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Implementation of a Human Activity Monitoring System through IoT Sensor and Blynk Cloud Platform

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Abstract

Human activity monitoring system plays a major role in the application of surveillance. It can be analyzed through cameras, sensors, and microphone. The traditional approach requires a human intervention for validating the human movement recorded by a surveillance camera and microphone. Therefore, the sensor based approaches are developed to make an alert signal through a buzzer or light, irrespective of the threshold value given to its output. But such sensor based technique also requires a human attention in the monitoring room. The motive of the proposed concept is to address such limitations by connecting the sensors with an Internet of Things (IoT) network and cloud platform for remote recording and monitoring purposes. The proposed work utilizes the Blynk IoT application and cloud server for the analytics.

Keywords: Activity monitoring, human recognition, IoT platform, cloud computing, mobile computing

1. Introduction

The human monitoring systems are applied to health tracking, personal assistance and activity monitoring kind of applications. The modern sensors like accelerometer and gyroscope are very active than the traditional sensors on estimating the human activity. In general the activity monitoring sensors are categorized into two types as wearable sensors and contact less sensors. The wearable sensors are widely used for healthcare applications and that requires a built-in power source with proper insulation. Also such wearable sensor requires proper contact over the human body for sensing the data [1, 2]. The contact less sensors are mostly connected in a fixed position to monitor the human activity over the

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customized area. The image based human activity monitoring system requires a supporting software for analyzing the human activity in the images and videos collected from the cameras. In recent years, the deep learning algorithms are widely employed in such applications for recognizing the human activity through a neural network architecture [3-5]. Figure 1 represents the graphical view of sensor based human activity monitoring system with their application.

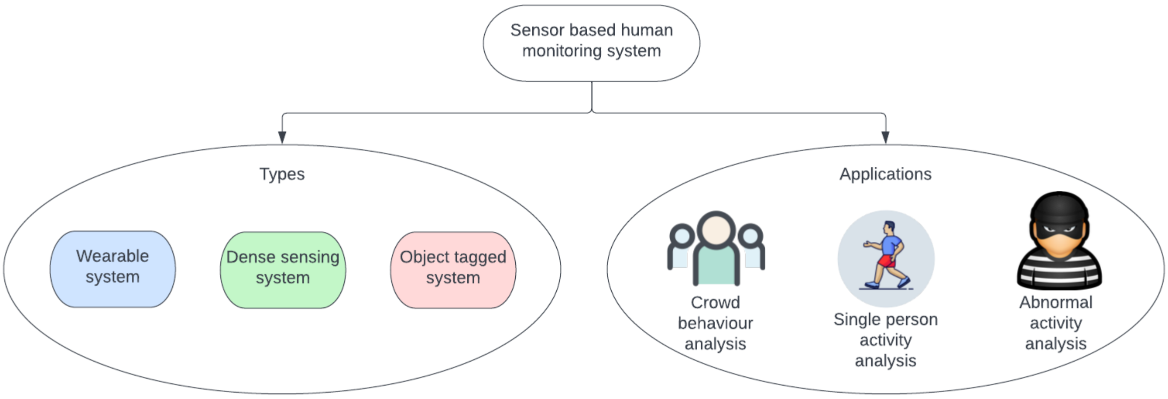

Figure 1. Types and applications of human monitoring system

1.1 Internet of Things (IoT)

IoT is a concept of connecting a module or hardware with an internet connection for remote monitoring an operation purpose. In present scenario, the IoT devices are connected with sensors and cloud service software for transmitting and receiving the data in an efficient manner. Figure 2 explores the factor that improved the usage of IoT system to certain extent.

1.1.1 Connectivity

The traditional IoT module needs a Wi-Fi peripheral device for establishing the wireless connectivity. Though, the modern IoT modules have a wide range of facility like 4G and 5G networks for enabling their connectivity with a cloud server. Hence the possibility of transmitting huge data from one place to another place becomes easier as the networks are moving their pockets faster.

1.1.2 Sensors

Sensors are the device that converts a physical parameter into a readable electrical signal. In general, the sensor component needs an amplification circuit for improving the quality of the electrical signal for processing. In recent days the sensors are available as a module that has a reliable amplification circuit over it. Therefore it saves the time required for designing an amplification circuit. Similarly the plug and play concept develops an interest to many researchers and students for implementing their work with IoT sensors.

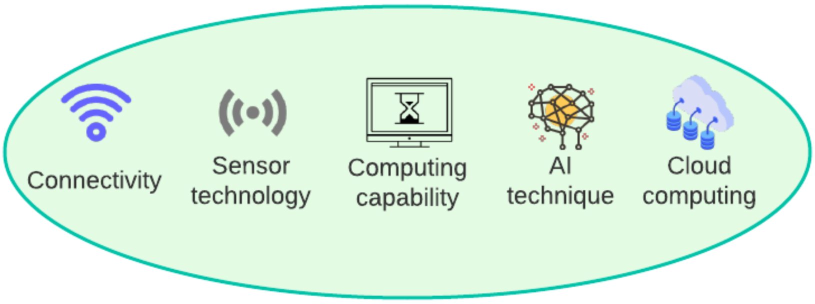

Figure 2. Technologies behind IoT systems

1.1.3 Computing

In general the sensors are designed to observe the continuous change from the environment. So the sensor based technique always needs a reasonable memory space for operation and processing capability for analysis. By the development of resource allocation on parallel processing improves the computational speed

1.1.4 AI Technique

Artificial Intelligence (AI) is a technique developed for doing several critical computations through neurological based operations. The AI based algorithms are employed to the sensor data for certain estimations and predictions. Weather and human health prediction are the widely employed applications based on AI techniques. As the AI approaches are using the neurological technique, it improves the performances of the outcome in an efficient manner.

1.1.5 Cloud Processing

Cloud processing enables the readings that are generated from the sensor unit to process in a remote place. The cloud system makes the IoT modules operate without a computer device for data processing and analysis. The cloud system receives the sensor generated output through an internet connection, that is employed with a mobile sim card module or Wi-Fi module connected with microcontroller. The cloud processing system are also available with a better GPU configuration value than the regular computer system and that improves the computational betterment. The cloud processing units are also readily available with a mobile application that allows the user to read and monitor the status of their connected system.

2. Related Work

A Recurrent-LSTIM and Bi-LSTM based technique was designed to estimate the continuous monitoring of human activity with classification. The work utilizes the information collected from the radar unit for the analysis. An experiment was performed with 15 person on predicting 6 various activities. The experimental outcome indicates an accuracy of 90% for training and 76% for the testing [6]. A human activity recognition method was performed using various CNN model and preprocessing approaches. The experimental work represents a better output of 85% accuracy on CNN with two convolutions and one dimensional filter [7]. A comparative analysis was performed between LSTM and CNN for human activity recognition model and the work utilizes the biometric data for the activity analysis. The work projects an accuracy of 92.4% for LSTM and 91.77% for CNN [8].

A deep neural network based CNN model was incorporated with gated recurrent unit for estimating human activity from the wearable sensors. The experiment was performed without a feature extraction phase and found maximum accuracy of 97.21% with WISDM dataset [9]. A recurrent neural network based on bidirectional LSTM was proposed to estimate the human activity at home with various sensors. The experimental result indicates an outcome of 95.42% in CASAS dataset [10]. A human activity recognition method based on smartphone sensor was performed using deep belief network with feature extraction based on kernel principal component analysis and linear discriminant analysis. The performance of the proposed model was also compare with SVM and ANN and found satisfied with accuracy of 95.85% [11].

The data extracted from the smartphone sensors are used to estimate the human activity extreme learning machine model. A Gaussian random projection was employed to weight the input data collected from the sensor for processing. The experimental work extracts an output of 98.88% [12]. Information extracted from surface EMG sensor and accelerometer was utilized to perform the human activity analysis. The technique also added with ad-hoc communication for transferrin the collected data. The work uses a KNN classifier and achieves accuracy of 85.7% [13]. A CNN based classifier with smaller Lego filter was trained with wearable sensors on each layer. The result indicates an accuracy rate of 98.82%

at WISDM dataset. The inference time of the proposed model was also comes around 100m seconds [14].

A human activity detection model was designed by analyzing the data extracted from the smartwatch sensors. A deep neural network was employed in the work with Bi-LSTM descriptor for feature analysis. The analysis indicates an accuracy attainment of 91% with reduced processing time [15]. A patient monitoring system was designed through human activity recognition technique using DNN algorithm. The DNN was structured with 3 layer CNN and LSTM. The experiment shows a better outcome of 94.52% over the SVM at 83.35% of accuracy [16]. An image based human activity recognition method was performed using multimodal feature fusion technique. The data are collected from RGB camera along with accelerometer and gyroscope sensors on 27 different human activities. The result indicates an accuracy of 98.3% when using KNN classifier where as it gave 96.3% with SVM model [17].

A deep belief network was structured to estimate the human activity with body sensor data. The raw data collected from the sensor are processed through kernel principal component and linear discriminant analysis before training it with the classifier. The experimental outcome indicates betterment over the SVM technique with 97.5% accuracy [18]. A multilayer bidirectional LSTM model was employed to detect the human activity and fall detection. The performance of the technique gives an accuracy of 96% with feature fusion [19]. A smartphone sensor based human activity recognition model was performed using mobile edge computing technique and deep learning algorithms. A CNN based classification approach was employed in the work with local feature analysis block. The experiment indicates betterment over the LSTM, MLP and SVM classifiers with 92.71% of accuracy [20].

3. Proposed Method

The motive of the proposed work is to sense the human activity on different actions from a remote location. The work architecture is shown in figure 3, where the sensor unit is implemented with accelerometers and gyroscope for recognizing the human activity and it is included with PIR sensor for recognizing the human presence in a room. The sensor unit is connected with an ATmega328P microcontroller for making an interface between the sensors and the IoT module. An ESP8266 wifi module is included in the work for transmitting the data collected from the sensor to Blynk server. Hence the microcontroller requires the corresponding Blynk libraries to be added before the interconnection begins.

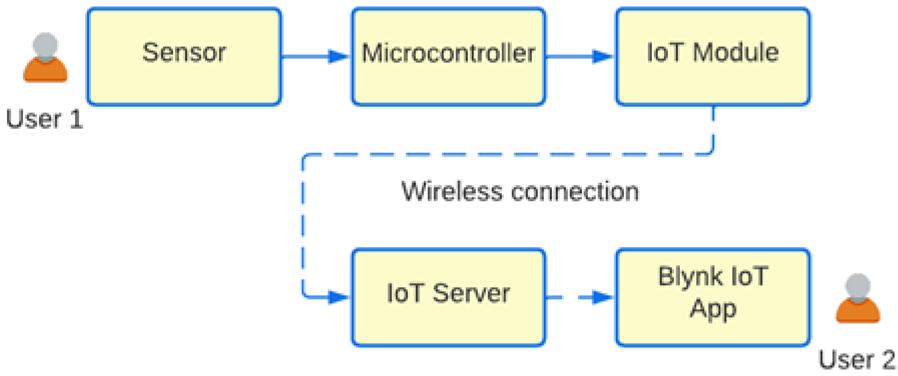

Figure 3. Architecture of the proposed work

The Blynk server allows the collected data to be stored in the server for temporary and permanent time and it makes the data to visible on different medium like chart or graph. In general, the Blynk application also has the ability to control or operate the connected unit with the respective hardware connection. In the proposed work the Blynk application is utilized for monitoring the human actions as a display unit. Hence the work allows the user 2 to read the response of user 1 on their actions.

4. Experimental Analysis

The work verifies the human action based on the change in value observed from the accelerometer and gyroscope sensors. The work calibrates the connected sensors and assigns a threshold value for observing the human actions. However, the proposed algorithm verifies the outcome of both the sensors and analyses them together to take the decisions.

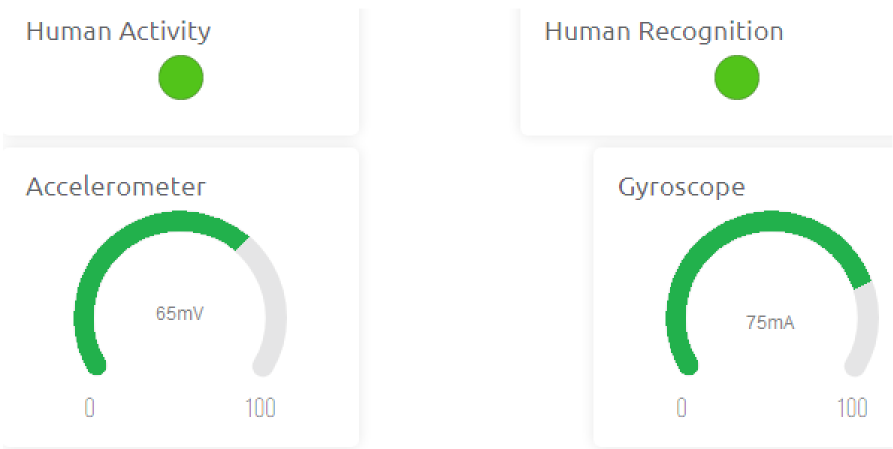

Figure 4. Output on human movement

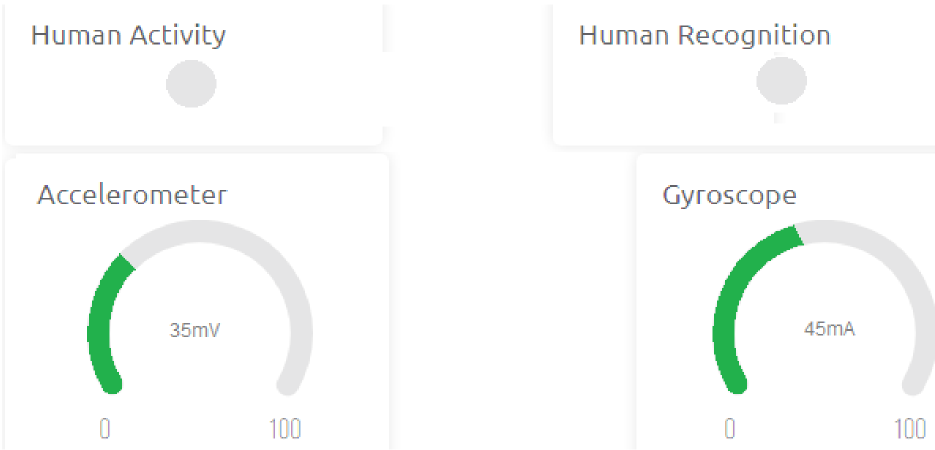

Figure 5. Output on NO movement

Figure 4 and 5 explores the outcome of human activity in Blynk application on different scenarios. The Blynk application is employed with a couple LED lights to project the output of the sensors. Similarly a couple of gauges are also included in the work to project the output of accelerometer and gyroscope sensors. The output on human movement is explored in figure 4 with the LEDs are in ‘ON’ position where the accelerometer and gyroscope readings are above 50mV and 50mA respectively.

At the same time Figure 5 indicates the LEDs in ‘OFF’ position when the readings are observed less than 50mV and 50mA on both the sensors. The human recognition LED is placed in the app to recognize the response of the human movement in a room with PIR sensor based on its digital outcome. It gives output high with 3V output when the sensor detects a human movement in its range. The range observation in PIR sensor can also be adjusted by varying the sensitivity and delay time knobs placed in the sensor unit.

5. Conclusion and Future Scope

Human activity is observed in the work with Blynk application. However, the work is not recognizing the type of action made by a human. The work can be extended by collecting the data from the sensors on different parameters for creating a dataset to train a neural network model. Therefore the work can recognize the human actions on different activity. The proposed work is equipped with a Blynk server and that can be also connected any kind of cloud server in adding the corresponding library over the microcontroller module. The performance of the proposed work is found satisfied, but there is delay in transmission is observed in the work due to communication delay of the server and internet.

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