International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 05 | May 2020 www.irjet.net p-ISSN: 2395-0072

A Comprehensive Study on Human Interaction with IoT Systems

Mubashira KM[1], Drisya MK[2]

[1]*Student, Dept. of ECE, Jyothi Engineering College Cheruthuruthy, Kerala, India*
[2]*Asst.Professor, Dept. of ECE, Jyothi Engineering College Cheruthuruthy, Kerala, India*

---***---

Abstract - *Internet of Things (IoT) is one among the trending technology in this digital era. Developments in network infrastructure and automated devices boosted the reach of IoT. The IoT can be defined as a network of internet-connected things (e.g., computers, vehicles, and sensors). These interconnected things exchange data between themselves and help people to access internet-connected devices, applications, and services anytime and at anywhere. The technological advancements mainly focused on how to make huge profit by enabling faster machine to machine communication. Still there is a challenge exists to provide an efficient and better interaction between human beings and IoT systems.*

User could either monitor or configure internet connected things at home, offices and any other places for control of various functions like temperature, humidity, lighting and other energy efficiency. Users can be of different types. Depending on them, dissemination of IoT became a great issue. Because, the users like children, elderly people and various kinds of disabled persons will be the intended customers of specific IoT devices. To make them comfortable with the products, their interaction with IoT devices should be smooth and easier. Here, in this paper we tried to evaluate some of the early published interacting systems developed by others. This will enable you to understand the working principles used by them and will help you to integrate various methods to develop a better interacting system devoid of limitations experienced by them.

***Key Words*: IoT, Man and IoT, Human interaction with IoT, IoT device controls, Human to machine communication, Smart Wearables, Gesture recognition, Speech recognition….**

1. INTRODUCTION

Internet of Things (IoT) has been emerging as a new phenomenon that will change the world. IoT will make an impact on different aspects of human life such as the economy, welfare, security, safety, etc. There are a lot of applications for IoT like smart homes, smart cities, healthcare, etc. IoT establishes interrelated computing devices, where each one has a unique identifier and can communicate with each other with minimum human intervention [1]. The number of internet-connected devices is now dramatically growing. According to a recent study on the prediction of IoT market share, the number of IoT devices will approach 100 billion and the total amount of data generated by the users and devices will reach 35 ZB by 2020 [2].

However, the current technologies mainly focus on improving the machine-to-machine communication/interaction, rather than the interaction between users and machines. For example, some IoT platforms designed for smart home automation provide a web-based UI and a mobile application to register, manage, and control the smart home appliances connected to them. Users must first open the website or the mobile application, explore a page to select a menu, find a room or location, and finally select the device to be manipulated from a list. After selecting the device, the users can check the status or control it by touching or clicking the buttons on the webpage or mobile page. However, this UI and procedure will become tedious and time-consuming to the users with the current rapid increase in the number of IoT ready devices. Additionally, users who are not familiar with smart devices, such as children and seniors, or those with limitations in accessing them, such as severely ill patients or the disabled, will encounter difficulties in using the IoT applications and services. This inconvenience will be a major obstacle to the dissemination of the IoT [3].

Typically, 'interaction' in the context of IoT means interfaces which allow people to either monitor or configure IoT devices. Some examples include mobile applications and embedded touchscreens for control of various functions (e.g., heating, lights, and energy efficiency) in environments such as homes and offices. Additionally, users who are not familiar with smart devices, such as children and seniors, or those with limitations in accessing them, such as severely ill patients or the disabled, will encounter difficulties in using the IoT applications and services. This inconvenience will be a major obstacle to the dissemination of the IoT. Thus, there is a need to investigate what kinds of interaction techniques could provide IoT to be more human oriented, what is the role of automation and interaction, and how human originated data can be used in IoT [4].

In this paper we tried to study some human-machine interacting systems. It includes a complete description on methodology and schemes of each system along with its limitations. This paper will make us aware about various interaction methods in detail.

2. INTERACTION SYSTEMS

Here we are going to look some of the interacting systems between humans and IoT devices which were already published before. They are using different principles and variety of algorithms to enable a better and convenient interaction. Even though, when they are tested in real time environment the users felt a lot of difficulties.

A. Hand Gesture Based Remote Control System Using Infrared Sensors and a Camera

Hand gesture recognition systems can be classified into three groups:-

i. systems using hand-held pointing devices
ii. systems using wearable sensors
iii. systems doing two dimensional image analysis

But it is not be practical to utilize gloves or similar equipment for gesture recognition. In this paper, a multimodal hand gesture detection and recognition system using differential Pyro-electric infrared (PIR) sensors and a regular camera is described. Any movement within the viewing range of the differential PIR sensors are first detected by the sensors and then checked if it is due to a hand gesture or not by video analysis. If the movement is due to a hand, one-dimensional continuous-time signals extracted from the PIR sensors are used to classify/recognize the hand movements in real-time. Classification of different hand gestures by using the differential PIR sensors is carried out by a new Winner-TakeAll (WTA) hash based recognition method. Jaccard distance is used to compare the WTA hash codes extracted from 1-D differential infrared sensor signals [5].

- The proposed multimodal system consists of a differential PIR sensor array and an ordinary camera for hand gesture recognition
- Pyro-electric Infrared (PIR) hand gesture recognition systems are all based on the on/off decisions of the analog circuitry of the PIR sensor

Methodology

- Data obtained from the PIR sensor array and the camera are transferred to a computer & processed together in real-time.
- Once any kind of motion is detected by one of the PIR sensors, the motion is checked whether it is due to a hand or not by the camera.
- If the source of the motion is a hand gesture, data received from the three different PIR sensors are evaluated at the same time to classify the hand gestures (e.g., right-to-left/left-to-right, upward/downward hand motions etc.)
- Classification of the hand gestures by the PIR sensor array is carried out by a new winner-take-all (WTA) hash based method.
- Wavelet based signal processing methods are used to extract features from sensor signals.
- This multimodal solution to the hand gesture detection and recognition problem is a good alternative to the existing methods because of its accuracy, low cost and low power consumption camera is just used for the detection of a hand and the hand gestures are classified using only the sensor array which in this case consists of three differential PIR sensors.
- Let x[n] be a sampled version of the signal produced by one of the PIR sensors.
- Wavelet coefficients are obtained after a single stage sub-band decomposition corresponds to [25 Hz, 50 Hz] frequency band information of the original sensor output signal x[n] because the sampling rate is 100 Hz.
- Output signal is filtered with an integer arithmetic high-pass filter corresponding to Lagrange wavelets followed by decimation by 2.
- Whenever the user wants to interact with an electrical appliance, he or she raises his or her hand with open fingers in front of the camera.
- The user can end the controlling action when he or she makes a fist.
- After detection of a fist by the camera, the multimodal system goes to standby mode
- If the user wants to give more commands, he activates the system again by showing his or her hands with open fingers in front of the camera.
- The system can detect and recognize hand gestures up to 1.5 meters.
- It is assumed that the distance between the user and the TV set is about 1.5 to 2 meters.
- It is also possible to increase the range using PIR sensors with more directional selectivity and range.
- There is a Fresnel lens in front of most PIR sensors. The quality of the lens improves the range of the sensor.

Limitations

- The 4x4 PIR sensor array has the capability to recognize a number of hand gestures but it cannot distinguish face and body gestures from hand gestures.
- PIR sensors respond to all hot bodies in their viewing range.

B. IoT based Mobile Healthcare System for Human Activity Recognition

In the modern health care applications, the usage of IoT technologies brings physicians and patients together for automated and intelligent daily activity monitoring for elderly people. Mobile devices and wearable body sensors are gradually implemented for the monitoring of personal health care and wellbeing. Integration of IoT in healthcare has led to initiate smart applications such as mobile healthcare and intelligent healthcare monitoring systems [6].

Mobile healthcare or m-healthcare is a key aspect of development in the forefront of this revolution Mobile health (mHealth) is a medical health infrastructure supported by mobile devices and IoT and it includes the usage of a mobile phone's core utility of general packet radio service (GPRS), 4G systems, global positioning system (GPS), and Bluetooth technology. The body sensor network (BSN) technology is one of the most effective technologies used in IoT-based modern healthcare system. It is essentially a combination of low-power and lightweight wireless sensor nodes which are used to monitor the human body functions. Human Activity Recognition (HAR) usually realized by collecting signals from IoT sensors and processing them via data mining techniques for classification. HAR is used for regular monitoring of patients with different disorders, locomotion, daily living activities, transportation and sports. The materials as well as methods used in the human activity recognition by using data mining techniques that are necessary in the mHealth applications. They are good in the projection of tangible results.

In this paper, they employed different machine learning techniques for HAR. The proposed HAR system is used to examine the human behaviour, which can be considered to be one of the most prominent areas in m-healthcare. A robust and precise HAR model is developed based on IoT technology. In this paper, they present a user-dependent data mining approach for off-line human activity classification and a robust and precise human activity recognition model is developed based on IoT technology. The proposed model utilizes the dataset contains body motion and vital signs recordings for ten volunteers of diverse profile while performing twelve physical activities for human activity recognition purpose.

Human Activity Recognition (HAR) became a prominent research area because of its significant contributions in human-centred areas of study targeting to enhance quality of life. HAR systems deliver information about behaviour and actions of the subjects [7]. This is usually realized by collecting signals from IoT sensors and processing them via data mining techniques for classification. HAR is used for regular monitoring of patients with different disorders [8] locomotion, daily living activities, transportationand sports [9] [10] [11]. HAR is a supervised learning problem since the activity recognition categorizes a given sensor dataset based on the activities [12].

The nature of health has gradually changed for the well-being of the people. This has been accomplished through the help of introducing smart phones, health checking gadgets, smart IoT, and individual computerized collaborators in the health sector. This has also produced a number of Apps introduced into the sector that enable the people to access health services. They offer quick information at a cheaper cost that enables the users to keep fit. This has appreciated a great impact towards the change of human being's lives. On the other hand, the data model facilities achieved the necessary developments in the sector. All these products including the mHealth and many others are a good revolution that is necessary in the world we are living today. They make our life easier especially elder people. The materials as well as methods used in the human activity recognition by using data mining techniques that are necessary in the mHealth applications. They are good in the projection of tangible results [6].

C. UbiCompass: An IoT Interaction Concept

It facilitates the discoverability of devices and the direction in which they are placed in a room. It runs as a watch face, so the devices that the user can interact with are always visible. Having a UI running in symbiosis with the watch face facilitates access to information at a glance. Since the user does not need to open an application, it is always there ready for interaction. It should be noted that everything else in the smart watch runs as usual. The devices, which the user can interact with, and their positions are updated automatically [13].

Fig -1: No device in focus

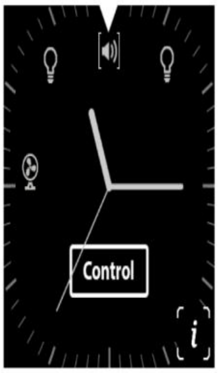


Fig -2: The Sonos sound system is in focus, indicated by a triangle and brackets.

Methodology

The user selects a device to interact with by moving his or her arm until the 12 o'clock position (i.e., north) is pointing at the device. When the device is in the line of sight, the user feels a distinct vibration and the device icon highlighted. This indicates it is ready to be selected. To make the prototype adaptable to other wearable devices in the future, a smartphone was used as a routing device to forward commands from the watch and to update the watch's interface depending on the status of the connected devices.

Limitations

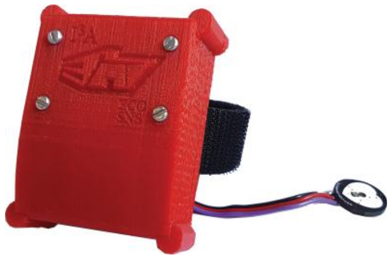
- User's position is not tracked and at this time
- The prototype works only within a limited area. The user cannot walk around the whole room.
- The inertial sensors that come with the smart watch are not very accurate and can sometime lag.
- Scaling issues: the prototype works for about ten devices. Adding more would clutter the watch face with icons.
- Simple interaction: the prototype works for simple interaction. If the user wants to make more complex adjustments of a system, another user interface would be more preferable.

D. OperaBLE: An IoT-Based Wearable to Improve Efficiency and Smart Worker Care Services in Industry 4.0

Industry 4.0 is leading the Fourth Industrial Revolution transforming traditional factories into smart factories governed by the Internet of Things. The Fourth Industrial Revolution has arisen to transform the current industry model and to introduce digitalisation into traditional factories improving production rates and promoting collaboration. This emerging revolution is the widely known Industry 4.0 [14]. The 4.0 attribute focuses on the Internet of Things (IoT) applied to industrial systems in order to interconnect objects, machines, and humans in smart factories. Collaborative tasks are encouraged by means of increasing production rates and minimising costs. This is achieved by introducing cyber physical systems (CPS) [15], perceived as the embeddedness of sensors to collect data and perform cognitive algorithms through the Internet. In order to assist smart factory employees, this paper introduces OperaBLE, a Bluetooth Low Energy (BLE) wearable proposal which is aimed at enhancing working conditions and efficiency in Industry 4.0 scenarios [16]. They have developed two innovative algorithms for OperaBLE focused on power awareness as the key-enabling attribute towards success:

1. Low-Frequency Movement Characterisation Algorithm (LoMoCA)
2. Adaptive Heart Rate Algorithm (AHRA).

It is an autonomous device able to learn behavioural patterns from individuals and, thus, enhance their working conditions. Although a specific hardware is proposed in this work to implement an evaluable wearable, the major contributions of OperaBLE lie in its functionality and, thus, in the proposed algorithms. The core system is the controller board which has an integrated BLE radio module used to transmit data. The device used is LightBlue Bean [17], a low-frequency board that includes I2C and SPI interfaces combined with multiple I/O pins. Regarding integrated sensors, it integrates a temperature sensor and a three-axis accelerometer. Finally, a low-frequency microcontroller, working at 8 MHz, is responsible for managing all parts.



a) Exterior design: OperaBLE with pulse sensor

b) Interior design: OperaBLE with accelerometer

Fig -6: OperaBLE, prototype used for experimentation

LoMoCA: Experiments

This section defines five baseline movements related to industry-based tasks, to check as many variants as possible and evaluate the system. The movements have been classified into two groups: the first one includes the so-called hammer, valve opening and assembly (movements thought to represent common industrial tasks for testing the algorithm with a progressive difficulty increase) and the second includes data request and notification (which provide support to help operators in their daily work). All movements were recorded as short movements to have a low number of samples and, thus, hinder the characterisation process.

AHRA Experiments

To test the accuracy of measurements provided by OperaBLE and the adaptability of the prototype to different workers and conditions. Three different workers were selected to carry out the first experiment, which consisted of extracting a bpm measurement while performing different tasks. The measurements where stored and compared to the ones calculated by characterising the average peak-to-peak time with a digital oscilloscope. During the experiment, the calibration routine defined in AHRA was used with three different test workers, 10 times for each subject. Eventually, they were asked to fulfil a form indicating whether they had felt fatigued or relaxed. AHRA is suitable for measuring the heart rate in different conditions and workers. The measured value coincided with the expected in repeated occasions, and the average accuracy rate of success reached during the experiment was 96.16%. Since the main aim of OperaBLE is to identify risky situations, the algorithm is accurate and appropriate for detecting harmful changes to notify nearby supervisors.

OperaBLE is flexible enough to characterise accurately any movement using low frequency, which enables its use in lightweight devices contributing towards a better use of the resources and an enhanced energy efficiency. The acceleration-based system developed permits data request operations by tapping on the surface of machines, avoiding the use of screens, or complex interfaces. It enables operators to send supervisors movement-based notifications immediately in case of emergency, which is essential to prevent accidents at work. Regarding well-being in smart factory spaces, three workers were selected for evaluating AHRA in different states. Measurements presented an average accuracy rate of success 96.16% using OperaBLE with respect to measurements provided by a digital oscilloscope, which enabled. OperaBLE to identify harmful conditions for workers such as stress or fatigue.. Results obtained during experimentation demonstrate how OperaBLE empowers human-machine collaboration embedding workers in closed-loop performance and ensuring non-harmful working conditions by means of power-aware algorithms. OperaBLE is due to bring digitalisation into smart factories, playing an essential role in the emerging wearable revolution to arise in the following years towards smart production systems.

E. Watch & Do: A Smart IoT Interaction System with Object Detection and Gaze Estimation

The proposed system consists of:

i. Object detection module

ii. Gaze estimation module

iii. Hand gesture recognition module

iv. IoT controller module

Watch Module

The hardware module called "*Watch*" is located at the centre of a room .This module ***estimates user's gaze position and detects the IoT devices*** installed in the room [3].

Watch module records the opposite side of the user

↓

Detect & recognize the types of IoT devices installed in the room.

↓

Detects the user's head region

↓

Computes a fine-grained head pose information (i.e., pitch, yaw, and roll)

↓

Estimate the user's gaze position

↓

Proposed system can identify the target device.

Do Module

It is installed around the user (e.g., near the arms) to detect hand gestures. *Do* module captures the user's hand gestures. A combination of hand gesture information and the type of selected IoT device is then translated into an IoT command and transmitted to IoT platforms. Finally, the device is manipulated according to the command. Therefore, the *Do* phase exploits a gesture recognition module with an embedded sensor and an IoT controller module which interacts with the IoT platform.

Do module captures the user's hand gestures.

↓

A combination of hand gesture information & type of selected IoT device

↓

Then translated into an IoT command

↓

Transmitted to IoT platforms.

↓

Device is manipulated according to the command

Watch module recognizes the position and the type of each installed device (i.e., a lamp, monitor, fan, refrigerator from left to right). If a user stares at a device at the left-most side, the *Watch* module detects the user's gaze position and predicts the type of the device to be controlled as a lamp. Finally, the user can turn the lamp on or off with a swipe gesture performed near the *Do* module installed around the user.

Gaze Estimation

Algorithm:

- Divide the physical space of the room into n x n virtual grids
- Collect user's head pose information for each grid
- The collected data are utilized to train a gaze estimator.
- Use the orientation of the face (i.e., pitch, yaw, and roll) and the distance between the Watch module and the user as head pose information for training a gaze estimator.
- A deep learning-based approach called deepgaze [18] was employed to compute the value of face orientation.

Object detection module

Recent deep learning approaches have shown excellent performance in terms of accuracy, but the low throughput has been a constraint for real-time use [19] [20] . Regression-based object detector, called YOLO demonstrates a comparable accuracy with improved speed (about 30~60 fps) [21].

YOLO framework:-

- Divides each input image into S x S grids
- Each grid predicts N bounding boxes and their confidence scores (which indicate whether the bounding box contains an object or not).
- Further, each grid is assigned a detected label with a class score.

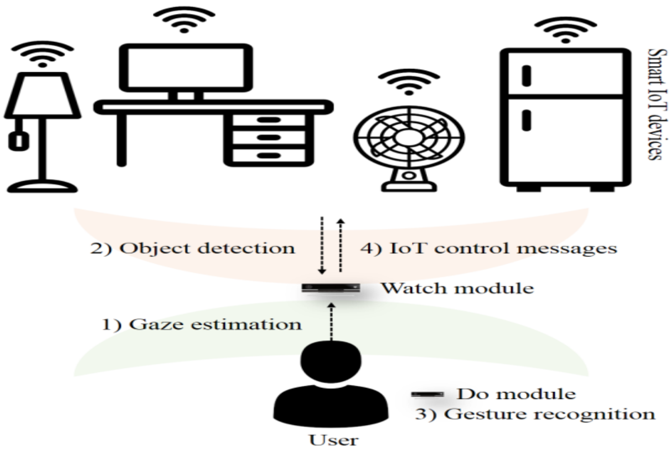


Fig -3*:* Example of the Watch and Do Implementation

Gesture Recognition

Gesture recognition is performed by a commercial gesture sensor module. This sensor supports the following nine hand gestures: "Up", "Down", "Left", "Right", "Forward", "Backward", "Clockwise", "Counter clockwise", and "Wave". User's hand gestures are associated to different actions according to the type of the selected IoT device. For simplicity, we assigned maximum four gestures (i.e., forward, backward, right, and left)

The main contributions of this approach to utilize head pose estimation and object detection technologies for IoT interaction. The previous works on gaze estimation focused on tracking the gaze position on a display. However, these approaches cannot be applied to the IOT environment that requires indoor gaze estimation. Here they solve this problem by:

1. A combination of object detection and implicit gaze estimation from the fine-grained head pose information.
2. Without any additional devices, such as a headband or watch, the users can specify the target device. The previous works used wearable devices to detect user's head pose or gaze direction, which can be uncomfortable for many users. With this model, the users can interact with the IOT devices intuitively by installing simple modules.

Limitations

1. For a gaze-based approach it is still challenging to accurately detect the user's intention to control a device. For example, the user's unintentional gaze on a certain device can be misdirected the system. To reduce this ambiguity, several works adopted device activation strategies which allow users to explicitly select a specific device or express the intention to a system. Rhythmic gesture patterns [22] or smooth pursuit techniques [23] are examples of activation strategies. These techniques help users express their intentions as well as select a specific device. Users must remember the activation gestures for each device type. In this regard, the *Do* module of the system will be improved by enabling a device activation feature. One possible solution would be to facilitate hover gesture detection on the *Do* module. Before gazing at a device, the users can place their hand over the *Do* module (i.e., hover gesture) for a short time. If this system detects the user's explicit intention and gaze toward a device, then the *Watch* phase will be processed normally.
2. In contrast to the conventional gaze estimation and tracking systems that work on a small display [24], this system cannot provide immediate display feedbacks. For example, a conventional gaze

tracking system prints a red or green dot on the screen to inform the user of current gaze estimation status. The feedback mechanism is closely related with the device activation feature. With a feedback mechanism, the users can be informed that a device has been selected accordingly and is waiting for the user's instructions or that an operation will be carried out soon. The approaches based on smart phones and smart watches can easily provide a device feedback through their application user interface. On the other hand, the models which do not have a display generally provide the feedback through the light effects around the target device. For example, if a user gazes at a fan and the system detects the user's intention to control the fan, then its surrounding leds flash for a short period.

3. The performance of indoor gaze estimation should be improved to guarantee the quality of the system. Even though the system achieves the highest performance, it still produces 10-15% false alarms. Fourth, the current form of object detection and classification approach has limited interaction angle (front 180-degree). For example, a user cannot interact with a device installed at the right or left side of the user. Finally, even though system interacts with the IOT platform, the derived benefits are currently limited. For example, a new category and its corresponding training images for iot device object detection can be dynamically updated with the IOT platform support.

F. Application of speech recognition technology in IoT smart home

This paper presents an approach to incorporate speech recognition technology in deploying Internet of Things (IoT) for smart home system. Combined with speech recognition technology, a complete smart home human computer interaction system can be realized. Nowadays smart home comprises of intelligent lighting, security alarms, fire alarms, temperature and humidity control etc. Users can interact with IoT systems through mobile phones, webpages. But the problem lies in the fixed position of switches. It may cause inconvenience in the user specific needs.

The system can be divided into MCU, monitoring module, security module, speech recognition module, power management module, WIFI communication module, OneNET Internet of Things platform and intelligent terminal [25-26]. In order to solve this problem, the smart home system uses the LD3320 module for voice recognition. User can personalize the smart home by issuing a voice command. At the same time, this paper also considers the error of speech recognition, and improves the accuracy of speech recognition of voice trigger and error absorption. It reduces the interference of misidentification and ensures accurate and efficient speech recognition [27].

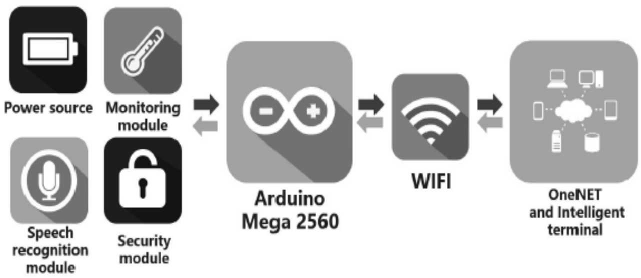


Fig -4*:* The overall structure of the smart home system

In this system, the MCU is the Arduino MEGA 2560 board. Through serial communication with each module, the MCU can acquire the real-time status of the sensor and process the data to realize the functions of the Internet of Things and the smart home [28]. After the user enters the password and verifies the fingerprint, the electromagnetic lock can be opened to enter the room. Password modification and fingerprint addition and deletion can be performed in the unlock state. Both password modification and fingerprint entry are recorded by two comparisons. The data of indoor temperature and humidity, light intensity and flammable gas concentration are collected by sensors in real time, and the Arduino board monitors and controls the corresponding equipment. When the indoor combustible gas concentration exceeds the standard, the buzzer will alarm. The MCU sends the sensor status data onto the ESP8266 through the serial port. The ESP8266 periodically uploads the current data obtained through the WIFI network to the OneNET cloud server, and the user can view it in real time on the mobile phone or the webpage.

The main purpose of speech recognition is to let the machine understand what people are saying. This system uses the technology of SI-ASR (Speaker-Independent Automatic Speech Recognition) [29]. VAD (Voice Activity Detection) , is performed on the beginning and end of the acquired signal, in order to identify and eliminate the long silence period in the sound signal stream. Pre-emphasis is a high-pass filter with a first-order finite excitation response, which makes the spectrum of the signal flat and less susceptible to finite word length effects. Speech framing is to cut the sound signal into small segments, each small segment is called a frame, the framing operation is realized by using the moving window function. Extracting the MFCC (Mel-Frequency Cepstral Coefficents) feature is a classic and effective feature extraction method. Simulating the physiological characteristics of the human ear, the speech signal is converted into a signal on the human ear's hearing scale, and then the current feature value is extracted from the converted signal to obtain the feature vector of the speech signal.

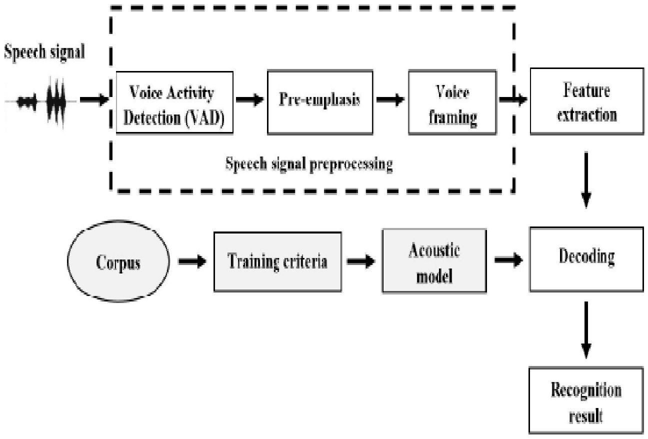


Fig -5*:* Speech recognition principle

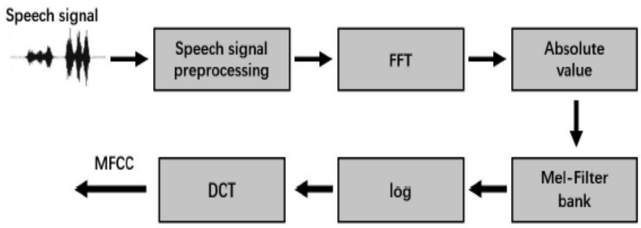


Fig -6*:* The process of extracting MFCC features

Limitations:

Speech recognition system cannot be guaranteed to be in an ideal use environment, so there is a possibility of misidentification.

- Many voice recognition commands in the smart home system, such as "turning on the lights" and "turning off the lights", occur frequently during daily communication. It is prone to misidentification. After setting the voice trigger action, the smart home system will only start monitoring and identifying other voice signals after the wake-up phrases are recognized.
- LD3320 converts the recognized sound signal into a speech feature through spectrum conversion, matches the data of the chip keyword list, and returns a keyword with the best matching of the speech feature as the recognition result. This means that when the user speaks a sentence that is similar to the keyword pronunciation (especially the pronunciation of the first few words is similar), the chip may be misidentified. These misidentified keywords are called spam keywords.

This paper introduces a complete smart home system from the perspective of speech recognition control, introduces the basic process of speech recognition and related algorithms, and discusses the application of LD3320 chip in smart home system .With the test results, it is known that the accuracy is high in the case of limited noise, but the accuracy is relatively reduced in the case where the noise is significant.

3. CONCLUSIONS

From the above detailed study we get an idea about different interaction methods used. Gesture recognition is carried out by sensors. Sometimes, wearable are used to communicate between user and devices. Wearing such devices is not user friendly and makes discomfort too. Nowadays everything has been automated. We realized about driverless car creates no traffic and accidents not more than manmade ones. The fact lies in automation. When man found out limitations of remote controlled devices due to our laziness, the sparking idea was speech recognition technology. But, misleading speeches and error responses by speech recognition modules creates problem. Fortunately, researchers found suitable algorithms for accurate speech recognition. Anyway, we realized that human versus IoT interaction is important rather than machine versus IoT systems. In this digital era, it may be an outdated observation. But if we were bothered about whole customers in this digital market, there will be demands for human friendly interaction systems for smart devices.

REFERENCES

[1] Social ethics in Internet of Things :An outline and review by Amin Shahraki, Faculty of Computer Sciences/ Department of Informatics , Østfold University College/ University of Oslo Halden / Oslo, Norway & Øystein Haugen , Faculty of Computer Sciences Østfold University CollegeHalden, Norway

[2] B. J. Borges Neto, H. T. Silva, M. R. Assunção, A. R. Mini, and A. A. Loureiro, "Sensing in the collaborative internet of things," *IEEE Sensors J.*, vol. 15, no. 3, pp. 6607–6632, Mar. 2015.

[3] DOI 10.1109/TCE.2019.2897758, IEEE Transactions on Consumer Electronics Watch & Do: A Smart IoT Interaction System with Object Detection and Gaze Estimation Jung-Hwa Kim, Seung-June Choi, and Jin-Woo Jeong

[4] Interaction and Humans in Internet of Things, Markku Turunen ,Daniel Sonntag, Klaus-Peter Engelbrecht, Thomas Olsson, Dirk Schnelle-Walka, and Andrés Lucero, Peng Wang ,Xiang Lu* , Hongyu Sun ,Wenhong ,College of Electronic Information Engineering ,Shandong University of Science and Technology ,Qingdao, China, Abdulhamit Subasi, Mariam Radhwan, Rabea Kurdi, Kholoud Khateeb Effat University, College of Engineering, Jeddah, 21478, Saudi Arabia

[5] F. Erden and A. E. Çetin, "Hand gesture based remote control system using infrared sensors and a camera," *IEEE Trans. Consum. Electron.*, vol. 60, no. 4, pp. 675–680, Nov. 2014

[6] IoT based Mobile Healthcare System for Human Activity Recognition, Abdulhamit Subasi, Mariam Radhwan, Rabea Kurdi, Kholoud Khateeb, Effat University, College of Engineering, Jeddah, 21478, Saudi Arabia

[7] B. P. Clarkson, "Life patterns: structure from wearable sensors," 2002

[8] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu,and P. Havinga, "Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey," presented at the Architecture of computing systems (ARCS), 2010 23rd international conference on, 2010, pp. 1–10

[9] B. Nham, K. Siangliulue, and S. Yeung, "Predicting mode of transport from iphone accelerometer data," *Standford Univ. Cl. Proj.*, 2008

[10] E. M. Tapia, S. S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," presented at the Pervasive, 2004, vol. 4, pp. 158–175

[11] J.-L. Reyes-Ortiz, L. Oneto, A. Sama, X. Parra, and D.Anguita, "Transition-aware human activity recognition using smartphones," *Neurocomputing*, vol. 171, pp. 754–767, 2016

[12] Y. Kwon, K. Kang, and C. Bae, "Unsupervised learning for human activity recognition using smartphone sensors," *Expert Syst. Appl.*, vol. 41, no. 14, pp. 6067–6074, 2014

[13] G. Alce, A. Espinoza, T. Hartzell, S. Olsson, D. Samuelsson, and M. Wallergård, "Ubicompass: an iot interaction concept," *Adv. Human-Computer Interact.*, vol. 2018, pp. 1–12, Apr. 2018

[14] Y. Lu, "Industry 4.0: a survey on technologies, applications and open research issues," Journal of Industrial Information Integration, vol. 6, pp. 1–10, 2017

[15] R. Rajkumar, I. Lee, L. Sha, and J. Stankovic, "Cyber-physical systems: the next computing revolution," in DAC '10 Proceedings of the 47th Design Automation Conference, pp. 731–736, New York, NY, USA, June 2010

[16] OperaBLE: An IoT-Based Wearable to Improve Efficiency and Smart Worker Care Services in Industry 4.0 ,Luis Roda-Sanchez , Celia Garrido-Hidalgo , Diego Hortelano , Teresa Olivares , and M. Carmen Ruiz

[17] Punch Through, "LightBlue family2018, http://www.punchthrough.com/bean

[18] M. Patacchiola and A. Cangelosi, "Head pose estimation in the wild using convolutional neural networks and adaptive gradient methods," *Pattern Recognit.*, vol. 71, pp. 132–143, Nov. 2017.

[19] R. Girshick, "Fast r-cnn," in *Proc. ICCV*, Santiago, Chile, 2015, pp. 1440–1448

[20] Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: towards real-time object detection with region proposal networks," in *Proc. NIPS*, Montreal, Canada, 2015, pp. 91–99

[21] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: unified, real-time object detection," in *Proc. CVPR*, LasVegas, NV, USA, 2016, pp. 779–788

[22] E. Freeman, S. Brewster, and V. Lantz, "Do that, there: an interaction technique for addressing in-air gesture systems," in *Proc. ACM CHI*, San Jose, CA, USA, 2016, pp. 2319–2331

[23] E. Velloso, M. Wirth, C. Weichel, A. Esteves, and H. Gellersen, "Ambigaze: direct control of ambient devices by gaze," in *Proc. DIS*, Brisbane, QLD, Australia, 2016, pp. 812–817

[24] D. W. Hansen and Qiang Ji, "In the eye of the beholder: a survey of models for eyes and gaze," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 3, pp. 478–500, Mar. 2010.

[25] Piotr Lech, "WiFi multi access point smart home IoT architecture,"Advances in Intelligent Systems and Computing, vol. 466, pp. 247-254,2016

[26] Sai Mounika Errapotu, Jingyi Wang, Yanmin Gong, "SAFE: Secure Appliance Scheduling for Flexible and Efficient Energy Consumption for Smart Home IoT" IEEE Internet of Things Journal, vol. 5, pp. 4380-4391, December 2018

[27] Application of speech recognition technology in IoT smart home, Peng Wang ,Xiang Lu*, Hongyu Sun, Wenhong LvCollege of Electronic Information Engineering ,Shandong University of Science and TechnologyQingdao

[28] Laura Rafferty, Farkhund Iqbal, Saiqa Aleem, "Intelligent multi-agent collaboration model for smart home IoT security" 2018 IEEE International

Congress on Internet of Things, ICIOT 2018 - Part of the 2018 IEEE World Congress on Services, pp. 65-71, 2018

[29] Abhishek Dixit, Abhinav Vidwans, Pankaj Sharma, “Improved MFCC and LPC algorithm for bundelkhandi isolated digit speech recognition,” International Conference on Electrical, Electronics, and Optimization Techniques, ICEEOT 2016, pp. 3755-3759, 2016