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IOT Based Several Humanized Activities for Health Observation

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Abstract-The digitalizing world simplifies our everyday processes with the help of an exclusive technology of IoT. Our proposed work removes the need for allotting a separate slot for the observation of human activities by the automatic monitoring of daily activities and clinical variations of humans. An innovative Human Activity Recognition system, exploiting the potential of wearable devices integrated with the skills of deep learning techniques is presented with the aim of recognizing the most common daily activities of a person at home. It is basically a wearable device that easily identifies the variation of the parameter in the human body of elderly care and medical diagnosing people. The status of a person is regularly observed and can be monitored. The designed wearable sensor embeds with an Accelerometer, Gyroscope, and a Magnetometer which is conceived for daily activity monitor and a Wi-Fi section to send data on a cloud service. Through these nine different activities can be highlighted with great accuracy. Which helps to monitor the people at home from anywhere.

Keywords:- Gyroscope, wearable device, accelerometer, magnetometer, internet of things (IoT), machine learning, activity recognition.

I. INTRODUCTION

Human activity recognition has emerged as an active area of research over the past few years. It is an important and challenging field that can support many novel ubiquitous applications. These applications range from smart homes, just-in-time information systems for office workers, surveillance, and interactive game interfaces to home healthcare.

Activity recognition is a multi-disciplinary research area that shares a connection with machine learning, artificial intelligence, machine perception, ubiquitous computing, human-computer interaction, as well as psychology and sociology. Thus, it has been drawing increasing interest from researchers in a variety of fields.

The Internet of things (IoT) describes the network of physical objects that are embedded with sensors, software, and other technologies for the purpose of Connecting and exchanging data with other devices and systems over the internet. The aim of an activity recognition system is to recognize the actions or activities of its users by unobtrusively observing the behavior of people and characteristics of their environments and take necessary actions in response.

For example, by means of recognizing activities in real-time, such systems could allow the development of just-in-time learning environments that educate and inform people by presenting information at the right time as they move through the environment.

Knowing what a person is doing will help determine the best time to interrupt the occupant to present them with useful information or messages. Someone preparing dinner represents a good opportunity for a teaching system to show words in a foreign language related to cooking. In a home environment, activity recognition systems can monitor users' activities over long periods of time in order to remind them to perform forgotten activities or complete actions such as taking medicine, help them recall information, or encourage them to act more safely. In a hospital environment, such systems can remind a doctor or nurse to perform certain tests before operating.

In a surveillance system, a behavior model can be developed by means of recognized activities which can enable the system to predict the intent and motive of people as they interact with the environment.

Moreover, in a production environment, such systems can ensure the quality of the product by monitoring the set of actions. Finally, these systems can also play a vital role in encouraging a healthy lifestyle among their users by suggesting small behavior modifications. For example, people can be encouraged to use stairs instead of an elevator or stand after a long period of sitting.

However, all these functions of sensing the environments, learning from past experience, and applying knowledge for inference are still great challenges for machines. Therefore, the goal of activity recognition research is to enable computers to have similar capabilities as humans for recognizing people's activities.

II. RELATED WORKS

The first step towards achieving the goal of recognizing activities of daily living is to equip activity recognition systems with sensing capabilities. Three approaches have been mainly employed for this purpose: video-based, environmental sensor-based, and wearable sensor-based.

1. Video-Based Systems:
These systems employ video cameras for tracking and physical activity recognition. This approach often works fine in a laboratory but fails in achieving the same accuracy under a real home setting due to clutter, variable lighting, and highly varied activities that take place in natural environments.

The complexity of dealing with changes in the scene, such as lighting, multiple people, and clutter offers additional challenges. Moreover, sensors such as microphones and cameras are mostly expensive. Finally, since these devices commonly serve as recording devices, they can also be perceived as a threat to privacy by some people.

2. Environmental Sensor-Based Systems:
Such systems are developed to monitor the interaction between users and their home environment. This goal is achieved by distributing a number of ambient sensors, especially binary on-off state sensors, throughout the subject's living environment.

The data gathered by these environmental sensors can be used to intelligently adapt the environment in the home for its inhabitants. Environmental sensor-based systems passively monitor their occupants all day, every day, thus requiring no action on the part of the user to operate.

A large number of parameters can be monitored in such systems, by employing a variety of sensors and the processing capabilities of a local PC. Ambient sensors, placed throughout the house, have fewer restrictions (size, weight, and power) than other types of sensors thus simplifying the overall system design. However, such systems are infrastructure-dependent and cannot monitor a subject outside of the home setting. Also, they exhibit difficulties distinguishing between the monitored subject and other people in the home.

3. Wearable Sensor-Based Systems:
Such systems are designed to be worn during normal daily activity to continually measure biomechanical and physiological data regardless of subject location and thus are an appropriate alternative for the recognition of daily human activities, especially bodily or physical activities.

Bodily activities require repetitive motion of the human body and are constrained, to a large extent, by the structure of the body. Examples are walking, running, scrubbing, and exercising. Wearable sensors are well suited to collecting data on daily physical activity patterns over an extended period of time as they can be integrated into clothing, jewellery, or worn as wearable devices.

Since they are attached to the subjects they are monitoring and are independent of the infrastructure, wearable sensors can therefore measure physiological parameters which may not be measurable using environmental or video sensors.

Moreover, such sensors are low-priced and unlike video sensors, they have not considered a threat to people's privacy.

A range of body-attached sensors including electromechanical switches, goniometers, accelero - meters, gyroscopes, pedometers, and lactometers, have been used to capture and analyze human movement in free-living subjects of these, accelerometers are becoming widely accepted as a useful tool for the assessment of human motion in clinical settings and free-living environments.

Accelerometers offer a number of advantages in the monitoring of human movement. Their response to both frequency and intensity of movement makes them superior to lactometers or pedometers, which are attenuated by impact or tilt. Some types of accelerometers can measure both tilt and body movement, and thus are superior to motion sensors that are incapable of measuring static characteristics.

III. PROPOSED SYSTEM

During the training phase the data, collected by the wearable sensor, are sent to the cloud, while in daily use they can be elaborated on board or sent to another device for further processing. For prototypal purposes, the data are elaborated offline and used to create the datasets exploited to design the neural network is proposed.

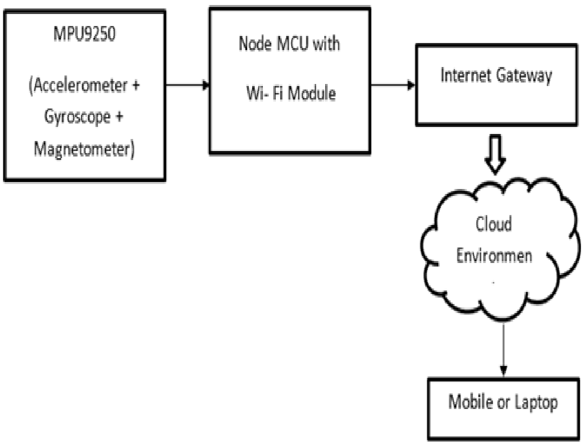

Fig 1. Block Diagram.

The MPU9250 module is used to collect human activities like walking, standing, sitting down, stay seated, standing up, lie down from the accelerometer, gyroscope, and magnetometer readings.

The Node MCU module will collect all the data from MPU9280 and update the values in the Thing speak cloud at every 20sec. This data is further processed and human activity is found. The ESP8266 is the name of a microcontroller designed by Espressif Systems.

The ESP8266 itself is a self-contained WiFi networking solution offering as a bridge from the existing microcontroller to WiFi and is also capable of running self-contained applications. This module comes with a built-in USB connector and a rich assortment of pin-outs.

With a micro-USB cable, you can connect Node MCU devkit to your laptop and flash it without any trouble, just like Arduino. It is also immediately breadboard-friendly. Node MCU is an open-source Lua-based firmware developed for the ESP8266 WiFi chip.

By exploring functionality with the ESP8266 chip, Node MCU firmware comes with ESP8266 Development board/kit Since Node MCU is an open-source platform, their hardware design is open for edit/modify/build. Node MCU Dev Kit/board consist of ESP8266 WiFi-enabled chip. The ESP8266 is a low-cost Wi-Fi chip developed by Espressif Systems with TCP/IP protocol. i.e Node MCU Development board.

A wearable activity recognition system can improve the quality of life in many critical areas, such as ambulatory monitoring, home-based rehabilitation, and fall detection. The human activity can be measured by using an accelerometer sensor, gyro sensor, and magnetometer sensor. These three sensors are used to get the accurate activity of a person when we using together. All three can be found in a single unit in the MPU9250 Sensor module. MPU9250 is one of the most advanced combined Accelerometer, Gyroscope, and Compass small size sensors currently available.

They have many advanced features, including low pass filtering, motion detection, and even a programmable specialized processor.

Having nearly 130 registers, however, with many settings, they are also very difficult to work with from code. MPU-9250 is a multi-chip module consisting of two dies integrated into a single QFN package. One die houses the 3-Axis gyroscope and the 3-Axis accelerometer.

The other die houses the AK8963 3-Axis magnetometer from Asahi Kasei Micro devices Corporation.

Hence, the MPU-9250 is a 9-axis Motion Tracking device that combines a 3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer, and a Digital Motion Processor (DMP) all in a small 3x3x1mm package available as a pin-compatible upgrade from the MPU-6515. With its dedicated I2 C sensor bus, the MPU-9250 directly provides complete 9-axis Motion Fusion output.

The MPU-9250 Motion Tracking device, with its 9-axis integration, on-chip Motion Fusion, and run-time calibration firmware, enables manufacturers to eliminate the costly and complex selection, qualification, and system-level integration of discrete devices, guaranteeing optimal motion performance for consumers.

MPU-9250 is also designed to interface with multiple non-inertial digital sensors, such as pressure sensors, on its auxiliary I2 C port. MPU-9250 features three 16-bit Analog-to-digital converters (ADCs) for digitizing the gyroscope outputs, three 16-bit ADCs for digitizing the accelerometer outputs, and three 16-bit ADCs for digitizing the magnetometer outputs.

For precision tracking of both fast and slow motions, the parts feature a user-programmable gyroscope full-scale range of ±250, ±500, ±1000, and ±2000°/sec (DPS), a user-programmable accelerometer full-scale range of ±2g, ±4g, ±8g, and ±16g, and a magnetometer full-scale range of ±4800µT. An Internet gateway is a network “node” that connects two different networks that use different protocols (rules) for communicating.

In the most basic terms, an Internet gateway is where data stops on its way to or from other networks. Thanks to gateways, we can communicate and send data back and forth with each other. Gateways can take several different forms from hardware to software - including routers and computers - and can perform a variety of tasks.

These can range from passing traffic to the next 'hop' on its path to filtering traffic, proxies, or protocol translations. Because gateways are, by definition, at the edge of a network, they are often combined with firewalls, which keep out unwanted traffic or 'foreign' computers from a closed network.

For Internet connections at home, the Internet gateway is usually the Internet Service Provider (ISP), who, in this case, offers access to the entire Internet through its network. If you have a Wi-Fi connection at home, your Internet gateway is the modem or modem/router combination that your ISP provides so that you connect to the Internet through their network.

All the collected sensor data will be gathered in Cloud Environment. The received useful sensor data is collected every 15 secs. From that data we can find human activities like walking, standing, sitting down, stay seated, standing up, lie down, etc. In this work, we using Thing Speak Open-source cloud for collecting and analyzing the activities.

1. Activity Classification:

The advent of deep learning has widely modified the approaches in signal processing and features extraction fields. In the past years, the features extraction was performed by manual analysis of the signals in its components, to create domain-specific features. Statistical and classical machine learning models were then trained on the processed version of the data.

A limitation of these approaches is that signal processing and domain expertise are required to analyze the raw data and collect the features to fit a model and this expertise would be required for each new dataset or sensor.

Another important limit of a classic machine learning approach in activities classification is the difficulties in being able to generalize the models against the variety of movements performed by different subjects. A Neural Network-based classification and the feature extraction method used and the activities are classified.

IV. EXPERIMENTAL RESULTS

Human Activity Recognition is an important technology in widespread computing because it can be applied to many real-life, human-centric problems, such as eldercare and healthcare. Activity recognition aims to recognize common human activities in real-life settings.

Accurate activity recognition is challenging because human activity is difficult and highly diverse. Several probabilities-based algorithms have been used to build activity. HAR has been approached in two different ways, namely using external and wearable sensors. In the former, the devices are axed in predetermined points of interest, so the inference of activities entirely depends on the voluntary interaction of the users with the sensors.

In the latter, these devices are attached to the user. The entire hardware is implemented and uploaded the accelerometer, gyroscope, and magnetometer values are updated in the cloud platform. The values are continuously monitored and the dataset is created.

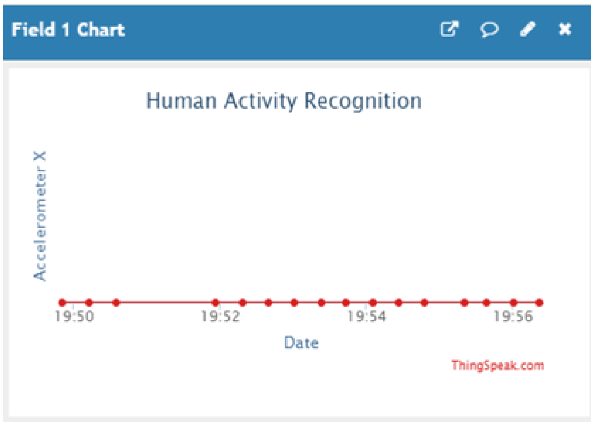

Fig 2. Accelerometer X.

The X coordinate of the accelerometer, which is used to measure the position and acceleration of the device. The coordinate represents the direction and position of the device at which acceleration occurred. It measures the acceleration of gravity in tilt-sensing applications.

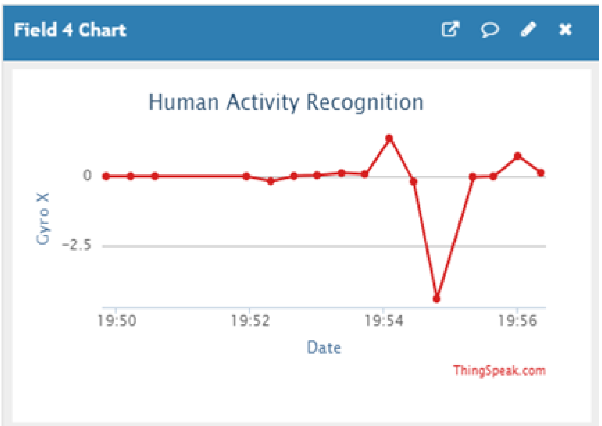

Fig 3. Gyroscope X.

These coordinate that measure or maintain rotational motion. A triple-axis MEMS gyroscope can measure rotation around three axes: X, Y, and Z. Thus it measures the angular velocity around a spatial axis.

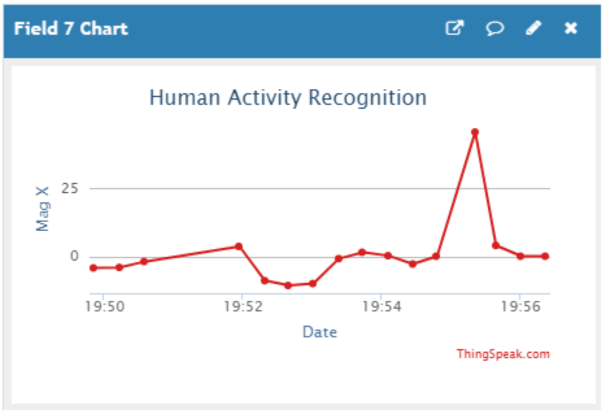

Fig 4. Magnetometer X.

The magnetometer block reads the strength of the magnetic field. The magnetometer sensor measures the magnetic field along the axes. The block outputs the magnetic field as a 1-by-3 vector in micro-tesla. The uploaded data downloaded from the Thing Speak cloud and the data set is used to test the person's activity. The features like Walking, Running, Standing, walking, upstairs, and walking downstairs are extracted through the MATLAB analysis.

V. CONCLUSION

In this work, an innovative IoT system for long-term personalized monitoring of the activities performed by a person at home is proposed. The system integrates a Wi-Fi wearable sensor and feature extraction techniques to give information on a number of activities with the aim to infer abnormal behaviours.

The approach presented has been conceived to be extended to systems requiring multiple wearable sensors giving information in a personalized manner. The activity classification has been performed with a relatively small training set.

This result is interesting because it shows the possibility to implement, quite easily, different HAR systems calibrated on different classes of problems for age groups of people. The presented system architecture exploits on board Wi-Fi connectivity and cloud computing to ensure a constant update of the network with new training sets when users are

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added. To this purpose, every data sample acquired by the sensor is transferred to the cloud.

The system architecture designed opens the door to an alternative approach that could take advantage of the use of FPGA technologies for the implementation of complex signal processing systems to produce tiny, wearable, and autonomous embedded HAR systems. Measurement of activities can be maximized (other than the nine). Using advanced systems results in the reduction of cost. Encoders used can be of more resolution and precision so that they can be used to make the system more precise.

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