CASE STUDIES IN LOW POWER MOTION SENSING

THESIS

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in the Graduate School of The Ohio State University

By

Debraj De

Graduate Program in Computer Science and Engineering

The Ohio State University
2009

Dissertation Committee:

Anish Arora, Advisor

Rajiv Ramnath
Copyright by
Debraj De
2009
Abstract

Wireless Sensor Networks hold great promise as an enabling technology for a variety of applications. Considering for instance wireless networks of motion sensors, which have diverse application in defense, mobility related technologies, clinical studies etc. Performance metrics for such applications include probabilities of event detection, false alarm, classification and mis-classification, detection latency, and lifetime of sensor. In this thesis we address research issues associated with these metrics, in particular the aspects of accurate sensing and power management. Our research focuses on two case studies in motion sensing: presence detection and activity monitoring.

Presence detection is a primitive of applications of motion sensing such as room occupancy detection. Towards the goal of developing a reliable and long lived conference room occupancy sensing system, we use a Pyroelectric InfraRed (PIR) sensor enabled Trio mote. We develop an occupancy sensing algorithm that shows reliability with no observed false alarms. Power management is achieved through a number of features, including duty cycling and dynamic stabilization. Proper selection of sampling speed and duration enable fast and reliable event detection. The resulting duty cycling algorithm yields an achievable lifetime of 68 days. Based on our analysis we also propose a modification in hardware design for improved lifetime.

Activity monitoring is a primitive of applications of motion sensing such as tracking human activity level. Towards the goal of developing an energy efficient framework for reliable and accurate human activity level indexing, we use a coherent pulsed doppler radar sensor. We characterize two classes of human motion: uniform gait and milling. Reliability comes with a discrimination algorithm that distinguishes between the motions of zero, one or many people. The algorithm shows rare occurrences of
false alarms. We formulated an index of human activity level that proportionally rep- represents motion activity intensity. We propose a power management technique that adapts to activity intensity in order to save energy for sensing. Based on our research, we identify further improvements for more energy efficient, reliable and accurate activity indexing.
Dedication

To my parents Alok Ranjan De and Atreyi De, who have taught me every virtue of life. Without their endless sacrifice, hard work, love, passion and support I would be in nowhere.
Preface

This thesis work focuses on two basic primitives for several applications of motion sensing: Presence Detection, and Activity Monitoring. The main research goals for low power efficient motion sensing are: reliable and accurate sensing, and power management. With these goals, an application of each of the primitives is addressed.
Acknowledgements

I would like to express my sincere thanks to my adviser Prof. Anish Arora for his continuous guidance and support. He gave me the invaluable passion and effort for quality research. I’d also like to thank my fellow labmates for helping me through valuable knowledge sharing and contribution in experiments. Finally, I wish to thank all of my family and friends for their support, love, patience and understanding.
Vita

June 06, 1982 .................... Born - Kolkata, India.
2005 ............................... B.E., Jadavpur University, Kolkata, India.
2006 - present ................... Graduate Student, The Ohio State University, Columbus, Ohio.

Fields of study

Major field: Computer Science and Engineering
Contents

Abstract ................................................................. ii
Dedication ............................................................... iv
Preface ................................................................. v
Acknowledgements .................................................... vi
Vita ................................................................. vii
List of Tables .......................................................... x
List of Figures ......................................................... xi

1 Introduction ...................................................... 1
  1.1 Motivation .................................................... 1
  1.2 Problem Statement ........................................... 2
  1.3 Related Work ................................................ 3
  1.4 Organization ................................................ 4

2 Presence Detection ............................................... 5
  2.1 Introduction .................................................. 5
  2.2 Goal ............................................................ 5
  2.3 Sensor Mote Hardware ....................................... 6
  2.4 Raw Data Collection and Analysis ......................... 8
  2.5 Power Management .......................................... 10
    2.5.1 Dynamic Stabilization ................................ 11
    2.5.2 Issue with Stabilization Time ......................... 13
    2.5.3 Speed and Duration of Sampling ....................... 13
List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Power consumption of Trio mote components</td>
<td>17</td>
</tr>
<tr>
<td>2.2</td>
<td>Power consumption of Trio components through timeline of duty cycling operation</td>
<td>17</td>
</tr>
<tr>
<td>3.1</td>
<td>Computation for discrimination: 1 person radial</td>
<td>47</td>
</tr>
<tr>
<td>3.2</td>
<td>Computation for discrimination: 5 people radial</td>
<td>47</td>
</tr>
<tr>
<td>3.3</td>
<td>Computation for discrimination: 10 people radial</td>
<td>48</td>
</tr>
<tr>
<td>3.4</td>
<td>Computation for discrimination: 1 person across</td>
<td>48</td>
</tr>
<tr>
<td>3.5</td>
<td>Computation for discrimination: 5 people across</td>
<td>49</td>
</tr>
<tr>
<td>3.6</td>
<td>Computation for discrimination: 10 people across</td>
<td>49</td>
</tr>
<tr>
<td>3.7</td>
<td>Computation for discrimination: 1 person milling</td>
<td>49</td>
</tr>
<tr>
<td>3.8</td>
<td>Computation for discrimination: 2 people milling</td>
<td>50</td>
</tr>
<tr>
<td>3.9</td>
<td>Computation for discrimination: 4 people milling</td>
<td>50</td>
</tr>
</tbody>
</table>
List of Figures

2.1 Components of Trio Sensor Mote ........................................... 7
2.2 Trio Circuit Board ............................................................ 8
2.3 Passive Infrared Subsystem ................................................. 9
2.4 PIR Motion Detection ......................................................... 10
2.5 Raw PIR data from empty conference room .......................... 11
2.6 Raw PIR data from occupied conference room ..................... 12
2.7 Typical dynamic stabilization pattern of PIR raw output ......... 12
2.8 Flow chart of Duty Cycling algorithm for conference room occupancy 15
2.9 Timeline of Duty Cycling algorithm for conference room occupancy 16
2.10 Common power supply in the problem of large stabilization delay .. 18

3.1 BumbleBee Radar Sensor .................................................... 20
3.2 Spectrogram: background noise ............................................ 24
3.3 Power Spectral Density: background noise ............................. 25
3.4 Spectrogram: 1 person radial motion ..................................... 26
3.5 Power Spectral Density: 1 person radial motion ....................... 27
3.6 Spectrogram: 5 people radial motion ..................................... 28
3.7 Power Spectral Density: 5 people radial motion ....................... 29
3.8 Spectrogram: 10 people radial motion ................................... 29
3.9 Power Spectral Density: 10 people radial motion ...................... 30
3.10 Spectrogram: 1 person across motion ................................... 30
3.11 Power Spectral Density: 1 person across motion ...................... 31
3.12 Spectrogram: 5 people across motion ................................... 31
3.13 Power Spectral Density: 5 people across motion ...................... 32
3.14 Spectrogram: 10 people across motion .......................... 32
3.15 Power Spectral Density: 10 people across motion .................. 33
3.16 Spectrogram: 1 person milling motion .............................. 33
3.17 Power Spectral Density: 1 person milling motion .................. 34
3.18 Spectrogram: 2 people milling motion .............................. 34
3.19 Power Spectral Density: 2 people milling motion .................. 35
3.20 Spectrogram: 4 people milling motion .............................. 35
3.21 Power Spectral Density: 4 people milling motion .................. 36
3.22 Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (1 person radial motion) .................. 37
3.23 Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (5 people radial motion) ................. 38
3.24 Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (10 people radial motion) ................. 39
3.25 Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (1 person across motion) ................. 40
3.26 Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (5 people across motion) ................. 41
3.27 Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (10 people across motion) ................. 42
3.28 Typical 1 person milling motion data for 2 seconds time bin and frequency range -30 Hz to +30 Hz ................................. 43
3.29 Typical 2 people milling motion data for 2 seconds time bin and frequency range -30 Hz to +30 Hz ................................. 44
3.30 Typical 4 people milling motion data for 2 seconds time bin and frequency range -30 Hz to +30 Hz ................................. 45
3.31 Activity Index vs Time Bin (1 person radial motion) ............... 52
3.32 Activity Index vs Time Bin (1 person across motion) ............... 53
3.33 Activity Index vs Time Bin (1 person milling motion) ............... 54
3.34 Human gait motion data from radar sensor (Source: M. G. Anderson et al, Design of Multiple Frequency Continuous Wave Radar Hardware and Micro-Doppler Based Detection and Classification Algorithms)  

3.35 Duty Cycling Algorithm  

xiii
Chapter 1

Introduction

1.1 Motivation

Sensors monitor phenomena in their surroundings and facilitate detection of events of interest. Motion sensors, as their name suggest, monitor motion activity and extract different parameters of observed motion. In recent years, there has been significant increase in research and applications in motion sensing. Motion sensors are being used in defense, mobility related technologies, clinical studies, etc. There are many kinds of motion sensors. Some of the most significant ones are: Pyroelectric InfraRed, microwave/radar, active infrared, proximity, ultrasonic, vibration, strain and video. There are many open research issues for different possible applications scenarios related to low power motion sensing. Two of the most significant research challenges are: sensing technique for reliable and accurate event detection, and efficient power management. Two basic primitives for several applications of motion sensing are: presence detection and activity level monitoring. In this context, we are motivated to explore the research challenges for the case studies of presence detection and activity level monitoring.
1.2 Problem Statement

In this thesis, our main goal is to address two main research challenges in motion sensing: accurate sensing and power management. This goal is realized in the context of two case studies in motion detection, namely: presence detection and activity level monitoring.

Presence detection means monitoring for the presence of one or more moving bodies. By way of illustration of this primitive, we choose room occupancy detection application. This application is chosen because it is relevant to our research interest of people centric sensing. It targets accurate and energy-efficient detection of the occupancy status of each room in a building and the on-line publication of this information. Otherwise, false alarms will undermine the use of automatic detection of room occupancy, and frequent changes of battery will make the system inconvenient to manage. A target for lifetime in such an application would be at least about 6 months to 12 months.

We assume that the bulk motion in a room will occur due to humans. Other motions will have insufficient return in a temporal sense. Discrimination of human motion from that of small animals or other large objects is outside the scope of this work.

So the research goals mainly are:

- Reliable room occupancy detection algorithm with no false positive or false negative.

- Power management for low power operation and long lifetime.

Activity level monitoring means continuous observation and tracking of intensity of motion activity. By way of illustration of this primitive, we choose the application of indexing and tracking human activity level. This application is chosen because it is relevant to people centric sensing and deals with research issues of detecting human mobility patterns. It targets reliable distinction between the motions of zero, one or many people. Otherwise the human activity level index may incorrectly depict hypo activity or hyperactivity. On detection of single person motion, it computes
1.3. RELATED WORK

a parameter that is an index to activity level of the person of interest. The index should be robust enough to varying scenarios. For example running on a track or on a treadmill with the same speed should correspond to same index value. This is because the level of these activities are same, although the displacements are different. The application uses power management for low power operation in order to have a long lifetime. A target for lifetime in such an application would again be several months.

We assume that the bulk motion will occur due to humans. Other motions will generate different motion patterns, which the radar sensor is not currently trained for. Motion of animals or vehicles is outside the scope of this work.

So the research goals mainly are:

- Algorithm to detect motion of one person.

- Reliable and accurate index for human activity level.

- Adaptive power management for low power operation and long lifetime.

1.3 Related Work

There is considerable work on motion sensing applications and related research issues. The work of Dutta et. al. [7], [9] explores the scope of low power motion sensing for detection of different kinds of events. There is a variety of hardware available for motion sensing. Trio sensor mote is a platform for low power motion sensing [10]. Another platform is the BumbleBee radar sensor [5]. Application of radar sensor for low power motion sensing is discussed in [8]. There are different signal processing techniques available for processing motion data from sensors. Some of the contributions on application of signal processing techniques are [12], [4], [1]. Sensing and characterizing human motion has been an interesting research direction. There is considerable amount of work on human gait motion, relevant signal processing and hardware platforms [3], [2], [13], [6], [11]. Some of these works analyze characteristic features of human motion by processing radar sensor signal. But there still are open research problems in human activity monitoring. One of them is indexing the human
activity level. Our work is different from existing ones in the sense that, it discrimi-
nates motion of zero, one and many people, and proposes an index parameter that is
proportional to human activity level.

1.4 Organization

We address the details of the case study of presence detection in chapter 2. Then we
address the details of the case study of activity level monitoring in chapter 3. Finally
we conclude in chapter 4.
Chapter 2

Presence Detection

2.1 Introduction

Presence detection means monitoring for the presence of one or more moving bodies. Presence detection using low power motion sensing is a basic primitive for several applications of Wireless Sensor Networks. As the use of this primitive, we focus on conference room occupancy detection application and related research challenges. Section 2.2 describes the research goal. Section 2.3 details the sensor mote hardware used and the principle of operation. Section 2.4 gives details of raw data collection experience and sensing algorithm. Then section 2.5 describes power management techniques and the final duty cycling algorithm. The source code for presence detection application is given in appendix A.1.

2.2 Goal

Our main focus is automatic tracking of conference room occupancy. The goal is to set up a network of motion sensors in the conference rooms in the Dreese Lab. ¹ There will be a motion sensor mote inside each conference room. Each of these sensors will return live information with accurate occupancy status of corresponding room. So the output of each motion sensor are: empty/occupied status and the room identifier.

¹This sensing layer is a part of the ongoing PeopleNet project.
CHAPTER 2. PRESENCE DETECTION

The mote will operate in duty cycled manner, with no external power supply within its expected lifetime. It will sense for any motion in the room, and then will apply a detection algorithm to decide whether the room is occupied or is empty. Upon the decision, it will send periodic update message through a network of static sensors, which will reach finally to the Base Station (the PeopleNet server).

2.3 Sensor Mote Hardware

For the target application of room occupancy detection, a correct and suitable motion detection technique is needed. We chose to use the PIR (Pyroelectric InfraRed) sensor which returns a scalar value of detected signal level. It doesn’t have any phase information. But this is sufficient for the purpose of target application. The PIR sensors are popular for detecting human and vehicle presence. These devices are the central component in many motion sensors for automatic lighting, security systems, electric doors etc. PIR sensors are a good choice for presence and motion detection owing to their low power, small size, high sensitivity, low cost, and broad availability. By way of sensor node and network platform, we have chosen the Trio mote.\(^2\)

One of the most important components of Trio sensor mote is the PIR motion sensor subsystem. A rechargeable lithium battery is its source of energy. The components of Trio sensor mote are shown in Figure 2.1. A closer look at the circuit board of Trio is shown in Figure 2.2.

The Kube Electronics C172 pyroelectric sensor is at the core of the PIR subsystem. The passive infrared subsystem on Trio is composed of several components:

- Kube Electronics C172 pyroelectric sensor
- Power control, power supply filter
- Active band pass filters
- A summing OPAMP

\(^2\)The Trio Mote is U.C. Berkeley’s third Open Experiment Platform for the DARPA NEST project.
2.3. SENSOR MOTE HARDWARE

![Components of Trio Sensor Mote](image)

- A window comparator

The detailed circuit diagram of PIR subsystem is given in Figure 2.3. Each PIR sensor has a 90 degrees field-of-view. The four PIR sensors are mounted on 90 degrees intervals so their fields-of-view overlap slightly. The sensing and active filter blocks operate in parallel, to a degree, until they are combined into a single analog signal at the summing op amp whose output is connected to an ADC input channel on the processor. PIR is a differential sensor, which detects the target as it crosses the beams produced by the optics as in Figure 2.4.

- How PIR works: A PIR detector is a motion detector that senses the heat emitted by a living body. PIR stands for PyroElectric Infra-Red. The sensor is passive because, instead of emitting a beam of light or microwave energy that must be interrupted by a passing person in order to sense that person, the PIR is simply sensitive to the infrared energy emitted by everything. When an intruder walks into the detectors field of vision, the detector sees a sharp increase in infrared energy. A PIR sensor is designed to turn on when a person approaches, but will not react to a person standing still. A moving person exhibits a sudden change in infrared energy, but a slower change is emitted by a motionless body. Slower changes are also caused
by gradual fluctuations in the temperature of the environment.

2.4 Raw Data Collection and Analysis

In order to design a reliable motion detection algorithm, as the first step history of raw sensor data and corresponding ground truth were collected. In the conference room real time environment raw PIR sensor data was collected. Through a significant amount of accumulation of raw data and ground truth, some key observations were made. From the raw data during empty room and during occupancy of room, we were able to detect a distinct signal threshold level for successful and error free detection.

It is observed that on detection of motion in conference room, the output PIR signal level goes above the f 800 (Figure 2.6). On the other side, in an empty conference room, the output PIR signal level is below value of 650 (Figure 2.5). Thus we have chosen to apply simple threshold based logic for occupancy detection purpose. We haven’t used any filtering algorithm for this application. Our assumption is that the
2.4. RAW DATA COLLECTION AND ANALYSIS

环境的会议室主要是无噪声的，很少有物体运动在空的房间。

所以基本的检测逻辑如下：在当前时隙，通过一个时间窗口W，PIR原始数据被采样。

1. 如果检测的信号水平超过阈值，即$V_{Th}$（通常为800），则房间被占用了。一个占有的状态无线电信息被发送，并更新当前时隙的日志。

2. 如果所有信号水平均低于$V_{Th}$，则：
   - 如果通过最后$N$（通常为3）的时隙至少有一个占用，那么一个占有的状态无线电信息被发送，并更新当前时隙的日志。
   - 如果通过最后$N$（通常为3）的时隙没有占用，那么一个空的状态无线电信息被发送，并更新当前时隙的日志。

图2.3: 非接触红外子系统
CHAPTER 2. PRESENCE DETECTION

2.5 Power Management

Power management is crucial in low power sensing. Relatively high power consumption of sensors and radio, and limited power supply necessitate efficient power management for sensing applications. In this section we have address issues of and improvements for power management. Finally we propose a duty cycling algorithm and calculate an expected lifetime.
2.5. POWER MANAGEMENT

2.5.1 Dynamic Stabilization

A system with Dynamic Stabilization has the intelligence to recognize when some of its output signal gets stabilized. A system without Dynamic Stabilization waits for a predefined delay until which the observed output signal is believed to be unstable. In our PIR subsystem on Trio, we have detected and analyzed some properties, that help us to implement Dynamic Stabilization. The advantage of using Dynamic Stabilization is that it reduces power consumption.

Whenever the PIR sensors change the state from power OFF or SLEEP to power ON, it takes some considerable time to stabilize the output PIR signal from Trio (the ADC output). We have observed and tested the stream of ADC output values when the PIR becomes powered ON. The observation is that independent of sampling speed, the ADC output stabilizes after a time with a tight upper and lower bound.

When the PIR is powered ON, the stream of signal value indicate some low values and then some high values. These clearly trigger false positives and false negatives, leading to incorrect detection of occupancy. Therefore in order to have the target application implemented without false positive or false negative, the detection system has to wait for a time, say, $T_{\text{wait}}$ only after which the ADC output will be sampled. We have made our system more efficient by making the stabilization time dynamic.

More detailed observation from the stream of ADC signal (when PIR is powered
CHAPTER 2. PRESENCE DETECTION

Figure 2.6: Raw PIR data from occupied conference room

Figure 2.7: Typical dynamic stabilization pattern of PIR raw output

ON) reveals that the PIR subsystem output to ADC first gives some low values and then some high values. Just after that, the PIR signal stabilizes and gives absolutely correct detection level without any system noise. This has been validated through a number of experiments. We have utilized this property to implement Dynamic Stabilization: after making PIR ON and after streams of samples of value 0xFFFF (i.e. detection value of 65535), when the PIR output signal level to ADC stops giving value of 0xFFFF, then the system decides that the output signal has stabilized. This triggers the sampling of the ADC for motion data observation. Dynamic Stabilization results in reduced power consumption by PIR sensor (by making PIR ON for lesser time).

As shown in Figure 2.7, when the sampling interval is chosen to be 125 ms, on powering the PIR ON, first there is a stream of on average 72 samples of 0x0000 value. Then there is the stream of on average 84 samples of 0xFFFF value. Then the PIR output to ADC gets stabilized.
2.5. POWER MANAGEMENT

2.5.2 Issue with Stabilization Time

One drawback of the PIR subsystem in use is its high stabilization time. In-depth testing shows that from the time of powering the PIR ON, it takes a while (about 20 seconds) for the ADC output to be stable and ready to sample for our application purpose. This large stabilization time eventually will increase power consumption in each period, because the PIR sensor consumes a relatively high amount of power: 0.88 mW when ON and 3 µW when OFF. This leads a high duty cycle and low lifetime.

Triggered by this problem, we have analyzed the circuit components from the PIR sensor to the ADC output. As shown in the circuit diagram of PIR subsystem (Figure 2.3), the output from the four PIR sensors first goes to the Summing Operational Amplifier, followed by a Band Pass Filter circuit. The final output from the filter circuit goes to the ADC. We have conducted experiments to understand stabilization time at different output stages by visualizing the signals on an oscilloscope. We have observed that it takes about 2 seconds to stabilize direct PIR output. It is also revealed that after direct PIR output stabilizes, it takes additional 7 seconds for the output of Summing Operational Amplifier to reach stable state. Then the filter circuitry takes another 11 seconds to deliver a stable output on ADC. So through this high stabilization delay, the PIR is ON and thus draining significant amount of power. This has brought a challenge, how to deal with this high stabilization time when our goal is low duty cycling and longer lifetime, which we address below, in section 2.5.5.

2.5.3 Speed and Duration of Sampling

While designing the duty cycling algorithm, the sampling speed and sampling duration for the PIR signal on ADC are key issues. According to the Nyquist Theory, the sampling speed has to be at least twice the frequency of the event triggering motion detection. So we need to estimate the typical frequency of such event that triggers detection of motion on (passive) PIR beams.

On the Trio mote, there are four PIR sensors with reflectors, each of which virtually throws a number of beams (passive beam) with an azimuth angle of about 90°. Now if any object passes through two consecutive beams, it triggers the PIR output
signal to change. From the specification of PIR subsystem, the angular separation between two consecutive beams (say $\theta$) is about $8^\circ$. We have also observed that typically, the radial distance between object (people in conference room) and the PIR sensor (say $r$) is about 180 cm. Therefore the amount of displacement by the moving object when it moves from one beam to the next beam (that triggers detection), (say $s$) is 25 cm ($s = r.\theta$). Now typically speed of human body parts in the application environment is 1 meter/s. Therefore it takes 0.25 seconds for the object to trigger motion detection. Therefore the frequency of the event of interest is 4 Hz. This necessitates the sampling frequency to be 8 Hz according to Nyquist theorem. Selection of this frequency assures successful motion event detection. So the sampling period is selected to be 125 ms.

While this is the logic underlying the selection of sampling speed, there is another kind of event that determines sampling duration. From some experiments it is realized that there is at least one event of body part movement of people (that triggers the detection) in every 10 seconds (in a conference room environment). Therefore the sampling duration is chosen to be 10 seconds.

2.5.4 Final Duty Cycling Algorithm

Here we describe our duty cycling algorithm. Figure 2.8 presents the flow chart diagram of the algorithm. In each period, the PIR is first turned ON and there is a wait for time $w_1$ for the stabilization delay of PIR. Then the ADC is sampled for raw PIR output through a time of $w_2$ and after that PIR is turned OFF. Then the radio is turned ON and the wait for radio start up for time $w_3$. After radio start up, the occupancy decision message is sent and then the radio is powered OFF. After that, the application goes to sleep (PIR OFF, radio OFF) for time $w_4$. Then again the PIR is turned ON and the process repeats. The timeline of each period is shown in Figure 2.9.

Now we formally describe the duty cycling algorithm:

Repeat

1. Turn PIR ON; $t=0$; $i = (i+1)\mod 4$;
2.5. POWER MANAGEMENT

Figure 2.8: Flow chart of Duty Cycling algorithm for conference room occupancy

2. Wait until PIR stabilizes ($t < w_1$).

3. If $(w_1 \leq t \leq (w_1+w_2))$ AND $(V(t) > 800)$, then
   - update status as occupied.
   - Turn PIR OFF
   - $\text{window}[i]=1$

4. If $(t=(w_2+w_1))$ AND $(V(t') < 800$ for all $t'$ such that $w_1 \leq t' \leq (w_1+w_2))$
   AND $(\text{window}[j]=1$ for at least one $j$, such that $((i-3)\text{mod}4 \leq j < i)$), then
   - update status as occupied
CHAPTER 2. PRESENCE DETECTION

Figure 2.9: Timeline of Duty Cycling algorithm for conference room occupancy

5. Else update status as empty

Next we present the selection of the parameters of the algorithm:

- \( w_1 \) (dynamic): typically 20 sec
- 125 ms sampling interval
- \( w_2 \) (upper limit): max 10 sec
- \( w_3 \): 1 ms (appx.)
- Radio TX time 4 ms (appx.)
- \( w_4 \): 120 s

2.5.5 Lifetime Analysis

Given the duty cycling algorithm and the selection of parameters, we now calculate the theoretically expected lifetime of the sensor mote for the desired application.
2.5. POWER MANAGEMENT

<table>
<thead>
<tr>
<th>Components</th>
<th>State</th>
<th>Energy</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIR sensors</td>
<td>ON</td>
<td>0.88 mW</td>
</tr>
<tr>
<td>PIR sensors</td>
<td>OFF</td>
<td>0.003 mW</td>
</tr>
<tr>
<td>Radio</td>
<td>Tx</td>
<td>48 mW</td>
</tr>
<tr>
<td>Radio</td>
<td>OFF</td>
<td>0.003 mW</td>
</tr>
<tr>
<td>MCU</td>
<td>ON</td>
<td>1.8 mA</td>
</tr>
<tr>
<td>MCU</td>
<td>OFF</td>
<td>0.0545 mA</td>
</tr>
</tbody>
</table>

Table 2.1: Power consumption of Trio mote components

<table>
<thead>
<tr>
<th>Time sub-slot</th>
<th>Components state</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1 = 20 s</td>
<td>PIR ON, Radio OFF, MCU ON</td>
<td>7.543 mW</td>
</tr>
<tr>
<td>w2 = 10 s</td>
<td>PIR ON, Radio OFF, MCU ON</td>
<td>7.543 mW</td>
</tr>
<tr>
<td>w3 = 0.005 s</td>
<td>PIR OFF, Radio SEND, MCU ON</td>
<td>54.663 mW</td>
</tr>
<tr>
<td>w4 = 120 sec</td>
<td>PIR OFF, Radio OFF, MCU SLEEP</td>
<td>0.20765 mW</td>
</tr>
</tbody>
</table>

Table 2.2: Power consumption of Trio components through timeline of duty cycling operation

Table 2.1 presents the power consumption fact of different functional components of Trio mote. Table 2.2 shows the calculation of power consumption through timeline of each period of duty cycling operation.

Now, the power supply from the lithium ion battery source is: $740 m\text{Ah}r \times 3.7V = 2738 m\text{Whr}$. From Table 2.2, the energy consumption in each period (of length $150.005s$) is $251.481315 m\text{Ws}$. Then the theoretical lifetime of the application is $68 days$. This lifetime is moderate with respect to the application. This brings new goal and challenge to find a better lifetime, either through modifying PIR hardware and revising the duty cycling technique, or through another kind of low power motion sensor.

Proposed improvement: One solution that can elevate lifetime by some amount is modifying the PIR component circuit a bit on the Trio board. As shown in Figure 2.10 in current configuration there is common power supply for the PIR sensors and the circuitry (summing op-amp and filter circuit). So the sensors and circuitry go ON or OFF simultaneously. We have seen in the analysis of stabilization delay that the circuitry takes total 18 seconds to stabilize, while PIR sensors stabilize in less
CHAPTER 2. PRESENCE DETECTION

Figure 2.10: Common power supply in the problem of large stabilization delay

than 2 seconds when made ON from SLEEP. Now, if there was isolated power supply for PIR sensors and for the circuitry, and the circuitry was ON all the time, then it would take less than 2 seconds to get stabilized output on the ADC. The power consumption of the circuitry (when ON) is much lower than the power consumption of PIR (when ON). Therefore this small modification of having isolated power supply for sensors and circuitry is expected to significantly elevate the lifetime of the application.
Chapter 3

Human Activity Level Monitoring

3.1 Introduction

Activity level monitoring means continuous observation and tracking of intensity of motion activity. Activity level monitoring using low power motion sensing is a basic primitive for several applications of Wireless Sensor Networks. As the use of this primitive, we focus on tracking activity level of human, more specifically a single human subject in environment of his/her daily life. Section 3.2 first describes the main research goal. Section 3.3 presents the details of the sensor mote hardware used and the working principle. Then section 3.4 discusses the process of raw data collection and analyses. Section 3.5 proposes the algorithm for distinguishing between motion of single and multiple persons. Section 3.6 presents a reliable human activity level index. Section 3.7 finally describes the power management issue and the adaptive duty cycling algorithm.

3.2 Goal

The goal is reliable and accurate human activity level monitoring index. A radar sensor is used to monitor activity level of any person of interest. Unlike the concept of operation of typical activity monitoring devices, the concept is to have an unattached sensor network observe activity level of subject from a distance. There are two major
research challenges:

1. Finding an algorithm that distinguishes between one person (the person of interest) motion and multiple persons motion.

2. Finding a reliable and fairly accurate index of activity level (of the person of interest).

The goal intends the realization of a framework that can observe a person of interest for a significant period of time and deliver periodic updates of his/her activity intensity level. This will help in the future, for example to develop a system that will enable fine grained activity monitoring of ADHD affected children going through stages of medication process, or will monitor sleep pattern of an infant.
3.3 Sensor Mote Hardware

In the conference room occupancy case study, the PIR sensor is used for relatively simpler goal of presence detection. But for human activity level monitoring, we need a motion sensor with richer information output. We have chosen to use the BumbleBee Radar Sensor. It is a coherent, pulsed Doppler radar. The radar sensorboard is connected to a Crossbow TelosB Mote for processing purpose Figure 3.1.

Being a pulsed Doppler radar, the BumbleBee measures radial velocity directly. Because it is coherent, it is possible to determine the sign of the velocity and measure the time structure of relative motion precisely, even for small motions. Range is not measured directly, but in some contexts it is possible to infer range from motion information. The radar produces phase information directly resulting in motion information with a resolution of a fraction of a wavelength (i.e. fractions of a centimeter of displacement) which is an order of magnitude finer than if the radar were non-coherent. This information can be received at a rate of 300 complex (i.e. real and imaginary pairs) samples per second. It is possible to control the range of detection by varying the potentiometer on the radar, or with the help of software. It uses about 38 mw of total power, has a range of 10m, and is form factor compatible with Motes.

Some of the important features of BumbleBee are:

- Coherent output (both I and Q channels).
- 60°conical coverage pattern.
- Responds to radial velocities between 2.6 cm/s and 2.6 m/s.

In our experiments, we have utilized the I and Q channel data for frequency response and other analyses.

1source: http://blog.xbow.com/xblog/sensor_boards/
3.4 Raw Data Collection and Analysis

It is crucial to have raw sensor data with ground truth. To analyze the signal characteristics pertaining to different motion patterns or scenarios. We have therefore conducted several experiments with recording of ground truth. Then from the motion response signal from the radar, we have done offline analysis with the help of different signal processing techniques. After data collection, the challenge is to find the most suitable signal processing techniques that will correlate different motion scenarios with their corresponding signal response. Here we describe the different experiments and our experience of signal analyses.

We have collected the raw data in form of streams of pair of I and Q channel data. The signal processing techniques used are suitable and reasonable for signal analysis and validation purpose in our research goal:

1. Spectrogram
2. Power Spectral Density (PSD)
3. Average Signal Power in a Frequency Band

The Spectrogram gives the short-time Fourier transform of the input signal. Power Spectral Density (PSD) describes how the power of a signal (i.e., a time average of signal energy) or time series is distributed with frequency. The integral of the PSD over a given frequency band computes the Average Power in the signal over that frequency band.

Experiments are conducted with different motion patterns:

- Radial walking (uniform gait)
- Across walking (uniform gait)
- Milling

- Uniform Gait: We define uniform gait by the type of motion where human legs and hands are oscillating with almost uniform period, and leg stride is almost the
3.4. RAW DATA COLLECTION AND ANALYSIS

same. Walking is a relevant example of uniform gait motion. In uniform gait, the oscillation period or stride can change, but not very abruptly.

- **Milling**: We define Milling by the type of motion, the human legs or hands are moving with non-uniform period or stride. In this kind of motion, the oscillation period or stride can change abruptly.

In radial motion, one or multiple people have walked towards the radar and then straight away from it on to the other direction. In ‘across’ motion, one or multiple people have walked (at a distance of half the maximum range) from one side of radar to the other side, normal to the radial direction. In milling motion, one or multiple people have executed casual movement of milling type motion in a small space (at a distance of half the maximum range). These varying movement patterns are used in order to analyze motion signal response with varying aspects like range, activity level, number of person, angle of motion, angle of sensor view, speed etc. This helps to make the desired activity level index more robust to all sorts of scenarios.

### 3.4.1 Experiment 1: walking human motion in radial and across direction

This experiment is conducted on the roof of a parking lot. This set up is chosen in order to have a large open field that is mostly free of unwanted background noise. The *BumbleBee* radar is kept in two set up: on the ground and on top of a ladder. An inclined view from the ladder can help the radar to view multiple moving people with more distinction. Then in different scenarios, 1 or 5 or 10 people have executed controlled radial and across motion. The raw data is then collected and analyzed offline.

**Experiment1A: Background noise with no person in the detection range**

In this experiment, the radar collects raw data with no person in the detection range. This is done in order to assess the signal in pure noise with no motion in range. Data is collected for fairly long time (about 100 seconds) for proper validation. Given are the response of the signal using different signal processing techniques.
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.2: Spectrogram: background noise

Experiment1B: 1 person radial walk

In this experiment, 1 person walks towards the radar from maximum range and then continuing away from the radar till maximum range. This is done to assess the signal response of single person radial motion. Given are the response of the signal using different signal processing techniques.

Experiment1C: 5 person radial walk

In this experiment, 5 persons walk towards the radar from maximum range and then continuing away from the radar till maximum range. This is done to assess the signal response of radial motion of multiple people. The goal is to discriminate events of single person motion and multiple person motion. Given are the response of the signal using different signal processing techniques.

Experiment1D: 10 person radial walk

In this experiment, 10 persons walk towards the radar from maximum range and then continuing away from the radar till maximum range. This is done to assess
the signal response of radial motion of even more number of people from the last experiment. The goal is to discriminate events of single person motion and motion of increasing number of persons. Given are the response of the signal using different signal processing techniques.

**Experiment1E: 1 person across walk**

In this experiment, 1 person walks across the direction of radar signal (along a line with perpendicular distance from the sensor as 5m i.e, the half the maximum range). The motion is from maximum range on one side to the maximum range on the other side of the sensor. This is done to assess the signal response of single person across motion. Given are the response of the signal using different signal processing techniques.

**Experiment1F: 5 person across walk**

In this experiment, 5 persons walk across the direction of radar signal (along a line with perpendicular distance from the sensor as 5m i.e, the half the maximum range).
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.4: Spectrogram: 1 person radial motion

The motion is from maximum range on one side to the maximum range on the other side of the sensor. The goal is to discriminate events of single person motion and multiple person motion. Given are the response of the signal using different signal processing techniques.

**Experiment1G: 10 person across walk**

In this experiment, 10 persons walk across the direction of radar signal (along a line with perpendicular distance from the sensor as 5m i.e, the half the maximum range). The motion is from maximum range on one side to the maximum range on the other side of the sensor. This is done to assess the signal response of radial motion of even more number of people from the last experiment. The goal is to discriminate events of single person motion and motion of increasing number of persons. Given are the response of the signal using different signal processing techniques.
3.4. RAW DATA COLLECTION AND ANALYSIS

3.4.2 Experiment 2: human milling motion

Besides walking activity, there are other major kinds of human motion. One of them is milling motion activity. In this kind of motion, two or more people move for the most part in arbitrary directions and patterns. We have conducted experiments with milling activity of 1, 2 and 4 people.

Experiment 2A: 1 person milling

In this experiment, 1 person comes into the range of the radar, stands in front of radar at a distance of 5 meter (half the maximum range). Then the person executes some random milling movements in a small range of space. This experiment is conducted to gather response of signal during mild motion activity of milling.

Experiment 2B: 2 persons milling

In the previous experiment, already 1 person is milling in the radar range. Now 1 more person comes from another direction (than in experiment 2A), and then these 2 persons keep milling at near about 5 meters from the radar. This experiment is
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.6: Spectrogram: 5 people radial motion

conducted to analyze the response of signal during mild motion activity of multiple people (2 people here).

**Experiment 2C: 4 persons milling**

In the previous experiment, already 2 persons are milling in the radar range. Now 2 more persons come from directions opposite to each other, and different from those in experiment 2A and 2B. Then all 4 persons keep milling at near about 5 meters from the radar. This experiment is conducted to analyze the response of signal during mild motion activity of large number of people (4 people here).
3.4. RAW DATA COLLECTION AND ANALYSIS

Figure 3.7: Power Spectral Density: 5 people radial motion

Figure 3.8: Spectrogram: 10 people radial motion
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.9: Power Spectral Density: 10 people radial motion

Figure 3.10: Spectrogram: 1 person across motion
3.4. **RAW DATA COLLECTION AND ANALYSIS**

Figure 3.11: Power Spectral Density: 1 person across motion

Figure 3.12: Spectrogram: 5 people across motion
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.13: Power Spectral Density: 5 people across motion

Figure 3.14: Spectrogram: 10 people across motion
3.4. **RAW DATA COLLECTION AND ANALYSIS**

Figure 3.15: Power Spectral Density: 10 people across motion

Figure 3.16: Spectrogram: 1 person milling motion
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.17: Power Spectral Density: 1 person milling motion

Figure 3.18: Spectrogram: 2 people milling motion
3.4. RAW DATA COLLECTION AND ANALYSIS

Figure 3.19: Power Spectral Density: 2 people milling motion

Figure 3.20: Spectrogram: 4 people milling motion
Figure 3.21: Power Spectral Density: 4 people milling motion
3.5 Discrimination: Single or Multiple Person

The main goal is to propose a reliable and accurate human activity level monitoring index. If there are multiple persons moving in the range of radar, the activity level calculated from the signal will result in inaccurate measurement because the detected activity level will be the result of all the signals due to motion of multiple people. Therefore the application has to be smart enough to detect if there is only one person (i.e., the test subject only) moving in the range, or if there are multiple people in the range. If it detects multiple people motion, then the radar basically discards the signal. Otherwise if detection denotes only single person motion, then the application goes ahead and determines the activity level index. So it’s crucial to distinguish between events of single person movement and multiple persons movement.

3.5.1 Observed Features

Spectrogram of raw sensor data from different experiments has revealed some characteristic features of uniform gait based motion and milling type motion. Figure 3.22,
Figure 3.23: Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (5 people radial motion)

Figure 3.23, Figure 3.24 show typical uniform gait (radial) motion data. Figure 3.25, Figure 3.26, Figure 3.27 show typical uniform gait (across) motion data. Then Figure 3.28, Figure 3.29, Figure 3.30 show typical milling motion data. Before describing the discrimination algorithm, first we define the concept of Dominant Return.

Dominant Return

*Dominant Return* is the major signal that is reflected from the moving object(s). It contains the most significant spectral density of the total reflected signal. We may formalize *Dominant Return* as follows. Say $PSD$ is the spectral density, a function of time ($t$) and frequency ($f$) in the spectrogram. Mathematically the spectrogram of selected time bin returns the Spectral Density matrix (say $PSD$). The rows of $PSD$ are divisions of frequency range and the columns of $PSD$ are divisions of selected timeframe. We need to retrieve only the dominant return (say $PSD_{dominant}(t, f)$) from the spectrogram of selected time bin. This is achieved in the following way.

For each unit time (say at time instant of $t'$):

- If $PSD(t', f) < 62.5\%$ of +60 dB, then $PSD_{dominant}(t', f) = 0$
3.5. DISCRIMINATION: SINGLE OR MULTIPLE PERSON

Figure 3.24: Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (10 people radial motion)

- Else $PSD_{dominant}(t', f) = PSD(t', f)$

This enables us to filter only the dominant return (index of significant motion information) and ignore other trivial components. It is observed from all set of experimental data that about +58 dB is the maximum power spectral density across time and frequency division.

**Characteristic Features**

We observe that uniform gait based motion (for example walking) generates dominant return of envelope type pattern of oscillation in the frequency range -100 Hz to +100 Hz. The milling type of motion generates dominant return in the lower frequency range of -20 Hz to +20 Hz. So for milling motion, the total frequency filling in -20 Hz to +20 Hz is significant. But when there are both uniform gait and milling motion happening through time (which is common in scenarios like changing motion type, or some person milling and some person walking), the spectrogram contains either or both patterns. This requires the discrimination algorithm to return correct result independent of type of motion occurring. Keeping this in mind, we have proposed
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.25: Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (1 person across motion)

desired discrimination algorithm. First we separately describe logic behind the discrimination techniques for uniform gait based and for milling type motion. Then these are combined into the generally applicable final discrimination algorithm.

Feature for uniform gait motion: The signal spectrogram for uniform gait based motion generates an envelope type (oscillation type) pattern with significant intensity (the dominant return). For this envelope, the outermost part with maxima and minima is due to the signal from periodic movement of legs. Near the middle of the envelope lies the signal from the human torso, which has a little variation in speed. In the midway lies the signal from oscillation of arms. The logic behind the proposed discrimination algorithm is that in usual human motion, there is an upper bound of oscillation frequency of human body part. The maxima in the envelope is from the motion of two legs. So for one person motion, the time period of maxima, i.e, the time difference between two consecutive maxima (say $T_m$) will have a lower limit (say $T_{min}$). $T_{min}$ denotes the minimum separation (in time) between oscillations from different human body. Now if there are multiple persons moving, there is a good probability in the selected time bin, that the time difference between two consecutive maxima
3.5. DISCRIMINATION: SINGLE OR MULTIPLE PERSON

Figure 3.26: Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (5 people across motion)

will be less than $T_{\text{min}}$. This is because those two consecutive maxima are due to leg motion of two different persons. This validates the logic behind the discrimination. These claims are supported by initial raw data in Figure 3.22. There is a way to make this technique at least partially robust to error in envelope extraction. Instead of minimum of the timegap between consecutive maxima, an average of timegap between consecutive maxima can be a better choice. We have used this average timegap in the proposed algorithm. There are some harmonics mixed with dominant return in figure, that causes some small error in envelope extraction. Therefore the data has to be processed and filtered in a more fine-grained manner. This is left for future work.

Feature for milling motion: For milling type of motion there is no such envelope type pattern in spectrogram. This is because for milling activity there is no specific uniform oscillation pattern of human legs, arms or torso. But one feature observed from experimental data is that, when there are more than one person milling, more frequencies in range -20 Hz to +20 Hz gets filled up in the time bin. This motivates us to use an algorithm that is threshold based on the amount of frequency filling.
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.27: Typical uniform gait motion data for 2 seconds time bin and frequency range -100 Hz to 0 Hz (10 people across motion)

in dominant return. So the parameter for discrimination here is the total count of frequency components in dominant return through the length of time bin (time bin is selected as 2 seconds).

Also the key observation is that for milling type of motion, the majority of power spectral density lies in the frequency range -20 Hz to +20 Hz. But for uniform gait based motion the power spectral density is distributed in the possible signal range -100 Hz to +100 Hz. This is utilized in proposed discrimination algorithm.

Null Motion

The case of no moving body in range is also distinguished by using threshold. Let $AI$ denote the log of sum of all the spectral densities of the Dominant Return in the time bin and across all frequencies. (This same term $AI$ is later used as Activity Index.)

$$AI = \log\left(\sum_{t=t_1}^{t_2} \sum_{f=low}^{high} PSD_{dominant}(t, f)\right)$$  \hspace{1cm} (3.1)

Where $t_1$ and $t_2$ are starting and ending time of the selected time bin respectively.
3.5. DISCRIMINATION: SINGLE OR MULTIPLE PERSON

Figure 3.28: Typical 1 person milling motion data for 2 seconds time bin and frequency range -30 Hz to +30 Hz

\[(t_2 - t_1)\] is the length of the time bin. The terms lowf and highf are the lower and higher limit of frequency range. For the radar sensor that we have used, lowf = -100 Hz and highf = 100 Hz. ]

Now if \( AI < AI_T \) then we conclude that there is no moving body in the range of radar. The threshold \( AI_T \) is selected as 1.00.

3.5.2 Proposed Discrimination Algorithm

First we define some parameters.

- \( Mul \): the final result of the algorithm of one person motion in range (denoted by \( Mul=0 \)), or multiple people in range (denoted by \( Mul=1 \)).

- \( P \): Power Spectral Density in frequency range -100 Hz to +100 Hz.

- \( P' \): Power Spectral Density in frequency range -20 Hz to +20 Hz.

- \( FF \) (in %): the percentage of frequency fill in dominant return in frequency range -20 Hz and +20 Hz.
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

Figure 3.29: Typical 2 people milling motion data for 2 seconds time bin and frequency range -30 Hz to +30 Hz

- $AI_T$: threshold for null motion. Typically $AI_T = 1.00$;
- $P_{Th}$: threshold for milling. Typically $P_{Th} = 50\%$.
- $FILL_{Th}$ : threshold for frequency fill. Typically $FILL_{Th} = 60\%$.
- $T$ : the average timegap between two consecutive maxima in the detected envelope. Typically $T = 0.3$ seconds.

Now we describe the discrimination algorithm.

Algorithm

REPEAT every 2 seconds time bin:
Input: $PSD$, $P'/P$
Outout: $Mul$

1. Compute $AI$.

2. If $AI < AI_T$ then terminate; Else continue;

44
3.5. DISCRIMINATION: SINGLE OR MULTIPLE PERSON

Figure 3.30: Typical 4 people milling motion data for 2 seconds time bin and frequency range -30 Hz to +30 Hz

3. If $P'/P > P_{Th}$ then call subroutine TASKMILL, else call subroutine TASKGAIT;

**TASKGAIT:**

1. From $PSD$, search for an envelope pattern in dominant return in frequency range -100 Hz to +100 Hz.

2. If an envelope pattern is detected AND $T > T_{min}$, then set $Mul=0$; Else set $Mul=1$;

**TASKMILL:**

1. Compute $FF$;

2. If $FF < FILL_{Th}$ then set $Mul=0$, else set $Mul=1$;

3.5.3 Validation

The calculated data from all the experiments have validated the correctness of proposed discrimination algorithm. The following tables display the results of computation for discrimination algorithm. Almost all the time correct decision is made.
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

There are little numbers of instance of time bin with wrong decision resulted (false negative).

The columns in the following tables denote following:

- **Bin**: serial number of time bin (each bin is of length 2 seconds)
- **P’/P**: % ratio of PSD in -20 Hz to +20 Hz to PSD in -100 Hz to +100 Hz
- **Env**: envelope detected (True/False)
- **T<T_{min}**: the condition for separation between envelope maxima (True/False)
- **FF**: % of filling in -20 Hz to +20 Hz
- **Mul**: final decision of one person in range ($Mul=0$) or multiple persons in range ($Mul=1$)
3.5. DISCRIMINATION: SINGLE OR MULTIPLE PERSON

<table>
<thead>
<tr>
<th>Bin</th>
<th>$P'/P$</th>
<th>Env</th>
<th>$T&lt;T_{min}$</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20.92</td>
<td>T</td>
<td>F</td>
<td>13.81</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>13.565</td>
<td>T</td>
<td>F</td>
<td>76.02</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>25.39</td>
<td>T</td>
<td>F</td>
<td>53.42</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>31.555</td>
<td>T</td>
<td>F</td>
<td>0.38</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>22.785</td>
<td>T</td>
<td>F</td>
<td>1.28</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>20.245</td>
<td>T</td>
<td>F</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>39.135</td>
<td>F</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>35.8</td>
<td>F</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.1: Computation for discrimination: 1 person radial

<table>
<thead>
<tr>
<th>Bin</th>
<th>$P'/P$</th>
<th>Env</th>
<th>$T&lt;T_{min}$</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>37.79</td>
<td>F</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>29.72</td>
<td>T</td>
<td>T</td>
<td>18.2</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>25.015</td>
<td>T</td>
<td>T</td>
<td>87.43</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>24.57</td>
<td>F</td>
<td></td>
<td>97.82</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>25.23</td>
<td>T</td>
<td>T</td>
<td>91.89</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>44.31</td>
<td>T</td>
<td>T</td>
<td>80.92</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>44.545</td>
<td>T</td>
<td>T</td>
<td>66.57</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>30.68</td>
<td>T</td>
<td>T</td>
<td>16.95</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.2: Computation for discrimination: 5 people radial

3.5.4 Failure in Discrimination

From the experimental results and observations we have predicted the scenario when the discrimination algorithm can possibly fail.

- When one/multiple persons are just entering the range of radar, because of low amount of dominant return it may denote no motion.

- When multiple people are well separated in space then varying amplitude of envelope patterns may result decision of one person motion.

- When one or multiple people are very close to the radar and within it’s blind range, it may result in decision of no motion.
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

<table>
<thead>
<tr>
<th>Bin</th>
<th>P'/P</th>
<th>Env</th>
<th>T&lt;T_{min}</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>33.415</td>
<td>F</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>30.33</td>
<td>T</td>
<td>10.19</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>25.23</td>
<td>T</td>
<td>79.96</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>22.56</td>
<td>F</td>
<td>98.78</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>25.08</td>
<td>F</td>
<td>98.39</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>40.61</td>
<td>F</td>
<td>94.51</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>35.81</td>
<td>T</td>
<td>41.63</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>29.165</td>
<td>T</td>
<td>31.44</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.3: Computation for discrimination: 10 people radial

<table>
<thead>
<tr>
<th>Bin</th>
<th>P'/P</th>
<th>Env</th>
<th>T&lt;T_{min}</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>39.105</td>
<td>T</td>
<td>F</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>26.03</td>
<td>T</td>
<td>F</td>
<td>0.99</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>25.55</td>
<td>T</td>
<td>F</td>
<td>50.76</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>41.45</td>
<td>F</td>
<td></td>
<td>92.14</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>27.32</td>
<td>T</td>
<td>F</td>
<td>46.25</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>25.03</td>
<td>T</td>
<td>F</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3.4: Computation for discrimination: 1 person across

3.5.5 Robustness

An ideal discrimination algorithm should be robust enough to different factors like:

- orientation of subject w.r.t the radar
- changing distance between the subject and radar
- all variations of speed
- varying activities

These robustness properties will ensure real world applicability for all possible scenarios. We have tried to make proposed discrimination algorithm robust to at least some factors like: orientation of subject w.r.t. radar, different variation of speed and somewhat to varying activities.
### 3.5. DISCRIMINATION: SINGLE OR MULTIPLE PERSON

<table>
<thead>
<tr>
<th>Bin</th>
<th>$P'/P$</th>
<th>Env</th>
<th>$T&lt;T_{\text{min}}$</th>
<th>FF</th>
<th>Disc</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>26.685</td>
<td>F</td>
<td>8.01</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>39.66</td>
<td>F</td>
<td>65.73</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>27.915</td>
<td>F</td>
<td>90.09</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>37.825</td>
<td>F</td>
<td>98.81</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>41.755</td>
<td>F</td>
<td>99.48</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>51.5</td>
<td>F</td>
<td>95.57</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>26.93</td>
<td>F</td>
<td>51.47</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>23.045</td>
<td>F</td>
<td>14.17</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>22.99</td>
<td>F</td>
<td>0.51</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.5: Computation for discrimination: 5 people across

<table>
<thead>
<tr>
<th>Bin</th>
<th>$P'/P$</th>
<th>Env</th>
<th>$T&lt;T_{\text{min}}$</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>18.155</td>
<td>F</td>
<td>1.25</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>19.21</td>
<td>F</td>
<td>53.1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>28.255</td>
<td>F</td>
<td>98.46</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>33.215</td>
<td>F</td>
<td>99.58</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>48.33</td>
<td>F</td>
<td>99.55</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>45.675</td>
<td>F</td>
<td>92.21</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>32.265</td>
<td>F</td>
<td>50.71</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>20.19</td>
<td>F</td>
<td>3.52</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>22.975</td>
<td>F</td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.6: Computation for discrimination: 10 people across

<table>
<thead>
<tr>
<th>Bin</th>
<th>$P'/P$</th>
<th>Env</th>
<th>$T&lt;T_{\text{min}}$</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>74.13</td>
<td>F</td>
<td>71.98</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>71.805</td>
<td>F</td>
<td>62.46</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>57.735</td>
<td>F</td>
<td>43.01</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>74.86</td>
<td>F</td>
<td>57.91</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>54.765</td>
<td>F</td>
<td>39.29</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>53.905</td>
<td>F</td>
<td>38.78</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>60.24</td>
<td>F</td>
<td>35.83</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>53.32</td>
<td>F</td>
<td>35.315</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>67.76</td>
<td>F</td>
<td>46.435</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>78.725</td>
<td>F</td>
<td>69.935</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.7: Computation for discrimination: 1 person milling
### Table 3.8: Computation for discrimination: 2 people milling

<table>
<thead>
<tr>
<th>Bin</th>
<th>P'/P</th>
<th>Env</th>
<th>T&lt;T_\text{min}</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>72.66</td>
<td>F</td>
<td>93.49</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>52.87</td>
<td>F</td>
<td>98.645</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>56.25</td>
<td>F</td>
<td>98.715</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>50.05</td>
<td>F</td>
<td>95.25</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>53.04</td>
<td>F</td>
<td>89.195</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>58.57</td>
<td>F</td>
<td>76.215</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>72.25</td>
<td>F</td>
<td>61.375</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>73.5</td>
<td>F</td>
<td>51.21</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>57.32</td>
<td>F</td>
<td>82.015</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>56.87</td>
<td>F</td>
<td>79.675</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3.9: Computation for discrimination: 4 people milling

<table>
<thead>
<tr>
<th>Bin</th>
<th>P'/P</th>
<th>Env</th>
<th>T&lt;T_\text{min}</th>
<th>FF</th>
<th>Mul</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>45.19</td>
<td>F</td>
<td>99.675</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>50.26</td>
<td>F</td>
<td>99.87</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>47.745</td>
<td>F</td>
<td>100</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>42.645</td>
<td>F</td>
<td>99.13</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>48.5</td>
<td>F</td>
<td>98.395</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>53.185</td>
<td>F</td>
<td>99.515</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>57.635</td>
<td>F</td>
<td>97.625</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>64.83</td>
<td>F</td>
<td>98.775</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>49.3</td>
<td>F</td>
<td>98.745</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.9: Computation for discrimination: 4 people milling
3.6 Activity Level Index

The main goal for this case study is to come up with a reliable and accurate indicator of human activity level. After detailed analysis of raw motion data from radar sensor, we have proposed the desired human activity level indicator (we call it Activity Index or AI).

3.6.1 Proposed Formulation

Looking at the spectrogram of motion data, it can be observed that some frequencies have significant spectral density (more filling of those frequencies). We call it dominant return. This set of high filling frequencies change over time because of oscillation of different parts of human body (legs, arms, torso etc.). Looking at these properties, it becomes clear that frequency components with significant spectral density (high filling) bear principal motion activity information. Therefore we define our Activity Index (AI) as logarithm of sum of those significant densities (high fillings) over the frequency range and over small time bin of 2 seconds.

\[
AI = \log(\sum_{t=t_1}^{t_2} \sum_{f=low_f}^{high_f} PSD_{dominant}(t, f))
\]  

[ Where \(t_1\) and \(t_2\) are starting and ending time of the selected time bin respectively. \((t_2 - t_1)\) is the length of the time bin. The terms low\(f\) and high\(f\) are the lower and higher limit of frequency range. For the used radar sensor low\(f\) = -100 Hz and high\(f\) = 100 Hz. ]

This proposed Activity Index (AI) efficiently removes trivial components and noise, and is a fairly accurate representative of motion activity level.

3.6.2 Experimental Data

Figure 3.31, Figure 3.32 and Figure 3.33 show some initial results for Activity Index calculation from our experiments. It has been observed that proposed formulation for Activity Index is somewhat dependent on range. During radial motion in Figure 3.31, same level of walking activity is executed with changing range (towards and then away
3.6.3 Range Dependence

The more efficient Activity Index should show same value for same activity level at different range. Therefore a more refined Activity Index can be:

\[
AI = \log\left(\sum_{t=t_1}^{t_2} \sum_{f_{\text{low}}}^{f_{\text{high}}} PSD_{\text{dominant}}(t, f) / f(R) \right) \tag{3.3}
\]

Where \( f(R) \) is a function of range \( R \). But we are not able to fully validate this refined Activity Index here with experimental data, because current version of BumbleBee radar doesn’t have range information. With modified hardware, it is possible to have range information on radar sensor. Then the refined Activity Index will be achievable for use in practice.
3.6. ACTIVITY LEVEL INDEX

3.6.4 Variations in Activity Index

This proposed Activity Index (AI) is a meaningful index of motion level of all body parts as a whole. But it doesn’t capture the motion level of different body parts. Sometimes a picture of activity of different body parts (separately) extracts more fine grained details. Realizing this and supported by real radar sensor data (some related works and our obtained data), we propose some parameters that capture motion level of individual body parts. From work of M. G. Anderson et al (Figure 3.34) and also partially supported by our initial data (Figure 3.22), it is possible to separate dominant return from human legs, arms and torso. On successful extraction of envelope, some envelope parameters show few more fine grained information about human activity level.

We define some parameters now. \( PSD_{\text{leg,dominant}} \), \( PSD_{\text{arm,dominant}} \), \( PSD_{\text{torso,dominant}} \) denote dominant PSD only from legs, arms, torso respectively. \( T_{\text{leg}}, T_{\text{arm}}, T_{\text{torso}} \) denote the period of oscillation of dominant return (we calculate as time difference between two consecutive maxima) from legs, arms, torso respectively. \( A_{\text{leg}}, A_{\text{arm}}, A_{\text{torso}} \) denote the range or span of oscillation of dominant return (we calculate as frequency
difference between maxima and minima) from legs, arms, torso respectively.

1. \( AI_{\text{leg}} = \log(\sum_{\text{timebin}} \sum_{\text{frequency}} PSD_{\text{leg,dominant}}(t,f)) \) represents total activity level of legs.

2. \( AI_{\text{arm}} = \log(\sum_{\text{timebin}} \sum_{\text{frequency}} PSD_{\text{arm,dominant}}(t,f)) \) represents total activity level of arms.

3. \( AI_{\text{torso}} = \log(\sum_{\text{timebin}} \sum_{\text{frequency}} PSD_{\text{torso,dominant}}(t,f)) \) represents total activity level of torso.

4. Individually each of \( T_{\text{leg}}, T_{\text{arm}}, T_{\text{torso}} \) through time represents how frequently the legs, arms and torso are moving (for example this can capture unusual shaking of arms or legs).

5. Individually each of \( A_{\text{leg}}, A_{\text{arm}}, A_{\text{torso}} \) through time represents the speed of legs, arms and torso (for example this can capture sudden unusual change of speed of body parts).
3.7. **POWER MANAGEMENT**

![Figure 3.34: Human gait motion data from radar sensor (Source: M. G. Anderson et al, Design of Multiple Frequency Continuous Wave Radar Hardware and Micro-Doppler Based Detection and Classification Algorithms)](image)

6. A trace of the ratio $T_{\text{leg}}:T_{\text{arm}}:T_{\text{torso}}$ through time can extract some unusual motion behavior (for example people running away or jumping).

7. A trace of the ratio $A_{\text{leg}}:A_{\text{arm}}:A_{\text{torso}}$ through time can also extract some unusual motion behavior (for example sudden fighting in public place).

One thing to note that separate analysis of different body parts motion is possible only for uniform gait motion, and not for milling motion. For milling motion, the sensor data doesn’t contain typical uniform oscillations of different body parts.

### 3.7 Power Management

Radar sensor can be significant consumers of energy. Due to the finite availability of energy source in deployment scenarios, it is crucial to do energy management in form of a Duty Cycling algorithm. Here we have proposed an efficient and adaptive Duty Cycling algorithm for our application purpose.
3.7.1 Key Properties

There are some important properties in our application that will help building efficient duty cycling technique. We have considered all these properties to finally come up with an efficient and adaptive Duty Cycling algorithm. Now we describe those properties and indicate how they are used in the proposed algorithm.

- The typical human motion has some considerable time interval for change of activity level. Human activities mostly don’t change abruptly in all the time. Therefore the sensor can sleep for some interval (we define as Interval of Activity or IoA), and at the same time do not miss any activity level change. This interval can actually adapt with time and subject. To realize this we have utilized the EWMA (Exponential Weighted Moving Average) method to dynamically update the interval.

- If the sensor analyzes that there are multiple people in the range of the radar, then it can sleep for more time than the scenario of one person in range.

- In each time bin, when sensor is ON, it first analyzes the presence of one or
3.7. POWER MANAGEMENT

multiple people in the range. Then only it does further analyses for activity level monitoring.

3.7.2 Proposed Duty Cycling Algorithm

Figure 3.35 describes the proposed adaptive Duty Cycling algorithm. The time period between \( t_0 \) and \( t_1 \) repeats continuously. To note that \( T_{IoA} \) (we define as Interval for Analysis) is also the time interval of recalculation of effective Interval of Activity (IoA).

The repeating period contains three important parameters: \( T_a, T_b \) and \( T_i \). These parameters make the duty cycling algorithm intelligent enough to adapt to the application requirement, while saving as much energy as possible. Now we describe the three parameters.

- \( T_a \) is the Analysis Window which denotes the time during when the application will recalculate the Interval of Activity (IoA).

- \( T_b \) is the Time Bin, denoting the small time bin during which the radar sensor wakes up and observes the activity level of target (after analyzing if there is one person in range).

- \( T_i \) is the effective Interval of Activity or IoA, denoting the calculated interval between changes of activity level. (This is actually the safe interval for the radar sensor to sleep, so that it doesn’t miss any significant change of activity level).

Here we propose the adaptive Duty Cycling algorithm. The time window \( T_{IoA} \) periodically repeats. The operations inside the repeating window \( T_{IoA} \) is described below.

1. Inside the repeating time window, the application makes the radar sensor ON for time \( T_a \). During this time of length \( T_a \), the sensor observes and analyzes the radar echo signals from the target.
CHAPTER 3. HUMAN ACTIVITY LEVEL MONITORING

- If it detects that there are multiple people in range, then the application makes the sensor OFF for time $T_{OFF}$. After time $T_{OFF}$, the application freshly restarts the repeating window $T_{AI}$.

- Else if there is only one person in range, the sensor is ON for time $T_a$. During this time, it recalculates the Interval of Activity or $IoA$. In order to do this, it tracks the activity level through some number of (say $n$) small Time Bin. After observing the current activity interval, the EWMA algorithm is applied to determine the dynamic average of $IoA$. Suppose $T_i$ is the value of dynamic average interval of activity level change.

  - Calculation of $T_i$: suppose $T''_i$ is the value of effective $IoA$ during the last period of calculation. At the very initiation of algorithm, $T''_i$ has a preselected value. Also let $T'_i$ is the observed Interval of Activity from raw sensor data in current duration of $T_a$. Then the updated value of $T_i$ is calculated from EWMA algorithm:

    \[ T_i = \beta.T'_i + (1-\beta).T''_i \]  
    \[ (3.4) \]

    The parameters $\beta$ is selected as 0.8;

2. Having calculated effective $IoA$ (i.e. $T'_i$) in the last time window $T_a$, the application makes the sensor periodically OFF for time $T_i$ and ON for time $T_b$ until the window length of $T_{IoA}$. $T_b$ is the small Time Bin, during which the sensor analyzes the signal.

   - If it detects multiple people, then it readily makes the sensor OFF for time $T_{OFF}$, after which it freshly restarts the repeating time window $T_{IoA}$.

   - But during the Time Bin $T_b$, if it detects one person in range, it calculates and records the activity level of the subject.

After surveying some research materials about human motion activity patterns, we have selected typical values for the parameters for purpose of our algorithm.

- $T_{AI} = 15 \text{ min} = 900 \text{ s}$
3.7. POWER MANAGEMENT

- $T_a = 20$ s
- $T_b = 2$ s
- starting value of $T_i = 10$ s
- $T_{OFF} = 30$ s
Chapter 4

Conclusions

In this thesis we have addressed mainly two research issues of motion sensing: accurate sensing for reliable event detection, and power management for long lifetime. Our research focuses on two case studies in motion sensing: presence detection and activity monitoring. By way of illustration, we chose two applications: room occupancy detection and human activity level indexing.

The room occupancy detection application with PIR sensor has yielded a number of research challenges. There are some modifications and improvements as possible future work. We have proposed a modification in hardware that is expected to significantly extend the lifetime. For this modification, the expected theoretical lifetime is still to be calculated. This requires independent analysis on the power consumption of summing and stabilizing circuitry in the PIR subsystem. Some more possible modifications are: (i) using standard deviation technique for sensing algorithm, (ii) background noise cancellation, (iii) enabling robustness to change of ambient temperature.

The human activity level indexing application with radar sensor has yielded a number of research challenges. There are some modifications and improvements as possible future work. We have proposed a fairly reliable and accurate human activity level index. But the activity index parameter needs more robustness. One more open problem is to successfully remove the harmonics from the signal response. As a possible tool, LPC Cepstrum Coefficients can be used to remove the harmonics. There
are some more possible improvements on power management, for example: (i) duty
cycling between pulses from the radar, (ii) adapting rate of pulsing with changing
rate of motion activity.
Appendix A

Source Code

A.1 Source Code for Presence Detection

Given is the TinyOS1.x source code for the conference room occupancy application.

- Header File pir.h:

  ```
  #define PIR_SAMPLING_PERIOD_MILLIS 125 // in ms
  #define OFF_TIME 12000 // in ms
  #define NUM_DECISION_WINDOW 4
  #define DETECTION_THRESHOLD 800
  #define FLOOR_NUMBER 2
  #define STOPTIME 10000 // in ms
  #define REPEATTIME 150005
  #define RADIO_START_TIME 2
  ```

- Configuration file confroomPIR.nc:

  ```
  #ifndef _CONFROOMPIR_H
  #define _CONFROOMPIR_H
  #endif
  ```
A.1. SOURCE CODE FOR PRESENCE DETECTION

```c
#include Pir;

configuration confroomPIR
{
}

implementation
{
    components Main, PIRC, LedsC, TimerC,
          PrometheusC,
          GenericComm as Comm,
          confroomPIRM;

    Main.StdControl -> confroomPIRM;

    // Prometheus mode
    confroomPIRM.PrometheusControl -> PrometheusC.StdControl;
    confroomPIRM.Prometheus  -> PrometheusC;

    // For PIR
    confroomPIRM.PIR  -> PIRC;
    confroomPIRM.ADC -> PIRC.PIRADC;
```

63
confroomPIRM. PirControl -> PIRC;

// For LED and Radio
confroomPIRM. Leds -> LedsC;
confroomPIRM. CommControl -> Comm. Control;
confroomPIRM. RadioSend -> Comm. SendMsg [4];

// For Timer
confroomPIRM. TimerControl -> TimerC;
confroomPIRM. ONTimer -> TimerC. Timer [unique (" Timer ")];
confroomPIRM. PIRSamplingTimer -> TimerC. Timer [unique (" Timer ")];
confroomPIRM. ActualSamplingTimer -> TimerC. Timer [unique (" Timer ")];
confroomPIRM. PIRStopTimer -> TimerC. Timer [unique (" Timer ")];
confroomPIRM. RadioStartTimer -> TimerC. Timer [unique (" Timer ")];

}

- Module file confroomPIRM.nc:

```c

#ifndef _PIR_H
#define _PIR_H
#endif

// Pir.h header file included
#include Pir;

module confroomPIRM
{
    provides
    {
        interface StdControl;
    }
}
A.1. SOURCE CODE FOR PRESENCE DETECTION

uses
{
  interface ADC;
  interface PIR;
  interface StdControl as PirControl;
  interface Leds;
  interface StdControl as PrometheusControl;
  interface Prometheus;
  interface StdControl as CommControl;
  interface SendMsg as RadioSend;

  // all timers
  interface StdControl as TimerControl;
  interface Timer as ONTimer;
  interface Timer as PIRSamplingTimer;
  interface Timer as ActualSamplingTimer;
    interface Timer as PIRStopTimer;
    interface Timer as RadioStartTimer;
}
}
implementation
{

  // status radio message structure
  typedef struct {
    uint8_t src;
    uint8_t type;
    uint8_t count;
  } RadioMsg;

}
// initialize variables
uint8_t movingwindow[NUM_DECISION_WINDOW];
uint8_t detect = 0;
uint8_t prom = 0;
uint8_t stabilized = 0;
int16_t val;
uint8_t curr_window = 0;
uint8_t i;
uint8_t num_detects;
uint8_t tosend = 0;

struct TOS_Msg data;

command result_t StdControl.init()
{
    call PirControl.init();
    call TimerControl.init();
    call CommControl.init();
    call Leds.init();
    call PrometheusControl.init();

    return SUCCESS;
}

command result_t StdControl.start()
{
    // a window of history of occupancy information
    for (i = 0; i < NUM_DECISION_WINDOW; i++){
A.1. SOURCE CODE FOR PRESENCE DETECTION

```c
movingwindow[i] = 0;
}
count_detect = 0;
call PirControl.start();
call PrometheusControl.start();
call CommControl.start();
call ONTimer.start(TIMER_REPEAT, REPEATTIME);
return SUCCESS;
}

command result_t StdControl.stop()
{
    return SUCCESS;
}

event result_t ONTimer.fired(){
    call PIR.PIROn();

    // enable battery charging
    if (prom == 0){
        call Prometheus.selectADCSource(TRUE);
        //call Prometheus.getADCSource()
        //call Prometheus.getBattVol();
        //call Prometheus.getCapVol();
        //call Prometheus.setAutomatic(TRUE);
        //call Prometheus.getAutomatic();
    }
```
APPENDIX A. SOURCE CODE

call Prometheus.setPowerSource(TRUE);
//call Prometheus.getPowerSource();
call Prometheus.setCharging(FALSE);
//call Prometheus.getCharging();
prom = prom + 1;
}
call PIRSamplingTimer.start(TIMER_ONE_SHOT, 2);
return SUCCESS;
}

event result_t PIRSamplingTimer.fired(){
count_detect = 0;
stabilized = 0;
call ActualSamplingTimer.start(TIMER_REPEAT,
PIR_SAMPLING_PERIOD_MILLIS);
return SUCCESS;
}

event result_t ActualSamplingTimer.fired(){
call ADC.getData();
return SUCCESS;
}
A.1. SOURCE CODE FOR PRESENCE DETECTION

```c
event result_t PIRStopTimer.fired()
{
    call PIR.PIROff();
    call ActualSamplingTimer.stop();
    call CommControl.start();
    RadioStartTimer.start(TIMER_ONE_SHOT, RADIO_START_TIME);
    return SUCCESS;
}
```

```c
event result_t RadioStartTimer.fired()
{
    if (detect==1){
        tosend = 1;
        movingwindow[curr_window] = 1;
    }
    else{
        num_detects = 0;
        for (i=0; i<NUM_DECISION_WINDOW; i++) {
            if (movingwindow[i]==1) {
                num_detects++;
            }
        }
        if (num_detects >= 1){
            tosend = 1;
            movingwindow[curr_window] = 1;
        }
        else{
            tosend = 0;
            movingwindow[curr_window] = 0;
        }
    }
}
```
APPENDIX A. SOURCE CODE

```c
    { 
    }
    }
    
curr_window++;  
if (curr_window == NUM_DECISION_WINDOW) {  
curr_window = 0;  
}
    
count_detect = 0;

    RadioMsg *message = (RadioMsg *)data.data;  
    message->src = TOS_LOCAL_ADDRESS;  
    message->count = FLOOR_NUMBER;  
    message->type = tosend;  
    call RadioSend.send(TOS_BCAST_ADDR,  
    sizeof(RadioMsg), &data);

    return SUCCESS;
    }

async event result_t ADC.dataReady(uint16_t sample)  
{
    val = sample / 4;  
    
    if( (((int16_t)val)!= 0) &&  
( ((int16_t)val)!= 65535) ){  

        stabilized = stabilized + 1;  
        if(stabilized==1){  
            call PIRStopTimer.start(  
            TIMER_ONE_SHOT, STOPTIME );  
        }
    }
```
A.1. SOURCE CODE FOR PRESENCE DETECTION

```c
if( ((int16_t)val) > 800 ){
    if(count_detect != 1){
        detect = 1;
    }
}
}
return SUCCESS;
}

event result_t RadioSend.sendDone(TOS_MsgPtr msg,
    result_t success)
{
    call CommControl.stop();
    return SUCCESS;
}

event void Prometheus.getPowerSourceDone(
    bool high, result_t success){}
event void Prometheus.getChargingDone(
    bool high, result_t success){}
event void Prometheus.getADCSourceDone(
    bool high, result_t success) { }
event void Prometheus.getAutomaticDone(
    bool high, result_t success) { }
event void Prometheus.automaticUpdate(
    bool runningOnBattery,
    bool chargingBattery,
    uint16_t batteryVoltage,
```
APPENDIX A. SOURCE CODE

```c
uint16_t capVoltage ) { }

event void PIR.adjustDetectDone( bool result ){ return ; }
event void PIR.adjustQuadDone( bool result ){ return ; }
event void PIR.readDetectDone( uint8_t val){ return ; }
event void PIR.readQuadDone( uint8_t val){ return ; }

}```

- Make file `Makefile`:

  COMPONENT=confroomPIR

  CFLAGS += -I$(TOSDIR)/interfaces
  PFLAGS += -DC2420_DEF_CHANNEL=26
  DEFAULT_LOCAL_GROUP := 0x9d

  TRIO_SENSORBOARD=$(TOSDIR)/../contrib/nestfe/nesc/sensorboard/trio
  PFLAGS += -I$(TRIO_SENSORBOARD)
  PLATFORMS=telosb
  include $(TOSDIR)/../apps/Makerules
Bibliography


