

Challenges in Developing and Deploying a PIR Sensor-Based Intrusion Classification System for an Outdoor Environment

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Abstract—The aim of the current paper is to describe the challenges faced during the development and deployment of a PIR sensor-based intrusion classification system in an outdoor environment. Some potential solutions to overcome these challenges are also presented. The challenges are of three types: (a) challenges in designing a sensor tower platform that is physically aligned to the accuracies demanded by the application, (b) challenges involved in implementing high-accuracy algorithms on a mote and, finally and perhaps most importantly, (c) challenges faced in attempting to operate a PIR-based sensor tower platform at temperatures close to that of the human body. A test deployment over a 15-week period, beginning Feb 6, 2016, was carried out within the campus of the Indian Institute of Science, Bengaluru. This period of deployment coincided with the peak summer season at which time the ambient temperature in Bengaluru ranged from 15°C to 38°C. This made it possible to study the behavior of the PIR-based sensor tower platform in settings where the ambient temperature is close to that of the human body.

Index Terms—Wireless sensor network, passive infrared sensor, intrusion detection, animation, wildlife protection, sensor network deployment, energy harvesting, 6LoWPAN.

I. INTRODUCTION

A Passive Infra-Red (PIR) based Wireless Sensor Network (WSN) was previously developed [1] to help mitigate human-wildlife conflicts occurring at the edge of a forest. PIR sensors were chosen as the sensing modality, motivated by the passive nature of the sensor, the relatively low cost, their wide commercial availability, and ability to operate in the absence of visible light. At the heart of the WSN is a PIR-based Sensor Tower Platform (STP) that was developed and field tested, which is capable of detecting and distinguishing between signals generated by motion of human, animal, and wind-blown vegetation (termed as clutter) [1]. Only a small subclass of animals were considered in the paper, those comparable in size and shape to a dog or a tiger. The chosen sensing modality was one of several that were considered and explored under the aegis of a collaborative Indo-US project¹. Since the appearance

¹This project was jointly funded by the US National Science Foundation (NSF) and the Indian Department of Electronics and Information Technology (DeitY). Other sensing modalities considered by other investigators in the project included pulse-doppler radar, buried-fiber-optic-cable-based sensing as well as acoustic sensing.

of [1], this WSN system has also been deployed on the campus of the Indian Institute of Science (IISc).

The aim of the present paper is to provide a description of the challenges encountered in developing, field testing, and carrying out limited deployment of such a system.

A. State-of-the-art and Challenges in an Outdoor Setting

PIR sensors work on the principle of pyroelectricity which causes them to respond to a change in incident radiation [2]. This property has been used in a wide range of applications including the detection of human beings in motion² [3]. The radiation W received by the sensor from a human at temperature T_h and the background at temperature T_{bg} is given by

$$W = K(T_h^4 - T_{bg}^4) \quad (1)$$

where, K is a constant that is a function of distance from the sensor, and the surface area of the radiating body [1], [4].

The use of PIR sensors in detecting human motion has been restricted mainly to indoor applications. Their use in an outdoor environment has been investigated only recently [1], [5]–[10]. An important challenge to be overcome here is to be able to distinguish between human and animal motion while rejecting false alarms arising from clutter.

In [9], Jacobs et al. developed a sensor platform that makes use of relatively expensive germanium lenses along with a high resolution PIR sensor to classify between human and animal motion. In comparison, the STP developed in the present paper makes use of inexpensive lenses and low resolution PIR sensors [1]. In [10], Zhao et al. investigated the problem of discriminating between humans and animals of shapes similar to dogs and geese using a single PIR sensor in conjunction with a multi-lens. The problem of rejecting false alarms arising from clutter is not, however, considered in their paper.

B. Outline of the Paper

Section II briefly describes the developed STP. Section III highlights the challenges faced in the development of the

²Some articles on the internet estimate that a human may radiate up to 100W of power.

STP along with a brief description of the approaches adopted to tackle these challenges. Section IV describes challenges faced in implementing detection and classification algorithms on a mote. Section V presents the networking architecture used to interconnect the nodes of the WSN. Sections VI and VII describe our experience of deploying a PIR sensor-based WSN in practical outdoor settings. Section VIII describes an experimental study carried out to understand the influence of background temperature on the PIR signal output. Concluding remarks are presented in the final section.

II. SENSOR TOWER PLATFORM DESIGN

The STP design involves the arrangement of an array of 8 sensors (labelled as A, B, C, D , and L_1, L_2, R_1, R_2) along with associated lenses (see Figs. 1(a) and 2). As will be seen, the use of an array gives the STP the spatial resolution needed to more accurately carry out classification tasks. The Field Of View (FOV) of the STP consists of a set of invisible beams (also called virtual beams) along which radiation is received. The intersection of the FOV with a given plane is termed as the Virtual Pixel Array (VPA) associated with the plane [1]. The VPA generated at a vertical plane, parallel to the face of the sensors and at a distance of 5m from the STP, is shown in Fig. 1(b). The sensors L_1, L_2, R_1, R_2 help in distinguishing between intrusions and wind-blown vegetative motion based on the type of motion (translational vs oscillatory) while the sensors A, B, C, D help in distinguishing between human and animal motion based on the difference in height. The STP is designed to classify in the distance range 5-10m. This is referred to as the operating range of the STP [1]. The STP is designed such that within a distance range of 5-10m, humans trigger sensor B while animals do not. Intruder classification relies on the VPA (associated with the plane along which the intruder moves) corresponding to sensors B and C being sufficiently spaced apart. This is achieved by using an appropriate vertical offset Δv for each sensor, with respect to the optical centre of the multi-lens associated to the particular sensor [1].

III. CHALLENGES FACED IN THE STP DEVELOPMENT

A. Error in Placement of Sensors

Problem faced: The STP design assumes that the plane containing the pixels (called the sensor die) within each sensor package lie precisely in the focal plane of the associated lens. However, the position of the sensor die within the sensor package is known only to a tolerance of $\pm 0.4\text{mm}$. Thus, in practice, the pixel plane will likely be misaligned by a distance Δf with respect to the focal plane of the lens as shown in Fig. 3(a). We will refer to Δf as the focal-plane offset. In such a case, it can be shown using geometric optics that the virtual pixels will be larger than expected, corresponding to a larger point-spread function. Figures. 3(b) and 3(c) show the VPA for $\Delta f = 0\text{mm}$ and $\Delta f = 2\text{mm}$, respectively³. The overlap in rows B, C of the VPA in the latter case may lead to a

³The VPA is determined using ray tracing and geometric optics.

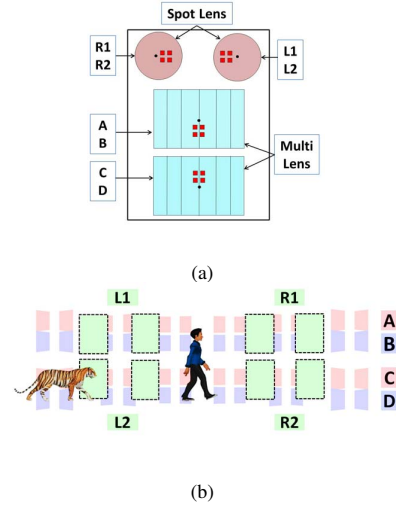


Fig. 1. The schematic in (a) shows the relative positioning of sensors and lenses, including the vertical offset Δv . The associated VPA, corresponding to an intruder plane at a distance of 5m, appears in (b).

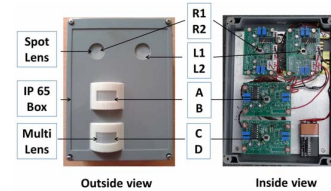


Fig. 2. Illustrating snapshots of the outside and inside views of the STP that was developed.

misclassification of tall animals as humans, as animals may, in some instances, trigger sensor B .

Solution: If the spacing between the two rows of virtual pixels corresponding to sensors B and C can be determined, then the vertical offsets of the sensors, Δv , with respect to optical-axis of their associated lenses can be readjusted appropriately to ensure that the virtual pixels are sufficiently spaced apart. However, this requires a method for testing of the VPA. A description of two procedures adopted to test the VPA is given below.

- *VPA testing using a modulated heat source and a moving STP:* The corresponding setup is illustrated in Fig. 4. An apertured iron box was found to serve well as a heat source⁴. Clearly, moving the STP is equivalent to moving the heat source as it is only the relative motion that is of relevance. The STP was mounted on a drafting board to enable its movement. The heat source was switched on and off by sliding a shutter in front of it. The movement of the shutter and STP were controlled using stepper motors interfaced with Arduino Uno boards. Webcams were used to provide feedback on the accuracy of the position of the STP on the drafting board.

⁴Several other sources such as a low-wattage bulb, container with heated water, a lit candle, and even a commercially available IR source were experimented with, but for various reasons they were found to be unsatisfactory.

continuously sampled signals from the sensors and the radio was switched on only when there was a need to communicate. The battery voltage was measured periodically (see Fig. 5(b)).

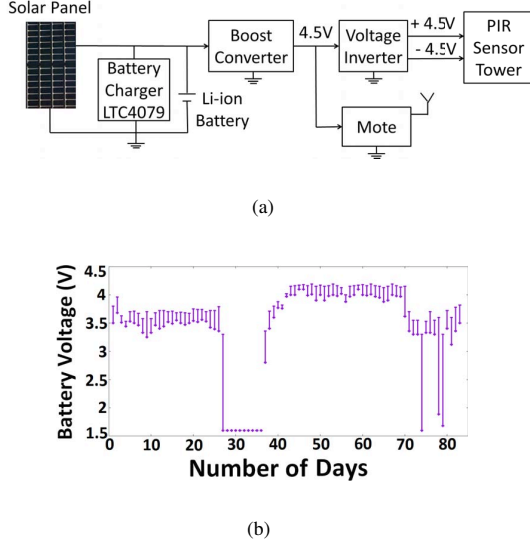


Fig. 5. (a) A block diagram of the energy-harvesting system and (b) a plot of the battery voltage with time as a result of the charging and discharging process over a period of 84 days. In the midst of the experiment, the high summer temperature caused the panels to curl up resulting in a drained battery (flat portion in the middle of the plot). To rectify this, the solar film was fastened with heat-resistant adhesive tape, upon which normal operation was restored.

IV. CLASSIFICATION ALGORITHM: EXPONENTIAL WEIGHTED ENERGY AND CORRELATION FEATURES

Keeping in mind the modest computational resources available on a mote, the detection and classification algorithm reported in [1] was employed which involves finding the energy and correlation-based features over a moving window of size W . The precise quantities calculated are given below.

- 1) Energy in all 8 sensors A, B, C, D and L_1, L_2, R_1, R_2 : The energy corresponding to sensor A is calculated as

$$E_A(m) = \sum_{n=m}^{m+W-1} s_A^2(n), \quad (2)$$

where, s_A is the output signal of sensor A and m is the sample number of the window over which the energy is calculated. The energy corresponding to the remaining sensors are calculated similarly.

- 2) Maximum cross-correlation parameter:

$$\rho_{\max}(i, m) = \max_k \frac{C(k, i, m)}{N}, \quad (3)$$

$$= \max_k \sum_{n=m}^{m+W-1} \frac{s_{L_i}(n+k)s_{R_i}(n)}{N}, \quad (4)$$

where, C is correlation between two signals, i represents the sensor pair (L_1, R_1 or L_2, R_2), k is the delay parameter, and N is a normalizing constant equal to $\sqrt{E_{L_i}(m)E_{R_i}(m)}$. For simplicity, $\rho_{\max}(i, m)$ will be denoted as $\rho_{\max}(i)$ in the later part of the paper.

Calculating these quantities on a computer is relatively easy. However, calculating them on a mote can be difficult. The algorithm was implemented on a Wismote and the sampling rate employed was 20Hz. The Wismote is equipped with an onboard MSP430 micro-controller and 16KB of RAM.

1) *Recursive calculation of correlation*: Calculating $C(k, i, m)$ can be performed with $O(W^2)$ complexity which requires buffering close to $4W$ samples. However, the computational complexity of the algorithm turned out to be an issue on a Wismote as the MSP430 micro-controller could not complete the calculation before the next sample became available. The computational complexity can be reduced by taking advantage of the fact that two consecutive windows differ by a single sample. Thus, $C(k, i, m)$ can be calculated in a recursive fashion as shown below. For $-W+1 \leq k \leq 0$ and $0 \leq k \leq W-1$, we have the respective recursions:

$$\begin{aligned} C(k, i, m+1) &= C(k, i, m) - s_{R_i}(m-k)s_{L_i}(m) \\ &\quad + s_{R_i}(m+W)s_{L_i}(m+W+k), \\ C(k, i, m+1) &= C(k, i, m) - s_{R_i}(m)s_{L_i}(m+k) \\ &\quad + s_{R_i}(m+W-k)s_{L_i}(m+W). \end{aligned}$$

This approach reduces the computation complexity to $O(W)$ but requires buffering close to $4W$ samples and $4W$ correlation values. The increase in the required memory, however, made it infeasible to compute energy features.

2) *Calculation of exponential weighted energy*: In order to overcome the challenge posed by the constraint on memory, the Exponential Weighted Energy (EWE) was computed as opposed to the actual energy in the window. The EWE corresponding to sensor A is calculated as

$$\hat{E}_A(m) = \alpha \hat{E}_A(m-1) + s_A(m)^2, \quad (5)$$

where, $0 < \alpha < 1$ is a constant chosen such that $\alpha^W = e^{-1}$. The EWE values for the rest of the sensors can be calculated in a similar fashion. Calculating $\hat{E}_A(m)$ requires storing just $s_A(m)$ and $\hat{E}_A(m-1)$.

Actual energy corresponding to sensors L_1, L_2, R_1, R_2 (E_{L_1, L_2, R_1, R_2}) needed to be computed for the correlation-based feature ($\rho_{\max}$). Thus, EWE features were computed only for the remaining sensors A, B, C, D ($\hat{E}_{A, B, C, D}$). Energy and correlation based features were appended to form the final feature vector ($\hat{E}_{A, B, C, D} \cup E_{L_1, L_2, R_1, R_2} \cup \rho_{\max}(1) \cup \rho_{\max}(2)$) that was passed on to a Support Vector Machine (SVM) classifier.

The intruder detection and classification accuracies obtained for $W = 200$ ($\alpha = 0.995$) are shown in Tables I and II. The accuracies for each level were obtained by performing a 5-fold cross validation and the total accuracy for each fold was found. The average classification accuracy corresponding to these 5 folds is reported. The intruder and clutter (similarly human vs animal) accuracies for the fold that corresponds to minimum total accuracy are also reported.

TABLE I
INTRUDER VS CLUTTER ACCURACY FOR
 $SVM(\hat{E}_{A,B,C,D} \cup E_{L_1,L_2,R_1,R_2} \cup \rho_{\max}(1) \cup \rho_{\max}(2))$

	Minimum	Average
Intruder	96.8%	96.5%
Clutter	92.6%	96.3%
Total Accuracy	95.5%	96.4%

TABLE II
HUMAN VS ANIMAL ACCURACY FOR $SVM(\hat{E}_{A,B,C,D})$

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

V. NETWORK SYSTEM ARCHITECTURE

Clearly, a key component of a WSN is the network itself. The network helps in interconnecting the STPs and a remote BS. The networking system developed here follows a distributed and modular architecture comprising of several subsystems, namely, SmartConnect, SmartClassify application, 6PANview, and a web-based GUI. These modules were implemented on a Wismote that had the Contiki Operating System (OS) running on it. One of the highlights of the architecture is its “all-IP” nature as it supports IP communication to all subsystems. Each of the subsystems is described below.

A. SmartConnect

SmartConnect is a field-interactive, iterative-network-design, and deployment tool for sensor networks that carry low rate measurement traffic, typical of environment or resource-monitoring applications. In SmartConnect, the Quality of Service (QoS) objective is converted to a hop-count bound on each sensor-base station path [13]. Given a set of potential good links, a related Steiner graph design problem is solved (to minimize number of additional relays required) using approximation algorithms developed in [14]. The on-field topology is built up iteratively starting with statistical link models, deploying relays suggested by the algorithms, measuring on-field link qualities, and updating the topology accordingly until QoS target is met [15]. If during network operation, the QoS drops below a target level, SmartConnect triggers a repair (requiring relay augmentation, or just re-routing). It interacts with the motes over the IPv6 network and can address each of the motes individually as all the motes are IPv6 enabled with IPv6 over Low power Wireless Personal Area Networks (6LoWPAN) stack running on them.

B. SmartClassify

SmartClassify is the intrusion detection and classification system. The intrusion is detected and classified by the STP and the alert is communicated to the BS via multi-hopping over the WSN.

C. 6PANView

6PANView [16] is the network monitoring system that is used to remotely monitor and manage the network. It runs a light-weight Simple Network Management Protocol (SNMP) agent to query the wireless motes for the monitoring activity. It uses a novel scheduling scheme which is application performance conscious and ensures that the main application performance objectives are not violated due to the monitoring activity. 6PANView keeps track of different parameters like battery voltage, number of parent switches, application data rate of each mote using time series graph.

The next two sections describe two deployment efforts carried out by us. The network architecture presented above was a critical component in both efforts.

VI. WSN DEPLOYMENT IN BANNERGHATTA BIOLOGICAL PARK

A small scale PIR-based WSN was deployed inside the Rescue Center, BBP for a period of two days. The WSN consisted of two STPs and a BS interconnected by a single hop network. One of the STPs was placed inside a lion's enclosure (see Fig. 6(a)) while the other was placed outside the periphery of the enclosure. A webcam interfaced with a Banana-Pi board was used to record the ground truth. The STP deployed inside the enclosure was brought down by the lion, shortly after deployment (see Fig. 6(b)- Fig. 6(c)). This was a learning experience for us as it brought out the need for better concealment and stronger STP mounting. The STP located outside the enclosure gave good classification results. The results were verified with the ground truth recorded by the webcam. A total of 24 detections were registered. There were no false alarms and misclassifications observed.

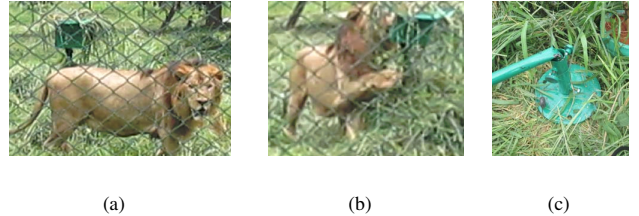


Fig. 6. Illustrating the need for strong STP ruggedization for deployments in regions where wild animals reside. The STP shown was placed inside the enclosure habited by a lion (in the rescue center of the Bannerghatta Biological Park, Bengaluru) which ended up mauling the STP despite providing a metal enclosure and making some attempts at camouflage.

VII. WSN DEPLOYMENT AT IISC

A second deployment was carried out at the Main Guest House (MGH), IISc from Feb. 6, 2016 through May 28, 2016. The objective of the deployment was to not only test the efficacy of the STP and WSN, but also, experience real-world deployment challenges at first hand. The MGH setup was also employed to investigate and document effect of temperature on signals from PIR sensor, that come into play when the STP is used at ambient temperatures close to human-body temperature (see Section VIII).

The deployment setting is illustrated in Fig. 7. The setup consisted of 2 STPs, a relay node, border router, Pan-Tilt-Zoom (PTZ) camera, web camera and web-server (see Fig. 8). The STP signals were interfaced with a Wismote. The Wismote is equipped with an MSP430 micro-controller, that has the Contiki OS running on it, and a CC2520 radio chip that supports IEEE 802.15.4 communication protocol. The relay node (also Wismote) was used for forwarding information regarding intrusions and network health to the border router using the 6LoWPAN protocol. The border router consisted of a Wismote and a Banana-Pi and was used to convert 6LoWPAN packets to IPv6 packets. These packets were then forwarded to the web-server via Ethernet. The web-server was used to trigger the PTZ camera, whenever it received information regarding an intrusion, to record and store a 10-second-long video. The video was used to verify the ground truth. The Webcam was installed to continuously record a video to identify missed detections. A snapshot of a few example intrusions detected by the STP are shown in Figs. 9(a) and 9(b). A summary of the performance of the deployed system is presented in Tables III and IV. In March, there were roughly 20% errors in classification, primarily due to the presence of a background temperature that was close to the temperature of the human body. A more detailed explanation can be found in Section VIII. In April and May 2016, by which time the ambient temperature had reduced considerably on account of pre-monsoon cloud cover in Bengaluru, classification was carried to a much higher level of accuracy of about 93%.

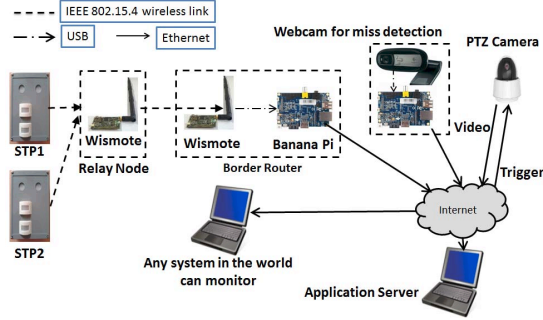


Fig. 7. Block diagram showing how the components of the deployment system including STP, PTZ camera, Webcam, server and the laptop of an end-user are interconnected through a network incorporating both wireless and wired links.

TABLE III
CLASSIFICATION ACCURACY OF DEPLOYED SYSTEM DURING MARCH
(FOR 2 DAYS)

Total Intrusions	Correctly Detected	Missed	Misclassified	False Alarms
518	446	25	47	31

VIII. STUDYING INFLUENCE OF BACKGROUND TEMPERATURE ON PIR SIGNAL OUTPUT

As can be seen from (1), the signal generated by the PIR sensor is highly dependent on the difference between the

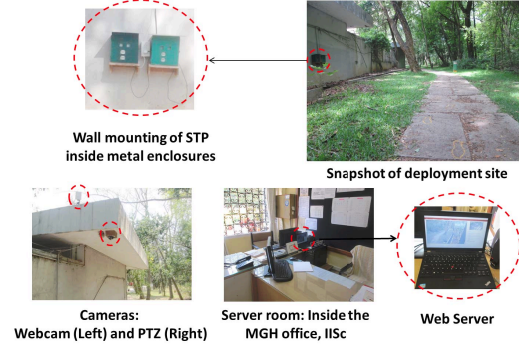


Fig. 8. Snapshots of the deployment, over a 15-week period beginning Feb 6, 2016, in the vicinity of the Main Guest House of IISc.



Fig. 9. Illustrating snapshots from the videos captured by the PTZ camera after being triggered by the STP. (a) Shows a human riding a bicycle and (b) shows a dog moving at night.

temperature of the intruder and that of the background [8], [17], [18]. In an outdoor setting, the background temperature can vary in both a temporal and spatial manner. As a result, the PIR signal generated in response to the same event at two different locations or at the same location and at two different times, can be very different. Clearly, these effects need to be considered in every aspect of the STP design. A study was carried out on the campus of IISc to study temperature effects and the results of this study are reported below. The experimental setup of the MGH was retained for this study.

The gain of the STP was set to obtain a large output voltage swing while still ensuring that the signal did not saturate at any point during the day⁸. For the purposes of the temperature-effects study, knowledge of the FOV of the STP in the MGH setting was needed. This was determined by using an electric iron placed on wheels and rolled along a channel to simulate a moving heat source.

The determined VPA associated with a vertical plane at a distance of 8m from the STP appears in Fig. 10(a). A comment relating to the STP's FOV is in order here since knowledge of the background temperature within the FOV of a given sensor is necessary to more accurately explain the signal generated at its output. We note that in the MGH setup, the background region within the FOV of sensors *A* and *B* consisted mostly

⁸The gain was set at 5:30 AM when the temperature difference between the human body and the background was expected to be close to the maximum for that day.

TABLE IV
CLASSIFICATION ACCURACY OF DEPLOYED SYSTEM DURING APRIL AND MAY (FOR 4 DAYS)

Total Intrusions	Correctly Detected	Missed	Misclassified	False Alarms
734	693	12	29	5

of vegetation (trees), while the background region within the FOV of sensor *D* is almost completely ground cover, while the background region within row *C* is a mixture of ground and tree cover (see Fig. 10(a)). Apart from the background temperature, the signal amplitude also depends on the speed of movement and to a certain extent even the gait. The speed and gait were controlled to minimize the variability in the signal output due to these parameters (see Fig. 10(b)).



Fig. 10. (a) The radiation received by different layers of the VPA can originate either from the ground surface (as in C_1 , C_3 and D) or else from vegetation (A , B and C_2). (b) In the experimental setup, to study varying temperature effects, the gait was controlled by making the intruder to move along pre-marked footsteps. Speed was controlled by walking in synchronism with beats generated by a metronome.

A. Observations

The signal strength of the PIR sensor can drop when the difference between the temperatures of the human body and background reduces. This phenomenon is captured in Fig. 11. In Fig.12, we see the impact of differences in background temperature corresponding to rows *B* and *C* of the VPA in instances where the temperatures concerned are close to that of the human body. This causes the signals at the output of sensors *B* and *C* to be similar at temperatures relatively far from that of the human body and quite different otherwise ⁹.

In Figs. 13(a) and 13(b), the point is made that at times, there was a spread in temperatures (caused for example by intermixed sunny patches and shadowed regions) even within a single row of the VPA and this can impact the nature of signal generated.

⁹The temperature measurements reported here were recorded using a thermal camera. We realized only later on that the temperature measurements from the thermal camera, as per the data sheet, are accurate only up to $\pm 5^\circ\text{C}$. While the temperatures reported here may not be precise, we believe that the qualitative picture presented here will remain unchanged even if repeated using a more accurate thermometer. We subsequently decided to use an IR thermometer whose measurements are accurate up to $\pm 2^\circ\text{C}$, and redo the experiment. However, by that time, the weather in Bengaluru had cooled down significantly as a result of pre-monsoon cloud cover and we were unable to replicate this particular temperature effect.

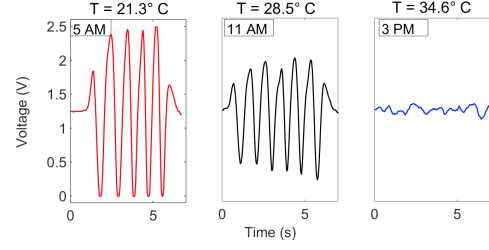


Fig. 11. Illustrating the variation in signal strength with variation in ambient temperature corresponding to different times of the same day. Temperatures reported here correspond to measurements recorded by the website <http://www.imdbangalore.gov.in/> for the city of Bengaluru on March 11, 2016.

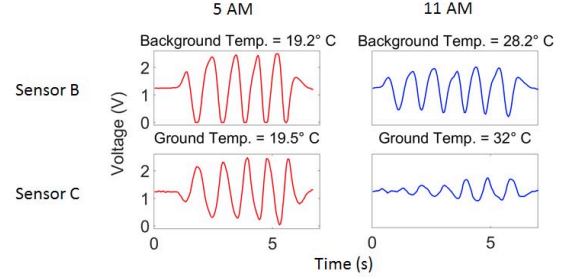


Fig. 12. This figure brings out the fact that changes in ambient temperature can result in significant changes in the *relative* strengths and waveforms of signals generated by different layers of the VPA. At 5AM, when the ambient temperature is low compared to human body temperature, rows *B* and *C* of the VPA generate similar signals, while at 11AM, when the temperatures are much closer to human body temperature, the signals are quite different. The reason for this is clear from Fig. 10(a), where one sees that while row *C* of the VPA picks up much radiation from the ground, row *B* gathers heat radiated only by vegetation. The temperatures reported here corresponds to measurements recorded by the thermal camera Ti-10 manufactured by Fluke.

The variation in background temperature can also cause events to be misclassified, see Fig.14(a) and Fig. 14(b). Another consequence of the variation in background temperature is that the direction of motion cannot be inferred by observing the polarity of the signal from a single PIR sensor alone. For a fixed direction of motion, the polarity of the PIR signal can reverse in situations when the background temperature switches from being relatively hotter, compared to the human body, to being relatively colder, or vice versa (see Fig.15). However, two sensors, whose fields of view are horizontally separated (as in our STP design), can be used to obtain the direction based on which sensor is triggered first.

1) *Potential Solutions*: Some potential solutions to offset these temperature effects include

- Employing an Automatic Gain Control (AGC) system based upon the use of digital potentiometers to amplify weak signals when temperature differences are small,
- Employing supervised machine learning classifiers which execute different classification algorithms based on the ambient temperature or else that employ feature vectors that are less temperature dependent. In the former case, ambient temperature could for instance be provided by a platform dedicated for this purpose, that passes on wirelessly temperature information to all nearby sensors,

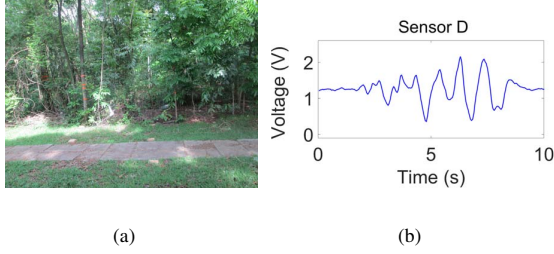


Fig. 13. Illustrating how spatial variation of ground temperature can affect the signal. In (a), the temperature of sunny patches of the ground (to the left) was found to be 31.5°C . This was close to the temperature recorded off clothing worn by a human intruder at that time, which was found to be 30.1°C . The temperature of the shaded region (to the right) was found to be 25°C . As a result, for a human walking from left to right, the initial portion of the signal shown in (b) has lower amplitude relative to the rest of the signal. The temperatures reported here correspond to measurements recorded by the IR thermometer Fluke 59 having an accuracy of $\pm 2^{\circ}\text{C}$.

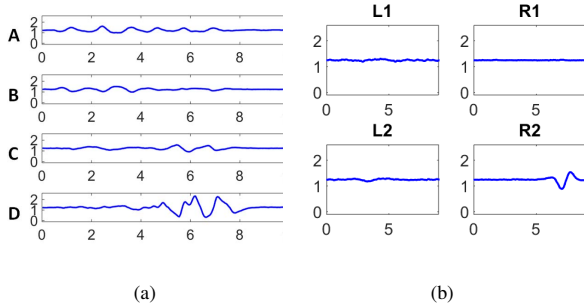


Fig. 14. Illustrating how misclassification can result when the background temperature is close to human body temperature, but varies across the VPA. In (a), the signals registered by rows A, B, C and D of the VPA corresponding to a human walk are shown. The lack of appreciable signal associated to rows A, B and C of the VPA is because the corresponding ambient temperature at the time, was close to the human body temperature whereas row D was at an elevated temperature when compared to human body temperature on account of radiation released by the ground. In this kind of cases, human may be misclassified as an animal. A similar phenomenon is displayed in (b), where VPA corresponding to L_2 fails to register the presence of the dog, again because the ground temperature in the vicinity of L_2 at that time was close to the temperature of the canine.

- A complimentary sensing modality (such as an optical camera) could also be used which is not temperature dependent.

IX. CONCLUSIONS

In this paper, our experiences in developing and deploying a PIR-based WSN for intrusion detection and classification were presented. Important take-away lessons include: (i) the need for precision mechanical alignment in building such systems, (ii) the need to devise a simple, yet effective means for testing the Virtual Pixel Array (VPA) of a designed Sensor Tower Platform (STP), and (iii) the need to take into consideration, the multitude of effects that come into play when the STP is operated at temperatures close to human body. Some possible suggestions have been presented here and it is our hope

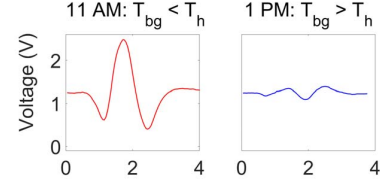


Fig. 15. Illustrating the reversal of polarity that takes place when the background temperature changes from being below human body temperature (11 AM) to rising above human body temperature (1 PM). The figures correspond to signals generated on March 11, 2016 at the IISc campus in Bengaluru.

that future researchers will find these suggestions useful in designing such systems.

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