Chapter 9

Applications of IoT

9.1 Introduction

In a smart environment, heterogeneous things send data to the gateway, fog node, or cloud using wireless protocols. Encryption of data is carried out in a secured smart environment. Further, things data analytic is used for automated decisions and making our life easier. The chapter discusses two use cases of smart environments, namely, smart healthcare, and smart city. This helps us in the visualization of the learned concepts of previous chapters. In particular, human activity recognition using wearable sensors and channel state information in a smart healthcare system is presented. The channel state information provides a device-free solution and hence, better than wearable sensors and image/video-based. The image and video-based approach breach the privacy of the user and require a large transmit bandwidth. The chapter also presents smart parking, smart farming, and smart air pollution monitoring for smart city applications. The smart system facilitates improved services to the users without any human intervention.

9.2 Smart Healthcare

Three applications are presented herein for a smart healthcare system: human activity recognition using wearable sensors, Channel State Information (CSI) based human activity recognition, and human health monitoring.

9.2.1 Human Activity Recognition Using Wearable Sensors

In this section, we present a human activity recognition (HAR) application using wearable sensors. The applications of HAR include remote patient monitoring, elderly people monitoring, and transportation amongst others. The wearable biomedical sensors are the following:

- Electromyography (EMG): To assess the health of muscles.

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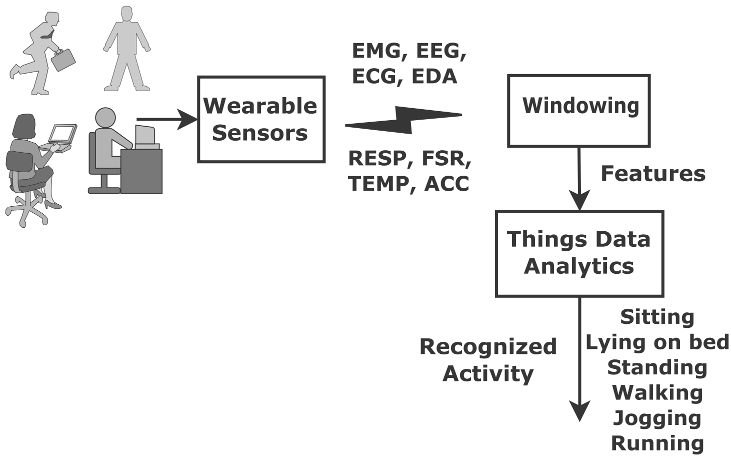

FIGURE 9.1: Human activity recognition using wearable sensors

- Electroencephalograph (EEG): To detect abnormalities in the brain waves.
- Electrocardiogram (ECG): To record electrical activity of the heart.
- Accelerometer (ACC): To measure acceleration of the body.
- Electrodermal Activity (EDA): To measure changes in the electrical properties of the skin.
- Respiration (RESP): To measures breathing rate.
- Force (FSR): To detect numbness of the body.
- Temperature (TEMP): To measure body temperature.

The other biomedical sensors are blood pressure sensor, Galvanic skin response sensor, airflow sensor, sound generator, body position sensor, snore sensor, alert patient button, spirometer, glucometer, and SPO2 pulse oximeter. The data from the things are sent using wireless technology such as Bluetooth, Wi-Fi, or LoRaWAN to the gateway, fog node or cloud for computational purpose securely. The activities that can be detected are classified into several categories. Those can be (a) sitting, (b) lying on a bed, (c) standing, (d) walking, (e) jogging, and (f) running to name a few. Wearable sensors based HAR is shown in Figure 9.1. The wearable sensors data change uniquely according to the activity. For example, the heart rate and body temperature increase from rest to intense activity conditions. The acceleration sensor gives the body accelerations in x, y, and z directions. There are several smart healthcare kits such as Biosignalplux, and eHealth Medical Development Platform for Arduino—MySignals HW Complete Kit to measures biomedical signals.

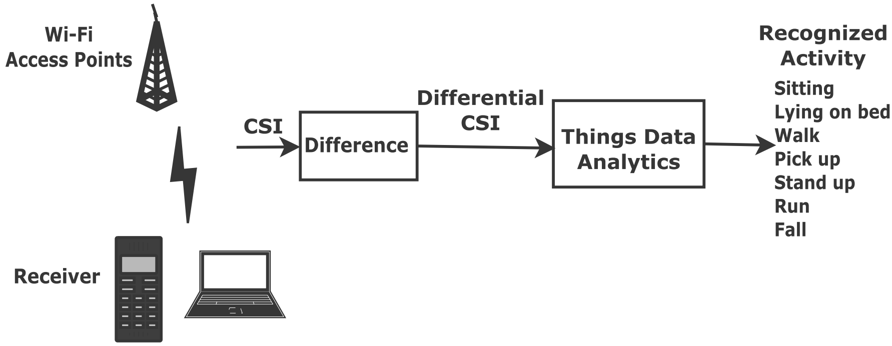

FIGURE 9.2: Human activity recognition using differential CSI

One can choose a biomedical kit depending on the requirements of specific biomedical signals, sampling rate, computation and storage facilities, ease of use, and cost amongst others.

We utilize data analytic technique for classification of different activities using wearable sensor data. If we use machine learning algorithm, we can extract features of wearable biomedical data for different activities. For instance, we compute mean, variance, standard deviation, skewness, kurtosis, minimum and maximum value, and many more as features. Notably, the deep learning algorithm automatically extracts features. In order to have multiple instances of a specific biomedical signal, the concept of windowing is used. The original time-series data is windowed to get different overlapping segments of a single time-series data. The feature is computed for each windowed signal. Subsequently, the features are fed to a classifier like kNN, naive Bayes, or support vector machine (SVM) algorithm. Finally, the activities are recognized based on the wearable sensor data. Notably, we can use fewer sensors also, however, multiple sensors provide complementary information and generally increases the activity recognition accuracy at the cost of computational complexity.

9.2.2 Human Activity Recognition Using Channel State Information

HAR algorithms may be classified into three categories: wearable sensor based, image/video-based and wireless link based. In the last section, we discussed wearable sensor-based activity recognition. However, wearable sensors may cause discomfort to humans. Image/video-based HAR consumes a lot of bandwidth during transmission and breaches the privacy of users. Therefore, we discuss wireless link-based HAR in this section.

We use CSI between transmitter and receiver to recognize the activity of a person as shown in Figure 9.2. Wi-Fi access points present in the environment act as a transmitter and smart device as a receiver. The medium between a transmitter and a receiver is called a channel. The CSI is a complex number and hence has both magnitude and phase. These magnitude and phase give a unique signature for different activities. A public dataset of CSI for activity recognition is of Stanford data dump of Ermon Group. Linux 802.11n CSI Tool is used to get CSI at 1000 Hz. The tool is built using Intel Wi-Fi Wireless Link 5300 802.11n MIMO. There are 90 subcarriers and each subcarrier has amplitude and phase. The first column of the CSI dataset is time-stamp. The second to ninety-first columns are amplitude data. Finally, ninety-second to one hundred eighty-first columns is phase data for 30 subcarriers times 3 antennas of a MIMO system.

Generally, the CSI contains the carrier frequency offset and sampling frequency offset as per literature. If we take the difference of two CSI for the same activity, the offset can be easily canceled. This soft computing approach enhances the activity recognition performance. The differential CSI is further fed to things data analytic for classification of different activities. The different classified activities are sitting, lying on the bed, walk, pick up, stand up, run and fall. One application of the sensed activities can be in a pacemaker for maintaining the required heart rate using a controller.

9.2.3 Human Health Monitoring

We detect anomalies in ECG and EEG data of a smart healthcare system. In particular, arrhythmia and seizure are detected using ECG and EEG signals, respectively. There are three main components of an ECG signal: P wave, QRS complex, and T wave. The P wave, QRS complex, and R peak represent atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively. There are 48 patients data in MIT-BIH arrhythmia database. The data has been collected using two-lead sampled at 360 Hz.

As we know QRS complex gives information about cardiac arrhythmias. The R peak is detected using the Pan-Tompkins algorithm. Subsequently, the classification of normal, ventricular, and super-ventricular beats are carried out. The challenge is that normal beat and superventricular beats are similar. Therefore, 2-stage data analytic is used as shown in Figure 9.3. In the first stage, ventricular beat is separated from the normal plus super-ventricular beats. In the next stage, the normal and super-ventricular beats are separated.

There is a class imbalance problem because of the abundance of normal beats and scarcity of abnormal beats. In order to balance the number of samples of both classes, upsampling of abnormal class data is done to increase the number of samples of this class. Similarly, the CHB-MIT dataset has scalp EEG recordings of 916 hours for 24 seizure patients. The dataset is used for the detection of seizures. Other biomedical signals from a smart healthcare system can also be integrated into the framework for anomaly detection using multi-sensor healthcare data.

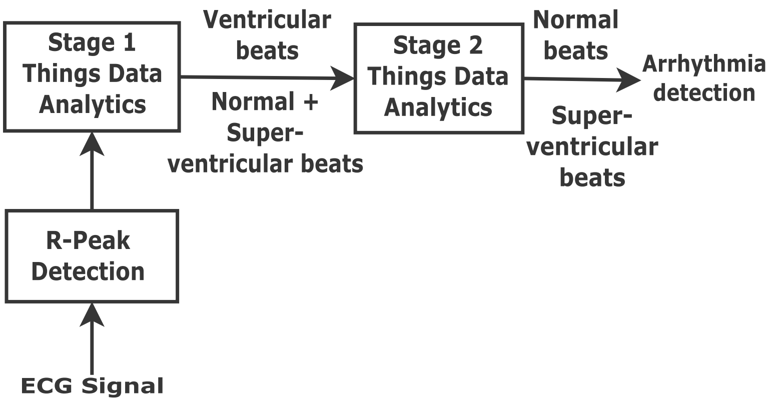

FIGURE 9.3: Arrhythmia detection using ECG signal

9.3 Smart City

We present herein three applications of a smart city project: smart parking, smart farming, and smart air pollution monitoring systems.

9.3.1 Smart Parking

In the metropolitan areas with big shopping malls and offices, we have a large number of vehicles with small and costly parking spaces. This leads to wastage of time and fuel, and traffic congestion in manual search of a parking space. A smart parking system is the solution in this regard for an urban area. In a smart parking system, the driver gets live information of vacant parking slots on his/her smartphone application.

The occupied or free slot in a parking area is detected using pressure or infrared sensors. The cost of an infrared sensor is low and transmits information using IoT protocols. When a car arrives at the entry, it is auto navigated to the nearest free parking slot as shown in Figure 9.4. The location tracking of the vehicle is carried out using RSS based localization algorithm. Note that, in underground or multi-story complex buildings, GPS does not work well. Therefore, we need to resort to the low cost and ubiquitous RSS measurements for the localization task. The location information helps in navigating the driver in a large underground parking area. On exit, the number of free slots is incremented by one. If the blockchain technology is adopted, the system negotiates the parking fee and payment is done securely without any human intervention.

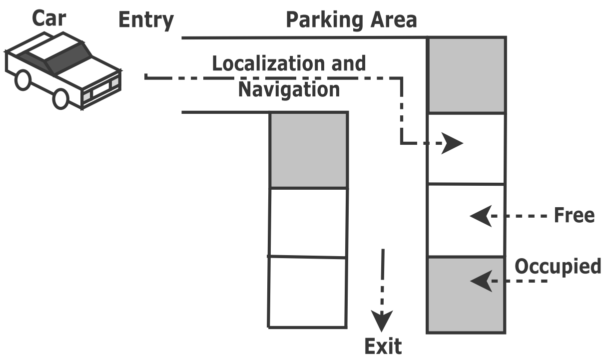

FIGURE 9.4: Smart parking system

9.3.2 Smart Farming

We use Meshlium 4G 868/900 AP based smart agriculture IoT vertical kit for data collection, data processing, and drawing inferences. This helps in enhancing crop productivity, measuring climate change, and animal health monitoring in real-time. Smart Agriculture PRO 868/900 PRO 5 DBi is a plug and sense kit and uses 6600 ma-h rechargeable battery and an external solar panel. The smart agriculture kit measures the following:

- Temperature
- Humidity
- Pressure
- Soil temperature
- Soil moisture up to 1.5 m and 4.5 m
- Leaf wetness
- Wind speed using anenometer, wind vane, and pluviometer
- Solar radiation

Similar to other smart systems, sensors measure soil and water (moisture) health, temperature, humidity, and light. We can also make use of a drone for data gathering from a large agriculture field. The collected data is further sent to the gateway, fog node or cloud using IoT protocols for processing as shown in Figure 9.5. Things data analytic is used for decision-making purposes. The location of animals grazing in the field is tracked using a localization algorithm. The overall cost reduces and the productivity increases in smart farming.

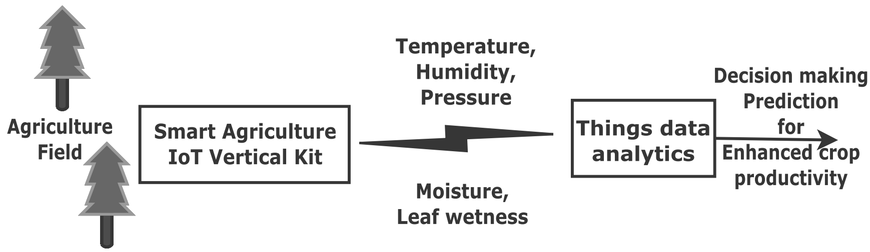

FIGURE 9.5: Smart farming system

9.3.3 Smart Air Pollution Monitoring System

Air pollution is caused by urbanization, transportation, industrial emission, dust, wildfire, and burning of fossil fuels. The solid and liquid particles of gases are suspended in air pollution. We use a smart pollution monitoring system for pollution control measures. We use air quality index as shown in Figure 9.6 like

- Ozone (O_3)
- Particulate Matter (PM) 2.5 and PM10
- Nitric dioxide (NO_2)
- Sulphur dioxide (SO_2) and
- Carbon monoxide (CO)

We use Meshlium 4G 802.15.4 AP-based smart cities IoT vertical kit which is simply a plug and sense kit. The power option is provided by 6600 mah rechargeable battery and external solar panel. The air quality indices are estimated on hourly, day wise and week wise basis. The data are sent to

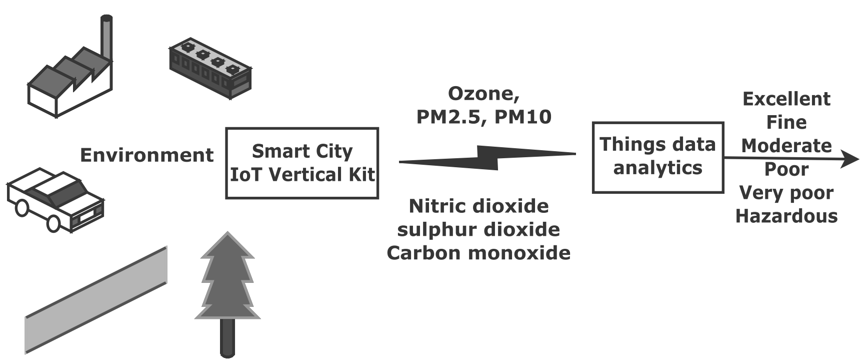

FIGURE 9.6: Smart air pollution monitoring system

the gateway, fog node or cloud node using IoT protocols. Subsequently, the following values are computed and mapped are

1. Excellent, range: 0 to 50
2. Fine, range: 51 to 100
3. Moderate, range: 101 to 150
4. Poor, range: 151 to 200
5. Very poor, range: 201 to 300 and
6. Hazardous, range: 301 to 500.

Hence, we designate our environment with one of these classes and know whether it is safe to live or not.

9.4 Summary

In this chapter, we presented two broad use cases of IoT networks, namely, smart healthcare and smart city. In particular, HAR using wearable sensors and CSI in a smart healthcare system are described. Further, human health monitoring using ECG and EEG signals are illustrated. Finally, smart parking, smart farming, smart air pollution monitoring systems are discussed in the smart city use case. These IoT applications are used for improved monitoring, improved control and operation processes, and automation purposes.

9.5 Exercises

1. Can we have wired things connected to IoT gateway?
2. Can we use 4G-LTE for data transfer from things to the gateway, fog node, or cloud?
3. Why do we not prefer undersampling to solve the class imbalance problem?
4. How do you take RSS measurements for localization in smart parking?
5. Which navigation algorithm do you leverage in smart parking?

6. What are the effects of air pollution on human health? Which community of the people are more vulnerable?
7. How do you determine the most polluted areas given air quality data on a city map?
8. What actions can be taken in case of the polluted areas?
9. In which application among healthcare and air pollution monitoring, a low computational time is desirable?
10. **Do It Yourself**: Design the IoT projects for some smart environments.