y_1 + x_1y_2$
$C(2,0) = x_0y_2$

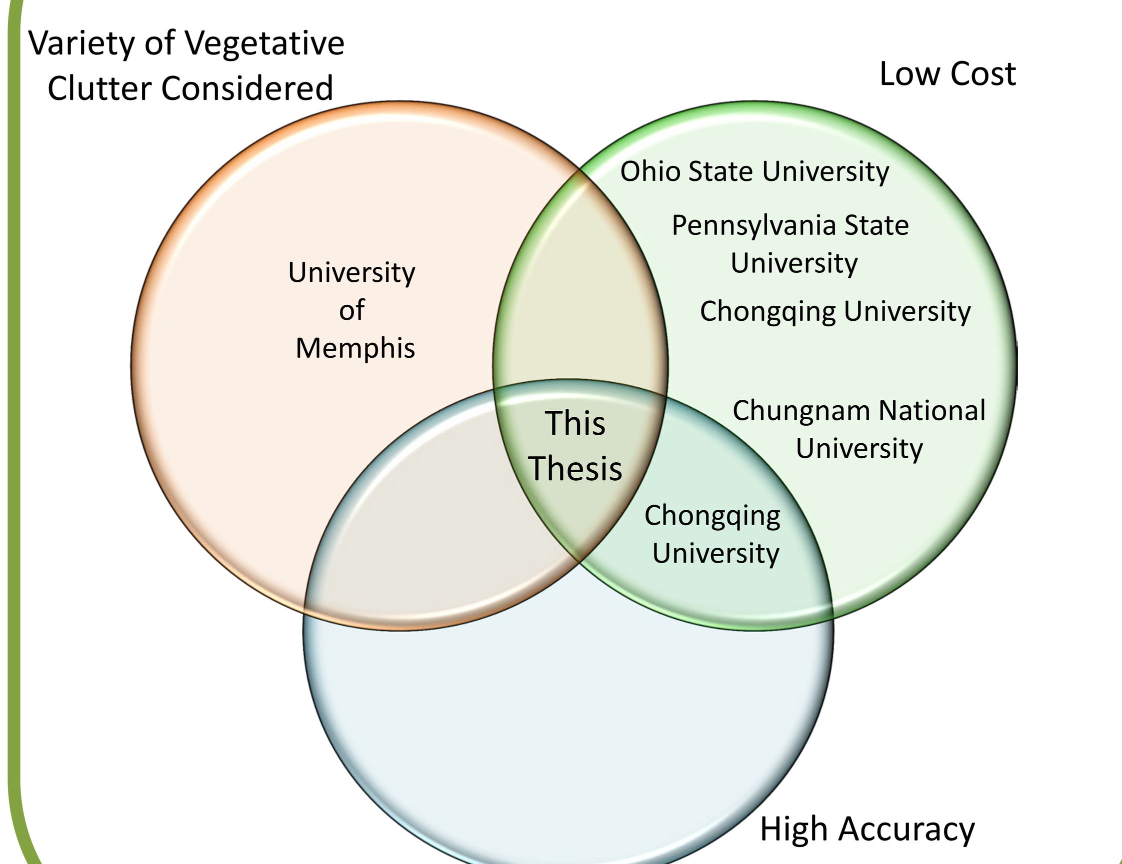
$C(-2,1) = x_3y_1$
$C(-1,1) = x_2y_1 + x_3y_2$
$C(0,1) = x_1y_1 + x_2y_2 + x_3y_3$
$C(1,1) = x_1y_2 + x_2y_3$
$C(2,1) = x_1y_3$

Reduces the computation complexity from O(W2) to O(W)

$$\hat{E}_A(m) = \alpha \hat{E}_A(m-1) + s^2{}_A(m)$$

Energy Calculation: Reduced Memory Requirements

Literature: PIR Sensors in an Outdoor Setting

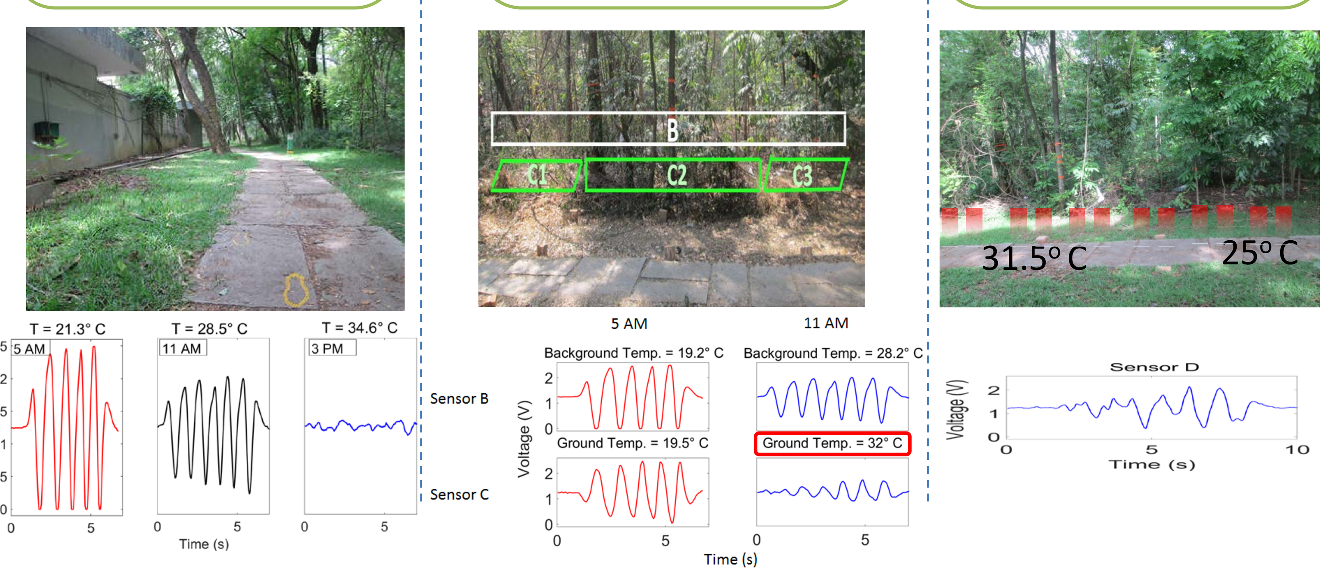


Impact of Background Temperature on PIR Signals

Dramatic drop in signal strength as ambient temperature approaches human-body temperature

Impact of temperature on different surfaces: background and ground

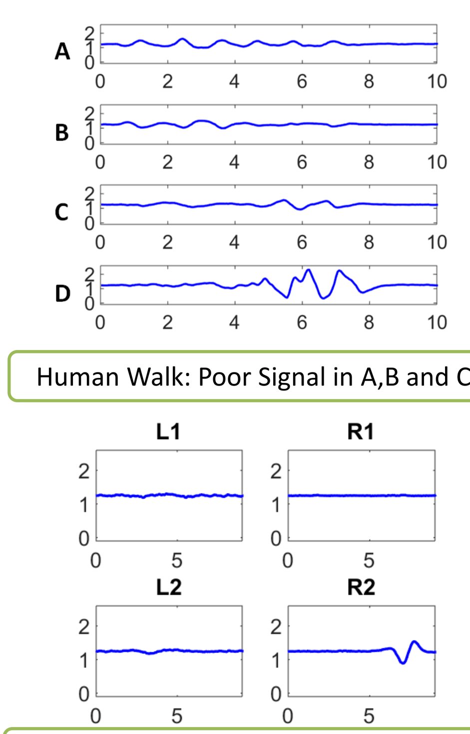
Impact of sunny and shadow patches: spatial variation



We are the first to recognize and study the impact of temperature on PIR signal [1]

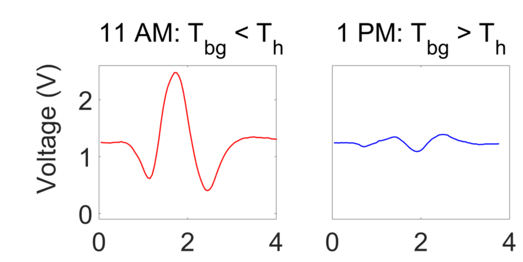
[1] Choubisa et. al. "**Challenges in Developing and Deploying a PIR Sensor-Based Intrusion Classfication System for an Outdoor Environment**", Eleventh IEEE International Workshop on Practical Issues in Building Sensor Network Applications (*SenseApp* 2016), November 2016, Dubai,

Consequence of Temperature on PIR Signals



Human Walk: Poor Signal in A,B and C

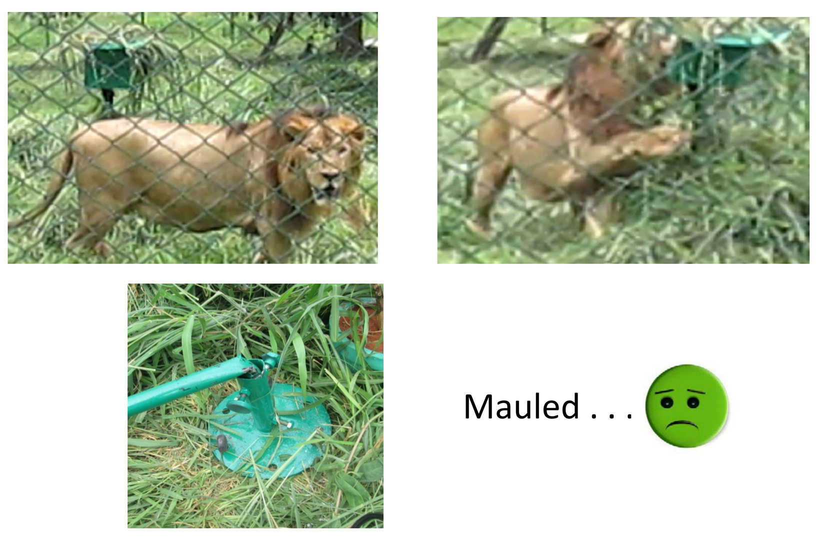
Dog Walk: Poor Correlation for L2 and R2



Polarity reversal for the human walk in same direction

Solution: Employ a complimentary sensing modality such as a low-power optical camera (Ongoing work)

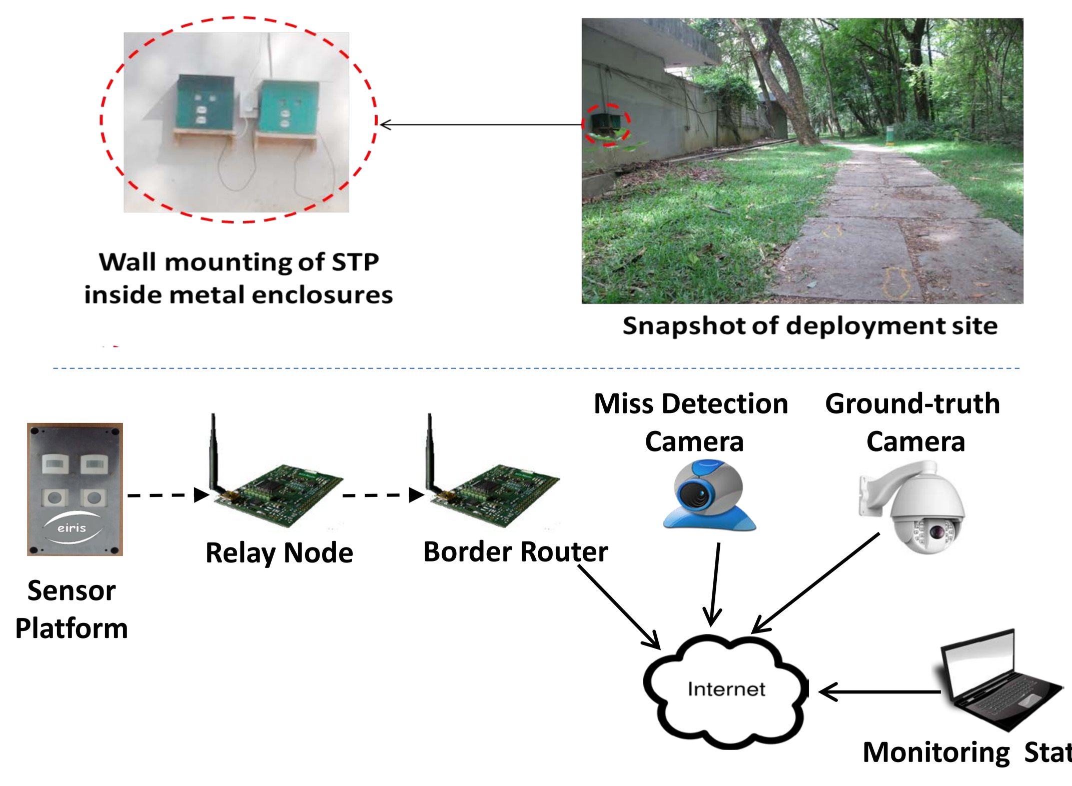
A Learning in Bannerghatta Park



Mauled . . .

Day 1: Platform deployed outside fenced area
24 detections registered - no false alarms or misclassifications
Day 2: STP shown placed inside the lion enclosure
Platform was mauled . . .

Deployment at Main Guest House (MGH) IISc



Demoed the sensor platform and MGH deployment at LCN, Dubai

Example: Captured Motions

Classification Accuracy Results

Exponential Weighted Energy and Recursive Correlation

Intruder vs Clutter

	Minimum Accuracy	Average Accuracy
Detecting Intruder	96.8 %	96.5 %
Rejecting Clutter	92.6 %	96.3 %
Overall	95.5 %	96.4 %

Human vs Animal

	Minimum Accuracy	Average Accuracy
Human Detection	92.1 %	96.9 %
Animal Detection	100.0 %	98.3 %
Overall	93.9 %	97.2 %

Classification via Support Vector Machine (SVM)

Deployment at Main Guest House, IISc

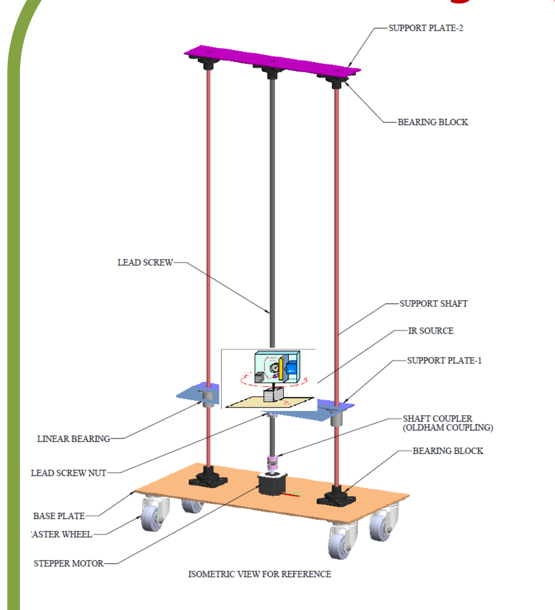
During **March** (2 days)

Intrusions	Correctly Detected	Misses	Misclassified	False Alarms
518	446	25	47	31

During **April and May** (4 days)

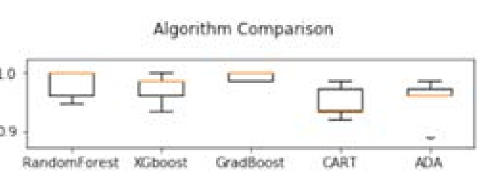
Intrusions	Correctly Detected	Misses	Misclassified	False Alarms
734	693	18	29	5

Ongoing Work



VPA Testing Station : tie-up with Centum Electronics

Intruder classification using optical camera



Comparing different features and classifiers

Design, development, study and deployment of a passiv**E** **I**nfra**R**ed based **I**ntrusion **S**ystem for an outdoor environment

Tarun Choubisa

ECE Department

Thesis Advisor: Prof. P. Vijay Kumar

WSN for the Minimization of Human-Animal Conflicts

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Exploring the use of WSN for the minimization of human-animal conflicts

Different Sensing Modalities

Pyroelectric Infra-Red (PIR)

Pulse Doppler Radar

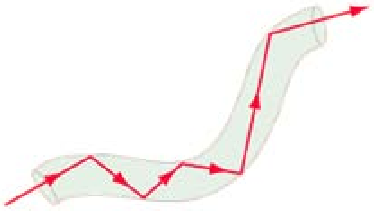
Fiber Optics

Our Focus

PIR

PIR

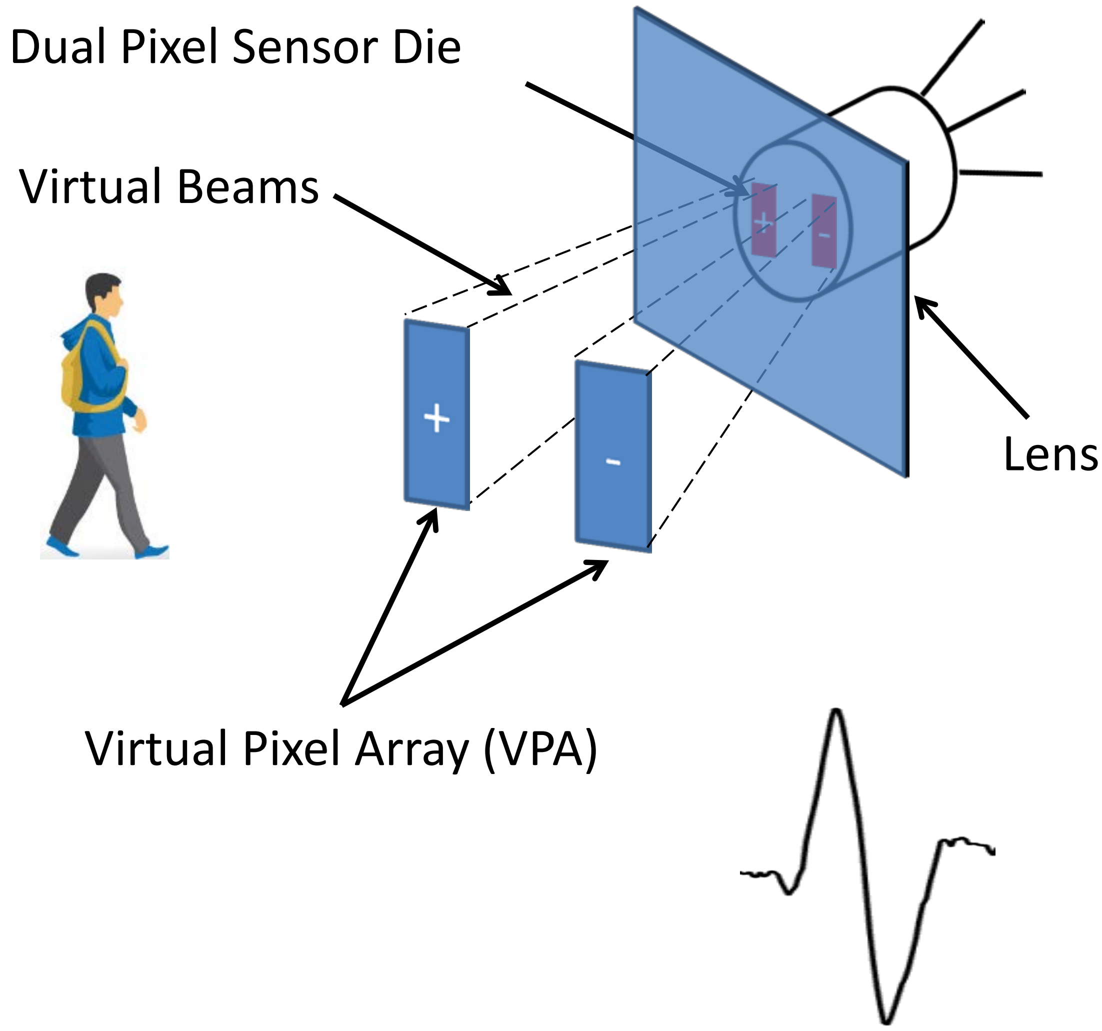
Pulse Doppler Radar



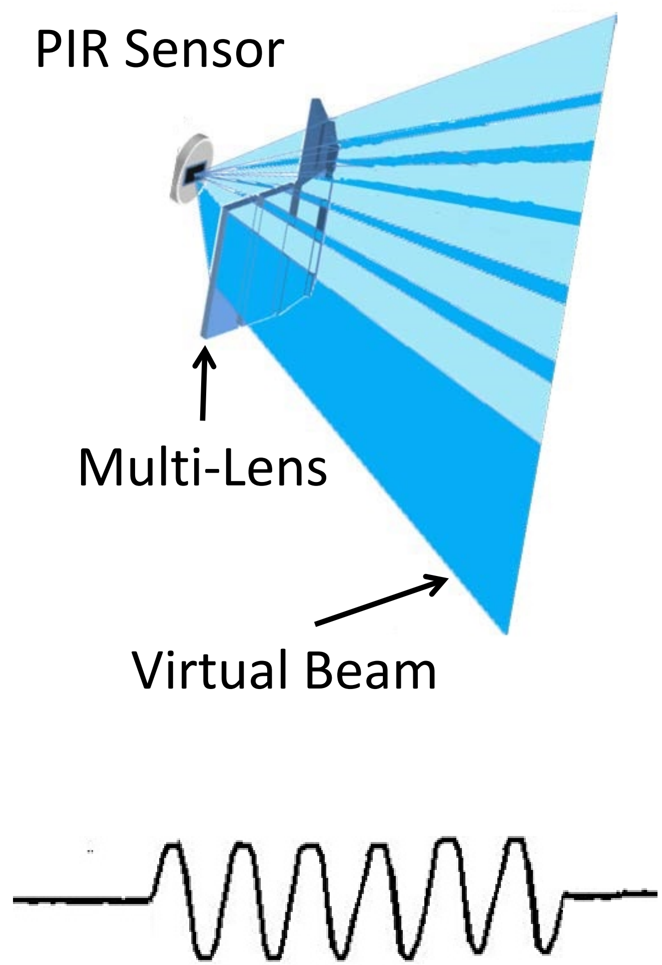
Fiber Optics

PIR Sensors: Detects Change in Incident Radiation

Signals generated from Intrusion

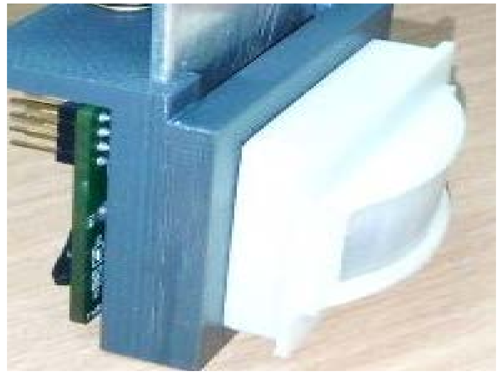


More sophisticated: multi-lens



Challenges Faced in Outdoor Deployments

False Alarms from Wind-Blown Vegetation

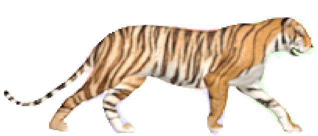


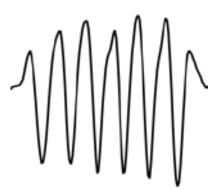
Wind-Blown Vegetation (Clutter)

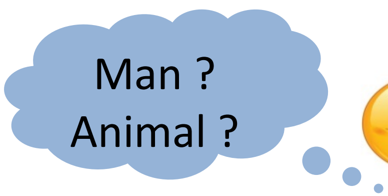
PIR Module

Output Signal

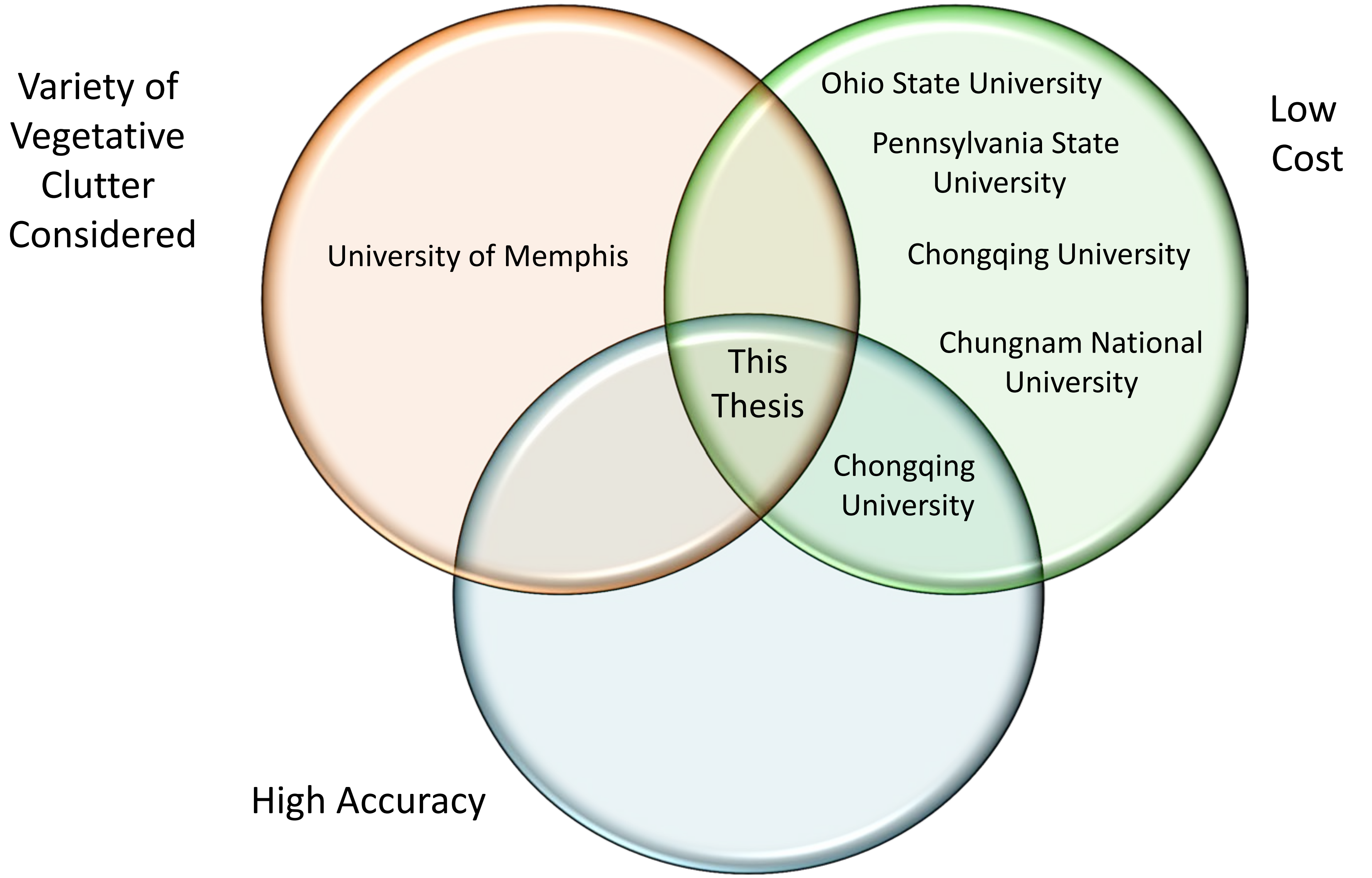
Need for Human/Animal Classification



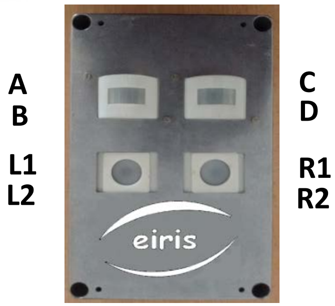




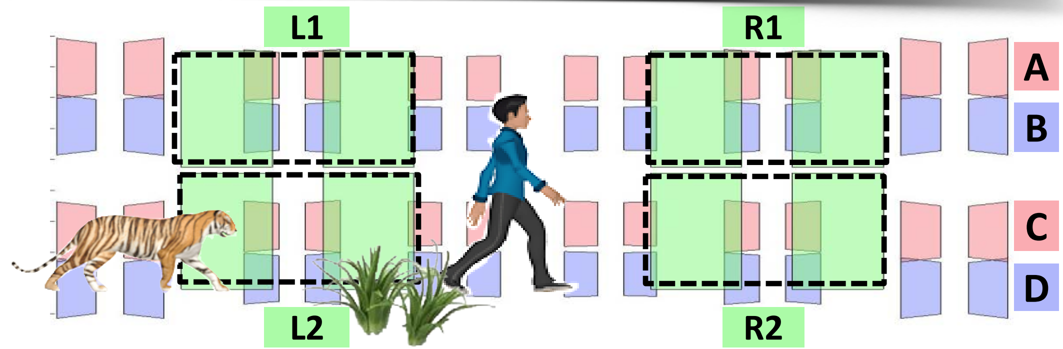
Literature Relating to the Use of PIR Sensors in an Outdoor Setting



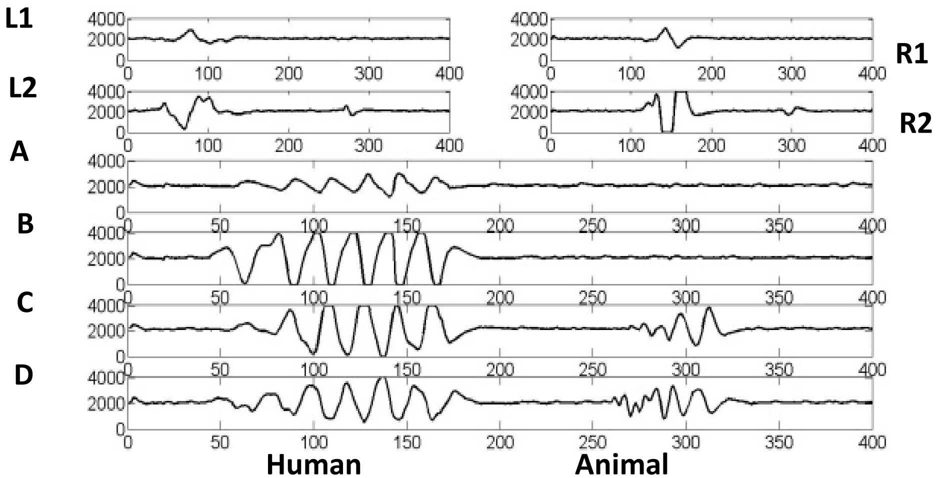
EIRIS: a passivE InfraRed based Intrusion System



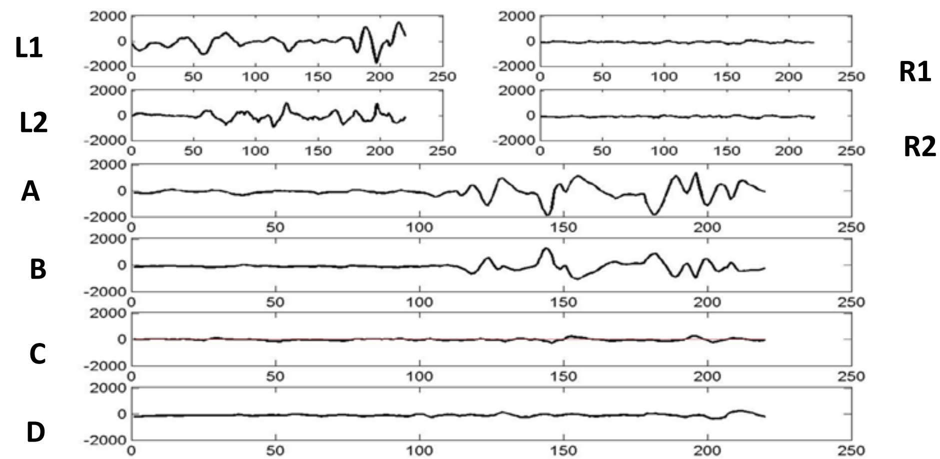
In-house developed PIR sensor platform



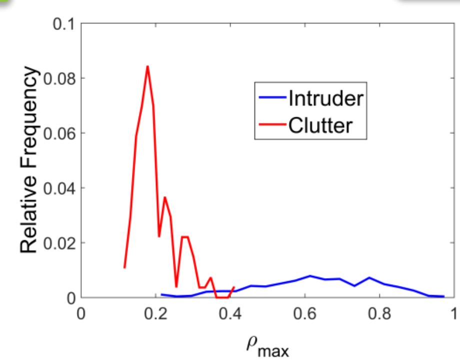
Designed VPA



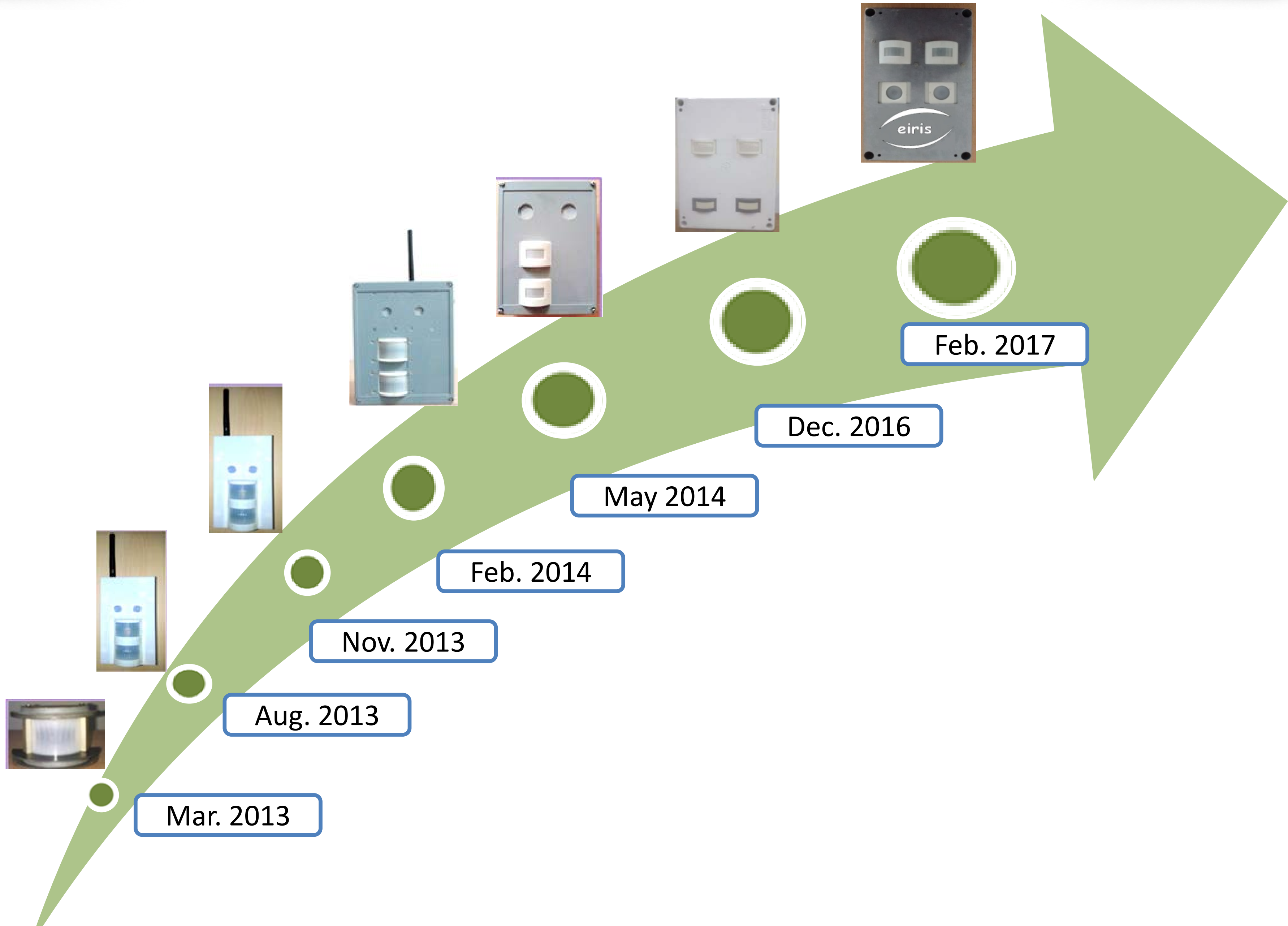
Intruder Waveforms



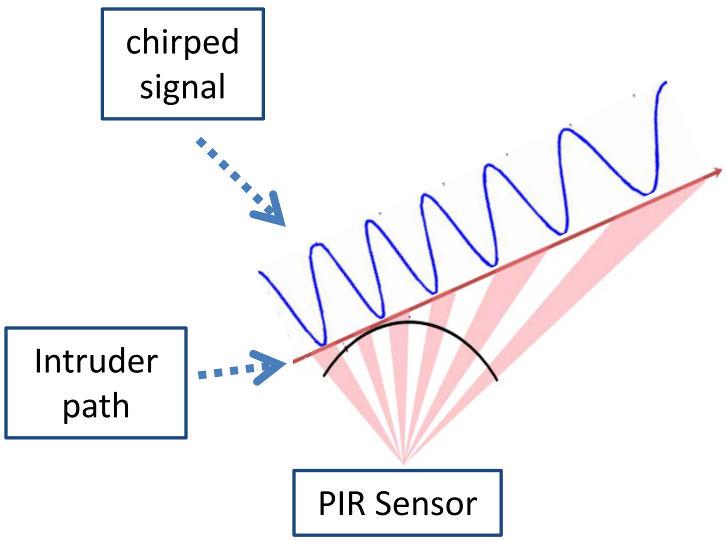
Clutter Waveform



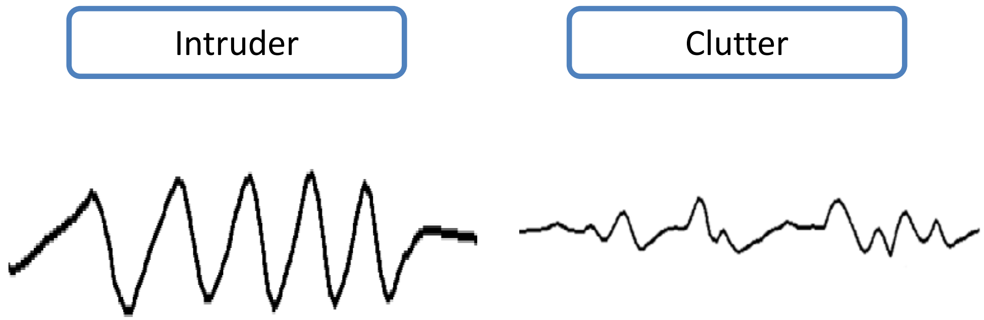
Evolution of Sensor Platform



Chirplet-Based Model For Intruder Detection

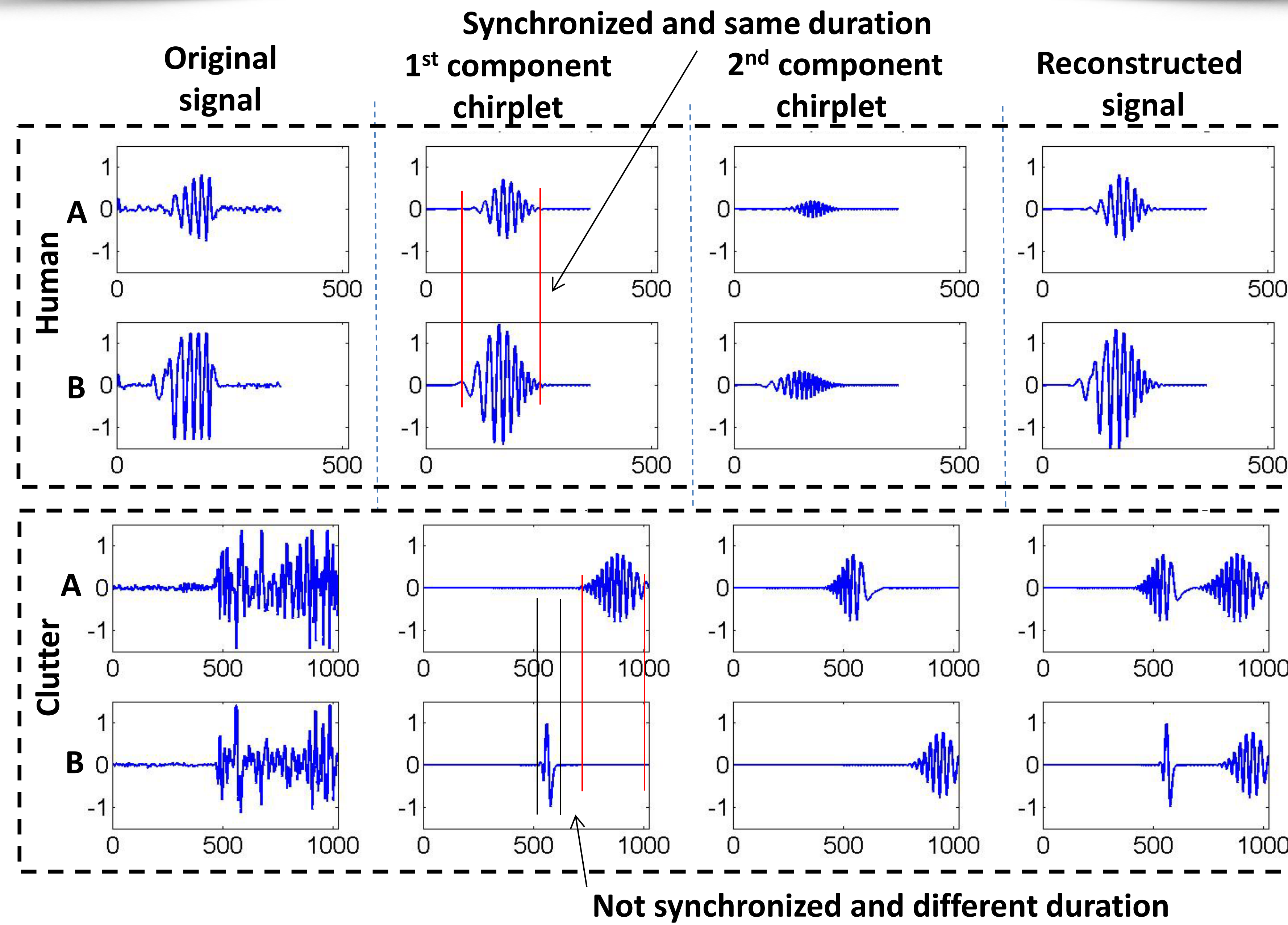


Explaining the chirp

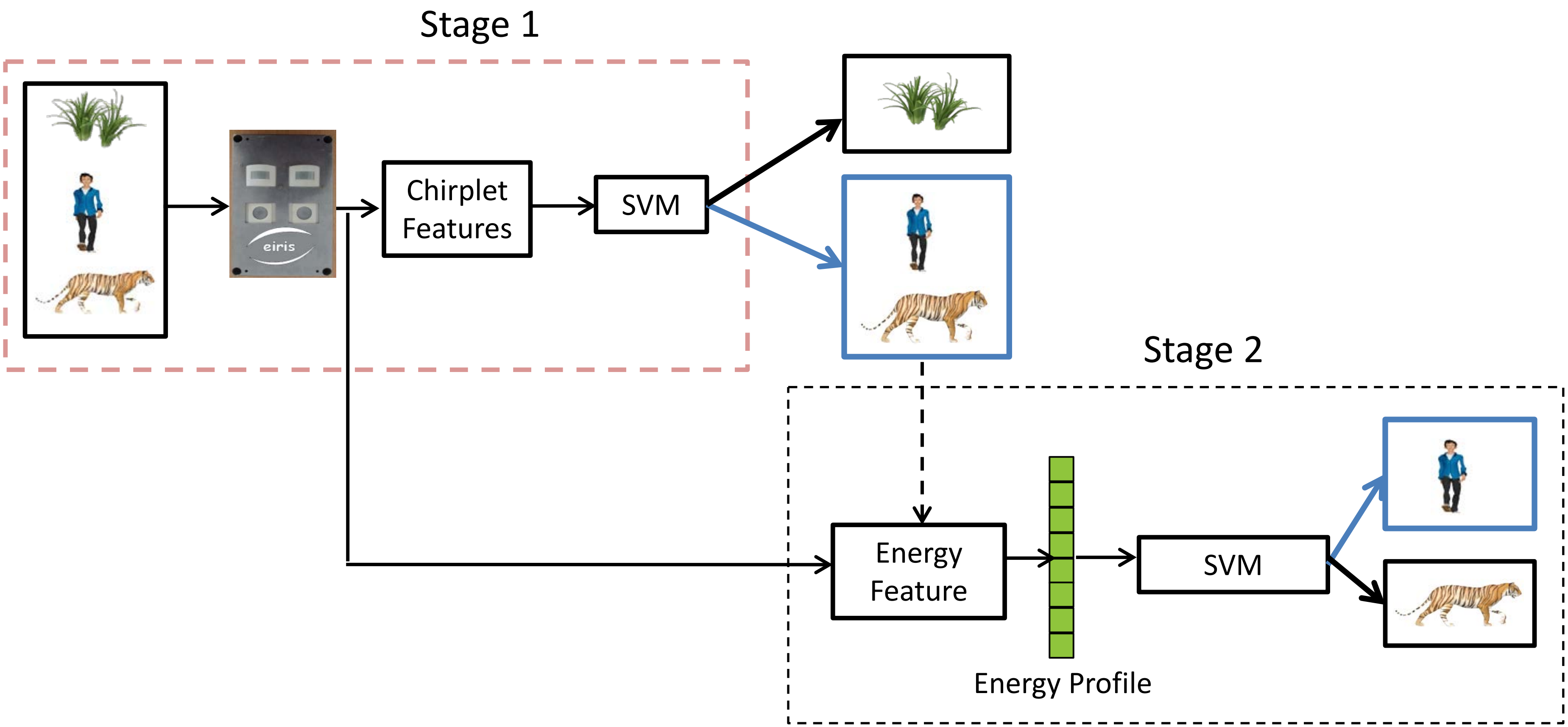


Observed Intruder and clutter signals

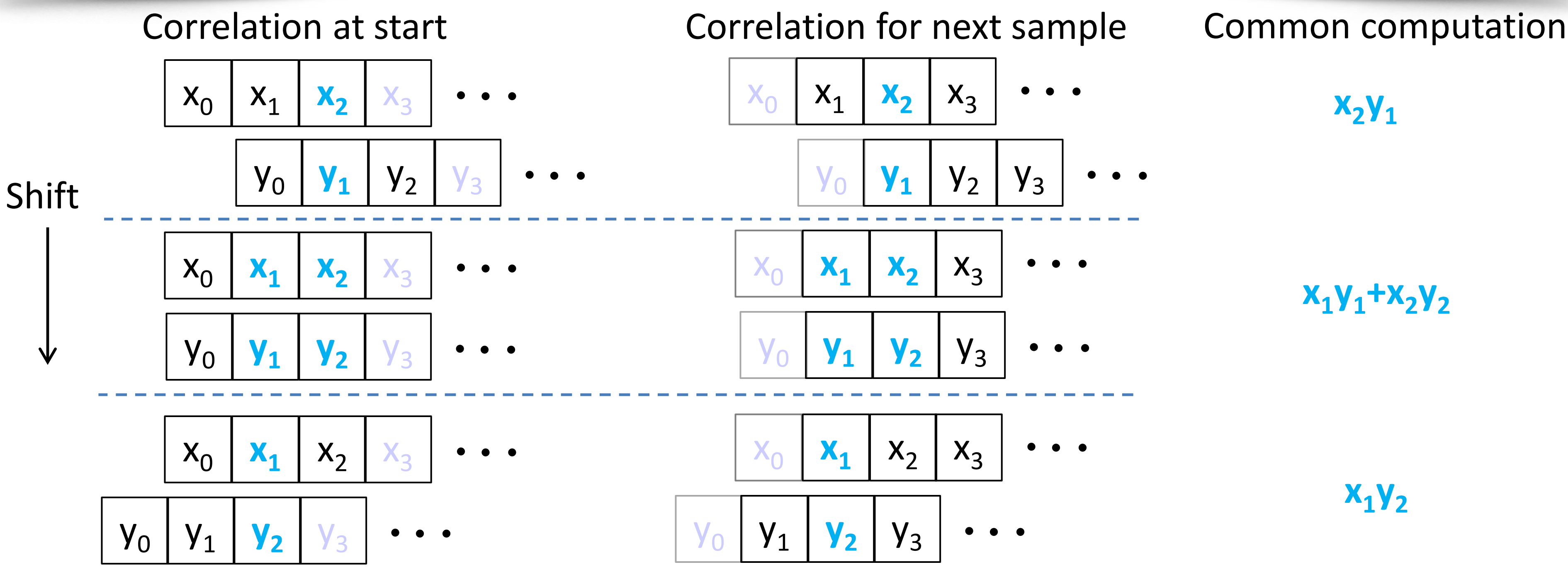
How Does Chirplet Decomposition Help?



Final 2-Stage Classifier: Classification Accuracy



Simplified Correlation and Energy Calculations



Reduces the computation complexity from O(W2) to O(W)

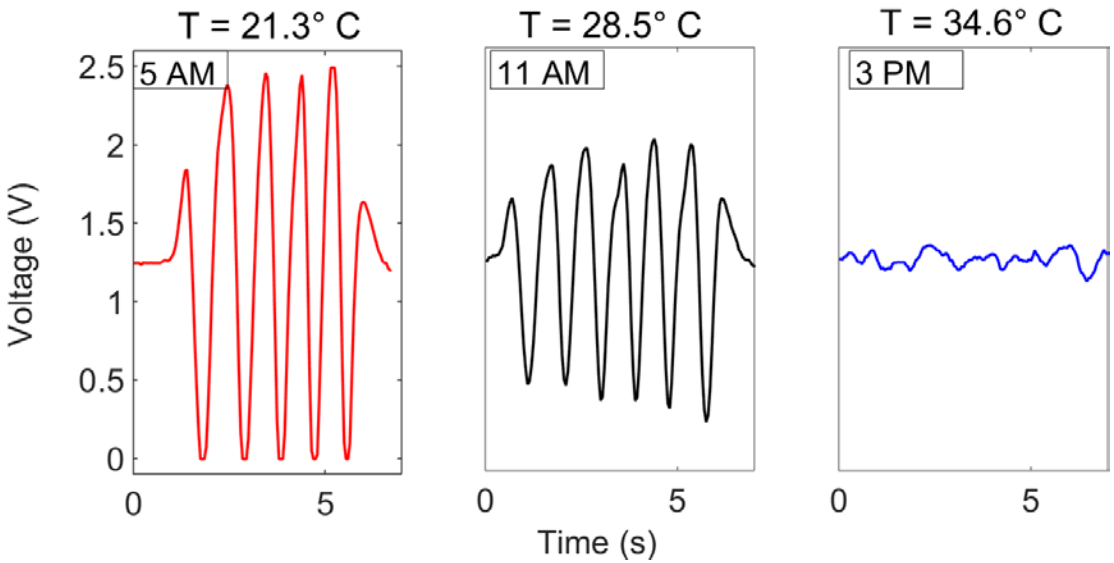
$$\hat{E}_A(m) = \alpha \hat{E}_A(m-1) + s^2{}_A(m)$$

Energy Calculation: Reduced Memory Requirements

	Clutter	Intruder	Human	Animal
Chirplet and Energy	98.5 %	99.4 %	98.0 %	98.7 %
Simplified Correlation and Energy	96.3 %	96.5 %	96.9 %	98.3 %

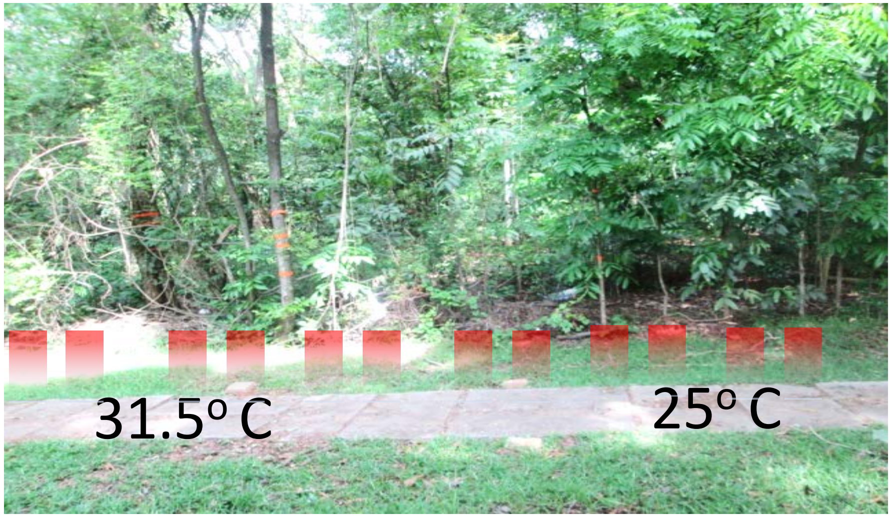
Impact of Background Temperature on PIR Signals

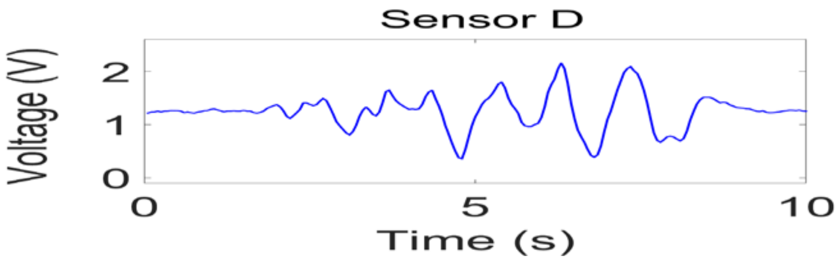
Dramatic drop in signal strength as ambient temperature approaches human-body temperature



Impact of Background Temperature on PIR Signals and Solution

Impact of sunny and shadow patches: spatial variation





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Solution: Employ a complimentary sensing modality such as a low-power optical camera (Ongoing work)

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A Learning Experience in Bannerghatta Park, Bangalore

Mauled . . .

Day 1: Platform deployed outside fenced area

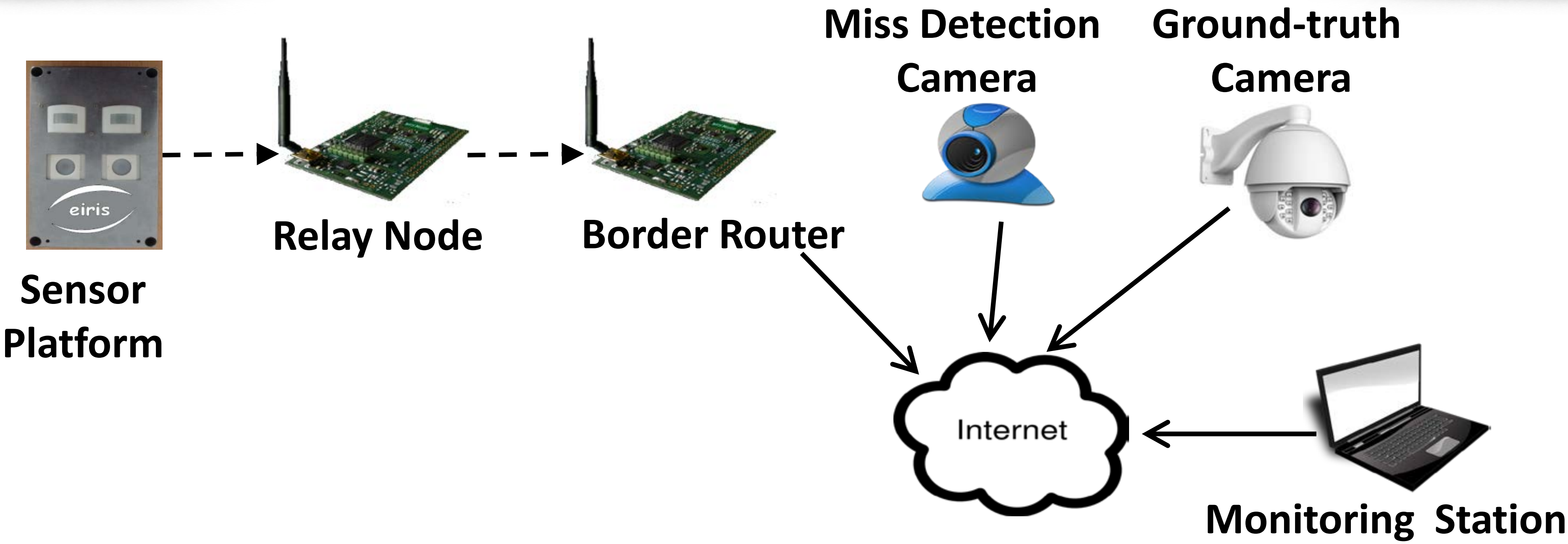
24 detections registered - no false alarms or misclassifications

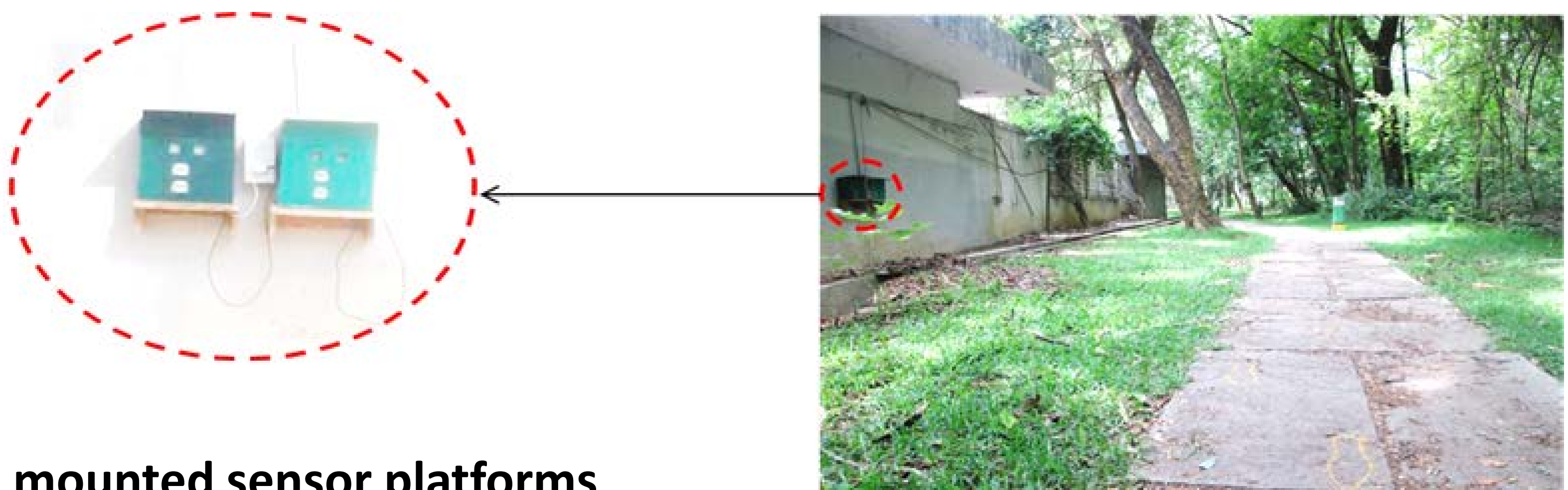
Day 2: STP shown placed inside the lion enclosure

Platform mounting was mauled …

Deployment: Bannerghatta Park, Bangalore, India

Deployment at Main Guest House, IISc





Wall mounted sensor platforms

Deployment Site

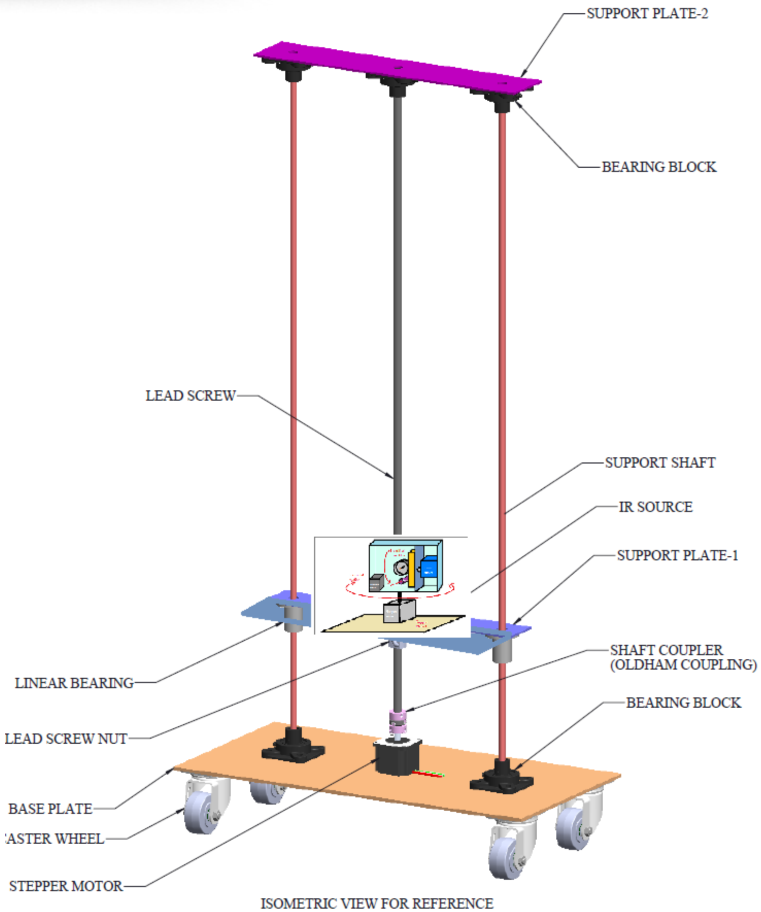
Example Intrusions: Classified by the Platform

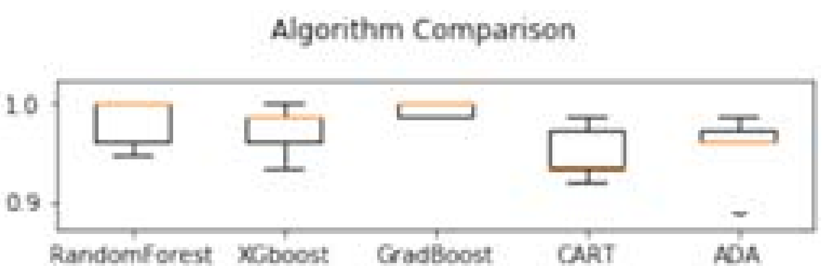
During April and May (4 days)

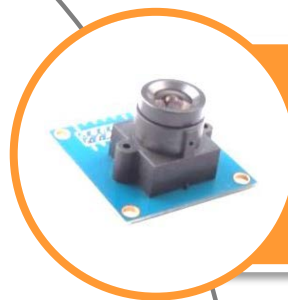
Intrusions	Correctly Detected	Misses	Misclassified	False Alarms
734	693	18	29	5

Demoed the sensor platform and MGH deployment at LCN Conference, Dubai

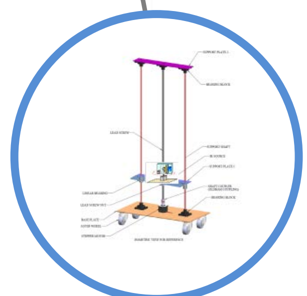
Ongoing Work



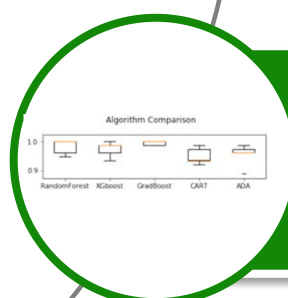




Camera as complementary modality



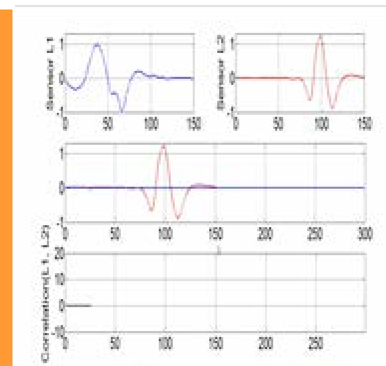
VPA testing Station: tie-up with Centum Electronics



Comparing different features and classifiers

Thank You! Questions?

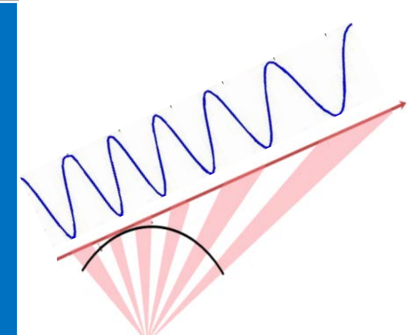
Remote Deployment



Algorithm Design

Platform

Signals

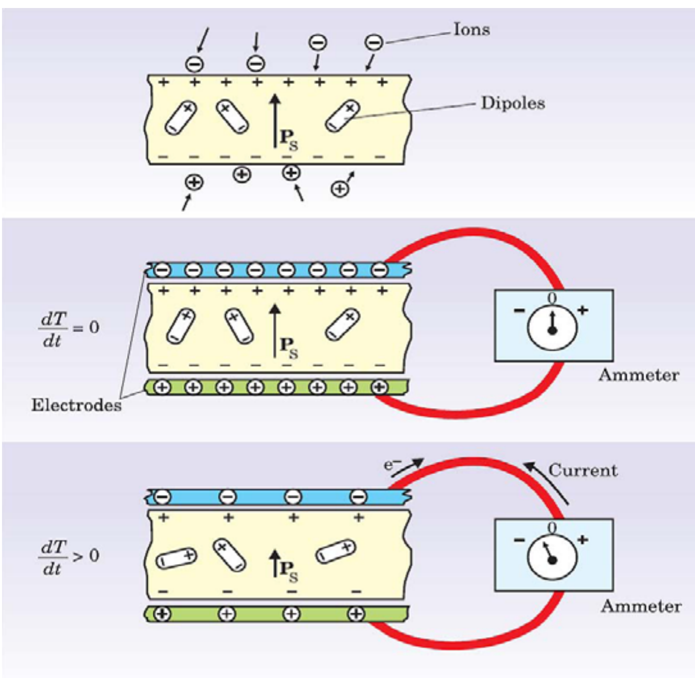


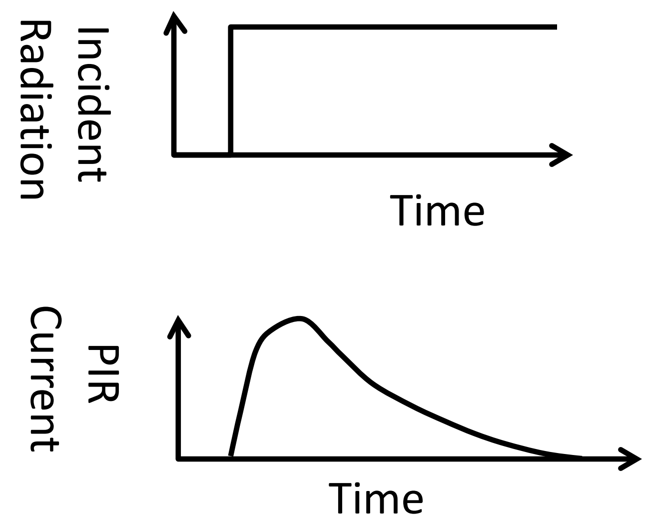
Backup Slides

PIR Sensing: Pyroelectricity

- PIR sensors work on the principle of pyroelectricity
  - Temperature (T) dependent spontaneous polarization Ps
  - Detects changes in incident radiation (w)

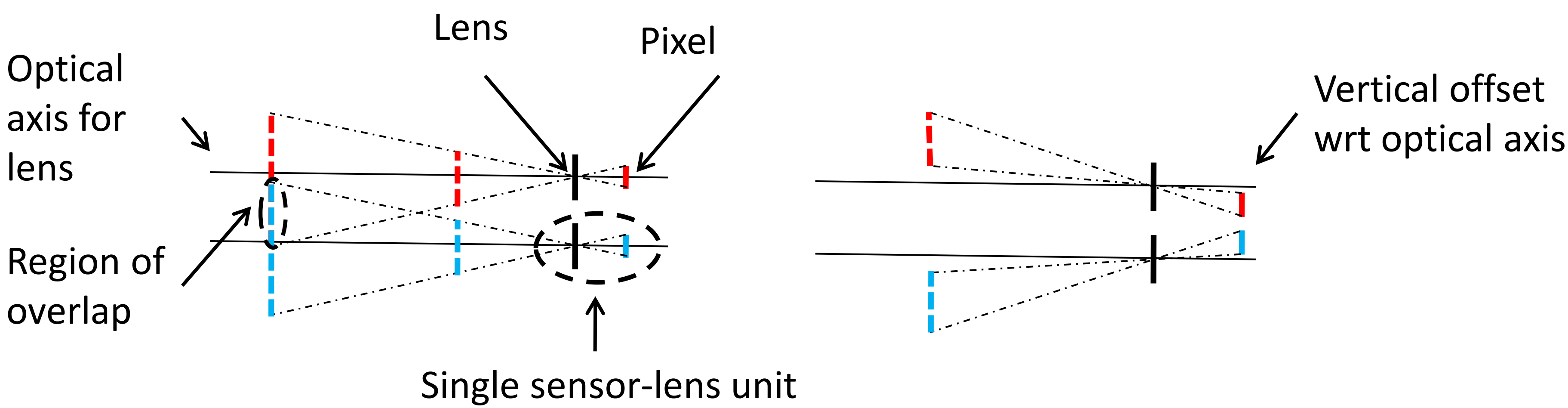
Δw → ΔT → transient current





Incident radiation and resultant current

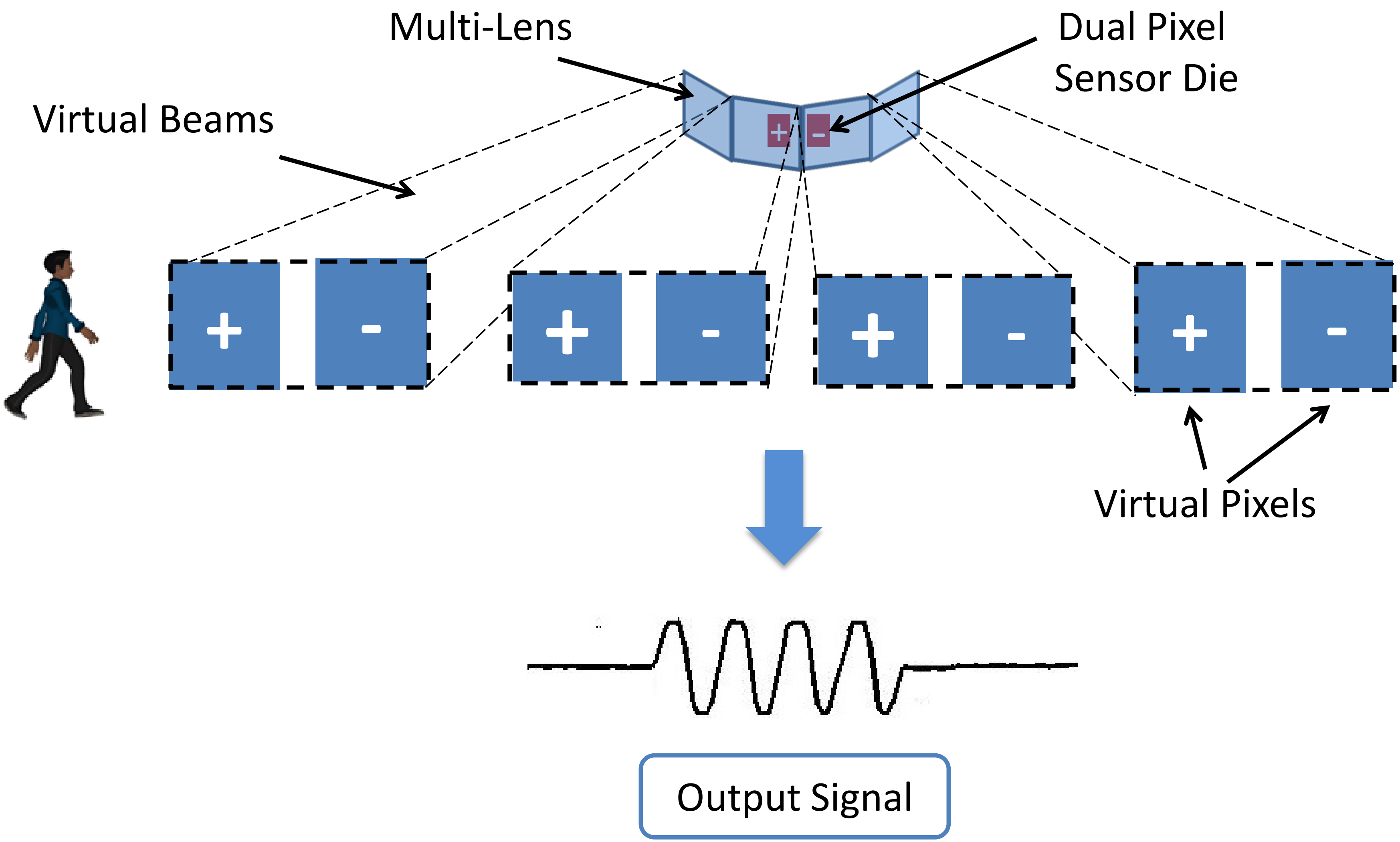
Preventing Overlap of VPA



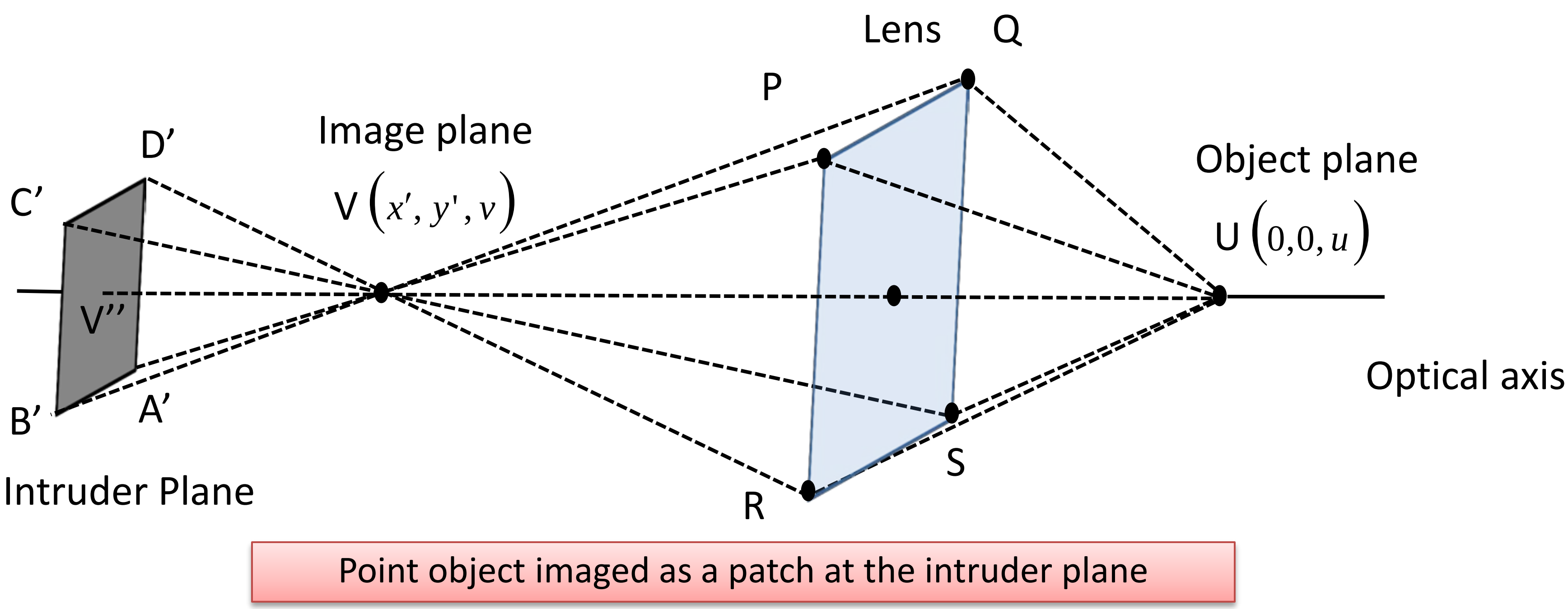
Effect of vertically offsetting sensor wrt lens to prevent overlapping beams

- The VPA generated by two sensor-lens units can overlap
  - Offset sensor wrt lens to prevent overlap

VPA when a Multi-lens is Used



Point Spread Function



- Object Plane has one and only one corresponding image plane
  - Intruder plane is not restricted to
- Blurred patch is called the Point Spread Function (PSF) of the lens
  - Viewed as impulse response of the lens
  - It is a scaled version of the lens aperture
- The spread (dimensions of the patch) is $h = A\left(\frac{d}{v} - 1\right)$

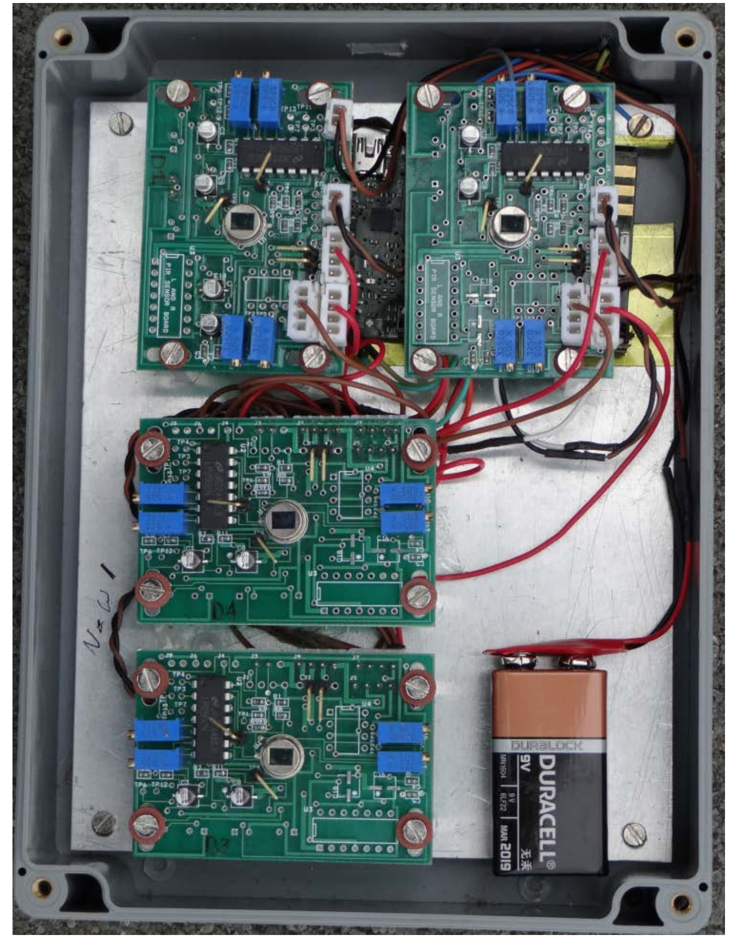
Literature Relating to the Use of PIR Sensors in an Outdoor Setting

Author Year	Type of PIR Sensor	Indoor or Outdoor	Target Range and Motion	Classification Approach	Test Environment(s)	Number of classes	Objects Classified	Accuracy	Comment
Lin [21] 2005	Single analog sensor	Outdoor	5m (approximately)	Frequency-domain filtering followed by adaptive thresholding	200 nodes, three sensing modalities	4	Humans, humans with ferrous objects, vehicles, absence of target	NS	Accuracy at individual sensor level not discussed
Arora et al [22] 2005	Single sensor with integrated cone optics	Outdoor	12m (Humans) and 25m (SUV)	Frequency-domain filtering followed by thresholding	0.3 Sq Km opening in a forest	3	Humans, vehicles and absence of target	NS	False alarms arising from moving vegetation not discussed
Wang [23] 2011	Dual-element sensor with 2-layer Fresnel lens	NS	NS	WPE plus LS-SVM	Summer and autumn; 6 humans and 2 dogs; 60 watt bulbs	2	Human versus non-human	91.20%	False alarms arising from moving vegetation not considered
Hong et al [24] 2012	Single, digital PIR with golf-ball type multilens	Outdoor	2m-15m	Neyman-Pearson detector under Bayesian model for (a) window energy and (b) alarm duration	Sensor placed in front of bushes, under 3 conditions: (a) hot and windless day, (b) clear and breezy day and (c) cool day with light wind	2	Human or false alarm	P_{FA} = 9.6%, P_D = 90%	False alarms from moving animals not considered
Gong et al [25] 2012	Single analog sensor	Both	NS	Coefficients of auto-regressive-process model + SVM	NS	2	Human versus non-human (dog, goose)	94.6% (outdoor)	False alarms arising from moving vegetation not considered
Jin et al [26] 2012	Single analog sensor with multilens	Outdoor	5m	CWT + SDF + SVM	3 sites along outdoor trail that included a dry creek bed and some choke points	4	Humans walking and running, animals, absence of target	91.70%	Smaller range of operation, false alarms not explicitly addressed
Chari et al [27] 2014	128-pixel linear array	Outdoor	10m-20m (transverse motion)	Height-width ratio and energy in Gabor-filter frequency bands fed as inputs to decision-tree-based classifier	(a) Arid terrain with thorn bushes and (b) Petting zoo having grass, trees, rolling hills	2	Human versus animal; animals included: small cows, ponies, horses, small donkeys	94%	More expensive lens, higher power consumption of sensor
Zhao et al [28] 2016	Single sensor with 3-layer multilens	Both	NS	EMD + SDF + SVM + Weighted-Voting	NS	2	Humans versus animals (dogs and geese)	99% (outdoor)	False alarms arising from moving vegetation not considered
Upadrashta et al (pesent paper) 2017	Array of 8 analog sensors & 4 multilenses	Outdoor	5m-10m	(Chirp, Correlation, Energy) + SVM on laptop (Energy, Correlation) + SVM on mote	Human and animal motion in a variety of vegetative clutter environments	3	Human versus short animals (dogs, leopard, tiger, wolf), absence of target	97%	Variety of vegetative clutter contained in data set

CWT: Continuous Wavelet Transform
EMD: Emperical Mode Decomposition
LS: Least Squares
SUV: Sport Utility Vehicle
NS: Not Specified
SDF: Symbol Dynamic Filtering
SVM: Support Vector Machine
WPE: Wavelet Packet Entropy

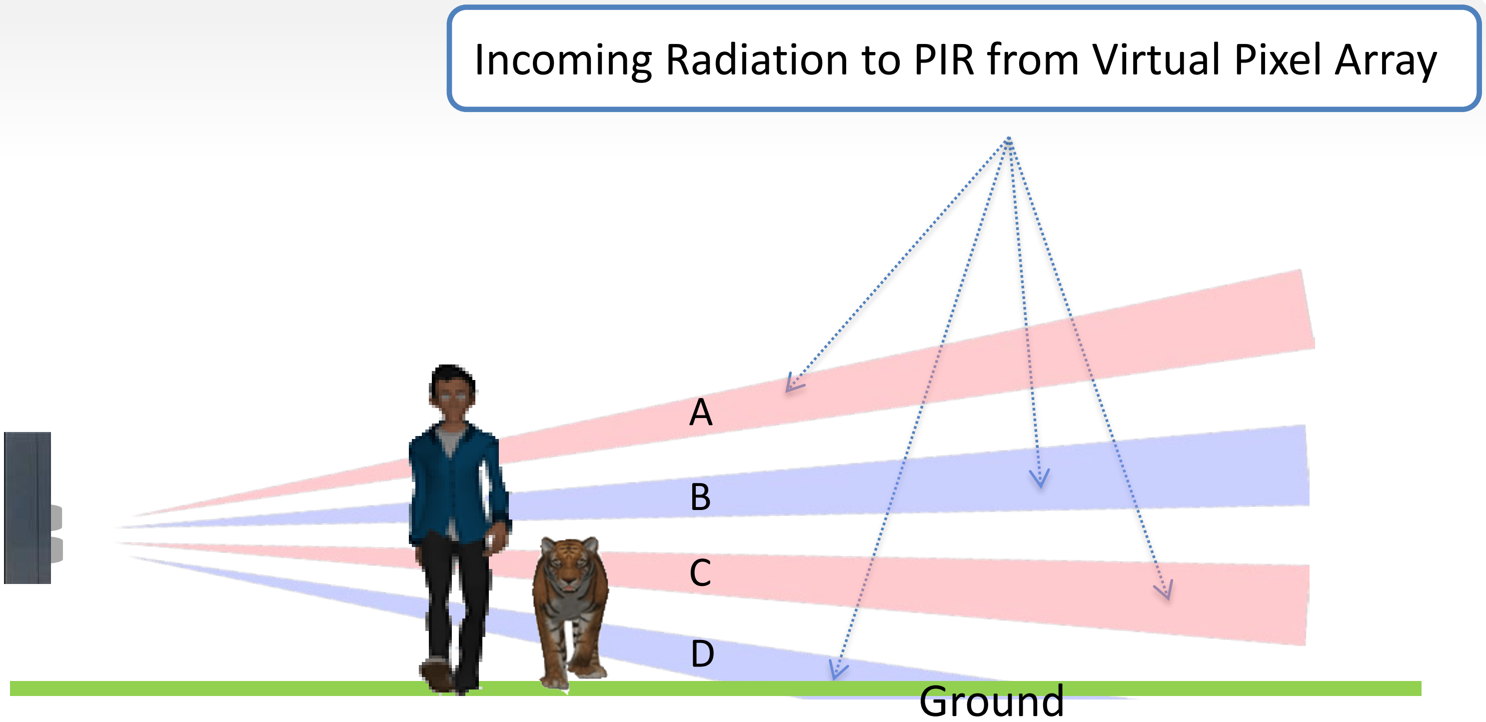
The Sensor Platform (SP)

Lenses on the outside

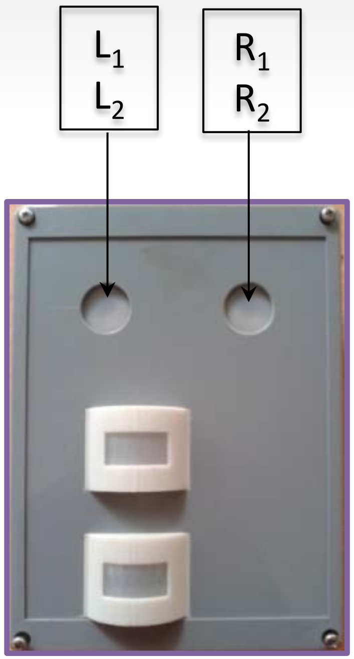


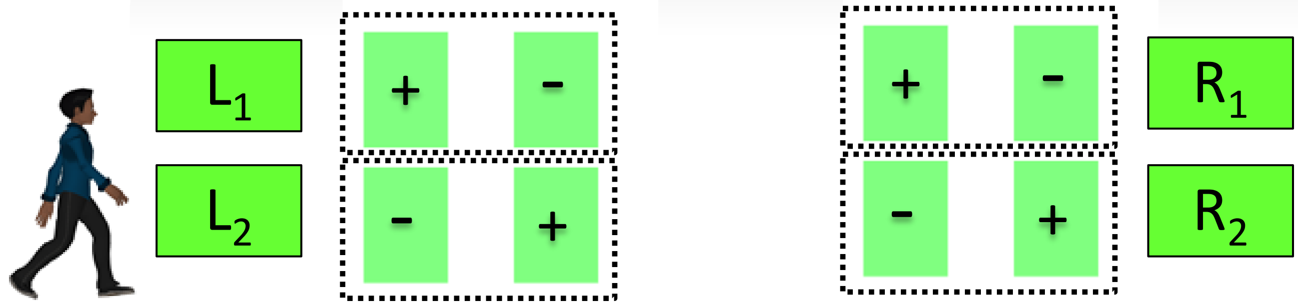
Sensors inside

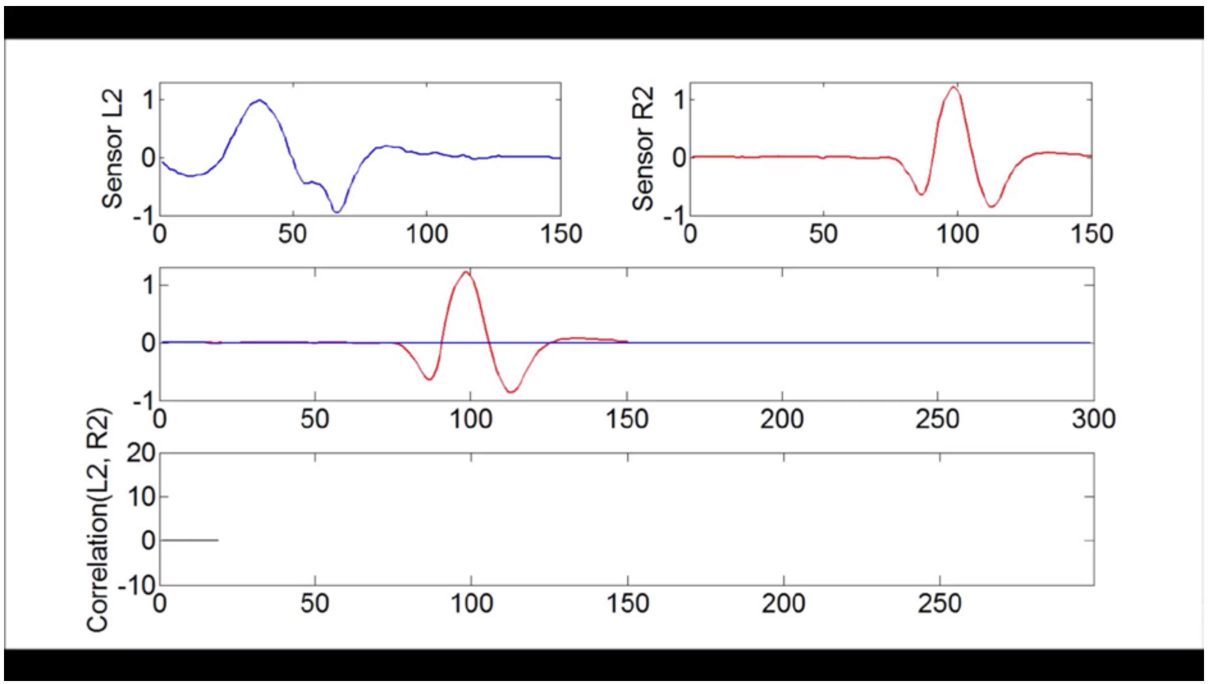
Simple, Height-Based Classification



Good Correlation in Case of an Intruder

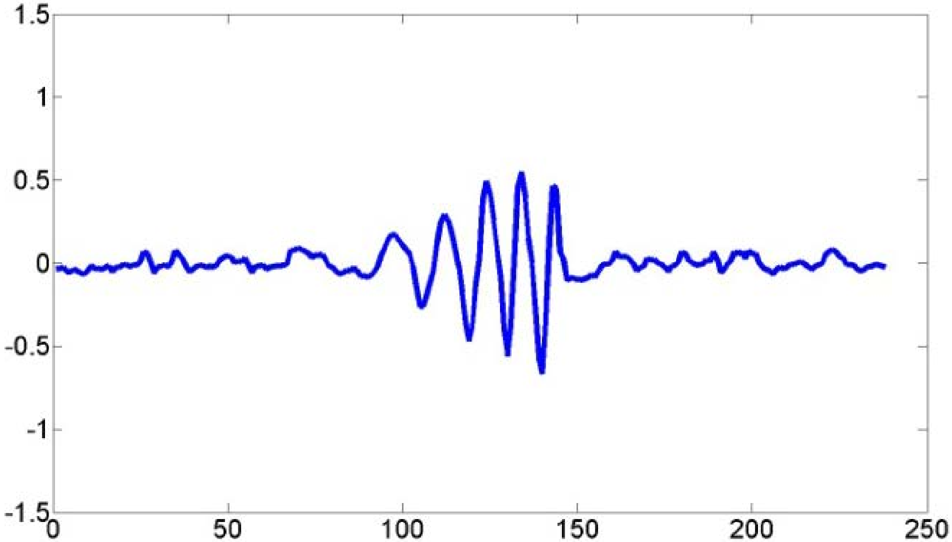


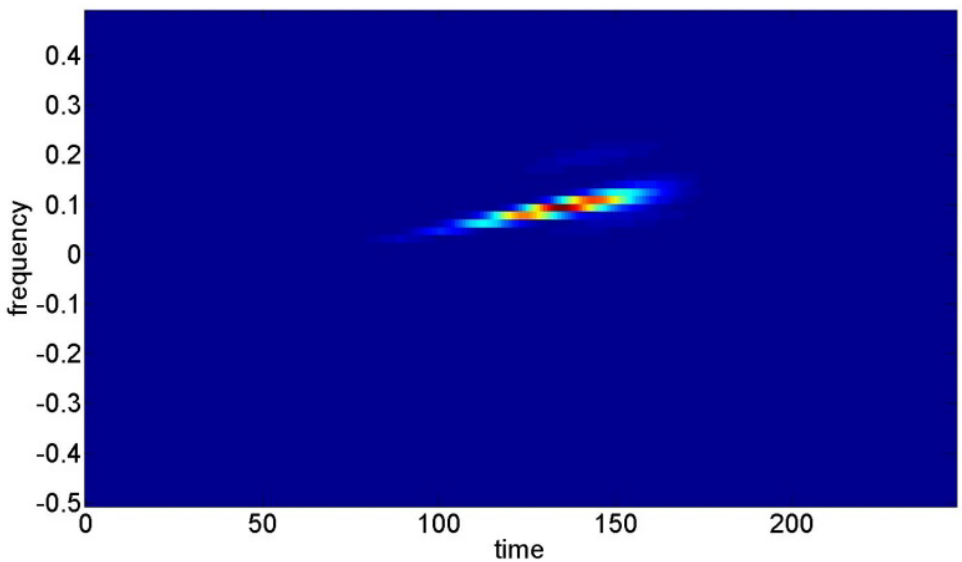


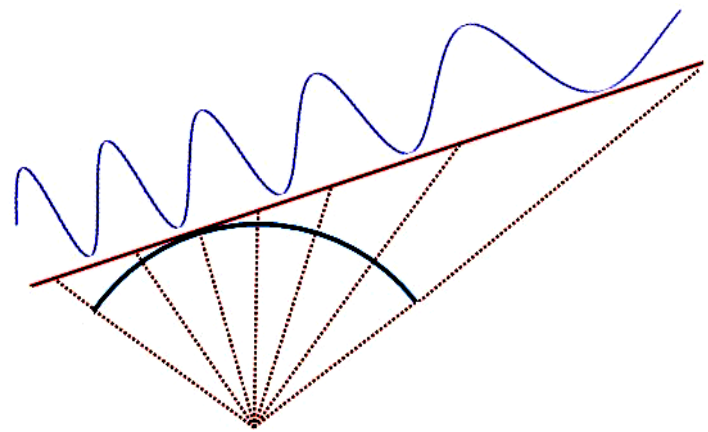


Intruder = Human / Animal

Intruder Signals Exhibit Chirp

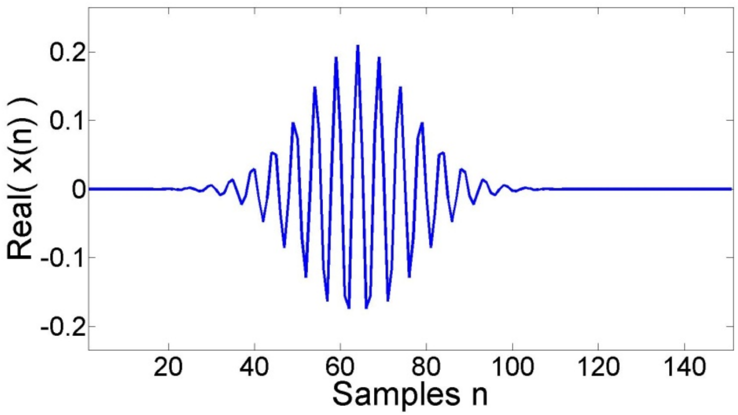




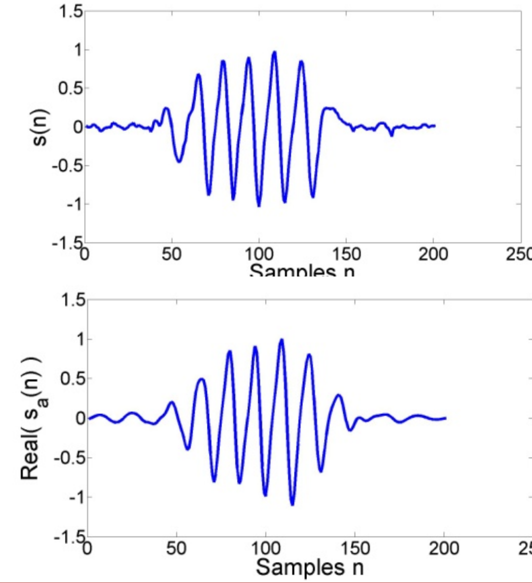


Intruder signal its corresponding Short-Time Fourier Transform

Intruder Detection via Chirplet Decomposition



Example chirplet

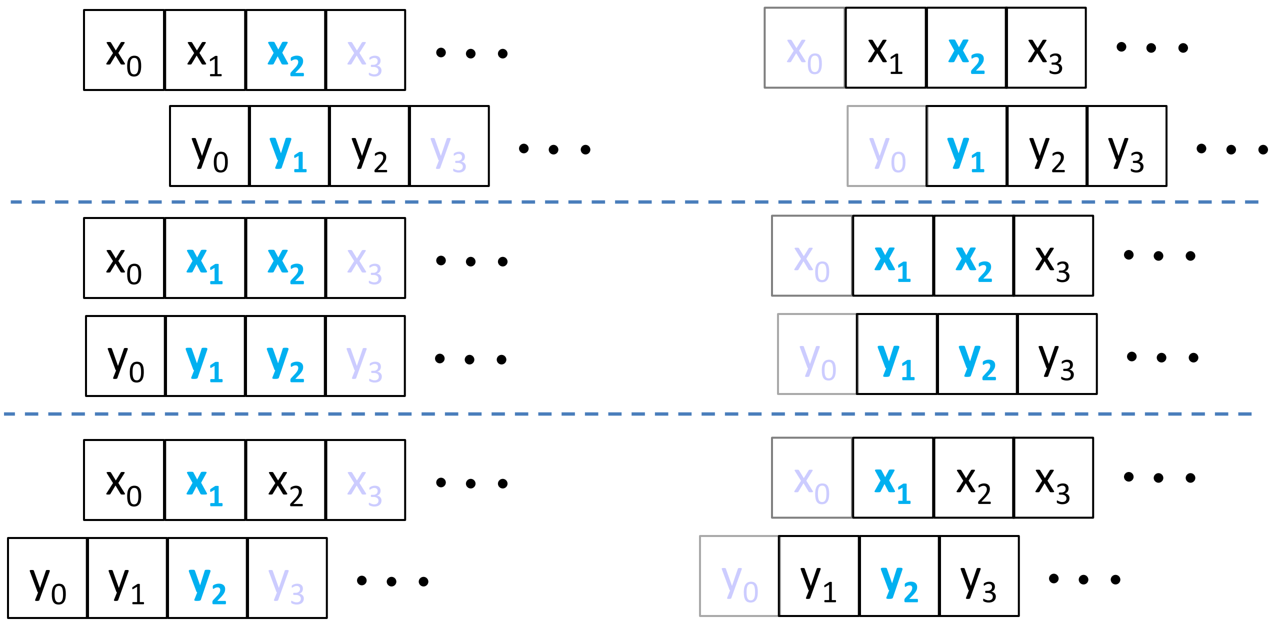


Real signal approximated by 3 chirplets

- 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*"

Simplified Correlation and Energy Calculations



Reduces the computation complexity from O(W2) to O(W)

$$\hat{E}_A(m) = \alpha \hat{E}_A(m-1) + s^2{}_A(m)$$

Energy Calculation: Reduced Memory Requirements

	Clutter	Intruder	Human	Animal
Chirplet and Energy	98.5 %	99.4 %	98.0 %	98.7 %
Simplified Correlation and Energy	96.3 %	96.5 %	96.9 %	98.3 %

Simplified Correlation and Energy Calculations

x_0	x_1	x_2	x_3	…

y_0	y_1	y_2	y_3	…

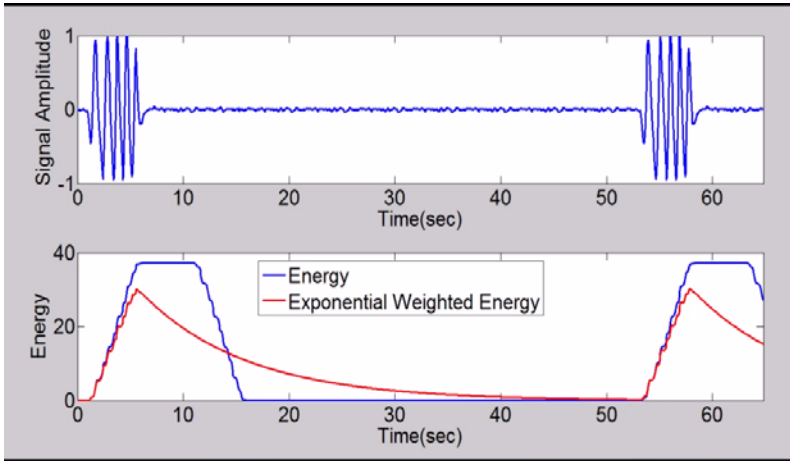
x_0	x_1	x_2	x_3	…

y_0	y_1	y_2	y_3	…

$$C(-2,0) = x_2y_0$$
$$C(-1,0) = x_1y_0 + x_2y_1$$
$$C(0,0) = x_0y_0 + x_1y_1 + x_2y_2$$
$$C(1,0) = x_0y_1 + x_1y_2$$
$$C(2,0) = x_0y_2$$

$$C(-2,1) = x_3y_1$$
$$C(-1,1) = x_2y_1 + x_3y_2$$
$$C(0,1) = x_1y_1 + x_2y_2 + x_3y_3$$
$$C(1,1) = x_1y_2 + x_2y_3$$
$$C(2,1) = x_1y_3$$

$$\hat{E}_A(m) = \alpha\hat{E}_A(m-1) + s^2{}_A(m)$$



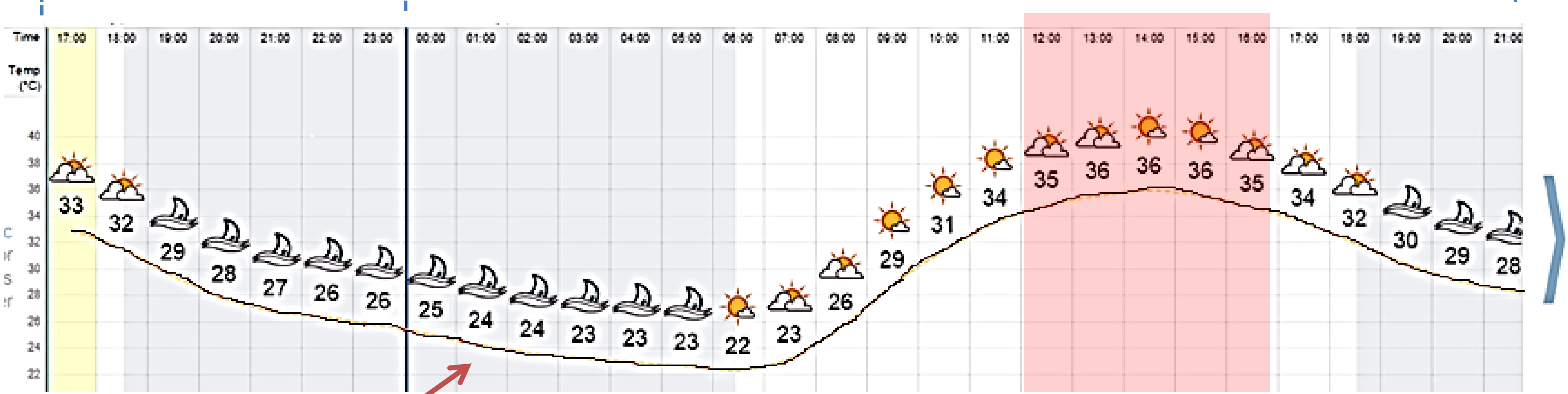
Reduces the computation complexity from O(W2) to O(W)

Reduced Memory Requirements

Temperature Variation in Bangalore during March

15th March, 2016

16th March, 2016

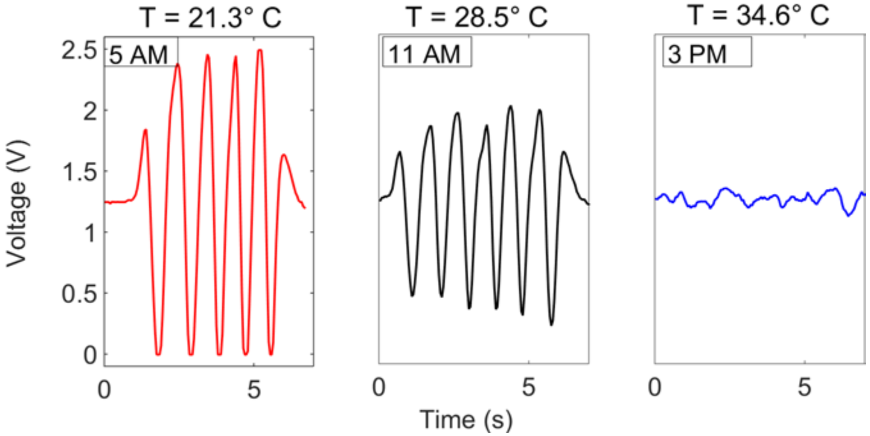


Hour-by-Hour Temperature Fluctuation

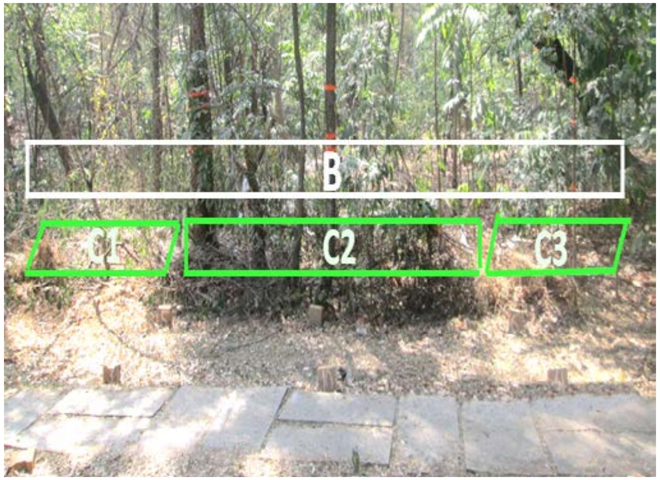
Time window in which PIR Sensor registered a weak signal

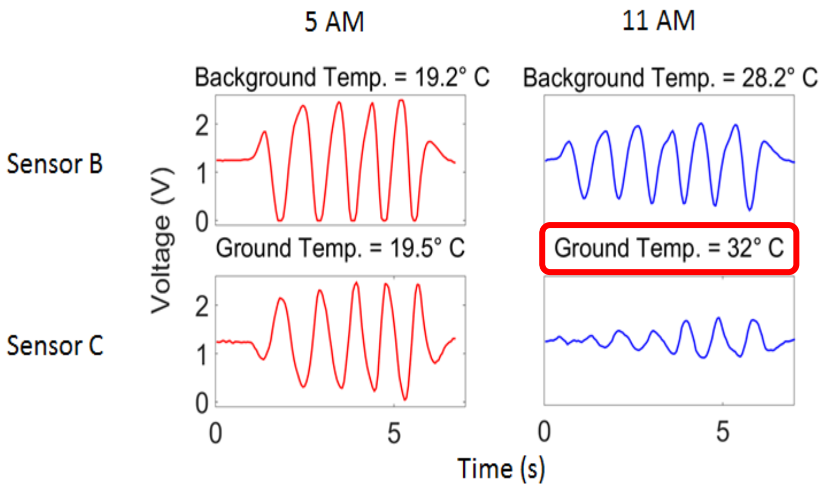
Impact of Background Temperature on PIR Signals

Dramatic drop in signal strength as ambient temperature approaches human-body temperature

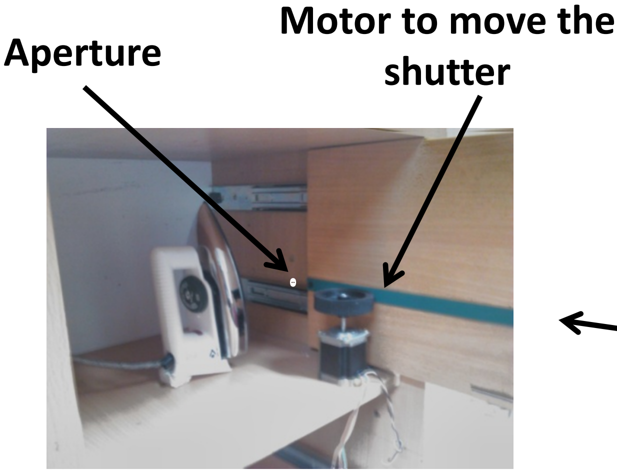


Impact of temperature on different surfaces: background and ground

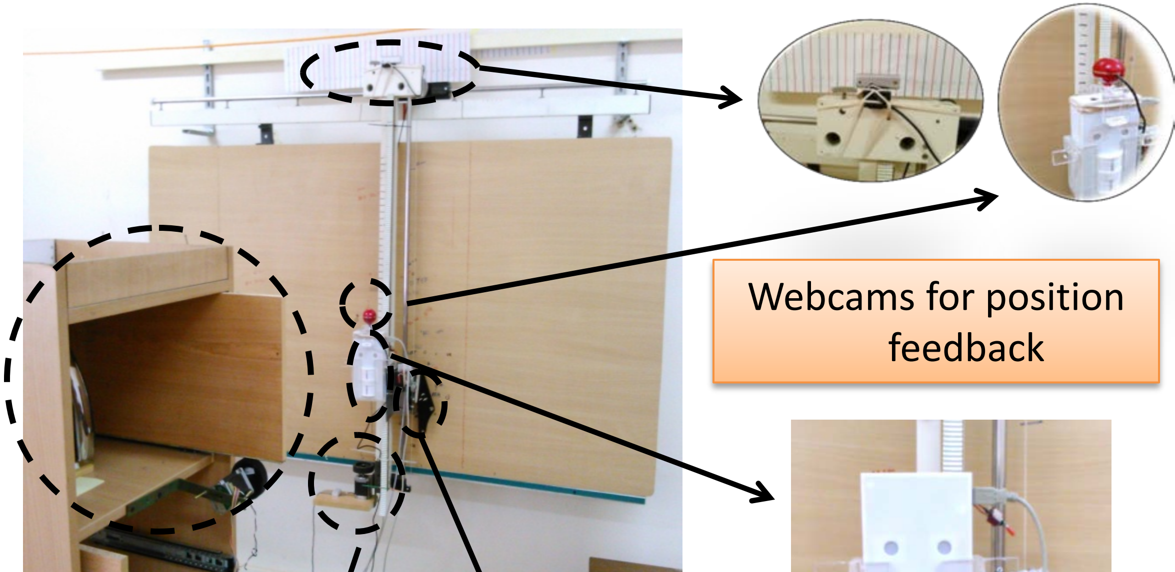




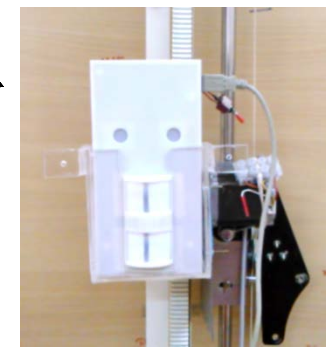
Experimental Setup: Drafter Board



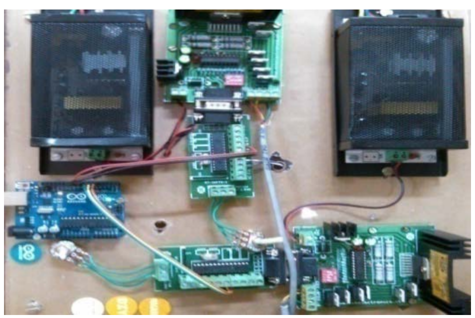
Heat source:
Iron box with wooden shutter



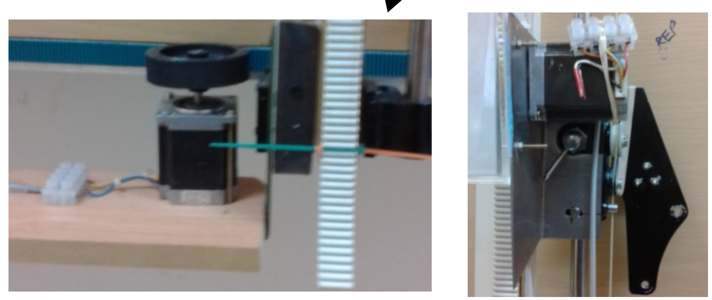
Webcams for position feedback



STP inside an acrylic box



Arduino-based control circuit



Stepper motors for moving STP

Experimental setup showing STP mounted on a drafter board