Advances in Automation Technologies for Lower-extremity Neurorehabilitation: A Review and Future Challenges

Wenhao Deng, Ioannis Papavasileiou, Zhi Qiao, Wenlong Zhang, *Member, IEEE*, Kam-Yiu Lam, *Member, IEEE*, and Song Han, *Member, IEEE*

***Abstract*—The world is experiencing an unprecedented, enduring, and pervasive aging process. With more people who need walking assistance, the demand for lower-extremity gait rehabilitation has increased rapidly over the years. The current clinical gait rehabilitative training requires heavy involvement of both medical doctors and physical therapists and thus are labor-intensive, subjective and expensive. To address these problems, advanced automation techniques, especially along with the proliferation of smart sensing and actuation devices and big data analytics platforms, have been introduced into this field to make the gait rehabilitation convenient, efficient, and personalized. This survey paper provides a comprehensive review on recent technological advances in wearable sensors, biofeedback devices and assistive robots. Empowered by the emerging networking and computing technologies in the big data era, these devices are being interconnected into smart and connected rehabilitation systems to provide non-intrusive and continuous monitoring of physical and neurological conditions of the patients, perform complex gait analysis and diagnosis, and allow real-time decision making, biofeedback, and control of assistive robots. For each technology category, a detailed comparison among the existing solutions is provided. A thorough discussion is also presented on remaining open problems and future directions to further improve the safety, efficiency and usability of the technologies.**

***Index Terms*—Lower-extremity neurorehabilitation; wearable sensors; biofeedback; assistive robots; big data analytics platforms; gait quantification, disease diagnosis and analysis**

I. Introduction

The world is experiencing an unprecedented aging process. In 2014, 46 million people lived in the United States are 65 or older, accounting for 15 percent of the total population. This number is projected to be 74 million in 2030, representing 21 percent of the total U.S. population [1]. Many diseases are strongly related to aging, such as cardiovascular, muscularskeletal, and neurological diseases. For example, stroke is the leading cause of serious, long-term disability in the United States, with approximately 795,000 people suffer a stroke each year, and the risk of having a stroke doubles each decade after the age of 55 [2]. Many stroke survivors suffer from difficulty in standing, balancing, and walking. As a result, the demand for gait rehabilitative training has increased rapidly in recent years. Currently the clinical gait training is primarily carried out by the physical therapists, who observe patients' walking patterns and use clinical measures to design the training plan, and provide active assistance and stimulation to help patients regain walking capability. However, those standard clinical approaches cannot fully satisfy the needs from patients, as they are labor-intensive, subjective, and expensive. Moreover, patients have to visit clinics regularly and only get treatment during training sessions. This is inconvenient and time-consuming, and the patients are unable to exercise at home and receive feedback from the therapists, which significantly slows down the rehabilitation progress [3], [4].

In observation of the increasing demand and current limitations of gait training practice, advanced engineering techniques have been introduced into this field to make the gait rehabilitation automated, efficient and personalized. This is a very popular but challenging research field as it requires interdisciplinary expertises in mechatronic engineering, computer science, neuroscience, and physical therapy, to list a few. In the past decade, we have seen tremendous advances in sensing, biofeedback and assistive device design and development. For example, instrumented treadmill and wearable sensors have been developed to measure force, torque, and kinematics during walking to facilitate disease diagnosis and training plan development [5]. Based on the collected sensor data, various biofeedback mechanisms have been developed to make the data intuitive and helpful for patients and medical professionals [6]. Numerous assistive robots have also been developed to provide walking assistance for different joints, and have been tested in clinical environments with patients to validate their efficacy in improving the gait training performance [7]. Despite the fast development in sensing, biofeedback and robotic technologies for gait training, several fundamental challenges remain to be solved before those technologies become really safe, reliable, efficient, and affordable. Moreover, large amount of real-time data will be generated with the massive implementation and deployment of sensors and robotics, and this brings in new challenges on 1) how to connect those sensors and store the large volume of data generated from them, 2) how to perform both batch and continuous analytics on those data, and 3) how to provide real-time decision making and feedback to the gait rehabilitative training.

We envision the emerging networking and computing technologies that are being developed along with the proliferation of Internet of Things (IoT) devices and big data analytics platforms will provide good solutions to address the aforementioned challenges. Fig. 1 gives an overview of the future smart and connected lower-extremity neurorehabilitation systems. It is expected that sensing, feedback and assistive devices will be interconnected with an unforeseen speed to form integrated body area networks (BANs) to perform nonintrusive and continuous monitoring of physical and neurological conditions of the patients. Novel and powerful computing platforms will be utilized to process the exponentially growing (mostly unstructured) data collected during the full course of the rehabilitation planning and training process. These powerful platforms will make it feasible to execute complex gait monitoring, analysis, and diagnosis methods online, which used to be run in local computing facilities offline with

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(Corresponding author: Wenlong Zhang)

W. Deng and W. Zhang are with the Polytechnic School, Ira A. Fulton Schools of Engineering, Airzona State University, Mesa, AZ 85212 USA (e-mail: {wdeng16, wenlong.zhang}@asu.edu).

Z. Qiao is with the School for Engineering of Matter, Transport and Energy, Ira A. Fulton Schools of Engineering, Arizona State University, Tempe, AZ 85281 USA (e-mail: zqiao7@asu.edu).

I. Papavasileiou and S. Han are with the Department of Computer Science and Engineering, University of Connecticut, Storrs, CT, 06269 USA (e-mail: {ioannis.papavasileiou, song.han}@uconn.edu).

K.-Y. Lam is with the Department of Computer Science, City University of Hong Kong, Hong Kong SAR, P.R. China (e-mail: cskylam@cityu.edu.hk).

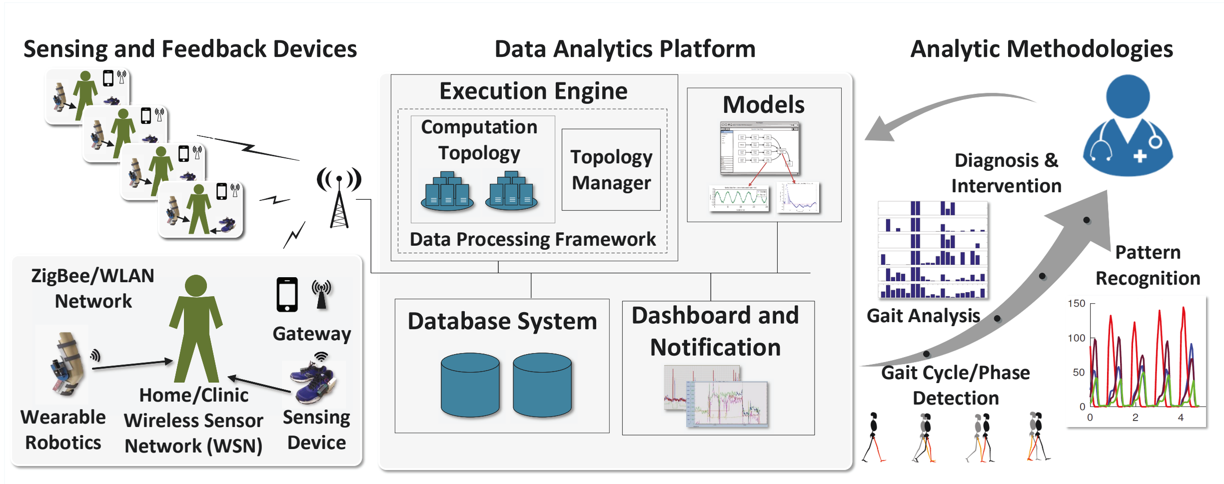

Fig. 1. Overview of sensing, feedback, networking and computing components in a smart and connected gait rehabilitation platform

frequent interrupt and intensive input from the medical professionals. The combination of these technological advances now has the true potential to close the loop of sensing, communication, decision making and feedback in gait rehabilitation systems, and is expected to significantly improve their responsiveness, efficiency and safety.

This survey paper provides a comprehensive review on recent advances in automation technologies in the IoT and Big Data era that can lead to smart and connected gait rehabilitation systems. Novel force and kinematic sensing techniques are summarized in Section II. Section III introduces various user interfaces and robotic devices to provide active feedback to patients and medical professionals. Section IV summarizes the desired key features of networking technologies in connected gait rehabilitation systems, and gives a comparison among the existing BAN technologies. In Section V, a systematical review on the computational methodologies is given for gait quantification, analysis, and pattern recognition. Most of these methods are based on recent advances in machine learning and data mining techniques. They are computation-intensive, and were not able to be executed online without the support of the emerging streamlined computing platforms which are also reviewed in Section V. Finally, a discussion on remaining open problems and future directions in gait rehabilitation research is presented in Section VI. Section VII concludes the paper.

II. Novel Sensing Technologies

There is a growing interest in utilizing smart sensing devices to facilitate gait rehabilitation in ambulatory settings as the traditional methods used by medical professionals can be subjective and inaccurate [5], [8]. Wearable sensors can offer a more accurate, convenient and efficient way to provide useful information on gait kinematics and gait kinetics. Gait kinematics studies the human motion and it can be measured using inertial sensors as well as motion capture systems. Gait kinetics refers to the study of forces and torques that result in the dynamic movements in a human gait. In this section, force, torque, and kinematic sensing will be surveyed. It should be noted electromyography (EMG) and electroencephalography (EEG) signals are often measured to help gait analysis as well, but they will not be included in this paper due to the page limit.

A. Force and Torque Sensing

Force and torque sensing plays an important role to understand human walking dynamics. For gait analysis and rehabilitation, force sensing usually takes place at the ground contact and torque sensing usually takes place at the joint level. With contact force and joint torque measurement, researchers are able to build full lower-extremity walking models [9], [10] to understand the causes for pathological gaits [11], and to determine the assistance that a robotic device should provide [12]. Ground contact forces (GCFs) [13] are important for classifying gait phases [14], [15], understanding human walking intention [16], and detecting abnormal gait [17] and fall [18]. To measure GCFs, force sensitive resistors (FSRs) are very popular given their low price and ease of use [19]–[22]. For example, a shoe-integrated wireless sensor system based on FSRs has been developed to provide quantitative gait analysis [23], as shown in Fig.2 (a). Force plates are often used in the clinical environment to provide high-accuracy GCFs measurements [24]–[29]. In order to collect GCFs outside a motion capture laboratory, a portable force plate (Fig.2 (b)) has been developed [30]. As shown in Fig.2 (c), Fiber-based force sensors have been used [31] to improve the user's comfortability but its measurement accuracy is generally low [32]–[34]. Pneumatic-based force sensing systems have been developed to measure GCFs [35]. For example, as shown in Fig.2 (d), a smart shoe system has been developed, where a silicone tube is coiled at the bottom of the insole and connected to a barometric sensor to estimate GCFs by the air pressure measurement [36]–[38]. In addition, soft force sensor based on embedded microfluidic channels (Fig.2 (e)) has been developed to measure both the normal and shear forces during ground contact [39]. Additionally, load cells have also been used to measure GCFs [40]. Instead of direct measuring torque during gait rehabilitation, torques are usually calculated through model-based estimation. Toque estimation can be achieved by inverse kinematics based on data from force sensing and human body segment parameters [41].

There have been several successful research and commercialized products using force and torque sensors. For example, a robot suit has been developed to enhance healthy users' activities and support physically challenged person's daily life by measuring and utilizing GCFs to estimate the motion intention of the user [44]. Moreover, a novel method to provide a distributed measure of the pressure interaction between the user and the exoskeleton at the right leg upper cuff has been proposed [45], in which the pressure between the user-exoskeleton contact area is obtained through a distributed pressure sensor, which can be served as an effective tool for real-time monitoring of the local stress on the user's skin and changing the exoskeleton control to avoid excessive local pressure possible. ReTiSense developed smart insoles called Stridalyzer with embedded

(a) (b) (c) (d) (e) (f) (g)

Fig. 2. Examples of wearable sensing systems for gait analysis: (a) Force sensitive resistor [23], (b) Force plate [30], (c) Fiber-based force sensor [31], (d) Pressure-based force sensor [36], (e) Soft force sensor [39], (f) Xsens IMU unit [42], (g) Micro IMU [43]

Comparison	FSR	Force plate	Fiber-based sensor	Calibrated pressure sensor
Accuracy	Medium	High	Low	High
Cost	Low	High	Low	Medium
Sensitivity	Low	High	Low	Medium
Flexibility	High	Low	High	High

TABLE I
COMPARISON BETWEEN DIFFERENT FORCE SENSING TECHNOLOGIES

Comparison	IMU	Motion capture systems	Computer vision	Encoder
Accuracy	Medium	High	Medium	High
Cost	Low	High	Medium	Medium
Sensitivity	Medium	High	Low	High
Portability	High	Low	Medium	Medium

TABLE II
COMPARISON BETWEEN DIFFERENT KINEMATIC SENSING TECHNOLOGIES

fiber-based force sensors, which can provide users with real-time tracking and analysis during walking and running. Commercialized smart socks with embedded fiber-based force sensors have been developed by Sensoria, which are able to identify injury-prone running styles and provide real-time feedback via audio cues based on force sensing. As a summary, the general characteristics of different force sensing technologies are compared in Table I. Force sensitive resistors, force plates, fiber-based sensors, and calibrated pressure sensors are compared for force sensing based on literature review and authors' own experience.

B. Kinematic Sensing

Kinematic sensing provides motion information of the user. Traditionally, encoders [46], [47] and inclinometers (tilt sensor) [48] have been used in kinematic sensing. Encoders generally provide accurate measurements but they need to jointly work with rigid mechanical segments [49]. Inclinometers have been used in measuring joint angle [50]. In recent years, inertial measurement units (IMUs) are widely used for analysis of human motion [51], postural orientation [52], estimation of step length [53], detection of fall [54] and estimation of gait phases [55]. IMUs usually consist of accelerometers and gyroscopes, sometimes also including magnetometers [56]. An accelerometer can be used to sense accelerations of an object to which it is attached [57]–[59], and gyroscopes can sense the rate of turning of an object and orientations can be estimated accordingly. Magnetometers can sense the earth's magnetic field strength and can be used to calculate the North Pole direction as an absolute reference direction. However, the gyroscope signals are subject to drift and the accelerometer measurements can be very sensitive. Signal interference with ferrous material nearby can cause inaccuracy of magnetometer measurement [60]. The IMUs are often used to estimate lower-extremity joint angles through sensor fusion. Kalman filters [61], [62], extended Kalman filters [63], [64], complementary filters [65]–[67], and particle filters [68], [69] have all been developed to deal with the accelerometer noise and gyroscope drift.

There are also several commercialized IMUs for motion analysis, for example, Xsens (Fig.2 (f)) developed different commercialized IMUs that can be used for real-time applications in gait analysis, rehabilitation, and injury prevention [42]. Moreover, as shown in Fig.2 (g), a micro IMU has been developed for motion analysis in portable and embedded applications [43].

Motion capture has been widely used for activity tracking, pose estimation, and movement recognition in rehabilitation purposes [70]. Typical motion capture systems are marker-based tracking systems and the markers can be passive [71]–[73] and active [74]. Passive markers only reflect incoming light while active markers can produce light to be collected by a camera system [75]. Gait analysis is one major application of motion capture in rehabilitation study. For example, a human motion tracking system for gait and dynamic balance training program has been developed [76]. Existing systems have demonstrated that motion capture helps accelerate recovery in human movement [70], [77], [78], but many challenges still remain due to the long time required for setting up the instrumentation, complexity for analyzing the data, low mobility, and high cost [75].

Human activity monitoring and recognition by computer vision systems have also been studied for human motion analysis and intelligent human-robot interactions [79]. Computer vision is often preferred because it can provide a mobile, non-obtrusive, and inexpensive solution [80] for whole-body tracking and human motion analysis without markers. Computer vision systems have been used for various human motion analysis applications which include tracking (segmenting and continuously monitoring humans), pose estimation (estimating the kinematics of humans) and recognition (recognizing the identity of individuals and their actions from images) [81]. In recent years, Kinect-based systems have been widely applied in physical therapy and rehabilitation [82], [83]. Compared to traditional RGB-based cameras, Kinect integrates in an infrared (IR) emitter and an IR depth sensor, and thus supports full-body 3D motion capture. Its Software Development Kit (SDK) also makes the development of rehabilitation-related applications much easier and faster. Despite all the recent technological advances, human motion analysis using computer vision is still a challenging problem mainly due to large variations in human motion and environment settings. With the development in artificial intelligence (AI), it is possible to employ those technologies to improve human motion analysis in gait rehabilitation [84]–[87]. Different kinematic sensing technologies are compared in Table II, which includes IMUs, motion capture systems, computer vision, and encoders.

III. NOVEL FEEDBACK MECHANISMS

Biofeedback, a technique for providing biological information in real-time, has been used for a few decades to help the patients regain their normal movements [6]. Haptic, auditory, visual feedback systems and brain-computer interfaces are commonly used in lower extremity rehabilitation [95]–[97]. With the information collected from such feedback systems, robotic assistive devices, such as exoskeletons and prosthetics, have been used to provide assistance

(a) (b) (c) (d) (e) (f) (g)

Fig. 3. Examples of robotic rehabilitation devices: (a) Indego Exoskeleton [88], (b) Hybeid Assistive Limb (HAL) [89], (c) Rewalk [90], (d) ETH Zurich Exoskeleton [91], (e) Quasi-passive Exoskeleton from Yale University [92], (f) Passive Robotic Ankle Exoskeleton From Carnegie Mellon University [93], (g) Soft Exosuit from Harvard University [94]

for both healthy or impaired users. Due to the page limit, this section focuses on biofeedback and exoskeleton for gait rehabilitation.

A. Biofeedback

Haptic sensations have been primarily provided through the system's high-frequency vibration. The advantage of haptic feedback is apparent as it allows for the user to free up their auditory and visual sensory channels for other tasks [98]. Wearable tactile feedback has been used to facilitate gait improvement in foot progression angle [99] and tibia angle [100]. An integrated haptic feedback (IHF) system is designed to provide post-stroke ambulatory subjects over-ground gait training [101]. This system contains a portable cane and a wearable vibrotactor array to generate kinesthetic and haptic feedback. Since the IHF system is relatively easy to use and low-cost, it could be a valuable tool to assist physical therapists in gait rehabilitation of patients with neurological disorders.

Virtual reality (VR) and augmented reality (AR) also have promising applications in rehabilitation. The major difference between VR and AR is the working environment. AR adds digital information to the image of current view to enhance the version of reality while VR uses computer technology to create an immersive virtual environment. There have been several successful healthcare studies using VR and AR. In [102], the performances of gait rehabilitation with a robot and VR system are compared with only a robot, and it shows that subjects walk faster and farther after using the robot and VR system. Also, a VR-based cycling training system for lower-limb balance improvement has been developed [103]. The functionality of the training system is tested with 10 stroke patients. Results of both bilateral pedal force and force plate test suggest that the subjects' standing balance is improved.

Brain-computer interface (BCI) is attracting great interest from the research community, and researchers are able to decode the neural signals associated with specific human functions such as lower-limb movement [97]. Many of techniques are investigated to achieve non-invasive BCI, such as magnetoencephalography [104], electroencephalography [105] and functional magnetic resonance imaging (fMRI) [106]. In [107], researchers also examine the possible benefits of assistive robots and BCIs in this field. In addition, the European Commission (EC) has funded a coordination and support action for the BCI community called BNCI Horizon 2020 in 2015 to provide a global perspective on the BCI [108]. This roadmap provides the community with a clear picture of the potential benefits and challenges of BCIs now and in the future.

B. Robotic Assistive Devices

Lower-extremity exoskeleton and orthosis are primarily developed for three types of applications: gait rehabilitation, human locomotion assistance, and enhancing the physical abilities of able-bodied humans [109]. In the form of actuation mechanism, exoskeletons are classified as: active, quasi-passive and passive devices. Compared to passive or quasi-passive devices, active exoskeletons are generally heavier, but they are able to adapt the level of assistance by tuning the actuator output force/torque in real time, which is more suitable for rehabilitation. For powered exoskeletons, hydraulic actuators, pneumatic actuators and electrical motor are commonly used to generate desired force or torque [88], [110], [111]. Hydraulic and pneumatic actuators usually provide higher power but both of them require additional supply system which makes such designs not portable and the intricate fluid dynamics of these systems are difficult to model and control [7]. In contrast, electrical motors are light and easy to control which makes this type of actuator a popular solution for portable rehabilitation device.

Researchers from both industry and academia are interested in rigid-link exoskeletons whose frames are pivoting about individual joints. Vanderbilt exoskeleton (commercialized as Indego), Hybrid Assistive Limb (HAL), ReWalk and Modular Lower Limb Exoskeleton from ETH Zurich (Figs. 3 (a)-(d)) use electrical motors as their actuators to provide assistance on multiple joints [88], [112], [113]. The research group from Ekso Bionics also uses DC motors to assist individuals with spinal cord injuries to stand and walk [114]. Quasi-passive and passive devices (Figs. 3 (e)-(g)) utilize elastic components to store and release energy based on different locomotions of human body. Commonly used electrical actuators are direct-driven motors and series elastic actuators (SEAs) [115]. Compared to the direct-driven mechanism, SEAs provide improved safety for the user since the elastic components will absorb the energy when the actuator outputs large amount of torque. In addition to the compliant feature, force controllable and back-drivable characteristics are also favored in the rehabilitation applications.

Effective control and optimization strategies are critical for lower-limb rehabilitation robots [116]. The overall control strategies can be classified into three levels [117]. High-level controllers are responsible for predicting the users locomotive intent based on signals from the user and environment [118], [119]. Mid-level controllers receive information about user's motion intentions from high-level controllers and translate those signals to output state for the robotic device as a desired profile [120], [121]. By directly controlling the actuator, low-level controllers minimize the error between the current measurement and desired value to track the desired profile [122], [123]. Commonly used techniques for the low-level control are PID control, adaptive control, and robust control. A PID controller is easy to design but finding the proper PID gains for a specific robot and user can be difficult. Both adaptive controllers and robust controllers are designed to deal with uncertainties from the robot, human, and environment. In [124], researchers calculate the active human torque components using the inverse dynamic algorithm and adapt the assistance level of the exoskeleton accordingly. While in [125], a robust control method is presented to control a knee assistive device. This method guarantees the controller is stable in the presence of modeling error in both stance and swing phases.

As a relatively new field, soft robotic devices refer to those with compliant materials/mechanisms and could generate large strains in normal operation [126]. Soft robots are primarily composed of easily deformable matter such as fluids, gels, and elastomer [127], which matches the elastic and rheological properties of biological tissue [128]. Many soft robotic devices have been developed for healthcare and rehabilitation purposes. The lower-limb soft exosuit (Fig. 3 (i)) developed by researchers at Harvard University is used to assist patients with muscle weakness and physical or neurological disorders [129], [130]. A design and control of a bio-inspired soft wearable robotic device for ankle-foot rehabilitation has also been presented [131]. In addition, active soft orthotic devices for assistance of ankle [131], [132] and knee [111], [133], [134] motion have been developed. However, accurate pressure or position control of a soft actuator is still an open problem due to the complicated material properties and fluid dynamics.

IV. Networking Technologies for WBANs

With the great advances of sensing and feedback technologies developed for lower-extremity neurorehabilitation, an ever-growing large amount of biosensing data is constantly generated, and needs to be transported to either a local or cloud-based computing system for processing, analysis and decision making. In addition, the control of feedback devices needs to be performed in a timely manner to optimize the user experience and training performance. To achieve these goals, networking techniques play a critical role to interconnect heterogeneous sensing and feedback devices to achieve fast, scalable and reliable data transport while preserving required security and privacy. Many Wireless Sensor Networks (WSN) and Wireless Body Area Networks (WBAN) based solutions have been proposed to attain these properties [135]–[138]. However the fast growing volume and complexity of the sensor data, the integration of assistive robotic devices, the user mobility and network co-existence issues bring in many new challenges in WBAN designs. Comprehensive surveys on the latest advances in WBAN research and development have been provided in [137], [139]–[143], and a selective list of recent 802.11 and 802.15.4 based WBAN solutions along with their key characteristics are summarized in Table III. In the following, we focus on reviewing four key parameters of networking technologies in WBANs: timing performance, reliability, scalability, privacy and security. We select these parameters due to their great importance to characterize how suitable a networking technology is to support real-time, reliable and secure communication among an ever-growing number of sensing and feedback devices. Please note that to provide further connectivity to cloud-based computing systems, Wide Area Network (WAN) infrastructures are generally employed. Review on networking technologies beyond the single BAN setting can be found in [137].

A. Timing Performance

Networking technologies employed for lower-extremity rehabilitation systems need to support real-time communication to close the loop of sensing, computing and decision making in physical rehabilitative training. Many factors can impact the timing performance of WBANs, and a major one is the employed data link layer protocols. For example, collision-based Media Access Control (MAC) protocols [140], [146] can achieve good network throughput especially when the network traffic is light [146], but cannot provide timing guarantees on the transmission latency and jitter. Time Division Multiple Access (TDMA)-based MAC protocols can provide bounded delay with a carefully designed communication schedule [144], but will experience significant packet loss when the network traffic grows. Many recent research efforts on WBANs also focus on the design of QoS profiles that provide the desired properties like low end-to-end delay [152]. Furthermore, the timing performance of WBANs may suffer from the mobility of the users. To address this problem, research efforts have been reported to design low-delay multi-hop protocols that can handle emergency messages [144], [149].

In addition to controlling transmission delay, time synchronization is another important design issue related to the timing performance in WBANs, as it helps not only in the design of MAC protocols, but also in the accurate data time-stamping. Extensive research work has been reported to design and evaluate time synchronization mechanisms among sensing and control devices in WBANs [150], [151], [153].

Comparing to sensing devices, assitive robots require much higher sampling rates ($\geq$ 1kHz) and have even more stringent requirements on bounding the transmission delays and jitters to provide desired control performance. In [154], a real-time high-speed wireless protocol called RT-WiFi was developed based on 802.11 physical layer. It was successfully integrated into a gait rehabilitation system and can support a sampling rate up to 6kHz. The design of RT-WiFi, however did not take energy consumption into consideration and is thus difficult to be directly applied on low-power sensing devices. We envision that an ideal real-time wireless protocol designed for WBANs will be configurable from software, and can be easily adapted to serve heterogenous sensing and control devices based on their different requirements on sampling rates and energy consumption.

B. Reliability

Reliable network connectivity is crucial to the success of connected rehabilitation systems, as critical health data need to be reliably transported to their destinations where intelligent decision making and feedback to the medical professionals and patients can be successfully and smoothly performed. As with the timing performance, the reliability performance can be considered either end-to-end or per link, and is typically reported in packet delivery ratio, in-order delivery, etc. [139]. The ubiquitous use of electromagnetic signals for wireless communication in clinic environments brings in serious challenges, such as increased and unpredictable interferences, and the “high mobility” and “group-based movement” make WBANs neither equivalent to wireless sensor networks nor mobile ad-hoc networks [155]. The work in [156] addresses these problems by proposing a social network based interference mitigation scheme for WBAN using acoustic signal processing and power management. Other research attempts solve the interference mitigation by using game theory in a distributed fashion [157] and coloring-based TDMA scheduling mechanisms [155].

The selection of the MAC protocols can significantly affect the reliability of the network. The CSMA/CA based protocols are generally not reliable for WBANs due to their unreliable clear channel assessment (CCA), traffic correlation, and heavy collision problems [140], [146]. On the other side, TDMA based protocols aim to minimize transmission conflicts, and thus have better reliability performance with appropriate retransmission mechanisms incorporated [144], [145]. The work in [140] reviews MAC protocols for

Method	Standard	Topology	Timing Performance	Reliability	Security & Privacy	Scalability
[144], [145]	-	Tree	High	-	Encr - Auth	High
[146]	ZigBee	Mesh	Medium	Medium	-	Medium
[147]	ZigBee/WiFi	Ad-Hoc/Tree	-	High	Encr - Auth	High
[148]	802.15.4	Mesh	Medium	-	Encr-Auth - Contx Priv.	Heterogen. Arch
[149]	-	Ad-Hoc	High	High	-	High
[150], [151]	ZigBee	Star	Medium	-	Encr [150] Encr - Auth [151]	-
[152]	802.15.{4,6}	Star	High	High	-	High

TABLE III

OVERVIEW OF REPRESENTATIVE BAN TECHNOLOGIES AND A COMPARISON OF THEIR KEY FEATURES

WBANs and concludes that TDMA mechanisms are good alternative as they can accommodate unpredicted sporadic events presented in the human physiological data. In addition to the MAC protocol designs, the designs of network architecture also affect the reliability of WBANs significantly. In general, the mesh topology is more reliable than the tree structure in the multi-hop WBANs, but the routing protocols need to be carefully designed to achieve performance balance between the desired reliability, the incurred network traffic and energy consumption.

C. Scalability

With the increasing number of sensors deployed in the rehabilitation systems, scalable networking technologies need to be employed to support the ever-growing volume of sensor data. Several factors can affect the scalability of the system at different layers of the communication protocols. In the MAC layer, contention and collision based protocols, like [152], are more scalable as they have no strict constraint on time synchronization, which makes them more preferred solutions compared to TDMA based technologies. Heterogeneous ad-hoc 1st-tier and multi-hop relay networks have been used to provide direct communication to the sensor nodes [149]. This architecture can incorporate high performance networks, like 802.11 to serve as backbone relay networks [147], which improves the scalability of the system significantly. Other research efforts aim to balance the power usage of the employed protocols and the network throughput. Hybrid solutions, like S-MAC [158], are attractive because they combine the benefits of contention and schedule based medium access mechanisms in order to scale to larger number of nodes. From the topology perspective, mesh and tree structures in WBANs can improve the scalability as there is no central bottleneck as in the star network topology [144], [146]–[148]. In addition to that, in order to reduce the data traffic within WBANs and from the WBANs to the cloud, edge computing technologies have been emerging, where the sensor nodes and gateways are being equipped with significant computing capability and storage capacity, so that the generated sensor data can be processed either in-network or at gateways, instead of transporting to the cloud [153].

D. Privacy and Security

Security protection and privacy preservation are among the most important issues in any networking technologies, especially in the healthcare industry where sensitive and private patient information is constantly exchanged [159]. The works in [142], [160] review security requirements, threats and solutions in WBANs, and [140] gives a survey on MAC layer security. The IEEE 802.15.4 standard classifies security modes into no security, encryption only, authentication only and encryption and authentication modes [140], [160]. Many existing WBANs use one or a combination of these modes, with most of them incorporating encryption and authentication mechanisms [145], [148], [151]. Due to the limited computing and power resources available on sensors, hardware accelerated security mechanisms are attractive solutions [148], while in the Application layer, novel biometric authentication methods have been used for designing secure WBANs [161], [162].

To preserve the privacy of the subject, de-identification of data is one of the ways that health related data are shared among systems and institutions [163]. By doing so, there is no direct way to identify where the subject data were collected from. Other ways to preserve the subject privacy include the dynamic privacy configuration rules change on the fly when an individual exhibits a behavior that is critical to his health and enable the authorized medical personnel to access vital data, which is otherwise hidden or available for anonymous statistical purposes only [148]. In [164], the authors consider the trade-off between individual privacy and system performance and introduce the notion of differential privacy, which can be used to formulate a performance optimization problem given a differential privacy requirement. Since networked rehabilitation systems are in essence networked control systems, this optimization framework can be employed in WBANs to achieve privacy-driven network resource management, while taking the other network performance, such as timing and reliability, into consideration.

V. COMPUTING METHODOLOGIES AND PLATFORM DESIGN FOR GAIT ANALYSIS AND DISEASE DIAGNOSIS

In this section, we review emerging methodology design for gait analysis and disease diagnosis, and streamlined computing platform design to perform these learning and analytic tasks in distributed and near real-time manner. We focus on popular algorithmic and computing methodologies that have been used for gait quantification, analysis, disorder diagnosis, and pattern categorization. The review starts with an overview of gait cycle, gait phase detection and gait parameters estimation. It then details the pattern recognition methods for classification and clustering of gait patterns. Figure 4 summarizes the methodologies that we will review in this section. At the end of this section, we review existing streamlined computing frameworks that can potentially serve as the computing platforms for large-scale networked rehabilitation systems.

A. Gait Quantification and Analysis

Gait quantification is important for objective gait assessment, analysis and diagnosis. It relates to the methods used for objective estimation of gait cycles and gait phases, and measurement of gait parameters which can be used to assess the severity of a subject's gait abnormality. Neurodegenerative disorders can affect the motor function of a patient and their gait. For example, Parkinson's disease (PD) is a complex disorder that is characterized by multiple symptoms such as bradykinesia, hypokinesia, muscular rigidity, and resting tremor [165]. In this subsection, we review methods and recent developments in gait quantification and analysis to estimate gait phases and gait parameters, including symmetry, balance and

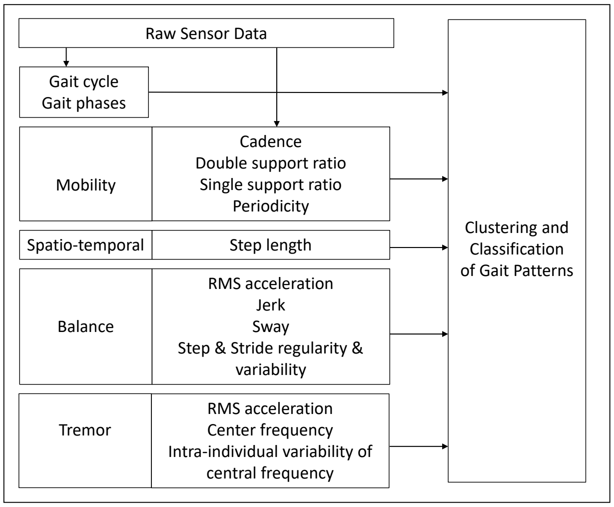

Fig. 4. An overview of methodology design for gait quantification, analysis and pattern recognition

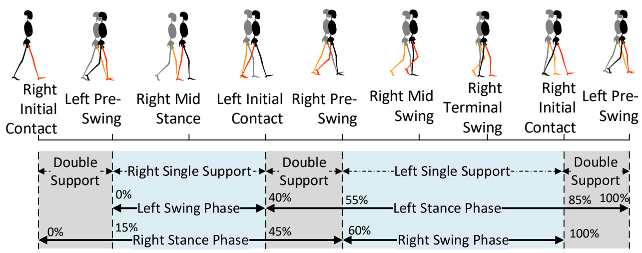

Fig. 5. An overview of gait phases, gait cycles, and basic mobility features [37].

stability, mobility and tremor detection. Please note this is not an extensive list of parameters. Depending on the patient condition, various other parameters can be introduced.

Gait cycle is the time interval between the same repetitive events of walking. Fig. 5 [166] gives an overview of two gait cycles at the lower two horizontal solid lines and gait phases at the top part. Typically there are eight gait phases for a healthy subject [36], [166], [167] (in Fig.5 terminal stance phase is not shown). However, in a pathological gait, some gait phases might be missing and the time allocation of gait phases might also be different from a normal gait. As discussed in Sections II-A and II-B, gait phase detection can be done with the use of GCF or IMU sensing devices. Various algorithms have been developed to classify all or some gait phases, such as Fuzzy logic rules [167], hidden Markov models [168], threshold-based rules [169], and Support Vector Machines (SVM) [170]. However, all the algorithms above require subjective input from both therapists and engineers. For example, the number of expected gait phases need to be pre-defined, or the threshold values of fuzzy logic rules and threshold-based algorithms need to be decided subjectively and they need to be adjusted for different subjects. As a recent development, in [37], [166] a new method is presented for real-time data-driven gait phase detection, which uses a parallel particle filter to estimate a Bayesian non-parametric model and does not require subjective input from experts.

To further study disorder specific gait abnormalities and symptoms, additional gait parameters are used in gait analysis and are calculated after the identification of gait phases. These gait parameter categories include but are not limited to mobility, symmetry, balance and tremor. Mobility is used to quantify gait, and includes general movement characteristics like cadence, single and double support ratio (Fig.5) and periodicity [171], [172]. Symmetry is another important gait parameter and is defined as a perfect agreement between the actions of the two lower limbs [173]. To calculate symmetry, mobility parameters (e.g., single support ratio) or spatio-temporal parameters (e.g., step length) can be used [172]. Symmetry indices (SI) have also been developed from GCFs data [173].

Balance or walking stability is mainly used to predict falls. In [174] multiple balance and stability measures are proposed, including RMS acceleration, jerk (time-series of first derivative of acceleration), sway (a measure on how much a person leans his/her body), step and stride regularity and variability. Lastly, tremor is a gait abnormality indicator and symptom of PD affected gait. In [175], the authors use a 2D stylus accelerometer to identify tremor in PD patients. It is observed that pathological oscillations are identifiable in the lower limbs through use of accelerometer measurements despite minimal evidence of tremor pathology during clinical examination. Features used include tremor intensity (RMS ACC recorded in 0.9 to 15 Hz band), center frequency, and intra-individual variability of center frequency.

Apart from studying sensor data for extracting features and parameters that are going to be used to evaluate and classify gait, analytic methods like Artificial Neural Networks (ANN) and gradient descent can be used to predict parameters that would otherwise need additional sensor types to be recorded. In [176], prediction of GCF during level walking is performed by employing an ANN and gait parameters like trajectory, velocity, and acceleration of the whole segment's mass center. In [177], a gradient decent based algorithm is used to predict the foot progression angle in real time, which is typically measured from marker-based motion capture systems. These methods can potentially be used in predicting parameters in home rehabilitation where expensive hardware equipment are harder to purchase. Finally, to overcome dispersement of gait patterns from patient's physical characteristics, such as weight, age and walking speed, novel normalization methods using dimensionless equations and multiple regression have been introduced, that can lead to statistically significant improved features and better classification performance [178].

B. Gait Pattern Recognition

In this subsection, we review classification and clustering techniques to capture and objectively evaluate gait abnormalities. The use of these learning methods aims to find groups of patients that contain similar sensing features and gait parameters, and thus may experience similar gait abnormalities. For this purpose, machine learning algorithms have been used to either perform cluster analysis or classification of gait patterns and to understand the importance of individual gait features. Domain knowledge has been used to define groups for classification of patients with relevant clinical meaning [179]–[181]. When such knowledge is not available, or not well understood, cluster analysis may be performed to explore underlying patterns in the data and group patients together according to their sensing features. The use of gait pattern recognition methods can significantly improve the outcome of gait rehabilitation in multiple aspects, such as assist in gait objective assessment, study gait changes due to disease progression [180], predict possible ongoing gait abnormalities, provide monitoring of gait outside the lab [182], [183], understand activations of multiple muscle groups [180], [184], develop targeted and personalized treatment [179], select patients for future studies [185] and develop a common framework for communication between clinicians [181].

Extensive research efforts have been reported to perform cluster analysis of post-stroke gait patterns to enable targeted treatment for patients within a cluster. In [186] non-hierarchical cluster analysis is used to categorize four subgroups based on the spatio-temporal, kinematic parameters, isometric torques, angle at the knee, and EMG data. Four clusters of patients are discovered, each having patients with similar gait abnormalities. Similarly, hierarchical cluster analysis of post-stroke gait patterns is conducted in [187], identifying three groups of patients with homogeneous levels of dysfunction. In [184] the authors present and validate a hierarchical clustering algorithm, being able to group strides and showing homogeneous onset-offset EMG activation intervals, which can be very important for designing therapeutic treatments tailored on the patient's needs. In [185], k-means clustering is used to group gait patterns in order to optimize participant selection in a biofeedback pedaling treatment.

Classification of abnormal gait patterns is another example of using machine learning methods in gait analysis for objective diagnosis [188]. For example, Unified PD Rating Scale (UPDRS), which is a representative clinical test scale for PD, not only relies on the experience of skilled clinicians, but also produces subjective judgment and can require very long time for recording of required items. The judgment is based on statistical scores rather than some unified objective rule-based system [189]. Using classification methods based on sensor data is therefore important as it provides a more objective judgment. Also, such methods can help reduce the workload of clinicians and let them rely on such computational methods to support and treat the increasing number of patients.

Classifying healthy from abnormal gait affected by a neurological disorder, such as PD or stroke, is one of the very well studied topics. Classification of post-stroke gait patterns against healthy gait is performed in [190] and [171], using kinematic and kinetic data. Classification of PD gait patterns against healthy gait is also studied. In [191] SVM and ANN are used to classify between PD and healthy gaits. In their experiments, twelve PD patients and twenty healthy subjects are asked to participate in the study and GCFs are measured using force plates. In [189] an open dataset of 93 PD patients and 73 healthy subjects is used for classification. Comprehensive preprocessing and wavelet analysis are used to extract features before data were fed to a neural network with weighted fuzzy membership functions. ANN are used in [192] to classify post-stroke patient's gait into three categories based on the types of foot positions on the ground at first contact: *forefoot, flatfoot,* and *heel*. Classification of gait based on groups derived from clinical knowledge is another well-studied topic [179]–[181]. [179] classifies hemi-paretic gait in three groups with two subgroups each. It shows the advantage of great usability in clinical routines without necessitating complex apparatus. In [180] the authors identify gait patterns in patients with Multiple Sclerosis by using concurrent recording of 2D video gait analysis, GCFs and surface EMG. They classify patients into 3 clinically meaningful classes based on the severity of their gait, including good, minimally impaired and moderately impaired walkers. In [181], the authors determine the extent to which gait disorders associated with traumatic brain injury are able to be classified into clinically relevant and distinct subgroups. Classification of gait patterns resulted from two major neurological disorders, i.e. PD and stroke, and healthy gait is performed in our recent research work [188]. An advanced classification algorithm, multi-task feature learning, is used to improve the classification performance and identify important gait features that can be used to distinguish gait patterns between the three groups. Finally, novel classification methods have been designed specifically for stroke related impairments, by utilizing geometrically unconstrained fuzzy membership functions to address the motion class overlapping issue with very low error rate [193].

Use of intelligent data analysis for lower extremity neurorehabilitation has the potential to uncover hidden data representations, but multiple challenges require attention. Clinically derived groups can be well understood by clinicians, but they are highly coupled with clinical experience and may lead to differences in interpretation and subjective evaluation. On the contrary, statistically driven classifications can define groups that only depend on the data and do not require expertise. A major difficulty however is interpretation of the derived groups, sensing features, and the possibility of creating artificial groups since these methods depend highly on the data and specific population used for the study. To overcome these challenges, future studies may need to design experiments with larger populations to reduce the non-generalizable results and design methods that assume the provided ground truth class labels may be unreliable to limit subjective bias from individual experts. Additionally, there is a lack of standardization, need for more studies on gait perturbation, severity and prognostic assessment rather than comparing healthy to pathological gait and more homogeneous protocols so that comparison between studies can be achieved [194].

C. Streamlined Computing Platforms

Based on the requirements on response time, gait analysis and disease diagnosis in rehabilitation can be done in either batch or streamlined manner. In batch-processing data are first stored and then analyzed. MapReduce [195] is a very popular batch-processing model, where data (key-value pairs) are divided in small chunks. Map tasks process these small chunks in parallel and Reduce tasks aggregates the intermediate results into final results. However such parallel big data processing frameworks do not naturally or efficiently support many important Data Mining and Machine Learning algorithms and can lead to inefficient learning systems. To avoid the scattered adaptation of mining and learning algorithms into the MapReduce framework, GraphLab [196] is introduced to support key machine learning and data mining algorithm properties, such as sparse computational dependencies, asynchronous computation, dynamic scheduling and serializability in large scale problems.

On the other hand, streamlined processing supports real-time processing on data streams or time-series data, such as those generated by smart sensing devices in rehabilitation systems. Streamlined computing platforms can provide a data pipeline for real-time gait monitoring, analysis, feedback and control, and thus significantly improve the response time of gait rehabilitation related learning and analytics tasks. Among the many existing real-time computing frameworks, Apache Storm [197] is a distributed framework which makes it easy to reliably process unbounded data streams. It uses custom created "spouts" and "bolts" to define information sources and manipulations to allow batch, distributed processing of streaming data. A Storm application is designed as a "topology" in the shape of a directed acyclic graph (DAG) with spouts and bolts acting as the graph vertices. Edges on the graph are named streams and direct data from one node to another. Together, the topology acts as a data transformation pipeline. From a high-level view, the general topology structure is similar to a MapReduce job, with the main difference being that data is processed in real-time as opposed to in individual batches. In Storm, all the data are stored in memory if the message exchanging happens in the same machine. This design makes Storm fast enough to process huge amount of data in real time.

Another alternative is the Apache Spark which is an open source cluster computing framework. In contrast to Hadoop's two-stage disk-based MapReduce paradigm, Spark's multi-stage in-memory primitives provide up to 100 times faster performance for certain applications. By allowing user programs to load data into a cluster's memory and query it repeatedly, Spark is well-suited to machine learning algorithms [198]. Some research efforts have also been made to integrate in the advantages of batch and streamlined data processing paradigms. In [199], the authors extend the MapReduce programming model to process streaming data. Their approach also includes two methods to predict streaming data workload in run time, so runtime Map and Reduce tasks can be increased or decreased.

To leverage all the computing infrastructures, many easy programming models and tools have been developed. For example, Spark provides a simple but expressive programming model that supports a wide range of applications, including ETL (extract, transform, load), machine learning, stream processing, and graph computation, which suit well for healthcare data processing [200]. The Spark API is centered on a data structure called resilient distributed dataset (RDD) which provides a form of restricted distributed shared memory. Continuous Query Language (CQL) is an expressing SQL-based declarative language for registering continuous queries against streams and stored relations [201].

Although the Storm and Spark computing frameworks have been widely used in many data analytics and decision making systems, their application in rehabilitation systems is still quite limited to the best of our knowledge. This may be attributed to the limited adaptation of large scale rehabilitation and the challenges associated with the different components, such as connectivity and distributed computing algorithms. To fill this gap, effective data stores need to be designed to support the increasing diversity and volume of sensor data collected from the rehabilitative trainings, and support both structured, and semi-structured/unstructured data. Furthermore, the streamlined computing platforms designed for rehabilitation need to be integrated or operate along with existing solutions for clinical decision support (CDS) systems [202] to support intelligent and objective decision making. However, interoperability and integration of different devices and heterogeneous system components should not compromise the effectiveness and security of the system [203], [204].

VI. Open Problems and Future Directions

Despite the great advances in various aspects related to lower-extremity neurorehabilitation, there are still many open problems that need to be addressed before these technologies can be safe, reliable, efficient, and affordable for patients to improve the training performance and quality of life.

User-friendliness for Wearable Sensors: Long-term continuous health monitoring will require novel energy solution especially for systems with multiple sensors [205]. Many ongoing research has focused on the development of micro IMUs [206] so that those sensors can be attached accurately at different joints of interests. Flexible pressure sensors are a good fit for rehabilitation purposes due to their compliance and light weight, but currently they can undergo only extremely limited strain [207]. Thus, it is important to develop flexible pressure sensors with a large measurement range. It is also important to address the problem of weight and comfortableness of wearable sensors. Besides the design of wearable sensors, some practical problems include end user centric design and ethical and safety issues, which are also extremely important for wearable sensors but are often ignored [208]. The fast advances in self-powered MEMS devices [209] and soft sensors [210] provide promising solutions to make future wearable sensors more durable and user friendly. Researchers have also started the discussion of ethical issues in ubiquitous wearable sensors from both sensor design and clinical implementation [211], [212].

Safe and Efficient Human-robot Interactions: Despite various types of sensing technologies available, at present most wearable sensor data are not fully used for robot control. Understanding how to interpret the sensor data is important for the design of robot control algorithms. With the rapid development in machine learning, deep learning and artificial intelligence, it is a popular topic to apply those learning techniques on robot control. However, many learning and control algorithms based on artificial intelligence require significant computing resources and powerful hardware, which makes them less applicable for wearable applications. Moreover, many artificial intelligence algorithms could lead to safety risks to patients wearable assistive robots [213]. So far very few exoskeletons have secured FDA approval for in-home use and it is really important to design robotic devices with higher safety standards so that the product can be accessible to customers easier. Cost is also another key factor for assistive robots to be popular in rehabilitation. For example, the price for HAL is between $14,000 and $19,000, which is not affordable for many patients. We have observed increased interests in the wearable robotics community on new algorithm framework to use model-based control for low-level motion force/motion control and machine learning for high-level planning to achieve both adaptation and robustness [214], [215]. Moreover, the emerging field of soft robotics also provided potential solutions to help with the safety issues due to its material compliance [216]. The U.S. National Science Foundation also identified soft robotics as one topic for its Emerging Frontiers in Research and Innovation program in 2018 [217].

Configurable and Adaptive WBAN Technologies: Despite the great advancements of WBAN technologies in recent years, many challenges remain. For example, human body movement needs to be better studied so that MAC and network layer protocols can be better adapted and become more reliable [139]. Also, existing network protocols may need to be further improved or even redesigned to support high bandwidth requirements [137] imposed by emerging rehabilitation systems and applications, especially with the integration of assistive robots. Network management solutions that support QoS [152], [218] also need to be further investigated, as they can help in balancing the available resources, while keeping up with the application requirements. Body energy harvesting solutions are also promising [139] and can help in supporting more resource-hungry requirements, such as increased security and local processing. The fundamental security requirements of the overall system are confidentiality, data integrity, accountability, availability and access control. To assure these requirements efficient encryption methods and key management protocols may need to be provided or further investigated [143].

Gait Analytics and Disease Diagnosis: Despite the great advancements of intelligent data analysis and its application in gait rehabilitation, the potential provided by such methods has not been fully exploited yet and many challenges remain [219]. For all the studies that employ new technologies to gait analysis, emphasis should be placed on the combined efforts of scientists to 1) increase human participant population sizes and patient characteristics to avoid creation of artificial groups from data-driven methodologies, 2) provide measurements in naturalistic environments, as it is likely to provide more realistic data [183], 3) study new or under-investigated topics (e.g. study of rigidity and non-motor domains for PD), as most of the studied topics involve classification of abnormal and normal gait, and 4) standardized and more stringent validation procedures [219], [220]. The high diversity of observed gait deviations, especially after stroke, limits the study to a small set of gait abnormalities [187], [192]. Furthermore, high quality research is needed to better understand the use of wearable sensors for the early identification of PD symptoms and for assessing fall's risk in this population [174]. Synergies between scientists are desired to improve the adoption of more objective statistically-driven classifications, which currently provide non-generalizable and artificial groups, compared to the clinically-driven classifications that are derived from the subjective clinical experience of the users [179]. To improve intelligent decision making and uncover hidden data representations and properties, contextual information may need to be taken into account, such as medication time-points, mindful state, alertness and EHR historic data [221]. To accelerate adaptation of distributed and scalable computing, statistical models need to provide objective assessment without need for extensive computing resources and selected algorithms need to be parallelizable and provide sparsity and effective feature selection.

Data Security and Patient Privacy: Protecting data security and patient privacy is an important but not extensively studied topic in this field. It is crucial that rehabilitation related data are kept intact at all levels of the analytic process from sensing to analytics. Security and privacy issues are especially important if we take into account the fact that gait data can be used as someone's identity, with extensive research efforts focusing on using gait for identification and authentication [222]. Appropriately securing such personal information can prevent identity theft and further personal data loss or theft.

VII. Conclusion

This paper gives a comprehensive review on the recent advances in automation technologies for lower-extremity neurorehabilitation. In the IoT and big data era, it is expected that mechatronics, communication and computing technologies, and health informatics are converging to close the treatment and rehabilitation loop for patients. The fast technology development makes it expectable that in the near future patients can conduct most of the training at home or local communities, while the medical professionals can access the wearable sensor and robot data remotely in real time, and provide high-level feedback and comments to the patients to guide their training. Given the broad range and fast advances of engineering technologies for lower-extremity neurorehabilitation, this survey paper focused on the recent advances on interdisciplinary approaches to enhance rehabilitation. It is expected that successful clinical trials will be conducted to validate the performance of connected wearable sensors and robots, as well as various data-driven approaches. We envision that these advanced technologies will become commercially available for the daily care of patients in the very near future.

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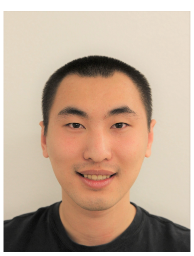
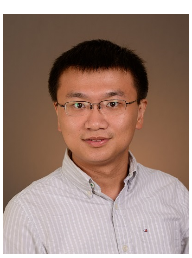
Wenhao Deng received his B.S. degree (magna cum laude) in Mechanical Engineering with Honors Research Distinction in 2015 from The Ohio State University. He received his M.S. degree in Mechanical Engineering and Applied Mechanics from University of Pennsylvania in 2016. He is currently pursuing his Ph.D. degree in Systems Engineering at Arizona State University. His research interests are in robotics, especially in rehabilitation and medical robots.

Ioannis Papavasileiou received the B.Eng. degree in Computer Engineering and Informatics from the University of Patras, Patra, Greece, in 2011; he is currently working towards the Ph.D. degree at the University of Connecticut, Storrs, CT, USA. His research interests include computing algorithms for gait analysis and biometrics, pattern recognition, ubiquitous computing, real-time and data-driven analytics.



Zhi Qiao received B.S. in Mechanical Engineering from the Dalian University of Technology, Dalian, China in 2015 and M.S. in Mechanical Engineering from the Arizona State University (ASU), Tempe, USA in 2017. He is currently working toward the Ph.D. degree in Mechanical Engineering at ASU. His research interests are in control theory, human intension estimation and human-robot interaction.



Wenlong Zhang received the B.Eng. degree (Hons.) in control science and engineering from Harbin Institute of Technology, Harbin, China, in 2010, and the M.S. degree in mechanical engineering in 2012, the M.A. degree in statistics in 2013, and Ph.D. degree in mechanical engineering in 2015, all from the University of California, Berkeley, CA, USA. He is currently an assistant professor in the Polytechnic School at Arizona State University, where he directs the robotics and intelligent systems laboratory (RISE Lab). Dr. Zhang’s research interests include dynamic system modeling and control, human-machine collaboration, and statistical learning.

Dr. Zhang received the Best Paper Award at the IEEE Real-time System Symposium in 2013, was a finalist of the Semi-plenary Paper Award at the ASME Dynamic Systems and Control Conference (DSCC) in 2012, and was a finalist of the Best Student Paper Award at the ASME DSCC in 2015. He received a Bisgrove Early Tenure-Track Faculty Award from Science Foundation Arizona in 2016.

Kamn-Yiu Lam received the BSc in computer studies and the PhD degree from the City University of Hong Kong in 1990 and 1994, respectively. He is currently an associate professor in the Department of Computer Science at the City University of Hong Kong. His research interests include real-time database systems, mobile computing, and cyber-physical systems and smart health services.

Song Han received the B.S. degree from Nanjing University, P. R. China in 2003, the M.Phil. degree from the City University of Hong Kong in 2006, and the Ph.D. degree from the University of Texas at Austin in 2012, all in Computer Science. He is currently an assistant professor in the Department of Computer Science and Engineering at the University of Connecticut. His research interests include smart and connected health, cyber-physical systems, real-time and embedded systems, and wireless networks. Dr. Han received the best paper award in IEEE real-time system symposium in 2013, and UConn research excellence award in 2015. His research is currently supported by NSF, UConn, UConn Health Center, and many industrial companies, including Emerson, Texas Instruments and Microsoft Research. Dr. Han is the member of IEEE and ACM, and the associate editor of ACM Transactions on Cyber-Physical Systems.