Abstract

In a typical open office building, about 30 to 40 percent of energy are consumed in systems such as air conditioning, ventilation, lighting and others. Nowadays most modern air conditioning systems in buildings does not take into account the actual occupancy and activities. This operation mode is inefficient and creates energy waste. Therefore, in order to achieve an efficient air conditioning usage, we need to take into account the mobility behaviour of occupancy in each zone of a building, which allows us to intelligently tune the air conditioning system according to the state of occupancy without compromising the comfortability. We deployed a video capturing and processing system to acquire temporal occupancy information. To this end, we develop a occupant counting software based on - Microsoft Kinect sensor platform. Our software system is capable of detecting and tracking human activity inside a building. One of the drawbacks of the current air conditioning system is the inability to adapt to the changing occupancy and activities instantaneously. Therefore, the management and control of an intelligent HVAC system should base on the dynamic occupancy data. In our research, we propose an approach for energy savings that integrates a real-time occupancy data with building management systems. This approach leads us to the creation of an occupancy monitoring and air conditioning control system based on dynamic occupancy counting. This system is able not only to-track mobility of occupants but also to show the status of its rooms. Based on the prediction of future occupancy level of particular zones of a building, an intelligent system can adjust air conditioning parameters optimally.In this thesis, we introduced a new concept of on human mobility detection and tracking in real-time based on people counter software.We provided the first study that use multiple Kinect sensor as a sensor in building monitoring and management. It has been shown how the Kinect could be applied successfully in the fields of detection and tracking. We proposed an occupancy model that display a visualized data and predicate a future occupancy through a Markov Model transition matrix.Through extensive real time testing of our system, the experimental results have showed a potential energy saving around 22.1% by applying a customized occupancy schedule and customized set point depend on occupancy density.

To this journey,

which reached the end.

To all those adventures

that have yet to come

This research was supported by the Government of Abu Dhabi to help fulfill the vision of the late President Sheikh Zayed Bin Sultan Al Nahyan for sustainable development and empowerment of the UAE and mankind.

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December 20, 2013.

Masdar City

Haleimah Zeyoudi

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CHAPTER 1

Introduction

The default settings of air conditioning system in a building assume a maximum occupancy all year round. As a result, there is an increase of energy waste represented in the Building Energy Data Book statistics at about 50% of total energy [1]. This proportion of energy consumed is spent in HVAC systems as shown in figure /reffig:energy. The top four end energy consumptions in building are mainly in: space heating, space cooling, water heating, and lighting which accounted for around 70% of the energy [1]. Open offices or institute offices are the types of buildings ranked at the top consumer in air conditioning energy among other building architectures.

Nowadays, the current state of technologies for achieving energy-efficient and sustainable buildings relies on wireless sensors which have a minimum energy reduction due to their own limitations. Therefore, there is an extreme demand for energy management and control in buildings. The actual energy management entails live occupancy measurement, which not yet existing. Building an occupancy management system is as significant as having an occupancy estimation system or an occupancy prediction system. Such a system should not ignore the usersâĂŹ comfort level since conditioning a room is not immediate and requires time for adjustments. Thus, if a room will be occupied within two hours with a large number of people, the HVAC system should know and adjust beforehand. The study of user mobility patterns based on occupancy data in buildings will help to predict room usage which can then be merged with the HVAC system to automate control in an adaptive manner.

Understanding human mobility, human behaviour and human occupancy patterns are key factors to successfully managing energy in buildings. There have been many approaches in studying occupancy patterns such as outlook schedules or using wireless sensors. In [2] the authors introduce a system of multiple adaptive sensor agents whose roles are to detect motion, read CO2, record sound levels, ambient light and check door status (open, close). This innovative application called Building-Level Energy Management Systems (BLEMS) is a multi-agent system utilizing fifty eight multi-modal sensors and numerous learning collaborative agents that adapt to the occupants' particular needs. It also contains 74 actuators related to the building's HVAC areas and two units for handling central air. In practice, patterns of occupants' activity are acquired through observation. HVAC operation is then optimized in response to the occupant models. In their system OBSERVE, Erickson et al. demonstrate in [3] how to use a wireless sensor network to collect real time occupancy data and to use it to create occupancy models. These models may be included in a building system for control strategies. With occupancy model predictions drawn from a sensor network-based control strategy, the authors confirm that they have achieved 42% annual energy saving without compromising the American Society of Heating, Refrigerating and Air-Conditioning

(ASHRAE) comfort standards. Xiang et al. present in the article Smart Personalized Office Thermal Control System (SPOT) [4] a smart personal thermal comfort system for use in an office environment. The role of this system called SPOT (Smart Personalized Office Thermal) is to find an acceptable balance between energy consumption and personal thermal comfort in an office environment. This is a reactive control strategy that takes into account real-time occupancy and personal thermal comfort. SPOT makes use of a collection of sensors including Microsoft Kinect to evaluate six parameters known to define human comfort: clothing, air speed, humidity, radiant temperature, air temperature and activity level.

Therefore, the ability to manage and control a HVAC system based on occupancy data requires a real time adjustment and comfort level measurement. Since different people perceive their environment differently, the idea of thermal comfort is not the same for all. The following is the key contribution of our work:

- We introduce a new concept of on human mobility detection and tracking in real-time based on people counter software.Our work on occupancy modelling uses occupants counter software that can detect people entering or leaving certain zone in real-time. We provide the first study that use multiple Kinect sensor as a sensor in building monitoring and management. It has been shown how the Kinect could be applied successfully in the fields of detection and tracking.We used a multiple Kinect sensor to detect the mobility of occupants around the different zones. The Kinect sensor act as a gate divider that divide open offices space into a virtual zones, which can be easily monitored and controlled. This monitoring system can distribute the human mobility through the building and state the different conditions of zones based on some analysis conducted on the collected data. For example, counting the number of people entering and leaving can reveal the arrival time of occupants and their leaving times, which can be taken as input to control over air conditioning system.

- We proposed an occupancy model that display a visualized data and predicate a future occupancy through a Markov Model transition matrix. We developed a Matlab library that creates lots of figures and files that enable the user to visualize the occupancy patterns. The library is capable to parse the log files into three different format, create graphs of daily,weekly,monthly and multi-month mobility patterns and create a transition matrix using Markov chain model which we used as a method to predicate the future occupancy pattern. The collected data is modelled using Markov Chain, where a state is defined as the status of the whole floor at certain time.As mentioned earlier, our sensor divide the open office floor into multi virtual zones, each zone can be represented as one letter of occupancy conditions Empty, Few, Average, Crowd. Each condition reflect a certain number of occupants like Empty for 0 occupants, and Few for less than 10 occupants, Average between 10—20 and Crowd above 20.These conditions should consider the occupancy density of the floor, and specifically of each virtual zones. The states of the building floor can be calculated using MM which generate transition matrix from one state to another. An example to that, if you have a five virtual zones as we have in our test-bed model, you will end up with a matrix of 1024 states started from EEEEE, ..., CCCCC . These states represent some level of energy consumption which can be useful as input data for the controller to the HVAC system for energy building management.

- We deploy a real-world test-bed located at Masdar Institute, using 7 Kinect sensor in i-Smart laboratory. Through extensive real time testing of our system, we able to draw some offline occupancy schedules that can be directly used in control and management system. We conducted a simulated control method using eQuest software, to evaluate our potential energy savings and the results showed that around 22.1% potential energy can be saved by applying a customized daily/weekly/monthly occupancy schedule and customized set point depend on occupancy density.

1.1 Thesis Statement - Objective

The main purpose of this research is to model an mobility pattern for human activity in buildings. Building a smart system that can detect and track people though the building and give an accurate occupancy data which will be analysed later to merged with an auto-energy controller system. Collecting occupancy data and building in feasible analysis graphs and plots will help in controlling the air conditioning system. The novelty of this work lies in the fact that unlike most building occupancy techniques (as summarized in chapter 3), our approach uses occupants counter software based on Kinect sensor. This approach will serve to minimize the high energy waste after the default setting of air conditioning in office buildings that assumed a maximum occupancy though whole days yearly. The work provides some analytic tools and recommendations for energy saving using collected occupancy data from our real world test-bed. It involves real-time monitoring and tracking with real-time test-bed creation. The work provides a prototype to understand human behaviour and mobility direction inside a building and to monitor and count people mobility for further control over HVAC. The research highlights solutions for automated control over HVAC in smart/intelligent buildings (test-bed used is explained in chapter: 6)

1.2 Research Contribution

The key contributions of this work are summarized as follows.

1. We develop an occupants counter software is implemented based on a Kinect sensor that counts the number of people entering or leaving certain zone through a virtual gate. The software uses the depth imaging technology of light structure feature provided by a Kinect sensor and it is able to detect/track human gestures, read directions (going inside/outside), calculate distance and count detected blobs.

2. We deploy a real-time test-bed, which located in i-smart laboratory at Masdar institute. We had data collected over 90 days.

3. We propose an effective control model using a customized occupancy schedule derived from monitored occupancy patterns towards optimized air conditioning in open office buildings.Also,We present an effective occupancy modelling based on a Markov chain to predict space occupancy . Our results can shows human mobility patterns,state the occupancy conditions of zones in a building

4. We propose a PCOM system which is a building monitoring system that can be used to gather information about occupants mobility and draw patterns about their activities in the building. The system shows the relation between collected data and possible controlling approaches over HVAC systems to save energy in buildings.

5. We build a Matlab library for analyzing the resulted logs from our occupants counter software. This codes is able to output visualized figures of human mobility and occupancy, give the conditions of zones in the building and

produce a Markov chain transition matrix with predicated future occupancy. The library available online for use and research.

1.3 Relevance to Masdar Initiative

UAE has been always supportive of the idea of sustainable development. It has a vision to develop Abu Dhabi, the capital of UAE with the objective of sustainable development and to make it a model for the rest of the world to look up to. Masdar Institute is considered as an open office building or educational building referred to building description definition [5]. Our system is using the MI laboratory as an implemented test-bed for our experiment which helps to track human behaviour at Masdar Institute and to study of human behaviour data for smart buildings. This will include a direct monitoring system that can be directly connected to the HVAC system for future control.

1.4 Thesis Organization

This thesis is divided into seven chapters. Chapter 1 introduces the research subject, contributions and the organization of the thesis. Chapter 2, presents the background of Human Detection/Tracking Sensors, the Microsoft Kinect sensor for human tracking, and a problem related to people-counting and building occupancy relationships. Chapter 3, provides a review of related work. It summarizes various building occupancy using different approaches, occupancy modelling and the Markov chain model which is used to model our results, occupancy data and different control strategies. We present the real world test-bed setup and logics of people tracking using a Kinect sensor in chapter 4. Chapter 6, presents the results analysis and discussions and provides an evaluation of the performance of our software. Chapter 5 presents the occupancy modelling, control approaches and potential energy savings. The final chapter summarizes this thesis and discusses future research perspectives in chapter 8.

CHAPTER 2

Background

This chapter presents background information about human detection and tracking approaches, techniques used to archive HDT and the most used sensing devices. In particular it gives a brief description the Microsoft Kinect for Windows (K4W) sensor. The human body is capable of a multitude of poses difficult to simulate. To alleviate this problem, Kinect stores a large database of motion captures of human actions. Thus, it is easily able to cover the wide variety of human poses in entertainment scenarios. So, we provide an overall picture of the methods and counting logic useful to our people-counter software in this research.

2.1 Human Detection and Tracking approaches

What is Human Detection and Tracking (HDT)?

Human detection and tracking is an area of interest and an active research subfield of object recognition. Detecting the presence of humans in a particular environment and planing resources accordingly are at the core of many problem-solving strategies in construction management. Human motion tracking includes capturing body displacements and limb movements, such as postures and gestures, of human targets. The possibility of detecting and tracking humans reliably, is a useful feature that is often incorporated into sophisticated applications. In the real world, there are scores of application domains of human detection and tracking. Some of these applications are:

Surveillance of sensitive areas like airports, museums and military installations. Appropriate software manages security cameras can help pinpoint suspicious activities and back-up a human operator's ability to monitor greater surfaces.

Seamless interaction between robots and humans in need of assistance at home (example: the elderly) or on the workplace (example:factory worker) can be enhanced with the implementation of human motion detection and tracking.

The film and television industries extensively use human motion detection and tracking systems to create in 2D and 3D accurate dynamic models. Later, these models will be immersed in a virtual environment of an animated movie.

Heating, Ventilation And Cooling (HVAC) control through human detection and tracking can improve energy and electricity consumption in smart buildings of many developed countries. An HVAC control strategy includes a monitoring system able to detect the actual number of occupants of a room in real time, which is this research about. In addition, this strategy should predict with a satisfactory accuracy through a learning mechanism, the potential number of occupants of a room [6]. Such prediction is important in order to overcome the necessary time delay between the instant of signal detection and the point where a room reaches an appropriate temperature, which we are trying to solve in this research.

Table 2.1: Sensing categories and examples

Sensing modality	Category and Signal type	Example sensors
Binary sensors (general)	Uninstrumented and either (passive, active)	Contact sensors, Breakbeams, PIRs, Ultrasound motion sensors
Motion sensors (binary sensor)	Uninstrumented and either (passive, active)	PIRs, Scalar Doppler-shift sensors
Pressure sensors (binary sensor)	Uninstrumented and passive	Piezo-resistors, Piezo-electric materials
Electric field sensors (binary sensor)	Uninstrumented and active	Capacitive floor tiles, Capacitive antennas
Vibration sensors	Uninstrumented and passive	Seismometers, Accelerometers, Electrostatic and Laser microphones
Shape-detecting networks (SDN)	Uninstrumented and active	Radio-tomographic networks, Ultrasonic-ranging networks
Cameras	Uninstrumented and either (passive, active)	CMOS and CCD image sensors, Specialized motion imager
ID sensors	Uninstrumented and passive	RFID, any radio, other communications
Chemosensors	Uninstrumented and passive	CO2 sensors, Humidity sensors
Device-to-device ranging (wearable)	Uninstrumented and active	Radio pairs, Radio-Ultrasound pairs
Environment recognition (wearable)	Uninstrumented and passive	WiFi fingerprinting, Wearable mic, cameras

Approaches in Human Detection and Tracking

There is an abundant literature on HDT that concentrates on information on five spacious-temporal parameters: presence, number, location, track and identity. The general process of collecting information related to subjects placed in a particular environment is called human sensing. Our objective in this section is to present the capabilities and limitations of current solutions proposed in a number of disciplines. Table 2.1 below depicts a set of sensing modalities, their categories and typical examples.

Therefore, we will present and compare *active vs. passive* sensors and *single vs. integrated* modalities in the context of the *instrumented* (subjects are equipped with wearable devices) vs. the *un-instrumented* (detection or tracking is done on a passive subject.) approaches. In addition, we will devote more attention to single

Table 2.2: Sensing modalities categories and examples

Sensing modality	Performance (Strong/Moderate/Weak)and Network Density					
Type	Presence	Count	Location	Track	Identity	N.D.
Binary sensors (general)	S	M	M	M	W	2
Motion sensors(binary sensor)	M	W	W	W	W	2
Pressure sensors(binary sensor)	S	M	M	M	W	4
Electric field sensors(binary sensor)	S	M	M	M	/	4
Vibration sensors	M	W	W	W	W	1
Shape-detecting networks (SDN)	S	M	M	M	/	6
Cameras	S	S	S	S	M	0
ID sensors	S	M	M	M	W	4
Chemosensors	W	/	/	/	/	0
Device-to-device ranging(wearable)	S	S	S	S	S	2
Environment recognition	Radio	Radio	Radio	Radio	Radio	X

modality where only one binary sensor (presence = 1/no presence = 0) is used to perform the actual detection and tracking showing in table 2.2.

HDT is by nature a complex process that includes issues as simple as adequate sensing to the delicate data-mining techniques. It is a challenging task for a number of reasons. The common obstacles to quality detection and tracking are ambient noise, device imperfection, environmental factors variation, fluctuation of data collected, background signal similarity and sometimes, intentional deception (adversarial scenario).

Our interest in this study is limited to the well known spatia-temporal properties related to the position and history (tracks) of human present in a chosen environment. These properties are presence (Is someone in the room?), count (How many person are there in the room?), location (Where is each person positioned?), track (What is the sequence of positions of this person?) and identity (Who is this person?). In addition, a Network Density (ND) parameter refers to the number of sensors necessary in providing a particular service in a given area.

Here, human presence can be detected through portable/wearable devices or RFID-enabled badges. In an energy-saving scenario, it is crucial that the system be aware of unoccupied rooms. While localisation may be instrumented (via GPS) or uninstructed (set of cameras), tracking (spatio-temporal coordinates) and identification are inherently dependent parameters. Tracking is possible thanks to the continuous identification of a person in a set of room occupants.

2.1.1 Sensor Technologies for HDT

The occupancy detection sensor is the key factor in controlling overventilation supplied to zones based on occupancy. Numerous existing methods showed the importance of counting people. Several kinds of counters that require contact with people, such as turnstiles, are used because contact type counters count very accurately. These counters, however, cannot be applied to spaces within commercial buildings because, except at a few critical places(e. g. , entrances), they obstruct the normal flow of people in work spaces and would require installation for each room [7].

Several kinds of sensors currently can provide information on occupancy, such as video cameras equipped with people counting software, optical tripwires and pyroelectric infrared (PIR) motion sensors that count the number of people crossing a particular area, and sensors that measure the concentration of CO2 in a space. Last sensors provide concentration readings in parts per million (ppm), which are indicative of the occupancy of a space. However, reliably correlating CO2 levels with actual occupancy is difficult because of the high variability of readings and slow response time of CO2 sensors. It also takes time for the CO2 concentration in a room to build up [8].

Wireless sensor networks have been widely used as supported technologies for monitoring, tracking and controlling Human Mobility. Most of studies designed a WSN for occupancy detection and result data analysis to send a final control function to the thermostat for HVAC monitoring. The authors of [9] [10] took the advantage of WSN sensors and nodes to capture data of temperature, humidity and people motion flows in executing a command for controlling the Air-conditioning power (ON/OFF) or wind flow direction by setting certain thresholds. The control used is simply done by sending a command or infrared signal to the thermostat depending on a real-time data collection from sensors to maintain certain level of power consumption. On these studies, any control demand is dependent on historical data with no more than a simple threshold setting is provided. Also, the number of sensors used is small, where this is not enough to reach the point of thermal control for wide-space rooms.

The authors of [11] highlighted another approach in occupancy detection by using sensors where they call them as the Tiny Agents to control the power consumption over a building. The tiny agents are distributed throughout the building and deployed in air-conditioning system to capture and send room temperatures and interact with the AC or other agents. A method of pre-cooling is applied to avoid the high consumption and provide thermal comfort, such approach showed a load reduction on peak time.

Motion detection based on PIR provides an indication of motion within the sensor (distance) range. By using them in pairs, PIR detectors can be used to determine the direction of motion, e. g. , a person entering or leaving a room through a doorway. PIR detectors, however, have limitations fort this application. First, the sensor range is limited, and individual PIR sensors are not good for monitoring 20 large spaces. Second , multiple people passing a PIR sensor (e. g. , in a doorway) at the same time may be undercounted.

Video cameras can provide information regarding people count and flow direction. These cameras if not properly installed and configured, can generate errors, arising from three main factors.

- video sensors are affected by lighting conditions. Low light levels can lead to single persons being counted multiple times.

- Turning a light switch on or off may trigger a sensor count. Second, multiple people crossing the field of view at the same time may be under counted.
- The video system may count several crossings at times when occupant pass under the cameras field of view.

Smart camera object position estimation system(SCOPES) [12] proposed the SCOPES system, a wireless camera sensor network for gathering traces of human mobility patterns in buildings. The claimed accuracy is of events counted correctly. While this system claimed 80% accuracy, its implementation cost is high. Other critical drawbacks include poor accuracy caused by difficulty in recognizing occupants whose clothing color is close to the back ground color and ambient lighting interference. SCOPES also has a shorter lifetime and higher power consumption than thermal imaging systems.

2.1.2 Automatic People Counter

An Automatic People Counter (APC) is a system that counts the number of persons entering and exiting a room. Many devices based on several technologies (ex. Cameras, infrared beams, vision) have been used with much success in commercial systems to count people indoor and outdoor. APC sold by companies such as Trafsys and Acorn are the most well known in the industry. APC are used mainly to gather intelligence, create visitor statistics in measuring marketing performance (shoppers per square foot), managing crowd capacity, monitoring occupancy in public buildings for safety purposes, and managing energy systems (ex. HVAC) in smart buildings.

The following technologies displayed in Table 2.3, have been recognized to be robust and have a high accuracy rate (+ 98%). However, they do have some weaknesses that justify caution and sometimes human intervention. Among moving object detection algorithms, it is good to know the simple and natural Frame

Table 2.3: Popular APC technologies with performance, features and price range

APC Technology	Performance	APC Features	Price range
Infrared beams	More than 90%	Most common technnology. Vertical or horizontal infrared beam across an entrance. Inexpensive, easy to operate, subject to interference	Cheap
Magnetic fields	/	Counting triggered by magnetic fields of metallic objects carried by people. Low accuracy to sensitivity to ambient interference.	Cheap
Computer vision	More than 95%	Closed-circuit television (CCTV) camera or IP camera as source of data. Highly accurate, scalable and flexible. Delicate implementation.	High cost
Thermal imaging	More than 98%	Array sensors to detect person heat. Highly accurate and scalable. Long life.	High cost
Artificial Intelligence	More than 96%	IR transceivers for a count zone. Based on AI technology. Wide range of conditions (outdoor, humans, object, darkness)	High cost
3D camera technology	More than 98%	Camera to reproduce human 3D vision	varied

Difference algorithm (difference between foreground and static background), the Running Gaussian Average, the Temporal Median Filter, the Mixture of Gaussian (proposed by Stauffer C et al), the Kernel Density Estimation and Eigen backgrounds.

Several experimental tracking algorithms have been developed by researchers for some special purposes. The *Kalman* Filter is an algorithm which provides a potent recursive approach to calculate the minimal mean of squared error. There have been other algorithms for target representation and localization, the Mean-shift algorithm for tracking non-rigid objects with a single camera.

Counting algorithms and techniques to improve accuracy have been developed over time. Many of these algorithms are based on computer vision like the multiple-people segmentation method and require image processing and analysis.

Research using neural networks to count subjects in video images as well as counting methods to detect a moving object direction through a template process, has also been proposed. There are also algorithms that use single or multiple lines as counting zones to indicate whether a subject has entered of left a particular room.

2.2 Microsoft Kinect Sensor

The name Kinect is a portmanteaufor the words **'(kin)etic'** and **'conn(ect)'**. The Kinect sensor is a motion sensing device with a IR Depth sensor , IR Emitter and microphone sound system built around RGB camera that able to tilt using accelerometer as showed in figure 2.1. Kinect array specification include angle viewing of 43 degrees vertically and 57 degrees horizontally of field of view, a vertical tilt range around 27 degrees and frame rate (depth and color stream) 30 frames per second (FPS)[1]

This is a motion sensing input that enables user to control a host system without physically touch a game controller via gesture and sound commands. Motion sensing can be electronically identified are optical detection and acoustical detection. Infrared light or laser technology may be used for optical detection because Kinect is an electronic sensor. The Kinect sensor also performs other functions such as voice recognition, facial recognition, and skeletal tracking along with motion detection [13].

The depth camera which is a virtual camera, is the result of displacement matching on the IR projector and real IR camera, each equipped with its own lens distortion. Classification of depth measurement techniques are showing in 2.2 above, Kinect depth is calculated based on structured light technology. The depth data from Kinect sensor is the distance, in millimeters, to the nearest object

[1]The resolution of the depth stream is dependent on the frame rate, and is specified by the DepthImageFormat Enumeration enumeration. The resolution used on our developed software is using Resolution640x480Fps30 which is 640 x 480; the frame rate is 30 frames per second.

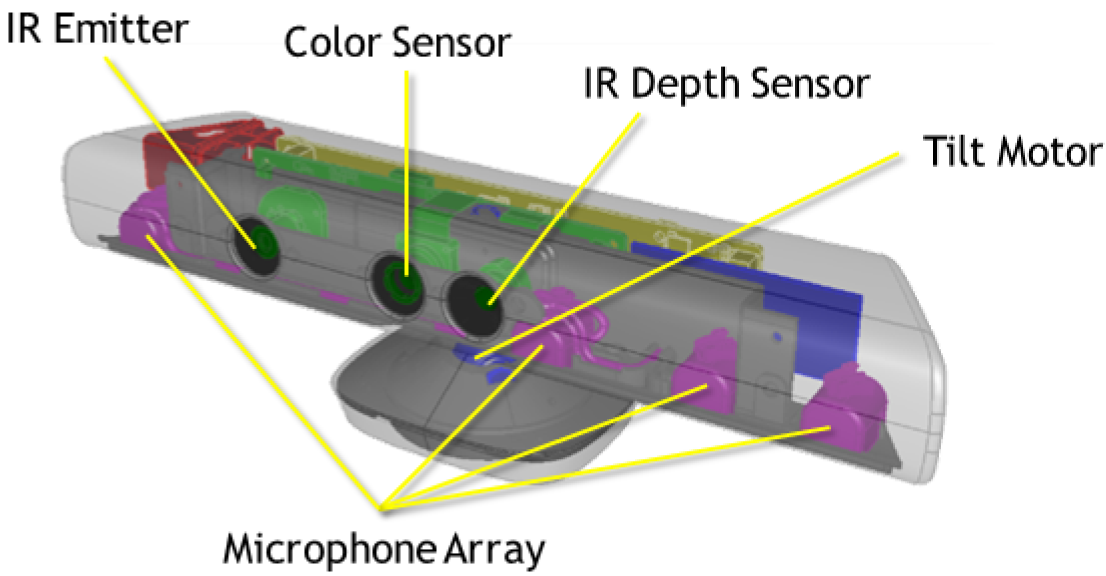

Figure 2.1: Kinect components

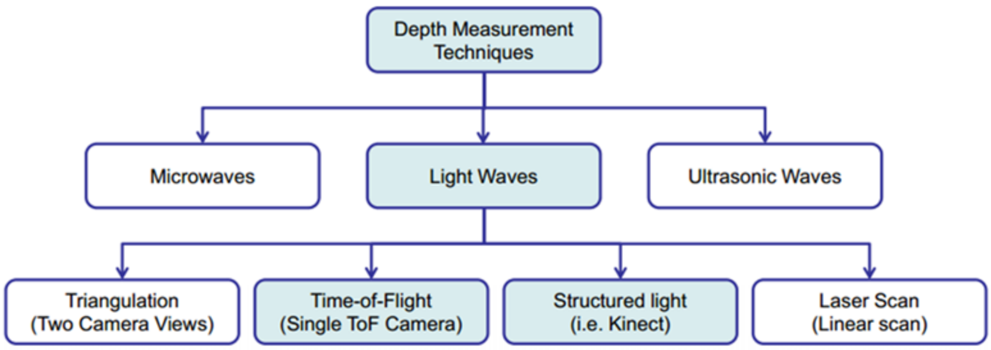

Figure 2.2: Classification of Depth Measurement Technique

at that particular (x, y) coordinate in the depth sensor's field of view.

Time-of-Flight (ToF) Imaging has similar approach of depth sensing which refers to the process of measuring the depth of a scene by quantifying the changes that an emitted light signal encounters when it bounces back from objects in a scene. a comparison between Kinect sensor and ToF camera is represented in Table 2.4 below.

Table 2.4: Time-of-flight (ToF) cameras vs. Kinect sensor camera

	ToF camera	Kinect sensor camera
Definition	ToF camera is a range imaging camera system that resolves distance based on the known speed of light, measuring the time of flight of a light signal between the camera and the object for each point of the image. So the ToF sensor estimate the distance from a scene point by the time of flight or RADAR (radio detection and ranging). It is a type of scanner less LIDAR, in which the entire scene is captured with each laser or light plus as opposed to point by point with a laser beam.	a motion sensing input device that enables users to play video games without using controller device using gesture recognition
Release	Around 2000, first purpose for civil application	Release by Microsoft on February 2012
Cost	$ 5000 $ 10,000 depend on product	$ 300
Advantages	Cover up to 60 m Distance resolution about 1 cm Resolution frame 320x240 pixels Provide 100 image per second Only one (specific) camera required No manual depth computation required Acquisition of 3D scene geometry in real-time Reduced dependence on scene illumination Almost no dependence on surface texturing	High resoltuion Robust and highly accurate
Limitation	High-accuracy time measurement required Measurement of light pulse return is inexact, due to light scattering Difficulty to generate short light pulses with fast rise and fall times Usable light sources (e. g. lasers) suffer low repetition rates for pulses	Some hardware limitation due to how far can the camera see.limited resolution, 640 x 480 pixels, though the RGB camera can run at the higher resolution of 1280 x 1024 pixels but this will result in a lower frame-rate
Application	Automotive applications Human-machine interface and gaming Measurement and machine vision Robotics	Games Gesture Recognitions Robotics

Kinect Software Programming

There are a variety of open source libraries for Kinect programming using PC's like libfreenect, openni and SDK. Open Kinect [14] is community of people who use libfreenect, a free and open source library for enabling Kinect programming in PC's run by Windows, Linux, and Mac. Open-Kinect support many wrappers like python, $c++, c\sharp$. Moreover, OPENNI [15] which is primarily developed by PrimeSense — the company behind Kinect's depth sensor's technology. libfreenect and OpenNI+SensorKinect are two competing, open source libraries/-drivers. libfreenect (Apache 2. 0 or GPLv2) derives from the initial, reverse-engineered/hacked Kinect driver whereas OpenNI+SensorKinect is derived from open source (LGPL) PrimeSense code. Another community provide what called RGBD [16] which is an objet database that can be used to develop a detector and tracker software using Kinect. Additionally, nestk library is provided by RGB-Demo open-source software which can be used to develop programs using Kinect as well. RGB-Demo support both RGB and Depth image and it works on Windows, Linux and Mac [17]. The official library from Microsoft Kinect SDK (software development kit) which supported on windows 7 or above and provide features of the Kinect, including color images, depth images, audio input, and skeletal data. The component of SDK is showed in figure 2.3 below:

The tracking mechanism in software technology used in Kinect enables advanced gesture recognition, facial recognition and voice recognition. The human body is capable of an enormous range of poses which are difficult to simulate. Instead, Kinect has a large database of motion capture of human actions. Thus it can easily span the wide variety of human poses in an entertainment scenario.

Gesture recognition is a definition in computer science and language technol-

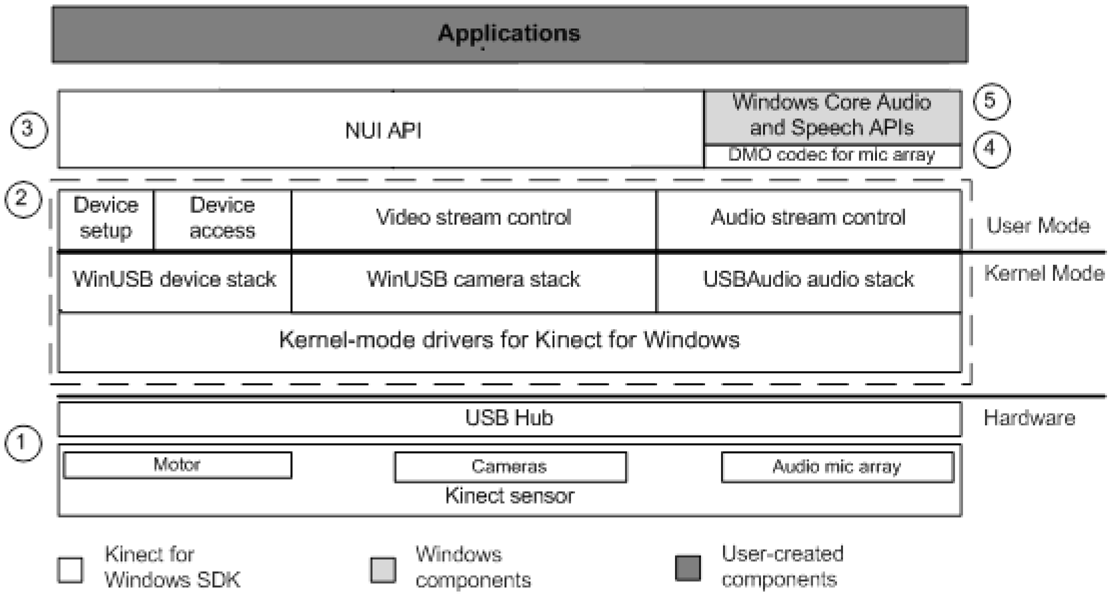

Figure 2.3: Kinect Software Development Kit Component

ogy that represent the human body motion or state via mathematical algorithm. Kinect enables gesture recognition in a way that the human motion is the key tool to control and use any Kinect game with the goal of interpreting human gesture. In our people-counting software, the head motion is the key control for blob detection in the top-view version while the full body motion (hand and arm) are the controller of our front-view people-counter software. Human gesture consists of head, hand, arm or a full body motion.

CHAPTER 3

Related Work

The purpose of this chapter is to highlight the related aspects of our approach in analysing the human mobility. Building occupancy has been the subject of intensive studies in the past years. Several approaches using building occupancy data to improve prediction and simulation of HVAC control have been proposed. Understanding human mobility and daily activity in a building in the busiest periods, gives more impact to energy simulation tools. This type of data will produce real-time HVAC control system with higher accuracy level in a more reasonable way than do current simulations.

3.1 HVAC control approaches

This section aims to introduce a number of HVAC control approaches that uses models or techniques that are related to our study. There is a growing number of academic and industrial contributions on HVAC control strategies with the common goal of reducing energy consumption in inhabited buildings. The majority of these contributions relies on occupancy models to produce occupancy simulations of an entire building. These simulations in turn would serve to calculate thermal loads with the intention of correctly provisioning an HVAC system.

There exist other remarkable approaches to HVAC control that deserve to be pointed out. Some of these approaches start with the simple idea that occupancy can be inferred directly from the analysis of occupants' movement within the different sections or outside of a building. There is no requirement nor constraint on the number of occupants and zones. To this end, these approaches like in [18]implement a Markov chain method to simulate the occupant's movement process. Here, the model is able to do two things with satisfaction: detect each occupant's location and evaluate the occupancy rate of each zone in the building.In addition, the model displays a realistic picture of daily building variation.

Others put an emphasis on probability densities instead of making specific predictions. These models make no future projection about the likelihood of presence nor do they mention the actual number of occupants. For example, Page et al in [19] model occupancy through a Markov chain. Here persons in particular zones of a building are modeled as time series that simulate their behavior. In Page's model, the main feature is the creation of an occupancy probability density on a daily basis. There is also the example of Richardson [20] who produced some realistic data by using a statical occupancy time-series. Liao et al. proposed in [21]an agent-based approach to characterize an occupant behavior. In addition, they used the probabilistic factors in agent behavior to suggest a graphical model restricted to a single occupant in a given room. Liao's approach is not sufficient in predicting occupancy because people move all around a building during the day.

Finally, it is worth mentioning fuzzy control, an artificial intelligence techniques which deals with non-linear and time-sensitive systems like HVACs. The use of intelligent and soft computing methods in HVAC control strategies is also well known. For example, since Fuzzy Logic Controllers (FLCs) inputs and outputs are real variables which can be mapped with a nonlinear function, they are adequate for engineering problems like optimizing HVAC systems. The next sections will provide an exhaustive list of contributions in intelligent control techniques in HVAC systems.

Intelligent control techniques in HVAC systems

Many authors have researched the implementation of intelligent controllers in HVAC systems either through fuzzy methods or through direct use. In the case of fuzzy methods, the purpose is to auto-tune the traditional Proportional-Integral-Derivative (PID) controllers instead of a manual adjustment of gains. A PID is a basic control feedback mechanism that is well known in industrial settings.

The works of Liang and Lu deals with the aspects of combining human learning with power control strategies in the design of intelligent and malleable HVAC control strategies [22]. Here, the authors used a minimum power control strategy which balances and reduces respectively the input power of an HVAC and the energy consumption. They also put into play six parameters : *occupancy level, ambient and radiant temperatures, air strenght, relative humidity, occupants' clothing*. Then, they designed a human learning strategy based on the Predicted Mean Vote (PMV) model. This allowed them to adjust the user's comfort zone by learning his/her preferences.

Fountain et al. were the first to introduce the idea of comfort zone in the design of control strategies in special occupancy contexts like hotels [23]. As explained above, comfort zone and human learning strategy have been applied together for thermal comfort control. In addition, Fountain used a Neural Network to circumvent the non-linear aspects of PMV calculation. Then the author proposed a lesser power control strategy with the variable air volume method in order to improve energy saving.

Jian and Wenjian proposed in [24] a neuro-fuzzy controller to supply air pressure in an HVAC control loop. The authors developed an interesting fuzzy system with only three rules in the knowledge base. Then, in order to improve the system parameters, they used a robust and adaptive neural network (NN) with three elements: *the error back propagation learning rule, the least squares method and a system integral controller in a secondary loop*. The robustness of the NN remains in spite of significant variations of HVAC parameters.

With a small number of rules in a Fuzzy System (FS), Arabinda has been able to create in [25] a Neuro-fuzzy controller (NFC) which saves significant computational time. He first designed an FS containing 36 rules of which a few are used for training in a back propagation algorithm. Then, he applied neural network made of three layers of respectively 2, 30 and 1 neurons. This NFC exhibited a noticeable improvement in peak and time for transfer functions in the air supply models in ANF and PID controller.

Alcal'a et al. acknowledge that FLCs (Fuzzy Logic Controllers) are useful for the implementation of expert knowledge and control of HVAC systems. Here, it's about using linguistic rules and facing the difficulty of the actual knowledge acquisition and elicitation when solving a particular HVAC control problem. They proceeded like with any expert system engineering. That is, a human expert in HVAC control was first extensively interviewed, his practical knowledge is extracted, elicited and then transformed into practical rules that make up an initial Knowledge Base (KB). Only a manageable number of control rules was necessary to partition the system because of the use of an expert knowledge. It is important to notice that in tuning the KB control parameters, there are two restrictions that had to be applied. With these restrictive approaches simultaneously improved the convergence and the number of evaluation. They are the followings:

1. Evaluation of multiple objectives - Objectives like thermal comfort and energy consumption would be the basis of evaluation parameters in selecting different criteria.

2. Quick algorithm convergence — Simulations are among the best way to evaluate the accuracy of a controller. Since these simulations take a long time to complete, it is important to select an appropriate tuning algorithm like the objective-weighting method in the steady-state GA which reduces the population size.

The authors designed accurate models to simulate two experimental test buildings. Then the traditional controller was compared with the controller with genetically tuned parameters in the same context buildings during ten days. In the end, the studied controller were implemented and tested. As a result, not only was the level of thermal comfort the same as the traditional physical setting but there was a noticeable decrease in energy consumption by more than 10%.

In the same line of thought, Gacto et al. proposed in [26] an advanced evolutionary Multi-Objective Genetic Algorithm (MOGA) to increase the performance of HVAC system GA tuning of FLCs. Then, others have used an adaptation of MOGA to determine their effectiveness in fast convergence. Besides, an intelligent crossover operator and a GA technique for incest prevention (population diversity without unecessary crossovers), have been used to improve the algorithm search ability.

Using soft computing methods is a popular approach for automatic generation of rule-based fuzzy systems (Fuzzy RB). Artificial Neural Networks (ANNs) and Evolutionary Techniques are two distinct approaches for the generation of rules in FS and the optimization of FS parameters. ANNs integrates the learning ability of NN with knowledge representation in fuzzy logic. This method is known as Neuro-Fuzzy System (NFS) and is often applied in solving problems that attempt to reduce error between output of an FS and the value of a target. In NFSs, fuzzy RB is the result of learning or adjustment of rules in RB and helps optimize a fuzzy database. The Evolutionary Technique applies evolutionary algorithms to automate knowledge acquisition in the controller of a FS. The result is then known as Genetic Fuzzy Systems (GFSs). Designing a fuzzy controller can be interpreted as an optimization problem where a Genetic Algorithm (GA) finds the best solution among potential solutions. An FS can rely on two different kinds of data organizations in a knowledge base: a database and a rule base. From this distinction, a GFS exhibits two approaches (the second being more delicate than the first):

1. One is known as the "Genetic Tuning" method. It focuses on improving the performance of a given FS trhough tuning.
2. The other, called "Genetic Learning" automatically generates a KB in FS.

Nowak [27] implemented an integrated fuzzy control algorithms and *Model Predictive Control* (MPC) algorithms to get an original HVAC control system. To this end, two separate MPC methods were used: *The Dynamic Matrix Control* (DMC) and the Generalized Predictive Control (GPC) algorithms. This hierarchical control structure displayed a satisfactory trade-off between two apparently irreconcilable needs: energy consumption and thermal comfort.

Pargfrieder and Jorgl [28] used an optimized FLC with seven variables and an evolutionary algorithm to decrease energy usage and keep the temperature level which defined with a valuable criteria. Here, 3 controllers were created for a unique HVAC system:

- a generalized predictive controller,
- an adaptive power profile-enabled fuzzy controller,

- a (Genetic Algorithm) GA-based, adaptive power profile-enabled fuzzy controller

These authors showed that their intelligent controllers can lessen occupants discomfort remarkably while maintaining energy savings. Clarke et al. [29] introduced the Generalized Predictive Control (GPC) as a technique for creating a sequence of incoming control signals. Its purpose is to optimize control. GP has a considerable robustness but is computationally expensive. As an example application, Soyguder and Alli [30] used the GPC technique in fuzzy sets for a unique HVAC system. Their methods included PID controllers to manage damper gap rates (temperature and humidity) of an HVAC system through an Artificial Neural Fuzzy Interface System (ANFIS). Similarly, Wang et al. [31]took advantage of the integration of a feedback control law drawn from the biological immune system (T cells) for an automatic tune-up of PID gains and universal approximation of FS. Promising results confirmed the effectiveness of Wang's Fuzzy ummune self-tuning PID controller in terms of system rise and setting response time and overshoot.

In contrast to other's researchers' approaches, Hongli et al. [32] designed a useful method where they derived a fuzzy controller from a PID controller by corresponding PID gains and FLC parameters. The advantage of this system stems from the fact that creating fuzzy rules and initiating a related controller is notoriously difficult for an elaborated HVAC system. It is interesting to notice that the Ziegler-Nichols and Astroms modified Ziegler-Nichols tuning method is an easier way of finding PID gains because experience has shown that the Fuzzy-PID controller outperforms traditional PID when it comes to tracking room temperature.

3.2 Building Occupancy Monitoring

The following sections will give more details about aspects of particular research that deals with real-time occupancy measurements, network of sensing, learning and prediction agents, occupancy-based demand response, an occupancy-based system called OBSERVE, a system called Smart Personalized Office Thermal Control System (SPOT) and a creative system that relies solely on occupants' feedback.

There are several occupancy-based methods that uses multiple sources of sensory input. Some suggest that occupancy can be represented using *linear regression models*. Data gathered for lighting, material loads and occupancy is evaluated with a building walk through survey. A noticeable limitation of this model is its dependence on energy usage to detect the presence of a person. More often, its estimation of occupancy is weak specially when dealing with large groups in a conference room. The same remark is true about conditioning as with energy consumption. Sometimes, the *EnergyPlus* tool is used to estimate savings. Here a reactive strategy is used in adjusting temperature based on occupancy. In other occasions, door activity detection and PIR sensors for presence detection are used to distinguish the status of a home between occupied, unoccupied, occupants awake or asleep. The estimation of this model does not seem to consider ventilation which is a significant source of energy consumption and ignores daily schedules like an occupant's activity on a Friday.

Markov Chain

In the work titled Occupancy-Based Demand Response [33], the authors introduce an HVAC control strategy to achieve efficient conditioning. It relies on demand response and the real-time monitoring and occupancy prediction.In this occupancy-based demand response approach, the authors describe an HVAC control strategy which utilizes a room occupant monitoring system. This system is able to detect in real time, the number of occupants of a room, infer its temperature and level of carbon dioxide ($CO2$). The most significant contribution of this research is the ability of this system to predict room occupancy. Prediction is necessary because it appears that in general, an HVAC system requires a little time to bring an ambient temperature to a certain level of human comfort according to the American Society of Heating, Refrigeration and Air-Conditioning Engineers. To achieve their goal, the authors created an occupancy model based on Markov Chain.

A *Markov chain* is described as a process in which we have a set of states $X = X_1, X_2, , X_r$. It starts in one of these states and moves successively. From a given state, the process moves, one step at a time, in sequence from one state to the next. When the chain is in state X_i it moves to the state X_j with an independent probability written p_{ij} . The set of all probabilities p_{ij} is arranged in a matrix called the transition probability matrix **P**. A Markov chain can be represented by the following equation:

$$P\{X_{k+1} = j | X_k = i, X_{k-1} = i_{k-1}, ..., X_1 = i_1, X_0 = i_0\}$$
$$= P\{X_{k+1} = j | X_k = i = P_{ij}(k)\} = P_{ij}$$
$$P_{ij} \geq 0, i, j \in I; \Sigma_{j \in I} P_{ij} = 1, i \in I$$

The most remarkable feature of this process is that every move depends only on the current state X_i and not, at any time, on the other states.The authors modeled room occupancy as a Markov chain by identifying each status of the room *(level of occupancy, vacant)* as a state to which a transition probability is ascribed for moving to the next state *(room status)*. From this model, occupancy includes ventilation and temperature control strategies which are then implemented in an EnergyPlus model. EnergyPlus is a building energy simulation software with many innovative simulation features like heat balance-based zone simulation, distributed air flow, thermal comfort, water usage, outdoor ventilation, and solar systems. It is used to optimize design and save on heating, cooling, lighting, ventilation, other energy flows, and water use. For this purpose, it takes charge of parameters like the components of the HVAC system, the level of occupancy, the climate and the construction material.

3.3 Model Predictive Control

In contrast to many approaches that focus on general aspects described in the section above, there are a variety of predictive and adaptive models designed for medium size contexts like offices, labs and classrooms.This section is aim to highlight the most recent occupancy modeling approaches in smart building.

In the contribution titled Network of Sensing, Learning and Prediction Agents [2] the authors introduce a system of multiple adaptive sensor agents whose roles are to detect motion, read CO2, record sound level, ambient light and check door status (open, close). This innovative application called Building-Level Energy Management Systems (BLEMS) is in fact a multi-agent system made of fifty eight multi-modal sensors, scores of learning collaborative agents that adapt to occupants' particular needs. In addition, it contains 74 actuators related to the building's HVAC areas and two unit for handling central air. In practice, patterns of occupants' activity are acquired through observation. Then, HVAC operation is optimized in response to the occupant models.

On the other hand, by creating an agent model of each occupant, it is possible to predict room occupancy rate. The purpose of this system is to create an appropriate balance between energy preservation and occupants' comfort through the use of machine learning techniques in areas that are likely to be occupied. This system has been successfully deployed and able to estimate occupancy with a 95% accuracy rate. The deployment setting is the premises of the University of Southern California (USC).

With OBSERVE, Erickson et al. show in [3] how to use a wireless sensor network to collect real time occupancy data and use it to create occupancy models. Such models may be included in a building system for control strategies. With occupancy model predictions drawn from a sensor network-based control strategy, the authors confirm that they have achieved 42% annual energy saving without compromising the American Society of Heating, Refrigerating and Air-Conditioning (ASHRAE) comfort standards.Here the authors' contributions are manyfold:

- Their occupancy modeling based on real-world data, relies on time-sensitive inter-room relationships in modelling occupancy.
- They suggest that models based on sensor-network data can be implemented in a HVAC control strategy in energy savings.
- They are confident that their predictive strategies achieve energy savings with full compliance with ASHRAE standards.
- They contend that assessing occupancy as a binary value is insufficient for HVAC control under PIR. That is to say, an accurate real-time occupancy is a necessary technique for HVAC control.

Xiang et al. present in the article Smart Personalized Office Thermal Control System (SPOT) [4] a smart personal thermal comfort system for use in an office environment. The role of this system called SPOT (Smart Personalized Office Thermal) is to find an acceptable balance between energy consumption and personal thermal comfort in an office environment. This is a reactive control strategy that takes into account real-time occupancy and personal thermal comfort. It rests on an original model of personal thermal comfort known as the Predicted Personal Vote (PPV) model. It attempts to predict a level of human comfort from several personal and environmental parameters. This system has been designed based on three simple ideas:

- An extension of the ISO 7730 standard related to the PMV (Predicted Mean Vote) model to the PPV (Personal Predicted Vote) model. The PMV which is a widely used for building temperature control, refers to a mean value of votes conducted by a fairly large group of persons on the ISO thermal feeling scale [+3, -3] as values in increment of 1, of the sensations of respectively hot, warm, slightly warm, neutral, slightly cool, cool, cold.

- An ensemble of sensors including Microsoft Kinect is used to evaluate necessary PPV parameters to help us infer a person's comfort level.

- A reactive control that is aware of the presence of occupants of a room, is used to maintain the PPV.

Since different persons perceive their environment differently, the idea of thermal comfort does not apply the same to all. To say that occupants of a room have an acceptable level of thermal comfort means that they are satisfied with the climate surrounding them. In other words, occupants have no particular desire to change the status of their environment because the combination of the following parameters is just perfect: Person clothing, Room temperature, Air velocity, Room Humidity, Air quality, Sound level and Light intensity.SPOT makes use of a collection of sensors including Microsoft Kinect to evaluate six parameters known to define human comfort: clothing, air speed, humidity, radiant temperature, air temperature and activity level. These parameters are essential to the PPV model which guides SPOT in controlling heating and cooling parts that maintain comfort.A prototype of this system has been implemented using Visual Studio 2010 and the K4W SDK v1.6. K4W is used with three objectives:

- To detect the presence of a person and his/her activity level in the room. That is to say, K4W is used as an occupancy sensor.

- To estimate the clothing level of a room occupant after finding its location. This process is achieved with an internal thermal sensor coupled with a tracking system.
- To enable occupants to customize the PPV parameters with simple a gesture like raising a hand for a particular comfort level.

To achieve similar results, other researchers have used the PMV model based on learning and predictive control in their building temperature control systems. Another interesting implementation called the Thermovote which invites occupants to vote on regular basis on the level of comfort in the room. Although this system sounds simple because it does not use the PMV model, its frequent solicitations of occupants for voting makes it somewhat invasive.In spite of its appealing features and effective results, the SPOT model of HVAC control has several inherent limitations related to the designers' initial restricting assumptions which are the following:

1. Work spaces are thermally isolated from one another.
2. Employees are confined to a personal space with no outside movement.
3. The calibration process of this device may require an entire day.
4. The SPOT system at $1000 is expensive at this time.
5. SPOT is blind to the state of windows and doors being closed or open.
6. The overall results of this research cannot be validated for lack of information.

In [34], Erickson and his colleagues describe experiments done with the SCOPES (Smart Cameras Object Position Estimation System) which is a wireless camera sensor network for collecting mobility patterns in a building. It evaluates occupancy with an accuracy of 80%. They built two prediction models that are applicable at an individual level: One is for describing occupancy and movement that rely on *Multivariate Gaussian distribution* to collected data and for predicting mobility patterns in the same context. Another is an agent-based model for the simulation of mobility patterns in HVAC control strategies. These models inspire studies like the following:

- learning and variations of occupancy sensor data for the evaluation of several energy management options.
- Accurate traffic estimation with best sensor localization
- Applying statistical traffic pattern from one to another location.

CHAPTER 4

Experiment and Test-bed Setup

This chapter discusses how the solution to the problem has been designed and implemented. We describe here the setup of human mobility tracking and detection system based on people-counter software using Microsoft Kinect sensor. A test bed is installed in a laboratory building called iSmart lab. The institute building is categorized under educational or office building depending on building description from [1].

4.1 Kinect-based People-Counter software

The software is written using Microsoft Visual $C\sharp$ 2010, project WPF application programmed using $C\sharp$ and XML languages. OS used is Windows 7 with Kinect Studio v. 1. 7. 0 and Developer Toolkit Browser v. 1. 7. 0 installed. Both type of Kinect is used and tested to be running on our software, Xbox Kinect and Kinect for windows. The software, should be run in windows 7 or above, with pre-installation of Kinect sensor drivers *(shortly by installing Kinect SDK)*.

Software Process:

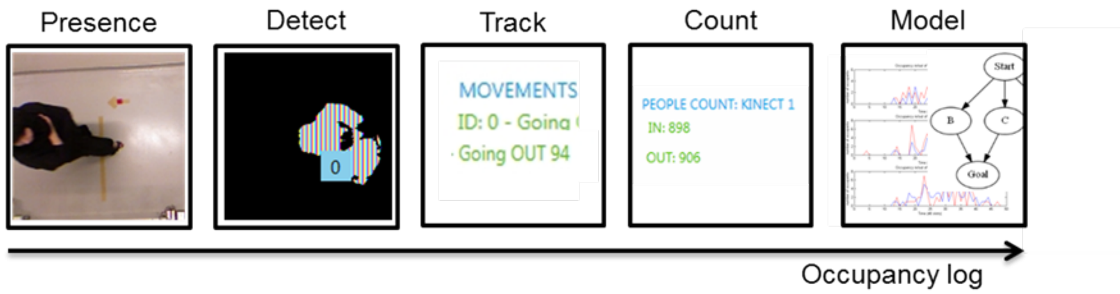

Figure 4.1: The Process of Our System, Detect the Presence of the Person, Track and Count then Start analysis through Logged data

1. **Kinect initialization start:** This function will lookup for any connected Kinect devices to your computer. If no device is connected: a box message will appeared to inform you about this fact. If you already connect your device and still get that message , check that you installed all required sensor drivers, this is important since Xbox Kinect require a pre-driver configuration. If you are using Kinect for windows, that wont be an issue since it's officially configured as input device. Another thing, check your cables connectivity, change the USB port to another one or wait while device is loaded. The software is conceived to handle two Kinects. When only on device is connected, you will be asked if you would like to connect a second one. If only one device is connected the window 4.2 part A will appears, if two is connected both windows will work as in part B 4.2. The software display both RGB and Depth image, Figure 4.3 show the GUI of our software. A logged file is created in the debugger folder.

2. **Capture frame events**:a part of initialization, make sure that both RGB and

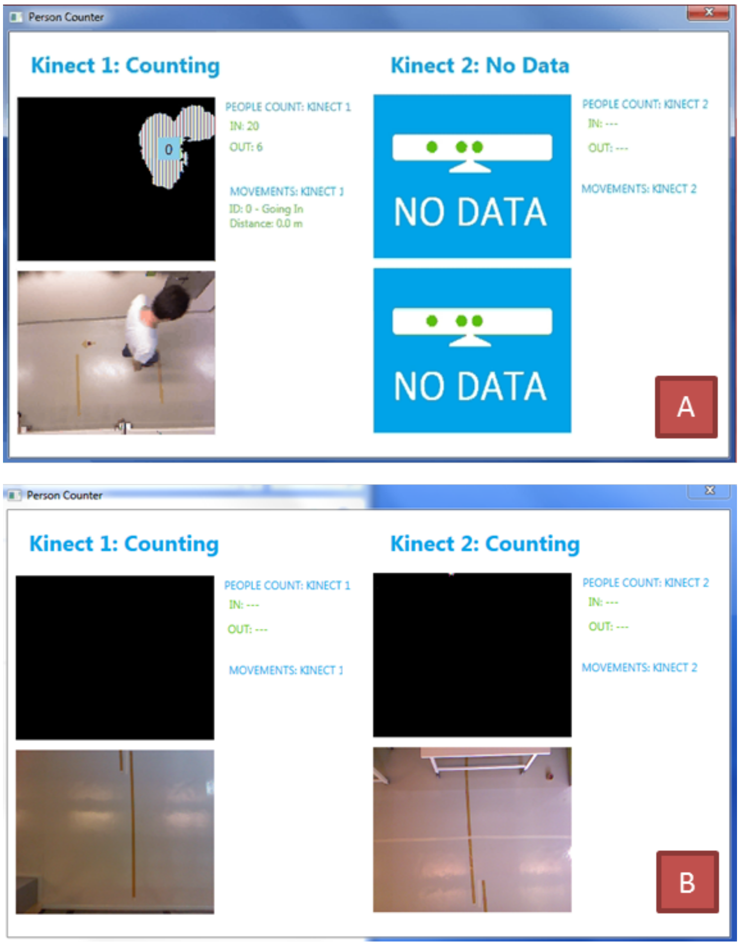

Figure 4.2: Software Window, A: one Kinect is connected and start counting. B: two Kinect is connected and start counting

Depth imaging are captured. This using MSDN Library refer to Microsoft. Kinect

```
ColorImageFrameReadyEventArgs: The event arguments
    provided in a KinectSensor. ColorFrameReady event
    when a frame of color data is ready.
```

3. **Depth camera feed generator:** Contains a per-frame buffer for depth data streamed out of a sensor. Also provides access to the dimensions and format

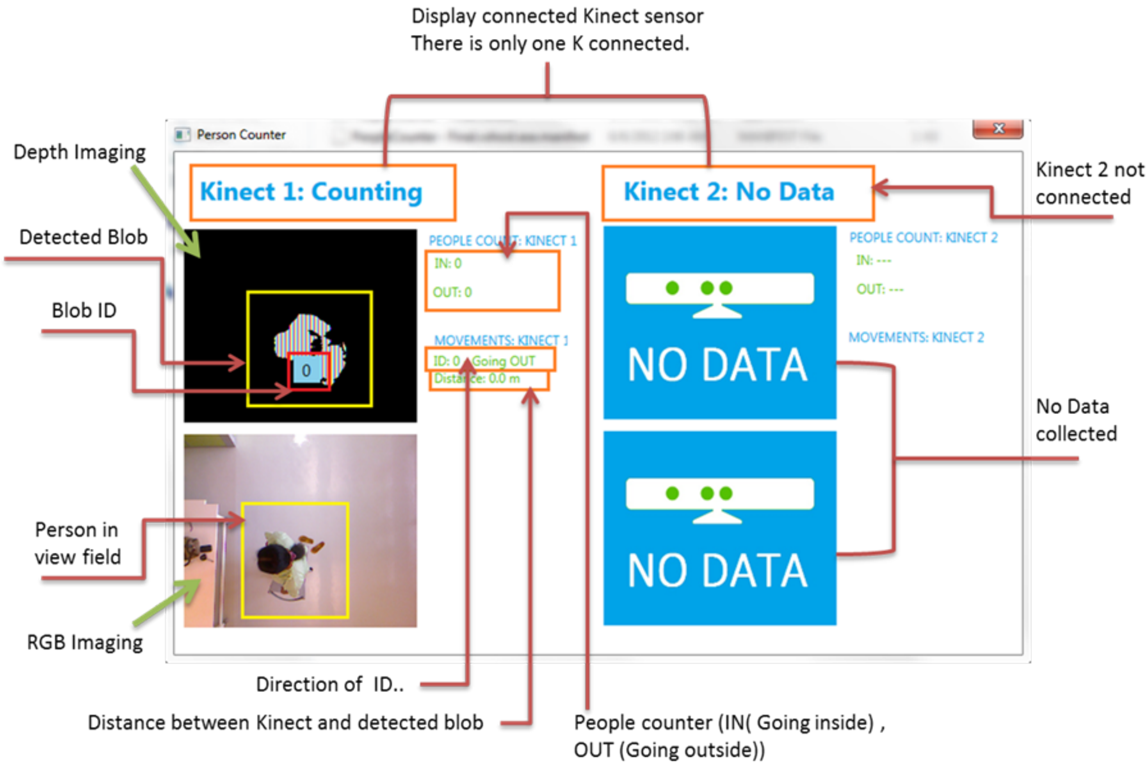

Figure 4.3: Overview of the GUI of our Kinect-based People Counter x

of the data in addition to mapping between skeleton and color coordinate spaces. Once our Depth imaging is ready we can start tracking blobs and draw markers.

4. **Generate Markers :** This draws a rectangle blue box among with unique ID of people under the camera. This ID is temporarily used for for the detection of multiple subjects passing in the field view. Kinect has a limited number of tracked people, while setting up the camera to front-view. But, with the vertical Kinect setting we can track up to maximum number in the view field as far as they are not close to each other, which if true will cause occlusion[1].

[1] occlusion occur when two person walked close to each other, the Kinect will consider them as one object and the depth data will get the distance of one of them. Please refer to chapter 8

5. **Blob Counter and Process :** Using bitmap to detect the head gesture in the image from depth data. Calculating the depth data and extracting the blob among the 30 frame captured.

```
Bitmap b = BitmapFromSource(bsource);
BlobCounter BCounter = new BlobCounter();
ColorFiltering FilterObjects = new
   ColorFiltering();
BCounter. FilterBlobs = true;
BCounter. MinWidth =50;
BCounter. MinHeight =150;
BCounter. ProcessImage(b);
Blob[] detectedblobs = BCounter.
   GetObjectsInformation();
return detectedblobs;
```

6. **Bitmap Source to Bitmap Convertor:** This is used to draw the ID number (blob counter number that generated previously) on the detected blob. bitmap sources is a core Windows Imaging Component (WIC) component that represents the bitmap pixels of an image. It can be an individual frame of a multiframe image, or it can be the result of a transform performed on a bitmap source. The bitmaps enables us to directly access the pixels of a bitmap source which supports any combination of read and/or write access to the bitmap pixels [35].

7. **Going IN/Going OUT Calc Start Kinect:** as mentioned before, we are using a virtual gate to count number of people. Our counter depends on the previously location of the detected blob in the image frame and its current location. Direction is counter as per increasing or decreasing "X" co-ordinates

of the person look for going in function and going out they accept two parameters *prev position* and *current position*. Then set the direction and change the counters when the threshold is reached, figure 4.4 shows the logic of counting in and out.

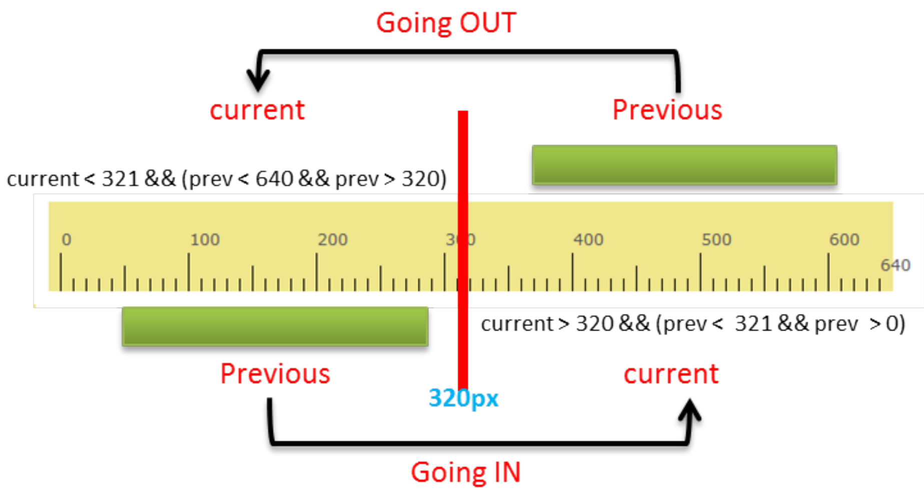

Figure 4.4: The function of Direction Calculation from Depth image

Also, you can get the distance of object from real distance to digital image in pixel by doing little mathematics to calculate the depth range space, where the depth data in Kinect is calculated in millimeter :

- Measure the area that is visible on the colour (RGB) image when you place Kinect sensor at certain height, example: 3 m high
- Now dividing that length by 640 will give you the distance per pixel
- Since the code works on the logic of pixels, we place the marker at 150, the actual distance will be 150*distance par pixel starting from the Kinect view area. For example let's say the visible area is 320 cm when you place the Kinect at 3 m high. Therefore, we have 640*480 image distance per pixel is 2 cm.

Remember, the Kinect image processing is using pixel which is a combination of dots in the digital image. 1 cm is a definite dimension. its based on the SI unit Meter. i. e 1/100 m while 1 pixel = 1 dot. So, To determine the size each pixel you need to know the resolution of the image frame you have, for us 640*480 Then, once you setup your Kinect, calculate the real distance in cm to know how the image is processing per px.

People tracking can be done using two methods 4.5. The Kinect sensor people tracking method are using the human posture, full or half body skeleton and more depth data imaging. An existing skeletal Tracking by MSDN library is able to recognize people and follow their actions using the infrared (IR) camera while at the front. Some limitations to this method are, that Kinect can only detect up to six people but actually track two of the six. Another method of people tracking is by fixing the camera into vertical direction, and start track the head. This method shows a good results in people counter fields. Both methods are developed into our software to enable us develop a fair comparison between both while track and count people. The functionality of our Kinect-based People-counter software versions (Top-view and Front-view) is explained in Table 4.1 below.

Kinect sensor Setup

For the Front-View version, the Kinect sensor setup horizontally as in 4.6 where it face the target gate or (entrance). This is an easy installation of Kinect since you can just place it on the top of desk or some selves on wall like in 4.7. The minimum distance between the detected person and the sensor should be more than 1. 2 m otherwise the subject may not be detected by the sensor. Also, for the full body skeleton the distance should ranges between 1. 2 to maximum 2. 5 m. Others, will not be captured by the sensor or you might adjust the distance parameter as we mentioned in 7

Table 4.1: The functionality of the two versions of our people-counter software

	Top-View Counter	Front-view Counter
Logic	The Kinect Camera(s) is placed on the top of the way facing downwards Camera(s) Capturing the Colour and Depth Information from the view Information is processed to find objects passing below the camera and following parameters are collected: Number of Objects Object Movement Direction Weather the object Crossing the threshold line Distance of the object center from the Sensor ID is assigned to each identified object	The Kinect Camera(s) is placed on the Front of the way facing downwards Camera(s) Capturing the Colour and Skeleton Information from the view Information is processed to find Skeletons passing from the front of the camera and following parameters are collected: Number of Skeletons Skeleton Movement Direction Weather the Skeleton Crossing the threshold line Distance of the Skeleton centre from the Sensor ID is assigned to each identified Skeleton
Kinect Detection	Check for the Number of Sensors connected If 0 show message (No sensor connected) and exit If 1 show message (The system can handle two sensors) if user choose to go ahead with one sensor then start, Else wait for the user to connect the second sensor. If 2 start with the further steps with no message	Check for the Number of Sensors connected If 0 show message (No sensor connected) and exit If 1 show message (The system can handle two sensors) if user choose to go ahead with one sensor then start, Else wait for the user to connect the second sensor. If 2 start with the further steps with no message
Enable Kinect Streams	Enable colour and depth sensor stream for all the connected sensors. Start the sensor in the program	Enable colour and Skeleton sensor stream for all the connected sensors. Start the sensor in the program
Blob tracking	Get the information from Depth and Colour Sensor and Pass it to the Blob Counter Filter the Blobs for Noise Count the Blobs Determine the motion direction based on the current and previous co-ordinates of the sensor. Determine the distance of the objects using depth sensor data	Get the information from Skeleton and Colour Count the Skeletons Determine the motion direction based on the current and previous co-ordinates of the Skeletons. Determine the distance of the Skeletons using (Z) coordinate from sensor data
Counting	If the object direction is going out and it crosses the threshold line, The OUT count is incremented If the object direction is going in and it crosses the threshold line, The IN count is incremented	If the Skeleton direction is going out and it crosses the threshold line, The OUT count is incremented If the Skeleton direction is going in and it crosses the threshold line, The IN count is incremented
Display	Colour Video and Detected blobs are shown on the UI IN and OUT counts are shown on the UI Currently visible objects are displayed with their IDs, directions and distance.	Colour Video and Detected blobs are shown on the UI IN and OUT counts are shown on the UI Currently visible Skeletons are displayed with their IDs, directions and distance.

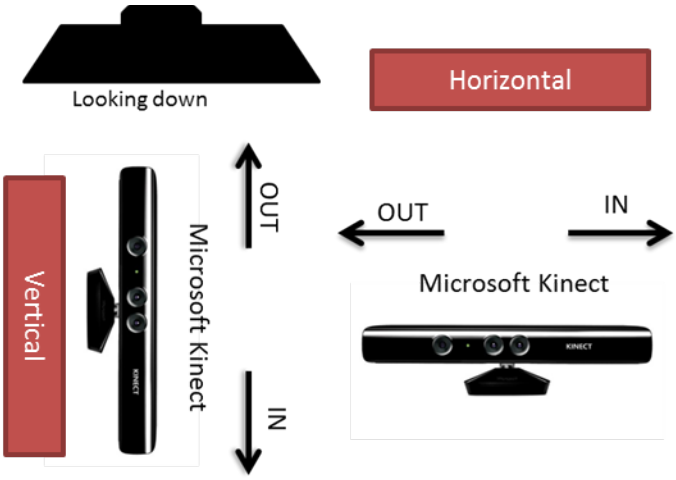

Figure 4.5: The two different settings of the sensor

For the Top-View, the Kinect should be placed vertically as in Figure 4.8. The distance should be a minimum hight of 1. 6 m and maximum hight of around 3–3. 2 m. The upper you go the wider the view-field covered, but you might lose some data since the sensor vision is up to around 4 m. We tested different height with corresponding view-field area in appendix.

4.2 Test-bed Setup

The test-bed is located in the i-Smart laboratory of one of the institute buildings, more precisely on the second floor of B2 building. This lab is occupied by Computing Information System students and profs. There are 7 professors assisted by 8 students and some fellowship engineers. The shape of the lab is showed in Figure 4.9 below.

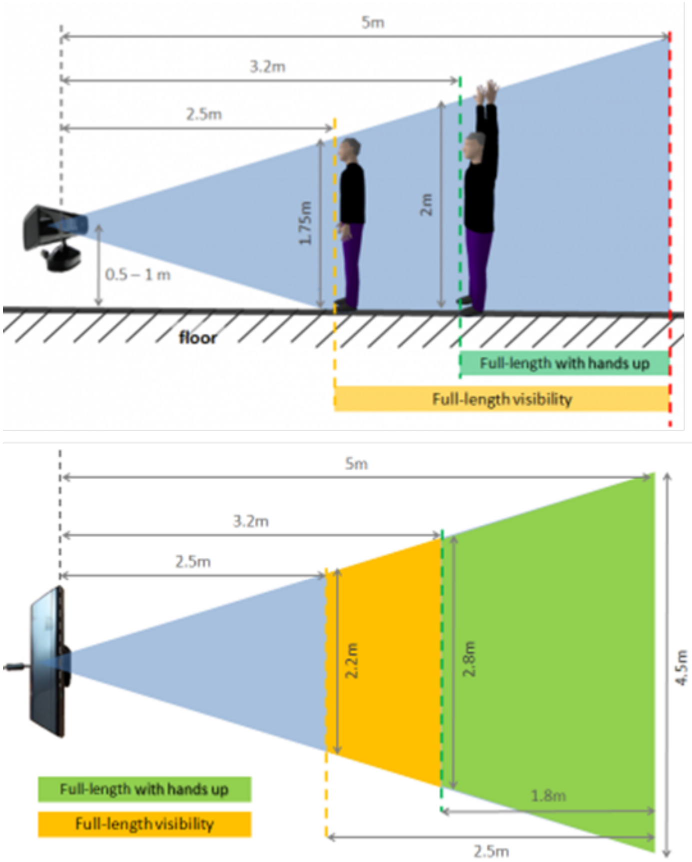

Figure 4.6: The Field of view of both horizontal and vertical Sensor Setup.

Design of the solution:

Let us consider a sample office floor (i-Smart) divided into virtual zones based on physical barriers. Below figure shows the layout of the hypothetical office.

The zones are continuously monitored by 8 Kinect sensors strategically placed on the gates of each zone. Their role is to record the inflow or outflow of people. Upon image processing *(which easily maintained from depth imaging using Kinect sensor)*, any event of change on occupancy of the zone is logged. Since we notice some limitations on the Front-View software due to limited number of tracked people in crowd, we setup all sensors on the lab ceiling and used the Top-view

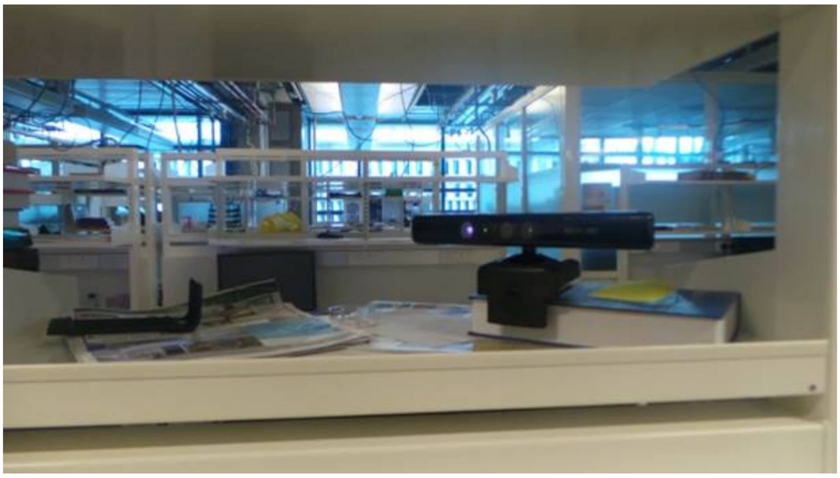

Figure 4.7: A Kinect sensor placed on a desk facing the entrance door, Front-View

Figure 4.8: A Kinect sensor placed in the ceiling and facing the floor, Top-View

version as in 4.11. Some areas were temporarily monitored using the Front-View where the flow doesn't exceed two person per walk. A sample log obtained for a single zone is of the format as shown below.

Date, timestamp, the IN counter and OUT counter records are logged.

Figure 4.9: Map of the second floor of the B2 building at MI.

The IN and OUT counter is incremented with time whenever some one enters the zone virtual gates. The figure below shows the corresponding directions of IN and OUT counters on our implemented system 4.12.

Figure 4.10: A layout of the floor of the building and the placement of sensors to observe the occupancy of the building

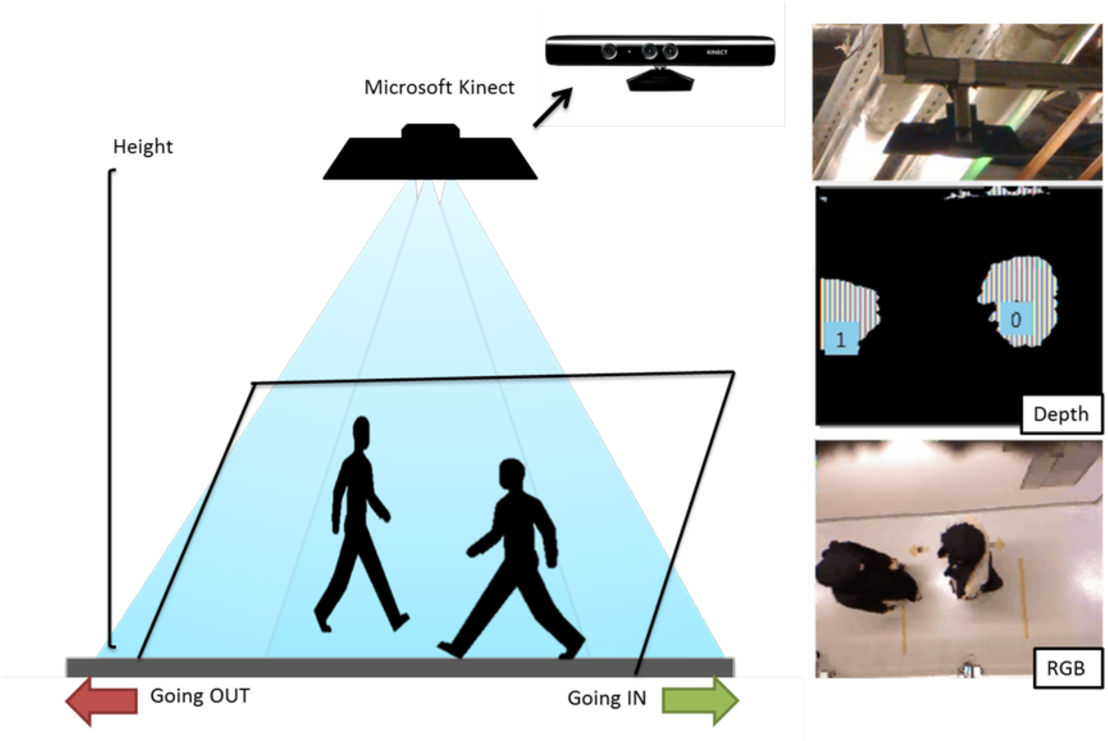

Figure 4.11: The architecture of our system

08/10/2013	22:51:30	IN:	0	OUT:	1
08/10/2013	22:51:31	IN:	0	OUT:	2
08/10/2013	23:30:30	IN:	0	OUT:	3
08/10/2013	23:58:15	IN:	0	OUT:	4
09/10/2013	05:17:21	IN:	1	OUT:	4
09/10/2013	06:35:36	IN:	2	OUT:	4
09/10/2013	06:36:20	IN:	2	OUT:	5
09/10/2013	07:09:11	IN:	3	OUT:	5
09/10/2013	07:15:04	IN:	3	OUT:	6
09/10/2013	07:25:46	IN:	4	OUT:	6

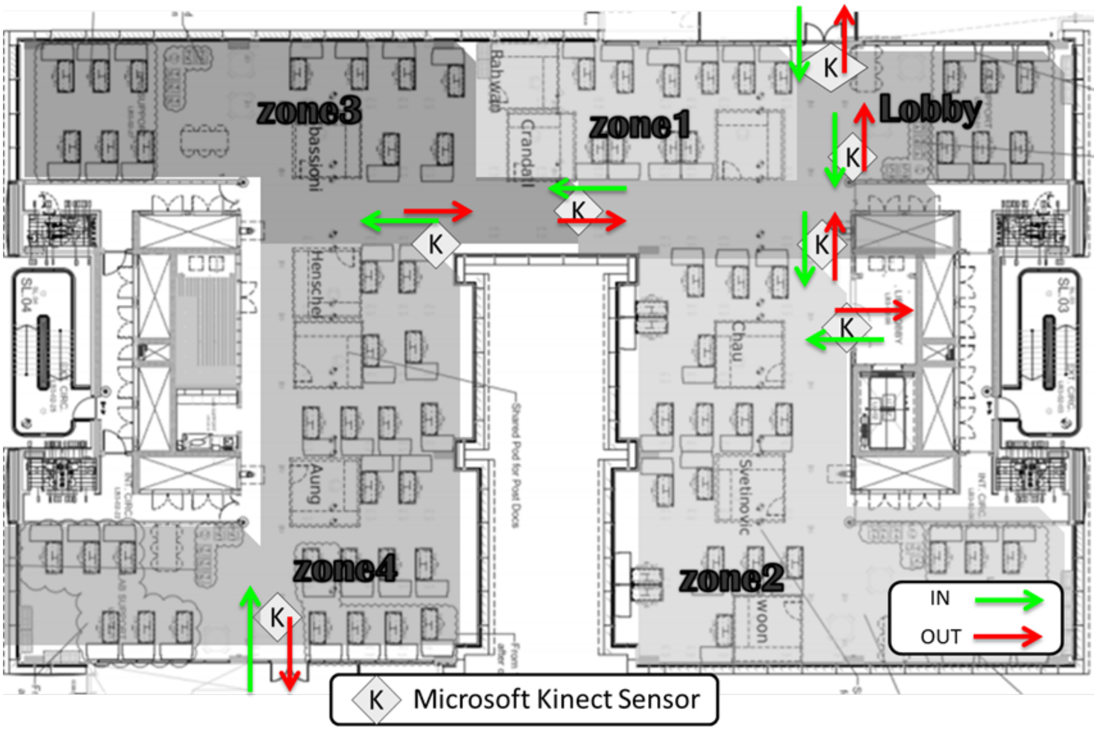

Figure 4.12: The IN and OUT directions on our test-bed

CHAPTER 5

Occupancy Modeling

This chapter describes our methodology for modelling occupancy data. By predicting the future of occupancy of a zone[1], an intelligent system can tune conditioning parameters gradually to reflect the predicted changes in time. There are many ways to predict this time series data such as regression techniques, Mixture Gaussian Model, Genetic Algorithms, Markov Chain Model and the Markov model. The latter is used to tackle the problem since it captures the temporal nature of occupancy changes along with the inter-room correlations and occupant usage of the areas [3].

5.1 Markov Chain Model

The prediction of the temporal dynamics of the occupancy in a zone is carried out using a Markov Chain (MC). It represents the chain of states which a process goes

[1] A zone is a part of a building whose HVAC system is controlled by a single sensor. The single sensor is usually, but not always, a thermostat. A zone doesn't necessarily have to be a closed office, it can be a part of large space floor

through and is usually defined as a process which can be observed at a discrete set of times. To design our observed data to easily fit the MC model, the number of occupants in each zone of the building is taken, and a threshold and a simple state is assigned to each observation after the threshold.

For example, let the number of zones be 3, and the occupancy in each zone be based on a threshold vector $(say[0,5,10,15])$. This assigns states like $(E)mpty, (F)ew, (A)verage, (C)rowd$ to each zone. i. e if in a zone the observed number of occupants (N) is zero then a state (E) is assigned to the zone. Similarly, if $N > 0$ and $N <= 5$, then the zone is assigned the state (F), for $N > 5$ and $N <= 10$, the state is (A) and so on. For a sample observed occupancy data of the building with 3 zones occupancy data at time t, their corresponding state is $[8,.22,0] \Leftrightarrow [F,C,E]$.

Using the occupancy distribution at any time t and the derived state vector, the state vector for time $t + \triangle t$ is predicted. The predicted state vector for $t + \triangle t$,. allows the prediction of which zones are likely to be more or less occupied. A two dimensional matrix encompassing the probability of all possible transitions is called a transition matrix.

Transition matrix:

The transition matrix is a square table with dimensions [Number of states X Number of states]. It is used to quickly obtain the probability of the transition from one state to another. The element of the matrix at any location (i, j) is the probability of transition from i^{th} state to j^{th} state which is designated as p_{ij}. Consider the following example of the state of a stock market [36]. The market exists as either, a bear, a bull or is in a stagnant state. Transitions can take place every week between any of these states. Figure 5.1 explains the state transitions which are derived from equation 5.1 and the corresponding transition matrix of the three states representing

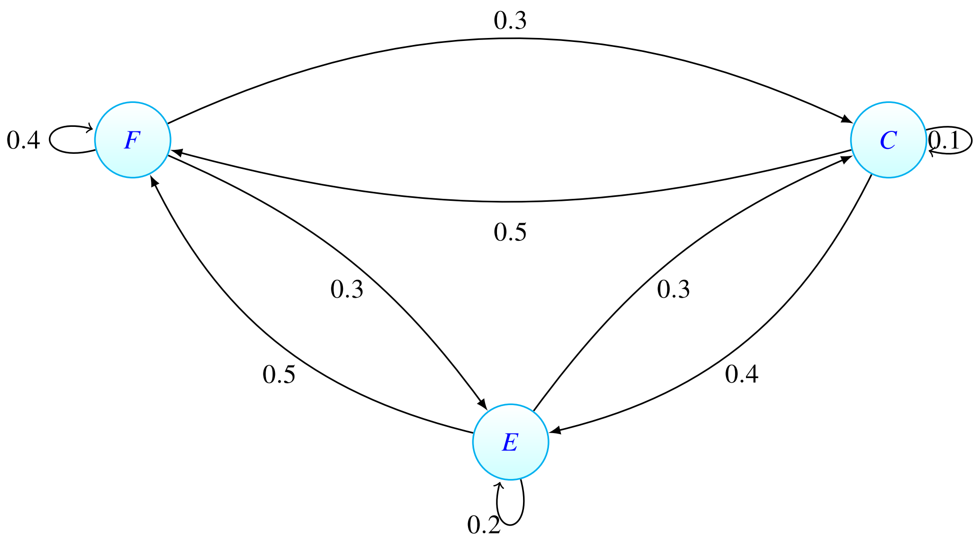

Figure 5.1: State diagram of Markov Chain problem involving states change from Empty, Few or Crowded which represent number of occupants in the building

the number of occupants in building.

$$P = \begin{array}{c} \\ Empty \\ Few \\ Crowded \end{array} \begin{array}{c} \begin{array}{ccc} Empty & Few & Crowded \end{array} \\ \begin{bmatrix} 0.2 & 0.5 & 0.3 \\ 0.3 & 0.4 & 0.3 \\ 0.4 & 0.5 & 0.1 \end{bmatrix} \end{array}$$

$$P(X_{t+1} = s_{t+1} | X_t = s_t, X_{t-1} = s_{t-1}, \ldots, X_0 = s_0) = P(X_{t+1} = s_{t+1} | X_t = s_t) \quad (5.1)$$

In P, all elements represent the probability of the transition from one state to another, including the same state. For example, element $(2,1)$ is the probability of the transition from the 2nd state which is (Few) to state 1 (Empty). Moreover, the value of $P22 = 0.4$, which represents the probability that there are a few number of occupants in the current state which will remain in the Few state for next time by 40%. One of the main properties of the transition matrix is that the sum of all elements in any row equals 1.

$$\sum_{i=const,j=0}^{k-1} P_{i,j} = 1, \text{where k is the number of states} \tag{5.2}$$

For any number of observations, the MC model can be easily applied to describe a single time step of event, i. e. considering the present state (at t) the states at an immediate future time-step at $t + \triangle t$ is described by the transition matrix. In order to understand the probability of the transition from the present state to any particular state after n time-steps $n\triangle t$, then it is possible to use the following equation.

$$P_{ij}^{(n)} = \sum_{r \in S} P_{ir}^{(k)} P_{rj}^{(n-k)}, \text{ where S is the state space of the Markov Chain} \tag{5.3}$$

In order to calculate the two-step transition probabilities it is possible to use the simplified form of the equation 5.3 below:

$$P_{ij}^{(n)} = \sum_{k=1}^{M} P_{ik} P_{kj} \tag{5.4}$$

Learning the Transition matrix:

The problem that is being modelled is a process, which is accustomed to changes with time. The occupancy observed in time over all zones is used to calculate the transition matrix. The occupancy of different zones is recorded in half hour time segments. For any zone, the probability of a particular transition is calculated by finding the ratio of the number of this transition with respect to the total number of transitions occurring.

$$P_{ij} = n_{ij} \sum_{k=1}^{M} n_{ik}, \text{where m is the possible number of transitions} \tag{5.5}$$

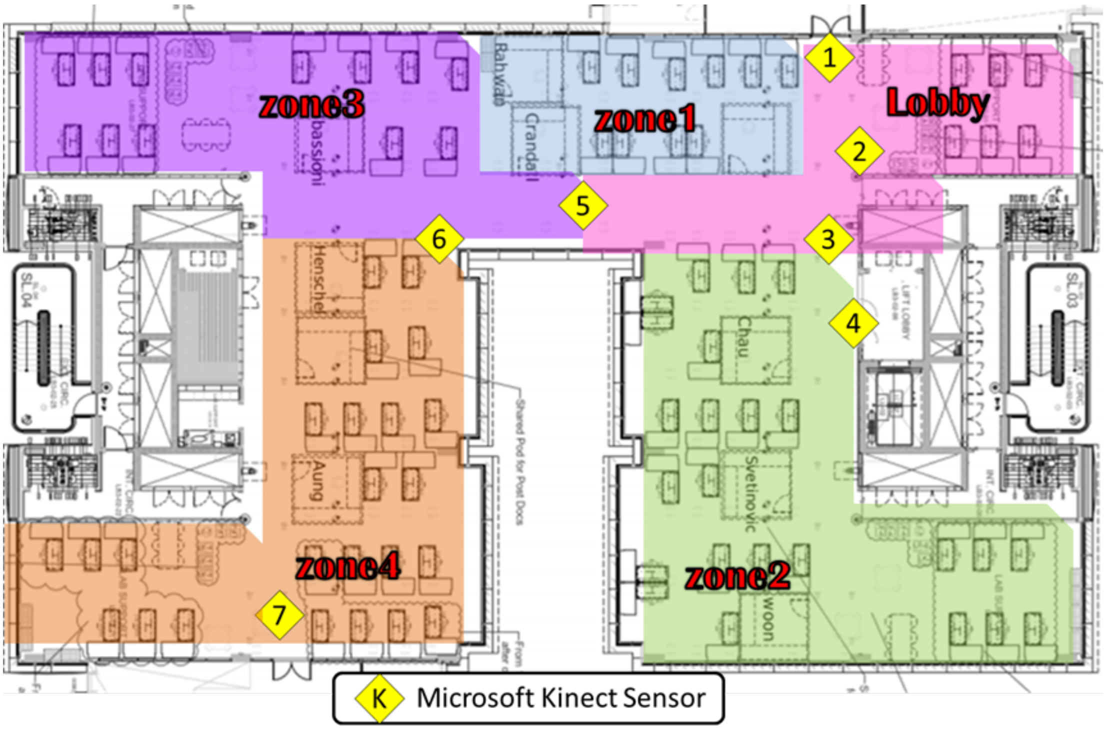

Figure 5.2: A building's floor layout and the distribution of Kinect sensors was used to observe the inflow and outflow of occupants. There are 7 Kinects deployed for this test-bed

After calculating the transition matrix with a suitably large data set, it is possible to identify similar patterns in a new set of observations.

Design of the solution:

It is necessary to recall that the design consideration of an office floor is divided into different zones based on physical barriers. The figure below shows the layout of the hypothetical office and the distribution of Kinect sensors among the floors 5.2.

As mentioned at the end of chapter 4, a log file was created with a format of the Table below 5.1:

08/10/2013	22:51:30	IN:	0	OUT:	1
08/10/2013	22:51:31	IN:	0	OUT:	2
08/10/2013	23:30:30	IN:	0	OUT:	3
08/10/2013	23:58:15	IN:	0	OUT:	4
09/10/2013	05:17:21	IN:	1	OUT:	4
09/10/2013	06:35:36	IN:	2	OUT:	4
09/10/2013	06:36:20	IN:	2	OUT:	5
09/10/2013	07:09:11	IN:	3	OUT:	5
09/10/2013	07:15:04	IN:	3	OUT:	6
09/10/2013	07:25:46	IN:	4	OUT:	6

Table 5.1: The output log file for mobility tracking with exact timestamp presenting the inflow and outflow for each sensor virtual gate

This data is then parsed and converted into a different format in order to compute the effective occupancy of a zone. The new format has 48 half hour time slots a day, and on each time slot the net inflow and outflow of people count are logged. A sample of the converted data which has 48 rows is shown below 5.2.

After counting the differences between the inflow and outflow of occupants, along with the previous estimate of the occupancy of each zone and the corresponding sensor gates, the net occupancy of each zone at a given time slot is calculated. A table can be formed which describes the number of occupants in each zone at all the time slots in 5.3.

This data is related to the threshold vector [0, 5, 10, 15] and assigned one of the four states E, F, A, C. This data is referred to as the state matrix in 5.4.

The number of possible states that can be observed in the building is equal to 5.6

$$(number of individual states)^{(number of zones)} \tag{5.6}$$

The total number of possible states of the building in this case is 1024, from all 5 zones conditions of different element combinations of E, F, A, C ranging from (E, E, E, E, E), (E, E, E, E, F), (E, E, E, E, M) to (C, C, C, C, C).

Since the transition matrix accounts for all the transitions, the size of the tran-

	09/10/2013	
00:00	0	0
00:30	0	0
01:00	0	0
01:30	0	0
02:00	0	0
.	.	.
.	.	.
.	.	.
21:30	1	1
22:00	1	1
22:30	0	1
23:00	2	3
23:30	0	1

Table 5.2: The converted data which has 48 time slot rows from the original log file

Lab1	Lobby	Lab2	Lab3	Lab4
0	2	0	0	0
0	0	10	0	0
0	1	0	6	1
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

Table 5.3: The occupancy data at each zone at each 48 time slot which represents the exact number of occupants present in a certain zone at time t

Lab1	Lobby	Lab2	Lab3	Lab4
E	F	E	E	E
E	E	C	E	E
E	F	E	M	F
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

Table 5.4: The condition of each zone depends on the number of occupants derived from occupancy data table

Time	00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30
Zone 1	0	0	3	8	9	9	10	15	11	10	11	5
Zone 2	8	8	8	4	12	10	12	18	20	25	3	0

Table 5.5: Example of occupancy data for two zones in a building

sition matrix is [1024 X 1024]. The transition matrix is then trained using the data above. The training is done using the equation 5.5, by counting the number of times a transition takes place divided by the total number of transitions. There is a possibility that the input data set is not exhaustive in nature. The transition matrix that is obtained is normalized row-wise to make the property in the equation true5.2.

After the matrix is trained, the implementation of the prediction system is simple and straightforward. With new observations as the state matrix is updated with time, for any new row obtained, the state vector is taken say (E, E, E, E, F) and a one-time step prediction is made by finding the row number in the transition matrix which represents the state vector (row 2) and the column number with the maximum probability value is taken. The state vector corresponding to the column number is the next predicted state of the building.

5.1.1 Sample Model

To understand how the problem is solved in-depth, a sample date is observed and used to train the transition matrix. Let us consider a building floor consisting of two zones. As the sensors observe the occupancy of each zone, with people entering or exiting any zone data is logged. After parsing these log files, it is possible to obtain the occupancy of each zone in 48 time slots a day. An example of such a table 5.5 formed for 12 slots are shown below:

For thresholds, the occupancy matrix with a threshold vector [0, 5, 10] and assigning individual states E, F, A, C we get the table below 5.6:

Time	00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30
Zone 1	E	E	F	A	A	A	A	C	C	A	C	F
Zone 2	A	A	A	F	C	A	C	C	C	C	F	E

Table 5.6: Representing the occupancy data, with transition condition

	EE	EF	EA	EC	FE	FF	FA	FC	AE	AF	AA	AC	CE	CF	CA	CC
EE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EA	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0
EC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FA	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
FC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AF	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
AA	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
AC	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1
CE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CF	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1

Table 5.7: The transition matrix presenting the transitions between states

For this problem, there are 16 possible combined states called state vectors. The transition matrix that is formed is of size [16 x 16]. From the above table, we see that there are 11 transitions. In a [16 x 16] matrix of zeros, for each transition observed the row number corresponding to the initial state vector is taken and the column number corresponding to next state vector is taken, and the element at (row-number, column-number) is incremented by 1. The output transition matrix would look like 5.7 below:

Normalizing the transition matrix row wise we get the table below 5.8:

The matrix has many empty rows, which shows that it is inadequately trained. After finding the transition matrix, the system is ready to predict future occupancy.

	EE	EF	EA	EC	FE	FF	FA	FC	AE	AF	AA	AC	CE	CF	CA	CC
EE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EA	0	0	0.5	0	0	0	0.5	0	0	0	0	0	0	0	0	0
EC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FA	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
FC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AF	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
AA	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
AC	0	0	0	0	0	0	0	0	0	0	0.33	0	0	0.33	0	0.33
CE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CF	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
CA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0.5

Table 5.8: The transition probability between states

For an observation of [zone 1, zone 2] equal to say [8, 13], we get the state vector [A, C]. The next state of the building can then be obtained by taking the row MC and finding the index of the maximum element in the row, which is CA, with probability 0. 0929.

CHAPTER 6

Results and Discussions

This chapter discusses and analyses data that is collected from our system. A human mobility detection system was implemented through a whole floor of a laboratory building. Since there might be difficulties and challenges in any deployment system, the sensors cover the most important paths/directions of lab areas that mostly students use. As a result, some accuracy might be lost due to people taking short-cut paths into the lab. Therefore, our test deployment is evaluated for accuracy of mobility detection4

6.1 Data Collection

At the time of this report, a total of three month of data has been collected from 7 Kinect sensors implemented in an I-smart laboratory at the MI building. The actual data collection started on the morning of September 15th. All Kinect were activated and connected to a central server where the logged files are stored and linked to a local-host web-server created at that central computer. The data collected is then parsed automatically using Matlab script to utilize a uniform timestamp of 48 slots. A sample of the occupancy data collected is shown below in table 6.1. Figure 6.12 shows snapshots of our software while detecting and tracking pedestrians.

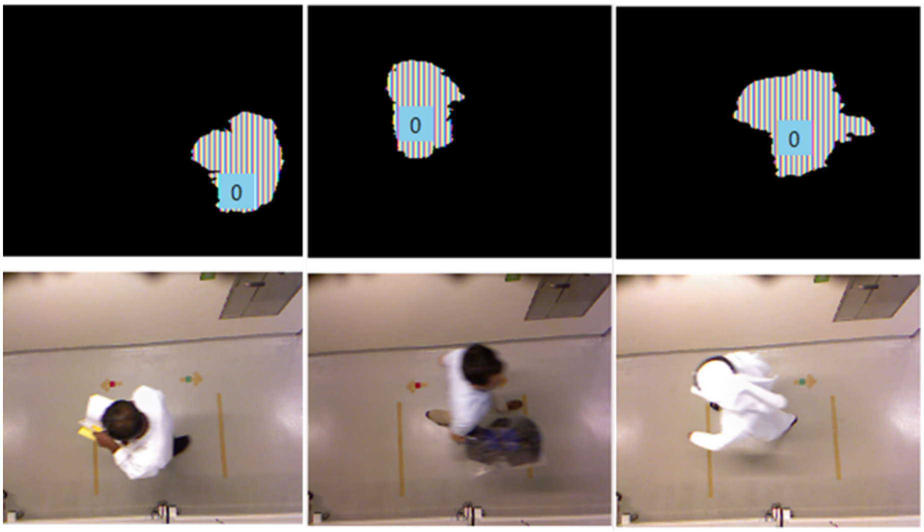

Figure 6.1: A Sample of detect method, Depth Data

The data show the number of students in a zone every half an hour starting at 00:00 AM until 23:30 PM throughout the day. The Table shows the occupancy data of the five virtual zones for Sunday September29th. When the results are presented, it is possible to map the number of occupants to each zone, or build a schedule which can reflect the actual use of the lab resources. For example, Table 6.1 displays data of the zone during the week starting from Sunday Setember29th until Thursday October3rd.

The occupancy that is observed on a random day is shown in Fig 6.2. At different time slots it is possible to see how the pattern changes. Although the figure looks random, with more careful analysis there are some important points that can be made and some conclusions that can be drawn about the activity of each zone. It is possible to see how the variations of occupant counts are high at time

Table 6.1: Occupancy data for Sunday Sep. 29

Time	Zone1	Lobby	Zone2	Zone3	Zone4
00:00	0	2	0	1	0
00:30	0	0	1	0	0
01:00	0	1	0	0	1
01:30	0	0	0	1	0
02:00	0	1	1	1	0
02:30	0	0	0	0	0
03:00	0	0	0	0	0
03:30	0	0	0	0	0
04:00	0	0	0	0	0
04:30	0	0	0	0	0
05:00	0	0	0	0	0
05:30	0	0	0	0	0
06:00	1	0	0	1	3
06:30	0	2	0	2	0
07:00	0	1	3	1	1
07:30	1	1	1	1	1
08:00	3	0	1	1	0
08:30	2	0	2	1	1
09:00	2	2	2	2	2
09:30	5	0	4	2	0
10:00	0	3	0	1	3
10:30	2	1	3	0	1
11:00	1	0	2	2	3
11:30	0	5	1	0	0
12:00	0	4	1	1	0
12:30	1	0	2	3	4
13:00	7	1	5	0	0
13:30	1	0	1	3	0
14:00	0	5	3	2	8
14:30	2	2	2	1	1
15:00	2	4	4	3	1
15:30	0	3	2	0	0
16:00	0	1	3	1	2
16:30	3	2	4	1	2
17:00	0	2	7	1	0
17:30	0	4	1	2	4
18:00	0	1	2	0	0
18:30	0	0	0	0	2
19:00	0	4	0	2	0
19:30	4	1	0	0	1
20:00	4	1	1	1	0
20:30	2	0	2	1	3
21:00	0	0	1	0	0
21:30	0	0	1	0	0
22:00	0	1	0	0	0
22:30	0	1	1	0	0
23:00	1	0	2	0	1
23:30	0	0	0	0	0

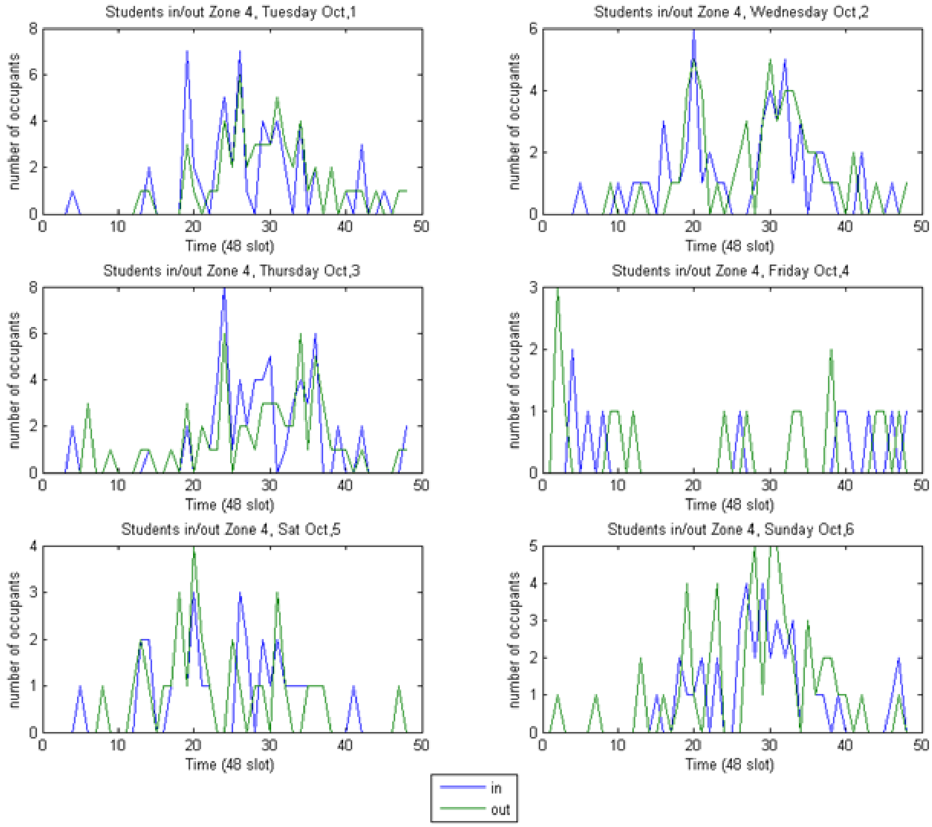

Figure 6.2: Occupancy of random days through the floor zones

slots 20 to 40 in almost all zones. These time slots are considered the most active time of the day. If the activity, i.e the physical movement of people around zones, are high at any specific time frame, then it becomes difficult to vary the temperature conditions of the zones. A measure of the activity of each zone seems valuable in optimizing the conditioning system parameters.

In figure fig:22 the same day of one week was compared. If Tuesday September 17th,October1st and October 8th are compared, it might be possible to notice the same occupancy schedule on the three days. This gives a pattern of a day during the week since the building is an educational and laboratory building.

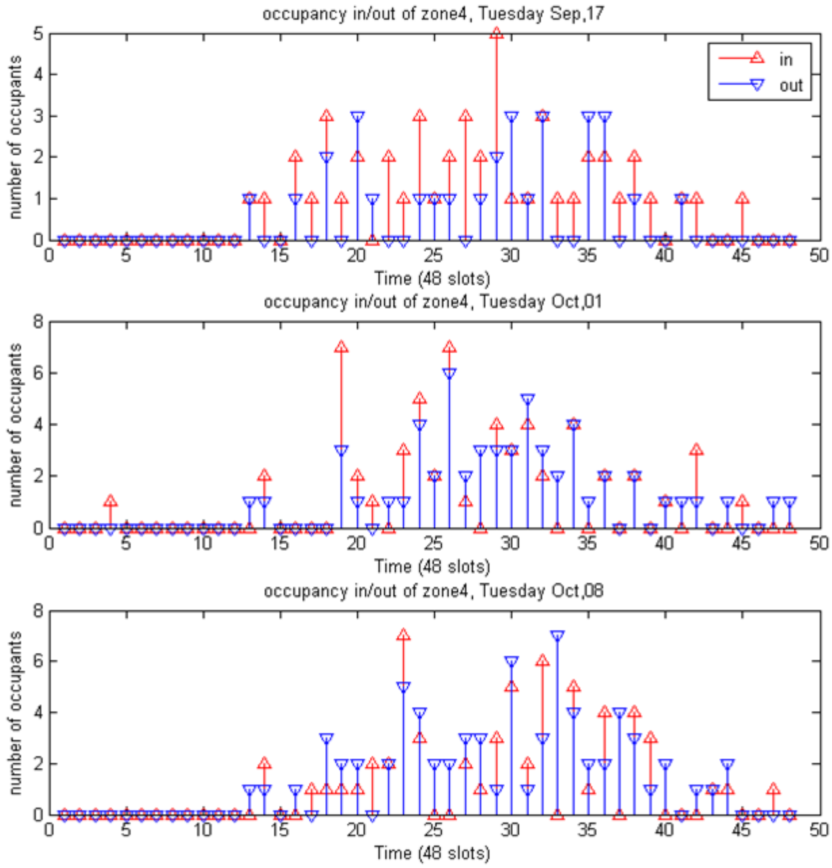

Figure 6.3: Comparisons of Tuesday through three weeks

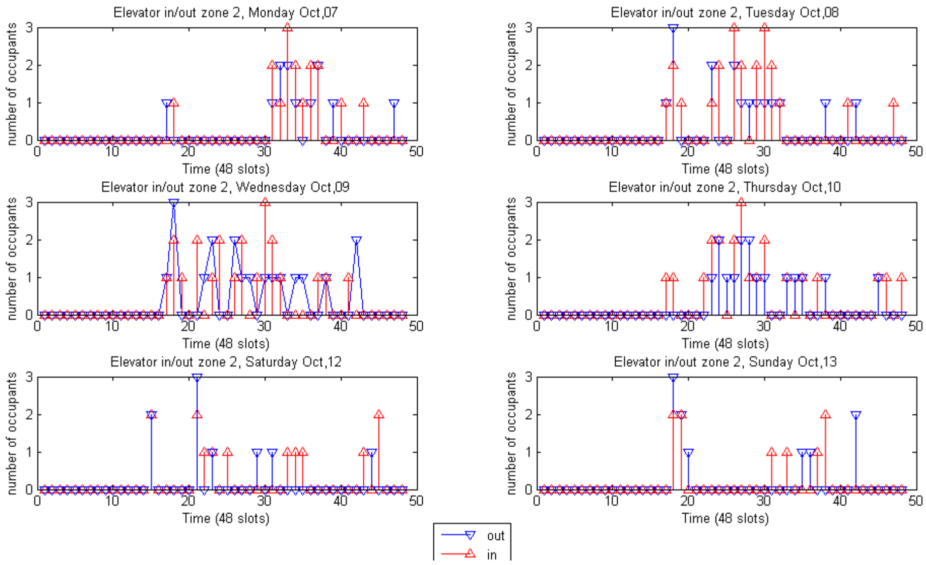

Figure 6.4: Elevator side, IN and OUT data from Zone2, through a week

It is possible to notice that few people are using the lab elevator. This is because the lab occupants that prefer using the stairs and walking around rather than taking the elevator due to the health benefits.

Figure 6.5 shows the exact measure of in/out counts of the different zones. All of the zones are plotted in the same figure to compare the in/Out counts of each zone. It is easy to see qualitatively that the flow of people around the different zones is constrained by the physical limitations of the building architecture. For example, when the top-second and top-third plots are compared, it is possible to see how when the OUT values are peaking in the former and the IN values are high in the latter, signifying that lobby and zone2 have a higher ratio of flow of people with respect to other zones connected to them. When comparing top-first and top-second plots it can be seen that the IN of both the plots are higher that their respective OUT. It is therefore safe to assume that they are quite independent in terms of the people flow.

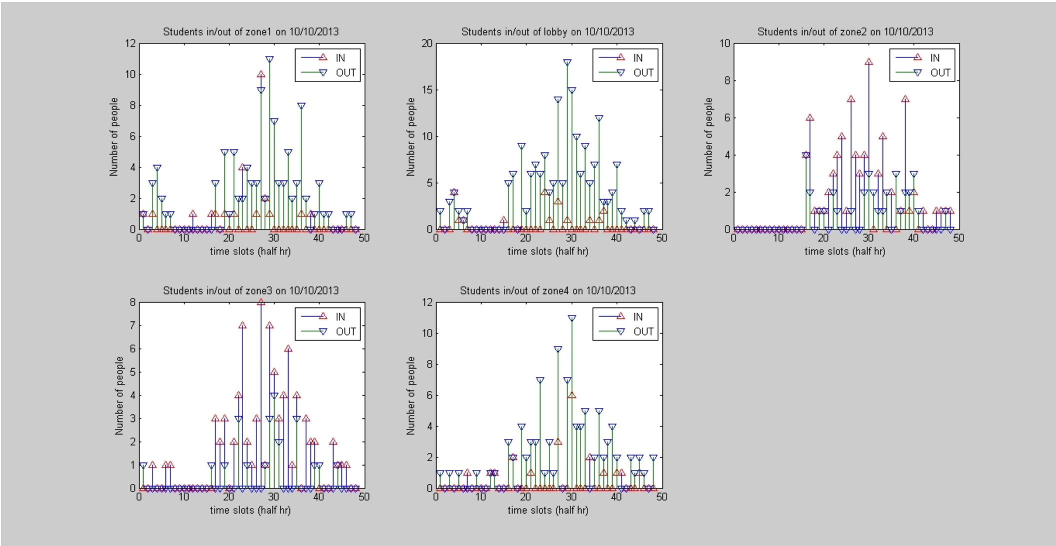

Figure 6.5: Stem charts of Occupancy of different zones in time

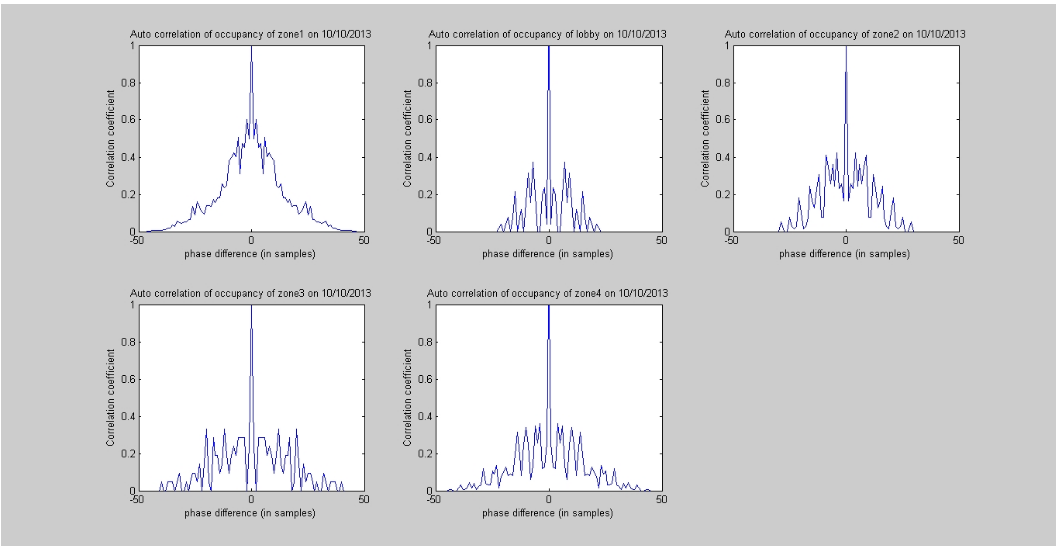

Figure 6.6: Autocorrelation of occupancy of different zones observed over time

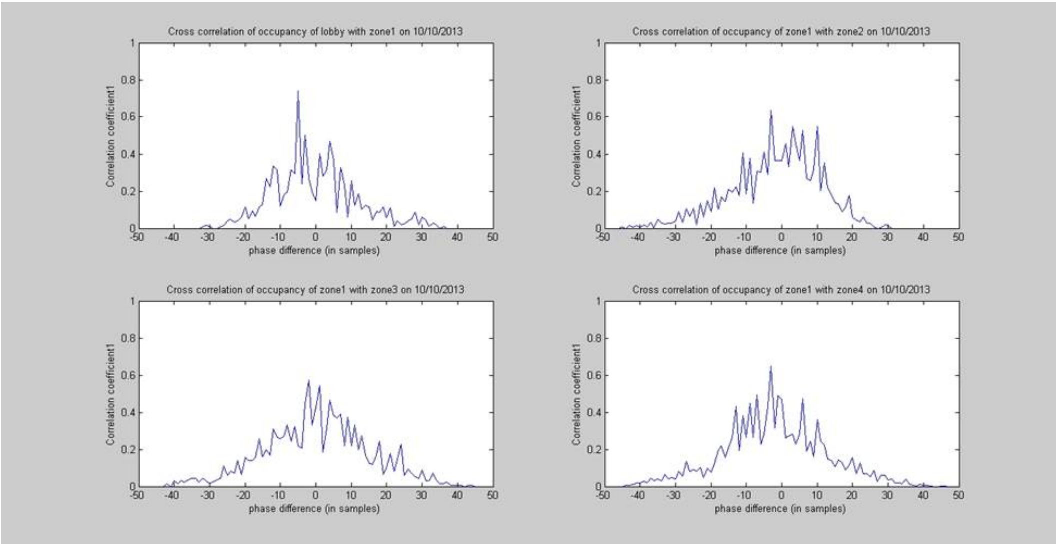

Figure 6.7: Cross-correlation of occupancy data from lobby zone with all the other zones

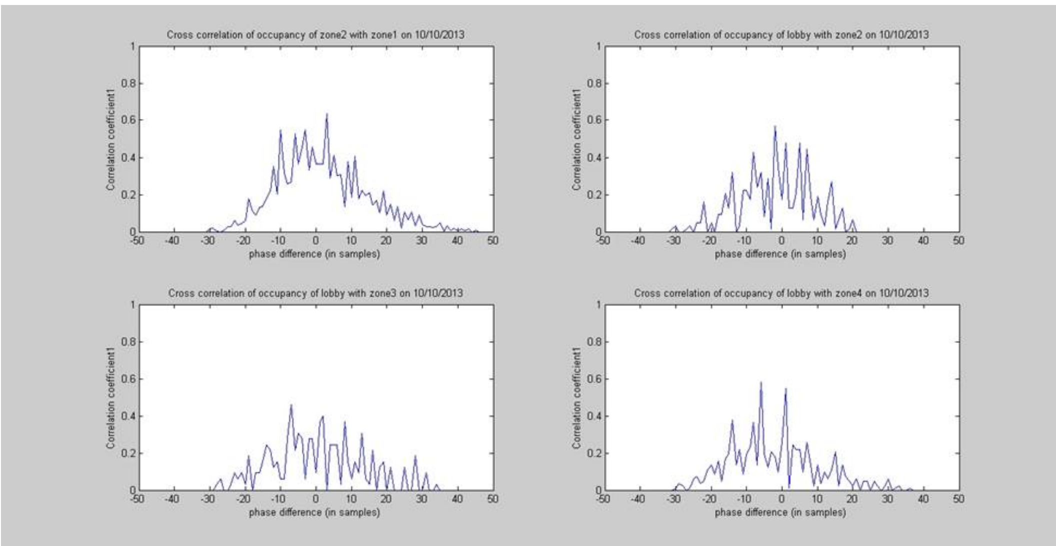

Figure 6.8: Cross-correlation of occupancy data from zone2 with all the other zones

Figure 6.6is a visualization of the auto-correlation of the occupancy data observed in different zones over time. As expected when the phase difference is zero, the correlation coefficient is the highest in all cases. Auto-correlation can be used to study the energy of a zone. The area under the curve is an effective measure of the energy of the zone, i.e how much activity takes place in time. If the activity is high, the sensitivity of the conditioning system needs to be high, since any small deflection in the prediction could lead to over conditioning or under conditioning. Using simple analysis of different time-series data with the auto-correlation operator, it is possible to see that the smoother the curve, the less chaotic the series is. Therefore, a measure of the absolute of the deviation of the curve over a windowed averaged curve would provide a value directly proportional to the error introduced by our prediction system. Based on the definition of correlation, it can be assumed that the more uncorrelated two data sets are, the lesser the correlation values plotted would be. Using that logic, it is possible to see how the pairs zone1 and zone2, lobby and zone1 are all well correlated with wide spectrums which are sometimes close to the maximum value, one. At the same time, the pairs lobby and zone3, lobby and zone4 show a minimum response to the cross-correlation function. The correlation coefficient at different phase differences becomes an effective measure of how related two zones are at different times of the day. This information becomes valuable since it provides a way to increase the accuracy of a prediction system, if required. By making a prediction system studying the cross-correlation curves, it can predict in which other zone the change in occupancy of a particular zone would be reflected more.

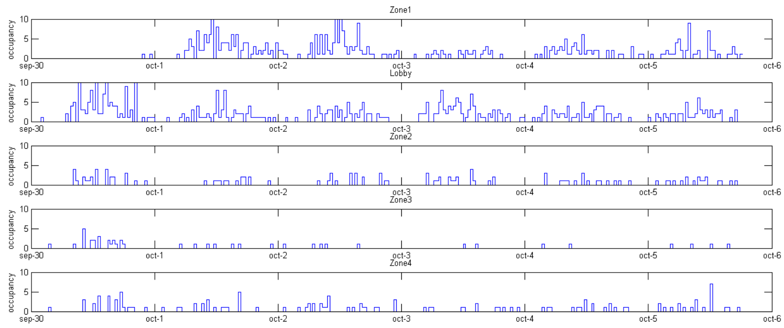

Figure 6.9: The mobility pattern during the week

6.2 Occupancy Patterns

From the collected data, it is possible to draw a schedule for each day. Since the lab is occupied by a number of students and professors it is possible to predict their lecture schedule and self study time. It is also possible to notice that there is a high flow within some zones depending on the facility that is provided there. Since the toilet and printers are located at lab 2 and lab 4, it is possible to notice the in and out flow during the day.

The data reveals several intrusting trends as in figure 6.9 below:

Zone1 and lobby have very high mobility since they are at the entrance of the lab. Most students and professors use this door to go to the meeting room which is next to the matador of the laboratory. The second high occupancy showed in zone 2 which reveals a dynamic pattern with a fixed schedule. Moreover, it is possible to notice that the average number of students in each zone area of the lab at time t is around 10.

A table summarizes the number of occupants at each zone during the month of October 2013. It is noted that the number of people getting out of this zone is higher than those entering the lab. This goes back to the fact that zone 2 occupied the fire door and exit stairs. This is where some students used them to enter the lab.

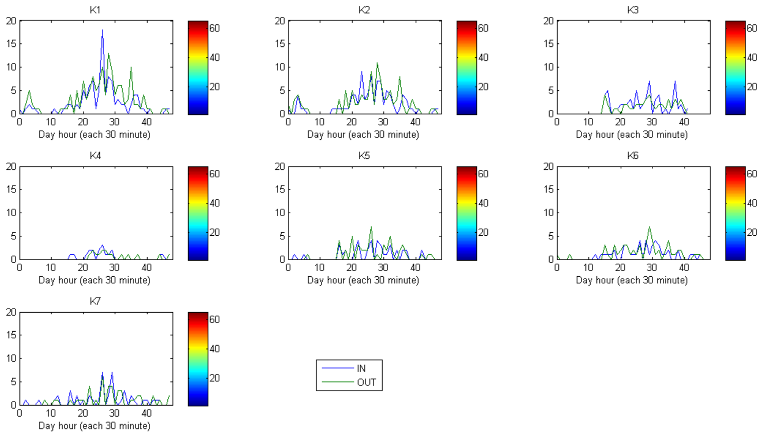

Figure 6.10: A Sample of detect method, Depth Data

This was missed in the experiment coverage.

6.3 Accuracy and Evaluation

Software evaluation

The software was more reliable than assumed when this project started. The software smoothly tracked and counted people. There are several problems that appear to be related to some physical limitations of the hardware. One of the most annoying problems is the USB port connection. If two sensors are connected to one port, the second sensor shouldn't be connected to the next nearest port. Sometimes, the computer couldn't find the sensor and the issue was resolved when the USB port was changed to another one. This means that the computer should have a sufficient number of ports. With the results that were obtained it can be stated that the software is approximately 95

To test the accuracy of our software, a round truth data was collected using a manual counter from a RGB camera video recorder, from 8:00 AM to 9:00 PM on Thursday September 27th. The results are shown in the table below:

Day	Zone1		Lobby		Zone2		Zone3		Zone4		Labaratory floor	
	in	out	in	out	in	out	in	out	in	out	IN	OUT
10-Oct-13	104	138	89	104	61	49	20	16	44	57	318	364
11-Oct-13	24	47	22	31	22	21	10	8	25	19	103	126
12-Oct-13	42	71	36	50	33	29	12	9	51	36	174	195
13-Oct-13	48	67	37	26	48	55	16	19	32	26	181	193
14-Oct-13	48	64	31	23	39	44	12	6	20	21	150	158
15-Oct-13	64	69	36	32	60	58	11	11	20	22	191	192
16-Oct-13	63	80	55	41	57	63	14	12	28	34	217	230
17-Oct-13	38	59	29	30	42	45	22	18	58	75	189	227
18-Oct-13	36	57	24	25	33	43	8	14	32	23	133	162
19-Oct-13	63	87	42	39	49	59	19	15	42	47	215	247
20-Oct-13	123	184	70	69	113	141	51	51	78	58	435	503
21-Oct-13	135	164	64	63	85	102	46	57	62	63	392	449
22-Oct-13	113	160	58	65	50	68	45	48	78	79	344	420
23-Oct-13	151	222	77	78	121	207	43	49	74	76	466	632
24-Oct-13	57	92	69	76	63	118	41	31	52	63	282	380
25-Oct-13	28	29	23	18	30	44	3	5	10	9	94	105
26-Oct-13	55	66	37	43	54	88	16	20	36	42	198	259
27-Oct-13	60	90	83	98	57	99	50	54	59	71	15	412
28-Oct-13	97	122	74	80	103	166	44	50	76	70	394	488
29-Oct-13	85	106	82	85	81	140	37	31	60	60	345	422
30-Oct-13	79	114	97	108	75	140	38	59	94	74	383	495
31-Oct-13	103	145	68	69	63	81	42	45	64	67	340	407
Average	73	102	55	57	61	85	27	29	50	50	253	321

Figure 6.11: The human Mobility of 22 days of October, 2013

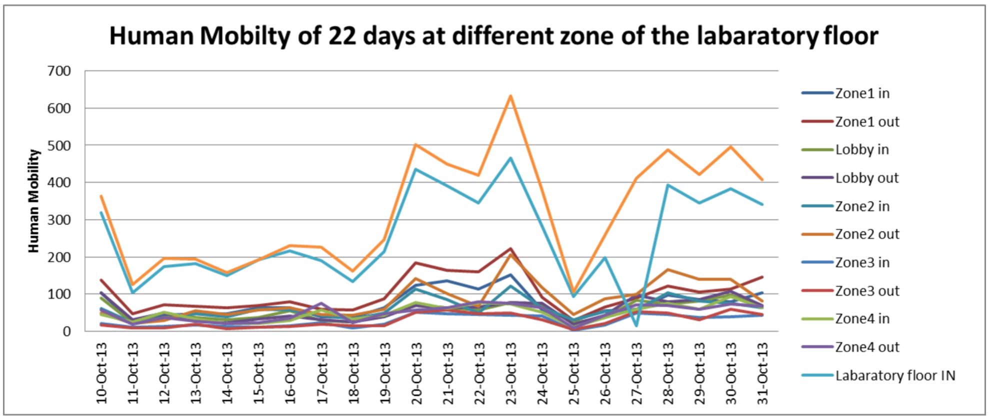

Figure 6.12: The human mobility patterns throughout month of October. We can note that the activity of the lab was less at the beginning of week of October10th since a vacation started for a week. By October 27th the activity start again. The most occupied zones are 1 and

	ManualCounting		Software Counting	
	In	Out	In	Out
k1	78	81	76	80
k2	102	113	101	115
k3	39	40	38	40
k4	23	15	21	14
k5	85	69	84	70
k6	23	33	22	33
k7	71	90	70	92

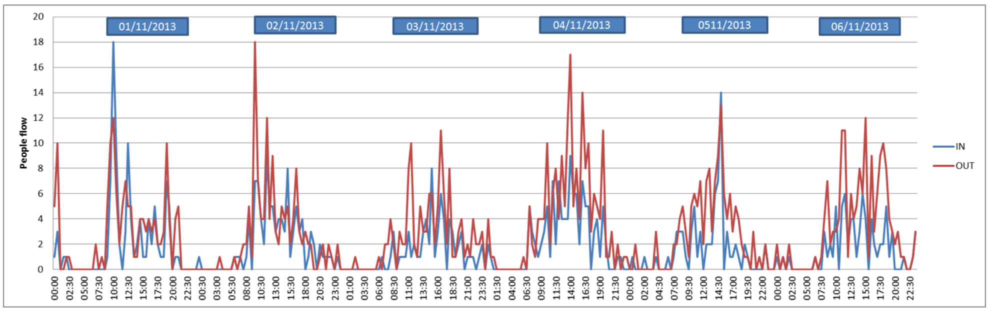

Figure 6.13: The inflow and outflow mobility captured by Kinect 1 during a week period

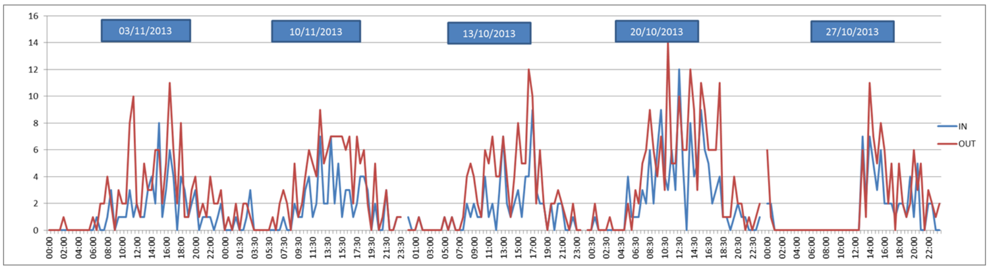

Figure 6.14: The inflow and outflow mobility captured by Kinect 1 of Sunday Pattern, Sunday 27 was a vacation day that we can find a huge gap in the morning portion

A comparison was made between the ground truth and the software readings over a 14 hour period from different kinect sensors. The system has an average accuracy of approximately 98.53% . This i shows that the software is less likely to have missing data. However, it is possible to notice that the counter incremented more than one time which caused the result to be above the ground truth. This last problem occurs when a person walks very slowly under the sensor or stops under the sensor view for a while. The sensor is accurate even in dark views. When the lights go off in the smart building, the Kinect can still detect the motion faster than the light motion sensors which have a delay time until the lights goes on again.

Figure 6.15: Kinect Sensor Dark Light View

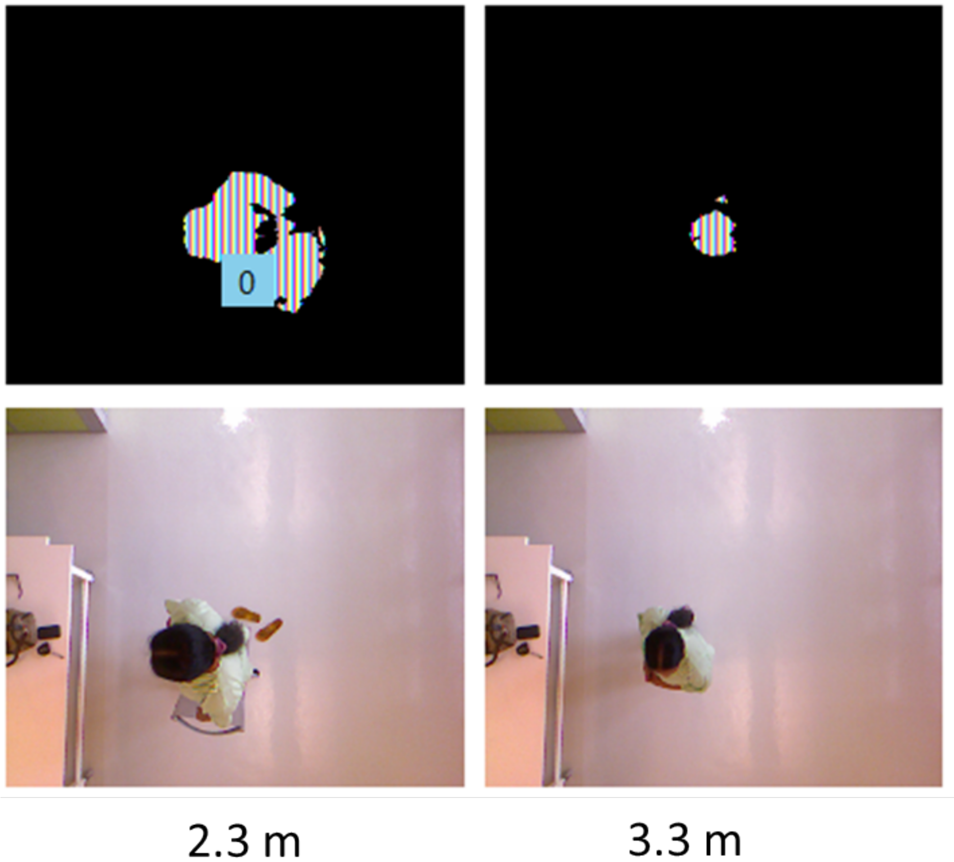

Figure 6.16: Depth Image in different hight settings

Deployment Challenges

Sensing noise: While reading the depth image two persons walking together might be considered as one person resulting with occlusion as in Figures 6.17, 6.18. This can be solved by applying image processing or image feature algorithms like water filling algorithms explained in [37] Environmental variations: Unexpected or sudden changes in environmental conditions are some of the most common sources of errors that occur in real-world scenarios. Therefore, Kinect lances might get some dirt or fog due to temperature change. It might also be infected with finger prints like in figure 6.19.

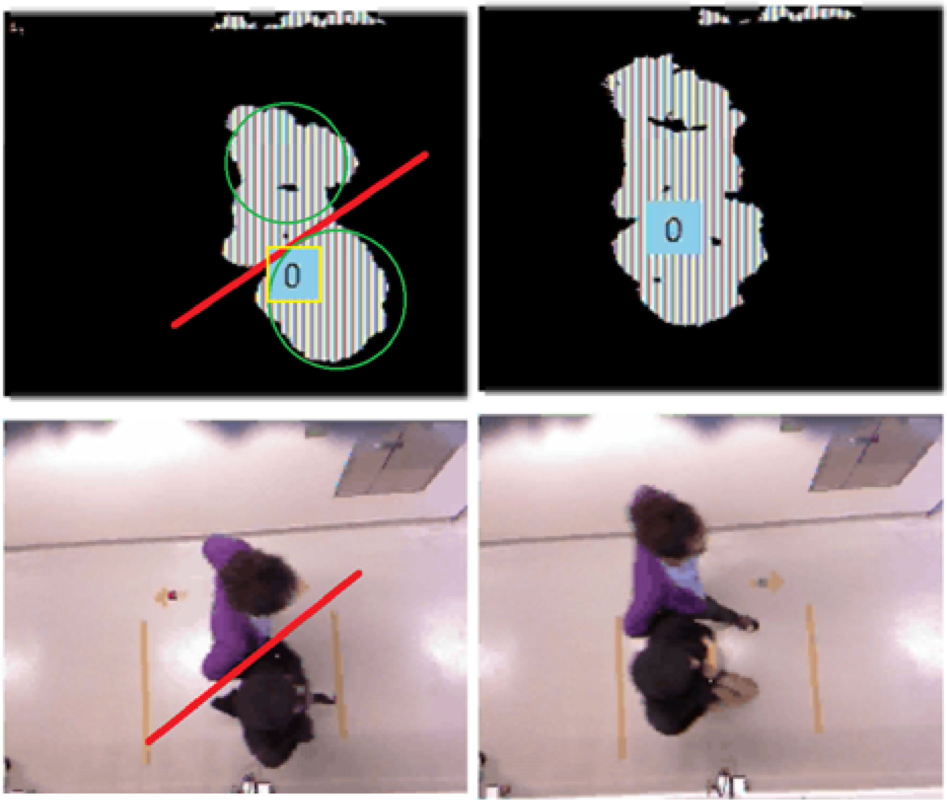

Figure 6.17: Sensing occlusion problem, when two persons walk close to each other, they are counted as one person

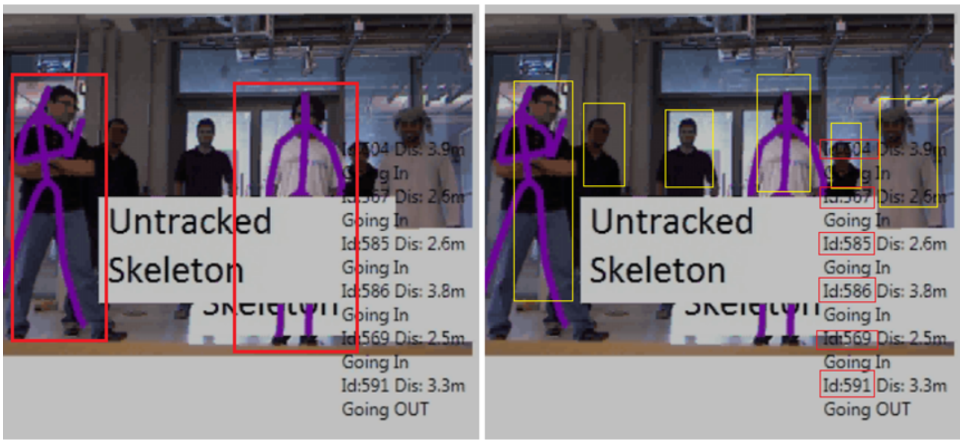

Figure 6.18: Limited number of tracked player, in horizontal view, The Kinect sensor can detect up to 6 people and track only 2 of them

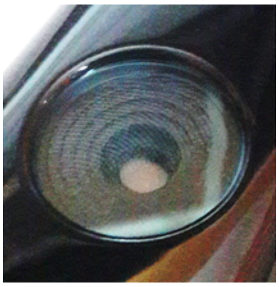

Figure 6.19: Fingerprint on the Kinect lenes while setting it

The idea of people-counter based occupancy monitoring helps in linking things together and displays the problem in a segmented framework. Our software detects each event while it tracks, detects and counts human mobility passing under a virtual gate at a time. Since open offices have no close-zones gates and don't limit human mobility directions, our software works perfectly at home or in a close-offices theme building. Our software is modelled to solve such stochastic problems. The further modelling approach will show a high accuracy in close zones buildings, where each zone is limited with one entrance door and one Kinect sensor can be

Figure 6.20: Depth Data got confused with the frame parameters after some times- This is uncertain and rarely happens, but still needs to be shown as a limitation. Once this occurs, the counter might increase more than one time in the reading or doesn't count at all

placed to tell the direction of the person. This can then indicate the occupancy plan. The software works perfectly when counting the number of people passing under the camera. More testing is still running to validate and troubleshoot the system. Both versions work well when setup to the correct parameters. This includes the distance from the people, sensor and the environment.

CHAPTER 7

Implications

There are many different methods of tracking and counting people (occupants) at a location to try achieve the goal of occupancy monitoring and energy management. Many of these methods have a low degree of reliability and are error prone because they may involve the participation of uncooperative people. Other methods involve sensory equipment which can provide some real-time data but have some limitations that are related to power availability, delay, or occupancy perception like the motion sensor. Moreover, there are no software and algorithms for accurate people counting that are imbedded in low cost micro processor systems. Solutions that are currently available commercially are relatively expensive (hundreds to several thousand US dollars per hardware unit) and make energy saving and a positive return on investment (ROI), very distant opportunities. HVAC control remains a promising technology in saving energy.

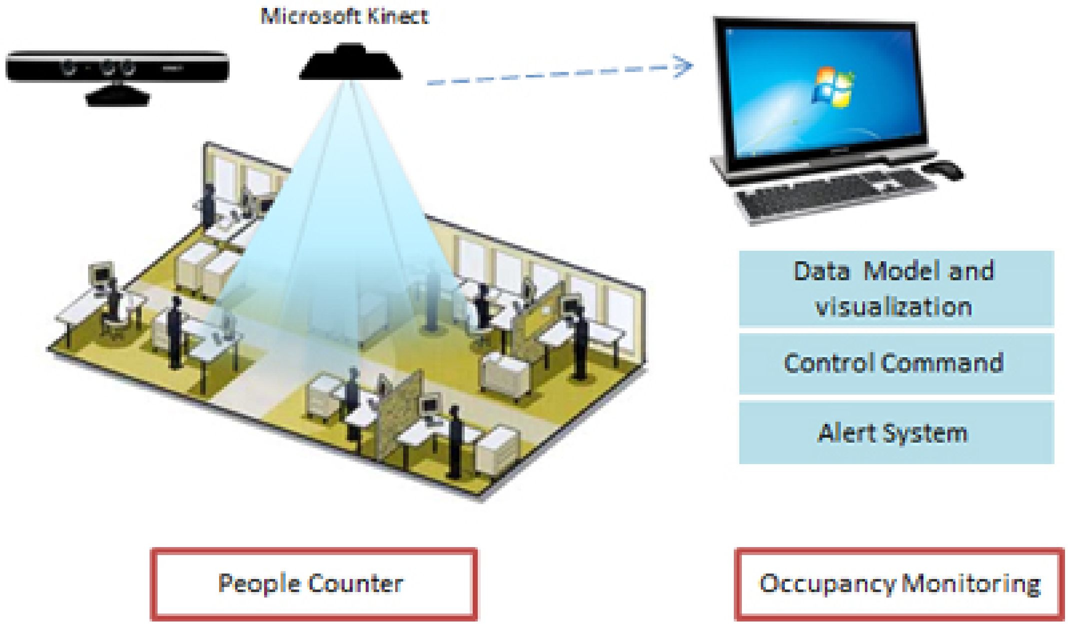

Figure 7.1: People Counter Occupancy Monitoring (PCOM) System

7.1 PCOM Control System

The main purpose of this paper is to investigate automated control and energy management in buildings. The occupant's mobility and behaviour in a building is an important parameter in controlling energy consumption. It is first necessary to analyze the data collected so that it can be used as an input for an energy controller. The occupancy data used is collected by a Kinect sensor from the occupants' counter software. The monitoring system is called: People-Counter Occupancy-Monitoring (**PCOM**) which is a central server that collects and generates visualized human mobility data in buildings.

The process flow on the PCOM system goes is as follows:

- First, a log file is generated from the Kinect sensor that is plugged into the Occupant's Counter software. This log file captured the mobility of occupants at each zone gate with a timestamp [1] of inflow or outflow activity.

[1] This captures the exact seconds/minutes/hour such as 12:30:09 that an occupants passed in the

.This type of mobility detection might be referred to as an event where a change is captured (tracked direction is logged).[2].

- All log files will be copied to a local central server where logs will be parsed and analysed to a uniform time of 48 slots each half hour, starting at 00:00 AM and ending with 23:30 PM table /reftable:samplelog presented how pared log look like.
- After the logs are parsed, they are used to derive occupancy data which represents (the exact number of occupants at each zone zi at time t). The logic of zone gates was used to contain the number of occupants. The formulas used to extract occupancy are[3]:
  1. $zone1 = k1_in + k2_out - k2_in$
  2. $lobby = k2_in - k2_out + k3_out - k3_in + k6_out - k6_in$
  3. $zone2 = k3_in - k3_out + k4_in - k4_out$
  4. $zone3 = k6_in - k6_out + k5_in - k5_out$
  5. $zone4 = k8_in - k8_out + k7_out - k7_in$
- The occupancy data is used on Markov Chain functions, which generates the transition matrix and a list of presenting states that represent the conditions of each zone (E)mpty, (F)ew, (A)verage or (C)rowded.
- The condition letter of each state can be displayed with different colours representing the level of occupancy at each zone.
- Events will be generated when the system repeat Z_{ic}(certain condition at a certain zone), and this can be connected to a simple control method like

field-view of the Kinect sensor, capturing the direction on IN or OUT.

[2] event is the action of occupants while entering or leaving a certain zone gate, this to help formulate the control more clearly

[3] refer to chapter for to the location map of sensors 4

N : is the number of occupants	z_i : is the virtual zone where $i = 1, 2, \ldots$	**Z**: is the number of virtual zones.
z_c : is the condition of the zone where $c = E, F, A, C$.	E: is the energy consumption.	C: is the cost in AED[4].
e : is the events created depending on c values.	T_m : time slot of human mobility that is presented in the first log files, this represents time from 00:00:00 up to 24:60:60.	T_o : time slots of occupancy after log parsed into 48 time slots, this represent time from 00:00 divided into half hours to 23:30.

cycling turn OFF/ON AC. For example, if the system repeats the condition Z_1 = E, an event will be created and a control command for turn OFF will be executed.

Since the AC energy consumption is directly affected by the operating period, the condition of states could present a certain energy cost level, where these Z_c can be used as a threshold in controlling the AC. Once the data is processed and the model is ready, the central server can act as the main controller that creates and executes a control command upon the events created from certain zone occupancy conditions (E,F,A,C). The central server is used to display the visualized human mobility data, create alerts when the system reach certain occupancy level thresholds and actively control the energy system in the building. The system is required to be running on a real-time model where data is collected and analysed at a time asymptotic.

Design PCOM for your space

It is necessary to explore additional details in the PCOM system. Example of an open offices floor space in figure 7.2 that can be divided into three equal space virtual zones as in figure 7.3, which can be covered with three Kinect sensors. It is also assumed that the lab is occupied by a maximum of 20 persons. Therefore, the states threshold will be: The Zone Conditions depend on **N:number of occupants**

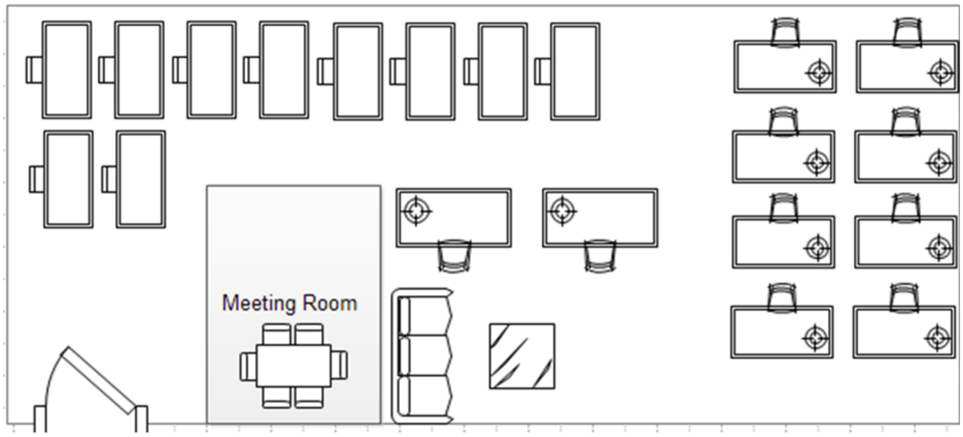

Figure 7.2: The open office floor layout

- (E)mpty where $N \leq 0$
- (F)ew where $0 < N \leq 5$
- (A)verage where $5 < N \leq 10$
- (C)rowded where $N > 10$

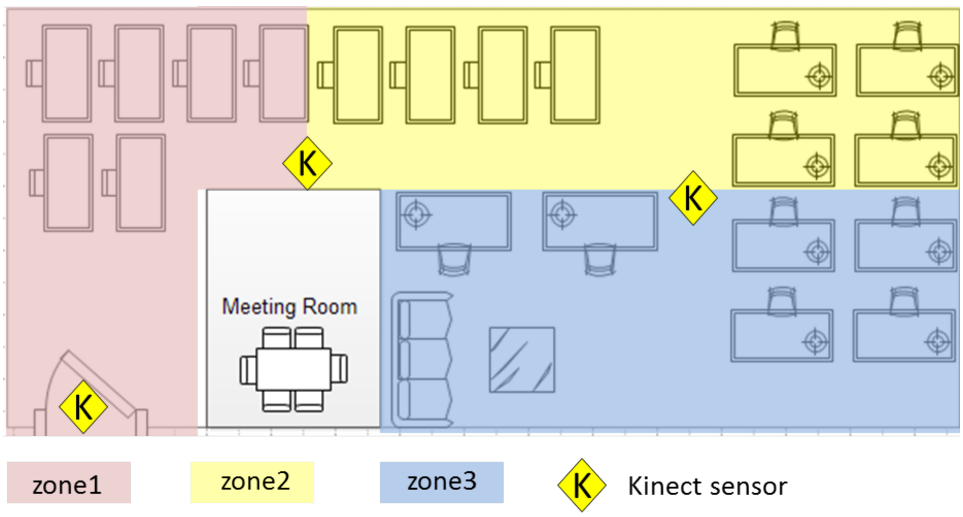

Figure 7.3: The virtual zone division

After running the software for a week, the results are shown as follows:

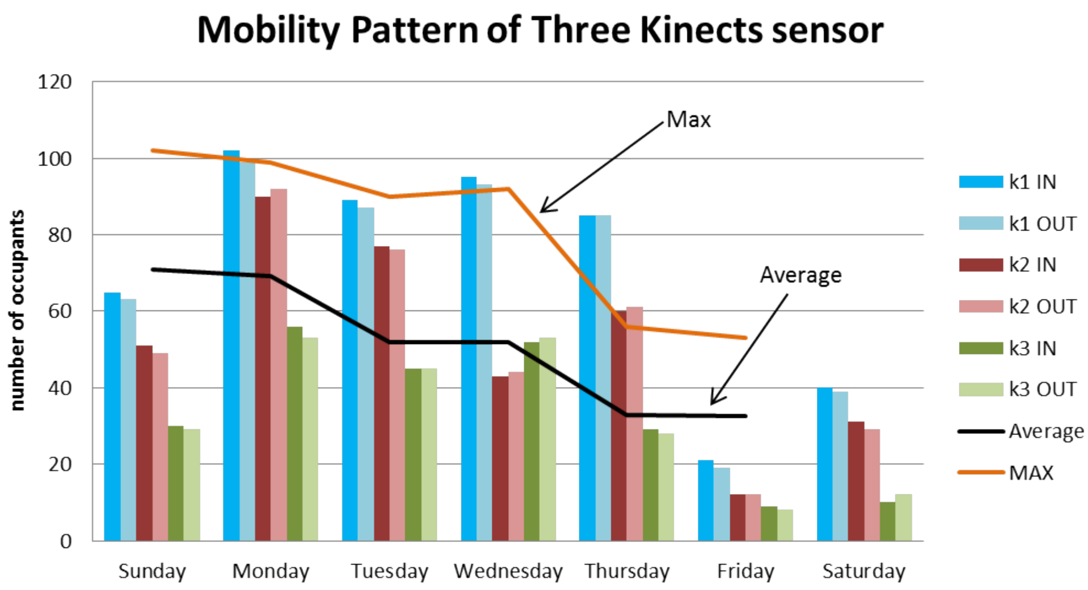

Figure 7.4: The total number of in and out activities observed during a week period

Days	k1		k2		k3	
	IN	OUT	IN	OUT	IN	OUT
Sunday	65	63	51	49	30	29
Monday	102	99	90	92	56	53
Tuesday	89	87	77	76	45	45
Wednesday	95	93	43	44	52	53
Thursday	85	85	60	61	29	28
Friday	21	19	12	12	9	8
Saturday	40	39	31	29	10	12

Table 7.1: The total number of in and out captured at the end of each day of the week using three Kinect sensors at three zones in the lab floor

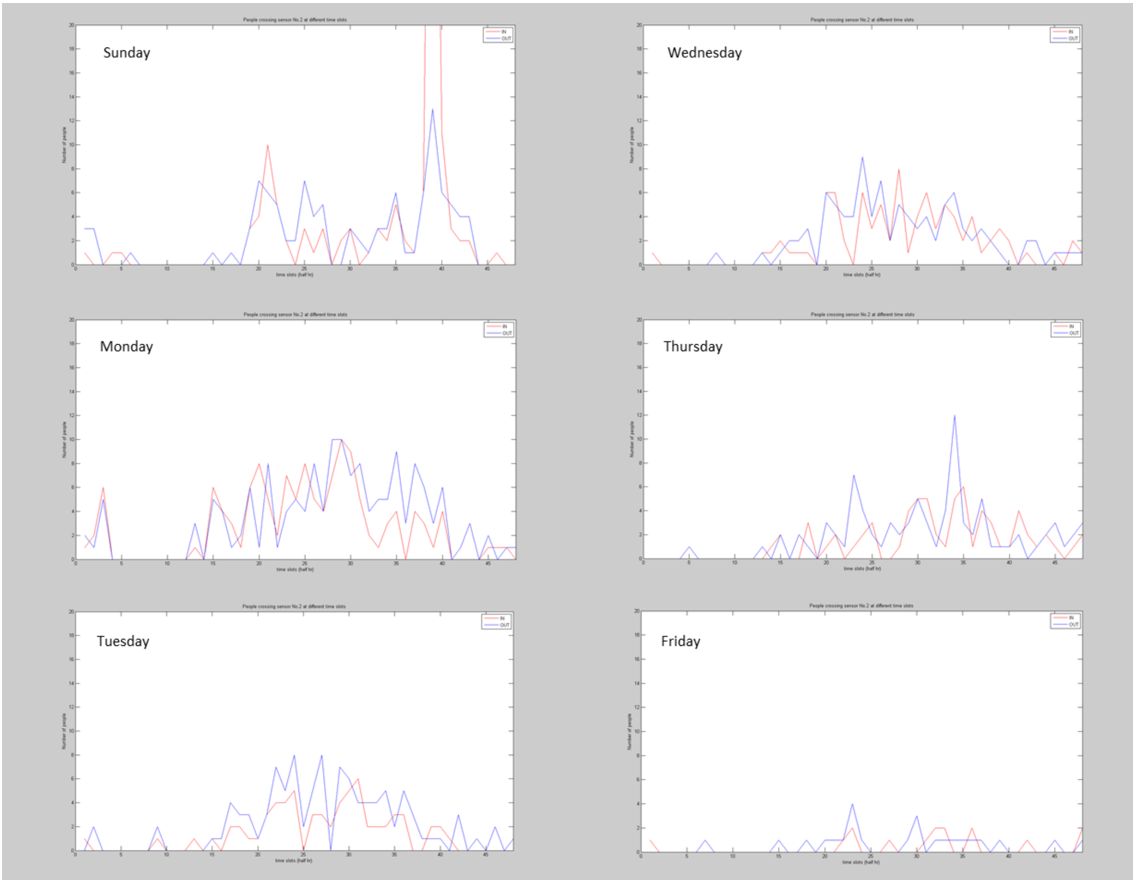

Figure 7.5: Mobility pattern flows of inflow and outflow during week days

It is possible to observe from the displayed figure a connection between the Monday and Wednesday schedule. The number of occupants dropped to around 0-2 persons after 12:00 AM, after which it starts to rise again around 8:00 AM in the morning. This is represented as a loop-back series on state (E,E,E) entrusted with few transitions to (F,F,F) where one or two people might occupy the lab. We also noticed that on Friday the set-point can be raised to a higher temperature, since the number of occupants doesn't exceed 5 per hour, which is steady at state (F,F,F). This observation can be made dynamically while the system is collecting more data. The most interesting observation can be programmed as an event for a certain control command.

The condition of each zone is created which presents the level of occupancy at z_i where $i = 1,2,3$ for T_o, figure 7.6 presents the level of occupancy at different times of the day. A control event can be created depend on the conditions of each zone and from that we can derive an occupancy schedule as in figure 7.7

7.2 Optimal control and planning

7.2.1 Air-Conditioning control

The simplest control in an HVAC system is the cycling or OFF/ON control to meet partial load conditions. If the building only needs half of the energy that the system is designed to deliver, the system runs for some period, turns off for the next period, and then cycles on again. As the building load increases, the system runs longer and its off period is shorter. An alternative method of control under part-load conditions is staging. When conditions call for half the design capacity, only two units operate. At 60% load, two units are base-loaded (run continuously), and a third unit swings (is either cycled or modulated) as needed. If it is assumed

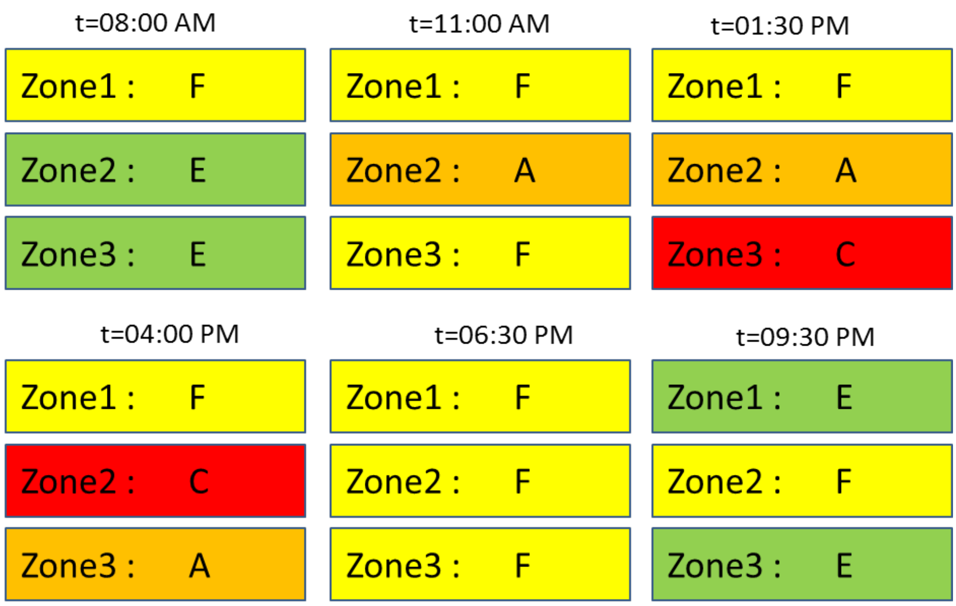

Figure 7.6: Condition levels represent number of occupants at certain time of the day

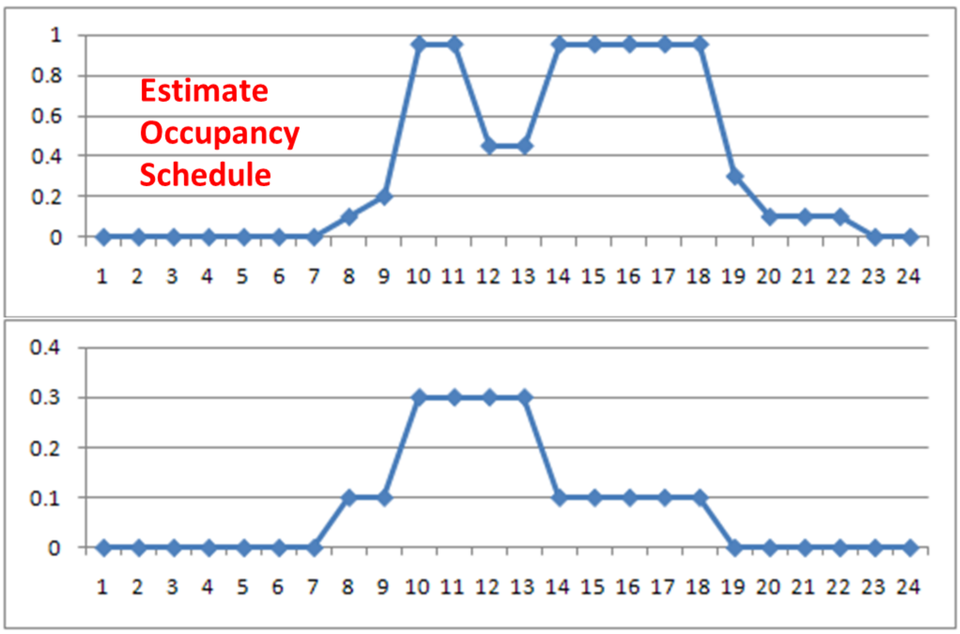

Figure 7.7: Sample of occupancy schedule that can be designed depend on the occupancy density, if the density is equal to 100 , then the 1 implies that 100 person are occupied the lab at that time, and so on

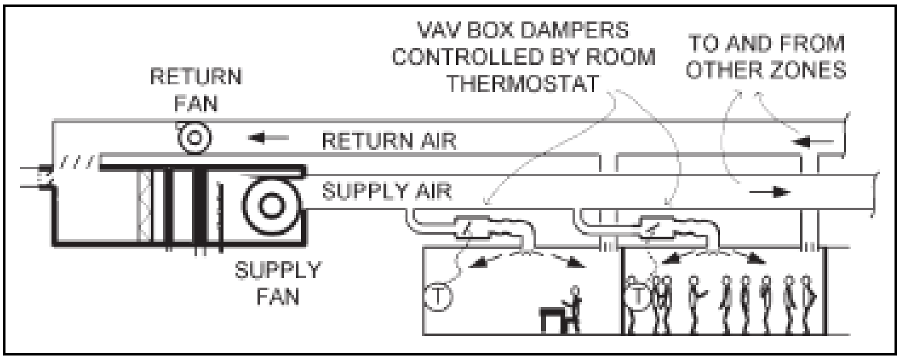

Figure 7.8: Variable Air Volume system

that Units 1 and 2 are base-loaded, and Unit 3 has just cycled on. The three ways of saving energy as mention in [38] are then: Turn it OFF, Turn it DOWN or Turn it IN. The first refers to the first control method of cycling while the second refers to the staging usage, where part of the units are put on cycling and the other parts are operated with a low set-point. The last one refers to replacing or changing the air conditioning unit with a new one for more efficiency.

On the other hand, there are many other factors that play important roles in controlling air conditioning systems. These factors are: **The person thermal comfort:** There are different factors that influence thermal comfort including: clothing (level of cloths), activity level(human body release heats), air flow(direction of air), air temperature (the level of cooling), and expectations(which vary from one person to another). **Space Size:** The small room size is different than a big one. The number of pieces of operating equipment is important since it releases some heat. To go on real-time controlling, it might consider the combined number of sensors that can include **Space Design :**the number of windows and doors in the building. Windows bring the heat load from the sun and doors release the air out of the cooling space. More factors can be found in [38]

These automated control systems require full coverage of all above factors in order to say that air conditioning systems have been controlled efficiently. A system has been created that can display and show the occupancy time. A dynamic control method can be modelled from this system. As mentioned earlier, a Markov chain was used to create a matrix that predicted the future of moving from one state to another. It is possible to benefit from these transition matrices by merging them to some controlling functions. For example, applying the simple set point control to the air conditioning system in figure 7.8[5] It is possible to set the thermostat point to a certain point matching a certain event that occurs on the monitoring systems. Saying that, the probability to move from $state = (E,E,E,E)$ to $state = (E,A,E,E)$ after a hour will manage to open the air conditioning system at zone2 which represents the average occupancy one hour later. The remaining zones will maintain the temperature depending on the status information. This can be easily read from the display colours.

The idea of building an automated control system might seem difficult to implement, but once all of the related factors are considered it will become easier. The controller logic will work as a robotic command generator depending on the events created from our occupancy monitoring system. The main controller is programmable to keep a log for all states and zone conditions of the building. When some states occur they will generate new events which imply creating a control command to resolve the event issues. Several examples of auto-building controllers have been discussed. This section is considered to be included as a future work.

[5]Buildings that are located in continuously warm climates, and interior spaces in any climate, require no heating, only cooling. For cooling-only situations, it would be ideal to supply only as much cooling and ventilation as the zone actually requires at the particular moment. A system that comes close to the ideal is the variable-air-volume system VAV. The variable air volume system is designed with a volume control damper, controlled by the zone thermostat, in each zone. The VAV system adjusts for varying cooling loads in different zones by individually throttling the supply air volume to each zone. Regardless of the variations in the cooling load, a minimum flow of ventilation air is always provided and care must be taken to ensure that the required volume of ventilation air is provided. [38]

7.2.2 Office Building Simulation

A net zero energy office building is simulated using the 'eQuest' building energy software adhering to Masdar Energy Design Guidelines (MEDG)based on the American Society of Heating, Refrigerating and Air-Conditioning (ASHRAE) 90.1. The office building is a two story building with a total floor area of $232m^2$. Each floor is divided into office space having a floor area of$195m^2$, kitchen and restrooms with a floor area of $18.58m^2$ each. Windows are placed on the north, east and west walls of the building with overhangs having a projection factor (overhang depth/window height) of 0.6. Two doors are placed on the north and east sides of the building. Windows and doors are not specified on the south wall to minimize heat gain through radiation. The window to gross wall area is kept at 29%. The cooling system specified is a packaged direct expansion unit which delivers cooling through ducting. The office space is designed for a total occupancy of 85 persons with $4.6m^2$ per person. The air requirements are specified according to ASHRAE standard 62.1. The office space is specified as 20cfm/person while the kitchen and restrooms flow rate are specified as 30cfm/person (Indoor air quality method 2011) each.

7.2.3 Energy Savings

We demonstrate the potential energy savings for applying an occupancy schedule into controlling the HVAC running time. The Masdar Energy Design Guidelines (MEDG)[6] It is used as a baseline for occupancy and thermostat set-points. Since, our simulated model is using a floor based, we using a data from three sensors as showed in 7.11.

The first control case, we tried to modify occupancy schedules and see the

[6]Masdar Energy Design Guideline (MEDG) has been developed specifically to serve as a mandatory framework for designing energy efficient buildings in Masdar City.

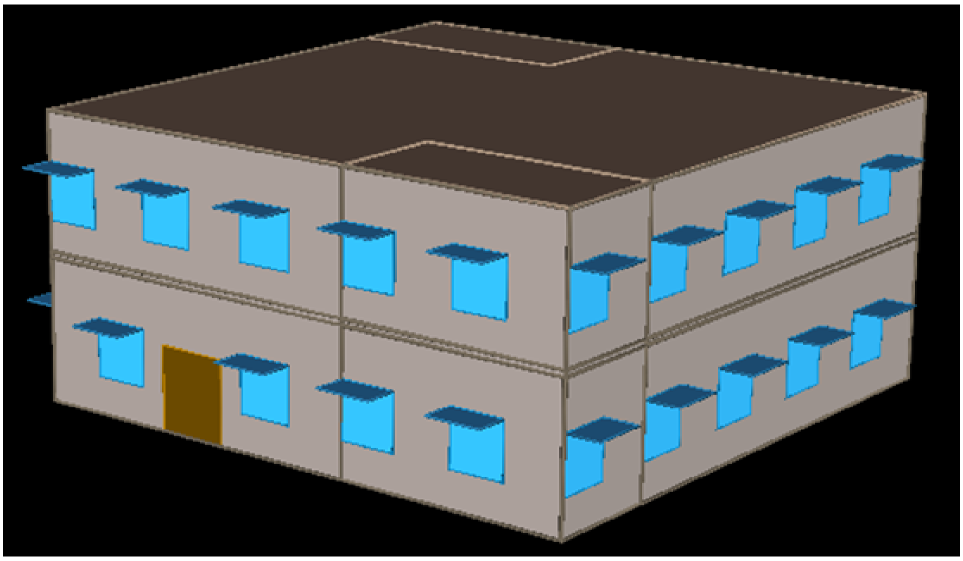

Figure 7.9: Office Building Model

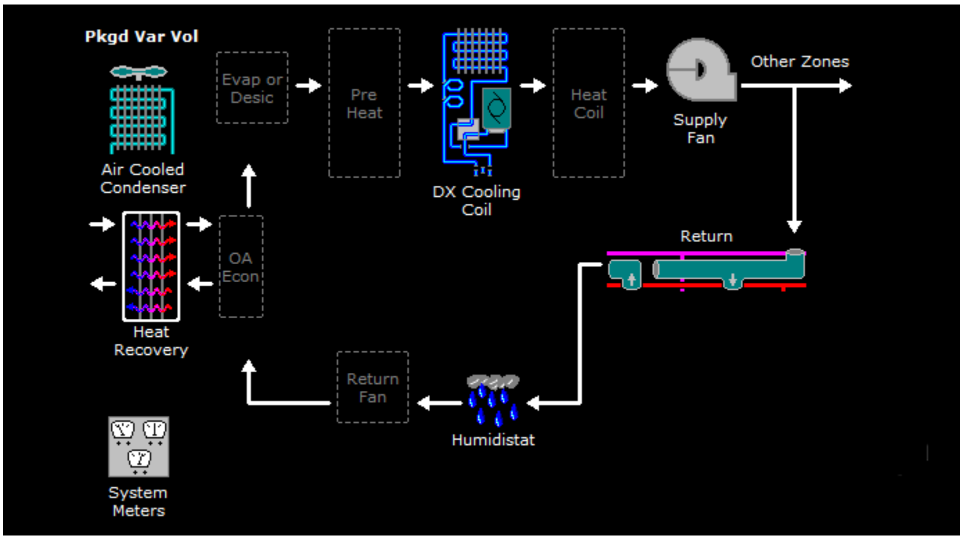

Figure 7.10: The air conditioning System used in simulated office building

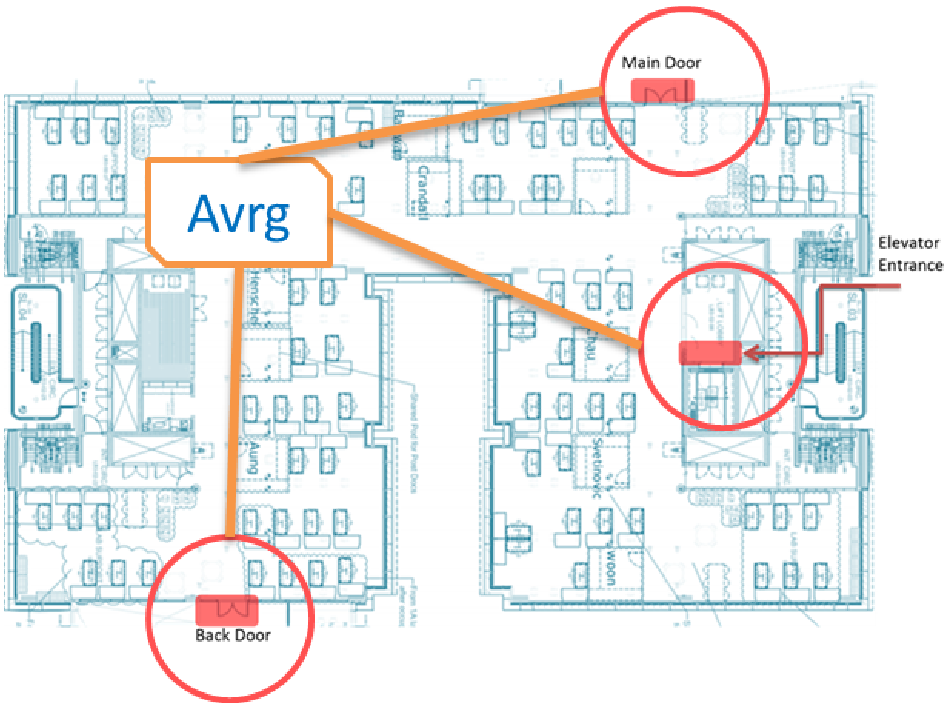

Figure 7.11: The occupancy data used to generate occupancy schedules to control simulated model

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Mdnt – 1:	10	10	10	10	0	0	10
1-2 am	10	10	10	10	0	0	10
2-3 am	10	10	10	10	0	0	10
3-4 am	0	0	0	0	0	0	0
4-5 am	0	0	0	0	0	0	0
5-6 am	0	0	0	0	0	0	0
6-7 am	0	10	0	0	0	0	0
7-8 am	10	20	10	10	10	0	10
8-9 am	10	20	10	10	10	0	10
9-10 am	20	30	20	20	20	10	10
10-11 am	30	30	20	30	10	10	20
11-noon	40	40	30	20	10	10	10
Noon-1	5	5	5	5	5	0	0
1-2 pm	30	60	20	30	60	20	10
2-3 pm	50	60	30	20	50	10	10
3-4 pm	30	70	20	30	40	10	10
4-5 pm	20	60	20	20	20	20	10
5-6 pm	10	30	10	10	10	10	10
6-7 pm	10	20	10	10	10	10	10
7-8 pm	10	10	10	10	10	0	10
8-9 pm	10	10	10	10	10	0	10
9-10 pm	0	0	0	0	0	0	0
10-11 pm	10	10	10	10	0	0	10
11-Mdnt	10	10	10	10	0	0	10

Hour of Day (Time)	Schedule for Occupancy	
	Percent of Maximum Load	
	Wk	Wknd
12 – 1 am	0	0
1 – 2 am	0	0
2 – 3 am	0	0
3 – 4 am	0	0
4 - 5 am	0	0
5 – 6 am	0	0
6 – 7 am	10	5
7 – 8 am	20	5
8 – 9 am	95	5
9 – 10 am	95	5
10 – 11 am	95	5
11 am – 12 pm	95	5
12 – 1 pm	50	5
1 – 2 pm	95	5
2 – 3 pm	95	5
3 – 4 pm	95	5
4 – 5 pm	95	5
5 – 6 pm	30	5
6 – 7 pm	10	0
7 – 8 pm	10	0
8 – 9 pm	10	0
9 – 10 pm	10	0
10 – 11 pm	5	0
11 pm – 12 am	5	0

Figure 7.12: Our customized daily occupancy schedules and weekday and weekend schedules from MEDG

impact on energy consumption for space cooling. The occupant's schedule — which is by default has a two schedules, one for weekdays and another for weekend — are replaced with a customized schedule for every day depend on our collected data from our monitoring system. The potential energy saving comparing between daily scheduled occupancy vs. unscheduled are showing in figure 7.13 derived from table 7.12 around 16.1% energy can be saved by using daily based schedule. Where the energy consumption was 14.32 KWhx000 with default schedule and decrease to 12.71 using the customized daily schedule.

In the second control case, We tried to modify the thermostat set-point schedules — where its is changed to meet a comfort level on weekdays with the occupants schedule from 8 AM to 6 PM. The temperature set-point in the default setting for MEDG was 75 F. This was changed that to a customized daily schedules which vary from day to another and from hour to next. The results raise the energy con-

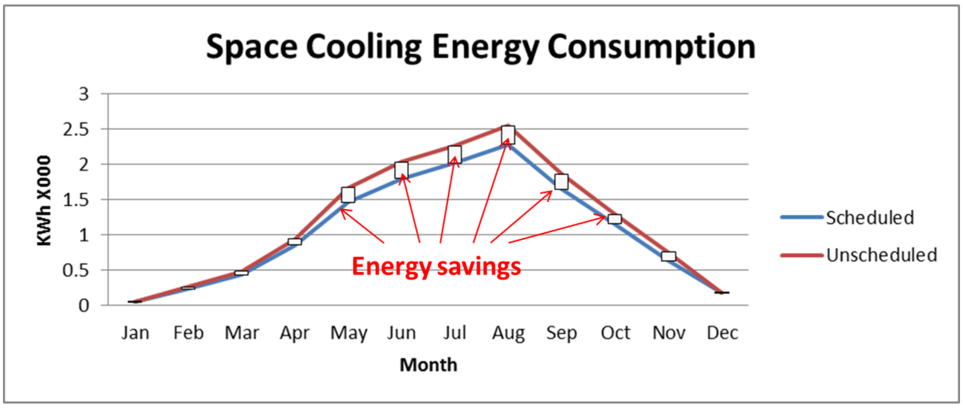

Figure 7.13: Energy saving of using daily occupancy schedules instead of weekday and weekend schedules showed in MEDG

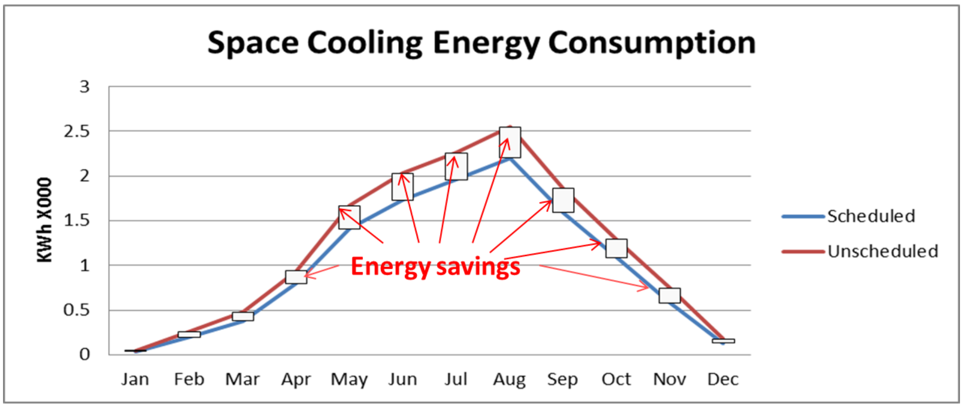

Figure 7.14: Energy saving of using daily thermostat set-point schedules instead of weekday and weekend schedules showed in MEDG

sumption to 22.1% as showing in figure 7.14 where the energy consumption was 14.32 KWhx000 with default schedule and decrease to 12.11 using the customized daily schedule.

There are a potential energy savings by using customized occupancy/setpoint schedules.Even this small percentage of energy savings, it will introduce a large impact in large buildings.The details of simulation settings and all schedules are explained in detail in the appendix.

CHAPTER 8

Conclusion

8.1 Conclusion

The original motivation for this study was to provide a fully automated control system for HVAC usage in smart buildings. In this thesis, a new concept of occupancy monitoring in real-time is investigated based on using human mobility detection and tracking via counter software. This is the first study that uses Kinect sensor in building monitoring and management. It has been shown how the Kinect could be applied successfully in the fields of detection and tracking. Kinect is revolutionary technology that enables people to visualize things with highly reliable accuracy. An occupancy model is proposed that displays visualized data and predicts future occupancy through a Markov Model transition matrix. This occupancy model is capable of presenting four different conditions for each zone in the building which refer to the level of occupancy in that zone. Every zone has a state which represents one of the four conditions of the occupancy level (E)mpty, (F)ew, (A)verage, (C)rowd. The model was also designed to alleviate the high cost of energy. Through extensive real time testing of our system, the experimental results have shown that it were able to predict future space occupancy with a satisfactory accuracy while managing incoming online problems. Based on these results, the system were able to inform us when it was possible to save energy during lower occupancy periods or to turn devices OFF/ON throughout the day. The key challenges in this study were the architectural design of open offices. Air-conditioning control also required previous knowledge of occupancy in order to meet a certain comfort level which shortened the cyclic control method. We implement and evaluate The monitoring system was implemented and evaluated in the real-world and concludes with these observations:

1. The occupancy pattern and activity behaviour can be easily derived from human mobility tracking data. It is possible to notice the working hours and the extra activities that are performed by the occupants throughout this collected data. It is interesting that it was possible to create some schedules and patterns..

2. The nature and structure of open office buildings are difficult to fully monitor and control. Even with the use of assumptions there will be a portion of the data that is lost.

3. The customized occupancy schedule for each day in the week provides better results than using one unified schedule for the weekday. Each day has its own schedule that must be recorded and should be used to adjust our energy consumption. Rather than assuming fully occupancy for a building, a simple monitoring system can run and utilize the usage in real time, and make adjustments accordingly.

We provided the first study that use multiple Kinect sensor as a sensor in building monitoring and management. It has been shown how the Kinect could be applied successfully in the fields of detection and tracking.We proposed an occupancy model that display a visualized data and predicate a future occupancy through a Markov Model transition matrix.Through extensive real time testing of our system, the experimental results have been showed a potential energy saving around 22.1% by applying a customized occupancy schedule and customized set point schedule depend on occupancy density.

8.2 Future Work

The problem to be solved is related to high HVAC energy consumption in open-offices or educational buildings. The issue with this type of building is related to the design of open spaces where there is no door. Therefore, tracking human mobility becomes difficult and requires smart intelligence systems to monitor occupancy activities. Studies show that there are a variety of simulations and predictive solutions to minimize the total cost. While a real-time solution is of interest, there are still some issues that must be considered. A wide variety of testing and validation methods were necessary for our system. Real-time control implementation is a research direction that we are interested in exploring in the future. In the interim, the focus is on improving our software to a level where it can provide more accurate data close to 99%. Furthermore, since the Kinect 2 will be released at the beginning of February 2014, it is hoped that this new version will deal with the existing physical limitations. The full functionality of our system will be examined in detail in an implementation the Kinect that includes voice commands with voice recognition features. Our future plans, will be to study how to generalize a customized occupancy and cooling thermal comfort schedule depending on the building design and other details.We also looking for enhance a real-time based control that able to adjust and manage while data is collected. Moreover,derive a generalized form of occupancy scheduling depend on building design develop the tracking software for more accuracy.

APPENDIX A

Snapshots

This chapter include different snapshot taking during the real-world experiment.

Figure A.1: Different snapshot of the software, different readings displayed

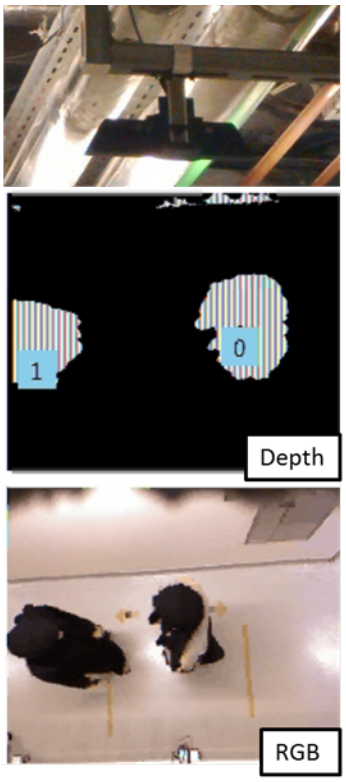

Figure A.2: The logic of our human mobility monitoring system

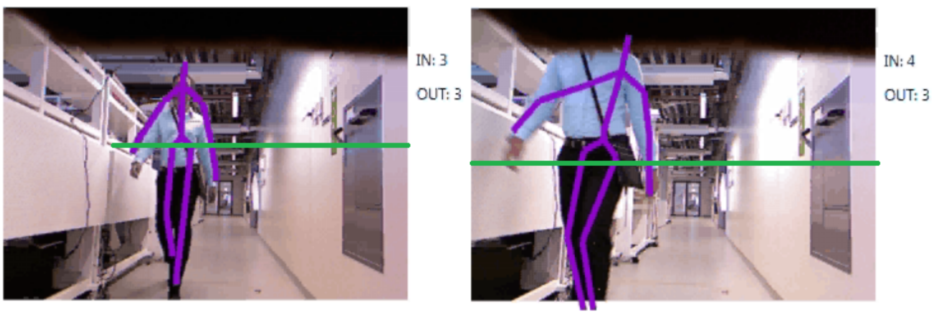

Figure A.3: The front view counting logic using virtual line

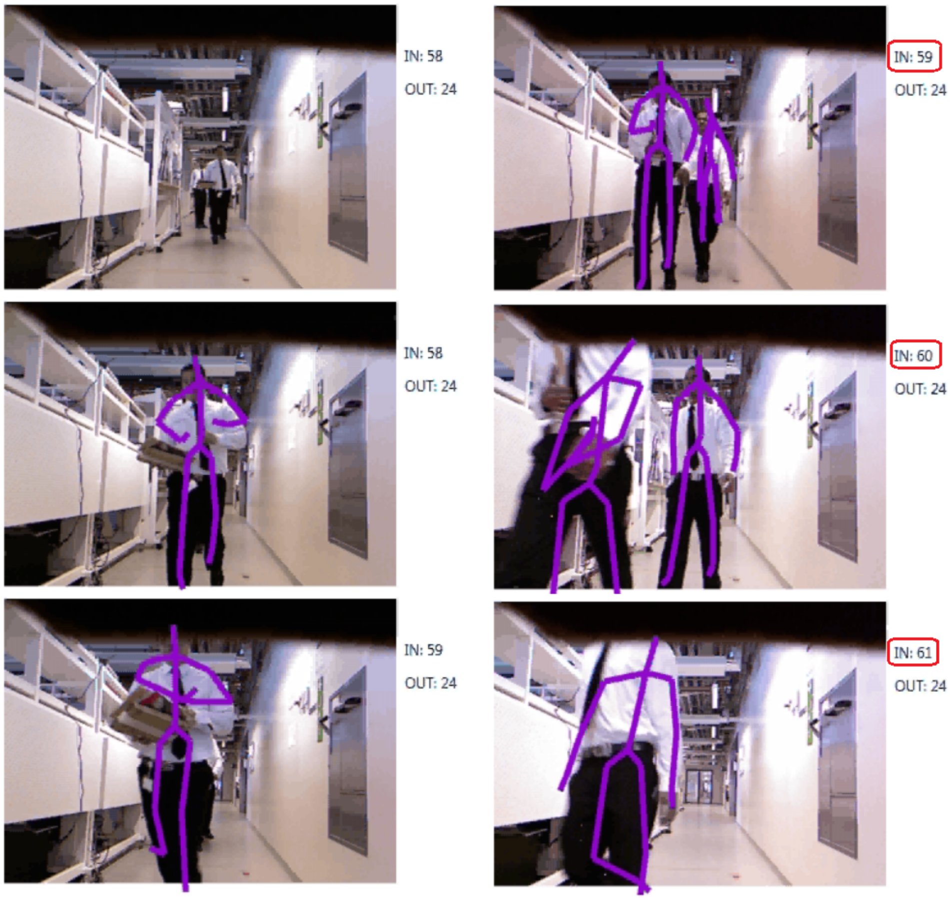

Figure A.4: Three people going in counter example

Figure A.5: Front-View data collection

Figure A.6: A person going out counter example

Figure A.7: Kinect Sensor Dark Light View

APPENDIX B

Software Implementation

Platform used: Windows 7, Microsoft Visual Studio 2012, SDK
you can download all requirements from Microsoft official Web page http://www.microsoft.com/en-us/kinectforwindowsdev/Start.aspx

Language used: C Sharp, XML

Our people counter software available at https://github.com/PCOM all scripts for parsing and analysing data is available at the same repository

For placing the Kinect on the ceiling, we use a clips with the TV Mount. And you will need a cable extension as well


TV MOUNT
FOR 360 KINECT


NYKO
EXTEND LINK
15 foot Flat Cable extension for Kinect™
Rallonge de 4,5 mètres pour Kinect™
15 FOOT CABLE FOR EASY INSTALATION
XBOX 360
KINECT

APPENDIX C

Human Mobility Collected Data Analysis

This chapter include a patterns of days and weeks through a sample of collected data from real-world experiment. This data include a sample from 01 Oct, 2013 until 15 Nov,2013. The schedule of different days and weeks take as a sample schedule that used to run the simulation in eQUEST software.

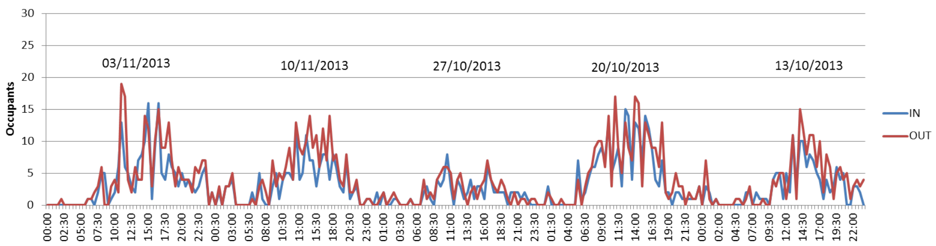

Figure C.1: Sunday pattern through a 40 days collected data from real-world experiment

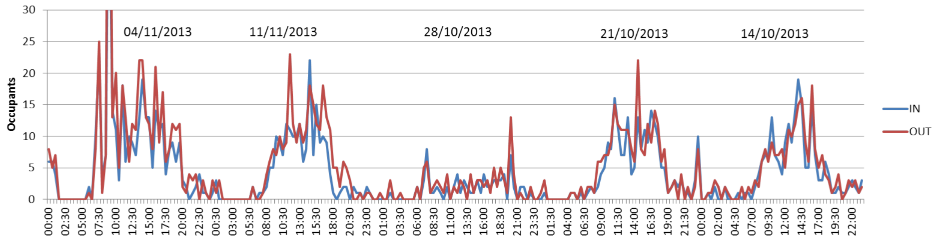

Figure C.2: Monday pattern through a 40 days collected data from real-world experiment

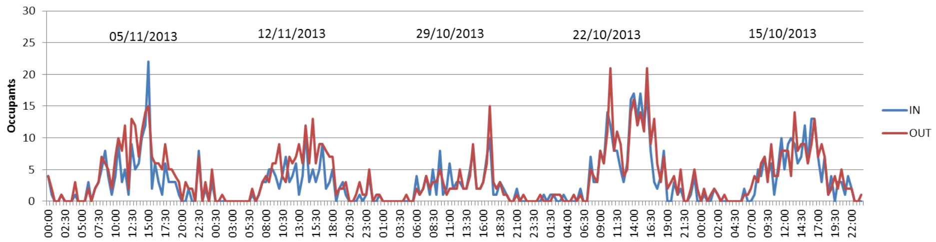

Figure C.3: Tuesday pattern through a 40 days collected data from real-world experiment

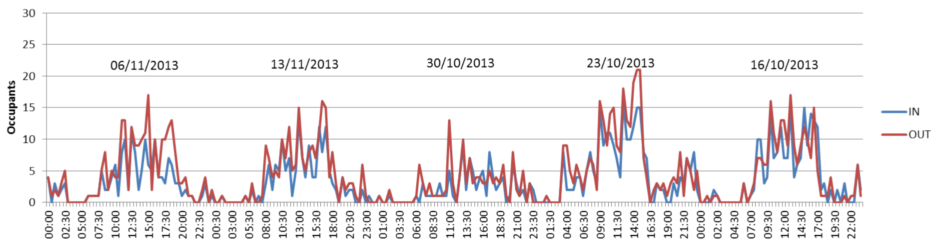

Figure C.4: Wednesday pattern through a 40 days collected data from real-world experiment

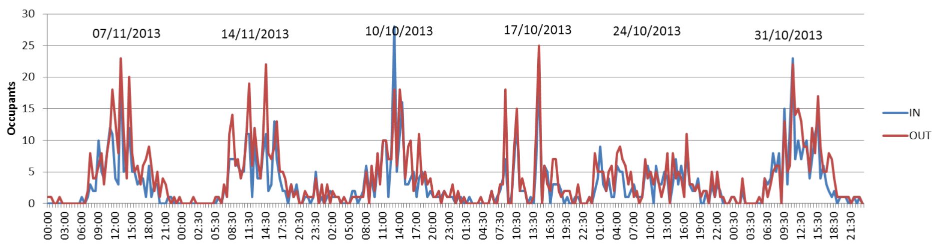

Figure C.5: Thursday pattern through a 40 days collected data from real-world experiment

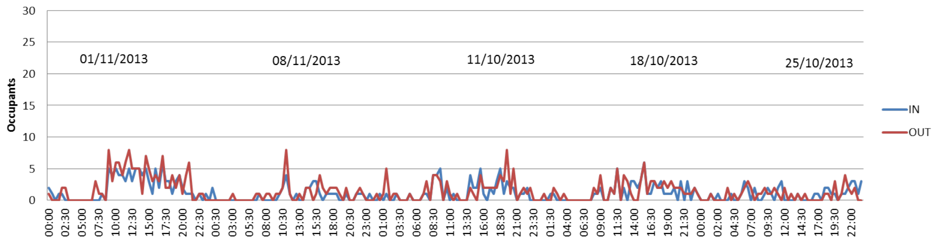

Figure C.6: Friday pattern through a 40 days collected data from real-world experiment

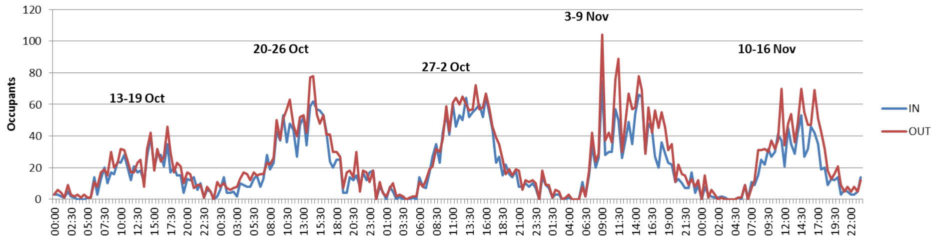

Figure C.7: Week Activity pattern through a 40 days collected data from real-world experiment

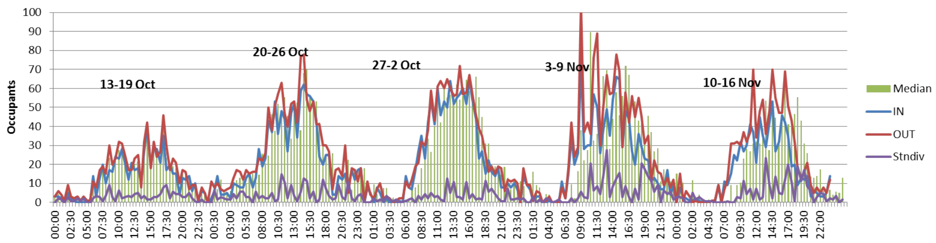

Figure C.8: Week Activity pattern through a 40 days collected data from real-world experiment

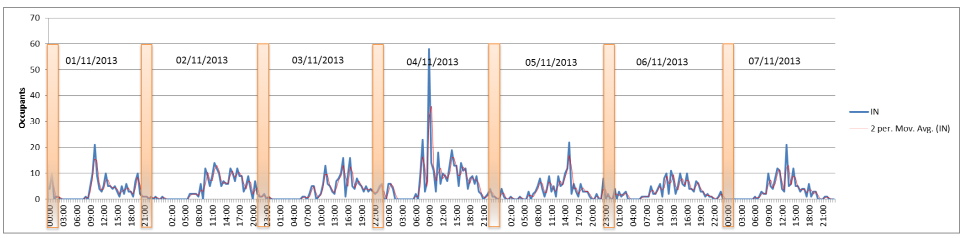

Figure C.9: Week Activity pattern through a 40 days collected data from real-world experiment

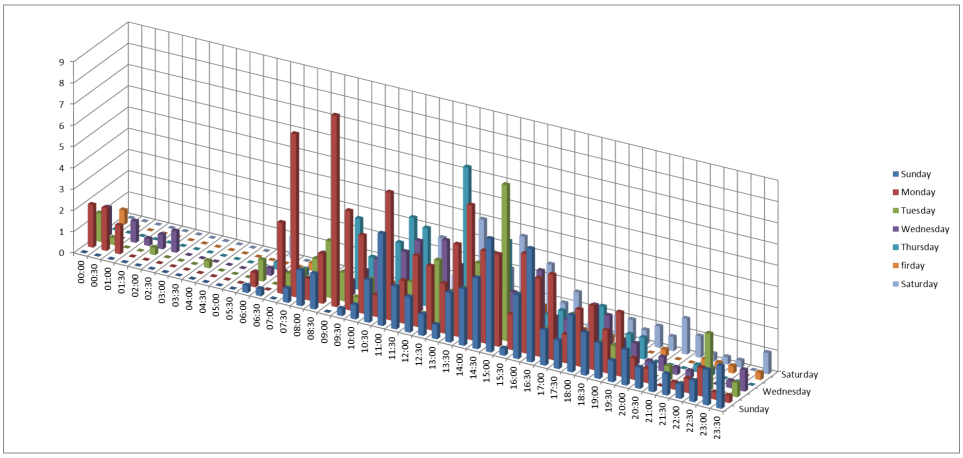

Figure C.10: Week sample schedule of 7 days average data from 40 days sample

APPENDIX D

eQUest settings

Hour of Day (Time)	Schedule for Occupancy		Schedule for Building Lighting		Schedule for Building Plug Loads		Schedule for HVAC System		Schedule for Temperature Set point (°C)	
	Percent of Maximum Load		Percent of Maximum Load		Percent of Maximum Load					
	Wk	Wknd	Wk	Wknd	Wk	Wknd	Wk	Wknd	Wk	Wknd
12 – 1 am	0	0	5	5	20	20	Off	On	28	28
1 – 2 am	0	0	5	5	20	20	Off	On	28	28
2 – 3 am	0	0	5	5	20	20	Off	On	28	28
3 – 4 am	0	0	5	5	20	20	Off	On	28	28
4 - 5 am	0	0	5	5	20	20	Off	On	28	28
5 – 6 am	0	0	10	5	20	20	Off	On	28	28
6 – 7 am	10	5	10	5	30	20	On	On	28	28
7 – 8 am	20	5	30	5	80	20	On	On	28	28
8 – 9 am	95	5	90	5	90	20	On	On	24	28
9 – 10 am	95	5	90	5	90	20	On	On	24	28
10 – 11 am	95	5	90	5	90	20	On	On	24	28
11 am – 12 pm	95	5	90	5	90	20	On	On	24	28
12 – 1 pm	50	5	80	5	90	20	On	On	24	28
1 – 2 pm	95	5	90	5	90	20	On	On	24	28
2 – 3 pm	95	5	90	5	90	20	On	On	24	28
3 – 4 pm	95	5	90	5	90	20	On	On	24	28
4 – 5 pm	95	5	90	5	90	20	On	On	24	28
5 – 6 pm	30	5	50	5	50	20	On	On	24	28
6 – 7 pm	10	0	30	5	30	20	On	On	24	28
7 – 8 pm	10	0	30	5	30	20	On	On	28	28
8 – 9 pm	10	0	20	5	20	20	On	On	28	28
9 – 10 pm	10	0	20	5	20	20	On	On	28	28
10 – 11 pm	5	0	10	5	20	20	Off	On	28	28
11 pm – 12 am	5	0	5	5	20	20	Off	On	28	28

Figure D.1: The Occupancy schedule as in Masdar Energy Design Guidelines used as a baseline

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Mdnt – 1:	10	10	10	10	0	0	10
1-2 am	10	10	10	10	0	0	10
2-3 am	10	10	10	10	0	0	10
3-4 am	0	0	0	0	0	0	0
4-5 am	0	0	0	0	0	0	0
5-6 am	0	0	0	0	0	0	0
6-7 am	0	10	0	0	0	0	0
7-8 am	10	20	10	10	10	0	10
8-9 am	10	20	10	10	10	0	10
9-10 am	20	30	20	20	20	10	10
10-11 am	30	30	20	30	10	10	20
11-noon	40	40	30	20	10	10	10
Noon-1	5	5	5	5	5	0	0
1-2 pm	30	60	20	30	60	20	10
2-3 pm	50	60	30	20	50	10	10
3-4 pm	30	70	20	30	40	10	10
4-5 pm	20	60	20	20	20	20	10
5-6 pm	10	30	10	10	10	10	10
6-7 pm	10	20	10	10	10	10	10
7-8 pm	10	10	10	10	10	0	10
8-9 pm	10	10	10	10	10	0	10
9-10 pm	0	0	0	0	0	0	0
10-11 pm	10	10	10	10	0	0	10
11-Mdnt	10	10	10	10	0	0	10

Figure D.2: The customized Occupancy schedule used in our simulation

Schedule for temperature set point C		
	wkday	wkend
Mdnt – 1:	28	28
1-2 am	28	28
2-3 am	28	28
3-4 am	28	28
4-5 am	28	28
5-6 am	28	28
6-7 am	28	28
7-8 am	28	28
8-9 am	21	28
9-10 am	21	28
10-11 am	21	28
11-noon	21	28
Noon-1	21	28
1-2 pm	21	28
2-3 pm	21	28
3-4 pm	21	28
4-5 pm	21	28
5-6 pm	21	28
6-7 pm	21	28
7-8 pm	28	28
8-9 pm	28	28
9-10 pm	28	28
10-11 pm	10	10
11-Mdnt	10	10

Figure D.3: Schedule for temperature set point used in our simulation

SDK Software Development Kit

HMM Hidden Markov Model

MM Markov Model

MPC Model Predictive Control

DMC Dynamic Matrix Control

GPC Generalized Predictive Control

HDT Human Detection Tracking

PID Proportional-Integral-Derivative

PMV Predicted Mean Vote

NN Neural Network

FS Fuzzy System

NFC Neuro-fuzzy controller

ANF Artificial Neural Fuzzy

FLC Fuzzy Logic Controllers

KB Knowledge Base

MOGA Multi-Objective Genetic Algorithm

Fuzzy RB rule-based fuzzy systems

NFIS Neural Fuzzy Interface System

GA Genetic Algorithm

GPC Generalized Predictive Control

PID Proportional-Integral-Derivative

PPV Predicted Personal Vote

PMV Predicted Mean Vote

BLEMS Building-Level Energy Management Systems

ANFIS Artificial Neural Fuzzy Interface System

USC University of Southern California

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning

SCOPES Smart Cameras Object Position Estimation System

WSN Wireless Sensor Network

ROI Return on investment

WIC Windows Imaging Component

MSDN Microsoft Developer Network

MEDG Masdar Energy Design Guidelines

eQuest engine QUick Energy Simulation Tool

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