Activity Recognition for Energy Efficiency in Workplace

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Abstract—**Human behavior based on its movement has become important in prediction of the various activities performed by an individual in smart environments. In Activity recognition we need to correctly identify and recognize the individual's current activities. In our paper we present a model for human activity recognition using sensor data. For sensor data we created three modules each comprising of a PIR, PING and LIGHT sensors. All these sensors gave us different sensor values of the people activities in performed in the lab. The three sensor modules were placed in the Robotics Lab of Dept. of Computer Science and data was collected for 4 days. We ran some widely used algorithms to recognize the human activities after data annotation. We were able to obtain good results on our datasets.**

1. Introduction

Recently the popularity of Smart Environments has grown with the merging of different technologies in machine learning, data mining and pervasive computing. In the last few years the state of art sensor technologies along with different recognition and prediction algorithms has resulted in the advancement in this area from different research groups. The main motivation behind this type of smart environments is to enable the various sensors to sense the surrounding areas and with any changes in the environment the smart systems should be able to automatically adapt to the new scenario.

In such an environment the human activity based on its movement becomes an important agent to be considered while designing any recognition or prediction model. The main topic of research here is based on how do we sense and respond to human activities. We need to correctly detect and identify the human agents along with recognizing their current activities. If the current activities of a human, based on his/her movement is correctly recognized, then we can predict the activities which helps us in training a model for smart environments. This smart environment if trained properly can help us in making fficient use of energy in such an environment.

The growth of technologies for the sensor and actuator has enabled us to closely monitor the surrounding and controlling the building utilities. The *sensor* perceives the surrounding environment and then the *actuators* act on it based on different types of agents being used like *goal based agents, utility based agents, learning agents* and similar such types of agents. Today most of the building's interior is well equipped with different types of sensors like temperature, humidity, light, CO2 and occupancy sensors. This type of sensors makes the building interior environment aware of the changes in the human state and surrounding which in turn finally controls the building utilities to adapt their services and resources to the user's context. Automatic lighting control, heating, ventilation and air-conditioning (HVAC) system adjustment, electrical outlet turn-off are some of the example of utility services in the building. This type of context-aware systems has utilized the human movement and its location as the principal form of the user's context. Therefore human movement tracking and its behavioral model has become one of the major technologies for contributing in activity-aware services in a smart environment. Providing services should not only be the single criterion here, as we also need to give our attention on how to provide those services in an energy efficient way by reducing the power consumption. While reducing the power consumption we need to see to it that the quality of services provided by such smart environments are not hampered. So we need to design an energy aware smart environment which is capable of providing such services in an efficient way.

In this project we designed a framework where the activity prediction is based on human movements in smart environments. For designing the framework, we setup three types of sensor - PIR, Ping and light sensors into a Raspberry Pi (four such Pi) were placed in the lab and data were collected and annotated manually. We then used some commonly used classifiers to recognize the activities and used some HMM model for activity prediction and accuracy of the designed models were calculated.

The rest of the paper is organized as follows. Section 2 describes the Related Work. Section 3 presents the architecture of the model being used for recognition and prediction of the human activities. Experimental setup and results are discussed in Section 4. Finally we conclude our work in Section 5.

2. Related Works

PIR sensor is used in various application for building smart environment, smart home or office and smart energy system. Han et al. [1] presents a way to estimate the occupancy and indoor environment quality of building with the help of distributed sensor network and statistical estimation method.

Tsai et al. [2] explains a method to reduce the standby power consumption in sleep mode of a personal computer with the help of socket to plug-in the PC monitor.

They [3] also present a method to reduce standby power consumption in lighting device based on PIR-sensor by attaching a device. Power consumption of this device is far less than power consumption in normal standby mode.

Yun et al. [4] they present a study of human movement detection and its identification with the help of set of PIR sensors. They placed three PIR sensor based modules in the hall to monitor the peoples.

Cook et al. [5] explains the approach of sliding a window over the sensor data and getting the activity that corresponds the most recent event in the window.

Tao Gu et al. [6] talks about the reorganization of human activity from the data of sensor. Also this task is challenging because activity performed by human are not only a simple / sequential but also a complex/concurrent.

3. System Architecture

To design and build a smart environment where we need to make the sensors understand the activities performed by a human based on its movement and behavior, we need to develop robust motion detection and tracking system using various sensors. A lot of researcher has been working on creating such a robust motion tracking system. We have used three types of sensors for detecting the movement of a human inside a lab and track his/her behavior in using the systems available in the same lab. The PIR and the PING sensor are used to detect the presence and the movement of human in the lab. Whereas a LIGHT sensor is used to detect whether a system in which a person is working is switched on or off. This data will help us to identify the areas where we can save energy. The details of how the sensors are placed and installed in the lab are discussed in Section 4. The smart environment which we are using to recognize the human activities is the Robotics Lab located at the Department of Computer Science and Engineering, Indian Institute of Technology Guwahati. Figure 1 describes the architecture which we used for recognizing human activities in the Robotics Lab.

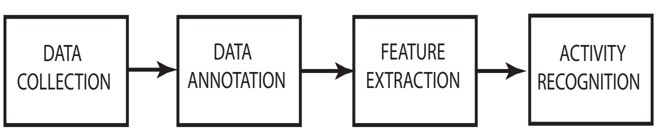

Figure 1. System Architecture for the Test-Bed, from [7]

There are four main parts in this system architecture. The first module shows that we need to collect data from the sensors, the next module is to annotate the collected data. After annotating the data we will extract the features from the data. Finally we would use a classifier to recognize the activities. The first three modules are discussed in details in the next section.

3.1. Recognition Model using *K-NN classifier*

We need to generate features from the annotated data and then we used a k-nn classifier to recognize the activities of a person moving around and working in the Robotics Lab.

3.1.1. Feature Extraction. Next we need to extract the useful features or attributes from the raw annotated data collected from the sensors. The raw annotated data file consists of five columns- the first column is for Date and Time, the second gives the PIR value, the third for the PING Value, the fourth column is the LIGHT value and the fifth column gives the class label for a given human activity. We need to select the features set properly else it will not be able to classify the data properly. Following five features are usually considered when dealing with this type of data for *PIR, PING and LIGHT*

1) *Energy (E)* = $\sum_{n=1}^{N} x_i^2$
2) *Standard Deviation (SD)* = $\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - M)^2}$
3) *Average (AV)* = $\frac{\sum_{i=1}^{N} x_i}{N}$
4) *Root Means Square (RMS)* = $\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
5) *Mean (M)* = $\sum_{i=1}^{N} x_i$

3.1.2. Activity Recognition. Figure8 gives a brief description of our human activity recognition architecture. We need to select from a set of activity labels $A = \{a1, .., aN\}$ the one which is most likely to represent the given feature value. Next we need to select the best classifier architecture for activity recognition. Different types of algorithm have been proposed for classification problem both for supervised and non-supervised learning. Supervised methods build class models using labeled data, whereas non-supervised methods try to discover the structure of the data. Among the various classifiers available, we have used the k-nearest neighbor algorithm. The results from [8] made it very clear that the k-nn model gave a very high accuracy compared to other model while recognizing the activities.

In our Recognition model using the k-nearest neighbor for classification, we have three sensor values PIR, PING and LIGHT for a given class for human activities. We identified four classes which was suitable for our problem. The classes are:

a) Sitting + Screen ON
b) Idle + Screen ON
c) Sitting + Screen OFF
d) Idle + Screen OFF

Class a) corresponds to when a person is sitting in front of the computer system and the system screen is ON.

Class b) denotes when no person is sitting in front the system but the monitor screen is ON, while Class c) and Class d) corresponds when the monitor screen is OFF while someone is sitting and not sitting respectively, in front of the system. We normalized the sensor values using the max-min approach before feeding the values into the classifier. In the k-nn classifier, we separated out the training data with the test data in the ratio of 67:33, which means 67 percent of the data was feed for training and the remaining 33 percent was used for testing purpose. We obtained some good results which is discussed in detail in the next section.

3.2. Recognition Model using HMM

3.2.1. Activity Recognition. The main challenge of activity recognition is that it should properly classify the streaming / online data. In classification task, we have proper set of fixed features, which can be used in machine learning algorithm (say linear classifier, logistic classifier, etc.) with fixed feature vector for classification of task, given it has been trained. But in case of activity recognition on streaming data, the whole problem is challenged with irregular activity occurrence and features of activity may not be available, when the classification task is performed. For example, when a person comes to his working place as mentioned in above environment, we get the activity like sitting, idle, with screen on/off, in case of sitting activity the time of start of this activity and end of this activity is not fixed it is dynamic. Here fixed feature activity recognition won't give the proper activity.

The dataset we collected from the environment setup done in robotics lab had limited activities to sensor data so we took dataset from CASAS, where we took cairo, milan [9] dataset which had sensor such as motion and door sensors, there are multiple sensors placed across the room and data is collected, sample of dataset is mentioned below.

```
2008-02-27  12:43:27.416392 M08 ON  Phone_Call begin
2008-02-27  12:43:27.8481   M07 ON
2008-02-27  12:43:28.487061 M09 ON
2008-02-27  12:43:29.222889 M14 ON
2008-02-27  12:43:29.499828 M23 OFF
2008-02-27  12:43:30.159565 M01 OFF
2008-02-27  12:43:30.28561  M07 OFF
```

Figure 2. A Snapshot of the casas dataset [9]

3.2.2. Methodology. In our approach, we have a sliding window which is moved over the stream of data, the events occurred in this window will belong to one of the activity. This activity and events are represented as Hidden Markov Model. HMM is a statistical model, which has hidden state (hidden node) and evidence state (observable node), where hidden node represents the activities and the evidence node represents the feature combination.

The features are that represent a sensor event are, Sensor, Time, Date, Previous. Where Sensor feature represents the sensor id, previous field represents the label of previous activity.

The prior probability that a sensor event belongs to any given activity is based on the number of sensor events that have belonged to each activity class in the dataset, the frequency of the events with respect to the activity is used to estimate the transition and observation table probabilities, as we get the observation event we use Viterbi algorithm to update likelihood of each activity.

Then the HMM will be trained with dataset as specified above method, then with test dataset the hmm will generate the activity label of sensor event sequence using hmm classifier.

The Result of HMM on cairo and melon dataset. HMM classified cairo dataset with 69.4% and melon dataset with 46.5% accuracy. In comparison of dataset cairo had given good results compared to melon dataset.

4. Experimental Setup

4.1. Adding Sensors to the Raspberry Pi

4.1.1. Light Sensor. The light sensor provides us the luminosity in the environment. We have fixed this sensor to the system monitor, which has been used to infer whether the system monitor is ON / OFF. Assuming each individual in the lab has an independent system, we can use this light sensor information to infer,

1) When did the individual start working each day
2) What is the total duration of working time, each day

Below is the sample from light sensor data. When we analyze the data, we could infer that the system monitor is ”ON” till the time-step 75 and beyond which monitor has been switched ”OFF” till time-step 220 approx. Later, the system monitor has been switched ”ON” again.

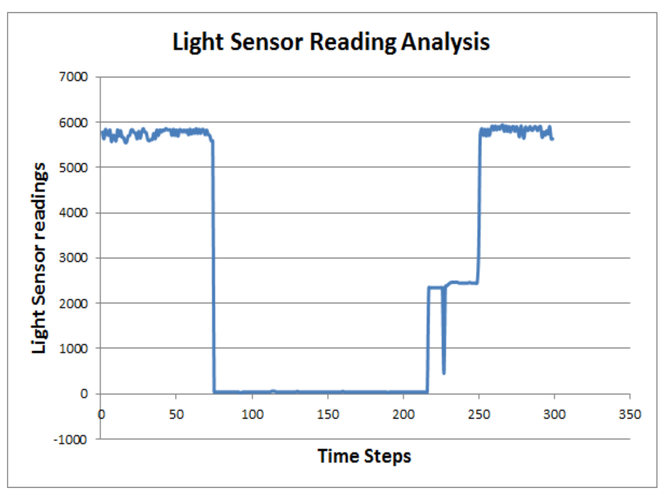

Figure 3. Light Sensor Reading Analysis

Since, the values are concrete for different activity, we can make use of the ”Mean function” to extract the feature out of the raw data. Thus, the system monitor's status (SCREEN ON/ SCREEN OFF) can be inferred from Light sensor alone.

4.1.2. PING Sensor. We used HC-SR04 Ultrasonic sensor to detect, if there is any object/human in-front of the system. We can use Raspberry Pi to trigger the sensor to send an ultrasonic pulse. The pulse waves bounce off from any nearby objects and some are reflected back to the sensor.

The sensor detects these return waves and measures the time gap between the trigger and returned pulse. We got the time and we know the speed of the sound waves, using which we can calculate the distance of the object in-front.

This information will be utilized to identify if there is any human in-front of the system(using the system/ sitting in-front of the system).

Let us analyze a snapshot of the values read from PING sensor. If the values of the PING sensor are high, it means that no sound waves have returned to the sensor, indicating there is no object in-front of the system. If the values are low, which means there is some object in-front of the system approximately in a distance equal to the value read from the ultrasonic sensor.

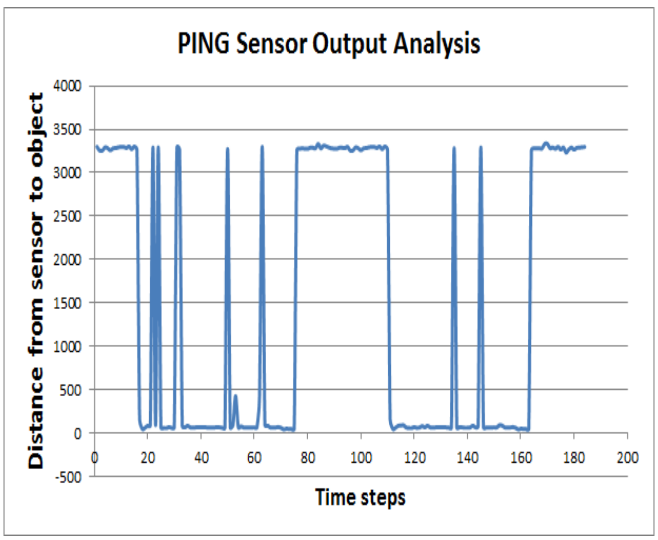

Figure 4. PING Sensor Output Analysis

In the above snapshot, when the values were high, there is no object in-front of the system. Later, the distance values dropped down significantly, which indicates there is some object, in our case a human was using the system. We could witness some spikes in the output from time-step 20 to 80, because during this time-step none of the sound waves returned to the sensor.

4.1.3. PIR Sensor. The PING sensor can be used to detect if there is any object present in-front of the system. But, how to differentiate an object/ chair from a human being. PIR is used to fill this gap.

PIR sensor can detects changes in the amount of infrared radiation it receives. Our bodies generate infrared heat and this heat would be picked up by the sensor, which can be used to detect the motion of a human being before the system.

This PIR sensor generally provides digital data, indicating any movement in-front of the sensor. We are extracting the raw analog values from the sensor, which has the potential to answer the direction of movement in-front of the sensor, which can be used for future enhancement. we then use an Analog to Digital Converter to convert this analog data to use for processing.

Let us analyze a snapshot of the PIR readings. When the values are constantly high, it indicates there is no activity in-front of the system (human activity). whenever there is some human movement in-front of the system, the PIR values drop down.

Here in our output till time-step 20, there is no activity before the sensor. From time-step 20, there are fluctuations in the reading, indicating some movement before the sensor. During time-step 20-60, a person has come in-front of the system and different spikes are registered because the user took some time to settle before the system.

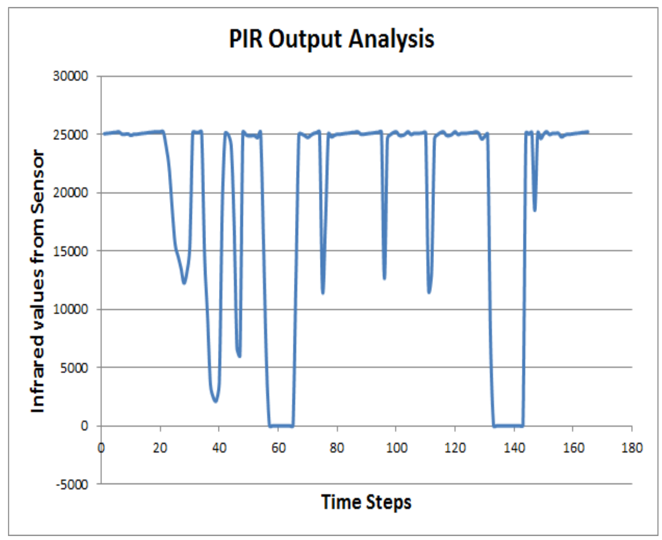

Figure 5. PIR Sensor Output Analysis

From time-step 70-135, the user is working before the system, the difference in values are due to the movement of the user before the system. Later, the user left the system at time-step 150.

4.2. Floor Plan in placing the Sensors

The following figure shows the Raspberry Pi's connection with the different sensors and the position of the mounting before the system. The Light sensor has been stuck to the monitor. The PING and PIR sensor has been mounted in a cardboard facing the user, such that it detects the activities of the user.

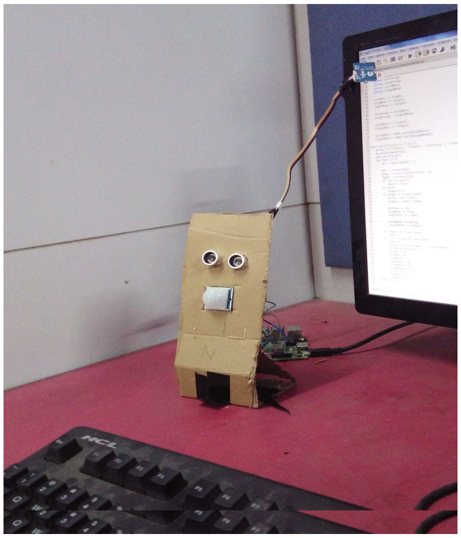

Figure 6. Pi Setup on System

4.3. Data Collection and Annotation

The data has been collected for 24 hours each day and it has been manually annotated.

The following is the snapshot of the readings from PING and PIR sensor, during a SITTING activity. SITTING activity cannot be recognized only with the help of PING sensor, due to the interruption of the PING values because of other objects like chair. Hence, PIR and PING is used as a combination to track this activity. If we analyze the data, we can infer that the PIR values show human motion from time-step 10-20 and the PING reading has dropped down ultimately at 22, indicating some person has come-in and sat before the system. Similarly, when the person leaves the system by time-step 40, PIR values vary and PING values pump up to higher value after the person has left the system.

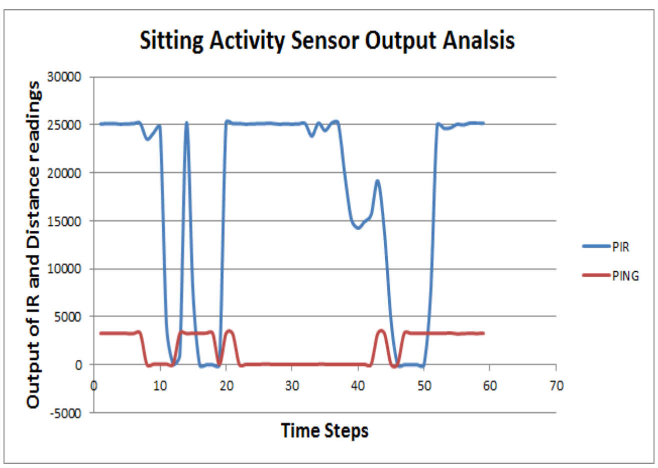

Figure 7. Output Analysis for Sitting Activity

4.4. Recognition Model Results

The following is the snapshot of the results obtained for recognizing the activity using K-NN classifier.

```
> predicted='SittingOFF+ScreenON', actual='SittingON+ScreenON'
> predicted='SittingON+ScreenON', actual='SittingON+ScreenON'
> predicted='SittingON+ScreenON', actual='SittingON+ScreenON'
> predicted='SittingON+ScreenON', actual='SittingON+ScreenON'
> predicted='SittingON+ScreenON', actual='SittingON+ScreenON'
Data Accuracy: 77.32426303854876%
Train Dataset: 1687
Test Dataset: 441
```

Figure 8. K-NN Recognition results

5. Conclusion

We have presented a human activity recognition system based on PIR, PING and Light sensor. With the help of PIR and PING sensor, we are analyzing the position of the human being and from Light sensor, we are getting information about his monitor screen status whether it is on or off.

We placed one PIR sensor and one PING senor on the desk of users and Light sensor on the monitor of computer. From the data, we are able to classify the activities in four categories eg: Sitting with screen on, Idle with screen on, Sitting and screen off, Idle and screen off.

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