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Human Safety Devices using IoT and Machine Learning: A Review

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Abstract—**Human safety has become one of the most targeted field for the researchers, owning it to its grave importance and the increased competition in the market for human safety gadgets. Hundreds and thousands of human safety devices (HSD) are being developed because of the rapid advancement in the field of Internet of things (IoT) that involve sensing technologies, embedded systems, wireless communication technologies, variety of sensors etc. An essential function of these devices is human activity recognition (HAR).Present human safety devices continuously track human activities with the help of sensors and track down any unusual activity by performing sensor data analysis (SDA)using machine learning (ML) algorithms. This paper aims at reviewing the latest reported systems for human safety and listing down the various sensors that can be used in human safety devices to detect unusual activities along with the machine learning algorithms that are used for the sensor data analysis.**

Keywords—human activity recognition; human safety devices; IoT; machine learning; sensors; sensor data analysis

I. Introduction

When it comes to utilizing the latest technological advancements in the field of safety, nothing is as important as safeguarding the human lives. Given the unpredictable nature of today's world where threat to human lives can take any form, it is very important to make significant improvements in the devices or gadgets that we deploy for protecting ourselves. Human safety devices (HSD) have come a long way and are yet to see many advancements due to the multifaceted nature of the problem these devices are aiming to solve. Some of the problems that pose a threat to human safety on a daily basis and are required to be protected against are the attack caused by a third person with bad intention, health issues arising either due to the pollution in our surrounding or from our own lack of attention, road accidents or any kind of mishappening in general.

A significant amount of research is undergoing in improvising these safety devices to make the devices more promising, reliable and advanced. One of the most important part of developing these human safety devices is identifying the human activity. Human activity recognition (HAR) refers to the process of identifying the activities performed by a person with the help of devices such as sensors, camera, etc., which are responsible for capturing the human motion in order to interpret the activity being performed [1]. HAR is being used extensively in care giving business to improve the quality of life for elder people and to improve the care giving process by automatic fall detection and prevention system [2] – [4].

One of the most widely used technology for HAR is wearable sensor technology. Wearable sensors have solved a lot of challenges in this field of activity recognition as there is a plethora of sensors available, all in different shape and sizes, to suit the needs of the researchers as well as designers of HSD. Sensors are being used to develop more comfortable and easy to carry devices for smart ward systems [5]. Sensors like accelerometers are most widely used for activity recognition [6]. Localization sensors such as radio frequency identification (RFID), ultrasound sensor, ultra wideband (UWB) sensors, etc., are being used to offer better assisted living lifestyle [7]. All devices around us today are becoming more and more multifunctional for example our smart phones which, because of the different types of sensors available in them, have become smart enough to provide a wide range of functionality right from detecting human motion [2] to detecting even earthquakes [8] with proper arrangements.

But collecting data using sensors is not enough to interpret human actions as some kind of analysis must be performed on the data being collected. In modern day HSD, this facility of sensor data analysis (SDA) is provided by machine learning (ML) and that too with great accuracy and reliability. Due to the immense popularity of artificial intelligence in various fields such as human-computer interaction, computer vision, healthcare, virtual reality, video games, object identification, weight estimation [9], etc., it has now become one of the most popular techniques amongst the researchers to perform SDA. The ML algorithms such as support vector machine (SVM), K-means clustering, random forest, hidden markov model (HMM) ,etc., are being used extensively for the task of SDA due to their effectiveness in mitigating the sensor data variability and noise due to deployment-specific environmental conditions [10].However compact, convenient or intelligent we may have made our safety devices for use, HAR still remains a complex and challenging task due to unresolvable challenges such as sensor motion, cluttered background, sensor placement, and inherent variability in the way activities are

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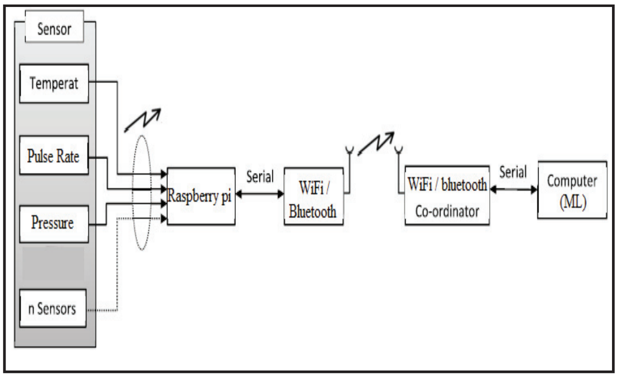

Fig. 1. General architecture of a human activity recognition system for a human safety device [12].

conducted by different individuals [11]. This review aims at the usage of the various types of sensing devices being used in the HSD and how these sensors data are being analyzed using ML.

The paper consolidates the information gathered from eight research papers dated from 2009 to 2017 in tabular format by listing down the various sensors being used to capture the human motion and also the ML algorithms which are being used for SDA.

The rest of this paper is organized as follows: in Section II the general architecture of HAR system which forms the core of the HSD is given; in Section III a formal introduction to sensors and machine learning is provided; in section IV the search and analysis of the literature is given; Section V presents the conclusion drawn from this study.

II. ARCHITECTURE OF THE HUMAN ACTIVITY RECOGNITION SYSTEM

The general architecture of a HAR system for human safety devices is represented with the help of a block diagram [12] in fig. 1. First block represents the sensors which are responsible for tracking the human activity. Sensors such as accelerometer, temperature sensor, heat sensor, pulse rate sensor, pressure sensor, etc., can be used depending upon the task of monitoring. The reading of the sensor(s) are then passed to a processing unit which consist of either a microcontroller or a single-board computer like raspberry pi.

The devices with simple microcontrollers are used by people for normal activities such as jogging, running or any other activity which do notinvolve processing the collected sensor data and only requires the user to look at the display to notice the measured value by the sensor.

For more complex tasks such as remote health monitoring or devices used for security purpose, the sensor data analysis is performed. The ML algorithms such as support vector machine (SVM), K-means clustering, random forest, hidden markov model (HMM), etc., are used extensively for the task of SDA. The collected data is passed to the processor with the help of either Bluetooth or Wi-Fi on the single board computer and is shared with the computer performing the analysis. In the end the results of the analysis are shown either with the help of graphs or some text. The single-board computers like raspberry pi are also capable of performing the sensor data analysis but for basic taskswhich do not involve much analysis due to their memory space and processing power constraints.

III. SENSORS AND MACHINE LEARNING

A sensor is a device or a subsystem which serves the purpose of detecting events or changes in its environment and then sending this information to a computer or some other monitoring unit. These are used to detect something as simple as light to something as complicated as brain signals of humans. Due to the advances in sensor technology and easy-to-use microcontroller platforms, the uses of sensors have expanded beyond the traditional fields of temperature, pressure or flow measurement and have led to the development of smart wearable devices that are becoming more intelligent and a necessary part of our daily life. Security, military, gaming, virtual reality, and communications etc., are the application areas of these wearable networks. The major contribution of these body worn sensors is in the field of medical where wearable units are mainly used for continuous and remote patient monitoring. Machine learning, on the other hand, is an application of artificial intelligence (AI) that provides systems the ability to exhibit human intelligence without being explicitly programmed. ML focuses on the development of computer programs that can access data and use it to learn for themselves. The process of learning involves data such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that are provided [13]. The primary aim is to allow the computers learn automatically without human intervention and adjust actions accordingly. Some of the most popularly used algorithms of ML fall in the categories of supervised algorithms, unsupervised algorithms, semi-supervised algorithms, and reinforcement algorithms. Some of the fields of application of ML are driverless vehicles, spotting spam mails, anomaly detection in critical systems, assistance in medical technology, sensor data analysis, etc. The application of ML in sensor data analysis have given the wearable devices their much needed intelligence. ML have made these devices more personal to the users due to the analysis performed on the sensor data which helps in getting better insights about the person wearing these devices.

IV. LITERATURE SURVEY

Michael et al. [14]explored a dense sensing approach which made use of radio frequency identification (RFID) sensor network technology to recognize human activities in a closed environment. Their activity detection system was overall divided into three main sub-systems namely the wireless identification and sensing platform (WISP), RFID sensor network (RSN) and the inference engine consisting of a hidden markov model (HMM). The WISP was placed on the various objects in the areas divided in the setup apartment such as on the mug, sugar jar or glass in the counter area or on the plate, butter or cereal in the kitchen table area etc. This WISP model included 3D accelerometer sensor, temperature sensor as well as a 32K flash program space and 8k serial flash. WISP was responsible for transmitting unique identifiers along with their most recent accelerometer readings which were collected by the RFID readers placed on the ceiling of the apartment. This RSN acted as a data source for the inference engine and based on the data the movement of various objects in the apartment led to the detection of various human activities. Their results showed a precision rate of 90% and a recall rate of 91% as compared to a precision rate of 95% and a recall rate of 60% when using an ibracelet instead of the RSN.

Sohini et al [15] took internet of things (IoT) and ML to the level where these technologies are used to ensure human safety. They came up with the design of a human safety band consisting of multiple sensors such as breath rate sensor, heart rate sensor, glucometer, sweat sensor, and optical blood flow sensor. These sensors were made responsible for collecting the respective readings and sending them to the mobile application (app) created by them. This mobile app is responsible to further take suitable action depending upon the readings of the sensor(s) which are being compared to the previously stored values in order to see if the new readings have crossed a certain threshold or if they are normal. In case the readings are normal the system continues to work normally; however, if the values are greater than the predefined threshold, immediate actions are taken such as informing friends and family members, informing the nearest police station or even the nearby hospitals. The emergency steps are taken on the basis of the decision taken by a decision tree algorithm running at the back of the app.

Daniel et al [16] went totally experimental by making use of the Microsoft Kinect one depth sensor for the identification of human mobility impairments which is generally used for video game purpose. Their framework involved a two-step process: First step was capturing the movements of a healthy person (without mobility issues) using the Kinect one sensor and then, Second step was comparing and evaluating the test participants motion sequence with the statistical mobility model generated from the data of a healthy person (using Kinect). They also proposed an automatic method to enable a fairer, unbiased approach to label the motion capture data. They proved, through their results, that their study is of great use for the analysis and quantification of human motion in order to support the clinicians and that their study can really help in the decision making process of the clinicians, whose observations are prone to human intervention and bias. Their framework was able to successfully identify the mobility concerns of a person with the mobility issues and this framework was also free from any human intervention or bias in the process of decision making.

Lee et al [17] suggested a unique approach for minimizing the road accident problems by analyzing the negative emotional response of a person while driving. They considered the negative emotional response to be one of the major indicators of the likelihood of an accident while driving a vehicle. These responses were divided into three categories namely fatigue, stress and relaxation. Fatigue included responses such as drowsy/bored. Stress included anxiety, panic, or anger and relaxation included neutral responses. They considered Stress and relaxation as negative emotional responses. These emotional responses were captured using three sensors i.e. Electromyography (EMG) sensor, Photoplethysmography (PPG) sensor and an inertial sensor. Working of all these sensors and their placement is described briefly in table 1. These sensors are connected to a microcontroller unit equipped with Bluetooth-enabled low energy module, which transmits the collected senor readings to a mobile phone which then extract the information from the sensors and determine driver's current emotion using trained SVM.

Zhi-xiao et al [18] prepared a system using IoT technology for indoor environment monitoring and control. Their system consists of multiple sensors such as temperature sensor, humidity sensor, combustible gas sensor, CO2 sensor and infra-red sensor. All these sensors are used for data acquisition and are responsible for monitoring the indoor environment parameters as well as passing these values to the controller raspberry pi. WeChat is made available to the user for checking the information of the indoor environment using an auto generated registration number by WeChat. The system works with the help of messages exchanged between the user through WeChat and the server. After completion of verification, the message request arrives at raspberry pi controller which process the data of the sensors and returns the result to the user. Not only does this smart indoor environment monitoring system displays the important data but it also facilitates the user by providing the control to turn on or off various equipment.

Tariq et al [10] wanted to test the performance of various ML classifiers offered by the ML tool WEKA for the purpose of indoor human localization. They made use of capacitive sensors for indoor human localization in a 3mx3m room to compare and analyze the performance of the various classifiers available in WEKA. The capacitor sensors were placed on the four walls of the room in order to detect the human motion. The sensors were used in load mode by connecting the sensor to one plate of the capacitor while the other plate was made of the environment and the human body to detect the change in the position of the person. After gathering the data, the data analysis was performed by using the WEKA tool which has a collection of ML classifiers such as SVM, Random Forest, Logit Boost and Bayes Net. The data gathered was intentionally left with a lot of noise in order to see how well does the WEKA set of classifiers perform even on the data with a lot of noise. Their results showed that Random Forest algorithm outperforms all the other WEKA classifiers in the task of detecting the position of the person in the room even by using the data with a lot of noise.

Anice et al [19] has stressed upon the importance of safety of elderly people living alone at home which are at a higher

TABLE I

RELEVANT CHARACTERISTICS OF SELECTED STUDIES.

Sr.No.	Paper Title	Sensor(s) used	Purpose of sensor(s)	Area covered by sensor(s)	µp/µc	Algorithm	Subjects Age	Subjects No.
1.	Recognizing daily activities with RFID-based sensors [14]	3D accelerometer (WISP module)	Calculates the angle at which the device is tilted w.r.t earth	Ceiling area of the a closed studio apartment	NM	Hidden Markov Model (HMM)	NM	10
		Temperature sensor (WISP module)	Calculates temperature of the various objects it is placed on					
		Gen2 RFID reader	Provides power to the WISP module & query it for sensor data	Placed on various objects in the apartment				
2.	MoveFree: A ubiquitous system to provide women safety [15]	Breath rate sensor	Measures the respiration rate of the person by observing changes in the Photoplethysmogram (pleth waveform)	Wrist of the person wearing the band with all the sensors	NM	Decision tree algorithm	NA	NA
		Heart rate sensor	Measures the heart rate by sensing the pulse of the person					
		Glucometer	Measures the glucose level in the blood of the person					
		Sweat sensor	Sense the sweat from on the persons skin					
		Optical blood flow sensor	It is a small chip integrating a laser diode, photodiode, and an optical waveguide used for checking the increased blood flow					
3.	Automated analysis and quantification of human mobility using a depth sensor [16]	Microsoft Kinect one-depth sensor	Captures human body motion and calculates the body lean angle which is the intersection between the ground plane and spine of the person	Entire human body	NM	K-means Clustering : for identification of optimum number of clusters SVM: for classification	NM	NM
4.	Wearable mobile-based emotional response-monitoring system for drivers [17]	Photoplethysmograp -hy(PPG) sensor	Measures pulse wave by measuring time of cardiac intervals or blood oxygenation	Earlobe of a person	AdaFruit Flora	SVM		10
		Electromyography (EMG) sensor	Measures muscle response or electrical activity in response to a nerve's stimulation of the muscle	Upper trapezius muscle of a person				
		Inertial motion sensor	Measures the orientation of the head during different emotional response states	Back of the head				

*Abbreviations:

WISP: wireless identification and sensing platform

Sr.No: Serial number

NM: Not mentioned

NA: Not applicable

w.r.t: with respect to

µp/µc: microprocessor/microcontroller

Sr.No.	Paper title	Sensor(s) used	Purpose of sensor(s)	Area covered by sensor(s)	µp/µc	Algorithm	Subjects	
							Age	No.
5.	EMACS: Design and implementation of indoor environment monitoring and control system [18]	Temperature sensor	Senses the temperature of the room	Indoor environment	Raspberry pi III	NA	NA	NA
		Humidity sensor	Senses the moisture in the room					
		Combustible gas sensor	Senses the gas leakage in the room					
		CO_2 sensor	Nondispersive infrared sensor used for measuring CO_2in the environment					
		Infrared sensor	Used for motion detection					
6.	Performance of machine learning classifiers for indoor person localization with capacitive sensors [10]	Capacitive sensors	Used to acquire the data about the persons position in the room	Walls of a 3mx3m room	Arduino Uno	SVM, Random Forest, Logit Boost, Bayes Net	NM	NM
7.	Accurate fall detection using 3-axis accelerometer sensor and MLF algorithm [19]	3-axis accelerometer sensor	Senses the change in the position of the human body	Sensor is present on a Samsung Galaxy S3 phone	NM	PCA: for dimensionality reduction Multi-level fuzzy min-max (MLF) neural network: for detecting falls	22-36	11
8.	Gesture recognition with wearable 9-axis sensors [20]	9-axis motion sensor	Consists of gyroscope, accelerometer, and magnetometer sensor Accelerometer: accelerometer measures linear acceleration of movement (directional movement of the device) [21] Gyroscope: adds an additional dimension to the information supplied by the accelerometer by tracking rotation or twist. Magnetometer: in addition to general rotational information, the magnetometer detects the relative orientation of the device relative to the Earth's magnetic north.	left wrist (in the direction of the veins)	NM	PCA: for dimensionality reduction LDA: for feature extraction SVM: for classification	NM	32

risk of severe damage, due to poor system for notifying caregivers and providing care at healthcare centers.They have identified this issue as a fall detection problem and have used a 3 axis accelerometer sensor on a Samsung Galaxy S3 phone to capture activities that are classified into two categories: falls and daily living activities. Falls include activities such as lying, front knee lying, sideward lying and back sitting chair. Daily living activities include standing, walking, jogging, moving down stairs, sitting on chair, and stepping in/out of a car. After collecting the sensor readings dimensionality reduction using Principal Component Analysis (PCA) is performed on the data to keep few but meaningful features which can represent the original data effectively. After this, they have used a hybrid neuro-fuzzy algorithm (MLF) which combines the benefits of both fuzzy logic and neural network to achieve higher accuracy in fall detection. They successfully detected the fall activities with a sensitivity value of 97.29% and specificity value of 98.70% on a public dataset.

Liu et al [20] focused on hand gesture recognition problems and recorded signals of eight kinds of hand movements i.e. up, down, left, right, clockwise circle, counterclockwise circle, turn left, and turn right with the help of a nine-axis motion sensor consisting of accelerometer, gyroscope and a magnetometer. The data of nine axis was recorded but the data of only accelerometer and gyroscope as kept for further processing as data received from magnetometer is irregular due to the noise. Further they performed dimension reduction on the data using PCA and after that, feature extraction was carried out using Linear Discriminant Analysis (LDA). Lastly SVM was applied for classifying the different hand movements.

Table 1 summarizes the relevant characteristics of the selected studies. It lists down the sensors used in various studies along with their purpose and placement as well as the algorithms which are used for the SDA. It also mentions the micro-processor/controllerused in these studies and the number of subjects on which the study is performed as well as their ages. From our observation, most of the devices or applications developed for the purpose of human safety, which also involve HAR, make use of the accelerometer sensor more often as compared to other sensors. The reason for the popularity of accelerometer sensors is that even the most basic human activity recognition task involves studying and understanding the motion of the human body, which is the fundamental and single most important property of accelerometer as it is used to measure the direction of the movement of the device or person it is placed on. The most commonly used algorithm for analyzing the sensor data is SVM as it has always provided the best accuracy as compared to the other algorithms when it comes to the task of classification.

V. Conclusion

In this paper, we have provided a review of the human safety devices that have human activity recognition at the center of them. HAR is the core of any safety device designed for humans as our activities tell a lot about our well-being. The human activity recognition has become a single solution to many problems from different domains such as remote/e-healthcare, human security, virtual reality, video games, road safety, etc., to name a few. Where IoT has opened up a world of immense possibilities for many fields including human activity recognition, ML has provided the long awaited intelligence to these devices. Together, these technologies have boosted the development of more light-weight, high-performance and comfortable wearable devices which are suitable to take on even the biggest challenges in the field of human safety and human activity recognition. In future we will see most of the devices interacting with each other, taking decisions on their own without requiring human intervention in order to serve better and change the world of wearable devices as we see it now.

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