Jacob, S., Alagirisamy, M., Xi, C., Balasubramanian, V., Srinivasan, R., R, P., Jhanjhi, N. Z., & Islam, S. M. N. (2021). AI and IoT-Enabled Smart Exoskeleton System for Rehabilitation of Paralyzed People in Connected Communities. IEEE Access, 9, 80340–80350.

Available online: https://doi.org/10.1109/ACCESS.2021.3083093

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

SPECIAL SECTION ON AI AND IOT CONVERGENCE FOR SMART HEALTH

Received May 8, 2021, accepted May 16, 2021, date of publication May 24, 2021, date of current version June 9, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3083093

AI and IoT-Enabled Smart Exoskeleton System for Rehabilitation of Paralyzed People in Connected Communities

SUNIL JACOB[1,5], MUKIL ALAGIRISAMY[1], CHEN XI[2], VENKI BALASUBRAMANIAN[3], RAM SRINIVASAN[4], PARVATHI R.[5], N. Z. JHANJHI[6], AND SARDAR M. N. ISLAM[7], (Member, IEEE)

[1]Department of Electronics and Communication Engineering, Lincoln University College, Petaling Jaya 47301, Malaysia
[2]School of Business, Nanjing University, Jiangsu 210000, China
[3]School of Science, Engineering and Information Technology, Federation University, Mount Helen, VIC 3350, Australia
[4]School of Electrical Engineering and Technology, Central Queensland University, Norman Gardens, QLD 4701, Australia
[5]Department of Electronics and Communication Engineering, SCMS School of Engineering and Technology, Kochi 683576, India
[6]School of Computer Science and Engineering (SCE), Taylor's University, Subang Jaya 47500, Malaysia
[7]Applied Informatics Research, Victoria University, Melbourne, VIC 3011, Australia

Corresponding author: Chen Xi (chenx@nju.edu.cn)

This work was supported in part by the National Social Science Foundation of China under Grant 21ZDA033, in part by the National Natural Science Foundation of China under Grant 71771118 and Grant 72071104, in part by the Ministry of Education Humanities and Social Sciences Foundation of China under Grant 18YJCZH146, and in part by the Key Project of Jiangsu Social Science Foundation under Grant 20GLA007.

ABSTRACT In recent years, the number of cases of spinal cord injuries, stroke and other nervous impairments have led to an increase in the number of paralyzed patients worldwide. Rehabilitation that can aid and enhance the lives of such patients is the need of the hour. Exoskeletons have been found as one of the popular means of rehabilitation. The existing exoskeletons use techniques that impose limitations on adaptability, instant response and continuous control. Also most of them are expensive, bulky, and requires high level of training. To overcome all the above limitations, this paper introduces an Artificial Intelligence (AI) powered Smart and light weight Exoskeleton System (AI-IoT-SES) which receives data from various sensors, classifies them intelligently and generates the desired commands via Internet of Things (IoT) for rendering rehabilitation and support with the help of caretakers for paralyzed patients in smart and connected communities. In the proposed system, the signals collected from the exoskeleton sensors are processed using AI-assisted navigation module, and helps the caretakers in guiding, communicating and controlling the movements of the exoskeleton integrated to the patients. The navigation module uses AI and IoT enabled Simultaneous Localization and Mapping (SLAM). The casualties of a paralyzed person are reduced by commissioning the IoT platform to exchange data from the intelligent sensors with the remote location of the caretaker to monitor the real time movement and navigation of the exoskeleton. The automated exoskeleton detects and take decisions on navigation thereby improving the life conditions of such patients. The experimental results simulated using MATLAB shows that the proposed system is the ideal method for rendering rehabilitation and support for paralyzed patients in smart communities.

INDEX TERMS Assistive technology, artificial intelligence, deep learning, exoskeleton, Internet of Things, smart connected community.

I. INTRODUCTION

According to a survey conducted by CD Revee foundation, 1 in every 50 is afflicted with paralysis mainly due to impaired nervous system causing physical disability from accidents, stroke, polio, cerebral palsy, spinal tumours etc. The average age of such disabilities has moved from 29 years to 43 years with respect to the year 1970 and 2018, respectively [1]. Rehabilitation centres are widely on the run to enhance the lives of people suffering from paralysis, or any type of physical disability. Even after recovering to normal life, many of them are re-hospitalized following the injury. The patient

The associate editor coordinating the review of this manuscript and approving it for publication was M. Shamim Hossain.

is also seen to develop pulmonary, digestive, circulatory, and other musculoskeletal ailments post rehabilitation. It is observed that the probability of death of patients having Spinal Cord Injury (SCI) is 2-5 times more than those who do not suffer from any such injury. The survival rates are worst for those in countries having low and middle-income [1]. Stroke survivors are most affected with impairment for either side of the body [2], [3] and the quality of life is affected by this impairment [3], [4]. It is also observed that there are many cases in which the stroke survivors experiences physical disability in 3 months. Further, it is reported that about 35% of total survivors experiences paralysis of leg. Moreover around 25% of the total number of survivors do not feel comfort in walking without taking any assistance [5]. Apart from the physical trauma, these patients are unable to make a livelihood, thus causing a financial crisis. They also compromise on their education and employment due to their physical illness, leading to depression.

Recently, the world has seen the rise of IoT and AI as two major technologies used in improving the efficiency, cost and usability of already existing systems and applications. With numerous applications using the IoT technology, the number of connected devices worldwide would be very huge. The healthcare market has immensely capitalized on this technology to improve the efficiency of various applications. This market is estimated to grow by 94.5 billion dollars in the year 2020. Currently, numerous researches are being carried out in this area and the increasing demand for efficient healthcare solutions will lead to a wider product adoption in the coming years currently [6], [7]. Also, securing the IoT network and devices from unauthorized breaches and attacks is yet another major challenge [8], [9].

In the field of healthcare, many systems for remote health monitoring have been developed. One of the most promising areas where clinical IoT can be used is healthcare and emergency treatment. Non-critical old age patients should be monitored remotely at home instead of a hospital. Providing the virtual and timely assistance has been on high demand since outbreak of corona virus, especially in the medical field. This calls for an advent technology of passive medical examination by exploiting the availability and feasibility of IoT, sensors and artificial intelligence. There are various sensor based systems that are proposed for monitoring the patients. These include ECG, Accelerometer, EEG, EMG, Blood Pressure, etc. Furthermore, to make the conditions of patients to the better level, various assistive technologies have been proposed. Exoskeletons has proven to be among one of the most reliable technologies that supports the rehabilitation and movement for the patients having paralysis [10], [11].

An assistive gait technique is embedded in the exoskeleton design to aid the paralyzed using effective coordination between several systems. Energy-efficient gait is developed on perfect coordination and synchronization between the central nervous system, somatosensory system and musculo-skeletal system [12], [13]. However, a spinal cord injury and related neurological disorder causes defective muscular movement, inability in balancing the body thereby imposing impairment in walking [14]. Neuroplasticity and related research have reinforced the need for intensive and repetitive function-oriented therapy as it claims to reorganize brain's areas that have been impaired. Studies show that the walking constraints and improved postural stability and body balancing are partially justified with the therapy [15]. Brain Computer Interface (BCI) controlled assistive technology is another paradigm that provides assistance and rehabilitation for the paralyzed [16]. To control the exoskeleton movement, Electromyography (EMG) sensors are employed that help in returning the information related to the human muscle acitivity [17]. But EMG signals are restricted to muscles and also have much limitations. The motor adaptability of the upper limb is predicted using resting-state functional connectivity. The system could identify effectiveness of robotic upper limb rehabilitation in different patients [18]. The clinical trials to investigate BCI training sessions' effectiveness on stroke patients with upper limb paralysis are being carried out. The results of the trial indicate that the BCI based assistive devices are effective for post-stroke rehabilitation [18]. Human intentions measured through cortical potentials were used to control the upper-limb exoskeleton movements. The BMI system eliminated the need for recalibration but resulted in large false positive rates [19].

But BCI technology devices are error prone and also hard to get continuous control because of the dynamic nature of the brain signals [16]. Cable-driven exoskeletons were also associated with rehabilitation which focused in eliminating the rigid-linked skeleton, providing a lighter and transparent design. But exoskeletons are limited by the constraints of weight, flexibility, and adaptability. To resolve these issues, an adaptive and flexible Brain Energized Full Body Exoskeleton (BFBE) for assisting the paralyzed was proposed in [10]. Assistive Mobile Manipulators (AMM) developed in ROS platform served as surrogates for the paralyzed thereby helping them to interact with real world by doing the basic tasks and socialize with others [20].

The authors in [21] discusses the categorization and various challenges encountered while designing in the area of Exoskeleton and Orthoses. The exoskeletons are classified into lower, upper limb and palm, and each variation is discussed in detail. To serve the rehabilitation, the discussion is made for different exoskeletons. Another milestone in the field of assistive technology is the introduction of hoist therapeutic device which aims at providing comprehensive therapy for the muscles and hence, proceeded with supervised and balance training. Therefore, it helps in augmenting the control of this system manually [22]. On considering the concerns raised on the availability of such assistive devices that focus mainly on the physical movements, the most effective solution to all the problems imposed by various assistive technologies is the smart exoskeleton, designed to help in rehabilitation and empower the paralyzed for a better lifestyle [23].

Recently Artificial Intelligence (AI) technology has given us immense opportunity to improve the performance of various healthcare applications in an efficient and well defined manner [24]–[26]. Integrating AI with IoT has become a promising solution to many issues in the healthcare domain, particularly wearable device networks and Body Area Networks (BAN) [27]–[30]. In this paper we propose an assistive model paving the evolution of smart cities using AI-IoT enabled smart exoskeleton for rehabilitation in connected communities. The model employs big data analytics from the intelligent sensors and actuators whose real time parameters are transferred via an IoT platform to a control parameter desired for the system. In the design, the ubiquitous network of intelligent sensor and actuators is attained by using IoT, and the transfer from IoT to real-time control desired for the proposed system is achieved using a AI enabled smart navigation module. An intelligent camera is deployed to serve the purpose by processing data from object detection and correction. This novel design uses RGB_D sensors to obtain the area with maximum power level which further collects the big data to be processed and sent to IoT. The predefined threshold values of actuators and motors of the assistive device will be sent as feedback data to the Big Database that also receives LoRa sensor values. The LoRa sensors feed the analogue values to the sensors to the exoskeleton, which is integrated and passes through a LoRa gateway to the IoT cloud to the caretaker through a mobile interface platform The big data is then processed and send to the IoT server using MQTT protocol via LoRa gateway. Data exchange between gateway and IoT cloud is further guided by a duplex mobile platform.

A. CONTRIBUTIONS OF THIS STUDY

The contributions of this research are,

1) We propose an AI and IoT assisted smart exoskeleton with efficient navigation that overcomes the limitations of the existing systems in flexibility, adaptability and ease of use.
2) Our proposed system uses IoT enabled SLAM (Simultaneous Localization and Mapping) for efficient navigation. Here the Artificial Neural Network approach of Global Bayesian with detector in closure loop is used. The system also reduces large requests on conventional gateway by classifying the requests into delay tolerant and delay sensitive requests.
3) Our proposed system scales up against high data collusion detection and avoidance to improve the data transmission to the cloud.
4) Our system achieves instant control of the exoskeleton by integrating the decisions of AI powered navigation sub-system with the IoT network

B. STRUCTURE OF THE PAPER

The rest of the paper is structured into four sections. Section II deals with the system architecture of the proposed system. Section III deals with mathematical analysis. Implementation and simulation results are included in section IV. The final section presents the conclusion of our work. The list of abbreviations is listed in Table 1.

TABLE 1. List of abbreviations.

Abbreviation	Description
DoF	Degree of Freedom
EMG	Electro Myographical
EEG	Electroencephalogram
BFBE	Brain Energized Full Body Exoskeleton
SDN	Software-Defined Network
BAM	Body-part Actuation Module
BCI	Brain Computer Interface
CU	Control Unit
BDACC	Big Data Analytic Connected Community
IoT	Internet of Things

The list of abbreviations is given in the Table 1.

II. PROPOSED FRAMEWORK

A. SYSTEM ARCHITECTURE

The proposed system is categorized into the following major components/modules which are; 1) BCI; 2) CU, and lastly, 3) Body-Part Actuation Module, 4)Navigation Module The collection of EEG signals is an important operation of BCI module. It converts signals into a compatible form for CU. The system design comprises of an exoskeleton aided with sensors to receive the analog data from LoRa and process it for movement of the limbs. The architecture consists of sensory hardware, sensory feedback and a sensory data base for detecting and processing the data to move the limbs. The sensory hardware is employed for the upper limb, lower limb and head neck units. Depending on the predefined threshold, each unit's sensory hardware compares it with the received analog value and sends a sensory feedback to the database. The data from various sensors is integrated into the sensory database which makes use of big data analytics. The captured sensory signal from LoRa and sensory feedback is processed and given to the microcontroller, which interacts with the IoT cloud via the LoRa Gateway. The IoT uses MQTT protocol to communicate between the LoRa gateway and IoT server. The IoT server exchanges data with the caretaker via an application program through mobile phones or desktops thereby appropriately guiding the patient. This automated exoskeleton enables the paralysed to exchange data from the sensors to the IoT platform and navigate according to the caretaker's instructions; thereby promoting a smart community. The security for the involved communication is assured among the paralyzed patients as well as caregivers with the help of NTSA algorithm which is encrypted twice. [31].

1) AI-POWERED REAL-TIME NAVIGATION WITH INTELLIGENT DECISION MAKING

For efficient navigation the proposed system uses IoT enabled SLAM (Simultaneous Localization and Mapping). Here the

Artificial Neural Network approach of Global Bayesian with detector in closure loop is used. The detector in closed loop analyzes the series of words received to predict that the captured image that comes from the current or previous locations. If detector in the closure loop is acceptable to the map of the graph, a constraint is attached and the error is reduced in that direction. For experimental purpose the system is equipped with RGB-D camera for 6DoF (Degrees of Freedom)and LiDAR mapping on exoskeleton. The navigation module is deployed with odometry for differentiating different color. The exoskeleton base is used to find the pose of the camera on the exoskeleton. It helps to map the visual odometry to exoskeleton frame. If the position of the camera is on the exoskeleton head position, the movement of the head influences the movement of the camera. This variation does not influence the visual odometry as there is an equal update in the exoskeleton head and body.

2) FEATURE EXTRACTION AND DETECTION

The Good Features to Track (GFTT) is used for feature extraction and detection as it is easy to tune the parameter and for different image property like size and intensity, it will give us uniform feature detection. The Vis/Max features decides on the average number of features to decide that scene. For GFTT the mask is the depth of the image. This will filter out the extracted features with wrong depth information.

The Feature Matching is having 3D feature extraction and descriptor from previous captured image. The matching is done by the searching the pixel in the neighborhood. The GFTT is having the direct influence of the optical flow without extracting the descriptor. This provides the unique feature convergence for the frame to frame.

3) PREDICTION OF THE MOTION

The motion prediction is used to detect the key features and the map feature should be there in the frame to frame. This depends on the transformation of motion from one frame to another. This enables the environment to have dynamic variation of the frame and having repetitive pattern to provide the perfect match with feature matching.

Figure 1 presents the block diagram of the AI assisted real-time navigation module integrated to the proposed system. The exoskeleton base determine the camera position on the head with respect to the base of the skeleton. It is the output for odometry transform with respect to the exoskeleton base. The motion estimation is computing the transformation using the extracted features in frame or map. The transformation is converged with adjustment to the local bundle. The features used is for all key or last key frame. The camera pose is adjusted with the transformation achieved and the visual odometry output is updated. The covariance is calculated using median deviation between extracted 3D features of the frame. For the estimation of the motion if the inlier is less than the threshold the frame and map is changed to the new value. For the updating of frame to frame the key frame is updated by the latest frame. For frame to map the key map is adjusted by the non-matching features of the current frame. The matched feature updated by local bundle is converged to new match. If the inlier is greater than the set threshold the unmatched features are removed and frame having no mapping features in feature map, it is discarded. IF the condition prevails that the camera pose and motion is having large difference compared to the predicted one, to calculate the transformation will be difficult. In this case the features are extracted and mapped without using motion prediction.

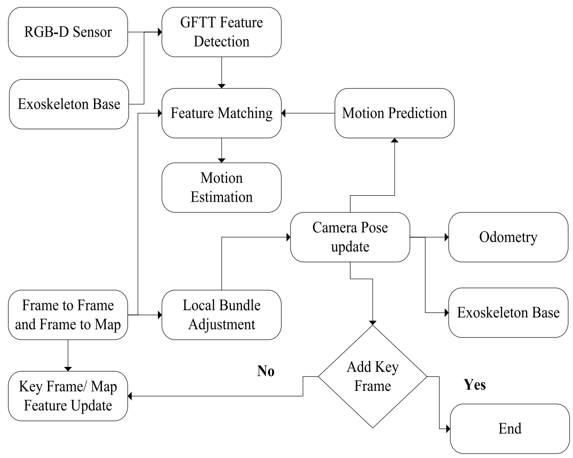

FIGURE 1. Real-time navigation with intelligent decision-making using SLAM.

4) THE EEG SIGNAL ANALYSIS

The EEG signal analysis due to non-linear behavior of the device is undertaken. Different stages induces different level of EEG noise. The EEG signal blocks at a small signal level behave as non-linear due to the effect of noise. The same blocks behave as non-linear at large signal level. This non linearity occurs due to the compression of EEG gain factor or unwanted or spurious frequency tones. In both the cases mentioned above, a minimum and maximum real-time power or dynamic range are required to ensure that the block in EEG will process EEG as required. If the device is not at the required dynamic range, it may lead to EEG signal distortion, interference with other RF signal, generation of multi-tone EEG frequency and multi-tone EEG frequency products. Variation of amplitude causes phase shift and regrowth or merging of a spectral component of EEG signal. The block having an I/P amplitude AI and an O/P amplitude is given as A_0. The EEG blocks can be treated as non- linear device and is modeled using Taylor series in terms of I/P amplitude A_I.

$$A_0 = A \times l_0 + A_1 \times l_1 + l_2 \times A_1^2 + l_3 \times A_1^3 + \ldots \quad (1)$$

and the Taylor coefficients are

$$\begin{aligned} l_0 &= A_0(0)[DCComponent] \\ l_1 &= \frac{dA_0}{dA_I}|A_0 = 0[LinearComponent] \\ l_2 &= \frac{d^2A_0}{dA_I^2}|A_0 = 0\ [SquaredComponent] \end{aligned} \quad (2)$$

A single sinusoidal EEG frequency is applied at the I/P of first stage,

$$A_I = K_0 \cos w_0 t \tag{3}$$

Substitute in above equation

$$\begin{aligned} A_0 &= l_0 + l_1 \times K_0 \cos w_0 t + l_2 \times K_0^2 \cos^2 w_0 t \\ &\quad + l_3 \times K_0^3 \cos^3 w_0 t + \ldots \\ &= (l_0 + \frac{1}{2} l_2 K_0^2) + (l_1 K_0 + \frac{3}{4} l_3 K_0^3) \cos w_0 t \\ &\quad + \frac{1}{2} l_2 K_0^2 \cos^2 w_0 t + \frac{1}{4} l_3 K_0^3 \cos^3 w_0 t + \end{aligned} \tag{4}$$

This results in EEG gain at frequency w_0 as

$$W = \frac{A_0(w_0)}{A_1(w_0)} = \frac{l_0 K_0 + \frac{3}{4} l_3 K_0^3}{K_0} = \frac{l_1 + \frac{3}{4} l_3 K_0^2}{eq:1} \tag{5}$$

Here l_1 and l_3 are having the same sign or phase, adding to the strength of EEG signal. Consider two single sinusoidal EEG frequencies, which are closely spaced at frequency w_1 and w_3

$$A_I = K_0(\cos w_1 t + \cos w_2 t) \tag{6}$$

From the above equation, it is

$$\begin{aligned} A_0 &= l_0 + l_1 \times K_0(\cos w_1 t + \cos w_2 t) \\ &\quad + l_2 \times K_0^2(\cos w_1 t + \cos w_2 t)^2 \\ &\quad + l_3 \times K_0^3(\cos w_1 t + \cos w_2 t)^3 + \ldots \\ &= l_0 + l_1 \times K_0 \cos w_1 t + l_1 \times K_0 \cos w_2 t) \\ &\quad + l_2 l_2 \times K_0^2(1 + \cos 2w_1 t) + l_2 l_2 \times K_0^2(1 + \cos 2w_2 t) \\ &\quad + l_2 \times K_0^2(\cos(w_1 - w_2)t \\ &\quad + l_2 \times K_0^2(\cos(w_1 + w_2)t \\ &\quad + l_3 \times K_0^3(\frac{3}{4} \cos(w_1 t \\ &\quad + \frac{1}{4} \cos 3(w_1 t)t + l_3 \times K_0^3(\frac{3}{4} \cos(w_2 t \\ &\quad + \frac{1}{4} \cos 3(w_2 t)t + \ldots \end{aligned} \tag{7}$$

In the expansion identity of trigonometric used, the O/P EEG spectrum consists of multi-tone in the form $xw_1 + yw_2$ where 'X' and 'Y' $= 0, \pm 1, \pm 2, \pm 3, \ldots$ In the above expression, the square terms give different EEG component like $2w_1$ (Second tones of EEG1 x = 2, y = 0 $2w_2$ (Second tones of EEG2 x = 0, y = 2 $w_1 - w_2$ (Difference frequency of EEG1 and EEG2 x = 0,y = −1 $w_1 + w_2$ (Sum frequency of EEG1 and EEG2 x = 1,y = 1 The EEG frequency terms w_1 and w_2 are close to each other and it can be easily filtered or rejected or paused by the filter. From the above expression the amplitude ratio of $w_1 - w_2$ or $w_1 + w_2$to the amplitude of $2w_1$ or $2w_2$ is 2. This indicates a decrease in σ d β power for second order EEG signal compared to sum and difference signal. The cubed EEG signal has six EEG terms as $3w_1, 3w_2$, $2w_1 + w_2$, $2w_2 + w_1$, $2w_2 - w_1$. The first four EEG terms will be far from w_1 or w_2 i.e., it will be outside the pass band set and the last two terms will be close to w_1 and w_2 and so depending on the requirement we can filter the EEG signals. For the multiple EEG signals having different amplitude and different frequencies and phases will cause interference at the O/P. The ratio of $2w_1 - w_2$, or $2w_2 - w_1$. Amplitude to the $3w_1$ or $3w_2$ will give 3.0 So the 9.54db EEG power will be less for third order EEG component compared to $2w_1 - w_2$ or $2w_2 - w_1$ terms. The object tracking and recognition in the proposed system is done by RGB-D(Tx) emitter and a RGBD receiver (Sensor). The range and tracking of RGB-D sensors are depicted in figure 3.

III. MATHEMATICAL ANALYSIS OF THE PROPOSED SYSTEM

The designed exoskeleton will exchange data from the sensors to the control station/caretaker through the IoT cloud using MQTT protocol. The RGB-D sensors form a path to the target's precise location, which is assumed to be an elliptical path on a 2D plane with the transmitter, target and sensor on the same plane. Further numerical analysis is carried out in the sensors generated data set by corrective mechanism resulting in the most optimized data set to track and monitor the target for energy and bandwidth efficiency. The ellipse is represented by

$$T_R + R_S = 2E \tag{8}$$

The RGB-D receiver sensor is receiving the signal due to the formation of the path at the upper part of the triangle along the target. The relative range of the proposed exoskeleton is given as

$$R_{AI-IoT-SES} = T_R + R_S - l \tag{9}$$

The T_R is the range between TX to target, RS is the range between the target to RGB-D sensor. L is the base line direct path between Tx and sensor. The Tx to target to RGB-D sensor is obtained by the proposed system ellipse equal to the sum

$$T_R + R_S = 2E \tag{10}$$

This defines the constant range ellipsoid. This is the condition of ellipsoid when the transmitter, target and sensor lie on the same plane. It forms a 2D-ellipse. The target can lie on the surface of the ellipsoid and its foci at the TX and sensor position. The possibility of the target lying somewhere on the ellipsoid, a single proposed system ellipse will not be sufficient to provide the exact state of the target. In order to localize the target accurately, the target position is triangulated and multiple measurement from multiple sensors are done. The localization problem is non-linear in nature resulting in a couple of possible target locations. These possible target locations are due to the intersection of 3 sensory ranges. The decision on the couple of possible target locations can be taken by developing more than 3 sensory ranges.

Consider the case of a paralyzed person wearing the sensing device that transfers medical and motor data to the personal area wireless device. The personal area wireless

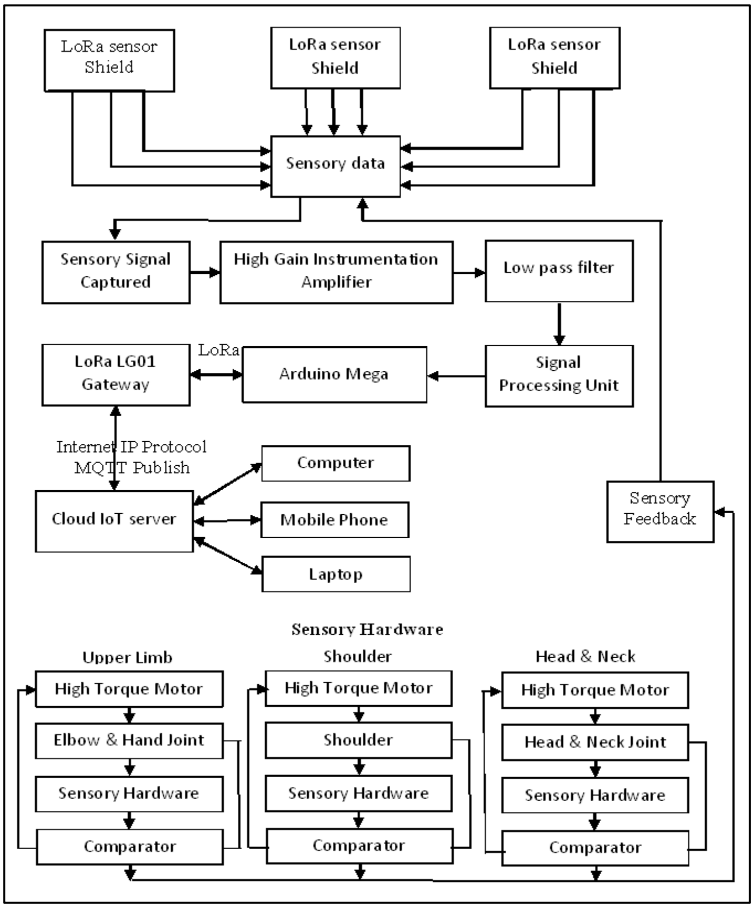

FIGURE 2. **Block Diagram of the AI and IoT powered smart exoskeleton system with LoRa Communication.**

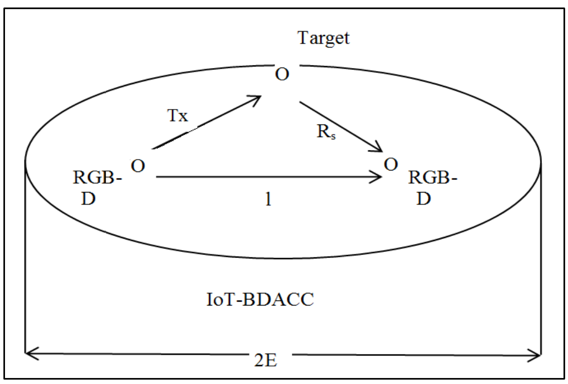

FIGURE 3. **Geometry of RGBD enabled AI-IoT-SES.**

device combines and integrates the sensory actuation data and transfers it to the IoT cloud. The data sensed, processed and transferred consumes a lot of resources and delays. The interpretation of the resources is the parameters received to complete the task for the paralyzed.

The P_i $(1 \;<=\; l \;<=\; s)$ are the different sensor nodes Io and L be the various personal edge device in the network. The paralyzed patient T1 has a group of sensor P_1, P_2, $P_3 \ldots P_s$. This group of sensors transfer information to the edge device 'L'. This edge device has permanent ID as $L_\epsilon 01, L_\epsilon 02, L_\epsilon 03, \ldots, L_\epsilon 0n$ and IoT device has permanent ID as P_{ID1}, $P_{ID2}, \ldots P_{IDS}$ and LED. The sensors in the sets at P_I, generates the sensing data R1, forms the optimized data set T_I. This optimized data set constitutes the paralyzed patient data set TTL, having patient sensory and medical data information. The collection of each sensor data will generate a data set of complete profile of paralyzed patient represented as P_i -> R_i -> T_i where $1 \;<=\; l \;<=\; s$ The AI-IoT-SES system level mapping is given by $P\_1, P\_2, P\_3, \ldots P\_S$ -> $R\_1, R\_2, R\_3, \ldots R\_S$ -> $T\_1\; T\_2, T\_3 \ldots T\_s \;=\; T_{Til}$ The proposed system is having memory for load processing, power requirement energy and band width. This throws the challenge monitoring and managing the resource allocation. The optimized data set resource allocation. The optimised data set for resources $(G\_1, G\_2, G\_3, \ldots G\_s)$ are generated for optimized resources for bandwidth $(B_{N1}, B_{N2}, \ldots B_{NS})$ memory $(M_{N1}, M_{N2}, \ldots M_{NS})$ processing $(P_{N1}, P_{N2}, \ldots P_{NS})$ and energy $(E_{N1}, E_{N2}, \ldots E_{NS})$ for the sensor data P_1, P_2, P_3, P_S, respectively. The paralyzed patient, sensory data has an optimised data set about resources. This resource shares of the processing, bandwidth, memory and energy status. They are represented as: For sensor P_i

$$G_l = (E_{Nl}, P_{Nl}, M_{Nl}, B_{Nl}(1 <= l <= s)) \tag{11}$$

The total energy for the paralyzed patient Ti is given by

$$E_{NT_i} = \sum_{d=1}^{s} E_{Nl} \tag{12}$$

The net processing power $l^{D}_{(NTi)}$ for sensoring device for paralyzed patent is given as

$$P_{NT_i} = \sum_{l=1}^{s} P_{Nl} \tag{13}$$

The net bandwidth $B_{(NT_i)}$ for sensing data the paralyzed patient IDS is given as

$$B_{NT_i} = \sum_{l=1}^{s} B_{Nl} \tag{14}$$

The net memory $M_{(NT_i)}$ for sensing data for the paralyzed patient is given as

$$M_{NT_i} = \sum_{l=1}^{s} M_{Nl} \tag{15}$$

The total resources at the paralyzed patient is

$$G_{Tl1} = \left\{ E_{NT1}, P_{NT1}, B_{NT1}, M_{NT1} \right\} \tag{16}$$

The phases are running parallel as energy allocation and processing power allocation. The initial assumption is to provide optimized resource allocation to the max value consider an example for sensor Pl. The optimized resources are

$$\begin{aligned} E_{Ns} &= U_l - U_{li} \\ P_{Ns} &= V_{li} \qquad (17) \\ M_{Ns} &= U_l - U_{li} \\ B_{Ns} &= X_{li} \qquad (18) \end{aligned}$$

The value of l lies in $1 <= l <= s$ where U_l, V_l, W_{li} and X_l are the optimized values for the different resources. Now assuming the exoskeleton to activate the moving forward task, the resource allocation completes this task of allocating resources for a set of predefined condition. Once the specific task for allocating the resource is accomplished, the optimized resources for the sensor P_{l_i} will become

$$\begin{aligned} E_{Ns} &= U_l - U_{li} \\ P_{Ns} &= V_l - V_{li} \qquad (19) \\ M_{Ns} &= W_l - W_{li} \\ B_{Ns} &= X_l - X_{li} \quad for\ 1 <= l <= s \qquad (20) \end{aligned}$$

The U_l, V_l, W_{li} and X_l represent the resources consumed to achieve a specific task. This helps in resource monitoring and keeps the track of resource allocated, non-utilized resources and the availability of resources. This will ensure the resource allocation algorithm reclaims the non-utilized resources and returns them to the existing available resources data set. The monitoring of the resources ensures that the number of resources to be estimated for the completion of the task. At the sensor, node level maximize E_{Ns}, P_{Ns}, M_{Ns} and B_{N_s} subject to the constraints as:

$$\begin{aligned} E_{Ns} &= U_l \\ P_{Ns} &= V_l \qquad (21) \\ M_{Ns} &= W_l \\ B_{Ns} &= X_l \qquad (22) \end{aligned}$$

At the sensor network level, it can be modeled as Maximize $\sum_{l=1}^{s} E_{Nl}$ $\sum_{l=1}^{s} P_{Nl}$ $\sum_{l=1}^{s} M_{Nl}$ $\sum_{l=1}^{s} B_{Nl}$ subject to constrain as $\sum_{l=1}^{s} E_{Nl} <= \sum_{l=1}^{s} U_l$, $\sum_{l=1}^{s} P_{Nl} <= \sum_{l=1}^{s} V_i$ and for others the same.

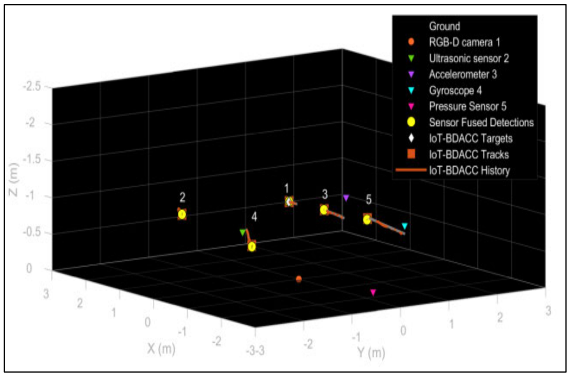

FIGURE 4. Convergence to the proposed system target.

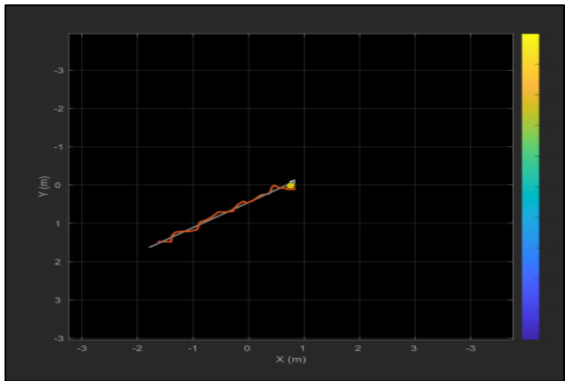

FIGURE 5. Convergence for RGB-D camera sensor.

IV. RESULTS AND DISCUSSION

For ease of use we define the proposed system as AI-IoT Smart Exoskeleton System (AI-IoT-SES) Figure 4 shows the convergence to AI-IoT-SES Target. The AI-IoT-SES Target and Track is used as the feedback for the convergence. The figure shows the placement of different sensors and cameras. The sensor detection fused the output of different sensors and cameras generating the feedback for the AI-IoT-SES target. The results show the continuous tracking and correcting until

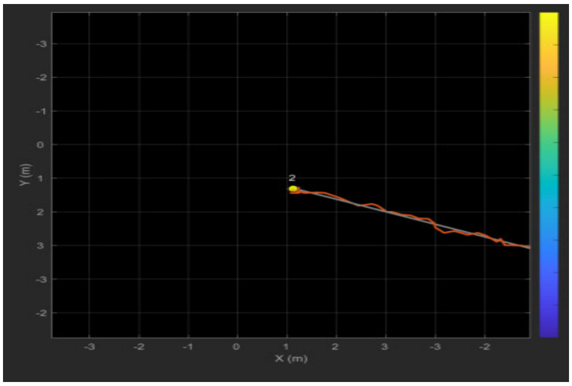

FIGURE 6. Convergence for Gyroscope/Accelerometer sensor.

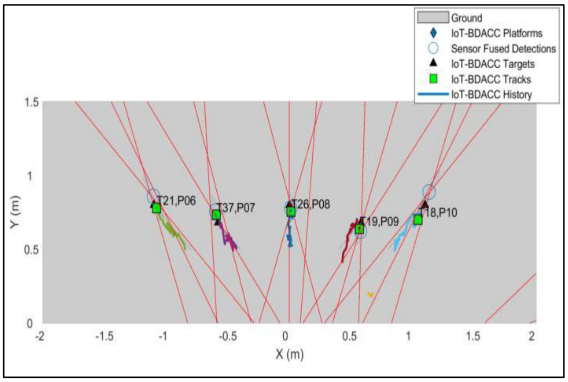

FIGURE 7. Sensor fusion detection for various tracks and paths.

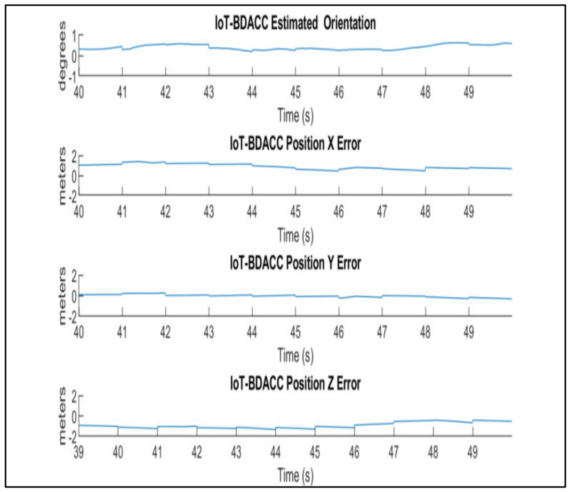

FIGURE 8. Estimated orientation and Position errors of exoskeleton for X,Y,Z direction.

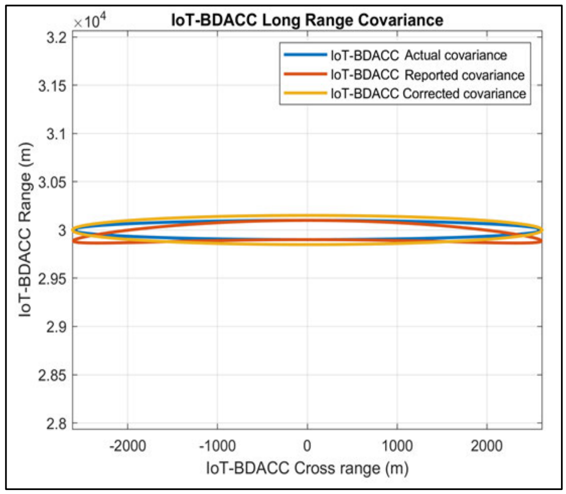

FIGURE 9. Converging to the target by corrective technique.

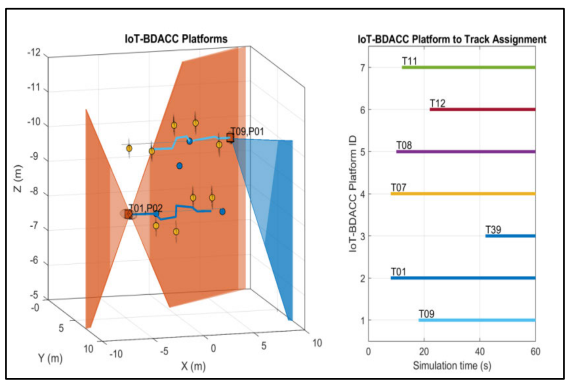

FIGURE 10. Proposed system track spectrum and track assignment.

the final data converges. This has been tested for individual sensor and cameras, then fusing it together. The target is tracked after corrective methods with the precision technique using AI-IoT-SES tracking history.

Figure 5 shows the convergence for the RGB-D camera sensor. The gray straight line is the AI-IoT-SES target path. The red line is the AI-IoT-SES track path. The yellow is the AI-IoT-SES target spot. The figure shows its convergence at the final destination where the user is visually targeting the object using RGB-D sensor. The RGB-D sensor variation scale is shown in y-axis.

In figure 6, the gray straight line is the AI-IoT-SES target path. The red line is the AI-IoT-SES track path. The yellow is the AI-IoT-SES target spot. The figure shows its convergence at the final destination where the user is targeting the gate using Gyroscope/Accelerometer sensor.

The figure 7 how the sensor fusion detection is corrected for different random paths with different track and target histories. This shows the precision with which the AI-IoT-SES converges.

Figure 8 shows exoskeleton's gate position for different X, Y, Z direction and its estimated orientation. It is seen that after a stipulated amount of time, the tracking is initiated and each axis has a level of accuracy at each instant.

Figure 9 shows how well the exoskeleton converges with the actual path. The actual path shown in blue line is corrected with the reported line shown in red. The difference is adaptively corrected for obtaining the correct path with minimum error.

In figure 10, the tracks T01 with path P02 is shown a spectral coverage in red. Similarly track T09 with path P01 is having a spectral coverage shown in blue. The track assignment figure gives the path followed for different tracks. The field of time is the time elapsed before identifying the track. Different tracks are observed to have different field of time.

V. CONCLUSION AND FUTURE WORK

To overcome the problems with the existing technologies, this paper presented a new assistive model paving the evolution of smart cities using AI-IoT enabled big data analytic connected communities with Smart Exoskelton System (AI-IoT-SES). The paper describes the design of an exoskeleton for the physically impaired, for commutation in smart cities with automatic limb control using an IoT platform with AI-powered navigation module. Here, a precise control of an exoskeleton is achieved by integrating multiple sensory hardwares to sense various parameters such as distance, obstacle avoidance, orientation, tilt, speed, and acceleration with high level of accuracy. Our proposed system used IoT enabled SLAM (Simultaneous Localization and Mapping) for efficient navigation. Here the Artificial Neural Network approach of Global Bayesian with detector in closure loop is used. The system also reduces large requests on conventional gateway by classifying the requests into delay tolerant and delay sensitive requests. Sensory feedback from the cloud is also included in the system for exoskeleton's corrective movement to avoid falls and other casualties. The results and graphs from the simulations showed desirable precision with minimal errors in tracking the target with appropriate convergence between feedback data and comparator data. The results were calculated for the accuracy of sensors to the feedback data to compute the precise motion and limb movement to obtain the target. The various paths and tracks allotted for attaining targets were plotted to compute errors in x, y, z directions and to obtain the exact orientation. Different fields of the time were obtained for various paths to target. The spectral coverage of the tracks corresponding to various paths was also studied. In future we plan to work on a AI and IoT enabled exoskeleton free system that can use a combination of EEG and EMG signals and help in rehabilitation of the paralyzed even without the help of caretakers.

REFERENCES

[1] (Accessed: Feb. 28, 2021). *Spinal Cord Injury Facts & Statistics*. [Online]. Available: https://www.sci-info-pages.com/spinal-cord-injury-facts-and-statistics/
[2] (Accessed: Feb. 28, 2021). *The Global Burden of Disease: 2004 Update*. [Online]. Available: https://apps.who.int/iris/handle/10665/43942
[3] J. M. Rondina, C.-H. Park, and N. S. Ward, "Brain regions important for recovery after severe post-stroke upper limb paresis," *J. Neurol., Neurosurgery Psychiatry*, vol. 88, no. 9, pp. 737–743, Sep. 2017.
[4] S.-M. Lai, S. Studenski, P. W. Duncan, and S. Perera, "Persisting consequences of stroke measured by the stroke impact scale," *Stroke*, vol. 33, no. 7, pp. 1840–1844, Jul. 2002.
[5] H. T. Hendricks, J. van Limbeek, A. C. Geurts, and M. J. Zwarts, "Motor recovery after stroke: A systematic review of the literature," *Arch. Phys. Med. Rehabil.*, vol. 83, no. 11, pp. 1629–1637, 2002.
[6] S. Mostafi, F. Khan, A. Chakrabarty, D. Y. Suh, and M. J. Piran, "An algorithm for mapping a traffic domain into a complex network: A social Internet of Things approach," *IEEE Access*, vol. 7, pp. 40925–40940, 2019.
[7] H. Lin, S. Garg, J. Hu, X. Wang, M. J. Piran, and M. S. Hossain, "Privacy-enhanced data fusion for COVID-19 applications in intelligent Internet of medical Things," *IEEE Internet Things J.*, early access, Oct. 22, 2020, doi: 10.1109/JIOT.2020.3033129.
[8] H. Lin, J. Hu, W. Xiaoding, M. F. Alhamid, and M. J. Piran, "Towards secure data fusion in industrial IoT using transfer learning," *IEEE Trans. Ind. Informat.*, early access, Nov. 17, 2020, doi: 10.1109/TII.2020.3038780.
[9] M. Letafati, A. Kuhestani, K.-K. Wong, and M. J. Piran, "A lightweight secure and resilient transmission scheme for the Internet-of-Things in the presence of a hostile jammer," *IEEE Internet Things J.*, vol. 8, no. 6, pp. 4373–4388, Mar. 2021.
[10] S. Jacob, M. Alagirisamy, V. G. Menon, B. M. Kumar, N. Z. Jhanjhi, V. Ponnusamy, P. G. Shynu, and V. Balasubramanian, "An adaptive and flexible brain energized full body exoskeleton with IoT edge for assisting the paralyzed patients," *IEEE Access*, vol. 8, pp. 100721–100731, 2020.
[11] V. P. G., S. Jacob, V. G. Menon, V. Balasubramanian, and M. J. Piran, "IoT-powered deep learning brain network for assisting quadriplegic people," *Comput. Electr. Eng.*, vol. 92, Jun. 2021, Art. no. 107113.
[12] D. Winter, "Human balance and posture control during standing and walking," *Gait Posture*, vol. 3, no. 4, pp. 193–214, Dec. 1995.
[13] K. Fouad and K. Pearson, "Restoring walking after spinal cord injury," *Prog. Neurobiol.*, vol. 73, no. 2, pp. 107–126, Jun. 2004.
[14] L. Sudarsky, "Neurologic disorders of gait," *Current Neurol. Neurosci. Rep.*, vol. 1, no. 4, pp. 350–356, Aug. 2001.
[15] J. Liepert, H. Bauder, W. H. R. Miltner, E. Taub, and C. Weiller, "Treatment-induced cortical reorganization after stroke in humans," *Stroke*, vol. 31, no. 6, pp. 1210–1216, Jun. 2000.
[16] S. Jacob, V. G. Menon, F. Al-Turjman, P. Vinoj, and L. Mostarda, "Artificial muscle intelligence system with deep learning for post-stroke assistance and rehabilitation," *IEEE Access*, vol. 7, pp. 133463–133473, 2019.
[17] G. Yin, X. Zhang, D. Chen, H. Li, J. Chen, C. Chen, and S. Lemos, "Processing surface EMG signals for exoskeleton motion control," *Frontiers Neurorobotics*, vol. 14, p. 40, Jul. 2020.
[18] I. Faiman, S. Pizzamiglio, and D. L. Turner, "Resting-state functional connectivity predicts the ability to adapt arm reaching in a robot-mediated force field," *NeuroImage*, vol. 174, pp. 494–503, Jul. 2018.
[19] A. A. Frolov, O. Mokienko, R. Lyukmanov, E. Biryukova, S. Kotov, L. Turbina, G. Nadareyshvily, and Y. Bushkova, "Post-stroke rehabilitation training with a motor-imagery-based brain-computer interface (BCI)-controlled hand exoskeleton: A randomized controlled multicenter trial," *Frontiers Neurosci.*, vol. 11, p. 400, Jul. 2017.
[20] X. Jin, A. Prado, and S. K. Agrawal, "Retraining of human gait—Are lightweight cable-driven leg exoskeleton designs effective?" *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 4, pp. 847–855, Apr. 2018.
[21] H. Herr, "Exoskeletons and orthoses: Classification, design challenges and future directions," *J. NeuroEng. Rehabil.*, vol. 6, no. 1, pp. 1–9, Dec. 2009.
[22] A. Agrawal, A. N. Dube, D. Kansara, S. Shah, and S. Sheth, "Exoskeleton: The friend of mankind in context of rehabilitation and enhancement," *Indian J. Sci. Technol.*, vol. 9, no. S1, pp. 1–8, Dec. 2016.
[23] T. L. Chen, M. Ciocarlie, S. Cousins, P. M. Grice, K. Hawkins, K. Hsiao, C. C. Kemp, C.-H. King, D. A. Lazewatsky, A. E. Leeper, H. Nguyen, A. Paepcke, C. Pantofaru, W. D. Smart, and L. Takayama, "Robots for humanity: Using assistive robotics to empower people with disabilities," *IEEE Robot. Autom. Mag.*, vol. 20, no. 1, pp. 30–39, Mar. 2013.
[24] M. S. Hossain and G. Muhammad, "Deep learning based pathology detection for smart connected healthcare," *IEEE Netw.*, vol. 34, no. 6, pp. 120–125, Nov. 2020.
[25] M. Alhussein, G. Muhammad, M. S. Hossain, and S. U. Amin, "Cognitive IoT-cloud integration for smart healthcare: Case study for epileptic seizure detection and monitoring," *Mobile Netw. Appl.*, vol. 23, no. 6, pp. 1624–1635, Dec. 2018.
[26] M. S. Hossain, "Cloud-supported cyber–physical localization framework for patients monitoring," *IEEE Syst. J.*, vol. 11, no. 1, pp. 118–127, Sep. 2017.

[27] S. Verma, N. Sood, and A. K. Sharma, "Cost-effective cluster-based energy efficient routing for green wireless sensor network," *Recent Adv. Comput. Sci. Commun.*, vol. 13, p. 1, Mar. 2020.
[28] S. R. Pokhrel, S. Verma, S. Garg, A. K. Sharma, and J. Choi, "An efficient clustering framework for massive sensor networking in industrial Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 4917–4924, Jul. 2021.
[29] S. Verma, N. Sood, and A. K. Sharma, "Genetic algorithm-based optimized cluster head selection for single and multiple data sinks in heterogeneous wireless sensor network," *Appl. Soft Comput.*, vol. 85, Dec. 2019, Art. no. 105788.
[30] S. Verma, S. Kaur, D. B. Rawat, C. Xi, L. T. Alex, and N. Z. Jhanjhi, "Intelligent framework using IoT-based WSNs for wildfire detection," *IEEE Access*, vol. 9, pp. 48185–48196, 2021.
[31] S. Rajesh, V. Paul, V. G. Menon, S. Jacob, and P. Vinod, "Secure brain-to-brain communication with edge computing for assisting post-stroke paralyzed patients," *IEEE Internet Things J.*, vol. 7, no. 4, pp. 2531–2538, Apr. 2020.

SUNIL JACOB received the M.Tech. degree in digital system and computer electronics from JNTU, Anantapur, and the Ph.D. degree in electronics from Bharathiar University, India. He is currently the Director of the Centre for Robotics, SCMS School of Engineering and Technology. He is also a Professor with the Department of Electronics and Communication Engineering. His project Muscles to Machine Interface for Paralyzed has been funded by the IEEE EPICS USA. His other funded projects, include bionic haptic arm, rejuvenating the cells of human body, de-addiction coil for drug addicts, smart keyboard for disabled person, low cost 3D printer, and wearable device for detection and prevention of heart failure. He was a recipient of the AICTE Chathra Vishvakarma Award, in electronics, in 2017, and the Young Gandhian Technological Innovation Appreciation Award, in 2018.

MUKIL ALAGIRISAMY received the bachelor's degree in electronics and communication engineering, in 2005, the Master of Engineering degree in communication systems, in 2007, and the Ph.D. degree in engineering, in 2012. She completed her Postdoctoral Fellowship, in 2015. She started her career as a Lecturer with the Hindustan Engineering College, India. She was working as an Assistant Professor with B. S. Abdur Rahman University, India. She joined the Stamford College, Malaysia, as a Lecturer. She is currently working as an Assistant Professor and a Coordinator for Master of Science in Electrical, Electronics and Telecommunication Engineering programs with Lincoln University College. She is currently an Associate Professor with the Department of Electrical and Electronics and Engineering, Lincoln University College. She has 12 years of experience in teaching subjects like data communication, analog and digital communications, digital signal processing, and satellite communications. Her research interests include sink mobility patterns, clustering, modulation, data aggregation, and compressive sensing techniques for wireless sensor networks.

CHEN XI received the Ph.D. degree. He is currently a Full Professor. He is also a Ph.D. Supervisor. He is also the Chair of the Marketing and Electronic Business Department. He is also a Visiting Scholar with the Michael G. Foster School of Business, University of Washington. He is also the Innovation Team Leader of Nanjing University. He is the project chief and sub project leader of more than 20 foundations, including the Key Project of the National Natural Science Foundation, the Key Project of the National Social Sciences Foundation, the National Science Foundation, and the National Ministry of Education Science Foundation. He is the author of more than 60 refereed journal/international conference papers and book chapters, more than 60 articles among them have been indexed by SCI/SSCI and EI, including lots of articles in JCR I and II sections. He has published two monographs and owned several national authorized patents. His research interests include business intelligence, services engineering and management, computational simulation experiments, and internet data analysis. Since 2011, he has been elected to the Ministry of Education for New Century Excellent Talents Scheme and three high level talents plans in Jiangsu Province. He received the 2015 Youth Award of Management in China, the Best Paper Award of Chinese Academy of System Simulation, and the Outstanding Achievement Award of Philosophy and Social Sciences of Jiangsu Province. He is the chair and the commissioner of some international/national academic associations, the chair of some technical committees, the chair of organization committee of some refereed conferences, and the associate editor and editorial member of some refereed international journals and conferences.

VENKI BALASUBRAMANIAN received the Ph.D. degree in body area wireless sensor network (BAWSN) for remote healthcare monitoring applications. He is currently with the School of Science, Engineering and Information Technology, Federation University, Mount Helen, VIC, Australia. He is also the Pioneer in building (pilot) remote healthcare monitoring application (rHMA) for pregnant women with the New South Wales Healthcare Department. He also founded Anidra Tech Ventures Pty Ltd., a smart remote patient monitoring. His research establishes a dependability measure to evaluate rHMA that uses BAWSN. His research opens up a new research area in measuring time-critical applications. He contributed immensely to eResearch software research and development that uses cloud-based infrastructure and a core member for the project sponsored by the Nectar Australian Research Cloud Provider. He contributed heavily in the field of healthcare informatics, sensor networks, and cloud computing.

RAM SRINIVASAN received the master's degree in electrical engineering from Central Queensland University, Melbourne. He is currently with the School of Electrical Engineering and Technology, Central Queensland University, Melbourne, Australia. He is also working on applying deep learning and machine learning techniques in healthcare and VANET with a Fellow Researcher Dr. Venki Balasubramanian. His research interests include power systems, numerical methods, artificial intelligence methods, deep learning, VANET, computer networks, and operating systems.

PARVATHI R. received the B.Tech. degree in electronics and communication engineering from Mahatma Gandhi University, India, and the M.E. degree in communication systems from Anna University. She is currently an Assistant Professor with the Department of Electronics and Communication Engineering, SCMS School of Engineering and Technology, India. Her research interests include the Internet of Things and communication systems.

N. Z. JHANJHI is currently working as an Associate Professor with Taylor's University, Malaysia. He has great international exposure in academia, research, administration, and academic quality accreditation. He worked with ILMA University and King Faisal University (KFU) for a decade. He has 20 years of teaching and administrative experience. He has an intensive academic quality accreditation background in higher education besides scientific research activities. He had worked a decade for academic accreditation and earned ABET accreditation twice for three programs at the CCSIT, King Faisal University, Saudi Arabia. He also worked with the National Commission for Academic Accreditation and Assessment (NCAAA), Education Evaluation Commission Higher Education Sector (EECHES) formerly NCAAA, Saudi Arabia, for institutional level accreditation. He also worked with the National Computing Education Accreditation Council (NCEAC). He has edited/authored more than 20 research books with reputed international publishers, earned several research grants, and a great number of indexed research articles on his credit. He has supervised several postgraduate students, including master's and Ph.D. He has awarded as a top reviewer 1% globally by WoS/ISI (Publons) recently for 2019. He is an Associate Editor of IEEE ACCESS, a Moderator of IEEE TechRxiv, a keynote speaker for several IEEE international conferences globally, an external examiner/evaluator for Ph.D. and master's for several universities, a guest editor of several reputed journals, a member of the editorial board of several research journals, and an active TPC member of reputed conferences around the globe.

SARDAR M. N. ISLAM (Member, IEEE) is currently working as a Professor with ISILC. He is also the Director of the Decision Sciences and Modelling Program with Victoria University, Australia. He is also a Distinguished Visiting Professor of artificial intelligence with UnSri. He is also a Distinguished Visiting Professor with AURAK. He has different disciplines of artificial intelligence, business analytics, digitalization, management science, and machine learning. His academic work has gained international acclaim in different areas, resulting in many 1) honors and awards; 2) distinguished visiting or adjunct professorial appointments in different countries; 3) appointment in editorial roles of journals; and 4) keynote speeches at international conferences in several countries. He has published 29 authored scholarly academic books in different disciplines, including business analytics, digitalization, and management science. Each of these books makes significant scientific contributions to the literature. These books are published by prestigious publishers and majority books are published in highly regarded book series. He has also published over 250 articles including a good number of top leading international journal articles in his specialized research areas. He has extensive experience in teaching, research, and doctoral supervision, for a long period of time in different countries. His research interests include artificial intelligence, analytics, machine learning, data science, blockchain, cybersecurity, mathematics, and applications in business, health, engineering, law, and sports.