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Wearables and the Internet of Things (IoT), Applications, Opportunities, and Challenges: A Survey

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ABSTRACT Smart wearables collect and analyze data, and in some scenarios make a smart decision and provide a response to the user and are finding more and more applications in our daily life. In this paper, we comprehensively survey the most recent and important research works conducted in the area of wearable Internet of Things (IoT) and classify the wearables into four major clusters: (i) health, (ii) sports and daily activity, (iii) tracking and localization, and (iv) safety. The fundamental differences of the algorithms associated within each cluster are grouped and analyzed and the research challenges and open issues in each cluster are discussed. This survey reveals that although Cellular IoT (CIoT) has many advantages and can bring enormous applications to IoT wearables, it has been rarely studied by the researchers. This article also addresses the opportunities and challenges related to implementing CIoT-enabled wearables.

INDEX TERMS Smart wearables, Internet of Things, cellular IoT.

I. INTRODUCTION

IoT-enabled wearables are smart devices that can be worn as external accessories, embedded in clothing and garments, implanted in the body, or even adhered to or tattooed on the skin. These devices are able to connect to the Internet in order to collect, send data and receive the information that can be used for smart decision making. These wearables are becoming an increasingly important part of IoT technology and their development is moving from being simple accessories to more specialized and practical applications. Smart wearables can interact with an array of other devices, such as smartphones, for the purpose of computing and communication.

Due to mobility of the human and animals, smart wearable devices are becoming increasingly important since they can collect and send the data on the move and accordingly receive information from the Internet which helps in making smarter decisions. The use of smart wearables can bring efficiency and optimization to the applications, enhance the quality of life, and increase productivity or safety.

The advancements in low power mobile networks, decrease in the size of electronic devices and sensors, as well as the advantages that the smart wearables can provide have enabled the development of wearable technology in a fast pace. We have witnessed a rapid development of smart wearable products adapted for various applications during the past few years. Smart watches, wrist bands, eye wears, headsets, ear-buds, body straps, foot and hand worn devices, and smart jewelries are some of the wearables that have been developed for different applications (Figure 1).

Fitness activity trackers were the first big wave of wearable devices in the market followed by Bluetooth headsets, smartwatches, and web-enabled glasses. The gaming industry added more wearables, with virtual reality and augmented reality headsets. However, the important life-altering applications in wearable technology is found mostly in health monitoring and medical use cases.

There exist several other works that have looked into different aspects of wearable technologies. For example, [1] provides a survey of available products in the market as

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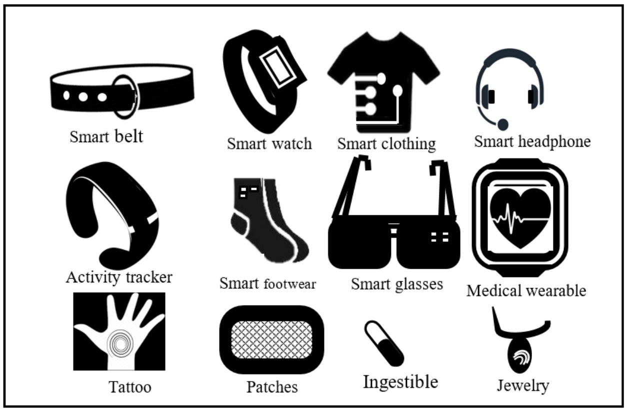

FIGURE 1. Different wearables developed for various applications.

well as the research prototypes. The authors in [2] surveyed all the existing electronic components used in the design of garments used in wearable devices. The article in [3] presents a survey of the sensors used in wearable devices. However, to the best of our knowledge, this paper is the first survey about the IoT-enabled wearables applications, opportunities and challenges where we focus on various clusters of smart wearables and classify the existing applications of these devices by addressing the fundamental differences of the algorithms associated within a specific application in each cluster. We also study the applications, opportunities and challenges of cellular IoT in more details as the authors believe that cellular IoT can be a game changer in the area of IoT-based wearable technology.

Since wearable IoT devices are battery operated, power consumption is considered as an important design factor. However, this does not mean that a wearable device cannot perform complex processing or it is limited in the amount of data that transmits due to extensive amount of power that in these situations will be consumed. In general, if the wearable IoT device performs a large amount of processing or transmits large amount of data, then its battery needs to be charged more frequently. This is quite possible in many applications and use cases. For instance, in a situation that the wearable IoT device is used to detect fall, the device might be worn during the time that the wearer is not asleep and can be charged during his/her sleep time. By the same token, the wearable IoT devices that are used during a sport activity, can drain the battery during the length of the activity which is usually a few hours and can easily get charged afterwards. It is clear that if a wearable IoT device is used to find the trajectory of a bird within a year, we not only need to limit the amount of processing and data transmission, but also try to find energy harvesting methods to increase the duration of battery life cycle.

Wearable IoT technology can bring endless opportunities for many applications. However, the true power of wearable IoT will be realized when there will be an integrated IoT system available. For this reason, most of the existing research papers connect to the Internet in one of the following two forms. First, the wearable IoT sends its data to the cloud or a server on the Internet to be saved for offline processing in future. The second form is to offload some of the computing from the wearable device. In this form, the wearable IoT device sends its data to the Internet for online processing and consequently the IoT device will receive some information that helps the IoT device to operate. The prevalence of wearable IoT can be fully recognized when we have integrated IoT platforms and when many issues regarding data ownership, policies on sharing data, privacy and safety issues are resolved.

The majority of the research works in the area of wearable IoT use unlicensed short range communication technologies such as WiFi and Bluetooth mainly to monitor the user's health, activity, location and ensure his or her safety. However, the application of such solutions is limited to the use of a gateway or mobile device to connect to the Internet. By the emergence of cellular IoT technologies (e.g., LTE-M and NB-IoT) introduced in 3rd Generation Partnership Project (3GPP) Release 13, new methods and applications are expected to be proposed for wearable IoT devices. In this paper, we reviewed the opportunities and challenges associated with cellular IoT-based wearables.

The remainder of this paper is organized as follows. In Section II, we survey and classify the applications of smart wearables. Section III discusses the use of cellular IoT (CIoT) in smart wearables. In Section IV, the open research challenges associated with wearable IoT is discussed. Future directions and conclusions are presented in Section V.

II. WEARABLE IOT CLASSIFICATION

To classify the applications of wearable IoT, and complete this survey, first, the state-of-the-art research works, papers and articles in this area were collected. This work is done by searching databases such as IEEE Xplore and Association for Computing Machinery (ACM) digital libraries. Then the related works are categorized in clusters according to their application and each research paper is placed in one of the clusters as shown in Figure 2. It is seen that for some of the clusters, there are a broader range of applications mostly due to their importance. Besides the main clusters, there are other wearable IoT devices that are used in other applications such as virtual games in order to enhance gaming experience, payment applications, and education. Investigating these other use cases are out of the scope of this survey.

In the following sections, each category is presented by listing the most significant published work.

A. HEALTH

The health wearable IoT device is mainly used for remote patient monitoring, treatment and in some cases for rehabilitation purposes. The sensors collect the health-related data and the device may perform limited computation prior to transmitting the user/patient's health information to the the Internet for further analysis. The device may also receive data to enable the user make further decisions. In many applications, the wearable devices are connected to

FIGURE 2. Most researched wearable IoT application clusters.

smartphones to analyze the collected data and then transmit it to a cloud computing-based framework such as Microsoft Azure or Amazon Web Services (AWS) in order to store, process, and analyze the data. Mobile health applications can be used to visualize the analyzed data and provide insight about the user/patient's health. Moreover, in treatment applications, the analyzed data can be used to send special commands to the wearable such as heating up the body or applying a shock.

1) HEALTH TREATMENT & REHABILITATION WEARABLE SYSTEMS

The IoT rehabilitation devices help disabled patients to maintain and improve their physical or mental abilities. In [4], a walker-based system for physiotherapy purposes is proposed which continuously monitors and evaluates the movement metrics of the walker and sends them to the cloud where data is analyzed, and the results are presented on a mobile application. An IoT-based armband for stroke rehabilitation is introduced by [5]. The wearable system measures the bio-potential signals and the analyzed data is transmitted wirelessly to a robot hand. Then, the received signals are interpreted using a machine learning algorithm to give users insight and feedback about their muscle movements. The robot hand assists the user in adjusting his/her posture and walking pattern in real time.

In [6], the researchers have designed a smart wheelchair which allows the disabled person to easily interact with the wheelchair via a mobile application that analyzes the data received from the sensors, and then visualizes the results for caregivers to remotely monitor the patient. The publication in [7], introduces a rehabilitation system which is designed and implemented to help stoke patients suffering from upper limb disability. This rehabilitation system exploits IoT through integrating gaming and wearable technology.

2) HEALTH MONITORING WEARABLE SYSTEMS

Depending on the type of sensors, the health monitoring wearables are classified into four major categories [8]:

1) Bio-potential sensors: electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), and photoplesmography (PPG) and etc.

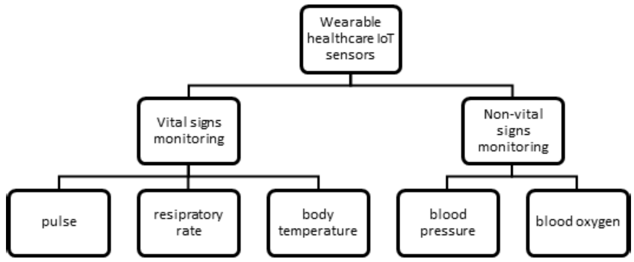

FIGURE 3. Taxonomy of wearable health care IoT sensors.

2) Motion sensors: accelerometer and gyroscope.

3) Environmental sensors: ultrasound, pressure, temperature and etc.

4) Biochemical sensors: transdermal glucose.

Analyzing the aforementioned signals gives extensive insight about the health status of the patient/user.

The figure below shows the taxonomy of the use cases for non-invasive wearable IoT sensors excluding implantable sensors [9].

Pulse rate can be read using wearables on the chest, wrist, earlobe, fingertip, and more via PPG, pressure, and radio frequency (RF). In [10], a monitoring wearable device is designed to detect the unambiguous changes in the heartrate. The wearable alerts the user by a vibration to take the necessary medicine. The researchers in [11] proposed a multisensory wearable system to collect the necessary data in order to warn the user of an impending cardiac arrest in the early stages. A low power communication module use a smartphone to collect the body temperature and heart rate and then signal processing techniques and machine learning algorithms are used to accurately diagnose and warn sudden cardiac arrests. The work done in [12], presents a system dedicated to monitoring the heart activity parameters using ECG mobile devices and sensors inserted in the fabric of the clothes. The assessed parameters are heart rate and respiration.

The wearables equipped with thermistor nasal sensor can measure the respiratory rate. The sensor counts the number of breaths taken by sensing the rise and fall of the temperature if the air exhaled [13]. In [14], a smart IoT solution is proposed for patients with asthma to measure their respiration rate. The measured data is securely sent to the cloud where the patient's information is analyzed. This system uses watermarking and signal enhancement techniques to secure the data transmission. In [15], using adhesive hydrogel, electrodes are placed on human chest to detect the pulsatile vibration created as a result of respiration. The proposed system is capable to be worn or attached to the user's shirt or chest belt. Then, collected data is digitized and wirelessly sent using an impulse radio ultra-wideband transmitter which operates in 3.1 to 5 GHz frequency range. Due to its small size, light weight, low cost and low power signal processing circuitry the proposed respiration monitoring system has gained attention by other researchers. In [16], the researchers have designed a portable wearable IoT device to monitor the respiratory rate where the sensor is implemented in a smart vest to constantly monitor Chronic Obstructive Pulmonary Disease (COPD) patients at home during the rest period between respiratory rehabilitation exercises. This total solution system also provides an e-health platform based on the Internet of Medical Things (IoMT) paradigm.

The body temperature is typically measured by thermistor-type sensors to detect the conditions such as hypothermia, heat stroke and fevers. In [17], a wearable, IoT cloud-based system is presented for real-time personal health monitoring. The collected data from the sensors can be viewed both on a cloud dashboard as well as an embedded display on the wearable. In [18], a tablet-shaped ingestible sensor is developed to measure the core-body temperature based on gastric acid power generation. A custom integrated circuit (IC) is prototyped which could wirelessly receive the temperature data transferred by a tablet-shape device of diameter 10mm and height 8mm.

Blood pressure (BP) is not considered a vital health sign and is frequently measured alongside the other three vital signs (i.e., pulse, respiratory and temperature). While most BP wearable devices are non-invasive, they are still obstructive. In many cases a chest wearable ECG is connected to the other sensors with some wires. As far as we are concerned there is no comfortable wearable device developed to continuously measure the BP with high accuracy. In [19], a survey on commercial wearable IoT devices to monitor the BP from a metrological point of view is presented. In this survey the lack of the traceability and reliability of the BP measurements is addressed.

Pulse oximeter sensors measure the blood oxygen using PPG signals. The most widely used form of such sensors are the wrist-wearable pulse oximetry wearables. In [20], a non-invasive wearable cardiac monitoring and alert system is proposed which can continuously measure the cardiac values and using pulse oximetry. This solution detects the saturation level of oxygen as well as blood volume variations in the tissues. The heart rate is obtained through filtering and processing the sensed signals. The mobile communication and GPS system enable emergency alerts when the measured cardiac values are out of the threshold values. Moreover, the system gives this opportunity to the user to self-trigger the alert system through Google voice assistant.

Some other wearable sensors with applications in healthcare could measure the blood glucose. For example, in [21], an ingestible smart drug is designed which circulates in the body and senses the glucose level by passing IR radiation. The measured blood glucose level is then transmitted to the smartphone wirelessly. Another application of IoT wearable devices is in mental wellbeing monitoring where physiological signs are collected through behavioral traits. In [22], an IoT-based wearable social sensing platform is developed through integrating behavior monitoring, privacy audio feature, and environment sensing in a naturalistic environment. In particular, privacy protected audio-wellbeing features are embedded into this platform to automatically evaluate speech information without the need to preserve raw audio data.

A summary of the aforementioned articles about healthcare IoT sensors in given in Table 1.

TABLE 1. Summary of healthcare IoT sensors in the literature.

	Sensed parameter	Sensor	Connectivity	Mobile app	Node process	Wearable	Ref
Rehabilitation	Orientation, force, distance	RFID, IMU, load cell, ultrasound	Wi-Fi & Bluetooth	Yes	No	Walker	[4]
	surface electromyography	sEMG	BLE	No	Yes	Armband	[5]
	Face image, eye blinks	camera	Wi-Fi	Yes	No	Face	[6]
	Deflections, acceleration, orientation	Accelerometer, gyroscope, flex	Wi-Fi	No	No	Leg, hand	[7]
Monitoring	Heartrate	SFH 7051	Wi-Fi	No	No	Wristband	[10]
		ECG and temperature	Bluetooth	Yes	No	Wristband	[11]
		ECG & inductive sensor WHMIS	2G GPRS	No	Yes	Leg, hand, chest	[12]
	Respiratory	Passive breathing airflow temperature change	Back-scattering	No	No	headband	[13]
		Vibration (piezoelectric)	impulse-radio ultra-wideband transmitter	No	Yes	Chest	[15]
		Capacitive	Bluetooth	Yes	Yes	Smart vest	[16]
	Temperature	LM35	Wi-Fi	No	No	Finger	[17]
		IC mounted on tablet-shaped ingestible	magnetic-field coupling	No	No	Ingestible	[18]
	Blood Pressure	piezoelectric	Wi-Fi	Yes	Yes	Cuff	[19]
	Blood oxygen	pulse-oximetry	GSM/GPRS	No	Yes	Bracelet	[20]
	Blood glucose	Near Infrared radiation	Wi-Fi	Yes	No	Finger	[21]
	Mental well-being	Audio, accelerometer and gyroscope	Bluetooth	Yes	Yes	Wristband	[22]

B. ACTIVITY RECOGNITION AND SPORTS

This category is related to applications where the wearables are worn during sport activities to record different metrics of the user/athlete activity in order to improve his/her performance Also, applications of this cluster consider gathering data regarding the recognition of daily activities of humans and animals. Although activity recognition can have some applications in medical diagnostics and out-of-hospital health-care, the applications belonging in this cluster cover use cases beyond health category.

In this section, we discuss the use of wearable IoT for two related activities. The first set of activities belong to recognition of daily physical activities [23] and the second one is related to activities that are related to specific sports [24]. The recognition of daily physical activities is usually dedicated to tracking routines and body movement related to skeletal muscles such as walking forward, walking backward, jogging, sleeping, running, going up or down the stairs, bending waist, frontal elevation of arms, bending knees, and jumping front or back. It also includes recognition of static postures such as sitting, sitting and relaxing, standing, laying down or the recognition of going from one posture to another such as going from standing posture to sitting one.

Generally speaking, IoT can bring an abundance of opportunities for sport players, organizations and fans to increase their efficiency and offerings by creating an environment in which athletes can receive better training or have access to data that helps to keep them healthier, coaches are able to analyze injuries or find metrics on player performance, and organizations can offer fan engagement strategies or allow fans to receive personalized offering from their favorite team. Wearable IoT is a game changer in sport activities. However, the use of wearable IoT is currently limited due to some leagues regulations and some challenges that need to be resolved. Yet, as more and more organizations recognize the advantages that IoT wearables can provide to players, coaches and fans, we will see that wearable IoT devices become more and more prevalent in sports. Even though, wearable IoT can provide endless opportunities to sports as explained above, in this section, we discuss those papers that are related to recognition of activities for specific sports such as skiing, climbing, martial arts, tennis, swimming, badminton, weightlifting, or baseball. It should be mentioned that the other opportunities mentioned above have not received much attention.

The human physical activity detection has found lots of attention [25]–[30], [23]. To detect human physical activity one or more sensors are installed on one or several wearable devices attached to the body. These sensors generate signals that can be analyzed to detect the type of activity and find the information that differentiates various activities. The existing methods usually achieve this goal in four stages. The first stage is pre-processing, noise cancelation and signal range adjustment which prepares the signal for the next stages. The second stage is feature extraction in which the features or parameters specific to the signal are extracted. The extracted features can usually be categorized as structural features or statistical ones. The structural features find the correlation among different signals. The statistical features can be found through time- or transformed-domain analysis of a signal. Example of statistical features are mean value, max value, peak, and size of signal. The transformation typically used for finding the statistical features are Fourier Transform (FT) [31], [32], Discrete Cosine Transform (DCT) [33], or Wavelet Transform (WT). The third stage is feature reduction which tries to find most important features that can be used in final stage by removing the redundant and irrelevant information. Classification is the last stage in which the reduced set of features are clustered to find patterns among various activities using a classification algorithm. Classification algorithms can be done using the probability of an activity according to a set of features and their probabilities [34], the simulates between features according to a dataset, transformation of features to a space that can help in identifying the type of activity [35], [36], hierarchy based model to map the features to activities based on a decision tree [37]–[39], or artificial neural network and machine learning algorithm [40], [41].

For sport activities, measuring and estimating the performance or efficiency of actions related to specific sport and providing feedback on parameters such as timing, angle or amount of applying or releasing a force can help improve the accuracy and performance. Using these techniques, players can get real-time feedback of their performance and improve their performance to make it more consistent. There are many papers that discuss the use of wearable devices for improving the quality of activities of a specific sport or even making the wearer do something that would not be possible without wearing the wearable device. The wearer usually receives a message to help him/her to understand the quality of performance or provide help on how to proceed. These messages might be seen on the screen of the wearable or on displays in some other places. The wearer also may receive the messages or an indication of a message using audio or haptics. The performance of activities related to many different sports have been researched such as badminton [42], [43], basketball [44], [45], rowing [46], [47], swimming [48], [49], hockey [50], skiing [51], [52], martial art [53], [35], weightlifting [54], tennis [55], baseball [56] and golf [57], [58].

C. TRACKING AND LOCALIZATION

This category, is used mainly for tracking human and animal, to determine their location online. Finding the position of a person or animal who is wearing a wearable device is important in many applications. Studying the trajectory trip of a bird, finding the location of a senior citizen in a care-home facility, analyzing the movement of the people who are visiting an exhibition, or pet tracking are some examples of these applications. A comprehensive study on localization using IoT technology is published in [59], but the study does not concentrate on wearable IoT. In general, the localization methods discussed in literature can be divided into two main categories. The ones that use offline training and the ones that without using offline training can determine the location. The training dependent methods can be classified into three clusters: 1) Fingerprinting 2) Stochastic-oriented models and 3) Machine learning based schemes. Fingerprinting has been studied extensively using various types of signals including general signal pattern, audio signal, video signal and motion [60], [61]. General signal pattern usually depends on the Received Signal Strength Indicator (RSSI) value of the wireless signal in which the location fingerprint is found through site survey and is recorded in a fingerprint data base. This fingerprint information is used later by a localization algorithm online to estimate the location. Fingerprinting can be used on visual information captured by a camera or audio signals captured by a microphone. The IoT devices can also use collaborative localization methods that are based on mutual position measurement of each IoT device as well as the relative distance of devices.

The non-training dependent category of localization method can also be divided into various clusters. The main

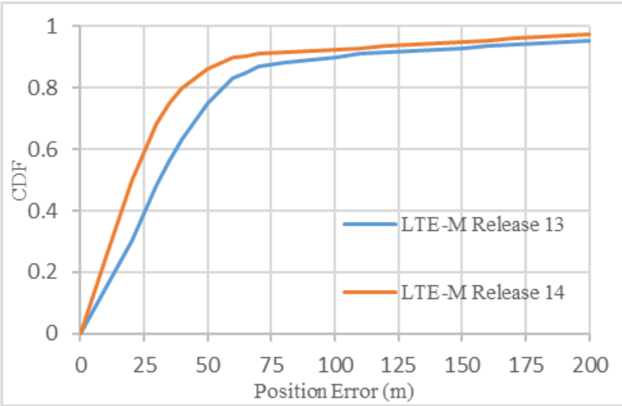

FIGURE 4. Simulation results showing the accuracy of positioning in LTE-M networks using Release 13 and Release 14.

cluster includes the methods that use geometric information to estimate the location based on multi-lateration, triangulation, region overlapping and other geometric related methods [62]–[66]. The other clusters of non-training category are mobility, path planning and statistical [59].

A method used in cellular IoT 3rd Generation Partnership Project 3GPP Release 14 for location estimation based on geometric cluster is Observed Time Difference of Arrival (OTDOA). 3GPP Release 13 does not provide any positioning information other than Cell Identity (CID), which indicates the cell that the IoT device is located at. In Release 14 not only development support for the feature of OTDOA is presented, but also the standard introduces enhancements to complete the User Equipment (UE) measurement requirements for enhanced CID. Note that OTDOA is a downlink-based positioning technique where an IoT device measures the times of arrival of the Positioning Reference Signals (PRSs) received from several nodes relative to a reference node's PRS transmission to form the reference signal time difference (RSTD) measurements. The RSTD measurements are then translated into a geographical hyperbola where the positioned UE is considered to reside. By considering multiple RSTD measurements, the UE position can be estimated to be at the crossover point of the corresponding hyperbolas. By measuring horizontal position error of the LTE-M network as shown in Figure 4, we can show the cumulative distribution function (CDF) of horizontal error position. It is clear that by using LTE-M network a resolution of approximately 50m is achievable horizontally which is suitable for many wearable applications.

D. SAFETY

This category belongs to the wearables that are used to provide safe environment for the users. For instance, a fatigue monitoring system can notify the alert the drivers who fall asleep at the wheel and notify the employers. Or as another example, the wearable devices can collect the air quality data in the mines to assure the worker's health and reduce risks for miners and costs for employers. Fall prevention and detection especially in elderly people are a major problem and there are many applications that wearable devices are used to detect or prevent the falls.

The wearable IoT sensors intended for safety mostly focus on three main applications: 1) fall detection and prevention 2) drowsiness fatigue detection 3) environmental condition monitoring.

1) FALL DETECTION AND PREVENTION

Accidental fall is a major issue for elder people. Even if a fall is not fatal, the effect of a fall degrades the quality of life substantially. To constantly monitor for fall events, the use of wearable devices are more applicable as compared to the other methods which use a fixed infrastructure such as fixed camera [67]–[69] or smart tile [70] due to lack of limitation in location determination or even scene blocking for those using camera. We hereunder discuss the literature that use wearable IoT for the purpose of fall detection or prediction.

To be able to detect fall usually the inertial sensors such as gyroscope or accelerometer are used. The fall detection system must be fast enough to detect fall fast to be beneficial. However, in order to detect fall events accurately and minimize false positive, the fall detection system must differentiate between a fall and other daily activities [71]. This can be done by finding parameters such as body posture, falling speed or angular velocity [72], [73]. It should be noted that some of these parameters not only vary from person to person, but also change with aging [74]. Therefore, to be able to detect falls correctly, the fall detection algorithms need substantial computation. The fundamental idea behind most fall detection and prevention algorithms is to use the motion information to differentiate between a fall and other types of daily activities. A fall can be characterized as an involuntary move which is not performed in a controlled manner and causes abrupt motion with fast speed. The most popular methods for fall prevention are threshold-based schemes in which the motion information such as vertical speed profile are compared with a set of threshold values to detect whether the person is stable, has fallen, or is about to fall. The threshold values can be fixed or adaptive values. In general, the fix value thresholds result in lower computational complexity, and lower performance as compared to the adaptive threshold schemes.

Adaptive thresholds can be dynamically calculated based on history and processing of individual data movement and motion information [75]–[77] or based on clustering of people according to their gender, height, weight and age [78]. In [79] pretested reference templates for each type of fall using comparison between the angles and angular velocities of the thigh segment between falls and normal activities are used for fall detection. Some other papers suggest the use of machine learning for this purpose [80]–[82] such as using [83]–[85] the Support Vector Machine (SVM) via feature selection procedures among a number of raw signals from the gyroscope and accelerometer sensors.

2) DROWSINESS-FATIGUE-DETECTION

In general, the drowsiness detection techniques and alerting systems can be classified into five categories as 1) image processing-based, 2) EEG-based, 3) artificial neural network-based, 4) vehicular-based and 5) subjective measures [86]. In all these techniques, powerful processors are required to process the complex computations and detect drowsiness or fatigue. Another alternative is to send the raw data into the cloud and put the burden of processing on the shoulders of the power servers.

In [87], a drowsiness-fatigue-detection solution to increase road safety is proposed. The system is based on wearable smart glasses and is composed of a pair of wearable smart glasses, an in-vehicle infotainment telematics platform, an onboard diagnostics-II-based automotive diagnostic bridge, an active vehicle rear light alert mechanism, and a cloud-based management platform. The detection system is capable to detect whether the driver is drowsy or tired in real time and once such a condition is detected, the other drivers are automatically alerted through the active vehicle real light alert mechanism. The collected data is also concurrently sent to a cloud-based management platform.

In [88], to detect the sleepy workers a low-cost EEG-based system is proposed. The modified safety smart helmet is worn by the worker and transmits the data to a local server which runs a random forest classifier algorithm to verify if the sleep condition is sever to alert the shift supervisor. If the worker falls down, a single Inertial Measurement Unit (IMU) sensor can detect the fall. A mobile application is also designed where the supervisor can constantly monitor the worker's status.

3) ENVIRONMENTAL CONDITION MONITORING

Hazardous environmental situations may result in serious health problems and it is crucial to deploy fast response systems in such environments to alert the workers. Moreover, the data gathered by the environmental wearable sensors provide useful insight about the environmental impact on subjects' health. The wearables may also be installed on vehicles or animals to form a mobile wireless sensor networks to predict hazardous conditions. For example the data gathered from the animals in different farms may help scientist to predict earthquake in a specific area.

The researchers in [89], presented a safety wearable equipped with a self-powered sensor network which uses Maximum Power Point Control (MPPT) solar energy harvesting, several low power environmental sensing nodes, and unlicensed log range wireless modules (i.e., LoRa). The wearable sensors measure the temperature, relative humidity, and ultraviolet (UV) index in the surrounding area. The collected measurements are sent to a gateway and a cloud server through a LoRa connectivity system.

In [90], a wearable safety application is proposed to detect hazardous conditions in the early stages and alert the workers. The system detects CO2, the temperature and relative humidity and then the data is communicated using an XBee DigiMesh module.

In [91], a wearable environmental sensor network to monitor the urban environment is presented. The system has seven environmental sensors including infrared temperature sensor, atmospheric pressure, accelerometer, temperature, relative humidity, ambient light, and IMU and the wireless communication is through Wi-Fi. The power consumption of the system is so low that the rechargeable battery may last up to seven days. The authors in [92], present a low-power wearable sensor network which measures CO2 concentration, the Earth's magnetic field, temperature and relative humidity. The communication scheme of this sensor network is based on Bluetooth technology.

E. OTHERS

Besides the four main clusters discussed so far, there are some papers that have used wearable IoT technology for other applications such as education [93], [94], virtual and augmented reality [95], [96], law enforcement [97], or spying [98]. Since there have not been lots of attention by the research community for these applications, we do not further discuss these use cases.

III. CIOT-ENABLED WEARABLE

We found that use of CIoT wearable has not received enough attention in the literature. In most cases the connection to the Internet for the wearable device is through the technologies such as Wi-Fi or Bluetooth Low Energy (BLE). The use of these two technologies which exist in any cellphone device has been discussed in many papers. The fact that all people carry a cellphone these days, even though not completely true, has become the assumption that has been used in many papers as justification for using cellphone as part of connectivity to the Internet. We have studied BLE technology and its practical strengths and limitations extensively [99]–[107] and believe that BLE is one of the enablers of IoT technology that has a good potential to be used in wearable devices. But, it is quite possible that CIoT will be the most widely used technology in the future for wearable devices. We believe the use of cellular IoT will be increased in a fast pace in future years and it will replace other types of IoT communication technologies such as Wi-Fi, or unlicensed Low Power Wide Area Networks (LPWAN) solutions (e.g., LoRa and Sigfox) in many use cases.

It is shown in the past that if the cost of equipment as well as data plan for cellular systems implemented by telecommunication companies are decreased, the users tend to prefer to use cellular technology. For example, in 90's when telecommunication companies provided cellphones with limited incoming and outgoing voice usage hours in their plan, the users would use cellphones mostly outside of their homes and offices, where landline systems were not available. As telecommunication companies reduced the price and offered unlimited calls during evenings and weekends and consequently unlimited incoming and outgoing voice calls, users showed interest

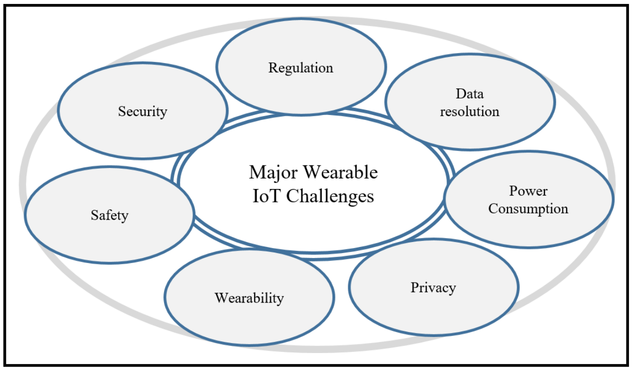

FIGURE 5. Major challenges of wearable IoT technology.

to use their cellphone even in places where landline systems were available. We have seen the same user behavior in data usage over the Internet. In the past, due to the cost of data usage and communication speed, users preferred to switch to Wi-Fi and connect to hotspots instead of cellular connection. However, as the cost of data usage is decreasing, more and more mobile users use their cellular connection to connect to the Internet in places where Wi-Fi connection is also available. Therefore, while there exist some IoT enabling technologies today that may be used for wearable devices in local area or solve the wide area coverage requirement of the IoT devices by using a cellular connection through a cellphone, they fall short as compared to two existing CIoT technologies of the 3rd Generation Partnership Project (3GPP), which are LTE-M and Narrow Band IoT (NB-IoT) in terms of coverage, scalability, interoperability, QoS, and security. LTE-M and NB-IoT are introduced in Release 13 of LTE technology. In LTE Release, 14, and 15, the enhancements of LTE IoT continued to provide cellular IoT connectivity to more IoT devices and in more diverse applications. It should be noted that the performance of CIoT will further hugely be advanced with more implementation of 5G cellular technology.

IV. IOT- ENABLED WEARABLE CHALLENGES AND FUTURE POSSIBILITIES

The major challenges of the wearable IoT devices as shown in Figure 5, are listed below:

1) DATA RESOLUTION OF WEARABLE SENSORS

Since it is of high importance that the wearable device must be comfortable when worn by the user and should consume low amount of energy, they are typically small in size and the sensors have lower resolution compared to non-wearable devices.

2) POWER CONSUMPTION

To minimize the human interaction and for wearable devices to operate for long hours without replacing or charging the battery, special considerations are to be taken into account while designing the wearables. For example, low power consumption systems or energy harvesting techniques such as micro-magneto-electric, thermoelectric, piezoelectric, or photoelectric harvesting methods are some possible options used in [108]. Among all energy harvesting methods, solar energy is considered as a strong candidate as it provides the highest power density. The disadvantage of solar energy is its limitation to day times and outdoor places.

3) WEARABILITY

The wearable IoT devices have to be comfortable when worn by the user. It is important that they are light and designed in such a way that they do not disturb the normal activities of the user. The tradeoff between the complexity of the computations and the weight of the wearable is one of the major challenges. In [109], the idea of smart clothing or wearable 2.0 for human-cloud integration is introduced which tries to solve the problem with discomfort caused by wearing multiple sensors in different part of the body for health care application.

4) SAFETY

All wearable IoT devices use wireless technologies to transmit their sensed data to another node, gateway or a base station. This wireless transmission involves radiofrequency radiation which could have negative impact on the user's health because the transceiver antennas are very close to his/her body. In those wearables that are worn on the head or eyes the radiation risks could be significantly higher. This safety concern is well addressed in [110] by reviewing the standard limits of human exposure to radio frequency electromagnetic energy and analyzing the radiation level of CIoT antennas. It is shown that the problem can be worse when the wearable CIoT device is transmitting in areas with poor coverage.

5) SECURITY

The complexity of the wearable IoT devices is typically reduced due to lightweight and less power consuming designs. Consequently, there could be less strong security features on such devices. One of the challenges in wearable IoT devices is how to implement security policies while keeping the complexity of the system as low as possible. In general, wearables are easy hacking targets due to poor encryption and protection.

6) REGULATION

There is currently a limitation in using wearable IoT devices in many industries due to lack of existence of proper regulations. For example, in sports fields and arenas, the use of wearable IoT devices are technologically feasible, but it is not being used due to the leagues regulations.

7) PRIVACY

The constant exchange of personal data such as vital health signals, dosage, and location between the wearable and the IoT hub can create an environment for privacy breaches. Typically, wearable IoT devices are on broadcast mode which makes them easily discoverable by other nodes in the network. Unauthorized nodes can steal the personal data if appropriate privacy policies are not applied. In such broadcast modes, the built-in hardware security technology of the IoT devices might not guarantee the protection of personal data against breaches. In [111] a broadcast-subscriber IoT model is proposed where the users' personal data are only shared with intended nodes such as healthcare facilities or devices authorized by the user.

There will be enormous number of applications and opportunities for wearable IoT devices. Using 3D printing, the next generation of these wearables will be boosted by lateralization of their design, fabrication, and distribution. For example by using this technology for health application, the patient can upload their disease profiles and download his/her individualized treatment tools to print them at home with low cost. By improvement in new energy harvesting technologies and existence of longer life batteries, the greater computational power will be allowed in wearable IoT devices. This increases their autonomy, implementation of feature extraction and classification and/or prediction, and allows an efficient employment of hardware resources. The most important opportunity in werable IoT will be realized when IoT data from various sources and devices are combined there will be an integrated IoT system available.

V. CONCLUSION

Wearable IoT can offer endless new opportunities in many real-life applications. This paper provided a survey on the most important efforts of the research community in the area of wearable and IoT. After identifying more than one hundred papers as the significant literature in this area, the papers were analyzed and divided in four major clusters based on their applications. The methods used for each cluster also were grouped.

Wearables have lots of potential when integrated IoT system becomes available. For this reason the true power of combining wearable and IoT has not been recognized. Also cellular IoT can revolutionize the wearable IoT industry which at this point has not received lots of attention among research community.

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